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Examining the Impact of Urban Neighborhood Disparities on the Treatment of Pediatric Overweight and Obesity Using Mixture Modelling

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EXAMINING THE IMPACT OF URBAN NEIGHBORHOOD DISPARITIES ON THE TREATMENT OF PEDIATRIC OVERWEIGHT AND OBESITY USING MIXTURE MODELLING

by

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Under the Direction of Lindsey L. Cohen, PhD

ABSTRACT

On average, specialized programs for pediatric overweight and obesity based on multicomponent behavioral interventions demonstrate efficacy. However, there is considerable heterogeneity in treatment response, particularly when considering attrition. Research on predictors of treatment participation and response suggests that many treatment failures are downstream consequences of broader social ecological factors. Advances in the availability of small-area spatial data on health outcomes has revealed large disparities in rates of pediatric overweight and obesity across neighborhood communities, suggesting a role for neighborhood-level variables. A growing body of research has demonstrated that aspects of the built (physical human-made features) and social environment are associated with pediatric overweight and obesity and proximal lifestyle behaviors. There is also some research to suggest that these factors impact treatment participation and response, particularly among disadvantaged communities. However, few studies combine neighborhood-level predictors with clinical treatment outcomes. Moreover, most studies utilize additive regression methods that are not able to capture the complexity of neighborhood environments. Using Geographic Information Systems (GIS) the present study examined the home neighborhood environments of participants in a pediatric weight management program. Mixture modeling was used to characterize latent classes of neighborhood environments, in terms of patterns among built and social environment features, and to predict treatment participation and outcomes by class. Results revealed disparities in home neighborhood environments in terms of overall accessibility (of built environment features), relative accessibility, and social environment. In addition, these disparities were associated with early attrition and weight management outcomes in theoretically consistent ways.

INDEX WORDS: Pediatric obesity, Weight management, Built environment, Social environment, Neighborhood, Mixture modelling

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DEDICATION

This dissertation is dedicated to my mother, father, and sister who have supported me in countless ways.

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Thank you to my academic adviser for your heartfelt mentorship and guidance. Thank you to my committee members for your contributions to this research. Thank you to my lab mates for your support, perspectives, and friendship.

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1 INTRODUCTION

Treatments for childhood overweight and obesity generally demonstrate positive effects on average; however, effect sizes are small and attrition rates are consistently high (Oude Luttikhuis et al., 2009). Thus, subgroups of patients differentially benefit from treatment. These subgroups can be characterized by social ecological factors, and several researchers have suggested that environmental barriers may be responsible for the limited success of interventions measured at the individual level (Epstein, Paluch, Roemmich, & Beecher, 2007; Maziak, Ward, & Stockton, 2007; Wickham, DeBoer, & DeBoer, 2015). Advances in small-area spatial analytics have demonstrated staggering disparities in health outcomes and obesity rates across neighborhood communities in the United States (National Academies of Sciences, Engineering, and Medicine, 2017). Epidemiological research utilizing Geographical Information Systems (GIS) methods has identified neighborhood-level built (physical human-made) and social environment features believed to underlie these disparities (Jia, Cheng, Xue, & Wang, 2017). These include factors that contribute to obesogenic environments, which are contexts that promote weight gain or interfere with weight loss (e.g., high density of fast food outlets, low availability of recreational space, poor neighborhood safety) (Jia, Cheng, Xue, & Wang, 2017; Kumar & Kelly, 2017; Swinburn et al., 2011; Swinburn, Egger, & Raza, 1999). Therefore, it is reasonable to hypothesize that these factors would impact treatment participation and response, particularly among disadvantaged communities. Unfortunately, few studies combine social ecological predictors with obesity treatment outcomes. Moreover, there is a general lack of translational research exploring treatment predictors, and most of the existing evidence on treatment predictors is within the context of randomized controlled trials of potentially limited generalizability (Epstein & Wrotniak, 2010). Finally, the variables that determine the degree to which a neighborhood is obesogenic are numerous and complex making analysis with standard linear regression techniques difficult (Boone-Heinonen & Gordon-Larsen, 2012).

The current study furthers the literature base by demonstrating the predictive relationship between disparate neighborhood environments and pediatric obesity treatment outcomes (e.g., attrition, change in standardized body mass index). Data was analyzed from a specialty pediatric weight management clinic serving a diverse, high risk (i.e., high occurrences of severe obesity, medical comorbidities, low socioeconomic status [SES] and racial minority status) population. A structural equation model, including a mixture model analysis, was used to characterized neighborhood types. Results revealed interrelated disparities in built and social environment features across neighborhood types which predicted treatment outcomes in expected ways.

1.1 Treatment of Childhood Overweight and Obesity

1.1.1 The obesity epidemic

Rates of childhood overweight and obesity in the United States have tripled over the last three decades, and they long ago reached epidemic proportions (Ogden, Carroll, Kit, & Flegal, 2014). Excess adiposity is typically defined using body mass index (BMI), which measures weight relative to height. Overweight is defined as BMI ≥ 85th percentile for age and gender, and obesity is defined as BMI ≥ 95th percentile for age and gender. Currently, about one in every three children or adolescents is overweight or obese (Kumar & Kelly, 2017). As a direct result, related health problems more typically seen in adult populations, such as type 2 diabetes, fatty liver disease, cardiovascular risk factors, and orthopedic complications, are increasingly becoming the purview of pediatric providers (Ebbeling, Pawlak, & Ludwig, 2002). There are significant lifelong impacts of childhood obesity in terms of increased medical expenditures, reduced quality of life, and lower life expectancy (Finkelstein, Graham, & Malhotra, 2014);

childhood obesity is an independent risk factor for premature mortality in adulthood, and 82% of teenagers with obesity are obese as adults (Wright, Parker, Lamont, & Craft, 2001). The recent trends in childhood obesity may result in the current generation of children having a lower life expectancy than their parents, for the first time in two centuries (Olshansky et al., 2005). Childhood obesity is one of the most important public health challenges facing society today, and its prevention and treatment are major public policy priorities (Grossman et al., 2017; O'Connor et al., 2017).

1.1.2 Multicomponent behavioral intervention

The recommended treatment for pediatric overweight and obesity (for those patients who do not show weight loss from primary care intervention) is family-based multicomponent behavioral interventions delivered by a specialized multidisciplinary weight management team (Barlow, 2007). There is wide variation in treatment programs even at the level of highly-controlled efficacy trials; however, these programs generally include the promotion of healthy dietary and physical activity habits with the core treatment components of nutrition counseling, physical activity counseling, and behavior modification (Janicke et al., 2014). Nutrition counseling typically emphasizes appropriate portion sizes, meal schedules, and shifting diet composition from calorie dense, sugary choices to fruits, vegetables, and high protein and fiber choices (Altman & Wilfley, 2015). Physical activity counseling emphasizes substituting sedentary activities (e.g., screen time) with physical activity of gradually greater duration and intensity (Janicke et al., 2014). Behavior modification strategies are based on the principles of cognitive behavioral and social learning theories (e.g., reinforcement, stimulus-response, vicarious learning) and encourage the recommended nutrition and physical activity changes by modifying the context of target behaviors (Epstein, Wing, Steranchak, Dickson, & Michelson, 1980). Techniques include contingency contracting, self-monitoring, social reinforcement, modeling, prompting, stimulus control, and skills training. In addition, programs are increasingly incorporating motivational enhancement strategies, such as motivational interviewing, as treatment components or as a counseling style for the delivery of other strategies (Altman & Wilfley, 2015; O'Connor, Burda, Eder, Walsh, & Evans, 2016).

1.1.3 Treatment efficacy

A number of reviews of randomized controlled trials (RCTs) of multicomponent behavioral treatments have been conducted. They generally conclude that multicomponent behavioral interventions meet standards for evidence based treatments, but produce modest results due to small effect sizes, variability in long term outcomes, and high attrition (Altman & Wilfley, 2015; Janicke et al., 2014; Oude Luttikhuis et al., 2009). The magnitude of the attrition problem is difficult to quantify because many studies do not report attrition and there are varying definitions of attrition among reporting studies (Dhaliwal et al., 2014; Oude Luttikhuis et al., 2009). However, the general consensus is that pediatric obesity programs are hindered by high dropout both within and outside of RCTs, with relatively higher rates in the latter (Dhaliwal et al., 2014; Mauro, Taylor, Wharton, & Sharma, 2008). A review of RCTs found attrition as high as 42%, with over half of studies reporting attrition higher than 20%; and an integrated review of RCTs and single-group studies found a median attrition rate of 37% and a maximum rate of 83% (Dhaliwal et al., 2014). Beyond high attrition, pediatric obesity treatments demonstrate other indicators of poor participation, including low adherence to lifestyle recommendations and low attendance rates (Dhaliwal et al., 2014; Mauro et al., 2008), which are negatively associated with weight loss outcomes (Golan, Kaufman, & Shahar, 2006; Kalarchian et al., 2009; Kitzmann, Dalton, & Buscemi, 2008; Saelens & McGrath, 2003; Wrotniak, Epstein, Paluch, & Roemmich, 2005). Understanding barriers to participation and subsequent lifestyle change is a key step to guiding future intervention development and helping clinics better tailor their treatments.

1.2 Social Ecological Approach to Predicting Treatment Response

In combating the obesity epidemic, current treatment approaches are effective on average, but there is variability in treatment responsiveness, particularly on an intent-to-treat basis. Thus, it is crucial that we identify factors related to treatment participation and subsequent weight outcomes. Study of treatment mediators and moderators provides important information on how, for whom, and under what conditions treatments work (Yirmiya, 2010). A recent update on the evidence base concluded meaningfully that to date, no robust mediators and moderators of treatment have been identified (Altman & Wilfley, 2015). This state of affairs is likely due to the sparseness of translational effectiveness research (Epstein et al., 2007) and the difficulty obtaining objective measures of mediators (e.g., food intake, exercise) (O'Connor et al., 2016). Barring consistent information on mediators and moderators, identification of predictors of treatment response is an important preliminary step. Potential treatment predictors can be identified across treatment, etiological, and epidemiological research; and this process should be guided by a theoretical framework (Mackinnon, 2011). A complete review of all the efforts to identify these variables is beyond the scope of the current research; however, an argument will be made for the adoption of a social ecological framework in examining treatment predictors. From this perspective, broader contextual factors come into focus as important potential predictors.

1.2.1 Predictors of weight outcomes

Attempts to identify predictors of weight outcomes have largely focused on variables at the individual and family level, which follows from the cognitive behavioral focus of treatment interventions; but there have been few consistent findings with limited implications for future treatment development (O'Connor et al., 2016). Younger age and lower degree of overweight at baseline are both robust predictors of treatment response (Altman & Wilfley, 2015). Among studies that specifically target parental weight loss, degree of parental weight loss is also a consistent predictor of child weight loss (Altman & Wilfley, 2015). Other, more preliminary predictors of better treatment response include greater social support (Moens, Braet, & Van Winckel, 2010), lower parental psychopathology (Fröhlich, Pott, Albayrak, Hebebrand, & Pauli-Pott, 2011; Moens et al., 2010), and more self-monitoring (Jelalian et al., 2010).

1.2.2 Predictors of treatment participation

The high attrition observed across treatment studies has led researchers to increasingly look specifically at predictors of treatment participation (though the dichotomy between participation and weight outcomes may be artificial). Research on predictors of treatment participation is nascent and there are few consistent findings, but the results do seem to suggest that social determinants of health are prospectively related to participation. Social determinants of health are social variables, such as ethnicity and socioeconomic status (SES), that have direct or indirect effects on health, due to the relative risk they confer to an individual within a particular social ecological context (Braveman, Egerter, & Williams, 2011). Black ethnicity, relative to white ethnicity, is often associated with study dropout, and lower family income is associated with lower compliance (Ligthart, Buitendijk, Koes, & van Middelkoop, 2017). In addition, participation in public health insurance, often a proxy for SES, consistently predicts dropout (Dhaliwal et al., 2014). The identification of social determinants of health as treatment predictors necessitates a broader view of the social ecological context in which these determinants come to confer risk.

1.2.3 Social ecological approach

The limited success in general of interventions that target individual determinants of behavior have led researchers to increasingly broaden their theoretical perspectives from cognitive behavioral models to social ecological models (Baranowski, Cullen, Nicklas, Thompson, & Baranowski, 2003; Epstein, Raja, et al., 2012; McKay, Bell-Ellison, Wallace, & Ferron, 2007). Generally, social ecological models situate individuals and behavior within a multilayered sociocultural, economic, political, and physical context (Baranowski et al., 2003). There are a number of empirical indications from multiple areas of research—etiological, epidemiological, treatment—that implicate social ecological factors in the development and maintenance of childhood obesity and by extension, treatment response (Maziak et al., 2007). First, the general consensus is that the population wide increases in obesity over the last several decades are due to changes in environmental factors that contribute to obesogenic environments—contexts that promote higher energy intake and lower energy expenditure (Epstein et al., 2007; Swinburn et al., 2011; Swinburn et al., 1999). These factors include the increased availability of energy dense, low protein foods and decreased availability of opportunities for physical activity (Swinburn et al., 1999). Second, epidemiological research has consistently implicated social determinants of health in the development of pediatric obesity. Ethnic minority communities and low SES communities are disproportionately impacted by pediatric overweight and obesity, and disparities have continued to widen over time (Frederick, Snellman, & Putnam, 2014; Ligthart et al., 2017; Samaranayake, Ong, Leung, & Cheung, 2012; Strauss & Pollack, 2001). Finally, as stated earlier, social determinants of health have been prospectively related to obesity treatment participation.

In summary, although obesity treatment typically targets individual and family level cognitive behavioral factors, there is evidence from multiple lines of research that indicates social ecological factors could be responsible for the heterogeneity in treatment response.

1.3 Social Ecological Model of Obesity

Social ecological models of obesity organize drivers along multiple levels of influence, from micro to macro (e.g., individual, family, neighborhood, school district; Davison & Birch, 2001) and across several environment types (physical, economic, political, sociocultural; Swinburn et al., 1999). Within these frameworks there are many, often intersecting, hypothesized pathways of influence from distal environmental drivers, to proximal individual behaviors (physical activity, food intake), to outcomes (BMI) (Maziak et al., 2007). As an hypothetical illustration, the combination of 1) neighborhood saturation of fast food restaurants offering inexpensive and convenient "comfort foods" (physical, political, sociocultural), 2) low availability and high prices of fruits and vegetables (physical, economic), and 3) limited time for food preparation (economic, sociocultural) could negatively impact a family's ability or inclination to eat healthful foods.

Overall, social ecological models highlight that obesity risk factors at the level of individual behaviors are, in part, downstream consequences of broader contextual drivers (Maziak et al., 2007). For example, research on fruit and vegetable consumption, may be missing key causal influences by focusing on knowledge and taste preferences over relative cost and availability (Maziak et al., 2007). Social ecological models also highlight that ecological constructs, such as obesogenic environments, are multidimensional and jointly determined by variables across environment types (physical, economic, political, sociocultural) (Marini & Burton, 1988; Nau, Ellis, et al., 2015). As such, they are best considered as the confluence of environmental indicators. Finally, the social ecological orientation suggests that broader contextual factors likely interact with individual and family social determinants or cognitive behavioral variables to influence health outcomes (Nau, Ellis, et al., 2015).

