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Associations between the built environment and physical activity from analyses of spatial clusters, trail use, and locations where physical activity occurs

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ASSOCIATIONS BETWEEN THE BUILT ENVIRONMENT AND PHYSICAL ACTIVITY FROM ANALYSES OF SPATIAL CLUSTERS, TRAIL USE, AND LOCATIONS WHERE PHYSICAL ACTIVITY OCCURS

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For my parents and sister

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Tamura, Kosuke. Ph.D., Purdue University, December 2015. Associations between the Built Environment and Physical Activity from Analyses of Spatial Clusters, Trail Use, and Locations Where Physical Activity Occurs. Major Professors: Philip J. Troped and David B. Klenosky.

Over the past two decades, an increasing number of scientific studies have examined associations between the built environment and physical activity and obesity. These studies have documented positive associations between environmental variables, such as population density, street connectivity, and composite measures of neighborhood walkability and physical activity. Studies have also shown inverse relationships between the presence of neighborhood grocery stores and recreational facilities and obesity. Despite this evidence, there continues to be limitations in built environment studies conducted to date. The three dissertation studies described here were designed to address several different aspects of built environment research that warrant greater attention.

The first study addressed the issue of whether physical activity and obesity is spatially clustered in relation to certain attributes of the built environment. Many previous built environment studies used geographically referenced data, such as geocoded home addresses and locations of facilities. The use of these types of data neglected spatial relationships among observations. The first study applied spatial analytic techniques to better understand geographic patterns of physical activity and

obesity. The second study used objective monitoring of adults with accelerometers and global positioning system (GPS) units to objectively examine how trails are related to physical activity. Although studies have shown that trail use is associated with higher levels of physical activity, most of this research has relied on self-report measures of trail use and physical activity. The third study examined relationships between objectively measured built environment variables and minute-by-minute physical activity linked to each other via GPS coordinates. This represents a newer, more spatially dynamic approach to investigating these relationships; one that is not exclusively focused on where a person lives.

In the first study, a spatial scan statistic was used to test for spatial clusters of physical activity and obesity. Nurses' Health Study participants (mean age = 69.9 ± 6.8 years) from California, Massachusetts, and Pennsylvania who completed survey items on physical activity (N = 22,599) and weight-status (N = 19,448) in 2004 were used in this study. Spatial clusters of physical activity were found in California and Massachusetts, whereas obesity clusters were found only in Pennsylvania. Adjusting for husband's education fully explained the physical activity clusters in California. In California and Massachusetts, population and intersection density in two higher physical activity clusters were significantly greater compared to areas outside the clusters. Overall, spatial clustering methods were able to detect higher and lower risk areas for physical activity and obesity. The results of the spatial analyses could be used to encourage researchers, practitioners, urban planners, and policy makers to design more geographically targeted interventions for both physical activity and obesity.

The second study examined whether objectively measured trail use was associated with physical activity and sedentary behavior. The study also quantified on-trail physical activity using two approaches: accelerometer counts only and both counts and GPS data. Participants (N = 141, mean age = 44.1 ± 13.0) were recruited on five trails in Massachusetts. They were asked to wear accelerometer and GPS devices for four days. Total physical activity, and daily minutes of light, moderate, and vigorous physical activity, and sedentary behavior were derived from accelerometer counts. A trail-use day was defined as a minimum of two consecutive monitoring minutes occurring on-trail. Linear mixed models were used to examine whether trail use was related to physical activity and sedentary behavior. Overall, statistically significant positive associations were found between trail use and physical activity. Trail use was associated with about 28 minutes of moderate physical activity per day compared to no trail use. On-trail vigorous physical activity minutes increased by 346%, based on accelerometer and GPS data compared to accelerometer counts only. This trail study provided evidence that adults engaged in more physical activity when they use trails. In addition, this study indicated that the use of both accelerometer and GPS data may be a useful method for classifying intensity of physical activity occurring trails; particularly facilities where bicycling is a common activity.

In the third study, accelerometer data linked to GPS data were used to estimate relationships between built environment variables and minute-by-minute physical activity among adults in Massachusetts, irrespective of where the activity took place. Generalized linear mixed models were used to examine associations between population density, street density, land use mix (LUM), greenness, and walkability within a 50 meter buffer around each minute and moderate-to-vigorous physical activity (MVPA) and light-to-vigorous physical activity (LVPA). Overall, statistically significant, positive associations between population density and MVPA and LVPA were found. In contrast, inverse associations were found between street density, LUM, and walkability and MVPA and LVPA, which was inconsistent with current literature.

Taken together, the three studies included in this dissertation – examining associations between the built environment and physical activity from analyses of spatial clustering, use of trails, and locations where physical activity takes place – contribute to our understanding of the relationship between the built environment and physical activity. These analyses should be used to inform further research on these topics; and eventually lead to the design and implementation of more effective location oriented physical activity interventions.

CHAPTER 1. INTRODUCTION

1.1 Introduction

Physical inactivity and the obesity epidemic are the major public health issues in the United States [1]. Although the health benefits of physical activity have been well-documented [1, 2], the majority of U.S. adults engage in less than the recommended 150 minutes of moderate-intensity activity per week [3]. Efforts to influence individuals to participate in regular physical activity and reduce obesity could be facilitated by creating physical activity-friendly environments [4] and healthy food environments [5].

Over the past two decades, broad-scale neighborhood environment and policy approaches to promote physical activity and decrease obesity at the population level have received increasing attention from physical activity and public health researchers [6, 7]. Evidence of relationships between the built environment and both physical activity and obesity has been documented in numerous review studies [4, 5, 8-18]. Studies have shown that certain characteristics of the neighborhood built environment, such as a greater mixture of commercial and residential land uses, higher population density, greater street connectivity, and better access to facilities [11, 16], are positively associated with physical activity [4, 12, 15] among adults [13, 14] and older adults [10, 18, 19]. In contrast, attributes of food environment, such as density of fast-food restaurants and convenience stores, are positively associated with obesity [20-22].

Although these associations between the built environment and physical activity and obesity occur within a spatial context (e.g., using geocoded addresses), the majority of prior studies have not taken the spatial relationships into consideration. For example, nearby spatially referenced observations tend to share common information. Ignoring spatial relationships in observations would result in violation of the statistical assumption of independent observations. Recently, a number of researchers have begun incorporating spatial dimensions into analyses to further understand geographic patterns of physical activity and obesity in relation to the built environment [23, 24]. Specifically, spatial cluster techniques may be a promising approach to detect geographic patterns in physical activity and obesity in relation to built environment attributes.

Spatial clustering methods have been applied to studies of certain cancers [25, 26] and diabetes [27]. Only a few studies have applied these techniques to physical activity and weight-status in relation to built environment attributes. For example, Huang and colleagues employed a spatial scan statistic to identify clusters of active transportation via walking and biking among adults in California [23]. They found several spatial clusters of high and low prevalence of active transportation [23]. Another recent study tested for spatial clusters of obesity in the U.S. and found two high and low obesity clusters [28]. However, there are three limitations of these studies: 1) covariate adjustments were limited to age and race; 2) limited evidence on built environment characteristics inside and outside clusters, and 3) spatial clusters of physical activity and obesity have not been tested among older adults. To address these limitations, the first study in this dissertation involved testing for spatial clusters of physical activity and obesity and spatial confounding (i.e., geographic distribution of covariates, such as income, walking limitations) using the data from Nurses' Health Studies (NHS) participants from California, Massachusetts, and Pennsylvania. Further, this study compared individual characteristics and objectively measured built environmental factors inside and outside the spatial clusters for both outcomes. Thus, the findings from this study would provide a better understanding of how spatial clusters of physical activity and obesity may be linked to built environment exposures. To date no published studies have been examined to detect spatial clusters of physical activity and obesity in relation to objective measures of the built environment attributes.

