Association between objective measurement of walking activity and neighborhood walkability

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A thesis

submitted in partial fulfillment of the

requirements for the degree of

Master of Science

University of Washington

2014

Committee:

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Program Authorized to Offer Degree:

Nutritional Sciences

Abstract

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Background: Walking is the most common form of physical activity (PA) among U.S. adults, and is the most popular choice of aerobic PA to improve overall health. Although walking has received increased attention in recent years as an important means to improve population health, more than half of U.S. adults do not get the amount of aerobic PA recommended for health benefits and approximately one third are entirely inactive.

Purpose: The purpose of this study was to quantify objectively measured walking bouts that occurred within the home neighborhood, and to examine the association between the number of walking bouts in the home neighborhood and neighborhood-level walkability.

Methods: This cross-sectional study involved 106 individual twins from the University of Washington Twin Registry who were participated in a larger, funded study. For the present study, accelerometer and GPS data were collected from each subject for two weeks for the purpose of quantifying walking bouts. The walking bouts were quantified within 1-, 2-, and 3-km straight-line and network home neighborhood buffers. A neighborhood walkability score was calculated using a commercially available algorithm (Walk Score®), which uses data from business listings, road networks, schools, and public transit derived from multiple sources to map the walking distance to amenities in nine different categories (e.g., schools, parks, restaurants, etc.), with each category weighted by importance. Mixed effect models were used to test for associations, which controlled for age, sex, body mass index, and annual income level.

Result: A total of 514 walking bouts were identified from 1464 person-days. On average, participants had 2.5 walking bouts per week, and each bout lasted 12 minutes. More walking bouts were quantified within straight-line buffers than network buffers of the same distance, and the counts of within-neighborhood walking bouts increased with buffer distance for both buffer types. A significant positive association was found between neighborhood walkability scores and the numbers of walking bouts within all neighborhood buffers ($p<0.01$); the counts within 2-km straight-line and 3-km network buffers showed the strongest association with neighborhood walkability.

Conclusion: Quantification of walking episodes within and outside of pre-defined neighborhood buffers of different scales and types specifies the locations for walking and allows us to better describe and elucidate walking behaviors. Furthermore, the walkability of the home neighborhood was associated with walking activity, providing insight into the effects of neighborhood environment features on walking behaviors among adults.

Introduction

Walking is the most common form of physical activity (PA) among U.S. adults and the most popular choice of aerobic PA to improve overall health (1). Regular participation in PA is beneficial for weight control and the prevention of various chronic diseases, including hypertension, coronary heart disease, type 2 diabetes, and mental health conditions such as anxiety and depression (2). Although walking has received increasing attention in recent years as an important means to improve population health (3) and the prevalence of walking has significantly increased from 2005 to 2010 according to some reports (4), more than half of American adults do not get the amount of aerobic PA recommended for health benefits and approximately one third are entirely inactive (5). Low PA can be influenced by several individual-level factors such as age, sex, health conditions (4), and socioeconomic status (6). However, recent studies have shown that PA levels can also be influenced by a host of environmental factors in one's neighborhood (7).

It has long been appreciated that people who live in urban areas walk more than people who live in suburban areas (8), suggesting the potential influence of neighborhood environment characteristics, such as the presence of sidewalks and density of road network connections, on walking levels. The ability of a neighborhood to support walking and other forms of PA can be summarized with a neighborhood walkability score (WS), which is based on measures of urban form such as street connectivity, land use mix, and residential density, as well as proximity to utilitarian destinations (9). Some studies suggest that residents from highly-walkable neighborhoods walk more than those who live in less-walkable neighborhoods (10). For example, a study among residents throughout King County, Washington, demonstrated that a 5% increase in neighborhood walkability was associated with a significant 32% increase in time spent on walking or biking for transportation (11). While this study showed a positive correlation between walkability and walking activity, the association may be questionable for three reasons. First, the measurement of walking activity relied on a self-report measure rather than an objective measure, and thus may not accurately reflect the actual amount of walking activity due to measurement error or bias (12). Second, the location of the walking activity is not specified in many studies, so it is unknown whether the walking activity actually occurred within the neighborhood or in some other distal location. Third, the very definition of what constitutes a neighborhood is debatable; most descriptions of “walkable neighborhoods” are based on ease of walking to amenities and urban form characteristics within pre-defined “buffers” around the home address such as 400-, 800- and 1600-meters (13-15). As WS is typically theoretically derived rather than empirically with objective data, whether these buffers accurately capture how the individual perceives his or her neighborhood is unknown.

To overcome problems related to recall and quantification of walking activity, objective methods such as accelerometry and Global Positioning System (GPS) are necessary for precise measurement (16). Accelerometry is commonly used in assessments of PA in various populations ranging from children to older adults (17, 18). A GPS provides precise location data and thus allows for the specification of the spatial and temporal context in which walking behavior occurs (19). Time-based integration of accelerometer and GPS data is a promising method to capture multiple aspects of walking behavior, because it provides objective measures of walking amount and location (19, 20).

