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Comparing the appropriate geographic region for assessing built environmental correlates with walking trips using different metrics and model approaches

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Abstract

There is growing international evidence that supportive built environments encourage active travel such as walking. An unsettled question is the role of geographic regions for analyzing the relationship between the built environment and active travel. This paper examines the geographic region question by assessing walking trip models that use two different regions: walking activity spaces and self-defined neighborhoods. We also use two types of built environment metrics, perceived and audit data, and two types of study design, cross-sectional and longitudinal, to assess these regions. We find that the built environment associations with walking are dependent on the type of metric and the type of model. Audit measures summarized within walking activity spaces better explain walking trips compared to audit measures within self-defined neighborhoods. Perceived measures summarized within self-defined neighborhoods have mixed results. Finally, results differ based on study design. This suggests that results may not be comparable among different regions, metrics and designs; researchers need to consider carefully these choices when assessing active travel correlates.

Keywords

Walking; built environment; neighborhood; GPS; activity spaces

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1. Background

Research suggests that the quality of the built and natural environment is associated with active travel and physical activity (Brownson et al., 2009; Ding and Gebel, 2012; Handy et al., 2002; Harris et al., 2013; Sallis et al., 2015). Some measures of the built environment are positively associated with active travel, such as land use mix (Frank et al., 2006), residential density (Ewing et al., 2008), and street network configuration (Berrigan et al., 2010; Ellis et al., 2016). One definition of walkability is an environment that provides support for walking or encourages physical activity (Brown et al., 2013; Forsyth, 2015). Two methods to assess the environmental supports for walking are sampling residents' perceptions and collecting audits of environmental features (Brownson et al., 2009). Research has also shown that both perceptual and audit metrics of a neighborhood are associated with physical activity (Ball et al., 2008; Gebel et al., 2011; Lin and Moudon, 2010; McGinn et al., 2007; Troped et al., 2011). However, many researchers have outlined steps to address inconsistencies in results and behavioral assumptions (Brownson et al., 2009). Suggested prescriptive steps include using environmental metrics that are comparable across studies, identifying and modeling the causally relevant built environment context, and using stronger research designs (Berrigan et al., 2015).

The assessment of built environment measures relies on the delineation of a geographic region that influences active travel (Berrigan et al., 2015; Lovasi et al., 2012; Moudon et al., 2006; Spielman and Yoo, 2009). Two common methods for delimiting this region for home-based travel are *neighborhoods* and *activity spaces*, with neighborhood referring to the community near an individual's home and activity spaces referring to the environment that an individual routinely experiences (Sharp et al., 2015). Neighborhoods can be defined by researchers or self-defined by participants (Coulton et al., 2001). Researcher-defined neighborhoods commonly use spatial buffers around participants' homes (Saelens et al., 2012) or census geography (Witten et al., 2012). Self-defined neighborhoods are captured by participant self-report (Bailey et al., 2014; Campbell et al., 2009; Gebel et al., 2011; Ivory et al., 2015) or by participant-drawn maps (Colabianchi et al., 2014; Siordia and Coulton, 2015; Suminski et al., 2015). Activity spaces are based on origin and destination travel diaries (Schönfelder and Axhausen, 2003) or Global Positioning System (GPS) data loggers (Chaix et al., 2013; Hirsch et al., 2014; Tribby et al., 2016; Zenk et al., 2011) to delineate the portion of an environment experienced by participants over a given time period.

Previous research into self-defined neighborhoods and activity spaces provides two perspectives with regards to explaining walking. For example, research on self-defined neighborhoods compares these regions to census tracts (Coulton et al., 2013, 2001; Spilsbury et al., 2012), assesses the accessibility of recreational or exercise facilities (Hoehner et al., 2005; Ivory et al., 2015), or uses self-defined neighborhoods to estimate an optimum home buffer size (Siordia and Coulton, 2015). Prior research with activity spaces explores how different Geographic Information Systems (GIS)-based analyses and representations produce different built environment summaries compared to researcher-defined neighborhoods (Boruff et al., 2012; James et al., 2014; Rundle et al., 2016; Tribby et al., 2016). But research directly comparing self-defined neighborhoods and activity spaces is not common (Perchoux et al., 2016; Yin et al., 2013). There are preliminary findings that the built environment composition of these areas are different, but still unresolved is how these differences are associated with travel activities (Perchoux et al., 2016). Finally, there is insufficient research on how variation in the spatial measurement of neighborhoods explains walking, depending on the type of built environment metric. Specifically, how do different measures in these regions vary in their explanation of walking trips?

The type of study design may have an effect on the association between built environment measures and walking (Berrigan et al., 2015). Most of the current research on this relationship is cross-sectional (Cummins et al., 2007; Fitzhugh et al., 2010; Lovasi et al., 2012; Saelens and Handy, 2008; Sallis et al., 2011). Internationally, stronger support for causal relationships between built environment qualities and active travel comes from longitudinal studies that measure the changes in individuals' active travel with changes in the built environment (Coevering et al., 2015), often using natural experiments or quasi-experimental designs (Brown et al., 2015; Goodman et al., 2013; Ogilvie et al., 2010; Saelens and Handy, 2008). However, there are few longitudinal studies that examine different geographic regions to assess changes in walking behavior with respect to changes in the built environment (Berrigan et al., 2015).