One of the key shortcomings in built environment and physical activity research is the primary focus on the home neighborhood environment and the assumption that most activity occurs within a buffer around the home. In other words, there has been a mismatch between exposures to certain environmental characteristics and locations where physical activity occurs [29]. There is a growing consensus that individuals' daily mobility is not limited to residential areas and relevant neighborhood environments for physical activity behavior are dynamic rather than home-centric [29]. To address this limitation, more researchers have recently begun using accelerometers and GPS devices concurrently to objectively measure physical activity and identify all locations where physical activity takes place. Dissertation study 2 used both accelerometer and GPS data to examine associations between objectively measured trail use and physical activity and sedentary behavior. The third dissertation study used accelerometer and GPS data to estimate relationships between the built environment and minute-by-minute physical activity.

To date, researchers simultaneously used accelerometers and GPS units to objectively monitor physical activity at certain places, such as home and school [30, 31], in parks, and in open spaces [30-34]. However, another component of the built environment, community trails and paths, has not been examined using both devices. Community trails and paths have been considered an important resource for supporting physical activity [35]. However, previous studies on trails have used exclusively self-reported surveys, which can result in potential recall bias [36]. Another limitation in these studies on trails is that self-reported measures focused on examining MVPA, since current physical activity recommendations for adults focus on this range of this intensity. However, there is increasing evidence that light-intensity physical activity may have positive health benefits [37]. Therefore, investigating how trails may also support light-intensity physical activity is a key area to explore. The second study addressed these limitations by examining associations between trail use and light, moderate, and vigorous physical activity and sedentary time using accelerometer and GPS derived measures of activity. A secondary aim was to quantify physical activity and sedentary time occurring on trails using two approaches, one using accelerometer counts only and the other using a combination of accelerometer counts and GPS speed. The findings indicated that the use of both data may be useful for classifying intensity of physical activity, particularly on trails where individuals are likely to be bicycling.

Previous studies using accelerometer data linked to GPS coordinates have provided evidence of relationships between the built environment factors and objectively measured physical activity. However, one key limitation was to focus on specific places (e.g., parks, schools, near residential areas), ignoring other potential environment features that may be related to physical activity. Simultaneous use of accelerometer and GPS devices allows researchers to assess dynamic individual daily mobility beyond a certain location. Only a few studies have contextualized locations where physical activity occurred around each GPS monitoring minute. These studies estimated relationships between neighborhood exposures and minute-by-minute or 30s epoch physical activity among children [38, 39]. Study 3 addressed this limitation by using both devices to spatially contextualize locations where physical activity occurred and to examine associations between objectively measured built environment around each GPS minute and minute-by-minute physical activity. The results of study 3 indicated that there were statistically significant positive associations between population density and MVPA and LVPA. However, other built environment variables were inversely associated with both outcomes. This study has significant public health relevance in a better understanding of environmental correlates, which could lead to more effective prevention efforts regarding physical activity.

1.2 Study Aims

1.2.1 Study 1

The purposes of this study were to identify spatial clusters (i.e., areas with high and low levels) of physical activity and obesity among older women in California, Massachusetts, and Pennsylvania, to examine whether the geographic distribution of demographic and health-related factors account for spatial clusters, and to compare built environment characteristics inside and outside clusters.

1.2.2 Study 2

The primary aim of the second study was to estimate relationships between trail use and physical activity and sedentary time. A secondary aim was to objectively quantify physical activity occurring on-trail among adults using two different approaches, accelerometer data only, and a combination of accelerometer and GPS data.

1.2.3 Study 3

The aim of the third study was to examine the associations between objective built environment measures factors and MVPA and LVPA linked to GPS coordinates among a sample of adults.

CHAPTER 2. LITERATURE REVIEW

2.1 Overview

The overall purpose of this chapter is to briefly review the literature relevant to the broad area of physical activity and public health. Specifically, it provides a review of literature on a physical activity and health promotion, conceptual framework for understanding correlates of physical activity, approaches to measuring the built environment, emerging approaches in built environment and physical activity research, and spatial data analysis in public health.

2.2 Physical Activity and Public Health

Physical inactivity is a major public health issue in U.S. populations [1, 3]. Lack of physical activity increases risks of cardiovascular disease, certain cancers, diabetes, hypertension, and obesity [1, 2, 4, 40]. In contrast, engaging in physical activity is one of the most effective ways to prevent and manage these chronic diseases and health conditions [1] and to improve one's quality of life [41]. Over the past two decades, guidelines for regular physical activity participation have been published and promoted [1, 2]. For example, according to the current physical activity guidelines from the U.S. Department of Health and Human Services (USDHHS), it is recommended that adults engage in at least 150 minutes of moderate activities per week (e.g., brisk walking) or 75 minutes of vigorous activities per week, or equivalent combinations [1].

Parallel to the development of the current physical activity guidelines, national efforts to increase participation in physical activity have grown. For example, the physical activity objectives for Healthy People 2020, a government initiative promoting national health, are that individuals across populations, including youth, adults, and older adults should engage in regular physical activity that includes participation in moderate- and vigorous-intensity activities [42]. Moreover, various societal sectors, such as environmental [43], educational [44], international [45], healthcare [46], media [47], non-profit [48], and recreational and sports sectors [49], have also been involved in the development of the U.S. National Physical Activity Plan, which was released in 2010 [50]. The U.S. National Physical Activity Plan is a broad range of initiatives that include policies and programs collaborating with public and private sectors aiming to promote physical activity in the U.S. populations.

Despite numerous national efforts to promote physical activity and to disseminate the health benefits of physical activity, the prevalence in self-reported no leisure time physical activity declined from 29.1% in 1996 to 24.1% in 2004 and was virtually stable, ranging from 24.0% in 2005 to 25.4% in2010 [51]. In addition, national surveillance data using accelerometers from the National Health and Nutritional Examination Survey (NHANES) showed that less than 4% of U.S. adults aged 20-59 years and less than 3% of older adults aged ≥ 60 years met physical activity recommendations [3].

2.3 Conceptual Framework for Understanding Correlates of Physical Activity

As noted above, the promotion of regular physical activity is one of the national public health priorities in the U.S. [50, 52]. During the 1970s, prevention strategies and interventions focused heavily on an individual's characteristics, choices, and behaviors [4]. However, during the 1980s, there was a shift in physical activity promotion strategies from individuals to a focus on the broader social and environmental context [4]. Thus, physical activity behavior was redefined as individual choices but these choices were thought to be influenced as well by interactions between people, social norms and values, neighborhood environments, and broader culture [53].

Over the past couple of decades, researchers and practitioners have increasingly emphasized the application of multilevel social ecological models which generally posit that physical activity behaviors are influenced by factors at the individual, interpersonal and environmental levels to identify changes in environment and policy which would increase population-level physical activity for longer periods [4, 54-57]. The major principle of social ecological models is that each level of influence can affect behavior, and individuals can influence and are influenced by environment. In the following sections, the evidence on individual (e.g., demographics, biological factors), interpersonal (e.g., social support) and environmental (e.g., social and physical environmental attributes) correlates of physical activity among adults and older adults is summarized.

2.4 Correlates of Physical Activity

2.4.1 Individual Factors

Several reviews have summarized the evidence on various types of individual-level factors that are related to physical activity [58-60]. Types of individual factors include demographic characteristics (e.g., age, gender, race/ethnicity), biological characteristics (e.g., weight-status), and constructs from individual-level behavioral theories such as the Transtheoretical Model (TTM), the Health Brief Model, the Theory of Reasoned Action, and the Theory of Planned Behavior.

Age, gender, race, socioeconomic status, education, and overweight/obesity have been consistently associated with adult participation in physical activity [14, 59, 60]. In general, the findings from the application of health behavior theories have shown mixed or no associations for specific constructs [58-60], except self-efficacy for physical activity. For example, researchers have found consistent evidence that people with higher self-efficacy engage in greater levels of physical activity and maintain their physical activity behavior [12, 14, 58-60]. King and colleagues found that behavioral skill incorporated with self-motivation accounted for a significantly large amount of variance in free-living physical activity [59]. Furthermore, other constructs, such as goal setting, feedback, self-monitoring, self-reinforcement, and self-efficacy were associated with physical activity [59].