Many of the hypothesized pathways of the social ecological model have yet to be empirically validated, and attempts to determine the relative importance of the various levels are currently limited (Kirk, Penney, & McHugh, 2010; Ohri-Vachaspati et al., 2015). However, as stated previously, much of the increase in obesity rates over time has been attributed to environmental changes that result in increasingly obesogenic environments. In addition, advances in Geographic Information Systems (GIS) and spatial analytics have revealed a high degree of heterogeneity in obesity risks and prevalence across neighborhood communities (Jia et al., 2017), which appears to underlie much of the disparities observed in ethnic minority and low SES groups (Gordon-Larsen, Nelson, Page, & Popkin, 2006). Most of the existing research is epidemiological in nature, but increasingly treatment researchers are including neighborhood variables as predictors in their studies.

1.4 Neighborhood disparities

The increased availability of more granular spatial data has revealed large disparities in health outcomes in the United States over small geographical areas, such as zip codes, counties, census tracts, and increasingly, person-centered neighborhoods (National Academies of Sciences, Engineering, and Medicine, 2017). For example, life expectancy was found to differ by as much as 25 years among neighborhoods in New Orleans (Evans, Zimmerman, Woolf, & Haley, 2012). Similar neighborhood disparities have been observed for childhood obesity. Pediatric obesity rates differ by as much as 150% across small-area neighborhoods within the same state, after controlling for child- and family-level covariates (e.g., race, family SES; Bethell, Simpson, Stumbo, Carle, & Gombojav, 2010).

Epidemiological studies of pediatric obesity have attempted to identify aspects of neighborhood communities that could underlie observed differences in obesity rates and related lifestyle behaviors. A majority of the variance, estimated at 67% by Nau et al. (2015), can be explained by features of the built and social environments.

1.4.1 Built environment

The built environment refers collectively to the constructed features of a neighborhood environment, such as parks, retail locations, roadways and walkways (Drewnowski et al., 2020). Past research has identified several features of the built environment that are associated with obesity rates and proximal weight-related lifestyle behaviors. These features generally contribute to the accessibility of physical activity opportunities or the accessibility of healthful and unhealthful food supply (Singh, Siahpush, & Kogan, 2010).

1.4.2 Accessibility of physical activity opportunities

Availability of space and opportunities for physical activity have been associated with obesity rates and physical activity behaviors. Reviews found that availability of recreational facilities is positively associated with physical activity levels (Kirsten Krahnstoever Davison & Lawson, 2006; Ding, Sallis, Kerr, Lee, & Rosenberg, 2011) in children and adolescents and negatively associated with obesity rates in adolescents (Dunton, Kaplan, Wolch, Jerrett, & Reynolds, 2009). Relatedly, a study found a positive association between the proportion of green space (e.g., parks) in neighborhoods and physical activity levels among children (de Vries, Bakker, van Mechelen, & Hopman-Rock, 2007). Neighborhood indicators of walkability—suitability to active transport—have also been associated with physical activity and obesity rates.

Reviews reported significant positive associations between neighborhood walkability, measured by the coverage of both sidewalks and controlled intersections, and the physical activity levels of children and adolescents (Ding et al., 2011; Ferreira et al., 2007).

Results suggest that child and adolescent obesity are related to indicators of opportunities for physical activity, including recreational facilities, parks, and walkability (Ding et al., 2011; Dunton et al., 2009). However, studies differ considerably in terms of the subset of environmental indicators studied, operationalization of indicators, and characteristics of their target population, limiting comparability (Ding et al., 2011; Dunton et al., 2009; Jia et al., 2017).

1.4.3 Accessibility of food supply

Access to fruits, vegetables, and other healthful foods (measured by distance from or density of grocery stores and similar vendors) varies considerably across geographic areas, with areas of low access being termed food deserts (Allcott, Diamond, & Dubé, 2017). Proximity and density of grocery stores have been negatively related to risks of childhood overweight and obesity in some (Chaparro et al., 2014; Jilcott et al., 2011; Y. Li, Robinson, Carter, & Gupta, 2015; G. C. Liu, Wilson, Qi, & Ying, 2007), but not all studies (Laska, Hearst, Forsyth, Pasch, & Lytle, 2010; Ohri-Vachaspati, Lloyd, DeLia, Tulloch, & Yedidia, 2013). Two reviews concluded that there are generally inconsistent findings (Galvez, Pearl, & Yen, 2010; Jia et al., 2017).

Beyond the lack of access to affordable healthful foods, increasing attention is focused on the over-supply of unhealthful foods, with areas of high density of unhealthful foods being termed food swamps (Cooksey-Stowers, Schwartz, & Brownell, 2017). Unhealthful food outlets include fast food restaurants and convenience stores (small retail outlets that sell a higher percentage of packaged foods at comparatively higher prices). Greater proximity and higher density of fast food restaurants and convenience stores have been related to higher rates of pediatric overweight and obesity in most studies that have examined these relationships (Jilcott et al., 2011; Larson, Wall, Story, & Neumark-Sztainer, 2013; Laska et al., 2010; Oreskovic, Kuhlthau, Romm, & Perrin, 2009; Oreskovic, Winickoff, Kuhlthau, Romm, & Perrin, 2009). Interestingly, a recent national population-wide study found that indicators of food swamps better predicted BMI than indicators of food deserts (Cooksey-Stowers et al., 2017).

In general, the research on availability of healthful and unhealthful foods suggests associations between availability of food types and obesity rates, with relatively stronger evidence for supply of unhealthful foods (Jia et al., 2017). However, the research base suffers some of the same limitations as the physical activity research; namely, inconsistent measurement and low comparability among studies (DeWeese et al., 2018; Wall et al., 2012).

1.4.4 Social environment

The neighborhood social environment encompasses the collective social-demographic composition of a neighborhood (e.g., average socioeconomic status of residents, ethnic composition), as well as factors that result from social processes and interactions, such as community cohesion and crime (Carroll-Scott et al., 2013; Suglia et al., 2016). In past studies, neighborhood socioeconomic status (SES) and crime have been related to childhood obesity rates and proximal weight-related lifestyle behaviors (Kimbro & Denney, 2013; Lovasi et al., 2013; Nau, Schwartz, et al., 2015).

1.4.5 Neighborhood SES

Neighborhood SES has been related to risk of childhood obesity over and above family SES (Boone-Heinonen & Gordon-Larsen, 2012; Greves Grow et al., 2010; Nau, Schwartz, et al., 2015). This is consistent with the general health behavior research wherein there are differences in pathways of influence to health behaviors between neighborhood SES and individual SES

(Greves Grow et al., 2010; van Jaarsveld, Miles, & Wardle, 2007). While the specific pathways of influence are not well understood, it is likely that neighborhoods with a high concentration of disadvantaged individuals and a low concentration of affluent individuals are systematically marginalized. These areas have less economic and political power and are afforded less investment and less protections (Mode, Evans, & Zonderman, 2016). For example, lower SES neighborhoods often have more advertisements (signs and billboards) promoting unhealthy behaviors (consuming sugar-sweetened beverages or smoking; Cassady, Liaw, & Miller, 2015). In addition, less investment in disadvantaged neighborhoods may result in lower quality built environment features for the same level of accessibility (McKenzie, Moody, Carlson, Lopez, & Elder, 2013). For example, parks with litter, graffiti, and overgrown vegetation are less likely to be used by residents (Miles, 2008).

1.4.6 Crime

Neighborhood safety is a crosscutting sociocultural aspect of neighborhoods that affects both walkability and other physical activity opportunities, such as the ability to utilize parks. A review reported an inverse association between neighborhood crime and physical activity in adolescents (Ferreira et al., 2007), and a number of more recent studies have reported positive associations between crime and obesity rates (Gartstein, Seamon, Thompson, & Lengua, 2018; Lovasi et al., 2013; Singh et al., 2010). Pediatric residents living in areas with unsafe conditions are likely forced to spend more time indoors engaging in sedentary behaviors rather than engaging in outdoor physical activity such as walking and playing in playgrounds (Kneeshaw-Price et al., 2015).

Although variables related to the neighborhood social environment, including neighborhood SES and crime, uniquely contribute to BMI rates, few studies have included these measures in the operationalization of neighborhood environment as a whole.

1.4.7 Characterization of neighborhood environments

Neighborhood environments as a whole have been difficult to conceptualize, define, and measure, and there is not yet consensus on how to do so (Kirk et al., 2010). The risk factors appear to be numerous and complex with a great deal of heterogeneity among individuals and intersectionality among variables (Jia et al., 2017). Most studies examine a limited set of components of neighborhood environments, independently, using linear regression methods (DeWeese et al., 2018). These additive regression methods are unable to adequately capture neighborhood environments, which are theoretically determined by the pattern of environmental risk factors (DeWeese et al., 2018; Nau, Ellis, et al., 2015). The research base could benefit from better characterization of neighborhood environments in such a way that takes into account contributions from multiple indicators across environment types (physical activity accessibility, food accessibility, crime, neighborhood SES) and the covariance among them (Boone-Heinonen & Gordon-Larsen, 2012; DeWeese et al., 2018; Nau, Ellis, et al., 2015; Wall et al., 2012).

Two epidemiological studies to date have applied a specific type of mixture model, a latent class analysis (LCA), to classify neighborhoods using indicators of neighborhood environments (DeWeese et al., 2018; Wall et al., 2012). Mixture modelling is a latent variable technique that assigns individuals to latent categorizations (e.g., neighborhood types) according to covariance among a range of manifest indicators (e.g., proximity to parks, density of fast food stores, crime rates). LCA is a specific type of mixture model that utilizes only categorical indicators. Both studies that employed a LCA found differences in obesity rates according to substantively meaningful classes that included environmental factors related to physical activity, and food supply. The latent categories found by Wall et al. (2012) were also distinguished by neighborhood SES. In both studies, the classes better predicted obesity rates than did additive regression analyses. Finally, results demonstrated that several indicators with weak bivariate associations with obesity rates nevertheless, contributed meaningfully to the formation of latent class membership. These studies exhibited the benefits of using LCA over other analysis techniques in terms of both characterizing obesogenic environments as a whole, and identifying individual predictors (DeWeese et al., 2018; Wall et al., 2012). Although these studies advanced the scientific approach to examining the obesogenic environment and contributed data linking the obesogenic environment to obesity, neither included obesity treatments; thus, it is still not known how obesogenic environments, as measured by mixture analysis, might influence treatment.

1.4.8 Obesogenic neighborhood environments as treatment barrier.

In addition to the cross sectional and longitudinal associations studied, naturalistic and quasi experimental studies have explored changes in obesity and related health behaviors in response to changes in built environments (e.g., building grocery stores) and public policy (e.g., food taxes, food bans) (Mayne, Auchincloss, & Michael, 2015), though few studies focus on youth specifically. Findings have been mixed. Built environment changes related to physical activity and public policy changes related to food purchases appear to have small effects (Epstein, Jankowiak, et al., 2012; Mayne et al., 2015), while increases in healthful food supplies (i.e., building of grocery stores and supermarkets) have not resulted in improvements in food buying patterns and health indicators (Allcott et al., 2017; Boone-Heinonen & Gordon-Larsen, 2012; Mayne et al., 2015). However, such findings do not preclude neighborhood factors from being important predictors or moderators of obesity treatment response. In fact, such findings may highlight the benefit, from a public health perspective, of studying the intersectionality between broader social ecological drivers and treatment response at the level of individuals (Epstein, Jankowiak, et al., 2012). As an illustration, increasing recreational facilities alone, without corresponding informational, motivational, and behavioral intervention, may not change physical levels; however, a lack of recreational facilities may act as a barrier when these interventions are applied. Initial findings from treatment researchers (reviewed in the next section) who have measured social ecological factors, supports this proposition. For example, Armstrong, Lim, and Janicke (2015) found that baseline access to parks did not predict treatment outcomes in a control group, but did in a physical activity treatment group. Stated differently, higher park density alone did not predict changes in obesity rates, but park density did facilitate treatment response when a behavioral intervention was applied.

1.5 Neighborhood Environments and Treatment

Given the early findings that treatment participation rates are associated with social determinants and that built and social neighborhood factors are theoretically- and empirically-implicated in obesity rates, it is reasonable to hypothesize that these factors would impact participation and outcomes in obesity clinics. Studying the association between treatment and neighborhood factors could help identify subgroups of individuals who respond differentially to treatment. Moreover, such research could advance public health perspectives by highlighting key pathways from public policy to outcomes of individuals.

No studies to date have examined the impact of neighborhood environment factors on treatment participation. A handful of studies have examined the predictive relationship between neighborhood factors and treatment outcomes, but only one study employed a multicomponent behavioral intervention. Two treatment studies found that outcomes of physical activity interventions were moderated by access to parks (Armstrong et al., 2015; Epstein et al., 2006), and a small pilot study of a physical activity intervention found that outcomes were moderated by crime rates (Broyles et al., 2016). Epstein, Raja, et al., 2012 found that change in zBMI (BMI z-scores standardized according to age- and gender-based norms) was predicted by the neighborhood variables of parkland, number of supermarkets, and number of convenience stores, among four RCTs of a multicomponent behavioral treatment program. However, non-significant findings were reported for housing density, park plus recreational area, and grocery stores. Also, the relationship between supermarket density and zBMI was opposite that hypothesized, with greater supermarket density predicting higher zBMI. The authors concluded that higher food supply in general may be a risk factor for obesity. In contrast, Fiechtner et al. (2016) found that supermarket proximity, controlling for fast food establishments, interacted with a technology-enhanced primary care obesity treatment to increase fruit and vegetable intake and lower zBMI. They attributed the contrary findings of Epstein et al. (2012) to a methodological artifact, arguing that distance to supermarket, net of fast food establishments, is a better indicator of access, while density may be a proxy for food establishment density in general (since fast food restaurants can often be found in industrial complexes) (Fiechtner et al., 2016).

1.5.1 Generalizability

With the exception of Fiechtner et al. (2016), the analyses conducted were at the level of efficacy trials. For a number of reasons this may limit their generalizability. To illustrate, the most relevant study to the current research, in terms of measurement of environmental indicators, and comprehensiveness of treatment (Epstein et al., 2012) excluded participants with comorbid psychopathology, severe obesity, and early indications of adherence problems. In addition, the study did not report race or ethnicity of participants, and it was conducted in a county of New York state with an 80% white population.

1.5.2 Interaction with individual and family factors

It is particularly important to study neighborhood effects in the context of diverse, inclusive samples, because there is likely intersectionality between neighborhood factors and individual and family factors, such as race and family SES (Boone-Heinonen & Gordon-Larsen, 2012). There are systematic influences that could make racial minority children more susceptible to home neighborhood level risk factors than their White counterparts. These include nonspecific factors such as increased exposure to early adverse life events and chronic stress, and disparities in healthcare access, delivery, and utilization (Centers for Disease Control and Prevention, 2013). In addition, several factors more specific to neighborhood environments and weight have been identified. Black and Latinx families are much more likely to be targeted by unhealthy food advertising via electronic media (Harris, Kumanykia, Ramirez, & Frazier, 2019). Thus, they could be impacted more by increased accessibility of unhealthy food options or could benefit less from accessibility of healthy food options. In addition, minority children are less likely to attend schools in healthful food environments or to benefit from public health initiatives in schools (Schuster et al., 2012). Therefore, they may be afforded less protection from an unhealthy home neighborhood environment.

Individual SES is suspected to interact with availability of both healthful and unhealthful foods. In the epidemiological literature, lower SES individuals are more vulnerable to higher saturation of unhealthful food outlets and don’t benefit as much from access to healthful food outlets (Boone-Heinonen & Gordon-Larsen, 2012). One possibility is that lower SES individuals are less likely to have access to reliable transportation and therefore may be more susceptible to accessibility in their more immediate environment. They also are less likely to be able to afford healthful food options even when there is neighborhood access to those options.