The overall goal of this study was to objectively quantify walking bouts that occurred within 1-, 2-, and 3-km buffers around the home location of each participant, and to examine the association between these walking episodes and the neighborhood WS. We hypothesized that the number of walking episodes within the home neighborhood would increase commensurate with the size of the neighborhood buffer used. We also hypothesized that participants living in neighborhoods with higher WS would have relatively more walking episodes within their home neighborhoods regardless of the buffer size used, compared to those living in neighborhoods with lower WS. Furthermore, the strength of association between walking episodes and WS would differ by neighborhood buffer such that walking episodes within the 3-km buffer would have the strongest association with WS, compared to the associations found in the 1 and 2-km buffers.

Methods

<u>Sample characteristics</u>

This study used a cross-sectional design. Subjects for this secondary data analysis were participating in a larger funded research project investigating the association of objective measures of physical activity and eating episodes with objective measures of urban form. Specifically, subjects in the present study were the first 106 individuals to complete the protocol of the parent study between June 2012 and October 2013. The parent study is ongoing and will ultimately include 200 identical adult twin pairs (400 individuals) raised together but now living apart within the Puget Sound region around Seattle, Washington. Twins for the parent study are volunteers from the University of Washington Twin Registry (UWTR). Construction of the UWTR is described in detail elsewhere (21, 22). All participants completed a survey that included items on zygosity, sociodemographics, height and weight, general health and common medical conditions, and lifestyle behaviors.

The 106 subjects for the present study who participated in the parent study all completed 2 weeks of intensive objective monitoring (see below for further details). The sample consisted of 52 twin pairs and 2 individual twins between 24 and 70 years of age with an average body mass index (BMI) of 27.4 kg/m^2. More females than males were included in this study; 84 participants had an annual income more than $50,000. Table 1 summarizes the characteristics of the study sample.

Measurements

In order to measure daily PA, subjects were instructed to wear an ActiGraph GT3X+ activity monitor (ActiGraph, LLC, Pensacola, FL) and a QStarz TR-Q1000XT GPS tracker (Qstarz International Co. ltd., Taipei, Taiwan) attached to a velcro belt worn around the waist for 2 weeks. Accelerometer counts measured by the activity monitor provide estimates of the time spent in various intensity categories, including sedentary and light-, moderate-, and vigorous-intensity PA (23). The device is a tri-axial accelerometer configured to measure the activity counts from each axis at 10-sec epochs. Mean vector magnitude, calculated as $\sqrt{x^2+y^2+z^2}$, where x, y, and z represent the activity counts from each axis, was used as the measure of accelerometer counts in this study.

GPS data, including latitude, longitude, and speed were recorded by the QStarz device at 10-sec intervals. The latitude and longitude information was used to locate whether walking episodes were within or outside of the home neighborhood, and the speed information was used to exclude non-walking activity, using an algorithm described below.

The accelerometer and GPS data streams were integrated into 60-sec epochs using common timestamps over the full 2-week period with ActiLife software (v.6.8.1, ActiGraph, LLC, Pensacola, FL), where GPS data were selected from the closest temporal matched intervals. Each record contained measures of date and time, accelerometer counts, latitude, longitude, and speed.

Neighborhood walkability was used as a measure of the “built” or physical environment, estimated using the commercially available Walk Score® index (24). Twin addresses were previously entered into the Walk Score® website, which uses data from business listings, road networks, schools, and public transit derived from multiple sources to map the walking distance to amenities in nine different categories (e.g., schools, parks, restaurants, etc.), with each category weighted by importance (25). The algorithm then uses distances, counts, and weights to create a continuous score normalized on a scale of 0-100, with 0 representing the least (i.e., car dependent) and 100 the most “walkable” neighborhood (Table 2) (25). This index has been used as a valid proxy of walkability for measuring access to walkable amenities in previous studies (13, 15).

Algorithm for walking bout identification

Walking bouts were identified through a classification algorithm, adapted from Kang et al., as shown in Fig. 1 (19). Walking was defined *a priori* as non-mechanical and human-powered travel associated with sustained light- or moderate-intensity PA for at least 7 minutes in duration with a 2 minutes tolerance of lower PA intensity within this interval (19). Light- to moderate-intensity PA bouts were identified by accelerometer counts between 2000 and 6166 counts per min epoch (cpe). Intervals having accelerometer counts > 2000 cpe for at least 7 minues with up to 2 minutes below that threshold during the 7 minutes interval were preliminarily considered walking bouts. The threshold of 2000 cpe represents light-intensity PA at a speed of 3km/h, indicative of walking, based on two studies that used the ActiGraph GT3X activity monitor to record the cpe during slow walking (26, 27). The upper bound of 6166 cpe, which corresponds to moderate-intensity PA at a speed of 6.4 km/h, is also indicative of walking (28); therefore, intervals with mean accelerometer counts > 6166 cpe were considered non-walking bouts (i.e., jogging or running). Sequential intervals with breaks ≤ 2 minutes were considered as one bout when the entire sequence of counts fulfilled the count criteria. The shortest PA bout identified through the accelerometry in the present study was 5 minutes when the 2 minutes lower-PA intensity occurred in the last 2 minutes of the 7 minutes time frame.