2.4.2 Interpersonal Factors

The results from previous studies have indicated that interpersonal or social factors may play an important role in physical activity participation [58-60].

Interpersonal characteristics include social support (e.g., family, peers) and constructs from Social Cognitive Theory (SCT) [14, 59-61], such as reciprocal determinism (i.e., interrelationships among individuals, behavior, and environment), observational learning, social norms, etc. There is strong evidence that social support from family and friends as well as support from other sources such as physicians, colleagues, fitness instructors or professionals, and exercise buddies are positive correlates of physical activity [14, 59-61].

SCT has been employed to explain physical activity behavior. The focus of SCT is on reciprocal interactions between individuals and their environments [62]. In other words, SCT suggests that human behavior is a dynamic and ongoing process in which individual and environmental factors and human behavior interact with each other [62]. The major constructs of SCT include environment, behavioral capability, reciprocal determinism, observational learning, outcome expectancies, reinforcement, and self-efficacy [14, 59-61].

2.4.3 Built Environment Factors

Built environment research on physical activity and obesity has grown rapidly over the past 15-20 years. The built environment is defined as the physical design of communities that provide opportunities for physical activity, such as mixture of land use (e.g., residential, commercial, facilities, water areas), large scale environmental characteristics (e.g., landscaping), and transportation systems [63]. To date, numerous measures of the neighborhood built environment have been studied, including perceived and objective measures of the built environment. Perceived built environment measures were derived based on self-reported surveys focusing on individuals' perceptions for neighborhood environments. Objectively measured built environments were derived from existing geographically referenced data (e.g., geo-coded home address) by using geographic information system (GIS) technologies [63]. The most common GIS data include population density, density of facilities, access to destinations, mixture of land use, street connectivity, safety from traffic and personal safety, and aesthetics [63].

2.5 Approaches to Measuring the Built Environment

2.5.1 Perceived Built Environment

Measures of perceived built environments are based on individuals' perceptions for neighborhood environments from self-reported surveys. Survey instruments such as Neighborhood Environment Walkability Scale (NEWS) and an abbreviated version (ANEWS) are used to determine an individual's perceptions of neighborhood environment. Most commonly assessed variables include residential density, LUM-access, LUM-diversity, street connectivity, walking and biking facilities, traffic safety, personal safety, and aesthetics [63]. These perceived measures of built environment have been tested for reliability and validity in recent years [64-66]. For example, test-retest reliability of a NEWS survey was conducted by Saelens and colleagues in 2003 [65] and found moderate to high test-retest reliability overall, including reliability of the NEWS subscales [65]. Recently, NEWS and ANEWS surveys were tested for factorial validity by Cerin and colleagues [64, 66]. The purpose of their research was to assess how well survey items in each subscale measured a particular latent construct for neighborhood walkability [67]. The results showed that diversity of destination, infrastructure for walking, aesthetics, traffic safety, residential density, and personal safety were positively related to transportation walking [66]. Furthermore, a cross-validation study, conducted to test the factorial validity of NEWS and ANEWS, confirmed that items in the subscales operated differently in different neighborhoods [64]. In addition, a recent study on factorial validity of the ANEWS demonstrated support for the construct validity of the ANEWS among older women in the U.S.[67]. One limitation of these studies is the question of whether or not these measures can be generalized to different populations [64, 65] since the measures were tested only among adults living in metropolitan areas [64, 65]. Further research is needed to test these measures across different age groups (i.e., youth, adults, older adults) and countries (i.e., non-English speaking countries) [64].

2.5.2 Objective Measures of Built Environment

There are mainly two approaches to create objective built environment variables: one using systematic observational methods (e.g., audits) with various neighborhood or street audit tools that have been developed, and the second, using public and private GIS datasets that can either be accessed for free or purchased through private vendors. For the first approach, audit tools are used for measuring quality and presence of the built environment attributes. Investigators utilize audit tools to evaluate characteristics of the physical environment which may not be available in GIS databases, such as the presence of street trees and the width of sidewalks [68]. Although the use of audit tools to measure the built environment attributes helps researchers capture important attributes of the built environment, a limitation of these techniques is that they can be time-consuming and require having well trained observers [63].

The use of GIS technologies to create objective measures of the neighborhood built environment that may be related to physical activity has grown rapidly since the publication of a few studies around 2000 [69]. GIS-based variables were derived from geographically referenced data (e.g., home addresses, longitude and latitude of locations) [63]. Commonly measured built environment characteristics using GIS technologies include population density, access to recreational facilities, street connectivity, greenness or vegetation index, and composite variables, such as LUM and walkability index [63]. Characterizing the built environment using GIS technologies is an efficient way to systematically create objective measures for studies among individuals in neighborhoods across large regions of interest [63].

One limitation is that because this is a new and emerging field of study that requires continuous development and refinement, methodologies regarding the creation and classifications of these objective built environment measures have not been standardized [63, 70, 71]. For example, geographic scales range from administrative boundaries (e.g., census tracts) to buffers with distance along the street network (100 meter, 500 m, 1 km, 1 mile, etc.) or buffers around participants' homes [63]. As each GIS-based variable using a different geographic scale might influence physical activity differently, the appropriate geographic scale for GIS-based measures still needs further investigation. It is important to note that understanding how to acquire, manage, and analyze GIS-based data requires a trained GIS staff and sufficient time to conduct these activities [63].

2.6 Evidence on Built Environment and Physical Activity

Ten review studies on built environment and physical activity between 2002 and 2012 were used to summarize evidence on associations between the neighborhood built environment and physical activity among adults and older adults. The literature includes studies using both perceived and objective measures of the built environment and a variety of physical activity outcomes, including transportation, recreational-related, and general physical activity. Seven reviews provided evidence on associations between the built environment and transportation-related physical activity (e.g., transportation walking, biking, walking for errands, walking and biking to work, etc.). Seven out of 10 reviews reported on associations between the built environment and recreational physical activity, such as leisure-time physical activity and exercise, walking, biking, and sports. Eight out of 10 review studies reported on associations between the built environment and general physical activity, such as total physical activity, total walking and biking, moderate and vigorous intensity activity.

To review this literature, five broad categories of built environment variables were adapted from Ding and colleagues [72]. These included 1) neighborhood environment (i.e., LUM) and access to destinations, population density, street connectivity, and walkability index); 2) recreational environment (access to and density of parks, open spaces, bike paths, and recreational facilities), 3) transportation environment (infrastructure for walking and biking, traffic safety), 4) social environment (personal safety from crime); and 5) aesthetics (enjoyable scenery, friendly neighborhood) [72]. In addition, relationships between built environment measures and weight-status are also briefly summarized.

2.6.1 Current Evidence on Built Environment and Physical Activity and Weight-Status

2.6.1.1 Perceived and Objective Measures of Built Environment and Transportation Physical Activity

Overall, there was some evidence (two out of five broad categories) demonstrating significant associations between perceived built environment attributes and transportation-related physical activity (e.g., walking and biking to work, and walking for errands, etc.) among adults and older adults across seven reviews (See Table 1). For example, perceived LUM/access to destinations, population density, street connectivity, walkability index, and infrastructure for walking and biking were consistently positively associated with transportation-related physical activity such as walking and biking among adults [12, 15, 71]. In contrast, the findings for associations between perceived traffic safety, personal safety, aesthetics, and transportation-related physical activity were mostly null or more equivocal.

Objective measures of the built environment such as LUM, population density, and infrastructure for walking and biking were positively and significantly associated with transportation-related physical activity [13, 71] (See Table 1). Mostly, mixed or null associations were found for other objective built environment variables, such as street connectivity, walkability index, recreational facilities, traffic safety, personal safety, and aesthetics, and transportation-related physical activity [11, 14, 71].

2.6.1.2 Perceived and Objective Measures of Built Environment and Recreational Physical Activity

Across seven literature reviews, evidence on relationships between the majority of perceived measures of the built environment and recreational physical activity (e.g., recreational physical activity, sports, walking, and biking) among adults and older adults were less clear (See Table 1). For example, perceived aesthetics such as enjoying scenery had consistent positive associations with recreational physical activity in two reviews [11, 16]. However, in two other review studies, the findings of associations between perceived aesthetics and recreational physical activity were null or mixed [18, 71].