Despite indications that the risk of residing in an unhealthy neighborhood environment is likely compounded by the individual level risk factors of race and family SES, no treatment studies to date have explored interactions among these factors.

1.5.3 Analysis methods

The contrary findings of Fiechtner et al. (2016) and Epstein et al. (2012) illustrate that the treatment by neighborhood environment research faces some of the same measurement challenges as the epidemiological research. There is a need for analysis methods that capture the intersectionality among indicators of neighborhood environments. Whereas two epidemiological studies demonstrated the value of employing mixture modeling to link environment and obesity rates (DeWeese et al., 2018; Wall et al., 2012), no studies have used mixture models to study whether neighborhood environments might predict obesity treatment outcomes. Moreover, despite evidence that individual SES and race/ethnicity interact with aspects of the neighborhood environment to influence behaviors and BMI, no studies have examined how these individual level variables may interact with neighborhood environments to predict treatment outcomes.

1.6 Summary

Pediatric obesity treatment is differentially effective for individuals, in part due to varying degrees of compliance and high attrition rates. Understanding the heterogeneity in the target population regarding risks and protective factors could have important implications for treatment development and the tailoring of treatments according to pre-treatment assessment. There are several indications that environmental risk factors likely function as barriers to obesity-related health behaviors. In particular, there have been relationships demonstrated between aspects of neighborhood environments and health behaviors and obesity rates in epidemiological research. It seems likely that environmental factors identified as obesogenic function as treatment barriers. However, due to the lack of research connecting environmental factors to individual level outcomes, there has not been strong, generalizable, empirical validation of this hypothesis. Moreover, the intersectionality among environmental characteristics and heterogeneity across individual level variables, such SES and race/ethnicity, result in a great deal of complexity that has not been explored in the context of obesity treatment.

1.7 Current Study

In the current study, archival data were examined from a pediatric obesity treatment clinic that serves a diverse, high risk population, in order to determine if home neighborhood environments impact participation and treatment response. A mixture model was used to characterize the heterogeneity of the sample and capture the intersectionality among the indicators of neighborhood environments. Table 1.1 lists all neighborhood indicators used in the mixture model. The modelled latent classes were regressed on participation variables and treatment response (zBMI) to determine if type of neighborhood environment predicts treatment outcomes. In addition, interactions between the latent classes and demographic variables (SES, ethnicity) were examined to capture additional heterogeneity in the sample.

Exploring the relationship between neighborhood environments and obesity treatment responsiveness could have important implications for personalizing treatment. Further, examining a potential pathway of neighborhood environments as treatment-limiting barriers could have public health implications.

Table 1.1 Neighborhood Environment Indicators

Built Environment-Accessibility of Physical Activity

1. Distance to closest recreational facility
2. Density of recreational facilities
3. Density of parks
4. Walkability

Built Environment-Accessibility of Food Supply

5. Distance to closest grocery store
6. Density of grocery stores
7. Distance to closest convenience store
8. Density of convenience stores
9. Distance to closest fast food outlet
10. Density of fast food outlets

Social Environment

11. Concentrated disadvantage
12. Concentrated affluence
13. Crime

1.8 Primary Aims and Hypotheses

1.8.1 Primary aim 1

To characterize heterogeneity in the home neighborhood environments of individuals among a diverse, high risk sample of overweight and obese treatment-seeking youth using a mixture analysis with indicators of the built and social environments.

1.8.2 Hypothesis 1

Among the home neighborhood environments of participants in a pediatric weight management program, between-neighborhood variability in one or more neighborhood indicators (access to physical activity opportunities, access to food supply, social environment; Table 1.1), or between-neighborhood variability in one or more patterns of relationship among these indicators, will characterize latent categories (≥ 2), according to accepted standards of model fit and classification quality.

1.8.3 Primary aim 2

To examine the predictive relationships between neighborhood environments and clinical measures of baseline risk (degree of overweight) and outcomes (participation and weight management) of overweight and obese youth participating in a specialty pediatric obesity clinic serving a diverse, high risk community.

1.8.4 Hypothesis 2

Participant categorizations according to their neighborhood environments will predict early dropout and participation rates. It is expected that youth in more obesogenic neighborhood environments—as characterized by lower accessibility of physical activity opportunities and healthful food, higher accessibility of unhealthful food, lower neighborhood SES, higher crime, or some combination of these factors—will have higher likelihood of early dropout and lower participation rates.

1.8.5 Hypothesis 3

Participant categorizations according to their neighborhood environments will predict baseline degree of overweight as measured by starting zBMI. It is expected that youth in more obesogenic neighborhood environments will exhibit higher starting zBMI.

1.8.6 Hypothesis 4

Participant categorizations according to their neighborhood environments will predict treatment outcome as measured by final zBMI adjusted for starting zBMI. It is expected that youth in more obesogenic neighborhood environments will exhibit higher final zBMI.

1.8.7 Hypothesis 5

The relationships of neighborhood environment with treatment response outcomes will be moderated by the demographic variables of race and insurance type (a proxy for SES). It is expected that the risk conferred by obesogenic neighborhood environments will be greater for participants with individual-level social risk factors, including participation in Medicaid or minority racial status. Alternatively, it is expected that the benefit conferred by health-promoting neighborhood environments will be less for participants with individual-level social risk factors.

2 METHOD

2.1 Participants

Study participants consist of 850 4- to 16-year-old (M = 11.24, SD = 2.78) children and adolescents sequentially enrolled in the Strong4Life clinic. Table 2.1 includes demographics characteristics of the sample. Ethnic composition of study sample is approximately 44% Black/African American, 27% White, 24% Latinx, and 5% other (Asian, Pacific Islander, or Native American). Approximately 65% of participants were Medicaid recipients. Medical inclusion criteria for participation in the Strong4Life clinic is BMI ≥ 95%ile for sex- and age-matched norm group or BMI ≥ 85%ile with corresponding weight-related comorbidities (e.g., hypertension, fatty liver disease). Because the definition of neighborhood varies drastically between rural and urban areas (Ohri-Vachaspati, Lloyd, Delia, Tulloch, & Yedidia, 2013), participants living in rural areas, as determined by census designation, were excluded from the study.

Table 2.1 Demographics

N	850	
	Mean	**SD**
Age	11.24	2.78
	n	**Percentage**
Gender		
Female	493	58%
Male	357	42%
Race		
Black	402	47%
Latinx	210	25%
White	216	25%
Other	13	2%
Unknown	9	1%
Health Insurer		
Medicaid	496	58%
Other	354	42%

2.2 Power analysis

The power of mixture modelling to detect latent classes is dependent on class separation, number of classes in the population, and number of indicators, among other determinants (Dziak, Lanza, & Tan, 2014). Given that the power of a mixture model is highly dependent on characteristics of specific data sets and the fit indices chosen and because theoretical formulas for predicting power are not available, Monte Carlo simulations are recommended (Muthén & Muthén, 2002; Nylund, Asparouhov, & Muthén, 2007). Using data from previous Monte Carlo simulations across several observational data sets and assuming median levels of class separation and class quantity, 14 indicator variables, and an alpha level of 5%, a sample size of 607 to 826 would be needed to achieve a power of 80% using the Boot Strap Likelihood Ratio Test (BLRT) (Dziak et al., 2014). Thus, the current study appears to be appropriately powered for the proposed mixture analysis.

2.3 Strong4Life Clinic

The Strong4Life clinic at Children's Healthcare of Atlanta (CHOA) is a multidisciplinary specialty weight management clinic serving children and adolescents with overweight, obesity, and weight-related comorbidities. The program is 12 months in duration. Visit frequency is tailored to meet the needs of individual families. The first follow-up visit is scheduled for one month; however, the remaining follow-up durations range from one to three months in the first half of the program and one to six months later in the program, similar to other multidisciplinary clinics (e.g., Skelton, DeMattia, & Flores, 2008). Initial visits are two hours in duration and follow-up visits are one hour in duration. At each visit, participants and attending family meet with members of the multidisciplinary team including a medical provider, a psychologist, a nutritionist, an exercise physiologist, and a nurse, as well as a social worker on an as-needed basis. Participants receive medical examination, nutrition and exercise counseling, behavioral interventions, and motivational enhancement interventions. Participants learn how to effectively set goals and track outcomes related to lifestyle changes in the areas of physical activity and nutrition.

2.4 Procedure

2.4.1 Chart review

The study was approved by the CHOA Internal Review Board (IRB). An anonymous retrospective chart review of Strong4Life records was conducted with patients records between January 2013 and June 2018. As an anonymous archival study, the current research was exempt from informed consent requirements.

2.4.2 Geographic Information Systems (GIS)

In order to objectively measure the obesogenic characteristics of participants' home neighborhood environments, GIS techniques were utilized. Using ArcGIS Pro 2.3 software (ESRI, Redlands, California, 2010), participants' home address data were geocoded—converted into latitude and longitude coordinates—and combined with publicly available spatial maps (e.g., park locations) or maps constructed from publicly available data.

2.4.3 Egocentric

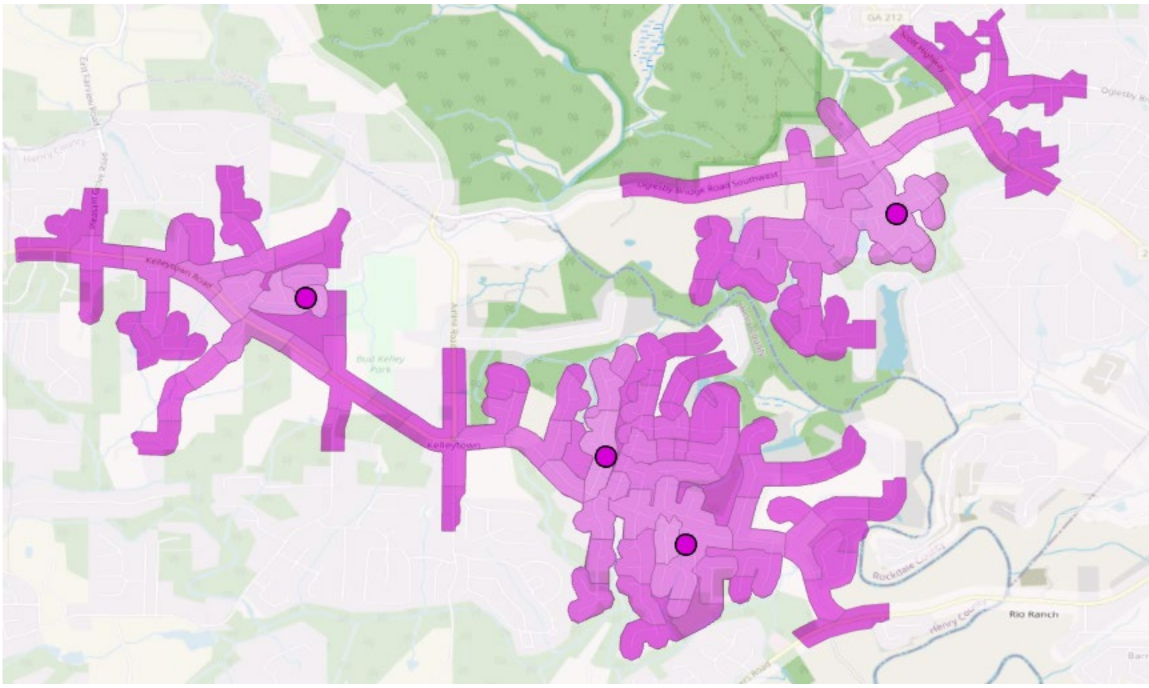
Whenever possible, egocentric measures were utilized to measure attributes of home neighborhood environments. An egocentric measure of a home neighborhood environment utilizes a participant's home address as a reference point to calculate distance to features or to create neighborhood spatial zones for density estimates. Egocentric measures of proximity and density are more valid than civic or administrative boundaries (Duncan et al., 2014).

2.4.4 Network distances

All distance metrics were calculated using network distances. Network distances use street map information to estimate more accurate measures of travel time than straight-line distance (Jia et al., 2017).

2.4.5 Density

The process for calculating density measures (e.g., density of fast food restaurants), involves creating a spatial zone around each participant's home address according to a chosen buffer size between home address and the perimeter of the spatial zone. The number of instances falling within the spatial zone are then counted. The current study created spatial zones utilizing distances along the road network. Therefore, each spatial zone varied in shape and included all features a participant could reach by traveling a certain distance (buffer size) along the road network in any direction. Figure 2.1 exhibits examples of spatial zones around participants' homes.



Home address

2,400m Network Buffer

Figure 2.1 Neighborhood spatial zones

There is little agreement on optimal the buffer size and very few sensitivity analyses have been conducted (Duncan et al., 2014; Ohri-Vachaspati, Lloyd, DeLia, et al., 2013). Therefore, creating density measures often involves choosing an arbitrary cutoff; and buffer sizes vary considerably between studies—anywhere from 400m to 8,000m, with most studies falling within the range of 400m to 2,400m (Jia et al., 2017). Some researchers have argued for smaller buffer sizes (e.g., 400m) because of past research demonstrating the deleterious impact of unhealthful food outlets located close to homes (e.g., DeWeese et al., 2018). Others argue that larger neighborhood sizes should be considered because individuals regularly travel greater distances for preferred shopping destinations (e.g., choice of grocery store; Liu, Han, & Cohen, 2015). Consistent with both of these positions, a sensitivity analysis of varying buffer sizes (400m, 800m, 1,200m, 1,600m, 2,000m, 2,400m) using data from the present study revealed that the positive association between convenience store density and zBMI was strongest at the smallest buffer size (400m), while the negative association between grocery stores and zBMI was strongest at the largest buffer size (2,400m).

To avoid losing important information about density with an arbitrary cut point, a probabilistic density calculation (Li et al., 2015) was utilized. The largest buffer size (2,400m) was chosen to capture information about density further away from homes; and each location was weighted by the distance from a participant's home to incorporate information about density closer to participant's homes. According to a widely used retail model, the probability of a location being frequented by a person is inversely related to the distance from a person's home (Li et al., 2015; Yingru Li & Liu, 2012). Specifically, all else being equal, the probability is adjusted by a factor of 1/D2 (D = distance from person's home to location). For the present study, densities were calculated using the following equation: $\sum_{i=1}^{n} 1/D_i^2$ (n = number of locations within a 2,400km travel distance ; D_i = distance from participants home for location i).

2.4.6 Commercial establishments

A publicly available database, InfoUSA (www.infousa.com), was used to identify and classify commercial food and recreational facility establishments using North American Industry Classification (NAIC) codes. The use of two data sources with cross-referencing could increase the validity of commercial establishment identification (Liese et al., 2010; Nau et al., 2015). However, due to cost, some researchers have foregone the use of a second database with minimal loss of accuracy and coverage (Forsyth et al., 2012).

2.4.7 Census data

Data summarized at the census tract was utilized to measure neighborhood sociodemographics (e.g., median household income). The census tract is the smallest geographic unit used by the U.S. Census Bureau for which the target sociodemographic metrics are available. Although egocentric measures are preferable, data summarized at the census tract level has been widely utilized to estimate neighborhood sociodemographics in previous studies (e.g., Duncan et al., 2014; Wall et al., 2012).

2.5 Measures

2.5.1 Background information

Child and family demographic variables were utilized as covariates in analyses. Child variables included age, gender, and ethnicity. Family variables included primary health insurance type. Distance from home address to clinic, a likely logistical barrier, was also examined as a potential covariate.