Light- to moderate-intensity PA bouts, determined using accelerometer counts of pre-defined speed ranges, were considered walking bouts only when their corresponding GPS data satisfied the following three GPS selection criteria. First, in order to provide sufficient spatial context information to distinguish between a walking bout and a non-walking bout, the GPS coverage ratio had to be ≥ 20% with at least 3 GPS records within a bout. Second, bouts that occurred within a small spatial extent, such as walking on a treadmill or doing household chores, were considered as dwells and thus non-walking activities. Note that the GPS points of a dwell bout could be similar to that of a walking bout when satellite reception was unstable and failed to locate GPS points accurately (29). Therefore, the following two steps were used to identify dwell bouts: 1) calculating the distances from each point to all other points within a bout, and 2) calculating the 95th percentile of the sum of distances of all points. Bouts with their 95th percentile ≤ 40 m were considered dwell bouts (29). Only bouts with ≥ 10 GPS records were screened for dwell bouts because those with few GPS records were likely to meet the criterion of a dwell bout. Finally, the GPS-derived median speed had to range between 2 km/h and 6 km/h, based on two studies that identified walking trips in free-living conditions using GPS data (20, 30).

Neighborhood buffer construction

Two types of neighborhood buffers were created in ArcGIS 10.2 (Esri International LLC, Redlands, CA). Figure 2A shows a straight-line buffer, which is a circle around a geocoded address at a given radius. Figure 2B shows a network buffer, which is a polygon with edges composed of endpoints from all possible journeys an individual could walk from home within a given distance. In comparison with straight-line buffers, network buffers provide a more accurate estimation of the actual land area for walking activity, because non-walkable areas such as rivers and lakes are excluded (31). In order to create the network buffers in Washington State, network data, including street lines and district boundaries, were downloaded from the King County GIS Center website (32) and imported into ArcGIS. Both neighborhood buffer types were drawn at 1-, 2-, and 3-km radii around the home location, for the purpose of defining home neighborhoods in different spatial distances. The cutoffs were selected based on a previous study showing that WS best reflected the walkable amenities within the 1.6-km buffer (13).

Quantification of walking bouts within the neighborhood

Walking bouts from all subjects were stored in a master table with each row containing subject ID, bout ID, and latitude and longitude. Containment of bouts within buffers was performed using the Spatial Join tool in ArcGIS, which determines whether points intersect with neighborhood buffers. Only bouts with all of their GPS points intersecting with the subject's neighborhood buffer area were considered walking bouts occurring within the neighborhood buffer (Fig. 2A using a straight-line buffer), whereas walking bouts partially within and outside of the neighborhood buffer (Fig. 2B using a network buffer) were considered walking bouts occurring outside of the neighborhood buffer.

Statistical analysis

Basic descriptive information is presented as means and standard deviations (SD) or percentages where appropriate. The association between walkability and walking bouts was first tested using a simple Pearson correlation, followed by a mixed model with count of walking bout (WB) as the outcome measure, the fixed factor of WS, and the random factor of twin pair, as shown in model 1.

Model 1: $E(WB_{ij}) = \beta_0 + \beta_1 WS_{ij} + a_i + e_{ij}$ *; where i=twin id, j=1, 2= (cotwin1/cotwin2)*

Because the WB numbers are small and include zero values, a square root transformation was performed on the WB in order to fit a normal distribution. This model examined WB, within three different *a priori* defined neighborhood radii and two different buffer types, as a function of WS while treating twins as individuals; ai and eij represent the random effects between twin pairs and within twin pairs, respectively. In model 2, the regression was adjusted for sociodemographic factors including continuous variables of age and BMI and categorical variable of sex. This model tested whether an increase in WS is associated with an increase in walking bouts while holding these other factors constant.

Model 2: $E(WB_{ij}) = \beta_0 + \beta_1 WS_{ij} + \beta_2 Age_{ij} + \beta_3 Sex_{ij} + \beta_4 BMI_{ij} + a_i + e_{ij}$

Because socioeconomic status has been found to be related to walking level (6), the regression model was further adjusted for categorical variable of income in model 3.

Model 3: $E(WB_{ij}) = \beta_0 + \beta_1 WS_{ij} + \beta_2 Age_{ij} + \beta_3 Sex_{ij} + \beta_4 BMI_{ij} + \beta_5 Income_{ij} + a_i + e_{ij}$

All analyses were conducted using the statistical software program Stata 11 (StataCorp LP, College Station, TX). *A priori* p-value of 0.05 was used to define statistical significance.