Across seven reviews, none of the objective built environment variables were consistently associated with recreational physical activity among adults and older adults. For example, the findings for associations between objective measures of LUM/access to destinations, street connectivity, walkability, and traffic safety, and recreational physical activity were null. However, the findings of relationships between population density, recreational facilities, and infrastructure for walking and biking were more mixed.

2.6.1.3 Perceived and Objective Measures of Built Environment and General Physical Activity

The findings from eight reviews on associations between perceived measures of the built environment and physical activity (not classified as transportation or recreational physical activity) were generally inconsistent among adults and older adults, with the exception of perceived aesthetics (See Table 1). There was consistent evidence demonstrating significant positive associations between perceived aesthetics (e.g., such as enjoyable scenery, attractive local neighborhoods, etc.) and physical activity, among adults and older adults in four reviews [10, 11, 14, 16]. However, in other reviews [13, 18, 71, 73], the findings for aesthetics were mixed or null. Mostly, there were mixed or null associations between LUM (including access and diversity of destinations), walkability index, and traffic safety and general measures of physical activity. In addition, there were no consistent associations found for population density, street connectivity, and recreational environment, infrastructure for walking and biking, and personal safety from crime.

Overall, the objective measures of the built environment were not consistently associated with general physical activity outcomes. For example, the findings for associations between objective measures of LUM/access to destinations, recreational facilities, and general physical activity were mostly mixed. Generally, associations between objective measures of population density, street connectivity, walkability index, infrastructure for walking and biking, traffic safety, and personal safety and general physical activity outcomes were mixed or null.

2.6.1.4 Perceived and Objective Measures of the Built Environment and Weight-Status

Generally, the evidence on associations between perceived and objective measures of the built environment and weight-status were less clear than they were for physical activity outcomes [4, 9, 20, 74]. For example, there was null or inverse associations between population density and obesity and BMI [75]. Walkable neighborhoods are thought to protect against higher weight-status. However, four review studies reported inconsistent relationships between walkability index and weight-related outcomes [4, 9, 20, 74]. In addition, other built environment factors such as urban sprawl index, LUM, and recreational facilities were not related to obesity and higher body mass index (BMI) [4, 9, 20, 74]. The majority of studies examining associations between perceived and objective built environment factors and weight-status relied on a cross-sectional study design. However, weight-status may change over time, so a longitudinal study design may be more appropriate for identifying the associations or impact of the built environments on weight-status [4, 20].

2.6.1.5 Summary

Overall, there was inconsistent evidence of associations between both perceived and objective measures of built environment and physical activity among adults and older adults. Despite these unclear relationships, perceived LUM was consistently associated with transportation-related activity, while there was some evidence of associations between perceived aesthetics and recreational physical activity. Overall, there were no consistent patterns across reviews on associations between measures of built environment and recreation and transportation-related physical activity among older adults, except for objective measures of LUM and general physical activity.

The evidence on built environment and physical activity summarized in this literature review is fairly consistent with the findings reported in a recent review of review studies [17]. In this meta review, the authors found street connectivity and

Table 2.1 Summary of literature reviews of associations between built environment variables and physical activity

Built environment characteristics	Neighborhood environment				Recreational environment	Traffic environment		Social environment	Aesthetics
Specific attributes	LUM/access to destinations	Population density	Street connectivity	Walkability index	Recreational facilities, etc.	Infrastructure for walking and biking	Traffic safety	Personal safety	Scenery
Transportation-related physical activity									
Perceived built environment									
# of associations[a]	3	2	1	2	0	1	0	0	0
# of no associations[b]	0	2	1	0	1	1	2	3	2
# mixed[c]	1	0	1	2	4	3	2	1	3
Objective built environment									
# of associations	1	1	0	0	0	1	0	0	0
# of no associations	0	1	1	0	0	0	1	0	2
# mixed	1	0	1	1	2	2	1	3	0
Recreation-related physical activity									
Perceived built environment									
# of associations	0	0	0	0	0	0	0	0	2
# of no associations	1	1	1	2	4	1	2	1	1
# mixed	4	1	0	0	1	2	2	4	1
Objective built environment									
# of associations	0	0	0	0	0	0	0	0	0
# of no associations	2	0	1	2	1	0	1	0	0
# mixed	0	1	0	0	2	1	0	1	0
General physical activity									
Perceived built environment									
# of associations	1	0	0	1	0	0	1	0	5
# of no associations	2	0	0	2	0	3	4	5	2
# mixed	5	3	2	1	7	2	3	2	1
Objective built environment									
# of associations	1	0	0	1	0	0	0	0	1
# of no associations	0	0	0	1	0	1	1	1	0
# mixed	4	1	1	0	4	1	0	0	0

Note: [a] indicates the number of consistent significant (positive (++) and negative (--)) associations between a built environment variable and physical activity. [b] indicates the number of consistently no associations (00) as well as almost no associations (0) between a built environment variable and physical activity. [c] indicates the number of mixed/inconsistent (+ or -) associations between a built environment variable and physical activity. See Appendix for detailed tables of summary literature reviews

Table 2.2 Classifications of strength of associations between variables and physical activity

% of studies supporting association	Summary code	Meaning of code
0	00	No association
1-33	0	Weak, almost no association
34-59	+ or -	Mixed, inconsistent
60-100	++ or --	Consistent positive or negative association

Note: If 6 out of 10 variables (e.g., LUM) in reviews are significantly positively associated with physical activity, this is coded as "++". If 5 out of 10 variables are significantly positively associated with physical activity, this is coded as "+". If 3 out of 10 variables are positively associated with physical activity, this is coded as "0". If no variables are associated with physical activity, this is coded as "00".

Table 2.3 Summary of associations between built environment variables and transportation-related physical activity from 10 literature reviews

Transportation-related physical activity		Neighborhood environment				Recreational environment	Traffic environment		Social environment	Aesthetics
Study characteristics		LUM/access to destinations	Population density	Street connectivity	Walkability index	Recreational facilities (access, density)	Infrastructure for walking and biking	Traffic safety	Personal safety	Scenery
Authors (year)	# of studies									
Humpel (2002)	19									
Trost (2002)	38									
Saelens (2003)	Not stated	P:++	P:++		P:++		P:++			
Owen (2004)	18	P:+			P:+	P:+	P:+; O:+		P:0	P:0
Wendel-Vos (2007)	47	P:-; O: +					P:+; O:++	P:0; O: -	P:0; O-	P:+
Saelens (2008)	29	P:++; O:++	P:+; O:++	P:+; O:0		P:00; O:+	P:0; O:+	P:+;O:00	P:+; O:+	P:+; O:0
Panter (2010)	36	P:++	P:++	P:++	P:++	P:+-	P:+	P:-		P:+
Durand (2012)	Not stated									
Conningham (2004)	27				P:+					
Van-Cauwenberg (2010)	31	O:+	P:+; O:0	P:0; O:+	O:+	P:+; O:+		P:0; O:-	P:0; O:+	P:0; O:00

Note: "P" indicates a perceived built environment variable, whereas "O" indicates an objective built environment variable. Classifications of strength of associations between a built environment variable and physical activity are shown as follows: "++": consistent positive association; "- -": consistent negative association; "+": positive, inconsistent/mixed association; " - ": negative, inconsistent/mixed association; "00": consistent no association; and "0": weak, almost no association.

