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The built environment and depressive symptoms among urban youth: A spatial regression study

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Abstract

This study evaluated spatial relationships between features of the built environment and youth depressive symptoms. Data used in this study came from the 2008 Boston Youth Survey Geospatial Dataset, which includes Boston high school students with complete residential information ($n = 1170$). Features of the built environment (such as access to walking destinations and community design features) were created for 400- and 800-m street network buffers of the youths' residences. We computed standard Ordinary Least Squares (OLS) regression and spatial simultaneous autoregressive models. We found significant positive spatial autocorrelation in all of the built environment features at both spatial scales (all $p = 0.001$), depressive symptoms ($p = 0.034$) as well as in the OLS regression residuals (all $p < 0.001$), and, therefore, fit spatial regression models. Findings from the spatial regression models indicate that the built environment can have depressogenic effects, which can vary by spatial scale, gender and race/ethnicity (though sometimes in unexpected directions, i.e. associations opposite to our expectations). While our results overall suggest that the built environment minimally influences youth depressive symptoms, additional research is needed, including to understand our results in the unexpected direction.

Keywords

Spatial epidemiology; Neighborhood effects; Built environment; Neighborhood walkability; Depressive symptoms; Youth

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1. Introduction

Depression is one of the most prevalent, debilitating and costly mental health conditions in the United States. In the National Comorbidity Surveys, a large population-based epidemiological sample of individuals living in the US, an estimated 12% of youth (Merikangas et al., 2011) and 16.6% of adults (Kessler et al., 2005) met DSM-IV diagnostic criteria for a depressive disorder, including major depression. Nationally-representative school-based studies, including the most recent Youth Risk Behavior Surveillance Survey, have found that almost 30% of high school students report serious and significant symptoms of depression, specifically feeling sad or hopeless nearly every day for the past 2 weeks, that interfere with functioning (Eaton et al., 2008).

Many epidemiologic studies have identified individual-level risk factors associated with depression, including female gender, exposure to stressful life events, child maltreatment and family history of the disorder (Dunn et al., 2011, 2012a; Hammen, 2005). A growing body of depression work has begun to examine neighborhood factors (Julien et al., 2012; Paczkowski and Galea, 2010; Beard et al., 2009; Galea et al., 2007). Most of these studies have evaluated macro-social neighborhood characteristics such as neighborhood poverty and neighborhood racial composition (Julien et al., 2012; Paczkowski and Galea, 2010; Beard et al., 2009; Galea et al., 2007). Only a handful of studies have examined built environment features of neighborhoods in relation to depression and depressive symptoms, and these studies suggest that the built environment may be implicated in depression/depressive symptoms (Kim, 2008; Mair et al., 2008). This fundamental gap in knowledge is problematic as environmental-level investigations can underscore specific *modifiable* aspects of the environment that may improve mental health. There are several pathways through which built environment can influence depression outcomes (Evans, 2003; Kim, 2008). For example, increased access to destinations (e.g. parks) and community design features (e.g. sidewalk access) could promote *socialization* (Leyden, 2003; de Toit et al., 2007; Cohen et al., 2008; Rogers et al., 2011) and *physical activity* (Ding et al., 2011), both of which contribute to better population mental health (Kim, 2008; Mair et al., 2008; Kawachi and Berkman, 2001; Teychenne et al., 2008). Moreover, urban density factors (such as highway density) could be linked with mental health conditions because noise from highways can create *stress*, which in turn could increase risk for depression (Lederbogen et al., 2011). Other built environment features (including green spaces such as parks) may reduce stress and increase relaxation, improving mental health (Bedimo-Rung et al., 2005).

While previous studies of the association between built environments and depression/depressive symptoms are informative, they have several key limitations. First, several studies examining the built environment–depression relationship have relied on the study participants' perceptions of the built environment. This is problematic when self-reported measures of mental health are also used (which is common in neighborhood research), as this may induce same-source bias, resulting in spurious associations (Diez-Roux, 2007). Second, studies that examine the influence of objectively measured built environments on depression/depressive symptoms have focused on adults (Weich et al., 2002; Galea et al., 2005; Kubzansky et al., 2005; Araya et al., 2007; Berke et al., 2007; Schootman et al., 2007; Stockdale et al., 2007; Sallis et al., 2009; Wilbur et al., 2009; Saarloos et al., 2011; Miles et al., 2012). This is a major gap, given that youth may be particularly susceptible to the effects of their built environments because, as compared to adults, they can have restricted mobility in their neighborhoods. Moreover, adolescence is a time when depression often emerges for the first time, suggesting that investigation of etiologic factors for depression among adolescent populations can provide new knowledge to guide the development of population-level strategies to prevent the onset of the disorder.

Most studies of the built environment use administrative neighborhood definitions (e.g. US census tracts). However, using individual's specific addresses rather than a proxy (e.g. administrative neighborhood boundary) is important, because they are more relevant to young people's social realities and health/wellbeing (Matthews, 2011). Defining neighborhoods with administrative units may also be inadequate for individuals living on the margins of those areas and thus could result in exposure misclassification, highlighting the salience of the more localized buffer-based neighborhood specifications. Although spatial units cannot be assumed to be independent, we are not aware of *any* of the published research examining the role of the built environment on depression/ depressive symptoms that utilized spatial analytic methods. Several studies examining relationships between built environment features and depression/depressive symptoms have applied multilevel regression models, perhaps as a way to account for spatial effects. Traditional multilevel models, however, do not necessary account for spatial autocorrelation and, at best, only account for spatial heterogeneity (Chaix et al., 2005a,b). The spatial arrangement of data is not captured by specifying one (or even multiple) hierarchy (hierarchies). It is important, when appropriate, to use spatial regression techniques to account for spatial dependence in depression. We are not aware of any research that has directly examined the presence of spatial effects in depression/depression symptoms among youth. However, some emerging research found spatial patterning of depression/depression symptoms among samples of adults (Mair et al., 2012; Gruebner et al., 2011). While the data generating process for spatial clusters is unknown (including for potential spatial clusters of depression/depressive symptoms), this may be due to common environmental features, and highlights the importance of explicitly accounting for space.

In addition to effect modification by neighborhood definition (e.g. spatial scale), demographic characteristics can be effect modifiers in the relationship between built environments and depression/depressive symptoms. For instance, the relationship between the built environment and depression may vary by gender and race/ethnicity, but with few exceptions has this been considered. Most studies not only fail to examine associations by population subgroups, but they also do not use a sizeable number of samples with racial/ ethnic minority populations, who have increased rates of youth depressive symptomatology (Wight et al., 2005) and depression (Roberts et al., 1997).

The purpose of this study is to evaluate spatial relationships between various features of the built environment, particularly access to walking destinations and community design aspects, and depressive symptoms among a racially and ethnically diverse sample of urban youth. To build on and address the limitations of previous research, we explicitly consider the issue of spatial autocorrelation usually inherent in spatial datasets, which often necessitates spatial regression approaches. In this study, we also evaluate effects by spatial scale, gender and race/ethnicity, with a geospatial dataset that consists of predominantly racial/ethnic minority youth.