The aim of this paper is to examine the geographic regions of walking activity spaces and self-defined neighborhoods for analyzing built environment associations with walking trips. We capture self-defined neighborhoods by having study participants explicitly delineate the spatial boundary of their neighborhood on a map. We construct walking activity spaces from home-based walking trips recorded with GPS. The first part of this study measures the geometric similarity of walking activity spaces and self-defined neighborhoods. This research question addresses a current shortcoming in existing research: what is the spatial similarity between the regions and do the regions vary within individuals between years? The second part of this study assesses the strength of walking trip models for the different geographic regions, using two different types of built environment measures: perceived and audit data. The final part of this study compares the difference in results due to using cross-sectional versus longitudinal research designs. This part also aims to assess the change in walking behavior due to a built environment intervention: a Complete Streets reconstruction. Complete Streets is a US transportation policy that promotes street design to accommodate all modes of transportation, with the goals of increasing safety for all road users and promoting active transport such as walking, cycling, and transit use (Laplante and McCann, 2008). This relates to international efforts to increase street safety and active travel, such as the Vision Zero policy to eliminate traffic deaths, or policies to improving cycling infrastructure (Johansson, 2009; Pucher et al., 2010).

2. Methods

To address the research question of geographic regions, we analyzed longitudinal data that includes built environment metrics from field audits, GPS and accelerometer data, participant-drawn maps, and neighborhood perception surveys. To allow comparison to other studies, we use an established built environment audit instrument and perceptual survey. This neighborhood experienced a built environmental intervention, namely, a Complete Streets intervention that includes the construction of a new light rail line, bicycle lanes, enhanced landscaping, and widened sidewalks (Brown et al., 2014). We compare data from before and after the intervention to investigate whether a substantial change in the neighborhood environment influences residents' walking trips by assessing the change in self-defined neighborhoods and walking activity spaces. We use a longitudinal, natural experiment design, with distance from home to the intervention as a proxy for exposure (Coevering et al., 2015).

The goal of this paper is to examine the geographic region for modeling built environment associations with walking trips. The first part of this study is how geometrically similar are walking activity spaces and self-defined neighborhoods? We compare the two regions using measures of area, shape, and overlap. These three measures give an indication of the spatial similarity and stability of the regions between years. The second part of this research is to measure the strength of the walking trip models for the two geographic regions by using different types of built environment measures. We assess the perceived data for the self-defined neighborhood and the audit data for the self-defined neighborhood and the walking activity space using cross-sectional models. The goal of these analyses is to assess the geographic region. The final part of this research examines the use of a longitudinal research design. We compare the effectiveness of longitudinal models to the cross-sectional models. The goal is to see which framework is better suited to modeling walking associations with the built environment.

2.1 Sample

The data for this project are from the Moving Across Places Study (MAPS) in Salt Lake City, Utah, USA. This project assesses built environment walkability, walking behavior, transit use, and physical activity before (2012) and after (2013) a complete streets intervention that includes the construction of a new light rail line, complete bicycle lanes, enhanced landscaping, and widened sidewalks (Brown et al., 2015). The data for this study are a subset (n=232) drawn from 536 participants whom we have GPS, accelerometer, and neighborhood perception data for both years. Participants' data for both years were included if they wore accelerometers (Actigraph GT3X+) at least three days for 10 hours per day in 2012. Non-wear hours were defined as hours with zero accelerometer counts per minute, allowing for up to 2 minutes of 100 counts per minute, following procedures used in a national study (Troiano et al., 2008). Three days of wear has been a standard used in previous research (Hart et al., 2011; Zenk et al., 2011). Participants also wore GPS data loggers (GlobalSat DG-100) to record travel activities. The GPS and accelerometer data were collected on a rolling basis for several months, in part to balance the positive or negative weather effects on activity.

The study recruited n=939 participants living within 2 km from the complete street intervention for the 2012 data collection wave; of these participants, n= 614 completed the 2013 data collection wave. Most of the attrition between 2012 and 2013 was because of participants moving residences (n=283, verified as movers or did not respond to 8 or more phone and in-person contact attempts), rather than refusals (n=34), or ineligibility (n=8). Of the n=614 who completed both data collection waves, n=536 had complete GPS data for both periods. The reasons for participants not having complete GPS data include failures to wear, recharge, or turn on the equipment properly, equipment failure or spending time indoors where GPS signals do not penetrate (Brown et al., 2015).

Sample recruitment was primarily through an initial mail invitation followed by door-to-door recruitment visits. For study inclusion, adults (≥18) were eligible if they could speak English or Spanish, expected to live in the area for at least a year, could walk a few blocks, were not pregnant, could give informed consent and provide survey data. Due to these eligibility requirements and Census boundaries that do not overlap precisely with the study area, it is difficult to evaluate representativeness. However, the subset of the sample was generally representative of the area in terms of gender (53% female subset, 51% sample, 48% area), Hispanic ethnicity (22% subset, 25% sample, 26% area) and average age (42 years old in subset and sample, 44 years old in area). We selected the subset from all participants, using the criteria of non-null self-defined neighborhoods and at least one home-based walking trip for both years. We compute the exposure to the complete street by calculating the street network distance from the geocoded home locations to the nearest point on the complete street.

The GPS data were classified by trip, trip stage, and travel mode by GeoStats (now Westat); details of this process have been published (Miller et al., 2015). The phrase ‘walking trips’ used in this study is the count of home-based, unlinked trip stages that are classified as walking mode, based on the average and standard deviation of the GPS measured speed. We selected walking trips that began or ended within 100m of the geocoded home location to account for several large apartment complexes in the study area. The classification is based on a published GPS trip mode classification algorithm, which had a correct classification of 97–98% of walking trips (Tsui and Shalaby, 2006); GeoStats’ research assistants reviewed trip stages and assigned modes with physical activity profiles, from the accelerometers, to ensure correct classification.