Table 2.4 Summary of associations between built environment variables and recreation-related physical activity from 10 literature reviews

Recreation-related physical activity		Neighborhood environment				Recreational environment	Traffic environment		Social environment	Aesthetics
Study characteristics		LUM/access to destinations	Population density	Street connectivity	Walkability index	Recreational facilities (access, density)	Infrastructure for walking and biking	Traffic safety	Personal safety	Scenery
Authors (year)	# of studies									
Humpel (2002)	19	P:+				P:+;	P: 0		P:-	P:++
Trost (2002)	38	P:+								
Saelens (2003)	Not stated									
Owen (2004)	18				P:0; O:0	P:0; O:+		P:+	P:+	P:++
Wendel-Vos (2007)	47	P:0; O: 0				P:0; O:+	P:+	P:0		
Saelens (2008)	29	P:+; O: 0	P:0; O:+	P:0; O:0		P:0; O:0	P:+; O:+	P:+; O:00	P:+; O:+	P:+
Panter (2010)	36									
Durand (2012)	Not stated									
Conningham (2004)	27								P:+	
Van-Cauwenberg (2010)	31	P:+	P:+		P:0; O:0	P:0; O:+		P:0	P:00	P:0

Note: “P” indicates a perceived built environment variable, whereas “O” indicates an objective built environment variable. Classifications of strength of associations between a built environment variable and physical activity are shown as follows: “++”: consistent positive association; “- -”: consistent negative association; “+”: positive, inconsistent/mixed association; “ - ”: negative, inconsistent/mixed association; “00”: consistent no association; and “0”: weak, almost no association.

Table 2.5 Summary of associations between built environment variables and general physical activity from 10 literature reviews

General physical activity		Neighborhood environment				Recreational environment	Traffic environment		Social environment	Aesthetics
Study characteristics		LUM/access to destinations	Population density	Street connectivity	Walkability index	Recreational facilities (access, density)	Infrastructure for walking and biking	Traffic safety	Personal safety	Scenery
Authors (year)	# of studies									
Humpel (2002)	19	P:0; O:-				P:+; O: -	P:00;	P:+; O:0	P:0	P:++
Trost (2002)	38	P:+; O:+						P:0	P:0	P:++
Saelens (2003)	Not stated									
Owen (2004)	18	P:++; O:+			P:0; O:0	P:+; O:+	P:0; O:0	P:0	P:0	P:++; O:++
Wendel-Vos (2007)	47	P:0				P:+	P:0	P:0	P:0	P:0
Saelens (2008)	29	P:+; O:+	O:+	P:+; O:+	P:++; O:++	P:+; O:+	P:+; O:+	P:++	P:+; O:0	P:+
Panter (2010)	36									
Durand (2012)	Not stated	P:+	P:+		P:+	P:+				
Conningham (2004)	27	P:-	P:-			P:+	P:+	P:+-	P:0	P:++/--
Van-Cauwenberg (2010)	31	P:-; O:++	P:+	P:+	P:0; O:0	P:+; O:-		P:0	P:+	P:00

Note: "P" indicates a perceived built environment variable, whereas "O" indicates an objective built environment variable. Classifications of strength of associations between a built environment variable and physical activity are shown as follows: "++": consistent positive association; "- -": consistent negative association; "+": positive, inconsistent/mixed association; " - ": negative, inconsistent/mixed association; "00": consistent no association; and "0": weak, almost no association.

walkability were significantly associated with transportation physical activity [17]. However, in the present review, in addition to these two attributes, LUM/access to destinations, population density and infrastructure for walking and biking were also significantly associated with transportation physical activity.

The findings from associations between the built environment and weight-status suggest that attributes of food environments such as density of fast food outlets seem to be consistently associated with weight-status outcomes. More careful selections of food environment attributes linked to diet and eating behavior, such as density, access, and availability of food outlets in a neighborhood, may be needed to better understand associations between the built environment and obesity.

2.6.2 Current Evidence on Trails and Physical Activity

Over the past decade, many built environment studies have demonstrated associations between perceived and objectively measured built environment factors, and physical activity [4, 14, 15, 18, 71, 76-78]. Among those built environment components, trails and paths have been recognized as a key neighborhood resource for encouraging physical activity among adults [79, 80]. Studies have demonstrated that newly constructed trails were positively correlated to physical activity [81, 82]. Another trail study showed that a park with a trail path had higher likelihood of being used for physical activity compared to parks without a trail [83]. A study investigating physical activity levels among trail users in the U.S. showed that individuals who used trails at least once a week were twice as likely to meet the current physical activity guidelines, as opposed to those who rarely or never used trails [84]. Application of built environment approaches, including constructing and increasing accessibility to community trails, has been addressed by public health researchers and practitioners to promote physical activity [35, 85].

2.6.3 Emerging Approaches in Built Environment and Physical Activity Research

To date, in most studies measures of the neighborhood built environment have focused on areas near or around the homes of participants [86]; for example, using some type of buffer around the home address. However, individuals are generally mobile and the relevant environmental exposures for physical activity have increasingly been recognized as being dynamic rather than static [86]. In recent years, GPS units have been used to track where individuals engage in physical activity. These locational data have been linked to data from accelerometers that measure levels of physical activity [87-89]. GPS and accelerometers can be used to determine one's exact location and activity level at a point in time and GIS technologies can be used to characterize the built environment exposures for each location recorded by GPS units [90]. Examining locational data via GPS units, which are linked to physical activity data from accelerometers, is an emerging field of a study.

Using simultaneous monitoring of participants with small GPS units and accelerometers, researchers have characterized the intensity and locations of physical activity among children [30, 31] and adults [88]. For example, in two studies researchers found that the majority of children engaged in moderate- and vigorous-intensity physical activity at school and at home [30, 31]. Furthermore, these studies showed that children generally do not participate in physical activity at parks and green spaces, which account for only 2-10% of their total daily activities [30, 31]. Fewer studies have examined where physical activity occurs among adults. For example, Troped and colleagues employed GPS and accelerometers to determine the locations and levels of physical activity occurring within one kilometer of the homes and workplaces of participants [88]. They found that there were positive associations of intersection density, LUM, and population density within a one km buffer around home with MVPA [88]. Alternatively, population density was the only variable that reached statistical significance within one km work buffer [88]. The findings from this study suggest that there exists a need for characterizing spatial locations other than those immediately surrounding home and workplace areas when examining relationships between the built environment attributes and physical activity. Two dissertation studies (2 and 3) employed GPS/accelerometer data to better understand associations between objectively measured trail use and physical activity; and to examine more dynamically relationships between built environment characteristics and objective physical activity occurring in all locations.

2.7 Spatial Data Analysis in Public Health

2.7.1 Rationale for Spatial Data Analysis

The application of spatial data analysis to examine public health issues such as physical activity and obesity is informed by interactions of three distinct fields of study: statistics, epidemiology, and geography [91-93]. When using spatial public health data, a key issue is described by geographer and statistician, Waldo Tobler in his quote, "Everything is related to everything else, but near things are more related than distant things" [94]. This suggests the statistical notion of spatial autocorrelation that pairs of observations nearby contain more similar attributes than ones farther away [95]. The issue of spatial autocorrelation is applicable to built environment studies as well. For example, it is assumed that individuals who live in the same neighborhood are exposed to similar environmental characteristics which differ from those of individuals who live in a different neighborhood. Therefore, geographically correlated observations reduce variability in observations (i.e., sharing common information) due to correlated observations as compared to the same number of independent observations [95]. This reduces the statistical precision of parameter estimates [95]. This issue strongly underpins the use of spatial analytic and statistical methods for types of data which the proposed studies employed.

2.7.2 Brief Background in Spatial Data Analysis in Public Health

Since the early nineteenth century, the use of disease maps in epidemiologic analyses of disease outbreaks has made significant contributions to the control of infectious disease [96]. The best known example is Dr. John Snow’s maps demonstrating spatial patterns of cholera cases around London water pumps in the 1850s [95-97]. With careful spatial analysis of cholera cases, he eventually discovered that contaminated water sources were causing the epidemic [95, 97]. The visual assessment of disease cases with maps has been a useful method in the field of spatial epidemiology [95, 96, 98, 99]. Application of infectious disease mapping has continued for cholera [100], influenza [101], measles [102], and a re-examination of the geographic distribution of plague in the fourteenth century [103].