Results

The descriptive walkability categories and the corresponding WS ranges (continuous values) are shown in Table 2. Among the 106 participants, roughly 1/3rd lived in 'Car-Dependent', 'Somewhat Walkable' and 'Very Walkable' categories, whereas less than 9% lived in the 'Walker's Paradise' category. On average, subjects lived in 'Somewhat Walkable' neighborhoods with a mean WS of 62 (SD = 22.5).

Walking bout identification

A total of 4,813 light- to moderate-intensity PA bouts of at least 5 minutes in duration were identified through accelerometry, spanning 1464 person-days for the 106 subjects, each of which had valid days between 12 days and 14 days. Of these, 514 PA bouts satisfied the GPS selection criteria and were classified as walking bouts (Table 3). Non-walking bouts comprised 64% of all PA bouts, of which 18% were dwell bouts and 46% were bouts out of range based on speed. Approximately 25% were considered as unknown bouts due to a low GPS coverage ratio. Each walking bout was an average of 12.0 ± 10.4 minutes, with the shortest being 5 minutes, according to the defined criteria for a walking bout, and the longest being 98 minutes. Participants had an average of 2.5 bouts per week, equivalent to a total of 30 minutes. A total of 20 subjects had no walking bouts identified though the algorithm over the 2-week period.

Quantification of walking bouts within neighborhood buffers

The number of walking bouts occurring within the 1-km, 2-km, and 3-km straight-line buffers were 139, 186, and 232, respectively (Fig. 3, left). Fewer bouts were identified within network buffers compared with those identified within straight-line buffers of the same buffer distance, 101, 145, and 196 bouts, respectively (Fig 3, right). Irrespective of buffer type, the number of walking bouts within a given neighborhood buffer increased with buffer size. More bouts occurred outside of neighborhood buffers than occurred inside of neighborhood buffers for all six buffers (i.e., 2 buffer types by 3 buffer sizes).

When separating walking bouts within neighborhood buffers by descriptive walkability category, the average number of walking bouts increased with walkability level, with the walker's paradise category having the highest number and the car-dependent category the lowest number (Fig. 4).

Association between walkability and walking level

Overall, a strong positive correlation was found between WS and the number of walking bouts, regardless of buffer distance or buffer type. The Pearson correlation coefficients between the total number of walking bouts over the 2-week period and WS are reported in Table 4, also showing that the strength of association generally increases with larger buffers.

In the univariate regression model (Table 5, Model 1), the square root of the total number of walking bouts showed a positive association with WS ($p<0.01$). After adjusting for individual-level sociodemographic factors (Table 5, Model 2), WS was the only independent predictor of walking bouts (p<0.01). However, after adjusting for sociodemographic factors and income level (Table 5, Model 3), both WS and sex had a significant association with walking bouts (p<0.01 and p=0.02, respectively); the total number of walking bouts directly increased with WS, and males tended to have more walking bouts than females.

When examining the influence of WS on the number of walking bouts within each buffer separately, the regression coefficients increased with buffer distance in all three models for network buffers (Table 6). Notably, WS showed the strongest association with walking bouts within 2-km straight-line buffers in Models 2 and 3.

Discussion

Walking bout identification

This study utilized a novel algorithm to identify walking bouts only using objective measures of accelerometeroy and GPS. This algorithm was adapted from Kang et al.(19), in which PA bouts were classified as walking or non-walking with accelerometry, GPS, and travel diaries. While previous studies have generally relied on self-report data to estimate amounts of walking, the present study demonstrated that it is possible to identify walking bouts solely based on objective measurement. Of the 4813 PA bouts of at least 5 minutes duration derived from accelerometry, 514 bouts were classified as walking and 3081 bouts as non-walking according to the algorithm used in the present study; 1218 bouts were considered as unknown due to the low GPS coverage. Non-walking bouts were composed of 877 dwell bouts and 2204 bouts with speeds out of range for what is generally accepted as walking (20, 30). Dwell bouts could be the consequence of activities performed within a small spatial extent such as walking on a treadmill or doing household chores such as gardening or vacuuming. Bouts with speeds out of walking range represented 45% of all PA bouts, most of which had a median speed below 2km/h. These low speed bouts could potentially represent slow movements at a work place, such as walking between offices. However, it is unclear why 962 bouts had a median speed below 0.1 km/h. Bouts with higher speeds could be biking or activities occurring in moving vehicles such as buses and trains. While PA bouts with low GPS coverage were considered as unknown bouts in the present study, bouts with incomplete GPS data were further classified with travel diaries by Kang et al. in their study and approximately 50% were walking bouts (19).

The average duration of a walking bout was 12 minutes, and the average frequency was 0.35 bouts per day. The mean duration of walking is similar to that reported by Kang et al. and lies within the range of previously reported data (33, 34). The 1998 Behavioral Risk Factor Surveillance System reported a remarkably longer duration of 34.5 min per bout; however, this study estimated only leisure-time PA via self-report, a method subject to measurement error and recall bias. The frequency of walking in the present study was smaller than that reported in previous studies (33, 34), possibly because the algorithm most likely classified some walking bouts with low GPS coverage as unknown bouts. The average percentage of people who walked at least 10 minutes per week, 56%, is comparable to that reported in the 2005 National Interview Survey but slightly lower than the 62% reported in the same survey in 2010 (4).