2.2 Walking activity spaces and self-defined neighborhoods

We calculate the walking activity space with Python 2.7.2 and ArcGIS 10.1. This is a set buffer around the GPS points; it is then dissolved to create one polygon. We use 200 meters for the GPS point buffer (Hirsch et al., 2014); typical buffers range from 200m to 1600m, depending on travel mode (James et al., 2014). For self-defined neighborhoods, we asked participants to free-hand draw on a paper map boundaries of what “you consider to be your neighborhood.” These were subsequently digitized by research assistants into a GIS database. Figure 1 shows a comparison between a selected participant’s walking activity space measure and their self-defined neighborhood in 2012, illustrating how the measures might differ. The data in the figure are uniformly spatially perturbed to protect privacy, but maintains their relative spatial relationship.

2.3 Geometric measures

The geometric measures we use to compare the walking activity spaces and self-defined neighborhoods are area, shape, and overlap. We use a compactness shape index to compare between areas: $S=\frac{Perimeter}{2\pi\sqrt{Area/\pi}}$(Bogaert et al., 2000). Values closer to 1 indicate a more compact area (closer to a circle); larger values indicate less compact regions. The overlap measure is the ratio between the overlap of the walking activity space and the self-defined neighborhood with the total self-defined neighborhood area.

2.4 Neighborhood built environment measures

For the perceived measures, we collected participants' neighborhood perceptions for the two data collection phases with surveys, using the Neighborhood Environment Walkability Scale abbreviated (NEWS-A) form (Cerin et al., 2006). NEWS-A is designed to capture the perceived neighborhood environment factors that may influence physical activity (Cerin et al., 2009). The instructions given to participants were to answer the groups of survey questions based on their neighborhood. We use the set of NEWS-A composite measures of aesthetics, safety from crime, residential density, diversity of land uses, ease of pedestrian travel, and traffic safety to compare with audit data.

Research assistants collected the audit measures of the built environment in the field during the two data collection phases using the Irvine Minnesota Inventory (IMI) for each street block face in the study neighborhood (both sides of the street, bounded by intersections) (Boarnet et al., 2006; Day et al., 2006). We use the street block length to weight the IMI items to control for the contribution of the length of individual blocks to the area total. The IMI composite measures are attractiveness (features that enhance the pleasure of walking, such as benches and flowers), safety from crime (high levels of outdoor lighting and well-maintained buildings, and the absence of incivilities or cues of danger from crime), residential density (single or multifamily dwellings), diverse destinations (kinds of public buildings, shops, or services and excludes unpleasant destinations), pedestrian access (ease of walking and the absence of barriers to walking), and traffic safety (how safe it is for pedestrians to cross the street) (Werner et al., 2010). We use the IMI naming convention for both the NEWS-A and the IMI composite measures in the analyses. Both of these environmental instruments have individual items that are aggregated into these dimensions. Although these dimensions are not composed of identical items, they are designed to capture the same major domains of the built environment associated with physical activity.

2.5 Statistical analyses

We use SAS v9.4 for all statistical tests. We use paired t-tests to compare the walking trips, the dependent variable, and GPS wear time between years to examine differences for individuals in the subset. The first set of comparisons is the geometric relationship between the self-defined neighborhoods and the walking activity spaces. We assess paired t-tests for differences within individuals for the measures of area, shape, and overlap. Second, we use Poisson regression models with a zero-truncated distribution for the 2012 and 2013 walking trip models. We do not include residents with no home-based walking trips because their walking activity space is undefined. We test the model residuals for spatial autocorrelation to determine whether the models are spatially biased. There is no significant spatial autocorrelation for the residuals (Moran's $I = -0.03$, $p=0.71$), so we do not add additional explanatory spatial variables (Rogerson, 2010). The first set of these models estimates the associations of walking trips with audit data for self-defined neighborhoods and walking activity spaces. The second set of models estimates the associations of walking trips with perceived qualities for self-defined neighborhoods.

The final set of analyses uses longitudinal data to examine the change in walking trips between years using ordinal logistic regression models. The outcome variable is the difference in walking trips, which we reclassify into 3 ordered categories: 1=fewer walking trips in 2013 than 2012; 2=about the same walks in both years; and, 3=more walks in 2013 than 2012. The break values are based on the first and third quartile values. Category one is the first quartile of walking trip changes (a change of −3 or fewer trips in 2013), category two is the second and third quartiles (a change between −2 and +6 trips in 2013), and category three is the fourth quartile (+7 or more trips in 2013). The first model assesses the change in walking trips with the change of audit data for the self-defined neighborhood. The second model uses the change in audit data of the walking activity space. The last model assesses the change in walking trips and the change in perceived measures of self-defined neighborhoods between years.

We omit the audit data metrics of attractiveness and crime safety from the models. These are correlated with each other and the other measures in the models. Spearman correlations between the two measures for the 2012 self-defined neighborhodoods ($r_s(230)=0.89$, $p<0.0001$). These metrics are mildy collinear with the diverse destinations and density metrics, but are more problematic when added separately to the models, so we omit them both. Attractiveness and crime safety are also omitted from the walking trip change model for the walking activity spaces because of a similar collinearity ($r_s(230)=0.79$, $p<0.0001$). We do not observe collinearity among the perceived measures for the 2012, 2013, and walking trip change models. There is a small fluctuation in sample size between models, because of some incomplete data. This does not influence the collinearity of the measures.