2.5.2 Recreational facilities

Access to recreational facilities was measured by network proximity as well as density of fitness centers, recreational sports facilities, and child and youth services facilities. Fitness centers and recreational sports facilities were identified according to the North American Industry Classification System (NAICS) codes using a commercial database. Specific child and youth services facilities that typically include access to physical activity (i.e., Boys & Girls Clubs of America and YMCA) were identified by name using the same commercial database.

2.5.3 Parks

Access to parks was measured by density of parks greater than 1 acre in size. Parks were identified using a publicly available GIS data set established for the state of Georgia (Georgia GIS Clearinghouse, Atlanta, Georgia, 2015).

2.5.4 Walkability

Walkability was operationalized by an index score (Mean = 100) that estimates the coverage of sidewalks and controlled intersections within a 15-minute walking distance (Ding et al., 2011; Ferreira et al., 2007).

2.5.5 Grocery stores

Access to grocery stores was measured by network proximity to and density of grocery stores and supermarkets (Gordon-Larsen et al., 2006; Greves Grow et al., 2010).

2.5.6 Convenience stores

Access to convenience stores was estimated by proximity to and density of convenience stores.

2.5.7 Fast food

Access to fast food was measured by proximity and density of limited service restaurants.

2.5.8 Social environment

Neighborhood SES was estimated using several census tract indicators of area levels of education, income, and employment. Given the high correlations among these indicators in previous studies and consistent directions of influence with obesity rates, two previously established factor weighted scales of disadvantage and affluence were calculated to summarize neighborhood SES (Carroll-Scott et al., 2013; Sampson, Morenoff, & Earls, 1999).

2.5.9 Concentrated disadvantage

The concentrated disadvantage scale was calculated using percentages of households receiving public assistance, residents living below the poverty line, households headed by a single female, and unemployed residents (Sampson et al., 1999).

2.5.10 Concentrated affluence

The concentrated affluence scale was calculated using percentages of adults with a college degree, households with high income, and adults with an executive or professional job (Sampson et al., 1999).

2.5.11 Crime

Neighborhood crime was estimated using the CrimeRisk index (developed by Applied Geographic Solutions) within a 15-minute walking distance of participants' homes (see DeWeese et al., 2018). The CrimeRisk index is a relative measure of crime based on the Federal Bureau of Investigation's (FBI) Uniform Crime Report (UCR).

2.5.12 Treatment measures

Obesity treatment attrition rates vary considerably depending on the exact definition used (Dolinsky, Armstrong, & Østbye, 2012; Nobles, Griffiths, Pringle, & Gately, 2017). Therefore, in accordance with previous effectiveness research (Ball, Perez, Nobles, Spence, & Skelton, 2017; Dolinsky et al., 2012; Hampl, Paves, Laubscher, & Eneli, 2011), for participation, both early dropout and participation rate were examined.

2.5.13 Early dropout

Early dropout was defined as participants not returning for their second scheduled appointment.

2.5.14 Participation rate

Participation rate was defined as the number of completed visits divided by the number of scheduled visits less the number of visits rescheduled within a two week period.

2.5.15 zBMI

Level of overweight was operationalized with zBMI. zBMI is preferred to BMI because there are non-linear relationships between BMI and age that differ in shape between genders (Law et al., 2014). zBMI is the most common outcome metric used in pediatric obesity studies (Oude Luttikhuis et al., 2009).

2.6 Data Analytic Plan

2.6.1 Mixture analysis

Mixture modeling is latent variable technique that has been used both to measure heterogeneity in treatment response (Lanza & Rhoades, 2013) and to characterize obesogenic environments (DeWeese et al., 2018; Wall et al., 2012). Mixture models categorize individuals into latent (unmeasured) groupings according to patterns of covariance among manifest (measured) indicator variables. In doing so, the technique is able to estimate measurement error in the indicator variables and the latent classes, which may be particularly important in the case of obesogenic environments because of the lack of agreed upon measures. In contrast to mixture models, linear regression techniques are more susceptible to bias when including many indicators into one model because of measurement error and multicollinearity. Also, mixture models have lower Type I and Type II error rates when examining interactions among predictors, compared to linear regression techniques used to test moderation (Lanza & Rhoades, 2013). Mixture modelling allows for pairing down of a potentially unmanageable numbers of variable cross sections (e.g., a 3-way interaction among 4-level variables involves 64 groupings of individuals), into those cross sections that are empirically and substantively meaningful (Oberski, 2016).

The current study performed Structural Equation Model (SEM) analysis to 1) establish latent categories of the neighborhood environment variable, and 2) explore the relationship between participants' membership in the latent classes and their outcomes from an obesity treatment. Structural equation models with latent class variables have two components, a measurement model that estimates values of a latent variable for each participant using manifest indicators (i.e., a mixture model), and an auxiliary model that estimates relationships between latent class membership and other manifest variables (i.e., outcomes, covariates) (Lanza, Tan, & Bray, 2013).

2.6.2 Data screening

Previous mixture-model analyses of neighborhood environments included only binary indicators (DeWeese et al., 2018; Wall et al., 2012). Continuous and ordinal indicators were included in the current mixture analysis rather than binary indicators, in order to minimize the potential loss of information that occurs with arbitrary cut points (Macia & Wickham, 2019). Crime, concentrated disadvantage, concentrated affluence, and walkability met normality assumptions and were included as continuous indicators. Due to right skew, log transformations were applied to proximity variables before including them as continuous indicators. The non-normality (high percentage of zeroes, skewness, and kurtosis) of density variables was such that data transformations were not able to approximate normality. Therefore, these variables were included as ordinal indicators with five categories (0 to 4). Following a similar process to that recommended by Macia and Wickham (2019), the zeroes in the data formed the first ordinal category, and a quartile split was applied to form the remaining four ordinal categories.

2.6.3 Mixture model

A modeling process was followed to determine the number of classes that best characterizes the data. Models with an increasing number of classes were specified (k = 1, 2, …n). Fit indices, Bayesian Information Criteria (BIC), Akaike's Information Criteria (CAIC), were recorded for each model. In addition, a log-likelihood ratio test, the Vuong-Lo-Mendell-Rubin Test, was performed at each step to determine if the increase in class size (k = n vs. k = n 1) resulted in a significant improvement in the respective model likelihood. In addition to fit, competing models were compared on classification quality. Models with high classification quality consist of groups with high intragroup homogeneity and low intergroup homogeneity (well-separated classes). Entropy was used to estimate classification quality. Finally, competing models were compared on parsimony and substantive considerations (i.e., did the groupings make sense based on known principles? were the classes of sufficient size?).

2.6.4 Predicting treatment variables

When predicting outcomes by latent classes, standard classify-analyze approaches are often used. Generally, these approaches assign participants to latent classes in one model and then include those latent class assignments in a second model that includes auxiliary variables (e.g., outcomes, covariates). Because these methods estimate latent class membership and perform outcome prediction in separate steps, they are unable to account for the measurement error (misclassification error) of latent class assignment in the estimation of auxiliary models (Lanza & Rhoades, 2013). The estimation of measurement error is one of the major advantages of latent variable approaches, and this benefit is lost with standard classify-analyze approaches. In addition, standard classify-analyze approaches often result in attenuated estimates of the relationship between the latent class variable and distal outcomes (Lanza & Rhoades, 2013).

Alternatively, including the mixture model and the auxiliary model in the same step risks the auxiliary variables influencing latent class assignment (Asparouhov & Muthén, 2014). In order to maintain both estimation of measurement error and stability in the estimation of the latent classes, 3-step approaches have been developed (Asparouhov & Muthén, 2014). Generally, these approaches include the steps of (1) estimating latent classes without auxiliary variables, (2) exporting class assignment based on posterior probabilities, and (3) estimating an auxiliary model that takes into account the misclassification in step 2 (Asparouhov & Muthén, 2014; Nylund-Gibson, Grimm, & Masyn, 2019). The manual 3-step BCH method was chosen for the current study because it is one of the most flexible 3-step approaches and it is the recommended approach for predicting distal outcomes with covariates (Asparouhov & Muthén, 2014; Nylund-Gibson et al., 2019).

Utilizing the manual BCH method, multiple-group regression analyses were conducted predicting early dropout, participation rate, and adjusted final zBMI by covariates (age, gender, and Medicaid participation, distance to clinic). In a multiple-group analysis the auxiliary model is estimated for each group (latent class). Regression coefficients were fixed across classes, while regression intercepts were allowed to vary across classes. Significant differences among intercepts correspond to significant differences in the outcome variable (adjusted for the influence of covariates), across the latent classes (Nylund-Gibson et al., 2019). For each outcome variable, the statistical significance of differences among intercepts was examined using an omnibus, Wald test. Pairwise comparisons between groups were also conducted and reported. Pairwise comparisons were reported regardless of the significance of the respective omnibus test. This diverges from the hierarchical procedure of conducting pairwise comparisons only following significant omnibus tests. However, some researchers recommend always conducting and reporting pairwise comparisons, despite the risk of increasing experiment Type-1 error, because of the variable performance of hierarchical procedures in simulation studies, even when applied to classic ANOVA (Chen, Xu, Tu, Wang, & Niu, 2018). The relationship between the Wald test and pairwise comparisons, and thus the performance of the hierarchical procedure, may be particularly complex and uncertain in the context of a BCH analysis. Therefore, the decision was made to conduct and report all pairwise comparisons.

Following the testing of differences among classes, two, two-way interactions were examined for each auxiliary model—Medicaid participation by latent class and race by latent class—in order to test the hypothesized moderation effects. For each hypothesized moderator (Medicaid participation or race) the corresponding regression coefficients were allowed to vary across classes. The Wald test was used to determine whether allowing the effect of Medicaid participation to vary across classes significantly added to the fit of the corresponding models (i.e., whether the interaction between Medicaid participation and class membership was significant). Likelihood ratio tests adjusted for MLR estimation were used to test the significance of the interactions between race and the latent variable.

3 RESULTS

3.1 Descriptive Statistics

Table 3.1 includes descriptive statistics of clinic variables, neighborhood social variables, and built environment variables. Table 3.2 includes bivariate correlation coefficients among study variables. The Pearson product-moment correlation coefficient is reported for correlations between continuous variables, and the Spearman's rank correlation coefficient is reported for correlations with ordinal variables. Starting and final zBMI were correlated, and each were correlated with recreational facility proximity and density, social environment measures, and distance to clinic (all p's $< .001$). Significant correlations between zBMI and neighborhood variables were in expected directions. Indicators of unfavorable social environment, crime and concentrated disadvantage, were positively correlated with zBMI, and concentrated affluence was negatively associated with zBMI. Recreational facility proximity (distance to nearest instance) had a positive association with zBMI and recreational facility density had a negative association.

Table 3.1 Descriptive Statistics

Variables	*n*	Mean	SD
Built Environment			
Distance to nearest feature			
Recreational Facilities	850	2.53	1.85
Grocery Stores	850	2.37	1.66
Convenience Stores	850	2.63	1.75
Fast Food	850	2.18	1.53
Density			
Recreational Facilities	850	1.83	2.739
Parks	850	1.12	2.284
Grocery Stores	850	2.03	2.765
Convenience Stores	850	1.18	1.585
Fast Food	850	4.25	5.601
Walkability	850	8.19	3.08
Social Environment			
Concentrated Disadvantage	850	0.00	0.75
Concentrated Affluence	850	0.00	0.97
Crime	850	123.25	74.18
Treatment-Related Variables			
Early Dropout	795	0.32	0.47
Participation Rate	795	0.61	0.24
Completed visits	850	2.53	1.81
Distance to clinic	850	44.76	41.71
Starting zBMI	850	2.39	0.39
Final zBMI	541	2.39	0.39

Table 3.2 Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Start zBMI	r																
2 Final zBMI	r	.975 ***															
3 Age	r	-.010	.016														
4 Walkability	r	-.065	-.054	-.052													
5 Crime	r	.137 ***	.160 ***	.003	.409 ***												
6 Disadvantage	r	.162 ***	.187 ***	-.025	.084 *	.492 ***											
7 Affluence	r	-.216 ***	-.235 ***	.009	.098 **	-.422 ***	-.732 ***										
8 CS Proximity	r	-.010	-.022	.046	-.396 ***	-.368 ***	-.205 ***	.201 ***									
9 Grocery Proximity	r	.044	.048	.041	-.490 ***	-.329 ***	-.145 ***	.073 *	.611 ***								
10 FF Proximity	r	.049	.044	.028	-.463 ***	-.288 ***	-.053	-.014	.575 ***	.669 ***							
11 Recreational Proximity	r	.127 ***	.123 ***	.041	-.424 ***	-.143 ***	.072 *	-.172 ***	.401 ***	.559 ***	.564 ***						
12 Distance to Clinic	r	.203 ***	.211 ***	.081 *	-.293 ***	.012	.112 **	-.240 ***	.094 **	.193 ***	.183 ***	.234 ***					
13 CS Density	r_S	.007	.010	-.041	.283 ***	.287 ***	.159 ***	-.185 ***	-.811 ***	-.432 ***	-.445 ***	-.291 ***	-.246 ***				
14 Grocery Density	r_S	-.017	-.023	-.043	.380 ***	.243 ***	.103 ***	-.117 ***	-.436 ***	-.826 ***	-.536 ***	-.429 ***	-.380 ***	.477 ***			
15 FF Density	r_S	-.033	-.035	-.024	.405 ***	.211 ***	.041	-.035	-.453 ***	-.560 ***	-.789 ***	-.462 ***	-.394 ***	.493 ***	.619 ***		
16 Recreational Density	r_S	-.099 ***	-.099 ***	-.057 *	.299 ***	.037	-.101 ***	.130 ***	-.281 ***	-.413 ***	-.426 ***	-.807 ***	-.382 ***	.311 ***	.442 ***	.486 ***	
17 Park Density	r_S	.026	.031	-.043	.312 ***	.186 ***	.076 **	-.008	-.216 ***	-.249 ***	-.205 ***	-.181 ***	-.350 ***	.208 ***	.279 ***	.233 ***	.199 ***

$^*p < .05$, $^{**}p<.01$, $^{***}p<.001$

3.2 Mixture Model

3.2.1 Class enumeration

Table 3.3 includes fit indices, entropy, minimum class size, and results of Vuong-Lo-Mendell-Rubin Tests, for the mixture model at each number of classes (k = 1, 2,...n). Two models were considered (k = 4 and k = 5) as candidates for the final model. A four-class model was chosen because the addition of a fifth class did not result in a significant increase in likelihood and there was less separation among classes in the five-class model. The entropy of the chosen model, .90, was well above the recommended cutoff for good entropy, .80 (Celeux & Soromenho, 1996).

Table 3.3 Class Enumeration

Classes (*k*)	BIC	AIC	Entropy	*LRT* Statistic	*p* value	Minimum Class Size
1	32066.542	31895.714	-	-	-	
2	29164.492	28856.052	.892	3081.907	.666	404
3	28209.724	27763.671	.907	1144.530	< .001	158
4	27751.009	27167.345	.903	650.999	< .001	163
5	27506.773	26785.497	.910	437.611	.057	81
6	27358.186	26499.298	.897	342.448	.177	71

3.2.2 Class characteristics

Patterns among indicators (built and social environment variables) within and between classes were examined in order to characterize the classes. There were differences among classes in three primary areas: overall accessibility of built environment features, relative accessibility of built environment features, and neighborhood social environment. Figures 3.1 and 3.2 depict values of built environment indicators by class. Figure 3.1 includes the means of standardized values of continuous built environment indicators—distance to nearest built environment feature (e.g., recreational facilities, grocery stores) and walkability—by class. Walkability is reverse-coded for the sake of comparisons. Lower values on the chart correspond to higher accessibility (lower distance to nearest feature or higher walkability). Figure 3.2 includes histograms by class for the densities of built environment features, which are ordinal variables with five categories (0-4). Right skew (higher percentages in lower categories) corresponds to lower density and lower access. Left skew (higher percentages in higher categories) corresponds to higher density and higher access. Figure 3.3 depicts values of social environment indicators by class.