Quantification of walking bouts

All walking bouts were assigned to be within or outside of six different neighborhood buffers based on three spatial distances and two definitions of neighborhood. Irrespective of buffer type, the number of within-neighborhood walking bouts increased with buffer size; however, regardless of buffer size or type, the number of within-neighborhood walking bouts was always smaller than the number of outside-neighborhood walking bouts. This suggests that people walked more often outside of their neighborhoods. One explanation is that many walking episodes started from a distal location instead of starting from home. For example, if a person works far away from home, the only chance for him/her to walk within neighborhood may be to and from the local bus stop (i.e., transportation related physical activity). In addition, many of the walking episodes possibly occurred at the work place, which may have been most likely outside of the neighborhood buffer. We did not geocode the work address and so are unable to investigate this possibility. Furthermore, there was no significant difference between the duration of walking within vs. outside neighborhood, which suggests that those walking bouts outside of the neighborhood are less likely to have started from the home location.

When comparing the number of walking bouts within the two types of buffers, more walking bouts were identified within straight-line buffers because a straight-line buffer covers a bigger area that completely includes a network buffer of the same distance (Fig. 2). Nevertheless, a network buffer represents a more reasonable walking pattern, because it's created based on street connection and excludes non-walkable areas such as rivers and lakes.

Association between walkability and walking level

Counts of walking bouts measured objectively were positively correlated with WS. The finding that participants walked more often when they lived in neighborhoods with higher walkability is consistent with a previous study demonstrating that residents of King county, Washington, spent more time walking when they lived in more walkable neighborhoods (11). In contrast to this study, which examined the association between the time spent on walking and walkability, the present study examined the association between the number of walking episodes that occurred specifically within neighborhoods and walkability. The validity of WS generated by the Walk Score® index as a measure of walkability has been tested in several U.S. metropolitan cities by calculating the number of walkable amenities within different buffer distances of 400-, 800-, and 1,600-meters, with the 1,600-meter buffer distance showing the strongest association with WS (14). The present study tested the walking-WS association using a different set of buffer distances, quantifying walking episodes within 1-km, 2-km, and 3-km buffers of two different types. When using the straight-line buffer, the 2-km radii buffer showed the strongest association with WS. However, when using the network buffer type, the strength of the association increased with buffer size and the 3-km radii network buffer showed the strongest association with WS. This suggests that walkability generated by Walk Score® best reflects the walking amenities within a 2-km straight-line neighborhood buffer or 3-km network buffer, at least based on our sample.

Interestingly, the counts of outside-neighborhood walking bouts were always higher than within-neighborhood walking bouts, and participants living in neighborhoods with higher walkability walked more outside their neighborhood than those living in neighborhoods with lower walkability. One possible explanation is that people who chose to live in more walkable neighborhoods tended to walk more no matter where they were, both within and outside of their neighborhoods. The Pearson correlation between the total counts of walking bouts outside of the neighborhood buffer and WS also showed a significant positive correlation for all buffers. Therefore, participants living in neighborhoods with higher walkability not only walked more within their neighborhoods but also walked more outside of their neighborhoods in comparison to those living in neighborhoods with lower walkability.

Limitations

There are some limitations worth noting in the present study. The sample size of 106 subjects is relatively small and the cross-sectional design preclude making causal inferences about walking behaviors and walkability levels among adults living within Washington State. A larger sample size and longitudinal designs are required for future studies.

The algorithm failed to classify 25% of PA bouts due to low GPS coverage, resulting in many walking bouts being coded as “unknown” bouts; therefore, the number of walking bouts reported in the present study could actually be lower than the actual number. This issue could be resolved by better GPS technology that enhances GPS signals, and modified experimental designs that ensure subjects have their GPS devices functioning normally throughout the data collection period. Alternatively, our classification method could have used data from a travel diary to fill in any “blanks” left by missing GPS data as in commonly done in other studies. However, we specifically wanted to restrict our analyses to walking bouts determined from objective measurement.

Lastly, walking behaviors may be influenced by geographical and climatic factors such as hills in the Seattle area and inclement weather during wintertime. These factors may have significantly changed the walking levels measured in the present study and should be considered when interpreting the association analysis.

Summary

In summary, the present study determined walking bouts using accelerometry and GPS data without reliance on self-report surveys and travel diaries. This method eliminated recall bias and demonstrated that the identification of walking activity can rely solely on objective measurement. Quantification of walking episodes within and outside of pre-defined neighborhood buffers of different distances and types specifies the locations for walking and allows us to better describe and elucidate walking behaviors. Furthermore, the relationship between walking level and neighborhood walkability provides some evidence for an association between neighborhood environment features and walking behaviors, as well as additional insights into the definition of what constitutes “walkable neighborhoods”.

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Table 1. Select characteristics of the study sample (N=106).