2. Methods

2.1. Sample and survey administration

Individual-level data are from the 2008 Boston Youth Survey (BYS) Geospatial Dataset, which includes 9–12th grade students in the Boston Public Schools system whose classrooms were selected to take the 2008 survey and provided the nearest cross-streets to their residential address (Azrael et al., 2009; Duncan et al., 2012, in press). Approximately 74% of Boston Public School students in the 2007–2008 academic year were eligible for free or reduced-price meals (Boston Public Schools at a Glance 2007–2008–2007), which is similar to the percentage of those schools included in the BYS (Green et al., 2011).

All 32 eligible public schools in the city were invited to take part in the BYS. Schools that exclusively served: adults, students transitioning back to school after incarceration, suspended students, or students with severe disabilities were ineligible. Twenty-two schools participated. The primary reason for school non-participation was scheduling difficulties (e.g. conflicts with mandatory standardized testing). Participating and non-participating schools did not have statistically significant differences in key school characteristics (e.g. racial/ethnic composition of students, drop-out rates, standardized test scores, student mobility rate). To generate the sample, 4–5 classrooms in the 22 participating schools were randomly selected for participation, yielding approximately 100–125 students per school.

The survey was administered to students by trained staff in the spring of 2008 during 50-min class periods. “Passive consent” was sought from parents (i.e., they had the opportunity to opt their child out of survey participation), and students were read a statement regarding assent prior to survey administration. Of the 2725 students enrolled in the classrooms selected for participation, 1878 (response rate = 68.9%) completed a survey. Most non-participants (85.5%) were absent from school on the day of survey administration. We obtained and geocoded complete address information to the nearest intersection from 68.8% of the Boston students who took the survey ($n = 1292$).

Limiting the sample to youth who completed all of the items on depressive symptoms and nearest residential intersection resulted in an analytic sample of 1170 youth. Of the students who completed the items on depressive symptoms, there was not a statistically significant difference between those who provided complete intersection residential addresses and those who did not (t-test = −1.65, $p > 0.05$).

2.2. Built environment variables

We used the data on the nearest intersection to the students’ residences as well as various available data from several sources to characterize a range of built environment features posited, based on extant theory and previous research, to influence depressive symptoms. The following built environment variables were created related to *access to walking destinations*: recreational open space density, park density, bus stops density, subway stop density, density of total retail destinations, density of total service destinations and density of total cultural/educational destinations. We also included the following built environment variables related to *community design*: median pedestrian route directness, intersection density, sidewalk completeness, average sidewalk width, average speed limit, highway density and residential density. Variable descriptions and data sources are listed in Table 1 and described in detail elsewhere (Duncan et al., 2012). We defined the youths neighborhood as 400- and 800-m street network buffers around the nearest intersection to their residence, because these distances are considered a proximal neighborhood environment for youth (Colabianchi et al., 2007) and because street network buffers, in comparison to circular buffers, are more relevant to human travel patterns (Oliver et al., 2007). The street network buffers were created from StreetMap streets excluding highways and ramps using the ArcGIS Network Analyst Extension. The street network buffers consisted of 50-m buffers around street center lines that extend along the network 400- and 800-m from the geocoded residential addresses. We note that in this study we used these ego-centric neighborhood definitions because buffer-based neighborhood definitions are increasingly used in neighborhood health effects research and these neighborhood definitions are likely to be more relevant to young people’s social realities and health/wellbeing than large administrative boundaries (Matthews, 2011).

2.3. Assessment of depressive symptoms

Depressive symptoms were assessed with an adapted version of the Modified Depression Scale (MDS) (Dahlberg et al., 2005). Students were asked to report the frequency of the five symptoms: In the past month, how often…(a) “Were you very sad?”; (b) “Were you grouchy or irritable, or in a bad mood?”; (c) “Did you feel hopeless about the future?”; (d) “Did you sleep a lot more or less than usual?”; and (e) “Did you have difficulty concentrating on your school work?”. For each item, response options ranged from 1 to 5. The five-point response options included: (1) never, (2) rarely, (3) sometimes, (4) often, and (5) always. Total scores were derived by summing all items among youth who had complete responses for all five items (range = 5–25), with higher scores indicating greater levels of depressive symptoms. The MDS has been shown to have good psychometric properties (Bosworth et al., 1999; Edwards et al., 2006; Goldstein et al., 2007; Tandon and Solomon, 2009), including good reliability and validity in a recent study among the 2008 BYS respondents (Dunn et al., 2012b). Of the 1292 youth in the BYS geospatial dataset, 122 youth did not complete the items on depressive symptoms assessed in the BYS instrument. Those who skipped the items on depressive symptoms were excluded from the study.

2.4. Other variables

Other individual- and neighborhood-level variables were used as covariates. Individual-level variables included: gender (male, female), race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, Asian and Other), age (years), nativity (US born, foreign-born) and the presence of other youth in household (yes, no). Neighborhood- level variables included: percent of non-Hispanic Black residents, percent of Hispanic residents, percent of households below poverty level and percent foreign born. All neighborhood-level measures were based on 2000 US Census Data, which were interpolated proportionally based on the census block groups for the youths’ defined neighborhood (i.e. values across block groups were weighted proportionately by each block group’s area within the defined buffer).

2.5. Spatial statistical analysis

First, we computed descriptive statistics on the sample for the individual and neighborhood characteristics. We also evaluated demographic differences in depressive symptoms.

2.5.1. Assessment of spatial patterns: geovisualization and global spatial autocorrelation—Geovisualization was conducted in ArcGIS 10 to map the built environment features and depressive symptoms, which facilitated the initial inspection of potential spatial patterns. A standard deviation (SD) map with an interval size of 1 SD was created to show the spatial distribution of depressive symptoms among the sample, i.e. how much variation there is from the mean of depressive symptoms across the study area (map colors were based on Color Brewer 2.0) (http://www.colorbrewer2.org). To formally quantify overall spatial patterns (or global spatial autocorrelation) in the neighborhood built environment features and depressive symptoms, we calculated the well-known Global Moran’s *I* statistic (Cliff and Ord, 1981; Bailey and Gratrell, 1995; Waller and Gotway, 2004). We specified a binary contiguity matrix based on the *k*-nearest neighbor spatial weights matrix of four (KNN = 4) for the Global Moran’s *I* calculations. KNN was selected as the structure for spatial relationships because: (a) we wanted all individuals to have the same number of neighbors; (b) this specification represents the influence of one’s most proximal neighbors; and (c) this specification results in everyone having neighbors (Anselin, 2002). We specifically chose a four nearest neighbor spatial weights matrix specification because it has previously been suggested that a spatial weights matrix specification between four and six neighbors is optimal and because it is accepted that applying an under-specified (fewer neighbors) rather than an over-specified (extra neighbors) weights matrix is better (e.g. for increased power) (Getis and Aldstadt, 2004; Griffith, 1996). This spatial weights matrix was then row-normalized. The Global Moran's I pseudo p-value was determined via a Monte Carlo simulation consisting of random replications ($n = 999$). Values for the Moran's I range between −1 and 1. A Moran's I value near 0 indicates a lack of spatial pattern, i.e. the null hypothesis of complete spatial randomness. A positive coefficient reflects similarity (similarly large or small values), whereas a negative coefficient reflects dissimilarity (large inverse values). A significant positive Moran statistic would indicate spatial association of similar levels of depressive symptoms. In other words, neighborhoods with high (low) levels of depressive symptoms would be neighbors to areas with high (low) levels of depressive symptoms. On the other hand, a significant negative Moran statistic (perhaps a less frequent phenomenon) would indicate that dissimilar levels of depressive symptoms cluster in space, i.e. neighborhoods with high (low) levels of depressive symptoms would have neighboring areas that would have low (high) levels of depressive symptoms. GIS mapping and tests of spatial autocorrelation for study variables can provide preliminary evidence for needing spatial regressions.