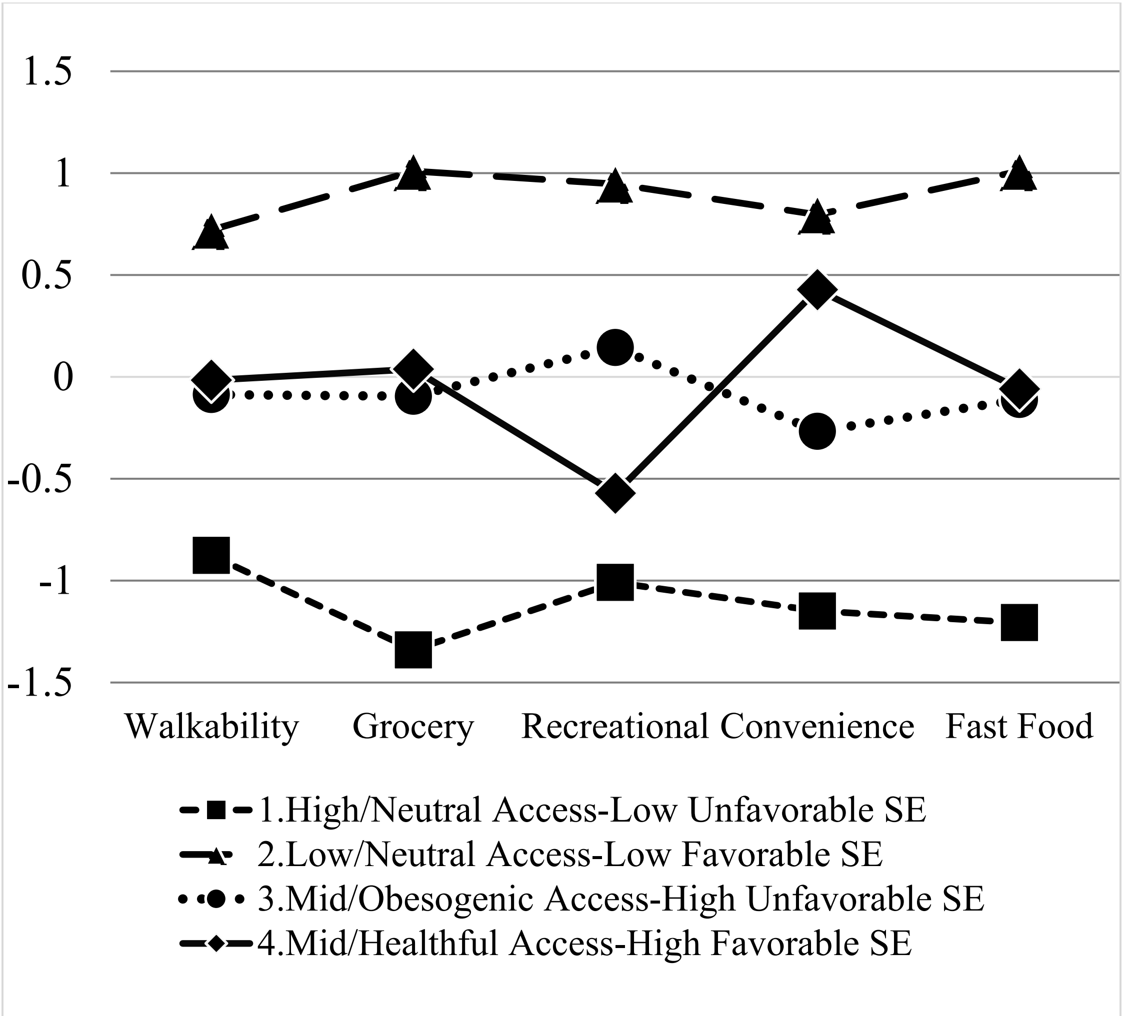


Figure 3.1 Built environment proximity of physical activity opportunities and food supply

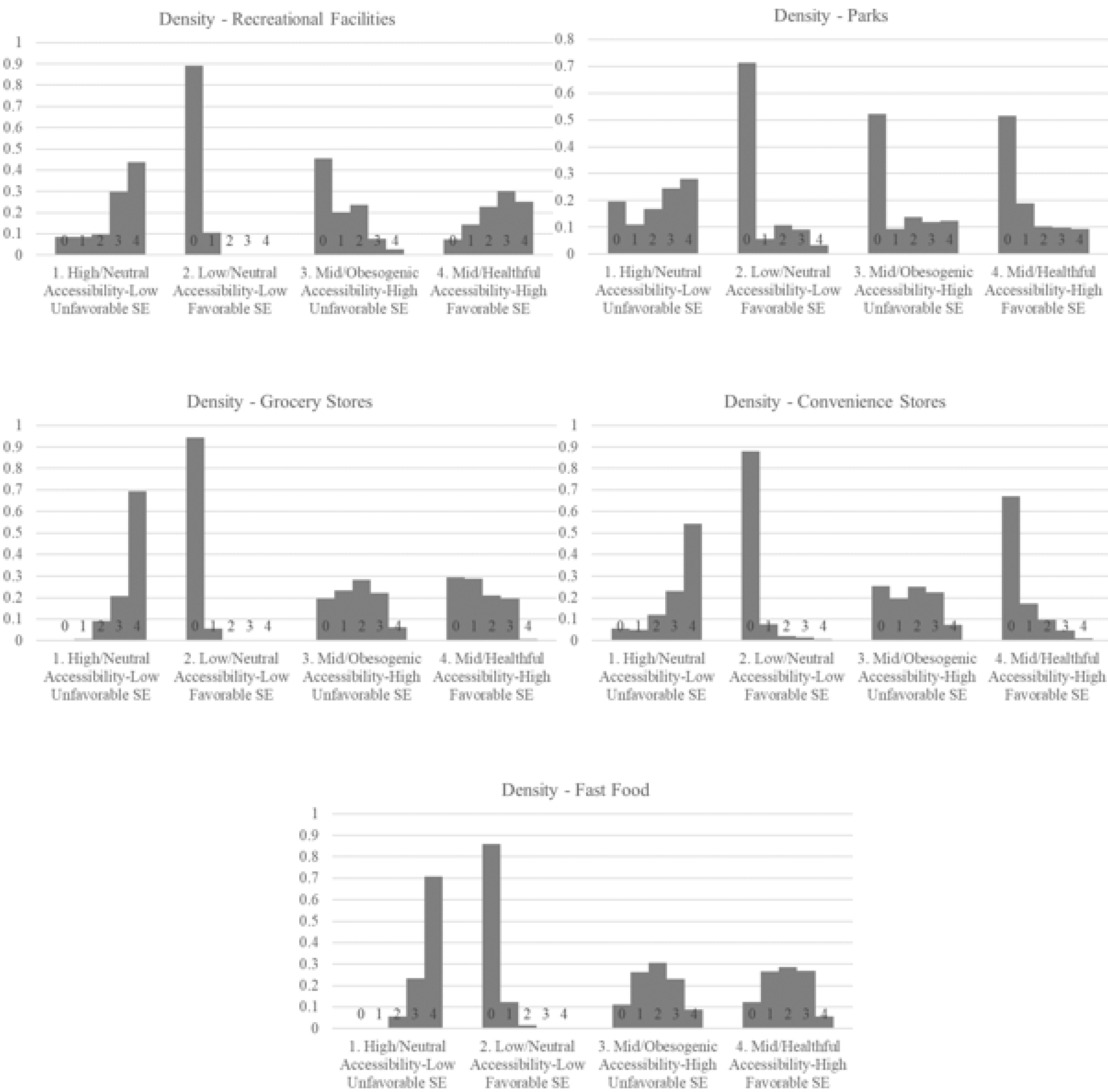


Figure 3.2 Built environment density of physical activity opportunities and food supply

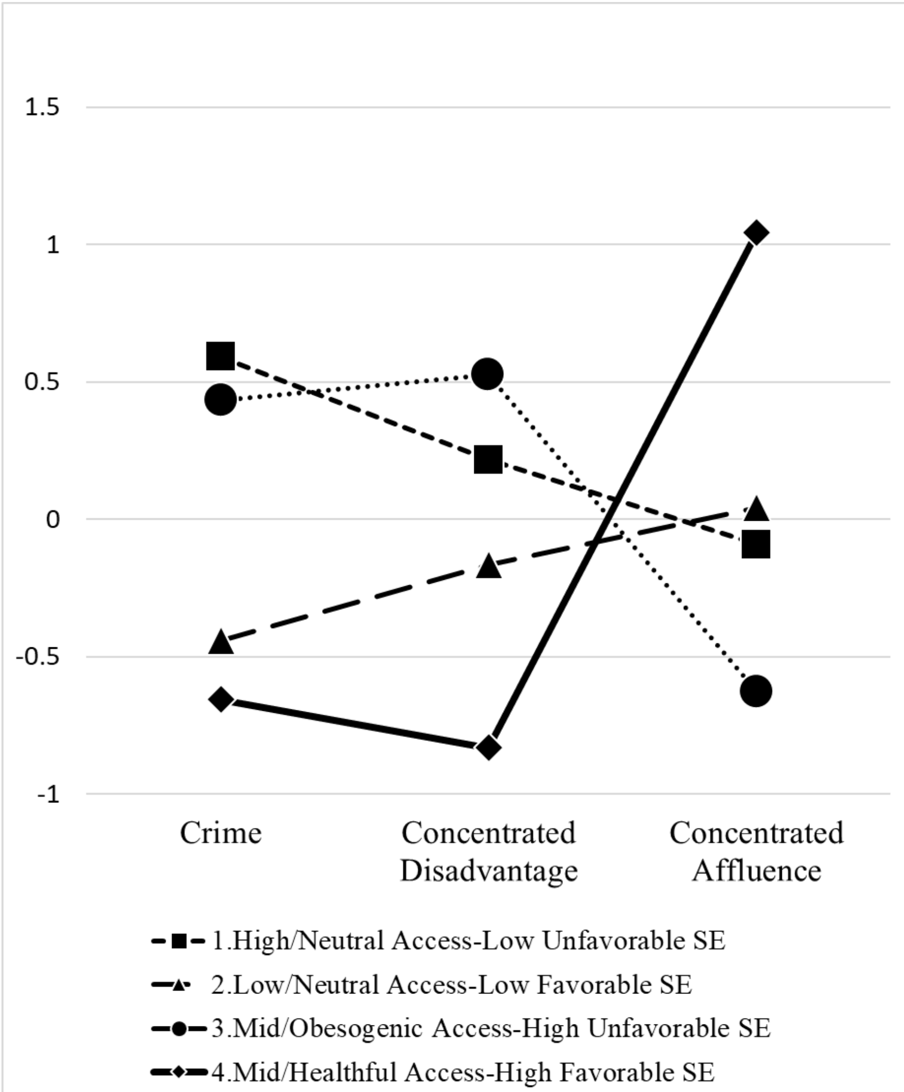


Figure 3.3 Social environment

3.2.3 Overall accessibility

Classes differed in terms of both neighborhood density of built environment locations and distances from nearest feature. For each feature (recreational facilities, parks, grocery stores, convenience stores, fast food), distance (Figure 3.1) and density (Figure 3.2) varied together so that classes with a higher density of a particular feature also exhibited lower average distance to closest instance of that feature. Walkability also varied with density and distances from nearest feature. Therefore, distance, density, and walkability were characterized by an accessibility dimension, with high accessibility corresponding to low distance, high density, and high walkability. Classes 1 and 2 were labeled as High- and Low-Accessibility, respectively. Classes 3 and 4 were both labeled as Mid-Accessibility.

3.2.4 Relative accessibility

The relative accessibility among types of built environment locations (recreational facility, parks, grocery, convenience store, fast food) appeared to differ across classes. Classes 1 and 2 exhibited flat relative accessibility across types of built environment features. Thus, classes 1 and 2 were labeled as having Neutral relative accessibility. Classes 3 and 4 exhibited variability in relative accessibility across types of built environment features. These classes exhibited differences in the accessibility of recreational facilities and convenience stores relative to other feature types. Moreover, the classes exhibited inverted patterns. Class 3 exhibited low relative accessibility of recreational facilities and high relative accessibility of convenience stores. Thus, class 3 was labeled as Obesogenic relative accessibility. Class 4 exhibited high relative accessibility of recreational facilities and low relative accessibility of convenience stores, and this class was labeled as Healthful relative accessibility. Closer examination of density figures (Figure 3.2) helps to illustrate the differences between these two classes in relative accessibility. In Class 4, 92% of participants had at least one recreational facility within 2,400m of their home, compared to 55% of participants in class 3. In Class 3, 75% of participants had at least one convenience store within 2,400km of their home, compared to 33% of participants in class 4.

3.2.5 Social environment

Patterns emerged among the neighborhood social environment indicators (concentrated disadvantage, concentrated affluence, and crime) within classes; and these patterns differed between classes. Classes either exhibited higher concentrated disadvantage relative to concentrated affluence or vice versa. Moreover, classes with higher disadvantage relative to affluence also had higher crime rates. These classes (1 and 3) were labeled as Unfavorable Social Environment (SE). The classes (2 and 4) with the inverse pattern (high affluence relative to disadvantage; low crime) were labelled as Favorable SE. In addition to exhibiting favorable and unfavorable patterns, the degree of the discrepancy between affluence and disadvantage was either high (more steep) or low (less steep). In sum, classes 1, 2, 3, and 4 were labeled as Low Unfavorable-SE, Low Favorable SE, High Unfavorable-SE, and High Favorable-SE, respectively.

3.2.6 Summary

Table 3.4 summarizes the characteristics of each of the four classes. Class 1, High/Neutral Accessibility-Low Unfavorable SE, exhibited the highest accessibility (i.e., lowest distance and highest density across built environment features and highest walkability). This class also exhibited an unfavorable social environment (i.e., higher disadvantage relative to affluence; high crime) but the discrepancy between disadvantage and affluence was less steep (less unfavorable). Class 2, Low/Neutral Accessibility-Low Favorable SE, exhibited the lowest accessibility across the built environment features. This class also exhibited a favorable social environment (i.e., higher affluence relative to disadvantage; low crime), but the discrepancy between affluence and disadvantage was less steep (less favorable). The two classes with Mid Accessibility, class 3 and class 4, differed in the patterns of relative accessibility. They also exhibited the largest differences in social environment. Class 3, Mid Access/Obesogenic Accessibility-High Unfavorable SE, exhibited an obesogenic pattern of relative accessibility with higher accessibility of convenience stores and lower accessibility of physical activity facilities.

This class also exhibited the most unfavorable social environment with high crime and a steep discrepancy between high disadvantage and low affluence. In contrast, class 4, Mid Access/Healthful Accessibility-High Favorable SE, exhibited a healthful pattern of relative accessibility with higher accessibility of recreational facilities and lower accessibility of convenience stores. Class 4 exhibited the most favorable social environment with low crime and a steep discrepancy between high affluence and low disadvantage.