Characteristic	
Age (years, mean ± SD)	41.7 ± 10.5
BMI (kg/m^2, mean ± SD)	27.4 ± 7.5
Sex (female, %)	75.5%
Income (above $50,000, %)	79.2%

BMI; body mass index.

Table 2. Distribution of participants (N = 106) by walkability categories, University of Washington Twin Registry, June 2012 to October 2013.

Walkability category	WS range	N	%
Walker's Paradise	90-100	9	8.5
Very Walkable	70-89	35	33
Somewhat Walkable	50-69	31	29.3
Car-Dependent	0-49	31	29.3

Table 3. Description of physical activity bouts using a classification algorithm, University of Washington Twin Registry, June 2012 to October 2013.

Type	Number	%	Total minutes	%	Duration (minutes)
					Mean ± SD
Walking	514	10.7	6160	11.1	12.0 ± 10.4
Non-walking					
Dwell	877	18.2	15693	28.2	17.9 ± 10.1
Speed out of range	2204	45.8	20362	36.7	9.2 ± 7.4
Unknown*	1218	25.3	13345	24.0	10.96 ± 8.13
Total	4813	100	55560	100	11.54 ± 9.06

*Unknown bouts were physical activity bouts with a GPS coverage ratio < 20%.

Table 4. Pearson correlation coefficients between walkability level and the number of walking bouts within buffers of different distances and types, University of Washington Twin Registry, June 2012 to October 2013.

Type	Distance (km)	Coefficient
Straight-line buffer	1	0.419*
	2	0.469*
	3	0.465*
Network buffer	1	0.394*
	2	0.449*
	3	0.463*

*Indicates $p < 0.01$.

Table 5. Linear regression mixed models predicting total walking bouts identified over 2 weeks (N=106), University of Washington Twin Registry, June 2012 to October 2013.

Independent variables	**Model 1**			**Model 2**			**Model 3**		
	B (SE)	**p-value**	**95% CI**	**B (SE)**	**p-value**	**95% CI**	**B (SE)**	**p-value**	**95% CI**
WS	0.02 (0.01)	<0.01	0.01 to 0.03	0.02 (0.01)	<0.01	0.01 to 0.03	0.02 (0.01)	<0.01	0.01 to 0.03
Sex				0.61 (0.31)	0.05	0.00 to 1.23	0.69 (0.31)	0.02	0.09 to 1.29
Age				-0.02 (0.01)	0.11	-0.05 to 0.01	-0.02 (0.01)	0.13	-0.04 to 0.01
BMI				-0.01 (0.02)	0.61	-0.04 to 0.02	-0.00 (0.02)	0.92	-0.03 to 0.03
Income							0.08 (0.05)	0.13	-0.02 to 0.17
Constant	0.48 (0.31)	0.126	-0.13 to 1.10	1.37 (0.80)	0.09	-0.20 to 2.93	0.64 (0.89)	0.47	-1.11 to 2.50

Table 6. Estimates of regression coefficients of walkability level predicting square root of walking bouts within buffers of different distances and types, University of Washington Twin Registry, June 2012 to October 2013.

Type	Distance (km)	Model 1		Model 2		Model 3	
		β_1	SE	β_1	SE	β_1	SE
Straight-line buffer	1	0.0196	0.0034	0.0203	0.0035	0.0203	0.0035
	2	0.0220	0.0036	0.0227	0.0037	0.0226	0.0037
	3	0.0224	0.0037	0.0224	0.0038	0.0223	0.0037
Network buffer	1	0.0173	0.0030	0.0171	0.0031	0.0173	0.0031
	2	0.0207	0.0034	0.0206	0.0035	0.0206	0.0035
	3	0.0221	0.0036	0.0224	0.0037	0.0227	0.0037

*p-values <0.001 for all β_1.

