The Built Environment and Location-Based Physical Activity

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Background: Studies of the built environment and physical activity have implicitly assumed that a substantial amount of activity occurs near home, but in fact the location is unknown.

Purpose: This study aims to examine associations between built environment variables within home and work buffers and moderate-to-vigorous physical activity (MVPA) occurring within these locations.

Methods: Adults (n=148) from Massachusetts wore an accelerometer and GPS unit for up to 4 days. Levels of MVPA were quantified within 50-m and 1-km home and work buffers. Multiple regression models were used to examine associations between five objective built environment variables within 1-km home and work buffers (intersection density, land use mix, population and housing unit density, vegetation index) and MVPA within those areas.

Results: The mean daily minutes of MVPA accumulated in all locations=61.1±32.8, whereas duration within the 1-km home buffers=14.0±16.4 minutes. Intersection density, land use mix, and population and housing unit density within 1-km home buffers were positively associated with MVPA in the buffer, whereas a vegetation index showed an inverse relationship (all $p<0.05$). None of these variables showed associations with total MVPA. Within 1 km of work, only population and housing unit density were significantly associated with MVPA within the buffer.

Conclusions: Findings are consistent with studies showing that certain attributes of the built environment around homes are positively related to physical activity, but in this case only when the outcome was location-based. Simultaneous accelerometer–GPS monitoring shows promise as a method to improve understanding of how the built environment influences physical activity behaviors by allowing activity to be quantified in a range of physical contexts and thereby provide a more explicit link between physical activity outcomes and built environment exposures.

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Introduction

Physical inactivity continues to be an important public health problem among the U.S. population and in numerous other countries. This is true despite a shift in behavior change paradigms from one dominated by a focus on psychological factors and individual responsibility to one recognizing that environmental factors are important in shaping healthy behaviors of populations, such as physical activity.[1–3] A growing body of evidence demonstrates positive associations between characteristics of neighborhood built environments, including higher levels of land use mix, population and residential density, and street connectivity, and participation in recreational and utilitarian physical activity.[4–6] Despite a rapid growth in this research and improved methods of measuring both the built environment (e.g., via GIS) and physical activity outcomes (e.g., via accelerometers), the current evidence base is still emerging. One area needing more work is use of an activity-monitoring approach that provides a more precise spatial match between built environment exposures and physical activity outcomes—an approach that spatially contextualizes physical activity behaviors.[7]

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Current evidence has not yet revealed the dynamic interactions among individuals, their environment, and their physical activity behaviors over time and space. Recent studies have examined relationships between objective built environment variables and objectively measured physical activity using an analytic approach that assumes activity occurs within a designated area surrounding a residential address[8] or within another defined neighborhood area.[9] The lack of specificity with respect to where physical activity occurred in these studies may contribute to dilution of the observed associations, resulting in an inability to observe true associations or an underestimation of the strength of real associations.

To address this limitation, a sample of free-living adults was monitored with accelerometer and GPS devices. The present study builds on previous research[7] by examining a larger sample over a longer monitoring period and using different methodologic approaches. The aims of this cross-sectional study were to (1) quantify moderate-to-vigorous physical activity (MVPA) occurring within buffers around home and work locations using accelerometer and GPS data and (2) examine associations between built environment characteristics and MVPA within the buffers (i.e., "location-based" physical activity).

Methods

Participants and Recruitment Procedures

Participants were adults (aged 19–78 years) who completed brief (5-minute) intercept surveys at one of five trails in eastern Massachusetts; were either walking, jogging/running, bicycling, or in-line skating; reported using the trail at least four times during the previous 4 weeks; and agreed to wear an accelerometer and GPS unit for 4 days. The sampling frame was limited to trail users because this project was a follow-up to a previous study examining physical characteristics of trails.[10]

The specific trail location, time of day, and day of the week for intercepts were systematically varied. Surveys were conducted for a minimum of 2 weekdays and 2 weekend days during fall 2004 and spring and summer 2005. Among 1194 trail users surveyed, 294 individuals (24.6%) initially agreed to participate in activity monitoring and provided contact information. Equipment was deployed to 178 individuals (14.9% of those surveyed). Among 116 individuals who provided contact information but did not participate, the primary reasons were schedule conflicts, loss of interest, or inability to re-contact them. Methods for the current study were approved by the Human Subjects Committee at the Harvard School of Public Health. Participants in the activity monitoring signed an informed consent form.