2.5.2. Ordinary linear regression and spatial regression models—We first estimated a standard Ordinary Least Squares (OLS) regression model, which rests on the often-untested assumption of independence of spatial units. Failing to account for spatial autocorrelation, when it exists, can result in biased parameter estimates and incorrect inference (LeSage and Pace, 2009; Ward and Gleditsch, 2008; Waller and Gotway, 2004; Bailey and Gratrell, 1995; Anselin and Bera, 1998; Anselin, 1988a). The spatial model selection (i.e. spatial lag model vs. spatial error model), if necessary, was based on Lagrange Multiplier (LM) tests (LeSage and Pace, 2009; Ward and Gleditsch, 2008; Waller and Gotway, 2004; Bailey and Gratrell, 1995; Anselin and Bera, 1998; Anselin, 1988a). Spatial models were also specified using the KNN = 4 weights matrix. We converted the asymmetric KNN spatial weights to make it symmetric because it simplifies computation and less is empirically known about asymmetric spatial weights matrices when estimating spatial autoregressive models (Bivand et al., 2008).

It is worth noting that the spatial lag model fits with our theory better, as it would suggest that levels of depressive symptoms in neighboring areas would be similar. The estimation of the spatial lag model can either be carried out by maximum likelihood (Anselin, 1988a) or by an instrumental variables (IV) estimation (Kelejian and Prucha, 1998). Maximum likelihood relies on the normality assumption of the error term while the IV method does not. The KNN 4 symmetric spatial weights matrix was used for the Moran's I test on regression residuals and the LM test against both spatial regression specifications to evaluate the OLS regression residuals for evidence of spatial autocorrelation (Anselin, 1988a,b; Anselin and Bera, 1998; Anselin, Bera, Florax, & Yoon, 1996; LeSage and Pace, 2009). The LM, importantly, suggests which spatial model (lag or error) should be used (Florax et al., 2003). If spatial models were necessary and were fit via maximum likelihood, the OLS and spatial models were compared using the Akaike Information Criterion (AIC), which examines overall model fit and model complexity (Akaike, 1974). Lower AIC values are considered better. Lastly, if spatial error models were fit, we computed the spatial Hausman test to compare the OLS and the spatial error model. This test is based on the null hypothesis that the specification is correct (LeSage and Pace, 2009; Pace and LeSage, 2008). However, it is important to note that in some circumstances there can be remaining residual autocorrelation in these spatial models, which require performing additional analyses. More complicated models that include spatial effects are possible, including a combo spatial model where spatial effects are accounted for including a spatial lag of the dependent variable and a spatial lag of the error term (sometimes referred to as 'SARAR', or spatial autoregressive model with autoregressive disturbances) (Kelejian and Prucha, 2010).

In models to examine the relationships between features in the built environment and depressive symptoms, we did not examine the effects of the various built environment features simultaneously on depressive symptoms due to expected multicollinearity (Leal et al., 2012), so separate models were run for each built environment feature, which allowed us to examine their unique contribution on depressive symptoms. In Model 1, we estimated the crude (unadjusted) association including the total sample. Model 2 included an interaction term between the neighborhood built environment feature and gender (male was the referent). Model 3 included an interaction term between the neighborhood built environment feature and race/ethnicity (non-Hispanic White was the referent). We ran the series of regression models including an interaction term for gender and race/ethnicity because we were substantively interested in exploring regression coefficients by gender and race/ethnicity. We included the interaction term in the models (as opposed to conducting stratified analysis) to formally evaluate effect modification and also because in models including an interaction term the spatial matrix is of the entire sample (when conducting stratified analysis the spatial weights matrix is only for that strata, which might not be fully appropriate).

To examine neighborhood effects by spatial scale, models were computed for the 400 and 800-m network buffers. After computing bivariate associations, multivariate models were computed controlled for available theoretical and empirically selected individual- and neighborhood-level covariates. To control for the clustering of students within schools we included school as a fixed effect. Some of the individual-level explanatory variables in our analysis contain missing observations. However, there is no missing information on the dependent variable. In order to be efficient and consider all of the available information on the spatial sample, our spatial weight matrix was defined over the entire sample (Duncan et al., 2012). Data analyses were performed using the R statistical software (R Core Team, 2012) version 2.15 with the *spdep* package (Bivand et al., 2008). Significance was established at $p < 0.05$.

3. Results

Characteristics for the analytic sample of the 1170 youth who provided their residential address are reported in Table 2. Approximately 75% of the youth were non-Hispanic Black or Hispanic. The mean age was 16.3 years (SD = 1.3). Over half were female and most were born in the US. The majority had at least one other youth living in their home. The mean for depressive symptoms, which was normally distributed, was 13.4 (SD = 4.3). Girls had higher level of depressive symptoms than boys (t-value = −8.28, $p < 0.001$). Although there was racial/ethnic variation in symptoms of depression, no significant racial/ ethnic differences were detected in our sample.

3.1. Assessment of spatial patterns: the built environment and depressive symptoms

Geovisualization suggested spatial patterning of the built environment features. We also found significant global spatial autocorrelation at the $p = 0.001$ level as assessed via the Global Moran's I for all of the built environment features examined at both spatial scales (data not shown but are available from the authors upon request). Importantly, geovisualization suggested some potential spatial patterns in depressive symptoms. The geography of depressive symptoms among the Boston youth is shown in Fig. 1. The Global Moran's I value for depressive symptoms was 0.092 (indicating low positive spatial autocorrelation) and this was statistically significant ($p = 0.034$).

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3.2. Spatial regression analyses for the built environment and depressive symptoms

The Moran's *I* evaluating spatial autocorrelation in the OLS regression residuals for the association between features of the built environment and depressive symptoms indicated that there was significant positive spatial autocorrelation (Global Moran's *I*: all approximately 0.08, all $p < 0.001$). The LM tests pointed at the spatial lag model in all models. The AIC values for the spatial lag models were lower compared to OLS models and the spatial autoregressive coefficient in the spatial lag model was significant across most models (most p = approximately 0.03 or 0.04), although marginally significant in a few models. For example, in the multivariate association between recreational open space and depressive symptoms for the total sample based on the 800-m network buffer, the OLS model AIC was 6093.5 while the spatial lag model AIC was 6091.1. In this model, the spatial coefficient was 0.09, with a p-value of 0.035.