Parallel to mapping disease cases, statistical methods have become more advanced and these advancements in statistics have contributed to spatial statistics during the late twentieth century [95, 99]. For instance, in the early twentieth century, with simple statistical analysis of disease cases, the examination of linkages between exposures and disease outcomes was incorporated in epidemiologic research [96]. In the past few decades, developments in statistical computer software have made it possible to examine associations between exposures and outcomes for a fairly large dataset [99]. This advancement in statistical analysis resulted in developments in spatial statistical techniques that allowed us to investigate spatial relationships between environmental risk factors and disease outcomes in recent years [98, 99].

With advancements in medical science in the early- and mid-twentieth century, the focus of public health concerns has gradually shifted from infectious diseases to chronic diseases such as certain cancers [25, 26] and diabetes [27]. Over the past decade, with the combination of mapping techniques for disease outcomes as well as advancement in spatial statistical techniques, epidemiologic analysis of chronic diseases has been extended to geographic patterns of lifestyle-related problems, such as physical activity and weight-status.

2.7.3 Spatial Clustering Techniques and Application to Disease Outcomes

Spatial analytic techniques have been used to investigate geographic patterns of certain outcomes. One way to examine these patterns is a spatial cluster detection analysis, which tests for areas with high and low prevalence of outcomes. The Centers for Disease Control and Prevention (CDC) define a cluster as actual or realized rare cases of a particular disease that is temporally and/or geographically clustered [104]. During the past decade, spatial clustering methods have been applied to studies of chronic diseases such as liver [105], colorectal [106], and breast [107] cancers, and diabetes [27, 108] . For example, researchers found spatial clusters of high rates of liver cancer [105] and diabetes [27]. Additionally, a spatial clustering method allows us to examine both spatial and temporal clusters of a certain outcome [109]. In other studies, spatial scan statistics were used to test for space-time clusters of breast [107] and colorectal [106] cancer and diabetes [108]. The authors found several space-time clusters of these outcomes across study periods and concluded that surveillance results from these types of spatial and space-time clustering techniques may have the potential for time trend monitoring for such chronic diseases.

2.7.4 Application of Spatial Analytical Methods to Physical Activity and Obesity

Recently, there has been a small, but increasing, interest in examining spatial patterns of physical activity [23, 24, 110] and weight-status [24, 28, 111-114] and only one study has investigated spatial patterns linked to built environment attributes [23]. For example, two U.S. studies used the spatial scan statistic [115, 116] to identify clusters of active transportation in California [23] and high/low body mass index (BMI) across the U.S.[28]. Four other studies employed the local Moran's *I* to detect high/low BMI clusters from five U.S. states [113], geographic patterns of obesity across the U.S.[114], overweight/obesity clusters across Canada [111], and high/low clusters of physical activity and obesity in Vancouver, Canada [24]. One study utilized the Getis-Ord General *G*, and found high BMI clusters among mothers and their children in Kenya [112].

In addition to detection of spatial clusters of physical activity and obesity, researchers in one study tested for spatial clustering of physical activity in relation to the built environment [23]. The authors identified several high and low rates of active transportation via walking and cycling among adults in the Los Angeles and San Diego counties of California [23]. Built environment characteristics inside and outside spatial clusters of active transportation were compared [23]. Investigators found higher population density, employment density, and intersection density in high prevalence clusters of active transportation, compared to the areas outside clusters. They also found that these built environment characteristics had lower values in lower prevalence clusters of active transportation [23].

2.8 Summary

The dissertation research seeks to fill the gap in the existing literature by examining spatial patterns of physical activity and obesity in relation to objective built environment variables among older women (Study 1). Further, it seeks to investigate associations between trail use and objectively measured physical activity and sedentary behavior (Study 2) and estimate relationships between objectively measured built environment variables and a minute-by-minute physical activity (Study 3). Research applying spatial clustering and examining associations that take into consideration the temporal and spatial context in the statistical models could shed light on intricate relationships between built environment and physical activity.

CHAPTER 3. METHODOLOGY

3.1 Overview for Study 1: Spatial Clustering

For this study a cross-sectional design was used to test spatial clustering of self-reported physical activity and obesity. This analysis focused on the NHS participants in Massachusetts (MA), Pennsylvania (PA), and California (CA). Associations of spatial clustering of self-reported physical activity and obesity in relation to individual demographic and objectively measured built environment variables were examined.

3.1.1 Specific Aims for Study 1

The purposes of this study were to identify spatial clusters (i.e., areas with high and low levels) of physical activity and obesity among older women in California, Massachusetts, and Pennsylvania, to examine whether the geographic distribution of demographic and health-related factors account for spatial clusters, and to compare built environment characteristics inside and outside clusters.

3.1.2 Design and Methods for Study 1

3.1.2.1 Study Participants

The NHS is a prospective cohort study of women's health initiated in 1976 with 121,700 female registered nurses. At enrollment, the participants were 30-55 years of age, and resided in 11 states. No restrictions for participation were made on the basis of ethnicity or race. However, participants were 97% white, reflecting the population of registered nurses at the time the study was initiated. Currently, NHS participants reside in all U.S. states. The cohort has been continuously followed with mailed questionnaires administered biennially on health outcomes, weight-related issues, and lifestyle factors such as physical activity.

This study used a cross-sectional design to examine 22,599 NHS participants residing in California, Massachusetts, and Pennsylvania who responded to the 2004 survey and met the following inclusion criteria: 1) reported at least one of four physical activities (i.e., walking, jogging, running, bicycling), body weight, and walking limitations, 2) reported being able to walk, 3) had a geocoded home address; and 4) did not live in a nursing home.

3.1.2.2 Physical Activity and Obesity Outcomes

In the 2004 NHS survey, participants reported the average amount of time they spent per week on each of the following physical activities during the previous year: walking (for exercise or walking to work), jogging (< 10 min/mile), running (≥ 10 min/mile), and bicycling (including stationary cycling). Participants also reported their usual walking pace outdoors (i.e., < 2 mph, 2-2.9 mph, 3-3.9 mph, ≥ 4 mph). The reproducibility and validity of these physical activity items were previously reported [117].

In accordance with Ainsworth's compendium of physical activities [118, 119] and previous NHS studies using physical activity data, a metabolic equivalent of task (MET) is assigned to each type of physical activity. Moderate-intensity activities have MET values from 3.0 to 5.9. Vigorous intensity activities have a MET ≥ 6.0. The 2008 Physical Activity Guidelines for Americans recommends that adults perform 150 minutes of moderate-intensity activity, which is roughly equivalent to 500 MET-minutes/week [120].

Two dependent variables were examined in this study. A binary physical activity outcome was created based on engaging or not engaging in 500 MET-minutes/week of walking [120]. Height self-reported in the 1976 survey and weight reported in 2004 were used to calculate body mass index (BMI= (weight in kilograms)/height in meters^2). The obesity outcome was defined as BMI ≥ 30.0.

3.1.2.3 Objective Built Environment Variables

Three types of objective built environment variables were created using GIS technologies: 1) population density; 2) intersection density; and 3) facility density. All built environment variables were created using a 1200 meter line-based network buffer around the geocoded home address of each participant [121].

Population density was calculated as the number of individuals per square kilometer of area within the 1200 m buffer by using Landscan data [122]. The data represent ambient population (integrating diurnal movements and collective travel habits), and incorporates road proximity, slope, land cover, and nighttime lights in addition to census counts. Intersection density was calculated by dividing the number of 3-way or greater intersections (nodes in street network) within 1200m network distances (from home address) by the total length of streets within 1200m buffer by using

StreetMapUSA [123]. Facility density (i.e., density of potential walking destination) was calculated by dividing the number of facilities by kilometers of road within each 1200 m buffer. It was created using a InfoUSA™ facility database [124] containing North American Industrial Classification System (NAICS) codes, as well as longitude and latitude for each facility (e.g., grocery stores, restaurants, banks, hotels, hospitals, libraries, and physical activity facilities) [125]. Further, eight different facility density variables were created to better understand associations of each type of facility density with physical activity and obesity outcomes. These eight types of facility density variables include retail, services, cultural/educational, physical activity, fast-food restaurants, full-service restaurants, convenience stores, and grocery stores.