Equipment

The Actigraph™ accelerometer (Model 7164) is a small, lightweight (42.6-g) uniaxial activity monitor that captures vertical acceleration and stores acceleration data as dimensionless units[11] referred to as activity counts. Previous studies[12–14] in both the laboratory and field have established the validity of the Actigraph for measuring the volume, intensity, and temporal patterns of activities such as walking and running. Accelerometers were initialized to collect data in 1-minute epochs. After each deployment, accelerometers were checked using the manufacturer's calibration device and recalibrated as necessary. Participants were instructed to wear the monitor on their right hip using an adjustable nylon belt.

The GeoStats (Atlanta GA) Wearable GeoLogger™ is a GPS device designed for collection of detailed travel data. Components included a data logger that records position and speed, a rechargeable battery, and a patch antenna (total weight ~ 0.45 kg). Small backpacks were purchased to house the units and the antenna was fastened to one of the shoulder straps (Figure 1). The GPS units were initialized to spatial coordinates within the metropolitan Boston area and were initially programmed to collect data at 5-second intervals. Subsequently, when a longer-lasting battery became available, this interval was changed to 1 second.

Data Collection

Research staff met participants at a public location (e.g., library, town hall, coffee shop) 1–3 days before activity monitoring began. Participants completed an informed consent form, were instructed on how to wear the equipment, and were given a daily log sheet for both devices. Participants were instructed to wear the accelerometer at all times, except when sleeping, bathing, or swimming, for 4 consecutive days (2 weekend days and 2 weekdays). They were also told to wear the GPS unit anytime they were outdoors, regardless of whether they were being physically active (e.g., walking) or traveling in a car, train, or bus. After the monitoring period, research staff met participants within 1–3 days to collect equipment and review log sheets.

Data Processing

Accelerometer and GPS data were downloaded using Actigraph and GeoStats software, respectively. For each participant, an analyst manually reviewed animations of the raw GPS data for the 4-day monitoring period and identified outlying points and discontinuities. Outliers resulting from poor GPS signals and multiple points clouding around stops were removed from the database. After this step, a processor was applied to aggregate the GPS points into 1-minute in-