The residuals from these maximum likelihood spatial lag multivariate models were normal and there was no presence of heteroskedasticity. Because there was remaining residual autocorrelation in these maximum likelihood estimated spatial lag multivariate models, we fit the SARAR model. In the SARAR model, the newly introduced spatial parameter for the error term was insignificant in most models while the spatial lag parameter was marginally significant or significant across models. Finally, the AIC was lower in the SARAR model as compared to the OLS model, but generally was slightly higher in the SARAR model than the maximum likelihood spatial lag model (all these results are available from the authors upon request). Therefore, the spatial lag model was the best model for these data and maximum likelihood was deemed the most appropriate for these data.

In Tables 3 and 4, we show the multivariate results from the spatial lag models estimated via maximum likelihood for the relationship between built environment features and depressive symptoms for the 400- and 800-m network buffers, respectively. For the 400-m buffer, we found a significant interaction between recreational open space density by Asian predicting depressive symptoms, finding a protective effect of recreational open space ($p = 0.037$). The derived coefficient from the interaction for Asians was −0.258 (the coefficient for the comparison group of Whites was 0.064). A significant interaction was found between density of subway stops and the other racial/ethnic category when predicting depressive symptoms, whereby a higher density of subways stops was associated with an increase in depressive symptoms for the 400-m buffer. For the 400-m buffer and the 800-m buffer, the interaction term for median pedestrian route directness by female predicting depressive symptoms as well as intersection density by female predicting depressive symptoms was significant; both were associated with an increase in depressive symptoms for girls ($p < 0.05$). For the 800-m buffer, park density predicting depressive symptoms had a significant interaction term for Blacks, whereby increased park density was associated with more depressive symptoms for them. The magnitude of effect was minimal across

4. Discussion and conclusions

This is the first study to examine relationships between various built environment features and depressive symptoms among youth. We are also the first to have explicitly considered spatial autocorrelation and one of few to examine neighborhood effects at multiple neighborhood scales and to consider demographic differences in effects in our studied association. In this study, we found significant spatial autocorrelation in all of the built environment features at both spatial scales, depressive symptoms and in the OLS regression residuals (highlighting the need for spatial models, which improved the model fit). There were some significant effects and some differences by spatial scale, gender and race/ethnicity in the relationships. We found a significant interaction between recreational open space by Asian predicting depressive symptoms at a small spatial scale, finding a protective effect of recreational open space. A significant interaction was found in the relationship between density of subway stops and the other racial/ethnic category when predicting depressive symptoms at a small spatial scale, whereby a higher density of subways stops was associated with an increase in depressive symptoms. At both spatial scales, the interaction term for median pedestrian route directness and intersection density by female predicting depressive symptoms were significant, suggesting an increase in depressive symptoms for girls. For the larger spatial scale, park density predicting depressive symptoms had a significant interaction term for Blacks, whereby increased park density was associated with more depressive symptoms. Therefore, some relationships between the built environment and depressive symptoms were in the unexpected direction, but most built environment features were not associated with depressive symptoms among youth in the sample, even when demographic differences were considered. Because the magnitude of effect was minimal across most significant results, results overall suggest that the built environment minimally influences youth depressive symptoms.

Like the present study, previous work suggested spatial patterning in built environment features (Auchincloss et al., 2007; Duncan et al., 2011, 2012, in press; Sharkey et al., 2011). In this study, we found spatial autocorrelation of depressive symptoms among youth, which as noted previously, fits with our theory. Therefore, it is not surprising to us that the specification tests suggested that the spatial lag model (used in this study) was most appropriate. Limited past research has examined spatial patterns in depressive symptoms, but the previous research similarly suggests that depression/depressive symptoms clusters spatially among adults (Mair et al., 2012; Gruebner et al., 2011). Spatial clustering in depression outcomes can occur due to a spatial interaction (true contagion) or a spatial reaction to a common feature (apparent contagion). For example, spatial interaction processes include neighborhood peer-effects, which could occur when youth interacting with other youth in their neighborhoods induce similar levels of health and wellbeing including perhaps symptoms of depression. If environmental factors, on the other hand, influence likelihood of depression, the process would be a spatial reaction process. While disentangling these effects remains methodologically difficult, spatial clustering of youth depressive symptoms was low in this study—suggesting limited true and/or apparent contagion. It is important to note though that emerging research suggests that spatial clustering of depression/depression symptoms might be due to spatial interactions among individuals, suggesting social network effects are at play (Kiuru et al., 2012; Rosenquist et al., 2011; Okamoto et al., 2011). Although both true contagion and apparent contagion may be possible, our study adds to research on apparent contagion, as it suggests that there is a spatial reaction to certain built environment features influencing depression likelihood, which is consistent with prior research (Weich et al., 2002; Galea et al., 2005; Araya et al., 2007; Berke et al., 2007; Sallis et al., 2009; Wilbur et al., 2009; Saarloos et al., 2011; Miles et al., 2012).

Some prior research found results in the unexpected direction, like our findings. For instance, Sallis et al. (2009) found participants in “high-walkability” neighborhoods had a higher depression score than those residing in “low-walkability” neighborhoods. Saarloos et al. (2011) found that increased land-use mix was associated with higher odds of depression and that retail availability was also associated with an increase in the odds of depression. However, it is also important to note that several studies find significant effects in expected directions. To illustrate, Berke et al. (2007) found that neighborhood walkability was associated with reduced depression. Galea et al. (2005) found that living in neighborhoods with poor quality built environments were associated with a higher likelihood of depression. Furthermore, some of the few studies evaluating the role of objective built environments on depression outcomes observed no significant effects (Kubzansky et al., 2005; Schootman et al., 2007; Stockdale et al., 2007). As previously highlighted, there are major differences between our study and the past research (e.g. sample, statistical methodology, spatial unit), which may serve as an explanation for some differences between our study and those previously published. Regarding spatial unit, most previous studies used administrative neighborhood definitions (e.g. US census tracts). The scale sensitivity of the neighborhood definition used is a fundamental aspect of the well-known modifiable areal unit problem (Open-shaw and Taylor, 1979; Arbia, 1989; Wong, 2009), which has been infrequently addressed in previous research on the relationship between built environments and depression outcomes. Our findings overall suggest that the effect of the built environment on depressive symptoms can vary by spatial scale, but there was no clear spatial scale that was most important. Additionally, it is important to note that this study examined several specific built environment features not examined in previous depression research (e.g. average speed limit and highway density).