3. Results

Table 1 presents the descriptive statistics of the control variables for participants that had GPS recorded home-based walking trips and self-defined neighborhoods for both years. The walking trips difference for participants is significantly different from zero. This indicates that there was an average increase of 2.16 walking trips ($t(231) = 3.89$, $p<0.0001$) from 2012 to 2013 for the sample. The GPS wear time is not significantly different between years ($t(231) = -0.40$, $p=0.69$), which allows an unadjusted comparison of walking trips and their difference. Furthermore, there is not a significant difference between accelerometer measured physical activity counts, adjusted for wear time, between residents living near (<800m street network distance) and far (≥801 to 2000m) from the complete street ($t(224.41)= -1.71$, $p=0.09$). This suggests there is not a selection bias in residential location and activity levels: residents who live closer to the complete street are not significantly more active than those who live farther away.

3.1. Geometric relationships between self-defined neighborhoods and walking activity spaces

We compare the geometric properties between the self-defined neighborhoods and walking activity spaces with three measures: area, shape, and overlap. Table 2 presents the descriptive statistics of these measures for 2012 and 2013. On average, we see that the overlap of the walking activity space measure with the self-defined neighborhood is less than 10%. We also find that less than half of the participants' walking activity spaces are completely contained within their self-defined neighborhood.

Our participants' neighborhood walks comprise a small portion of their self-defined neighborhood. Table 3 displays the paired *t*-tests results for the geometric differences between walking activity spaces and self-defined neighborhoods. We see that for individuals, the walking activity space has a significantly smaller area than the self-defined neighborhoods for 2012 and 2013 (p<.0001; Table 3). We see that the shape indices of these areas are not significantly different for 2012 (p=.38), but are for 2013 (p<.0001). Finally, we find only one significant difference of these measures between years: the shape of the walking activity space (p=0.0038). These results suggest that there is stability in the size of self-defined neighborhoods and walking activity spaces for individuals between years, but the shape of the walking activity spaces became more compact.

3.2 Audit data for self-defined neighborhoods and walking activity spaces

This section compares the audit data of the built environment for two spatial units: the walking activity space and the self-defined neighborhood. The goal is to see which spatial area is a better fit for describing neighborhood walking trips. For the 2012 walking activity space model, the density coefficient is negative and significant (Table 4). Increases in the 2012 audit measures of residential density in the walking activity space goes with a decreases in the log walking trips. Finally, living closer to the complete street is associated with more walking trips.

For the 2012 self-defined neighborhood model, greater density and traffic safety audit scores are related to more walks (Table 4). More audit measured pedestrian access is associated with fewer walks (Table 4). While both models have different significant variables, the walking activity space model has a better fit, with the adjusted McFadden's R^2=0.19, compared to 0.11 for the self-defined neighborhood model. Furthermore, this comparison highlights the difference in the relationship of built environment audit data to walking trips, due to the different spatial regions.

For the 2013 walking activity space model, greater pedestrian access audit scores are associated with more walking trips (Table 5). However, greater pedestrian access in the 2013 self-defined neighborhood is related to less walks (Table 5), similar to the estimated relationship in 2012 (Table 4). The variables associated with less walking are density (similar to the 2012 walking activity space, Table 4), diversity and traffic safety (Table 5). For the 2013 self-defined neighborhood model (Table 5), greater density is associated with more walking trips. This is similar to relationship estimated for the 2012 self-defined neighborhood model (Table 4). There is agreement between the 2013 models in that higher audit measured diversity is associated with fewer walks. The walking activity space model has a better model fit (0.17) than the self-defined neighborhood model (0.08) for 2013 audit data.

3.3 Perceived qualities of self-defined neighborhoods and walking trips

In 2012, less perceived diversity of destinations and greater perceived pedestrian access are associated with more walking trips (Table 6). In 2013, both greater perceived attractiveness and crime safety are related to more walking trips (Table 6). The models of perceived measures in the 2013 self-defined neighborhoods and the 2012 self-defined neighborhoods exhibit different significant variables suggesting a change in the relationship between perceptions and walking.

3.4 Longitudinal changes in walking trips

This section assesses the geographic region for measuring the changes in walking trips using audit data and perceived qualities. Table 7 presents the model estimates for the ordered walking trips category (fewer walks, same walks, and more walks) and change in audit data for the self-defined neighborhood. The one significant variable is the difference in attractiveness. For a one point increase in the audit measure of attractiveness of the self-defined neighborhood between the two years, the odds of more walks versus the combined categories of the same and fewer are 1.27 times greater, given the other variables are held constant. Similarly, for a unit increase in attractiveness, the odds of the combined more and the same walks categories are 1.27 times greater than the fewer walks category, holding other variables constant. The change in the audit data model for the self-defined neighborhood (Table 7) has the same model fit (0.08) as the walking activity space model (Table 8). However, none of the variables of interest are significant in the difference in audit data of the walking activity space model (Table 8).

The final analysis models the walking trip count category and changes in perceived neighborhood measures (Table 9). The one variable of interest that is significant is the change in perceived traffic safety. The interpretation is that for a unit increase in perceived traffic safety between 2012 and 2013 in the self-defined neighborhood, the odds of more walks versus the combined categories of the same and fewer are 1.30 times greater, given the other variables are held constant. Additionally, for a unit increase in perceived traffic safety, the odds of the combined more and the same walks categories are 1.30 times greater than the fewer walks category, holding other variables constant.

These results suggest that both perceived and audit measures within the self-defined neighborhood are relevant to increase walking trips, although the measures are not the same. We find that an increase in perceived traffic safety is related to more walking (Table 9). We also find that an increase in the audit measure of attractiveness is related to an increase walking (Table 7). Lastly, we find that the distance to the complete street in the longitudinal models is not significant in predicting changes in walking trips. This contrasts with the estimated cross-sectional models, where the relationship of closer proximity to the complete street is associated with more walking trips.