3.1.2.4 Covariates

The following covariates were included in the spatial clustering analysis: participant's age, nurse's education (RN degree, bachelors, graduate degree), husband's education (high school graduate or less, bachelors, graduate degree), walking limitations (yes: limited a lot or a little for walking; no: not limited at all), previous chronic diseases (yes/no: had heart disease, cancer, diabetes), smoking status (past, current, never), and the Alternate Healthy Eating Index (AHEI), which was developed to assess an individual adherence to U.S dietary guidelines [126].

3.1.3 Statistical Analysis

Descriptive statistics were used to summarize all study variables: physical activity outcomes, built environment variables, and covariates. A spatial scan statistic [115, 116] was utilized to test for spatial clusters of self-reported physical activity and obesity. First, unadjusted tests were performed separately for each state. A relative risk (RR) was computed for each spatial cluster along with a radius of the cluster. Monte Carlo testing was used to determine statistical significance of clusters. Statistical significance of the clusters was defined as a p-value less than 0.05 [115, 116]. Subsequently, models were adjusted for the geographic distribution of one covariate at a time. Adjusted covariates for physical activity included age, nurse's and husband's education, educational attainments, median household income, walking limitations, previous chronic disease, and obesity. For obesity analyses, covariates included age, nurse's and husband's education, educational attainments and median household income, walking limitations, previous chronic diseases, AHEI, smoking status, and physical activity. As possible impacts of the neighborhood built environment on weight-status could take longer to appear than the effects on physical activity behaviors, obesity analyses were restricted to women who had lived at their address ≥ 4 years (N = 19,448). Lastly, comparisons of socio-demographic, health-related, and objective built environment characteristics of participants inside and outside were performed. SaTScan^{TM} version 9 and SAS version 9 for UNIX were used for the analyses.

3.2 Overview for Study 2: Trail Use

This study utilized a cross-sectional study design with the use of accelerometer and GPS devices to examine relationships between trail use and objectively measured physical activity and to quantify monitoring minutes occurring on study trails.

3.2.1 Specific Aims for Study 2

The aims of the second study were to estimate relationships between trail use and physical activity and sedentary time and to objectively quantify physical activity and sedentary behavior occurring on-trail based on accelerometer counts only and a combination of GPS speed and counts.

3.2.2 Design and Methods for Study 2

3.2.2.1 Study Participants

Participants for this accelerometer/GPS study of trail use and physical activity were recruited from 1194 adults who completed trail intercept surveys at five trails in Massachusetts in the fall of 2004 and the spring/summer of 2005. Survey respondents who reported using the trails at least four times in the past four weeks were asked to participate in a second study in which they would wear an accelerometer and a GPS unit for a four-day period. Out of 294 individuals who expressed interest in the study and provided contact information, 178 wore the two devices. About 74% of the participants were white, 19.7% were African-American or black, and 6.8% were other races. Slightly over half (52.4%) of the participants were women.

3.2.2.2 Data Collection

Participants and a research assistant met prior to the beginning of the monitoring at public spaces. Participants were instructed to wear both accelerometer (Actigraph^{TM} Model 7164, data collected at 1-minute epochs) and GPS (GeoStats Wearable

GeoLogger™, with data recorded at 5-second intervals) devices and were provided log sheets to record activity monitoring. After the four activity monitoring days, research staff received log sheets and two devices from the participants.

3.2.2.3 Data Processing

The procedures of data processing have been previously described [88]. A research analyst reviewed the raw GPS data over the four-day monitoring period for each participant to identify outliers. GPS and accelerometer data were merged using their respective time stamps and processed into a database with one record for each minute of activity.

A valid day of accelerometer monitoring was defined as ≥ 600 min of wear time based on procedures used with the National Health and Nutrition Examination Survey [3, 127]. The definition of a valid GPS monitoring day (≥40 minutes) was previously described [88]. Among 178 participants, 147 met the accelerometer and GPS criteria for having at least one valid day of monitoring. Out of the 147, four participants were not included since they did not live in Massachusetts, and two had no demographic data, resulting in a final sample of 141 participants. Two datasets were utilized: 1) accelerometer monitoring minutes linked to GPS readings (N = 60,342); and 2) all accelerometer monitoring minutes with or without GPS data (N = 460,744). For statistical purposes, both datasets were aggregated at the person-day.

3.2.2.4 Physical Activity Outcomes

The raw output for each minute of monitoring from the accelerometer is referred to as an "activity count." Using cut-points developed by Matthews and colleagues, each minute of activity in the database was classified as "inactive" (0-99 counts), "light" (100-759 counts), "moderate" (760-5724), and "vigorous" (≥5725) [128, 129]. Light physical activity, moderate physical activity, vigorous physical activity, and sedentary behavior were expressed as mean min per day. Additionally, total physical activity outcome was created based on daily mean activity counts per min.

3.2.2.5 Determination of Monitoring Minutes On or Off Trails

An on-trail variable representing when study participants engaged in activities on study trails or off trails (1 = on-trail, 0 = off-trail) was created by a GPS vendor (Westat, Rockville, MD: https://www.westat.com/). All GPS monitoring minutes were used to verify this on-trail variable from the vendor using ArcGIS 10 (ESRI, Redlands, CA). Manual inspection of the monitoring minutes to identify the location as on- or off-trail was conducted. To be determined as on-trail minutes, two sequential minutes were required to take place on-trail. We investigated all monitoring minutes simultaneously with preceding and following GPS minutes to evaluate discontinuity of activity. These procedures involved simultaneous investigations of the following aspects: average speed of each monitoring minute, distance of activity for each minute, and accelerometer counts of each minute.

With visual assessment of monitoring minutes, the on-trail classifications from the vendor to our trail classification were compared using Cohen's kappa statistic (i.e., the measure of concordance between the two variables). Landis and Koch's classification of kappa statistics was used and the coefficient was 0.89 (p-value = 0.035). As we found almost perfect agreement between the vendor's classification and ours [130], we used our on-trail variable in identifying trail use day.

3.2.2.6 Classification of Intensity of Activity On-Trail using GPS and Accelerometer Data

Two approaches to determine activity taking place on the five trails were explored: 1) accelerometer counts only and 2) both accelerometer and GPS data. Based on average speed from GPS data, intensity of activity on-trail was redefined using metabolic equivalent (MET) value from the compendium of physical activities for bicycling [131] and accelerometer counts. If the average speed for a minute was ≥ 9.52 mph (MET = 6.0 [131]), then the activity was defined as vigorous intensity. If the average speed for the minute was ≥ 2.5 mph and < 9.52 mph (MET = 3.0 – 5.9) and the activity count was < 5725 then the activity was classified as moderate intensity. Light intensity and sedentary behavior were defined using the Matthews thresholds described previously [128, 129].

3.2.2.7 Trail Use Days

A dichotomous variable, whether a participant utilized a trail on a given activity monitoring day (1 = day with trail use, 0 = day without trail use), was created. To be determined as a trail use day, at least two consecutive minutes needed to occur on-trail. This operational definition is similar to one employed in a park use study in which investigators defined a park visit day as one when the participant was in the park for at least three consecutive minutes or longer [132].

3.2.2.8 Covariates

Covariates included in the statistical analyses included: age, gender, race (white or non-white), education (undergraduate degree or less, some graduate or more), first time using trail (< 3 years, ≥ 3 years), origin when using trail (home, or other origins), usual reason for using trail (exercise/recreation, transportation, both exercise/recreation and transportation), trail sites (Cutler Reservation, Franklin Park, Minuteman Bikeway, Nashua River Rail Trail, Southwest Corridor), and monitoring minutes on weekdays versus weekend days.

3.2.3 Statistical Analysis

Descriptive statistics were conducted to summarize variables used in this study. Multilevel models (PROC MIXED in SAS version 9.3, Cary, NC) were employed to examine associations of trail use days with total physical activity (counts per minute); mean daily minutes of light, moderate, and vigorous physical activity, and sedentary behavior. The unit of analysis for the statistical analyses were person-day based on daily minutes of physical activity and sedentary behavior for trail users (N = 429 person-days). An intraclass-correlation coefficient was used to evaluate the extent to which the total proportion of variability in each outcome came from the variability between participants as compared to variability within participants for each outcome. Age-adjusted models were first examined. Subsequently, models were fully adjusted for age, gender, race, education, trail site, and time of week. Additionally, the model for sedentary time was adjusted for physical activity. Alternatively, models for light, moderate, and vigorous physical activity minutes were adjusted for sedentary behavior. All the analyses were conducted using PROC MIXED with SAS version 9.3 (Cary, NC).