There are several possible mechanisms explaining the relationships found, including those for specific subgroups. Recreational open space can promote physical activity (Ding et al., 2011), which in turn could reduce depressive symptoms (Teychenne et al., 2008). Recreational open spaces may also beautify neighborhoods and as such could promote positive mental health (Bedimo-Rung et al., 2005). It is unclear, however, why the finding between recreational open space and depressive symptoms was only significant for Asians. We recognize that subways stops provide access to transportation, access to job opportunities and increased city mobility. In our 2004 and 2006 surveys though, youth reported feeling unsafe on the trains/ buses (Azreal et al., 2009) and crime may occur at subway stations (Loukaitou-Sideris et al., 2002), suggesting that crime may promote fear and psychological stress. This might explain why density of subways was associated with increased depressive symptoms among youth in the other race/ethnicity. However, it is unclear why this finding was only significant for one racial/ethnic group (the youth who self-identified as belonging to an other racial/ethnic group). We were surprised to find that median pedestrian route directness and intersection density (components of street connectivity) were associated with increased depressive symptoms among girls, because both have been associated with increased youth physical activity (Ding et al., 2011), which could result in a reduction in depressive symptoms (Teychenne et al., 2008) and because median pedestrian route directness and intersection density (two hallmark features of increased neighborhood walkability) could increase social interaction/contact and therefore increase neighborhood social cohesion, social ties, social support and social networks (Leyden, 2003; de Toit et al., 2007; Cohen et al., 2008; Rogers et al., 2011), which, in turn, may reduce depression/depressive symptoms (Kim, 2008; Mair et al., 2008; Kawachi and Berkman, 2001). Although these results may be counterintuitive at first glance, we speculate that median pedestrian route directness and intersection density may be picking up another variable (such as crime) (Matthews et al., 2010), which could be associated with poor mental health. Further, busy intersections may be particularly noisy and lead to stress, increasing depression (Lederbogen et al., 2011).

Given our sample of urban predominantly low-income racial/ethnic minority youth, knowledge of the geography of Boston (including racial residential segregation) (Logan and Stults, 2011; Iceland et al., 2002) and our past findings that indicate park density might be associated with increased BMI *z*-scores among Black youth (Duncan et al., 2012), we were not surprised to find that park density was associated with increased depressive symptoms among Black youth. Parks in Black neighborhoods may be suboptimal, and may contain trash, public intoxication and illicit drug sales, which may negatively influence mental health. There may also be racial differences in perceptions of the built environment and crime. As an example, Black youth who live near parks may believe that it is worse than it really is because of stories about how they were perceived to be in previous years. In addition to the possibility that the built environment may not contribute much to depressive symptoms among youth in general, it is important to note that several of the non-significant associations might be due to inadequate variation for some built environment features, which would inhibit the ability to detect significant associations. We also recognize that youth with more severe depression might not have participated in the study or completed the entire survey, which may underestimate the association of interest, if participation/completion is associated with a built environment feature. Furthermore, it is also important to note that youth might not use or actually be exposed to resources in their residential neighborhoods that can be related to mental health. They may be more likely to use businesses and social services near their schools. Indeed, because Boston students often go to schools distant from their residential neighborhoods, it may their school neighborhoods that might be most salient to their mental health.

Additional research is needed to examine the role of the built environment in mental health among youth and other populations; this work should be done across spatial contexts. We recognize the value of both quantitative and qualitative studies in this research. While access to the built environment may be important for health/wellbeing, future studies should also examine the quality of built environment features (which is rarely examined); this distinction may matter for health/wellbeing. Future research should query use of built environment neighborhood resources (e.g. recreational open space). Longitudinal and experimental studies can provide evidence of causality and are a way to better control for heterogeneity, and therefore, if possible, should be conducted to advance this research. All future studies should consider potential effect modification by neighborhood definition (e.g. spatial scale), gender and race/ethnicity, which requires diverse definitions of a neighborhood environment and larger sample sizes. Appropriate neighborhood definitions should be selected including perhaps buffer-based neighborhood definitions, if possible. Self-selection into neighborhoods should be addressed in future research on built environments and youth mental health. Because there is little information on the validity of data on GIS built environment features, future research should investigate validity of the data and/or use validated GIS datasets. Additionally, when collecting original data, future research should consider sampling data based on the spatial exposure of interest (e.g. level of neighborhood walkability) (Downs et al., 2010; Delmelle, 2009; Lee et al., 2006). Last, future research in this area could apply spatial modeling approaches. One novelty of this study is that we had significant spatial autocorrelation in the OLS residuals, necessitating the need for spatial lag regression models. The spatial lag parameter was statistically significant across models, demonstrating that the explicit use of a spatial econometrics specification improved the model fit. However, in the spatial lag model, there was some remaining residual autocorrelation. Although we fit a more complex spatial model (i.e. SARAR), the spatial parameter was marginally significant or significant in models, suggesting that more complex specifications do not improve upon the simple spatial lag models and, thus, they are not appropriate for our set of data. Taking an explicit spatial perspective improves the results obtained with the simple OLS model and removed the bias due to the omission of a relevant variable (i.e. the spatially lagged dependent variable).

Some limitations should be considered when interpreting our results. Youth may not use, or actually be exposed to resources in neighborhoods (e.g. recreational open space) that can be related to their mental health. While the four nearest neighbor spatial weights matrix used in this study facilitates comparison with our previous research and is statistically justified (Duncan et al., 2012), we recognize that the “neighbored” youths might not actually know each other but only capture a “social effect” (i.e. the average of the member of the reference group) (Manski, 1993). We cannot conclude that the built environment is causally related to depressive symptoms, given the cross-sectional design. However, we note that the built environment exposures (mainly collected in 2006) precede depressive symptoms (collected in 2008). Reliance on self-report of depressive symptoms is a limitation. However, as previously indicated, the instrument we used to assess depressive symptoms has been shown to be reliable and valid in this sample of youth (Dunn et al., 2012b) and because we obtained objective information on the neighborhood environment using self report of depressive symptoms would not induce same-source bias (Diez-Roux, 2007). Although we have no reason to believe there is any selection bias, it is a possibility. We recognize that some selection bias might exist in that youth with high levels of depressive symptoms may not have taken the survey or not completed all items used to assess depressive symptoms. It is also important to highlight that positional accuracy in both the exposure and outcome is important in spatial analysis. Errors can exist in spatial datasets, including positional errors, errors of omission and spatial features that no longer exist. Because we used data from a variety of secondary sources, there is a potential for misclassification. However, this was necessary to examine multiple aspects of the built environment including aspects not examined in previous depression research. Empirical research shows that errors in spatial datasets are likely to bias relationships between spatial variables under investigation and health towards non-significance (Boone et al., 2008), which may be an additional potential explanation of our overall non-significant findings. Additionally, because we used national and local spatial datasets to create a wide range of built environment features, concern for error may be reduced to some degree (local spatial datasets may be less error prone). The intersection addresses we obtained may also contribute to location misclassification. While location misclassification can produce incorrect estimates and reduce the power to find real associations, the effect of using intersections on location misclassification is likely to be minimal, since all study subjects live in an urban environment, which generally has a dense street network with small block sizes. Importantly, we found no evidence of geographic bias (Oliver et al., 2005), because there were no differences by depressive symptoms with regards to who provided geocodeable information and who did not. These results did not account for multiple comparisons. Low statistical power for some demographic interaction analysis (e.g. race interaction effects) is a limitation due to small samples sizes for certain groups. Although we control for several potential confounding variables at the individual- and neighborhood-levels, we were unable to account for several potentially important factors such as parent’s socioeconomic position. Residual confounding due to the effect of not including household income likely is not as much of a concern in this study as it might be in other research because of our sample of predominantly low-income urban youth. Similarly, residential selection bias might not be much of a concern in this study because it is less plausible that adolescents chose the neighborhoods that they live in. Adjusting for variables (e.g. demographic characteristics) that may be associated with neighborhood selection, which we did, may reduce bias related to it. Results from this study might only be generalizable to low-income youths in similar urban locations at similar spatial scales.