Table 3.4 Class Characteristics

	1. High/Neutral Accessibility-Low Unfavorable SE	**2. Low/Neutral Accessibility-Low Favorable SE**	**3. Mid/Obesogenic Accessibility-High Unfavorable SE**	**4. Mid/Healthful Accessibility-High Favorable SE**
Characteristics-Detailed				
Overall Accessibility				
Distance to Nearest	Low	High	Mid	Mid
Density	High	Low	Mid	Mid
Walkability	High	Low	Mid	Mid
Relative Accessibility				
Convenience Stores	Neutral	Neutral	High	Low
Recreational	Neutral	Neutral	Low	High
Social Environment				
CA vs. CD	CA < CD	CA > CD	CA < CD	CA > CD
Degree	Low	Low	High	High
Crime	High	Low	High	Low
Characteristics-Summary				
Overall Accessibility	High	Low	Mid	Mid
Relative Accessibility	Neutral	Neutral	Obesogenic	Healthful
Social Environment	Low Unfavorable	Low Favorable	High Unfavorable	High Favorable

Note. Distance to Nearest refers to average distance to closest instance across built environment features. Density refers to density of built environment features. CA = Concentrated Affluence. CD = Concentrated Disadvantage. Degree refers to the size of the difference between CA and CD.

3.2.7 Class demographics

Table 3.5 contains estimated demographics by latent class. Percentage of female participants and average age did not differ significantly among classes, $.070 \geq p$'s $\leq .894$, $.075 \geq p$'s $\leq .835$, respectively. Percentage of patients participating in Medicaid was significantly higher in classes with unfavorable social environments (classes 1 and 3) compared to classes with favorable social environments (Classes 2 and 4), p's $< .001$. Percentages of participants identifying with a minority racial group differed significantly between each pair of classes (.000 > *p*'s ≤ .041). The percentage of minority participants tracked level of social environment, with less favorable social environments corresponding to higher percentages of minority participants. The percentage of black participants similarly differed among classes, with one exception. There was a high percentage of black participants in class 2. Similar to the pattern of Medicaid participation, the percentage of Latinx participants differed significantly between classes with unfavorable social environments (1 and 3) and those with favorable social environments determinants (2 and 4; *p*'s < .001).

Table 3.5 Class Demographics

	Class			
Variables	**1**	**2**	**3**	**4**
n	163	233	286	168
Age	10.9	11.4	11.2	11.5
Gender				
Female	57%	64%	56%	55%
Male	44%	36%	44%	45%
Race/Ethnicity				
Black	44%	56%	56%	27%
Latinx	37%	13%	32%	19%
White	19%	30%	11%	51%
Other	1%	1%	1%	4%
Medicaid	75%	42%	77%	34%

3.3 Predicting Treatment Variables

3.3.1 Early dropout

The omnibus test indicated that differences among classes in log-odds of early dropout were nonsignificant, $\chi^2(3) = 6.229$, p = .101. However, pairwise comparisons indicated significantly higher log-odds of early dropout in class 3, relative to class 2, $b = 0.461$, $p = .029$. The effect size was small, $OR = 1.586$.

Log-odds of early dropout was adjusted for the covariates of age, gender, race, distance from clinic, and Medicaid participation (Table 3.6). The omnibus test of differences in log-odds among classes was nonsignificant, $\chi^2(3) = 5.931$, $p = .115$. However, pairwise comparisons indicated that class 3 had a significantly higher log-odds of early dropout relative to class 2, $b = 0.500$, $p = .026$ (Figure 3.4). The effect size was small, $OR = 1.649$.

Regarding covariates, race was the only significant predictor of early dropout. Latinx participants had a significantly lower log-odds of early dropout than White, $b = -0.602$, $p = .018$, and Black, $b = -0.809$, $p < .001$, participants. Effect sizes were small: $OR = 1.826$ and $OR = 2.246$, respectively.

There was a significant two-way interaction between race and class membership in predicting adjusted early dropout $\chi^2(9) = 18.272$, $p = .032$. Within class 3, Black participants had a significantly higher log-odds of early dropout than Latinx, $b = 0.960$, $p = .003$, and White, $b = 1.352$, $p = .007$, participants. Effect sizes were small, $OR = 2.612$, and medium, $OR = 3.865$, respectively. Within class 4, Latinx participants had a significantly lower log-odds of early dropout than White participants, $b = -2.728$, $p = .010$, and Black participants, $b = -2.411$, $p = .026$. Effect sizes were large: OR = 15.302 and OR = 11.145, respectively. The effect of race was nonsignificant in class 1 and class 2.

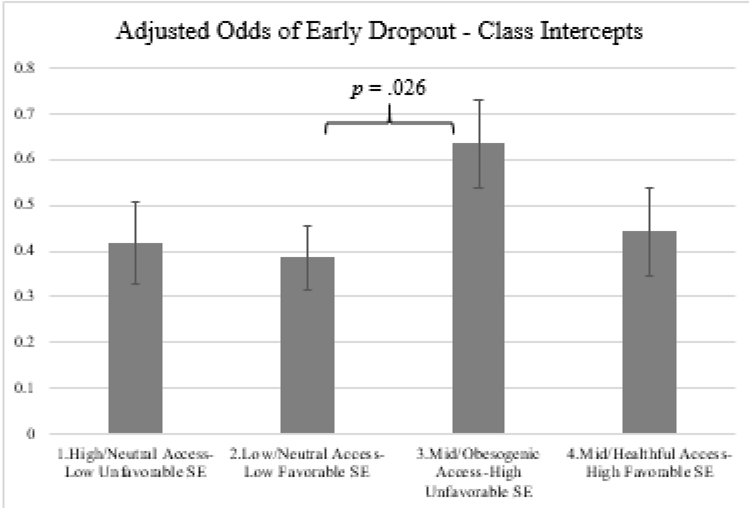
From the perspective of class membership, the differences among classes in log-odds of early dropout were nonsignificant (omnibus test and pairwise comparisons) for White participants and Latinx participants; while the differences among classes were significant for Black participants. For Black participants, the omnibus test of class differences was significant,

$\chi^2(3) = 10.425$, $p = .015$. Pairwise comparisons revealed that membership in class 3 significantly increased the log-odds of early dropout relative to class 1, $b = 0.819$, $p = .015$, and class 2, $b = 0.817$, $p = .004$. Effect sizes were small: $OR = 2.268$ and $OR = 2.264$, respectively.

The two-way interaction between insurer status and class membership in predicting early dropout was nonsignificant.

Table 3.6 Multiple-group Regression Model Predicting Log-odds of Early Dropout

Regression coefficients				
Variable	***b***	***SE***	***p***	***OR***
Age	-0.110	0.078	0.158	0.896
Gender	-0.009	0.160	0.954	0.991
Black	0.191	0.198	0.335	1.210
Latinx	-0.602	0.255	0.018	0.548
Medicaid participation	0.130	0.180	0.470	1.139
Distance to clinic	-0.041	0.085	0.630	0.960
Class-specific intercepts				
	b_0	***SE***	***p***	
Class 1	-0.872	0.197	< .001	
Class 2	-0.954	0.165	< .001	
Class 3	-0.455	0.141	< .001	
Class 4	-0.816	0.195	< .001	
Pairwise comparisons				
	b	***SE***	***p***	***OR***
Class 1 vs. Class 2	0.083	0.261	0.751	1.087
Class 1 vs. Class 3	-0.417	0.244	0.087	0.659
Class 1 vs. Class 4	-0.055	0.280	0.843	0.946
Class 2 vs. Class 3	-0.500	0.224	0.026	0.607
Class 2 vs. Class 4	-0.138	0.260	0.595	0.871
Class 3 vs. Class 4	0.362	0.255	0.156	1.436



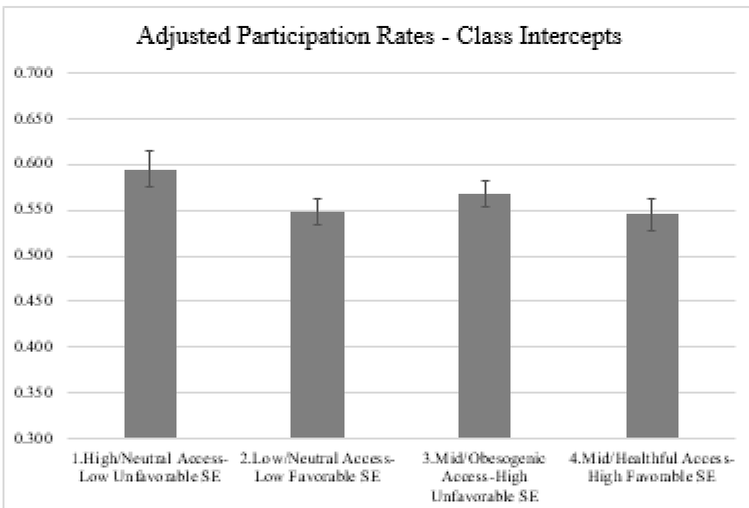


Figure 3.4 Class-specific intercepts for early dropout and participation rate

3.3.2 Participation rate

The omnibus test indicated that differences among classes in average participation rate were nonsignificant, $\chi^2(3) = 6.794$, p = .079. However, pairwise comparisons indicated a significantly higher average participation rate in class 1, relative to class 2, b = 0.061, p = .009. The effect size was small: β = 0.292.

Participation rate was adjusted for the covariates of age, gender, race, distance from clinic, and Medicaid participation (Table 3.7). The omnibus test of differences among classes was nonsignificant, $\chi^2(3) = 4.447$, $p = .217$ (Figure 3.4). Pairwise comparisons were also nonsignificant, $.062 \leq p\text{'s} \leq .845$.

Race was the only covariate with a significant relationship with participation rate. Black participants had a significantly lower average participation rate than White ($b = -0.067$, $p < .001$), Latinx ($b = -108$, $p < .001$), and other ($b = -0.155$, $p = .005$) participants. Effect sizes were small to medium: $\beta = -0.318$, $\beta = -0.510$, and $\beta = -0.737$, respectively.

The two-way interactions between race and class membership and between insurer status and class membership in predicting participation rate were nonsignificant.

Table 3.7 Multiple-group Regression Model Predicting Participation Rate

Regression coefficients				
Variable	***b***	***SE***	***p***	***β***
Age	0.000	0.000	0.552	-0.001
Gender	0.016	0.015	0.280	0.075
Black	-0.067	0.019	< .001	-0.318
Latinx	0.041	0.023	0.076	0.193
Other race	0.088	0.057	0.118	0.419
Medicaid participation	-0.018	0.017	0.281	-0.086
Distance to clinic	0.000	0.000	0.296	-0.001
Class-specific intercepts				
	b_0	***SE***	***p***	
Class 1	0.595	0.019	< .001	
Class 2	0.549	0.014	< .001	
Class 3	0.568	0.015	< .001	
Class 4	0.545	0.018	< .001	
Pairwise comparisons				
	b	***SE***	***p***	***β***
Class 1 vs. Class 2	0.046	0.025	0.062	0.218
Class 1 vs. Class 3	0.027	0.024	0.261	0.128
Class 1 vs. Class 4	0.051	0.027	0.062	0.240
Class 2 vs. Class 3	-0.019	0.021	0.371	-0.091
Class 2 vs. Class 4	0.005	0.024	0.845	0.022
Class 3 vs. Class 4	0.024	0.026	0.354	0.113

3.3.3 Staring zBMI

Starting zBMI, zBMI at first visit, was examined across classes. The omnibus test indicated significant differences among classes in starting zBMI, $\chi^2(3) = 21.407$, $p < .001$. Pairwise comparisons revealed significantly lower starting zBMI in class 4 relative to class 1

(b = -0.100, p = .026), class 2 (b = -0.148, $p < .001$), and class 3 (b = -0.170, $p < .001$). Effect sizes were small: β = -0.255, β = -0.378, and β = -0.434, respectively.

After adjusting starting zBMI for the covariates of gender, age, race, and Medicaid participation, the omnibus test was no longer significant, $\chi^2(3) = 6.155$, p = .104 (Table 3.8). However, pairwise comparisons indicated significantly lower starting adjusted zBMI in class 4 relative to class 2, b = -0.087, p = .024, and relative to class 3, b = -0.087, p = .040 (Figure 8). Effect sizes were small: β = -0.225 and β = -0.225, respectively.

Examination of covariates revealed that Medicaid participants had significantly higher adjusted starting zBMI than non-Medicaid participants, b = 0.094, p = .001. The effect size was small, β = 0.241. In addition, Black participants had significantly higher adjusted starting zBMI relative to White participants, b = 0.168, $p < .001$, and Latinx participants, b = 0.233, $p < .001$. Effect sizes were small to medium: β = 0.432 and β = 0.600, respectively.

Table 3.8 Multiple-group Regression Model Predicting Starting zBMI

Regression coefficients				
Variable	***b***	***SE***	***p***	***β***
Age	-0.005	0.006	0.404	-0.012
Gender	-0.033	0.026	0.202	-0.085
Black	0.168	0.033	0.000	0.432
Latinx	-0.065	0.041	0.111	-0.168
Other race	-0.005	0.102	0.963	-0.012
Medicaid Participation	0.094	0.029	0.001	0.241
Class intercepts				
	b_0	***SE***	***p***	
Class 1	2.382	0.032	< .001	
Class 2	2.420	0.026	< .001	
Class 3	2.420	0.025	< .001	
Class 4	2.332	0.029	< .001	
Pairwise comparisons				
	b	***SE***	***p***	***β***
Class 1 vs. Class 2	-0.038	0.042	0.368	-0.098
Class 1 vs. Class 3	-0.038	0.041	0.356	-0.098
Class 1 vs. Class 4	0.049	0.045	0.270	0.127
Class 2 vs. Class 3	0.000	0.038	0.998	0.000
Class 2 vs. Class 4	0.087	0.039	0.024	0.225
Class 3 vs. Class 4	0.087	0.042	0.040	0.225

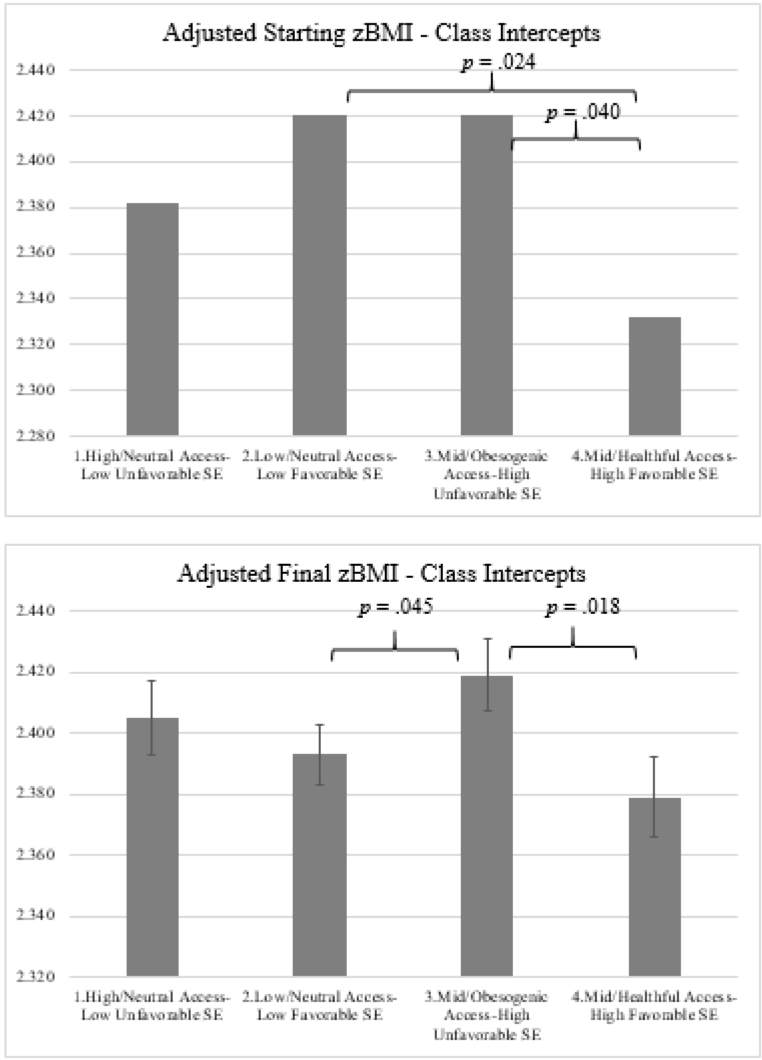


Figure 3.5 Class-specific intercepts for starting zBMI and final zBMI

3.3.4 *Adjusted final-zBMI*

zBMI at last completed visit, final zBMI, adjusted for starting zBMI and number of completed visits, was compared across classes. Only participants with at least two completed visits were included in the analysis (n = 531). The omnibus test indicated that the differences among classes were nonsignificant, $\chi^2(3) = 5.996$, $p = .112$. Pairwise comparisons indicated that adjusted final zBMI in class 3 was significantly greater than adjusted final zBMI in class 4, b = 0.041, $p = .017$. The effect size was small, $\beta = .103$.