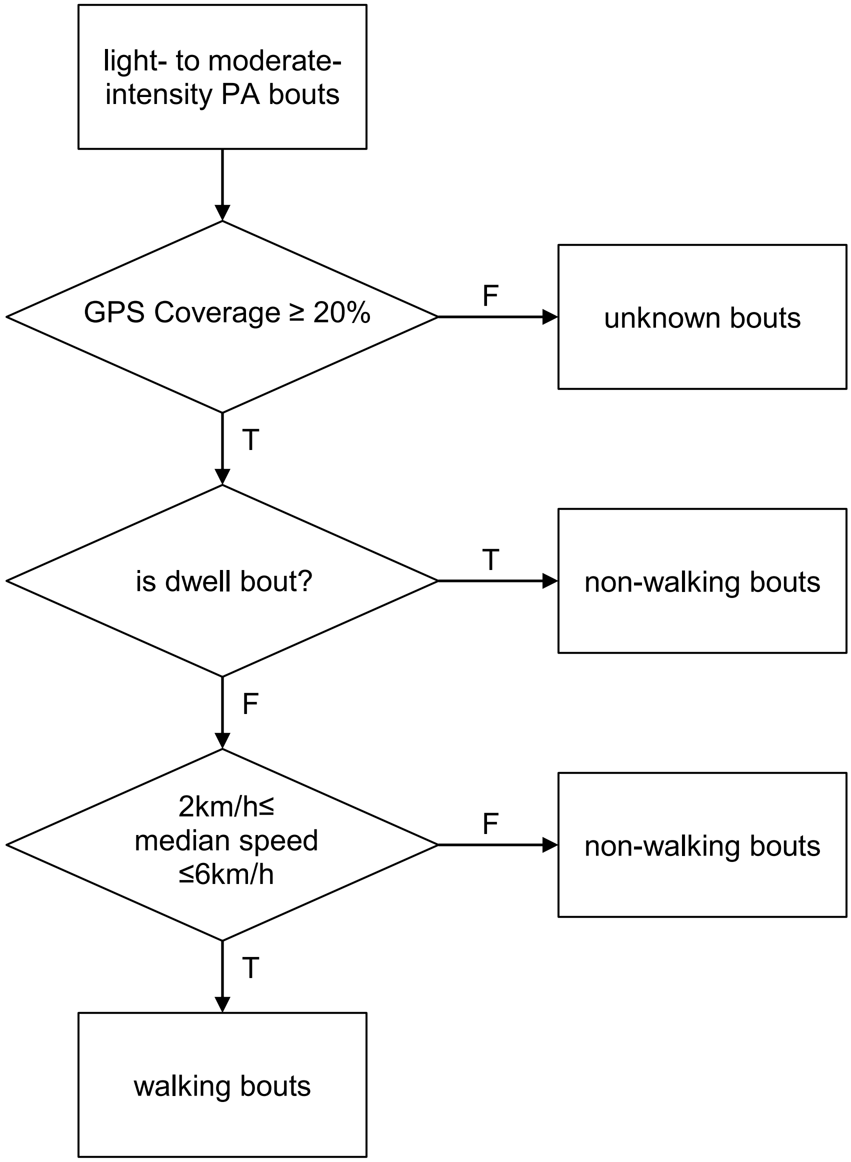

Figure 1. The decision-tree algorithm classifies physical activity bouts as walking or non-walking.

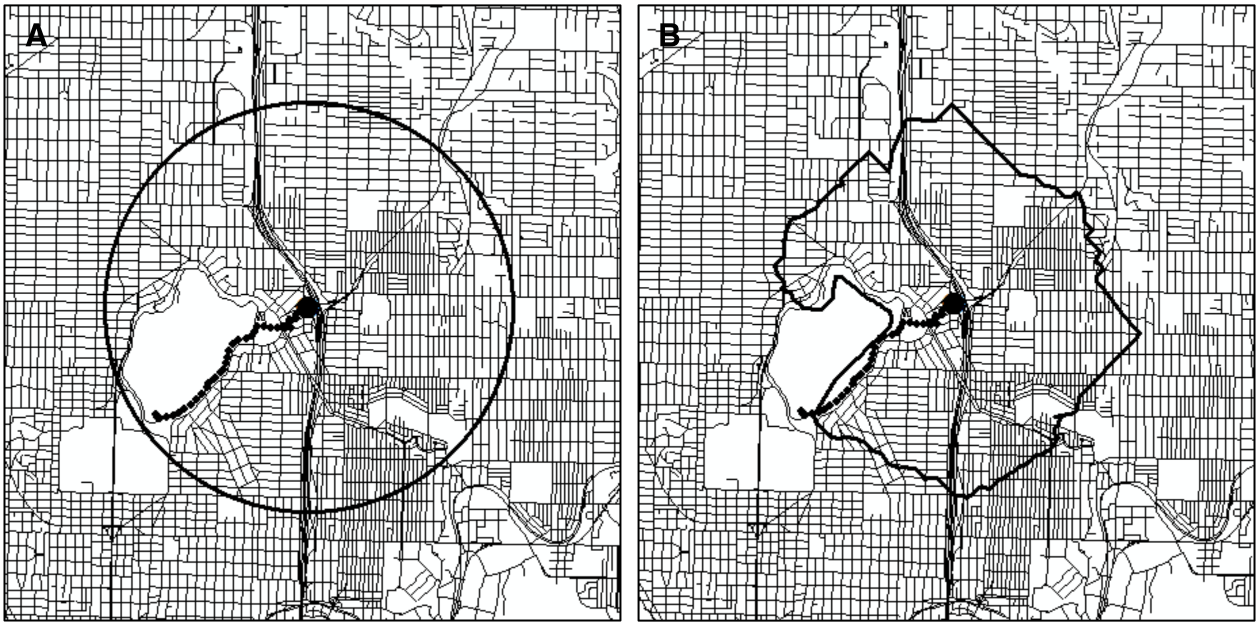

Figure 2. Two neighborhood buffer types drawn around the home location with all GPS points from a walking bout. (A) A walking bout entirely inside of a 2-km straight-line buffer. (B) A walking bout partially inside and outside of a 2-km network buffer.