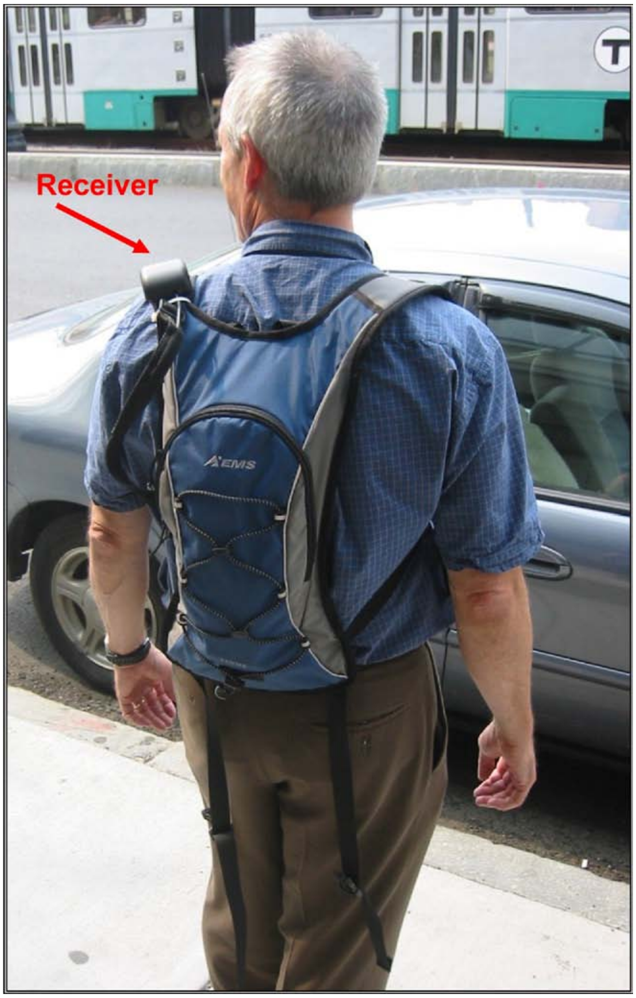

Figure 1. GPS unit with receiver on shoulder strap

tervals that temporally aligned with the accelerometer data. GPS and accelerometer data were merged using their respective time stamps and processed into a database with one record for each minute of activity. The precision of the clock systems and synchronicity of the GPS and accelerometer data that allowed for merging were described previously.[15] GPS coordinates for each monitoring minute (starting and ending latitude and longitude) were imputed prospectively in cases where a missing GPS reading followed a monitoring minute with "actual" (nonimputed) coordinates. This last known GPS point position was maintained for each minute until a new reading was obtained.

Physical activity summary variables were created for monitor wearing time (minutes/day); average counts per minute per day; and for time (minutes) spent in moderate (1952–5724 counts/minute) and vigorous activity (≥5725 counts/minute).[12] Valid days of monitoring were based on both accelerometer and GPS criteria. A valid accelerometer day was defined as ≥600 minutes of wear time, determined using the algorithm developed by National Health and Nutrition Examination Survey.[16,17] To establish criteria for a valid GPS day, the distribution of non-imputed GPS readings for 642 participant-days of monitoring that had valid GPS readings were examined. GPS monitoring time ranged from 2 to 601 minutes per day, with mean and median values of 130.7±90.1 and 113.0 minutes, respectively. A minimum value equivalent to 1 SD below the mean (i.e., ≥40 minutes) was selected as the criterion for a valid GPS day. Of 178 participants, 151 met the accelerometer and GPS criteria. Three additional individuals were excluded because their home or work address was missing or was not considered valid, resulting in a final sample=148.

Geographic Information System Processing: Location-Based Physical Activity Variables

A GIS road layer (StreetMap 2005) was used for geocoding addresses and to create network buffers. In total, 174 home addresses and 87 work addresses were successfully located using standard geocoding procedures (of 174 and 96 participants who provided these addresses, respectively). Participants who provided work addresses reported one work site only, thereby obviating the need to geocode and quantify activity within multiple work buffers. Areas within a 1-km road network distance of home and work locations were delineated using network polygon buffers. This buffer size is consistent with recent studies.[8,18,19] Turning restrictions applicable to vehicular traffic were not used in the network buffer algorithm because the intention was to model pedestrian movement. Interstates, major highways, and off-ramps were excluded from the street network.

Dichotomous (yes/no) location variables, created using GIS procedures, characterized where a participant was during each monitoring minute. The last GPS point recorded during each minute was used to represent the spatial location associated with the corresponding accelerometer reading. Minutes occurring within 50 m of home and work addresses were identified based on straight-line distance from geocoded addresses to the GPS coordinates (point) for a given minute. These variables were used to estimate activity occurring indoors at home and work or within close proximity to these locations. Spatial queries were also applied to create location variables that identified whether GPS coordinates occurred within a participant's 1-km home or work buffer. Location variables for the 50-m and 1-km buffers were mutually exclusive. If a given minute was identified as falling within the 50-m buffer, it was coded as not in the 1-km buffer. Location-based physical activity variables were then created using the GPS and accelerometer data for each monitoring minute. Summary activity variables were created for each of the four buffers examined (50-m home and work, 1-km home and work). An illustration of location-based physical activity occurring near one participant's home and work is shown in Figure 2.