4. Discussion

This study evaluates two potential geographic regions for assessing the relationships between the built environment and walking trips. It first examines the spatial relationships between self-defined neighborhoods and walking activity spaces. It then assesses the geographic region question by using two measures of the built environment: audit data and perceptual survey data, for two separate years. The final part of this study examines geographic regions using longitudinal walking trip change models for assessing the effect of audit and perceived changes in the built environment.

For the first part of this study, we estimate the relationship between self-defined neighborhoods and walking activity spaces using the geometric measures of area, shape, and overlap. We find that the size of self-defined neighborhoods is significantly larger than walking activity spaces revealed over a one-week observation period. While observation over longer time periods may reveal larger walking activity spaces, we assume that a typical week provides a reasonable representation of routine exposure to the local environment. This result is comparable to findings that walking activity spaces are smaller than neighborhoods using home-based buffers in walkability research (Rundle et al., 2016.). Previous research also finds that self-defined neighborhoods are smaller than census geographies, but there is substantial variation based on the built environment context (Coulton et al., 2013).

We also find that the walking activity space shape changes between years: they become more compact. In comparison, the shape of the self-defined neighborhoods is stable between years. Further analysis will answer how the shape of the walking activity spaces changes, such as are they more compact because they are directed towards the complete street? Finally, the overlap between walking activity spaces and self-defined neighborhoods and their areas are statistically stable between years. This is insightful because this evidence of stability suggests reliability of these areas. Furthermore, self-defined neighborhoods are generally inclusive of walking activity spaces, meaning that analysis using neighborhoods will capture routine exposure centered on home-based trips. The novel analysis of the geometric relationships between the walking activity spaces and self-defined neighborhoods establishes their relationships for single years and their stability or variation between years. This provides a foundation for future research to explore the built environment correlates of the change in the spatial properties of neighborhoods between years.

The second part of this study assesses geographic regions using audit measures and perceived survey data. We compare models of the audit data of the walking activity spaces and self-defined neighborhoods with their associations with walking trips. These findings suggest that residents' exposure to audit data measures of the built environment within walking activity spaces have a higher correlation with walking than audit data measures within their self-defined neighborhoods. This result supports other research (Boruff et al., 2012) that finds better model fit using a spatial scale more specific to walking behavior, at least for audit measures. However, we find different relationships between audit measures and walking trips based on the geographic regions, also supporting previous research (Rundle et al., 2016; Spielman and Yoo, 2009). We also find variation in the significant perceived measures between years, reflecting changing perceptions or the sensitivity of cross-sectional models.

The final part of this study evaluates the appropriate geographic region by modeling changes in self-defined neighborhood and walking activity space measures to explain changes in walking trips. We find that both types of built environment measures of the self-defined neighborhood better explain changes in walking between years than audit measures of walking activity spaces. For self-defined neighborhoods, we find an increase in walking related to an increase in the audit measure of attractiveness and an increase in the perceived traffic safety. Other researchers have found increases in walking due to a new pedestrian path (Fitzhugh et al., 2010; Goodman et al., 2013), but few studies have examined the effects of the intervention on an existing street. This suggests that changes in the self-defined neighborhood, both perceived and audit measures are more important than changes in the walking activity space to explain changes in walking trips. We do not find significant variables for the change in the audit data measures for walking activity spaces. Whereas for the cross-sectional models, we find that the audit data of the walking activity space appears to be a better geography to explain walking trips, we do not find the same relationship using a longitudinal model. This is likely because the walking activity spaces encompass smaller areas and that these areas capture little variability in the built environment between years.

The built environment change in our study area is a complete streets intervention and we measure exposure to that change via a street network distance measurement. We find a negative relationship to walking trips in the cross-sectional models: the further a resident lives from the complete street, the fewer the walking trips. However, distance from the intervention does not explain the change in walking between years. This suggests that the distance from the renovated complete street does not significantly explain the one year change in home-based walking trips. However, a distance effect was observed in the larger sample of residents in this same neighborhood. Residents living near the complete street after it was completed increased their active travel along the complete street corridor and used it more than residents living farther away (Brown et al., 2016). Other studies have found a distance effect after a two year follow-up after the intervention was completed (Goodman et al., 2013). The effect of distance and how it is modeled needs further study for its role in generating complete street walking trips.

This study examined representations of actual movements compared with representations of perceived neighborhoods on modeling associations with walking trips. This study also examined the relation between improvements in a single street and changes in actual movements (walking activity space) and participants' descriptions of their neighborhood (perceived spatial boundaries). Data showed changes in perceptions and movements that might be related to the environmental improvements. Our study is unique in tracing changes over time in relation to the environmental changes and supports the idea that the environmental improvements precipitated the increases in walking activity. However, we were not able to study the psychological micro-processes that might have supported and shaped participants' changed behaviors and perceptions. Although valuable, our description of the changes is limited to these two data points, one year apart. Indeed, it is likely that participants differed in how the change processes unfolded over the one year between the intervention and follow-up. Some participants might have expanded their defined neighborhood and exploratory behavior slowly while others may have made larger changes quickly. For example, participants who were able to use the new light rail may have initially walked farther simply for transit, but became more comfortable and conducted more exploratory behaviors in other parts of the neighborhood. Without more frequent data collection, it is impossible to trace the micro-level changes in our measures.