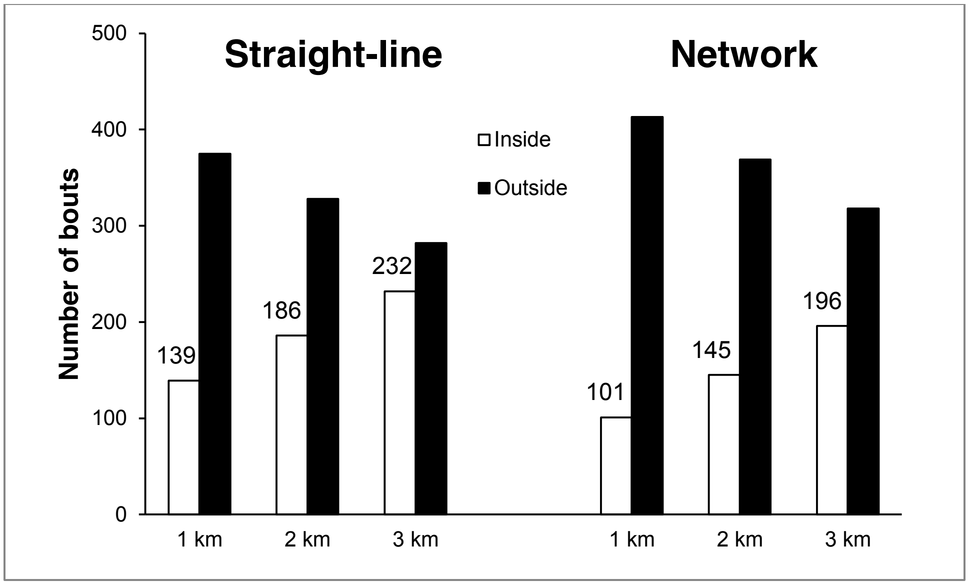

Figure 2. Number of walking bouts within and outside of neighborhood buffers of different distances and types for 106 subjects over 2 weeks of monitoring, University of Washington Twin Registry, June 2012 to October 2013.

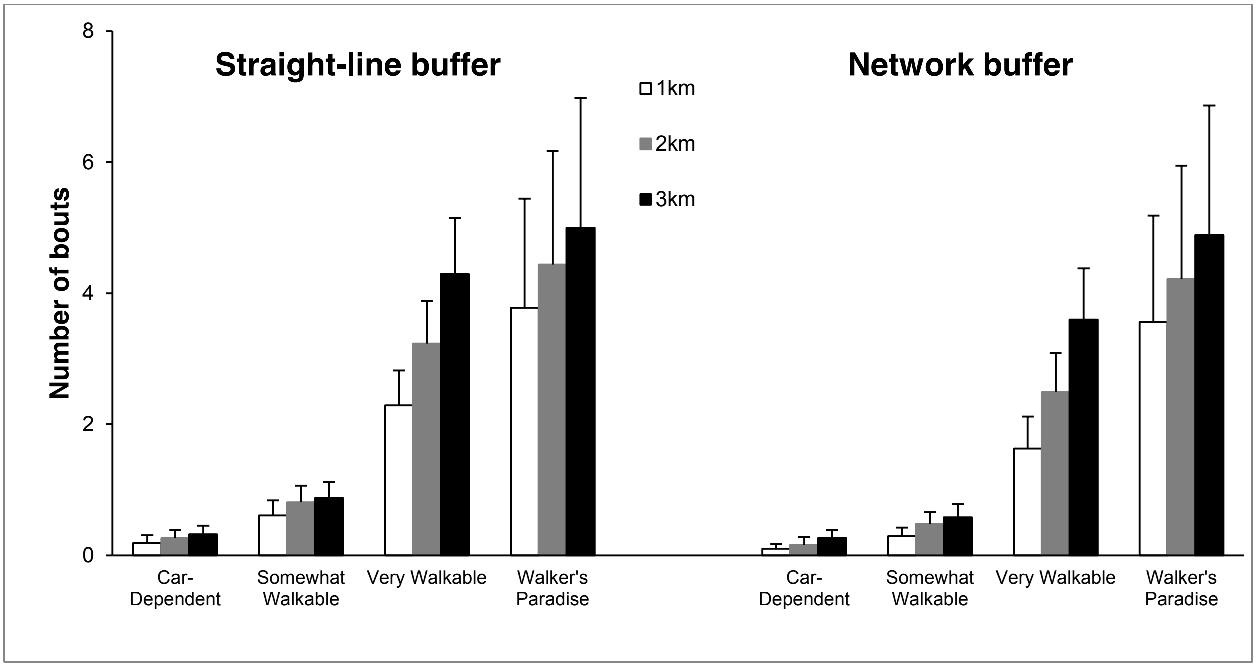

Figure 3. Average number of walking bouts within buffers of different distances and types over the 2-week period, stratified by descriptive walkability categories, University of Washington Twin Registry, June 2012 to October 2013.