Geographic Information System Processing: Built Environment Variables

Within the 1-km home and work buffers, five built environment variables that have been used in previous studies were created:[4,6,20–24] intersection density (connectivity); land use mix; residential population density; housing unit density; and a vegetation index (see Table 1). Intersection density was defined as the number of intersections within the network buffer divided by the total street segment length within that buffer (intersections per km). Land use mix was estimated using 1999 land use data provided by the Massachusetts Office of Geographic and Environmental Information (MassGIS, www.mass.gov/mgis/). Four categories of land use (residential, commercial, recreational, and urban public) were used in an entropy formula developed earlier.[18] Population and housing unit density within network buffers were estimated from Census 2000 data at the block group level using methods modified from earlier work.[25] Greenness within network buffers was estimated using a satellite image of the study region captured on September 27, 2000, by the Landsat Enhanced Thematic Mapper Plus sensor. The normalized difference vegetation index (NDVI) is commonly used in environmental remote-sensing applications and has been shown to be a significant predictor of plant health, percentage of vegetated ground cover, and photosynthetic green biomass.[26] The NDVI is a unitless metric that compares reflectance values in satellite remote sensing measurements. NDVI values range between +1 and −1, with higher values indicative of healthy green vegetation and lower values characteristic of nonvegetated land cover. Greenness was estimated as the mean NDVI within network buffers following methods used in previous studies that found this variable to be a significant predictor of smaller increases in child BMI[23] and increased pedestrian trail traffic.[22]

Figure 2. Location-based physical activity for participant over 4 days (A) with inset showing activity around home (B)

Statistical Analysis

Descriptive statistics (Ms and SDs) were used to summarize total MVPA and activity accumulated within buffers (i.e., location-based physical activity). The percentage of total activity time within each buffer classified as MVPA was also calculated. Five separate multiple linear regression models (one for each built environment variable) were used to esti-

Table 1. Operational definitions for built environment variables within 1-km home and work network buffers

Built environment domain	Specific variable	Operational definition and data source(s)
Street connectivity	Intersection density (intersections per kilometer)	Number of intersections within network buffer divided by total street segment length (in kilometers) within buffer. Intersections and street segment lengths obtained from ESRI Street Map 2005 Data.
Land use mix	Land use mix	Land use data from Massachusetts GIS 1999 aerial photography (36 categories collapsed into five categories)—measure of evenness of uses across five categories
Density	Residential population density	Number of people estimated within network buffer from 2000 Census divided by area of residential land use within buffer (in square kilometers)
Density	Housing unit density	Number of housing units estimated within network buffer from 2000 Census divided by area of residential land use within buffer (in square kilometers)
Greenness	Vegetation index	Average Normalized Difference Vegetation Index (NDVI) within buffer using Landsat satellite image from September 27, 2000

mate associations between the built environment variables within the home buffer and mean minutes per day of MVPA, controlling for potential confounding by age, gender, and race. Associations with total and location-based MVPA were examined. Both outcomes had non-normal distributions; therefore, square root transformations were used. Location-based physical activity around work was also non-normally distributed. Because of the large number of observations with zero values, square root and log transformations did not provide adequate correction. Therefore, associations were estimated using a generalized linear model (Poisson regression). All data analyses were completed in 2009.

Results

Participant and Monitoring Characteristics

Participants were aged 44.0±13.0 years on average with no significant differences by gender. Twenty-seven percent of the sample was nonwhite and about twice as many women as men were African-American or black (Table 2). Overall, participants were well educated. Women tended to live in areas with higher intersection density, land use mix, and density, as compared to men (Table 2). Alternatively, the vegetation index was slightly higher for men than women. None of these gender differences were significant.

Forty-nine percent of 148 participants (n=72) had 4 valid monitoring days; 22% (n=32) had 3 days; 17% (n=25) had 2 days; and 13% (n=19) had 1 valid day. The average number of monitoring days was 3.1±1.1; average monitor-wearing time was 14.4±1.6 hours/day; and mean counts/minute/day was 492.3±198.1. The average number of daily monitoring minutes within the 1-km and 50-m home buffers was 201.8±198.4 and 194.7±199.1 minutes, respectively. Among a subset of participants with work addresses (n=80), mean minutes in the 1-km and 50-m work buffers were 134.9±130.9 and 52.9±103.2, respectively. Mean monitoring minutes in the 1-km and 50-m work buffers were lower on weekend days (28.1±84.3 and 9.4±70.1, respectively) and substantially higher on weekdays (268.5±234.0 and 108.0±172.9, respectively).