In addition to starting zBMI and number of completed visits, final zBMI values were adjusted for the covariates gender, age, race, and Medicaid participation (Table 3.9). The omnibus test of differences among classes was nonsignificant, $\chi^2(3) = 6.174$, $p = .103$. However, pairwise comparisons indicated that class 3 had a significantly higher adjusted final zBMI than class 2 ($b = 0.027$, $p = .045$) and class 4 ($b = 0.041$, $p = .018$; Figure 8). Effect sizes were small: $\beta = 0.069$ and $\beta = 0.105$, respectively.

Regarding covariates, age, $b = 0.006$, $p = .004$ and number of completed visits, $b = -0.010$, $p = 0.004$, were significant predictors of adjusted final zBMI. Effects sizes were small: $\beta = 0.015$ and $\beta = -0.026$, respectively.

The two-way interactions between race and class membership and between insurer status and class membership in predicting final adjusted zBMI were nonsignificant.

Table 3.9 Multiple-group Regression Model Predicting Adjusted Final zBMI

Regression coefficients				
Variable	***b***	***SE***	***p***	***β***
Starting zBMI	0.964	0.018	< .001	2.500
Visits	-0.010	0.003	0.004	-0.026
Age	0.006	0.002	0.004	0.015
Gender	-0.014	0.009	0.138	-0.036
Black	0.014	0.011	0.208	0.037
Latinx	-0.017	0.015	0.279	-0.043
Other race	-0.052	0.047	0.272	-0.134
Medicaid	0.008	0.010	0.449	0.020
Class intercepts				
	b_0	***SE***	***p***	
Class 1	2.405	0.012	< .001	
Class 2	2.393	0.010	< .001	
Class 3	2.419	0.012	< .001	
Class 4	2.379	0.013	< .001	
Pairwise comparisons				
	b	***SE***	***p***	***β***
Class 1 vs. Class 2	0.012	0.014	0.401	0.031
Class 1 vs. Class 3	-0.015	0.015	0.318	-0.038
Class 1 vs. Class 4	0.026	0.017	0.125	0.068
Class 2 vs. Class 3	-0.027	0.013	0.045	-0.069
Class 2 vs. Class 4	0.014	0.014	0.333	0.036
Class 3 vs. Class 4	0.041	0.017	0.018	0.105

4 DISCUSSION

On average, pediatric weight management programs demonstrate efficacy (e.g., Oude Luttikhuis et al., 2009). However, a large percentage of participants do not benefit, particularly when considering attrition (Oude Luttikhuis et al., 2009). Although treatment failure is not well understood, indications are that social determinants of health play a key role (Dhaliwal et al., 2014; Ligthart et al., 2017). Therefore, it is vital to consider the socioecological context of pediatric patients (Baranowski et al., 2003; Epstein, Raja, et al., 2012; Maziak et al., 2007; McKay et al., 2007). Increased availability of small-area spatial data has revealed profound disparities in pediatric obesity rates in the Unites States at the level of neighborhoods (Bethell et al., 2010). Manifold and widely observed health disparities among neighborhoods have led public health experts to conclude, unequivocally that “place matters.”(National Academies of Sciences, Engineering, and Medicine, 2017, p. 79)

There is a rapidly growing field of study dedicated to determining which environmental factors are responsible for observed neighborhood disparities. Several built and social environment characteristics of neighborhoods have been identified as potential determinants of pediatric obesity (e.g., accessibility of physical activity opportunities, accessibility of food, crime, neighborhood SES; Ding et al., 2011; Galvez et al., 2010; Nau, Schwartz, et al., 2015) based on associations with obesity rates in general clinical and epidemiological samples. In addition, there is a small but growing literature demonstrating that built and social environment factors are important predictors of outcome in pediatric overweight and obesity treatments (Armstrong et al., 2015; Broyles et al., 2016; Epstein, Raja, et al., 2012; Epstein et al., 2006; Fiechtner et al., 2016). However, most studies of neighborhood factors are limited by poor measurement of the neighborhood environment and an inability to capture likely complex relationships among neighborhood variables (DeWeese et al., 2018; Nau, Ellis, et al., 2015; Wall et al., 2012). The result of which is often contradictory findings among studies (e.g., Jia et al., 2017). In addition, there is limited evidence that neighborhood factors predict treatment response in pediatric weight management programs.

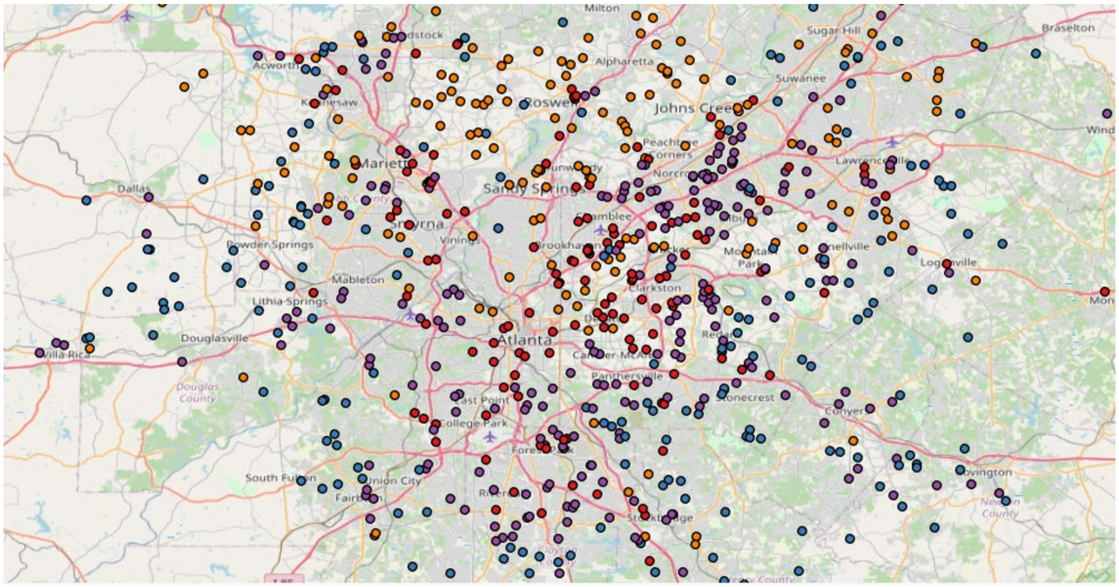
The present study sought to examine heterogeneity among pediatric weight management participants in terms of neighborhood environment. The first primary aim was to identify neighborhood types using built and social environment indicators expected to be related to pediatric obesity. The second primary aim was to determine whether the ensuing groupings predict treatment variables in a weight management clinic, including participation in the program and zBMI.

Geographic Information Systems (GIS) techniques were used to examine the neighborhood environments of participants. Neighborhood variables believed to be associated with pediatric obesity were analyzed. Built environment variables included accessibility of physical activity opportunities and accessibility of food supply. Social environment variables included neighborhood concentrated disadvantage, concentrated affluence, and crime. A latent-variable mixture analysis was conducted to capture the heterogeneity in neighborhood environments by identifying neighborhood types (classes) according to between-class variability in levels of neighborhood variables and according to between-class variability in relationships among neighborhood variables. Treatment variables, including early dropout, participation rate, and zBMI, were compared across classes. In addition, interactions among classes and child- and family-level variables were examined.

4.1 Mixture Analysis

Consistent with expectations, the heterogeneity in home neighborhood environments indicated multiple neighborhood types (four classes), each with distinguishing features. The classification quality of the model was above recommended levels. The analysis identified both neighborhood features that differ across neighborhood types and patterns among neighborhood features that differ across neighborhood types. It helped to rule out thousands of possible neighborhood types (13 binary indicators = 8,192 possible cross sections) and focus the analysis on those types most likely to exist given the data. The four classes identified differed according to three dimensions: overall accessibility, relative accessibility, and social environment.

Assigning participants to their most likely class revealed that their home neighborhoods were generally dispersed with some apparent clustering of neighborhood types around regions in the Atlanta-metro area (Figure 9; These data are presented for illustration purposes only; given that a latent and person-centered approach was used, no interpretations based on civic areas are provided.)



- Class 1. High/Neutral Access-Low Unfavorable SE
- Class 2. Low/Neutral Access-Low Favorable SE
- Class 3. Mid/Obesogenic Access-High Unfavorable SE
- Class 4. Mid/Healthful Access-High Favorable SE

Figure 4.1 Participant residence by class

4.1.1 Overall accessibility

The analysis revealed differences in overall accessibility for a subset of participants. About half of the sample exhibited either high or low accessibility. This is consistent with past findings of disparities in the availability of both food supply and physical activity opportunities between neighborhoods (Ding et al., 2011; Galvez et al., 2010). However, accessibility of all built environment features (recreational facilities, parks, walkability, grocery stores, convenience stores, fast food) tended to vary together across classes. Past mixture analyses of neighborhood features revealed similar results (DeWeese et al., 2018; Wall et al., 2012). This suggests that in low access neighborhoods, the detrimental effects of low availability of healthful food supply (grocery stores) and physical activity opportunities is at least partially offset by low availability of unhealthful food supply. The inverse would be true for high access neighborhoods. This may help explain why some studies examining these factors individually were not able to detect effects (e.g., Laska et al., 2010; Ohri-Vachaspati et al., 2013).

4.1.2 Relative accessibility

Overall, accessibility of built environment features tended to vary together, but there was a potentially important distinction in relative accessibility between classes. Specifically, class 3, Mid/Obesogenic Accessibility-High Unfavorable Social Environment (SE), exhibited an obesogenic pattern with high convenience store access and low recreational facilities access (relative to all other built environment features). In contrast, class 4, Mid/Healthful Access-High Favorable SE, had a healthful pattern—low convenience store and high recreational facilities access—that was the inverse of the pattern observed in class 3. These findings suggest that while relative accessibility is not a factor in every home neighborhood, it may be an important factor to consider for a considerable portion of home neighborhoods (estimated at 53% of current sample). This heterogeneity suggests that analyses examining relative food access (e.g., Luan, Law, & Quick, 2015) may produce weaker estimates of relative accessibility when measuring average effects. Given results from the current study, it is possible that relative accessibility is attenuated at more extremes levels of accessibility, since the Low-and High-Access groups exhibited neutral relative accessibility, while both the Mid-Access groups exhibited obesogenic or healthful relative accessibility patterns.

4.1.3 Neighborhood social environment

The finding that neighborhood social environment comprises a potentially important distinguishing feature is consistent with past analyses that have attempted to characterize neighborhood environments using the covariation among both built and social environment features (Nau, Ellis, et al., 2015; Wall et al., 2012). Wall et al. (2012) and Nau et al, (2015) included neighborhood SES indicators in their neighborhood models and found that these indicators distinguished neighborhood environments. Consistent with the present study, Wall et al. (2012) also included crime in their model and found that crime was inversely related to SES. DeWeese et al. (2018) did not include indicators of neighborhood SES in their mixture model. However, the authors included social variables as covariates in their regression analyses and found that many of the effects of their latent variable were confounded by the social variables of Neighborhood SES and crime (DeWeese et al., 2018), which is also consistent with the present study. In short, consistent with past research there were disparities between neighborhood types as indicated by the variables of concentrated disadvantage and affluence and crime.

4.1.4 Relationship between relative accessibility and social environment

There was a potentially important association between relative accessibility and social environment observed in the present study. The two classes that exhibited divergent levels of relative accessibility, class 3 (Obesogenic) and class 4 (Healthful), were also strongly differentiated by neighborhood social environment. Classes 3 and 4 exhibited the most unfavorable and the most favorable social environments, respectively. The nature of the association between relative accessibility and social environment was consistent with theory (Macintyre, 2007)—youth living in neighborhoods that were more disadvantaged and had higher crime also had lower relative accessibility to a subset of physical activity opportunities and higher relative accessibility to a subset of unhealthful food options; whereas those youth who lived in neighborhoods with more affluence and lower crime had higher relative accessibility to a subset of physical activity opportunities and lower relative accessibility to a subset of unhealthful food options. This finding is consistent with past studies that found negative associations between convenience store access and neighborhood SES (e.g., Chuang, Cubbin, Ahn, &

Winkleby, 2005) and positive associations between recreational facilities access and neighborhood SES (Moore, Diez Roux, Evenson, McGinn, & Brines, 2008). Results of the current study suggest it may be that relative accessibility to obesogenic or healthful built environment features tends to occur at the extremes of neighborhood social environments in expected ways.

4.1.5 Summary

Overall, the mixture analysis revealed disparities in accessibility and social environment among neighborhood types. Moreover, the data suggested synergistic patterns among features. No single class could be labeled as clearly obesogenic or clearly healthful because proposed benefits in one variable were often offset by detriments in another variable. In addition, there appeared to be relationships among features across classes. For example, obesogenic relative accessibility co-occurred with high unfavorable social environment and healthful relative accessibility co-occurred with high favorable social environment. These findings reinforce the need to examine a confluence of neighborhood features when studying neighborhood environments (DeWeese et al., 2018; Nau, Ellis, et al., 2015; Wall et al., 2012). Moreover, these results set the stage for examining how disparities in neighborhood environment may impact disparities in health outcomes. The analyses suggest that disparities in pediatric obesity rates and treatment outcomes may be due to overall accessibility, relative accessibility, social environment, or a combination of these factors.

4.2 Prediction of treatment variables

4.2.1 Outcome disparities

Consistent with hypotheses, there were a number of significant differences among the four classes on treatment variables. After accounting for child- and family-level factors (i.e., race, age, health insurer status, gender), membership in class 3, Mid/Obesogenic Access-High Unfavorable SE, was a risk factor whereas membership in class 4, Mid/Healthful Access-High Favorable SE, was a protective factor.