In conclusion, findings from the spatial regression models indicate that the built environment can have depressogenic effects among youth, which can vary by spatial scale, gender and race/ethnicity (though sometimes in unexpected directions, i.e. associations opposite to our expectations). While our results overall suggest that the built environment minimally influences youth depressive symptoms, additional research is needed, including to understand our results in the unexpected direction.

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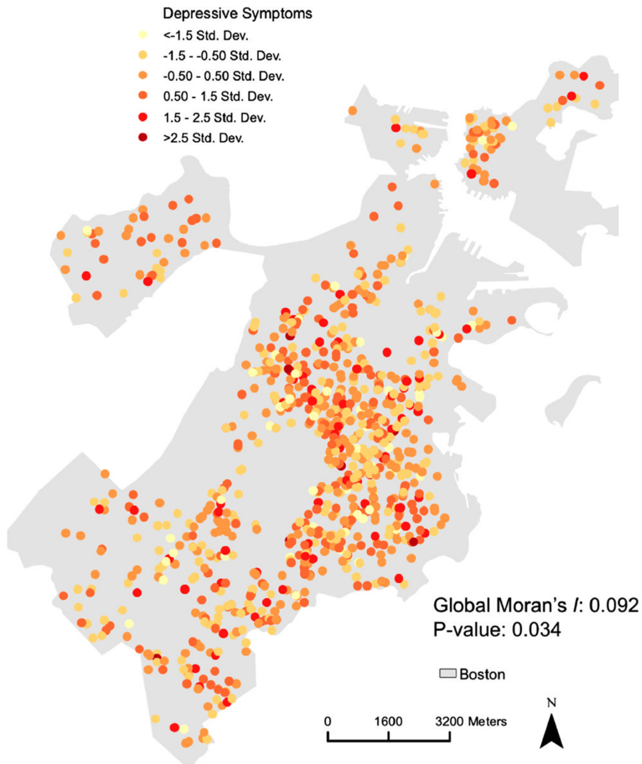

Fig. 1.

The geography of depressive symptoms among urban youth, 2008 Boston Youth Survey Geospatial Data (n = 1170). *Note*: Depressive symptoms were categorized based on standard deviations (SD), with an interval size of 1 SD. A low standard deviation indicates depressive symptoms close to the mean level of depressive symptoms, whereas a high standard deviation is farther from the mean level of depressive symptoms. A negative standard deviation indicates those below the level of depressive symptoms, whereas a positive standard deviation indicates those higher than the mean level of depressive symptoms. Map colors from http://www.colorbrewer2.org, by Cynthia A. Brewer, Penn State Geography.

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Table 1

Built environment variables: descriptions and data sources.

Built environment variable	Operational description	Data source (Year)
Access to walking destinations		
Recreational open space (density)	Recreational open spaces including parks, playing fields, school fields, and playgrounds, which could be privately or publicly owned facilities	Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, Information Technology Division (2007)
Parks (density)	State and local parks including playgrounds and other types of parks	Environmental Systems Research Institute (ESRI) Data and Maps (2006)
Bus stops (density)	Massachusetts Bay Transportation Authority (MBTA) bus stops	Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, Information Technology Division (2007)
Subway stops (density)	Massachusetts Bay Transportation Authority (MBTA) subway stops	Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, Information Technology Division (2007)
Retail destinations (density)	Total retail destinations (e.g. clothing stores, pharmacy/ drug stores, bookstores)	Environmental Systems Research Institute (ESRI) Business Analyst InfoUSA Business Locations (2006)
Service destinations (density)	Total service destinations (e.g. post offices, banks, credit unions)	Environmental Systems Research Institute (ESRI) Business Analyst InfoUSA Business Locations (2006)
Cultural/ educational destinations (density)	Total cultural/educational destinations (e.g. movie theaters, schools, libraries)	Environmental Systems Research Institute (ESRI) Business Analyst InfoUSA Business Locations (2006)
Community design attributes		
Median pedestrian route directness	Median of the ratio of distance between one point and another via the street network and straight-line distance between the two points; values closer to 1.00 represent a more direct route or a more connected network	Environmental Systems Research Institute (ESRI) Business Analyst Info USA Business Locations (2006)
Intersection density	The number of street intersections; intersections are defined as street network nodes with 3 or more associated street segments excluding highways	Environmental Systems Research Institute (ESRI) Data and Maps Street Map (2006)
Sidewalk completeness	A 0 is no sidewalk and a 100 indicates presence of sidewalk on both sides; calculated excluding sidewalks in parks, informal paths and cut-throughs and excluding roads with medians	Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, Information Technology Division (2007)
Average sidewalk width	Calculated in meters, excluding sidewalks in parks, informal paths and cut-throughs and excluding roads with medians	Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, Information Technology Division (2007)
Average speed limit	Calculated in miles per hour	Environmental Systems Research Institute (ESRI) Data and Maps Street Map (2006)
Highway density	Percentage of area that is highway traveled right of way; highways are defined as primary roads with limited access or interstate highways	Office of Geographic Information (MassGIS), Commonwealth of Massachusetts, Information Technology Division (2007)
Residential density	US census block group occupied housing units were weighted proportionally for the youths' defined neighborhood	US Census (2000)

Notes: All density measures are expressed as per square kilometer. We limited all retail, service and cultural/educational walking destinations to locations with fewer than 250 employees to filter out large businesses (e.g. Costco and Home Depot); businesses with more than 250 employees may inhibit the neighborhoods walkability (e.g. by having large parking lots) (Krizek, 2003). All variables were created using ArcGIS version 9.3 with the Massachusetts state plane projection North American Datum (NAD) 1983.

Table 2

Sample characteristics, 2008 Boston Youth Survey Geospatial Dataset (*n* = 1170).

Depressive symptoms (mean, SD)	13.40 (4.28)
Age in years (mean, SD)	16.31 (1.27)
Gender (%)	
Male	44.17
Female	55.83
Race/ethnicity (%)	
White	10.33
Black	42.47
Hispanic	32.75
Asian	7.36
Other[a]	7.09
Nativity status (%)	
US born	73.68
Foreign born	26.32
Other youth in household (%)	
Yes	85.32
No	14.68

[a]Includes non-Hispanic youth who were bi- or multi-racial, American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, or youth who did not fit into any of the specified race categories.