Moderate-to-Vigorous Physical Activity by Location

The median distance from home to locations where minutes of MVPA took place was 1855 m (mean=7413.5±17,438.8 m). Table 3 displays results for MVPA at all locations and within home and work buffers. The average time spent in MVPA was 61 minutes per day. On average, participants accumulated 6 minutes of MVPA per day within their 50-m home buffer and 14 minutes within their 1-km home buffer. The corresponding proportion of daily monitoring time within the 1-km home and work buffers of MVPA was 11.6% and 8.2%, respectively. There were no significant differences between men and women in either mean minutes of activity or the proportion of time spent in MVPA in both home and work buffers.

Associations Between Built Environment and Location-Based Physical Activity

Associations between the five built environment variables within the 1-km home buffers and total MVPA (i.e., physical activity irrespective of location) were nonsignificant (Table 4). However, higher levels of intersection

Table 2. Demographic and built environment characteristics for study participants (N=148[a]), % (*n*) unless otherwise indicated

	All	Men	Women
Race			
White	73.5 (108)	78.6 (55)	68.8 (53)
African-American/black	19.7 (29)	14.3 (10)	24.7 (19)
Other	6.8 (10)	7.4 (5)	6.5 (5)
Hispanic or Latino			
Yes	1.4 (2)	0.0 (0)	2.6 (2)
No	98.6 (144)	100.0 (70)	97.4 (74)
Educational level			
Some college or less	19.1 (28)	21.4 (15)	16.9 (13)
Undergraduate degree	38.1 (56)	34.3 (24)	41.6 (32)
Some graduate school or above	42.9 (63)	44.3 (31)	42.6 (32)
Built environment (M [SD], median)			
Intersection density	5.25 (1.50), 5.48	5.08 (1.52), 5.34	5.40 (1.47), 5.55
Land use mix	0.52 (0.23), 0.54	0.49 (0.22), 0.52	0.55 (0.24), 0.59
Residential population density	9205.0 (9134.6), 7800.6	7836.8 (7222.6), 5998.3	10463.8 (10486.1), 9024.9
Residential housing unit density	4156.6 (4764.7), 3251.8	3452.1 (3784.7), 2437.9	4804.7 (5460.8), 3640.0
Vegetation index	0.25 (0.14), 0.23	0.27 (0.14), 0.25	0.23 (0.14), 0.21

[a]Sample sizes for each variable vary slightly because of missing data.

density, land use mix, residential population density, and residential housing unit density were associated with higher levels of MVPA within the 1-km home buffer. The vegetation index was inversely associated with MVPA within this buffer. The amount of variance in location-based MVPA explained by the five separate adjusted regression models ranged between 11.4% and 13.6%. The variance explained by the built environment variables alone (i.e., unadjusted models) ranged between 4.7% and 8.2%. Interactions between gender and race/ethnicity and each built environment variable were examined (models not shown). Significant interactions were found between gender and intersection density and between race/ethnicity and residential population density. In stratified models, intersection density was positively related to MVPA within women's home buffers, but not for men. Addi-

Table 3. MVPA at all locations and within home and work buffers, M (SD)

	All locations	Home buffer 50 m		Home buffer 1 km		Work buffer 50 m		Work buffer 1 km	
	Minutes	% time[a]	Minutes	% time	Minutes	% time	Minutes	% time	Minutes
Moderate									
All	53.8 (30.5)	9.7 (23.2)	5.7 (7.9)	10.4 (14.6)	12.9 (15.5)	7.8 (22.9)	1.5 (4.0)	7.5 (9.5)	7.6 (8.8)
Men	52.8 (30.3)	8.9 (21.3)	6.1 (7.9)	10.9 (14.4)	12.0 (15.5)	7.2 (22.1)	1.8 (4.2)	8.4 (11.5)	7.5 (7.7)
Women	54.8 (30.8)	10.4 (24.9)	5.3 (8.0)	9.9 (14.8)	13.7 (15.5)	8.5 (24.6)	1.3 (3.8)	6.5 (6.6)	7.7 (9.9)
Vigorous									
All	7.0 (13.3)	0.1 (0.3)	0.3 (1.1)	1.2 (6.4)	1.1 (3.3)	2.8 (16.7)	0.1 (0.6)	0.7 (1.8)	0.9 (2.6)
Men	8.3 (15.4)	0.1 (0.4)	0.4 (1.4)	1.9 (9.1)	1.5 (4.3)	5.0 (22.4)	0.2 (0.9)	0.9 (1.8)	1.3 (3.2)
Women	5.8 (11.1)	0.1 (0.2)	0.2 (0.7)	0.5 (1.3)	0.9 (2.1)	0 (0)	0 (0)	0.4 (1.7)	0.5 (1.6)