Some limitations of this work are the examination of the subset of participants that have home-based walking trips for both years. This may lead to some insignificant relationships in our models because of insufficient statistical power from a smaller sample size. For example, there was too little variability in our sample to estimate significant changes in audit data measures for walking activity spaces and their effect on changes in walking trips, resulting in no significant variables. Furthermore, expanding this analysis to include participants without home-based walking trips in both years may better explain not only what environments are supportive of walking, but neighborhoods that are potentially unsupportive. A further improvement to this study is to compare neighborhoods and environmental qualities for all the participants and all their travel modes. This will better explain neighborhood size difference and may better inform the influence of the built environment on walking. Additionally, including walking trip tours, not only unlinked walking trips that start or end at home, would contribute more to the understanding the appropriate spatial analysis scale. Similarly, an analysis of the portion of self-defined neighborhood not covered by the walking activity space may reveal measures of why residents' avoid certain portions of their self-defined neighborhoods (Rundle et al., 2016). Moreover, we assess all home-based walking trips and do not assess walking for leisure or transport separately. Trip purpose is a difficult concept to implement as walking trips often have multiple purposes (Handy et al., 2002). We only assess two time points, one year apart, but the inclusion of follow-up at a longer time from the completion of the intervention may allow more time for resident's perceptions and travel activity to change (Goodman et al., 2013). Lastly, the mismatch in relationships between audit and perceived measures with walking may be due to the use of different individual built environment items in these composite measures (Brownson et al., 2009). For example, the NEWS-A measure of pedestrian access has an item about walkways that connect cul-de-sacs, whereas the matched IMI pedestrian access measure does not contain an item for cul-de-sacs; cul-de-sacs are in the IMI traffic safety measure.

5. Conclusion

This study examines geographic regions for explaining the relationship between the built environment and walking trips. It assesses the model fit for audit data for two different geographic regions: walking activity spaces and self-defined neighborhoods. Also, it assesses perceived data for self-defined neighborhoods and uses two types of study design: cross-sectional and longitudinal. First, we find that self-defined neighborhoods are much larger than walking activity spaces. Second, we find that the association of the built environment and walking trips varies by geographic region, measurement type, and the study design. We see that the self-defined neighborhoods and walking activity spaces have different associations between audit and perceived measures with walking trips. These findings suggest that the appropriate geographic region for these two types of measures, with regard to walking outcomes, is different.

Researchers need to consider the context dependent nature of built environment measurement tools when analyzing environmental exposure and active travel. This selection depends on the research question and the operational neighborhood definition. Specifically, for cross-sectional models, audit measures are better measured at walking activity spaces than at self-defined neighborhoods. This relationship does not necessarily hold for the longitudinal models, but this may be due to a small sample and lack of built environment variance. Lastly, we see that the geographic region and the built environment associations with walking are different depending on the research design. Cross-sectional study designs produce different results between years, whereas both of the longitudinal self-defined neighborhood models better explained changes in walking trips, compared to the longitudinal walking activity space model. This instability in relationships between time points is a major shortcoming of cross-sectional research designs and highlights the need to analyze longitudinal data (Næss, 2015). Our results agree with previous calls for longitudinal study designs using a natural experiment to assess the effect of changing the built environment.

The novel contributions of this study are the comparison of two geographic regions, self-defined neighborhoods and walking activity spaces, using two built environment measures, audit and perceived, and two study designs, cross-sectional and longitudinal, to explain built environmental associations with walking trips. The results of this study provide a firm grounding for understanding the appropriate geographic region to assess walking trips, but future research needs to further examine these relationships. First, the interaction between perceived and audit measures may better explain changes in walking trips than modeling their influences separately. Second, the agreement between perceived and audit measures and the potential of the temporal lag of perceptions with audit data requires additional research. For example, how long after an environmental intervention do nearby residents' incorporate the change into their perceptions and self-defined neighborhood? Third, continued investigation is needed into the appropriate geographic regions to capture the causal effects of audit and perceived measures to influence walking trips. Finally, more research is needed on the spatial variation across a neighborhood in self-defined neighborhood sizes and by socio-demographic characteristics (Coulton et al., 2013; Ivory et al., 2015) and how these sizes change due to the environmental intervention. This study adds insight into the important discussion on geographic regions in assessing walking and the built environment in the field of public health.

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Highlights

- We assess walking with audit and perceived built environment measures
- Spatial measures are walking activity spaces and self-defined neighborhoods
- Findings indicate that environmental measures have preferred spatial extents
- Researchers need to consider varying spatial measures to assess walking correlates