Pediatric patients in class 3 had a significantly higher log-odds of early dropout compared to class 2, Low/Neutral Access-Low Favorable SE. Class 3 pediatric patients also had higher starting zBMI compared to those in class 4. Youth in class 3 exhibited a significantly higher final adjusted zBMI compared to those in classes 2 or 4. In addition to these differences, class 4 patients had a significantly lower starting zBMI than class 2 patients. Overall, these findings are consistent with the hypothesis that home neighborhood environment, characterized by indicators of the built and social environment, confer relative risk or protection in terms of baseline BMI and treatment outcomes in a pediatric weight management clinic. In addition, the disparities observed between class 3 and class 4 appear largely consistent with hypothesized risk and protective factors. That is, the class with the most obesogenic relative accessibility and unfavorable social environment conferred risk, whereas the class with the most healthful relative accessibility and favorable social environment conferred protection. This is largely consistent with past research that has identified high relative accessibility of unhealthful food (Luan et al., 2015), low absolute accessibility of physical activity opportunities (Ding et al., 2011; Dunton et al., 2009), low neighborhood SES (Boone-Heinonen & Gordon-Larsen, 2012; Greves Grow et al., 2010; Nau, Schwartz, et al., 2015) and high crime (Gartstein et al., 2018; Kimbro & Denney, 2013) as risk factors for pediatric obesity.

These findings contribute to the growing argument that neighborhood disparities in pediatric obesity rates are related to disparities in built and social environment features. In addition, the current study extends those findings to multicomponent treatment outcomes in a high-risk pediatric weight management clinic. Findings were largely consistent with the handful of studies that examined relationships between features of neighborhood environments and single-component obesity treatment outcomes (Baranowski et al., 2003; Maziak et al., 2007; McKay et al., 2007) and the one study that examined relationships between built environment features and a multicomponent treatment outcome (Epstein, Raja, et al., 2012). In addition, these findings build on the research in several key ways. Utilizing a person-centered multivariate approach (mixture modeling) with an inclusive sample allowed the current study to better understand different neighborhood types and how they differ from one another. In addition, it allowed for the estimation of the totality of neighborhood effects on treatment outcomes, which is important because there appears to be synergistic and offsetting effects among different neighborhood features. This allowed for better estimation of where the overall disparities in treatment outcome are occurring (i.e., in what types of neighborhoods). Moreover, the present study demonstrated effects on attrition outcomes in addition to weight management outcomes.

It is notable that participation rates did not differ among the four classes. Given that the frequency of scheduled visits is individualized it may be that youth with early participation barriers are scheduled less frequently, which could attenuate differences in participation rates.

4.2.2 Sources of disparity-lifestyle change

Given that neighborhoods were measured as a whole, it cannot be determined definitively which individual features of neighborhoods specifically contributed to associations with treatment variables. However, examining the distinguishing characteristics of classes can suggest likely candidates. The features of class 3, Mid/Obesogenic Access-High Favorable SE, and class 4, Mid/Healthful Access-High Favorable SE, suggest that relative accessibility to recreational facilities and convenience stores; neighborhood social disadvantage, affluence, and crime; or the combination of built accessibility and social environment aspects may account for the differences in baseline as well as final BMI and early attrition. Considering these characteristics, the patterns of risk and protection were consistent with hypotheses and past research (Boone-Heinonen & Gordon-Larsen, 2012; Ding et al., 2011; Kimbro & Denney, 2013; Luan et al., 2015; Nau, Schwartz, et al., 2015).

4.2.3 Built environment - relative accessibility

Regarding relative food supply, results suggest that access to unhealthful food outlets relative to healthful food outlets is a more important factor than absolute access. This may be because food establishments compete for the attention and income of patrons and it is the net result of that competition that effects the health of an area (Luan et al., 2015). According to this perspective, families in class 3 may have had to make a greater effort to avoid unhealthy food options in favor of healthy food options. This is consistent with the findings of Fiechtner et al. (2016) that grocery store access net of fast food establishments predicted weight management outcomes; and it explains why some studies looking at absolute access identified healthful food facilities as risk factors (e.g., Epstein et al., 2012).

For recreational facilities it is less clear how relative access may impact outcomes, because unlike food locations, recreational faculties are not necessarily competing with unhealthful food options. However, research into buying patterns suggest that unhealthful food establishments are often visited by individuals on the way to and from other destinations (Kerr et al., 2012). The benefit of increased recreational facilities may be greater in areas where there are less likely to be unhealthy food establishments on the way to and from these locations. Therefore, participants in class 4 may have been tempted less often by unhealthy food options when attempting to engage in physical activity.

4.2.4 Social environment

These findings are consistent with past research that indicates lower neighborhood SES and high neighborhood crime are risk factors for pediatric obesity (Boone-Heinonen & Gordon-Larsen, 2012; Greves Grow et al., 2010; Nau, Schwartz, et al., 2015). Previous studies that demonstrated a negative relationship between physical activity and crime (Ferreira et al., 2007) suggest that participants in class 3 relative to class 4 may experience barriers to outdoor physical activity, due to safety concerns. Moreover, past research examining the relationships between Neighborhood SES and the quality of built environment features (McKenzie, Moody, Carlson, Lopez, & Elder, 2013) and level of unhealthy advertising (Cassady et al., 2015) suggests that participants in class 3 could have been hindered by lower quality physical activity outlets (recreational facilities, parks) and healthful food stores and may have been inundated with advertisements promoting unhealthy behaviors.

4.2.5 Sources of disparity-participation

As detailed above, epidemiological research suggests how the identified neighborhood environments may have affected participants' starting and ending BMIs. However, this is the first study to examine the impact of neighborhood environments on participation (early dropout and participation rates). Past research on attrition in weight management programs suggests that discouragement from poor weight management results is an important determinant of attrition (Dhaliwal et al., 2017; J. A. Skelton & Beech, 2011). Thus, the same neighborhood factors that impacted weight may also have impacted dropout. Perception of the relevance and usefulness of information provision in weight management programs has also been identified as a source of attrition (Dhaliwal et al., 2017). It is possible that participants in class 3, who were facing environmental barriers to healthy lifestyle change, found the information related to cognitive and behavioral change less relevant and useful compared to participants in other classes.

4.2.6 Interaction with race and insurer status

Consistent with past research, Medicaid participation and race were significant predictors of participation (Dhaliwal et al., 2014; Ligthart et al., 2017). Specifically, Medicaid participation was a risk factor for early dropout, and Black racial identity was a risk factor for both early dropout and lower participation rates. It was hypothesized that neighborhood level risk factors would interact with child- and family-level risk factors to predict outcomes in such way that neighborhood level risk factors would be compounded by child- and family-level risk factors. Specifically, it was hypothesized that the risk/benefit conferred by neighborhood environment would be stronger/weaker for Medicaid participants relative to non-Medicaid participants and for racial or ethnic minority participants relative to White participants.

Moderation analyses provided some support for an interaction between neighborhood and race. Specifically, there was a significant two-way interaction between neighborhood and race in predicting early dropout. The nature of the interaction was such that neighborhood environment was not associated with dropout for White participants, but it was associated with dropout for both Black and Latinx participants. In addition, the nature of the significant neighborhood effects differed between Black and Latinx participants. For Black participants, membership in class 3, Mid/Obesogenic Access-High Favorable SE, was a significant risk factor for early dropout. In contrast, for Latinx participants membership in class 4, Mid/Healthful Access-High Favorable SE, was a significant protective factor for early dropout. The interaction with Black race relative to other races was consistent with expectations, but the interaction with Latinx race was opposite of expectations. One possible explanation for this contrary finding is that the nature of dropout may differ between classes. For example, participants in class 4 could exhibit more dropout due to early success. If that were accurate then less early success would lead to less dropout.

4.3 Summary

Results of the present study demonstrated that there were patterns among neighborhood built and social environment variables that indicated disparities in home neighborhood environments across individual participants in a weight management clinic. Participant home neighborhoods were distinguished by overall accessibility of built environment features, relative accessibility of built environment features, and social environment. Neighborhood environments were predictive of early attrition and weight management outcomes. Two neighborhood environment types were identified as conferring either relative risk or relative protection. These neighborhood types were distinguished by relative accessibility of built environment features and social environment; and results were largely consistent with hypothesized environmental risk factors. Participants living in the neighborhoods with unhealthy relative accessibility—lower access to recreational facilities and higher access to convenience stores—and disadvantaged social environments exhibited the worst outcomes. In contrast, participants living in neighborhoods with favorable relative accessibility—higher access to recreational facilities and lower access to convenience stores—exhibited the best outcomes. Moreover, consistent with expectations, there was some evidence of intersectionality between individual level and neighborhood level determinants. Specifically, the effect of neighborhood was moderated by race in predicting early dropout.

4.4 Implications

These results suggest that within the participant population of a given weight management clinic, there may be significant but predictable disparity in home neighborhood environments, and the resulting groupings may be partly responsible for observed differences in participation and weight outcomes.

4.4.1 Multilevel assessment and intervention

It may benefit clinicians to consider participants' neighborhood environments, in addition to child- and family-level factors, as baseline predictors of differential treatment success. Moreover, treatment may require multilevel intervention that attends to neighborhood level factors as well as individual cognitive and behavioral factors. Interventions could potentially be tailored to meet the needs of children and families residing in different neighborhood environments. For example, these findings suggest that it might be prudent to implement additional efforts to offset early dropout from treatment for children coming from neighborhoods with relatively fewer physical activity opportunities and healthful food establishments as well as social environment risk factors (e.g., concentrated disadvantage, crime).

4.4.2 Public policy

There are potential public policy implications of the current research. Past research on the impacts of investing in neighborhood environments (e.g., building grocery stores) on obesity has demonstrated mixed and unconvincing results (Mayne et al., 2015). This has led some to persist in the belief that investing additional resources in disadvantaged neighborhoods offers a poor return. However, the present study suggests just one of the ways that a lack of community investment could create barriers for those living in disadvantaged areas—stifling intergenerational change, and widening health disparities over time.

4.4.3 Measuring neighborhood environments

In addition, the results of the present study suggest that when considering neighborhood environments, it is important to examine a confluence of built environment and social environment factors. Results suggest that for the greater Atlanta area, relative access and neighborhood social environment may be particularly important features. However, the distinguishing features of neighborhood environments likely differ across geographies. Therefore, it would be beneficial to perform similar analyses for each individual clinic or metropolitan area.

4.4.4 Residential segregation

The identification of disparate subgroups within the pediatric patient population of a single clinic, begs the question of how these disparities in neighborhood environments came to be. Although not a primary aim of the present research, demographic statistics revealed that Black and Latinx participants were significantly more likely to reside in communities with disadvantaged social conditions. Persistent residential segregation in the United States has been the result of structural political, civic, judicial, and economic processes (e.g., redlining), and it is both a result and a source of racial disparities (Smith, Blackman Carr, El-Amin, Bentley-Edwards, & Darity Jr, 2019). Segregation by race in the Unites States has been shown to be more pronounced than segregation by SES (National Academies of Sciences, Engineering, and Medicine, 2017). A White person of low SES is more likely to live among neighbors with a range of SES levels, which affords opportunities for upward mobility and benefits from shared resources (National Academies of Sciences, Engineering, and Medicine, 2017). In contrast, racial minorities are more likely to live in areas of concentrated poverty (National Academies of Sciences, Engineering, and Medicine, 2017). The results of the present study are consistent with the hypothesis that residential segregation leads to disparities in childhood obesity through disparities in neighborhood environmental conditions (Smith et al., 2019).

4.5 Limitations

There were a number of limitations to the present research that should be considered when drawing conclusions or making inferences.

4.5.1 Measurement of access

There may be important variables to consider in addition to density, proximity, and North American Industry Classification System (NAICS) codes that determine effective access to physical activity opportunities and healthful and unhealthful foods. These could include such variables as quality, size of a location, and cost. For example, smaller or lower quality parks and grocery stores could result in reduced access in physical activity opportunities and healthful foods, respectively; these nuances would not be accounted for in the current study. Regarding pricing, just as grocery stores generally offer better access to affordable healthy food options than convenience stores, there may be similar differences between different types or chains of grocery stores. Some studies have attempted to examine the variables of quality, size, and pricing, but they generally involve labor intensive procedures of surveying individual locations.

In the present study, variance due to differences in unmeasured variables like quality, size, and pricing may have contributed to measurement error. This highlights the benefit of using a latent mixture model to characterize neighborhood environments. However, these variables may also vary systematically with other study variables, and it may be of benefit to explore those associations. For example, as suggested above, it is possible that neighborhoods with unfavorable social environments may also have access to lower quality grocery stores or parks, suggesting lower access to healthful food and physical activity opportunities for the same level of density and proximity.

4.5.2 Child- and family-level variables

The present study could have benefited from additional information at the child- and family-level to include as covariates and in moderation analyses. Classes clearly differed on important demographic measures including race and insurer status. Efforts were made to account for these differences, but additional measures, such as measures of family SES, could help parse the individual and community level variance; moreover, there are likely additional child- and family-level variables that are important in determining effective access. These may include whether or not the family owns a car or are located near public transportation, which has been found to be relevant in other studies (Dunton et al., 2009).

The present study attempted to examine intersectionality between child- and family-level variables and neighborhood using moderation analyses. This decision precluded the examination of more complex interactions (such as a three-way interaction between race, neighborhood, and Medicaid participation) due to the high number of variable cross sections involved (32) and the reduction in power. A second mixture model that includes child- and family-level variables, along with neighborhood classification, may be better able to examine the intersectionality among these variables.

4.5.3 Measurement of mediators

The present study was able to demonstrate relationships between neighborhood factors and outcomes in weight management programs, but the mechanisms of action are unknown. Measurement of intervening variables, such as diet and physical activity changes could help elucidate these connections and improve the research.

4.5.4 Type I error

Regarding outcome measures, the majority of the reported significant effects resulted from pairwise comparisons between classes, and the omnibus tests of significance were generally nonsignificant (the exceptions were the significant moderation effect and subsequent examination of neighborhood effects by race). However, the significant pairwise tests appeared to illustrate a consistent and—despite small effect sizes—clinically meaningful pattern of findings.

4.6 Future Research

The present study indicated that variability in or generally poor treatment response in pediatric weight management programs (e.g., Dhaliwal et al., 2014) is due in part to heterogeneity in home neighborhood environments and the interrelationship between home neighborhood environments and child-level variables. Future research could examine hypothesized mediators of the neighborhood effects. Regarding participation outcomes, additional studies in this area could measure participant engagement and survey reasons for dropout or limited participation. Regarding weight management, investigations could measure activity levels and diet, or even more proximal variables such as shopping patterns and composition of available food in the home. Determining the mechanisms of action from neighborhood environments to proximal lifestyle behaviors to weight outcomes, could help clinicians tailor their treatments accordingly. In addition to determining options for tailoring intervention, future research could determine the feasibility and acceptability of capturing neighborhood level variables and utilizing that information to tailor treatment at the individual clinic level.

4.7 Conclusions

Increased availability of fine-grained spatial data has revealed shocking health disparities across residential communities in the United States (National Academies of Sciences, Engineering, and Medicine, 2017). A prominent public health expert poignantly summarized the state of affairs when she concluded, “Your zip code is a better predictor of health than your genetic code” (as cited in Roeder, 2014). The present study sought to examine the disparities in neighborhood environments among pediatric weight management participants. The primary aims were to effectively characterize heterogeneity in neighborhood features and to determine whether resulting groupings predicted participation in the weight management clinic and weight management outcomes. The technique of mixture modeling was able to identify four latent classes of neighborhoods that differed in terms of built environment overall accessibility, built environment relative accessibility, and neighborhood social environment. About half of the sample resided in neighborhoods that conferred risk or protection, in terms of relative accessibility and neighborhood social environment. Membership in those areas was predictive of participation and weight management outcomes. In addition, there was some evidence of interaction with child race. Results suggest that disparities in neighborhood environments account for some of the differential treatment response that commonly occurs in pediatric weight management programs. Future studies could examine mechanisms of action and determine options for tailoring treatments according to a participant’s home neighborhood environment.

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