[a]% time represents proportion of time within the 50-m or 1-km buffer spent in MVPA.
MVPA, moderate-to-vigorous physical activity

Table 4. Associations between built environment variables and location-based MVPA within 1-km home buffers[a,b]

Built environment variables	Total MVPA, all locations	Location-based MVPA within 1-km home buffer
Intersection density (connectivity)		
Estimate	0.01788	0.43372
SE	0.03969	0.11866
$p>\|t\|$	0.6531	0.0004
Adjusted R^2	0.0126	0.1136
Land use mix		
Estimate	0.03436	3.01284
SE	0.24916	0.76308
$p>\|t\|$	0.8905	0.0001
Adjusted R^2	−0.0041	0.1293
Residential population density		
Estimate	0.00000139	0.00006987
SE	0.00000623	0.00001925
$p>\|t\|$	0.8241	0.0004
Adjusted R^2	−0.0039	0.1152
Residential housing unit density		
Estimate	0.00000606	0.00014096
SE	0.00001168	0.00003583
$p>\|t\|$	0.6046	0.0001
Adjusted R^2	−0.0023	0.1287
Vegetation index		
Estimate	−0.24911	−5.37040
SE	0.43639	1.28832
$p>\|t\|$	0.569	<0.0001
Adjusted R^2	0.0135	0.1363

[a]All models were adjusted for age, gender, race/ethnicity, and education.
[b]Sample size for each model ranged from 142 to 146.
MVPA, moderate-to-vigorous physical activity

tionally, residential population density was positively associated with location-based activity for whites, but not for nonwhites.

Unadjusted models predicting activity within work buffers indicated that intersection density was inversely associated whereas residential population and housing unit density were positively associated with MVPA (Table 5). In adjusted models, only residential population density and housing unit density remained significant.

Discussion

Using a novel method of combining accelerometer and GPS data, the authors found associations between built environment variables within 1-km home buffers and location-based MVPA, but no associations between these variables and total MVPA. In adjusted analyses, only residential population density and housing unit density within a 1-km work buffer were related to MVPA occurring within that area.

This is one of the first studies to simultaneously monitor free-living adults with accelerometers and GPS devices, objectively quantify what the authors refer to as "location-based physical activity," and examine relationships between objective measures of the built environ-

Table 5. Associations between built environment variables and location-based MVPA within 1-km work buffers[a]

Built environment variables	Unadjusted models	Adjusted models[b]
Intersection density		
Estimate	–0.0205	–0.0140
SE	0.0215	0.0221
$p>\|t\|$	<0.0001	0.527
Land use mix		
Estimate	0.00004032	0.00003167
SE	0.00004609	0.00004659
$p>\|t\|$	0.3817	0.4966
Residential population density		
Estimate	0.00000236	0.00000395
SE	0.00000106	0.00000112
$p>\|t\|$	0.0264	0.0004
Residential housing unit density		
Estimate	0.00000488	0.00000783
SE	0.00000212	0.00000227
$p>\|t\|$	0.0215	0.0006
Vegetation index		
Estimate	0.0185	−0.2969
SE	0.2533	0.2637
$p>\|t\|$	0.9417	0.2601

[a]Sample size for each model ranged from 75 to 77.
[b]Adjusted for age, gender, race/ethnicity, and education

ment and location-based activity outcomes. Also, although recent studies have examined relationships between the built environment and walking to work,[27] there do not appear to be any previous attempts to characterize the built environment within a buffer around work and examine effects on physical activity within that buffer.