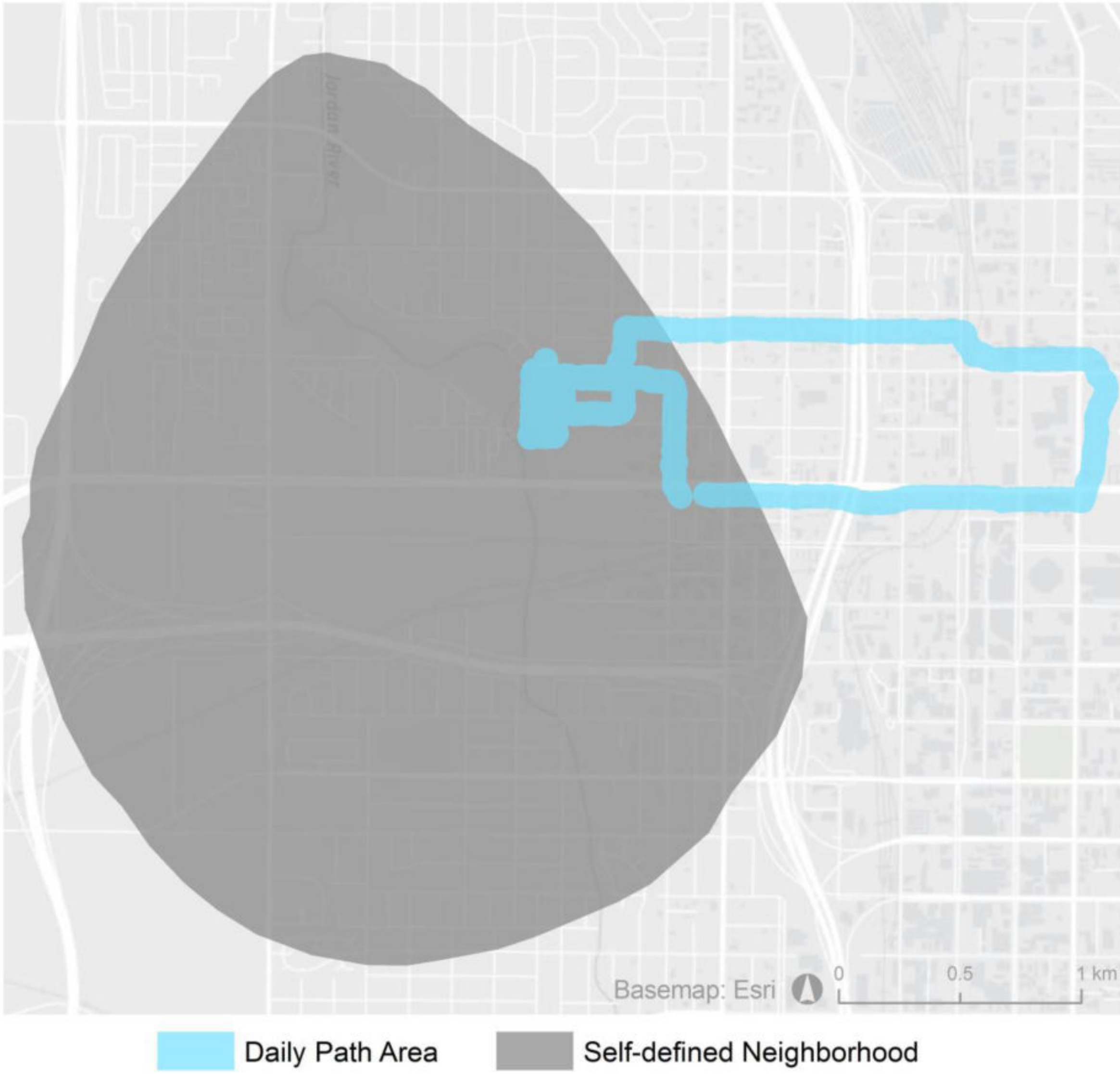

Figure 1.
Comparison between a participant's walking activity space measure and self-defined neighborhood. Data are spatially perturbed.

Table 1

Descriptive statistics (means or proportions) of the subset of participants and Census area estimates (where available)

	Sample subset		Area estimates
n=232	**M**	**SD or SE**	**M**
Employed (1=yes)	0.61	0.49	–
Hispanic (1=yes)	0.22	0.41	0.26
Gender (1=female)	0.53	0.49	0.48
Obesity status (1=BMI>30)	0.36	0.48	–
Age	42.22	15.35	44.0
Years residence	6.95	9.91	–
Distance to complete street (m)	859.10	527.28	–
2012 walking trips	7.49	7.37	–
2013 walking trips	9.65	8.41	–
Difference[+]: 2013–2012 walking trips	2.16[*]	0.56	–
2012 GPS wear time (min)	4776.33	1150.25	–
2013 GPS wear time (min)	4740.36	951.30	–
Difference[+]: 2013–2012 GPS wear time (min)	−35.97	88.50	–
Difference[#]: 2012 Near-Far wear time adjusted physical activity counts	−251.10	1148.40	–

[+]Paired t-test.

[#]2-sample t-test.

[*]$p<0.05$.

Table 2

Descriptive statistics of area, shape index, and overlap averages with 95% confidence interval

n=232	Area (km^2)	Shape Index	Proportion Overlap with Self-defined	Count of Walking Activity Spaces within Self-defined
2012				
Activity space	0.14 (0.12, 0.16)	1.77 (1.67, 1.87)	0.086 (0.074, 0.098)	98
Self-defined	2.15 (1.74, 2.55)	1.54 (1.03, 2.05)		
2013				
Activity space	0.12 (0.09, 0.14)	1.61 (1.50, 1.72)	0.090 (0.076, 0.10)	102
Self-defined	2.13 (1.71, 2.56)	1.28 (1.19, 1.37)		

Table 3

Paired *t*-tests of geometric differences (n=232)

2012 Activity space - Self-defined	**Mean**	***p***
Area (km^2)	−2.01 *	<.0001
Shape	0.23	0.38
2013 Activity space - Self-defined		
Area (km^2)	−2.02 *	<.0001
Shape	0.33 *	<.0001
Change (2013–2012)		
Area (km^2)		
2013 Activity space - 2012 Activity space	−0.021	0.088
2013 Self-defined - 2012 Self-defined	−0.014	0.94
Shape		
2013 Activity space - 2012 Activity space	−0.16 *	0.0038
2013 Self-defined - 2012 Self-defined	−0.26	0.32
Overlap with Self-defined		
2013 Activity space - 2012 Activity space	0.0037	0.65

*Bonferroni adjusted *p*<0.0056.