Table 3

Multivariate results from spatial lag models of depressive symptoms regressed on built environment features, 400-m network buffer.[a]

Access to walking destinations	B	SE	*p*-value	Community design attributes	B	SE	*p*-value
A. Recreational open space (density)				*A. Median pedestrian route directness*			
Model 1				Model 1			
A: Total Sample	−0.007	0.033	0.837	A: Total Sample	0.364	0.782	0.642
Model 2				Model 2			
A: Male	−0.011	0.047	0.820	A: Male	−1.690	1.258	0.179
A X Female	0.007	0.059	0.908	A X Female	**3.329** *	1.600	0.038
Model 3				Model 3			
A: White	0.064	0.085	0.456	A: White	−0.707	2.359	0.764
A X Black	−0.032	0.100	0.752	A X Black	1.003	2.611	0.701
A X Hispanic	−0.098	0.100	0.324	A X Hispanic	2.930	2.843	0.303
A X Asian	**−0.258** *	0.123	0.037	A X Asian	1.631	3.818	0.669
A X Other	0.077	0.143	0.588	A X Other	−2.116	3.354	0.528
B. Parks (density)				*B. Intersection density*			
Model 1				Model 1			
B: Total Sample	−0.002	0.047	0.958	B: Total Sample	−0.000	0.004	0.982
Model 2				Model 2			
A: Male	−0.051	0.068	0.453	A: Male	−0.010~	0.006	0.091
A X Female	0.086	0.089	0.333	A X Female	**0.017** *	0.008	0.024
Model 3				Model 3			
B: White	0.083	0.133	0.531	B: White	0.001	0.009	0.898
B X Black	0.012	0.151	0.938	B X Black	−0.002	0.011	0.825
B X Hispanic	−0.214	0.155	0.166	B X Hispanic	−0.001	0.011	0.949
B X Asian	−0.100	0.189	0.596	B X Asian	−0.014	0.014	0.295
B X Other	−0.167	0.219	0.447	B X Other	0.029	0.018	0.117
C. Bus stops (density)				*C. Sidewalk completeness*			
Model 1				Model 1			
C: Total Sample	0.009	0.010	0.347	C: Total Sample	−0.011	0.012	0.349

Access to walking destinations				Community design attributes			
	B	SE	*p*-value		B	SE	*p*-value
Model 2				Model 2			
A: Male	0.012	0.014	0.411	A: Male	0.004	0.015	0.811
A X Female	−0.005	0.019	0.814	A X Female	−0.032	0.021	0.137
Model 3				Model 3			
C: White	0.042	0.031	0.177	C: White	−0.036	0.037	0.329
C X Black	−0.026	0.034	0.458	C X Black	0.039	0.040	0.328
C X Hispanic	−0.054	0.036	0.134	C X Hispanic	0.011	0.041	0.781
C X Asian	−0.011	0.047	0.808	C X Asian	0.042	0.052	0.423
C X Other	−0.065	0.050	0.195	C X Other	0.017	0.060	0.774
D. Subway stops (density)				*D. Average sidewalk width*			
Model 1				Model 1			
D: Total Sample	0.026	0.086	0.764	D: Total Sample	−0.741~	0.435	0.088
Model 2				Model 2			
A: Male	0.033	0.115	0.778	A: Male	−0.167	0.565	0.768
A X Female	−0.014	0.155	0.929	A X Female	−1.265	0.793	0.110
Model 3				Model 3			
D: White	−0.186	0.218	0.393	D: White	−0.354	1.120	0.752
D X Black	0.178	0.254	0.484	D X Black	0.006	1.283	0.996
D X Hispanic	0.281	0.267	0.293	D X Hispanic	−0.805	1.311	0.539
D X Asian	0.200	0.286	0.486	D X Asian	−0.944	1.700	0.578
D X Other	**0.828** *	0.409	0.043	D X Other	−0.975	2.118	0.645
E. Retail destinations (density)				*E. Average speed limit*			
Model 1				Model 1			
E: Total Sample	0.001	0.006	0.841	E: Total Sample	0.143~	0.080	0.074
Model 2				Model 2			
A: Male	0.007	0.010	0.472	A: Male	0.152	0.112	0.173
A X Female	−0.009	0.012	0.445	A X Female	−0.017	0.148	0.906
Model 3				Model 3			
E: White	−0.008	0.017	0.631	E: White	0.570~	0.343	0.097
E X Black	0.032	0.021	0.119	E X Black	−0.349	0.363	0.335

Access to walking destinations	B	SE	*p*-value	Community design attributes	B	SE	*p*-value
E X Hispanic	0.003	0.021	0.867	E X Hispanic	−0.521	0.362	0.151
E X Asian	−0.006	0.021	0.797	E X Asian	−0.517	0.403	0.200
E X Other	−0.001	0.032	0.976	E X Other	−0.460	0.441	0.296
F. Service destinations (density)				*F. Highway density*			
Model 1				Model 1			
F: Total Sample	0.023	0.037	0.537	F: Total Sample	−0.069	0.058	0.240
Model 2				Model 2			
A: Male	0.052	0.058	0.371	A: Male	−0.043	0.079	0.579
A X Female	−0.047	0.072	0.515	A X Female	−0.053	0.107	0.620
Model 3				Model 3			
F: White	0.010	0.086	0.905	F: White	−0.087	0.147	0.553
F X Black	0.063	0.117	0.589	F X Black	0.037	0.212	0.863
F X Hispanic	0.085	0.113	0.452	F X Hispanic	−0.014	0.172	0.935
F X Asian	−0.103	0.107	0.336	F X Asian	0.064	0.174	0.711
F X Other	0.140	0.158	0.375	F X Other	−0.229	0.628	0.715
G. Cultural/educational destinations (density)				*G. Residential density*			
Model 1				Model 1			
G: Total Sample	−0.005	0.011	0.602	G: Total Sample	−0.000	0.001	0.502
Model 2				Model 2			
A: Male	−0.010	0.014	0.477	A: Male	−0.001	0.001	0.197
A X Female	0.010	0.020	0.628	A X Female	0.001	0.001	0.260
Model 3				Model 3			
G: White	−0.007	0.022	0.740	G: White	−0.002	0.001	0.262
G X Black	0.022	0.028	0.430	G X Black	0.002	0.002	0.187
G X Hispanic	−0.017	0.031	0.579	G X Hispanic	0.001	0.002	0.523
G X Asian	−0.024	0.032	0.460	G X Asian	−0.001	0.002	0.727
G X Other	0.073	0.050	0.143	G X Other	0.003	0.003	0.185

B = Beta; SE = Standard Error.

~ $p < 0.10$;

* $p < 0.05$ (bold);

** $p < 0.01$ (bold).

[a]Model 1 estimates the association between the built environment and depressive symptoms among the total sample; Model 2 estimates the studied association and includes an interaction for gender; Model 3 estimates the studied association and includes an interaction for race/ethnicity. For each model, we evaluate the estimated effect of each built environment feature separately. All models are adjusted for individual-level race/ethnicity, individual-level gender, individual-level age, individual-level nativity, individual-level family structure (other youth in household), neighborhood-level percent of Black residents, neighborhood-level percent of Hispanic residents, neighborhood-level percent of households below poverty and neighborhood-level percent foreign born for the 400-street network buffer. Regression estimates are also controlled for school using indicator variables.