Previous studies examining associations between GIS-derived built environment measures and physical activity measured with accelerometers provide the most appropriate basis of comparison for the present study. Only one other published study has simultaneously monitored free-living adults with accelerometers and GPS devices and examined these data in relation to the built environment.[7] Although investigators were limited by a small sample size (~30), they also found no associations between objective built environment variables and total MVPA. Also, consistent with the current study, it has been found[7] that compared to adults who performed a majority of their physical activity outside their neighborhood, adults performing most of their activity within their neighborhood lived in areas with higher density, street connectivity, and land use mix. In a study of adults from metropolitan Atlanta, investigators found that an objective measure of walkability, consisting of land use mix, net residential density, and intersection density, was positively associated with moderate physical activity assessed with accelerometers.[8] This is consistent with findings in the present study for location-based physical activity. However, contrary to the Atlanta study, there was no relationship between built environment variables and MVPA accumulated at all locations. Also, each built environment variable examined in the current study appears to have explained more variance in location-based physical activity than what the Atlanta study found for total moderate activity. Indirectly, this supports the proposition that researchers may see stronger effects of built environment variables when physical activity outcomes are spatially linked to specific physical contexts.

The results from the current study generally support the notion that higher levels of land use mix, street connectivity, and density are related to higher levels of physical activity. Alternatively, the finding that landscape greenness within 1-km home buffers was inversely associated with physical activity appears inconsistent with recent studies in adults and youth,[23,24,28,29] which have found positive effects of greenness on outcomes such as trail traffic and BMI. The presumed link is both perceptual and pragmatic; green landscapes may be visually appealing and greenness can be indicative of spaces conducive to outdoor physical activity (e.g., parks, greenway trails, and sports fields). In the present study the vegetation index within home buffers showed strong negative correlations with the other four built environment variables, ranging from −0.70 to −0.83. Therefore, in buffers with higher levels of street connectivity, land use mix, and density, greenness was lower. The relative influence of vegetation index on activity may vary across different contexts and may take a subordinate role to connectivity and density in more-developed areas. Further research is needed to determine the interactive effects of greenness and other built environment variables.

In addition to providing a more explicit link between physical activity outcomes and built environment exposures, a potential contribution of the present study is the quantification of MVPA in different physical contexts that included home and work buffers. For example, it was found that on average, more MVPA occurred outside of home and work buffers than occurred within these areas (66.7±25.2% and 81.9±24.0%, respectively). This finding suggests the need for more careful consideration of spatial context in future studies of built environment and physical activity, including the need for more-dynamic models of spatial context beyond home and work environments.

Several limitations should be addressed in future research. The GPS data-processing decisions were challenging and need further testing and refinement. For example, it is not clear whether missing GPS data represented someone not wearing the device (i.e., noncompliant) or someone inside a building where signals were lost. Missing GPS data were prospectively imputed using the last available coordinates; the validity of this approach needs further assessment. An integrated GPS–accelerometer device could help identify the causes for missing GPS data. For example, missing GPS data combined with the presence of accelerometer activity counts could indicate physical activity occurring indoors or in a location with poor reception. A clear determination of time indoors could not be made in the present study. Therefore, 50-m buffers were created as a proxy measure for time indoors. Improved GPS instrumentation, geographic data layers, and processing procedures may allow for a more definitive determination of time indoors. The possibility of a Hawthorne effect from wearing the GPS unit cannot be ruled out, since the units weighed about a pound and were stored in a small backpack. However, no participants indicated that wearing the devices affected their activity patterns. A key limitation of the current study was the fact that the sample was selected from highly educated, regular trail users in one state, who had physical activity levels that were higher than those of the general U.S. adult population.[17] The results are likely not generalizable to the population at large. Finally, the cross-sectional design precludes making causal inferences about effects of the built environment on location-based physical activity.

Simultaneous accelerometer and GPS monitoring has the potential to yield new insights into the dynamic nature of the relationships between the built environment and physical activity behaviors. This monitoring approach allows activity to be objectively quantified in different physical contexts and thus provides a more explicit link between physical activity outcomes and built environment exposures. Eventually, evidence obtained from studies employing combined accelerometer–GPS assessments may be used to inform the development of more-effective physical activity interventions that utilize environmental and policy-level strategies and target specific behavior settings.[30]

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