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Table 4

2012 walking trips as a function of audit data of the walking activity spaces (n=223) and self-defined neighborhoods (n=225)

	Walking Activity Space			Self-defined		
Variables	**Estimate**	**SE**	***p***	**Estimate**	***SE***	***p***
Intercept	2.83**	0.17	0.0001	2.46**	0.79	0.002
Density	−0.11**	0.039	0.004	0.25*	0.12	0.05
Diversity	−0.0058	0.017	0.73	0.10	0.055	0.07
Pedestrian access	0.0020	0.0055	0.72	−0.071**	0.018	0.0001
Traffic safety	−0.0027	0.0057	0.64	0.091**	0.024	0.0002
Distance to complete street	−0.00012*	0.000054	0.03	−0.00017**	0.000055	0.002
Adjusted McFadden's R^2	0.19			0.11		

* $p<0.05$;

** $p<0.01$. Models are significant at $p=0.01$ using the Pearson statistic in a χ^2 test. Control variables are employed, have car, female, white, obese, years residence, area, and GPS wear time.

Table 5

2013 walking trips as a function of audit data metrics of the walking activity space (n=221) and self-defined neighborhood (n=228)

	Walking Activity Space			Self-defined		
Variables	**Estimate**	**SE**	***p***	**Estimate**	**SE**	***p***
Intercept	2.24**	0.17	0.0001	4.90**	0.73	0.0001
Density	−0.069*	0.033	0.04	0.31**	0.11	0.005
Diversity	−0.054**	0.016	0.0005	−0.12*	0.062	0.05
Pedestrian access	0.022**	0.0046	0.0001	−0.051**	0.019	0.008
Traffic safety	−0.014**	0.0032	0.0001	−0.0039	0.0092	0.67
Distance to complete street	−0.00021**	0.000048	0.0001	−0.00033**	0.000049	0.0001
Adjusted McFadden's R^2	0.17			0.08		

* $p<0.05$;

** $p<0.01$. Models are significant at $p=0.01$ using the Pearson statistic in a χ^2 test. Control variables are employed, have car, female, white, obese, years residence, area, and GPS wear time.

Table 6

Walking trips as a function of perceived qualities of the self-defined neighborhood for 2012 (n=225) and 2013 (n=222).

	2012 Self-defined			2013 Self-defined		
Variables	**Estimate**	**SE**	***p***	**Estimate**	**SE**	***p***
Intercept	3.09**	0.15	0.0001	2.43**	0.14	0.0001
Attractiveness	0.042	0.029	0.14	0.13**	0.025	0.0001
Crime safety	−0.036	0.027	0.19	0.066**	0.025	0.009
Density	−0.0084	0.025	0.74	−0.017	0.024	0.46
Diversity	−0.057*	0.028	0.05	0.020	0.025	0.42
Pedestrian access	0.090**	0.030	0.003	−0.035	0.025	0.16
Traffic safety	0.048	0.027	0.08	−0.010	0.025	0.68
Distance to complete street	−0.00020**	0.000053	0.0002	−0.00026**	0.000047	0.0001
Adjusted McFadden's R^2	0.10			0.12		

* $p<0.05$;

** $p<0.01$. Models are significant at $p=0.01$ using the Pearson statistic in a χ^2 test. Control variables are employed, have car, female, white, obese, years residence, area, and GPS wear time.

Table 7

Change in walk trip count categories (2013–2012) as a function of change in audit data of the self-defined neighborhood (n=228)

Variables	Odds Ratio Estimate	95% CI	*p*
Attractiveness	1.27*	(1.01, 1.58)	0.04
Crime safety	0.96	(0.68, 1.35)	0.80
Density	2.14	(0.65, 7.12)	0.21
Diversity	1.10	(0.63, 1.92)	0.75
Pedestrian access	0.95	(0.74, 1.22)	0.67
Traffic safety	0.90	(0.79, 1.04)	0.16
Adjusted McFadden's R^2	0.08		

*Wald χ^2 $p<0.05$. Model is significant at $p=0.05$ using the log likelihood χ^2 test. Control variables are employed, have car, female, obese, years residence, area difference, distance to complete street and GPS wear time difference.

Table 8

Change in walk trip count categories (2013–2012) as a function of change in audit data of the walking activity space (n=219)

Variables	**Odds Ratio Estimate**	**95% CI**	***p***
Density	1.16	(0.82, 1.63)	0.40
Diversity	1.05	(0.92, 1.19)	0.49
Pedestrian access	0.98	(0.95, 1.02)	0.33
Traffic safety	1.00	(0.96, 1.04)	0.88
Adjusted McFadden's R^2	0.08		

[*] Wald χ^2 $p<0.05$. Model is significant at $p=0.02$ using the log likelihood χ^2 test. Control variables are employed, have car, female, obese, years residence, area difference, distance to complete street, and GPS wear time difference.

Table 9

Walk trip count difference categories (2013–2012) as a function of changes in perceived measures of the self-defined neighborhood (n=222)

Variables	**Odds Ratio Estimate**	**95% CI**	***p***
Attractiveness	1.12	(0.83, 1.51)	0.47
Crime safety	1.05	(0.77, 1.44)	0.75
Density	0.94	(0.71, 1.24)	0.64
Diversity	0.87	(0.65, 1.15)	0.33
Pedestrian access	1.03	(0.79, 1.35)	0.83
Traffic safety	1.30*	(1.00, 1.69)	0.05
Adjusted McFadden's R^2	0.08		

*Wald χ^2 p=0.05. Model is significant at p=0.05 using the log likelihood χ^2 test Control variables are employed, have car, female, obese, years residence, area difference, distance to complete street and GPS wear time difference.