Table 4

Multivariate results from spatial lag models of depressive symptoms regressed on built environment features, 800-m network buffer.[a]

Access to walking destinations				Community design attributes			
	B	**SE**	***p*-value**		**B**	**SE**	***p*-value**
A. Recreational open space (density)				*A. Median pedestrian route directness*			
Model 1				Model 1			
A: Total Sample	0.040	0.062	0.520	A: Total Sample	0.418	0.889	0.638
Model 2				Model 2			
A: Male	0.023	0.081	0.775	A: Male	−1.867	1.197	0.119
A X Female	0.030	0.096	0.754	A X Female	**4.958****	1.746	0.005
Model 3				Model 3			
A: White	−0.101	0.145	0.488	A: White	−0.377	2.757	0.891
A X Black	0.217	0.169	0.199	A X Black	0.207	3.139	0.947
A X Hispanic	0.153	0.164	0.351	A X Hispanic	1.197	3.054	0.695
A X Asian	−0.118	0.220	0.593	A X Asian	0.310	4.637	0.947
A X Other	0.461~	0.236	0.050	A X Other	2.854	4.517	0.527
B. Parks (density)				*B. Intersection density*			
Model 1				Model 1			
B: Total Sample	0.196~	0.106	0.065	B: Total Sample	−0.002	0.005	0.769
Model 2				Model 2			
A: Male	0.014	0.154	0.923	A: Male	−0.014~	0.008	0.067
A X Female	0.312	0.191	0.104	A X Female	**0.022***	0.010	0.022
Model 3				Model 3			
B: White	−0.262	0.262	0.317	B: White	0.005	0.012	0.653
B X Black	**0.786***	0.310	0.011	B X Black	−0.006	0.015	0.693
B X Hispanic	0.370	0.311	0.235	B X Hispanic	−0.010	0.015	0.518
B X Asian	0.242	0.389	0.535	B X Asian	−0.024	0.017	0.165
B X Other	0.740~	0.449	0.099	B X Other	0.020	0.022	0.372
C. Bus stops (density)				*C. Sidewalk completeness*			
Model 1				Model 1			

Access to walking destinations	B	SE	*p*-value	Community design attributes	B	SE	*p*-value
C: Total Sample	0.024	0.018	0.175	C: Total Sample	−0.012	0.014	0.405
Model 2				Model 2			
A: Male	−0.003	0.025	0.913	A: Male	0.007	0.019	0.689
A X Female	0.050	0.032	0.113	A X Female	−0.040	0.025	0.114
Model 3				Model 3			
C: White	0.013	0.053	0.806	C: White	0.007	0.036	0.856
C X Black	0.020	0.058	0.734	C X Black	−0.017	0.042	0.680
C X Hispanic	0.005	0.060	0.933	C X Hispanic	−0.035	0.043	0.419
C X Asian	0.033	0.075	0.665	C X Asian	0.010	0.058	0.861
C X Other	−0.027	0.080	0.732	C X Other	−0.023	0.064	0.723
D. Subway stops (density)				*D. Average sidewalk width*			
Model 1				Model 1			
D: Total Sample	0.129	0.121	0.285	D: Total Sample	−0.560	0.535	0.295
Model 2				Model 2			
A: Male	−0.014	0.168	0.933	A: Male	−0.194	0.681	0.775
A X Female	0.239	0.197	0.224	A X Female	−0.795	0.915	0.385
Model 3				Model 3			
D: White	0.328	0.306	0.284	D: White	1.128	1.183	0.341
D X Black	−0.265	0.375	0.479	D X Black	−1.745	1.399	0.212
D X Hispanic	−0.110	0.360	0.760	D X Hispanic	−2.152	1.452	0.138
D X Asian	−0.454	0.358	0.205	D X Asian	−2.447	1.796	0.173
D X Other	0.846	0.565	0.134	D X Other	−2.473	2.210	0.263
E. Retail destinations (density)				*E. Average speed limit*			
Model 1				Model 1			
E: Total Sample	−0.007	0.009	0.470	E: Total Sample	0.128	0.124	0.304
Model 2				Model 2			
A: Male	−0.007	0.013	0.571	A: Male	−0.000	0.169	0.998
A X Female	0.002	0.017	0.928	A X Female	0.239	0.213	0.263
Model 3				Model 3			
E: White	−0.009	0.023	0.702	E: White	0.485	0.395	0.219

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Access to walking destinations				Community design attributes			
	B	**SE**	***p*-value**		**B**	**SE**	***p*-value**
E X Black	0.013	0.030	0.663	E X Black	−0.403	0.442	0.362
E X Hispanic	0.009	0.028	0.742	E X Hispanic	−0.328	0.435	0.451
E X Asian	−0.008	0.028	0.764	E X Asian	−0.532	0.458	0.246
E X Other	−0.010	0.047	0.822	E X Other	−0.199	0.580	0.732
F. Service destinations (density)				*F. Highway density*			
Model 1				Model 1			
F: Total Sample	0.009	0.035	0.803	F: Total Sample	−0.113	0.071	0.113
Model 2				Model 2			
A: Male	−0.007	0.046	0.881	A: Male	−0.101	0.095	0.287
A X Female	0.033	0.063	0.598	A X Female	−0.024	0.123	0.845
Model 3				Model 3			
F: White	0.019	0.050	0.705	F: White	−0.084	0.160	0.598
F X Black	0.130	0.128	0.308	F X Black	−0.008	0.257	0.975
F X Hispanic	0.081	0.113	0.474	F X Hispanic	−0.066	0.195	0.735
F X Asian	−0.087	0.075	0.245	F X Asian	0.015	0.195	0.938
F X Other	0.216	0.223	0.333	F X Other	−0.441	0.400	0.270
G. Cultural/educational destinations (density)				*G. Residential density*			
Model 1				Model 1			
G: Total Sample	−0.009	0.012	0.467	G: Total Sample	−0.001	0.001	0.229
Model 2				Model 2			
A: Male	−0.022	0.017	0.207	A: Male	−0.002	0.001	0.154
A X Female	0.023	0.022	0.291	A X Female	0.001	0.002	0.409
Model 3				Model 3			
G: White	0.010	0.025	0.704	G: White	−0.001	0.002	0.446
G X Black	−0.020	0.034	0.571	G X Black	0.001	0.002	0.606
G X Hispanic	−0.029	0.035	0.405	G X Hispanic	0.000	0.002	0.943
G X Asian	−0.030	0.032	0.351	G X Asian	−0.002	0.003	0.455
G X Other	0.049	0.061	0.421	G X Other	0.004	0.003	0.275

B = Beta; SE = Standard Error.

~ $p < 0.10$;

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[*] $p < 0.05$ (bold);

[**] $p < 0.01$ (bold).

[a] Model 1 estimates the association between the built environment and depressive symptoms among the total sample; Model 2 estimates the studied association and includes an interaction for gender; Model 3 estimates the studied association and includes an interaction for race/ethnicity. For each model, we evaluate the estimated effect of each built environment feature separately. All models are adjusted for individual-level race/ethnicity, individual-level gender, individual-level age, individual-level nativity, individual-level family structure (other youth in household), neighborhood-level percent of Black residents, neighborhood-level percent of Hispanic residents, neighborhood-level percent of households below poverty and neighborhood-level percent foreign born for the 800-street network buffer. Regression estimates are also controlled for school using indicator variables.