3.3 Overview of Study 3: Built Environment and Physical Activity

This study employed a cross-sectional study design using accelerometer data linked to GPS coordinates collected from adults who live in Massachusetts to spatially and temporally contextualize locations where physical activity occurred. Built environment variables were created using a 50 meter buffer around each GPS monitoring minute.

3.3.1 Specific Aim for Study 3

The aim of the third study was to examine the associations between objectively measured built environment factors and MVPA and LVPA among a sample of adults.

3.3.2 Methods for Study 3

Study participants, data collection, and accelerometer/GPS data processing are the same as in Study 2.

3.3.2.1 Study Participants

Study participants (n = 147 of 178) satisfied both the accelerometer and GPS criteria for a valid monitoring day and had at least one valid day. Participants who did not live in Massachusetts (n=4), and did not provide demographic information (n=2) were excluded from the analyses, resulting in a final analytic sample of 141 participants. Additionally, accelerometer data without GPS coordinates were not used for the analyses.

3.3.2.2 Physical Activity Outcomes

Using the same cut-point approach used in Study 2 to classify intensity of activity for physical activity for each minute, two binary physical activity outcomes were analyzed in this study. One binary outcome was created with each minute classified as MVPA vs inactive and light. The other was created based on each minute classified as light, moderate, or vigorous versus sedentary time.

3.3.2.3 Built Environment Variables

A spatial and temporal approach was used to characterize the built environment. These were created using 50 meter circular buffers for the locations encompassed by each minute of activity monitoring, based on the starting and ending latitude and longitude for each minute [38]. In other words, the built environment variables were created for actual locations where physical activity occurred (i.e., light, moderate, or vigorous intensity) and locations where physical activity did not occur (i.e., inactive or sedentary time). The following built environment variables were created including population density, street density, LUM [88], walkability [133], and greenness [134, 135].

To date, there is no consensus on which buffer sizes should be used for examining built environment attributes around minute-by-minute GPS/accelerometer points among adults. For example, one study recently examined associations between built environment variables (e.g., population density, presence of recreational facilities, and fast-food outlets) and minute-by-minute physical activity among adolescent females [38]. These researchers used a 50 meter circular buffer around each GPS/accelerometer point to create the built environment variables [38]. Based on the previous literature, adolescent females were understood to typically walk 66.6 to 93.3 meters per minute. To handle a lack of independence of the built environment variables, these researchers used a 50 meter circular buffer [38]. In contrast, the participants in the present study were adults who engaged in various types of physical activity, such as walking, running, or biking or motorized transportation. Walking speeds for adult pedestrians usually range from 72 to 144 meters per minute [136, 137]. Depending on the types of activity, the speed and distance covered within a minute could vary substantially. To avoid the lack of independence between built environment variables, a 50 meter buffer was used to examine built environment for each GPS/accelerometer point. All built environment variables were created using ArcGIS version 10 (ESRI, Redlands, CA).

Population density was created using U.S. Census 2000 data at the block group level and was calculated as the number of persons per square kilometer of area within the 50 meter buffers for each monitoring minute . Population at the census block group level was linked to each GPS minute. Each 50 meter buffer could overlap more than one census block. In such case, population density would be uniform in each census block [138]. Based on the area of the census block within the buffer, they assigned a proportion of the population in the census block to the buffer [138]. Using TIGER files from U.S. Census 2000, street density was calculated by dividing the total length of street network within the buffers around a GPS minute by the total land area within the buffers. A higher street density indicates higher street connectivity. A LUM variable was created using

Landuse2005 from the Office of Geographic Information in Massachusetts [139]. LUM was computed with an entropy formula used in previous studies [133, 140] that estimates the mixture of various types of land uses within the buffer (i.e., residential, commercial, recreational, and urban public). The possible values of LUM range between 0 (no diversity) and 1 (maximum diversity). A greenness variable was created using Landsat satellite image 2000, and was measured using the normalized difference vegetation index (NDVI) [135] within the buffer. NDVI values range from +1 (i.e., healthy green vegetation) to -1 (i.e., non-vegetated land cover) [135]. In previous studies higher greenness was inversely related to children's BMI [135] and positively associated with greater pedestrian trail traffic [134]. A walkability index is a measure used to describe the extent to which an environment is supportive to walking and active lifestyles [133]. A walkability index was created within the buffer around each GPS/accelerometer point using LUM, population density, and street density variables [133]. A normalized distribution (z-score) for each variable was summed to create a walkability index [133]. Higher values for the walkability index are generally indicative of a neighborhood built environment supportive of physical activity.

3.3.2.4 Covariates

Socio-demographic factors were examined as covariates. Survey items on age, gender (i.e., male/female), race (i.e., white, black, Asian, other), ethnicity (i.e., Hispanic/Latino: yes or no) and educational attainment (i.e., high school, college, post-grad) were included in the statistical models.

3.3.3 Statistical Analysis

Descriptive statistics were conducted for study variables. Analyses to estimate associations between built environment variables and physical activity were performed using the generalized linear mixed models (GLMM; PROC GLIMMIX in SAS) that deal with a multilevel data structure (e.g., minute-by-minute observations nested within individuals). In this study, a unit of analysis was minute-by-minute of physical activity. The total GPS/accelerometer monitoring minutes for the analyses were 60,342. As a first step, separate GLMMs were fitted for each built environment variable, age, and each of the two physical activity outcomes (MVPA, LVPA). Subsequently, GLMMs were fitted with all four built environment variables (i.e., population density, street density, LUM, and greenness index) in the model and sociodemographic covariates for both MVPA and LVPA outcomes. Since the walkability index was a linear combination of population density, street density, and LUM, GLMM was fitted for walkability with covariates.

CHAPTER 4. SPATIAL CLUSTERING OF PHYSICAL ACTIVITY AND OBESITY IN RELATION TO BUILT ENVIRONMENT FACTORS AMONG OLDER WOMEN IN THREE U.S. STATES

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Note: Headings, sub-headings, and a reference style and its numbering have been modified from the original published version.

4.1 Abstract

Background: Identifying spatial clusters of chronic diseases has been conducted over the past several decades. More recently these approaches have been applied to physical activity and obesity. However, few studies have investigated built environment characteristics in relation to these spatial clusters. This study's aims were to detect spatial clusters of physical activity and obesity, examine whether the geographic distribution of covariates affects clusters, and compare built environment characteristics inside and outside clusters. **Methods:** In 2004, Nurses' Health Study participants from California, Massachusetts, and Pennsylvania completed survey items on physical activity (N = 22,599) and weight-status (N = 19,448). The spatial scan statistic was utilized to detect spatial clustering of higher and lower likelihood of obesity and meeting physical activity recommendations via walking. Clustering analyses and tests that adjusted for socio-demographic and health-related variables were conducted. Neighborhood built environment characteristics for participants inside and outside spatial clusters were compared. **Results:** Seven clusters of physical activity were identified in California and Massachusetts. Two clusters of obesity were identified in Pennsylvania. Overall, adjusting for socio-demographic and health-related covariates had little effect on the size or location of clusters in the three states with a few exceptions. For instance, adjusting for husband's education fully accounted for physical activity clusters in California. In California and Massachusetts, population density, intersection density, and diversity and density of facilities in two higher physical activity clusters were significantly greater than in neighborhoods outside of clusters. In contrast, in two other higher physical activity clusters in California and Massachusetts, population density, diversity of facilities, and density of facilities were significantly lower than in areas outside of clusters. In Pennsylvania, population density, intersection density, diversity of facilities, and certain types of facility density inside obesity clusters were significantly lower compared to areas outside the clusters. **Conclusions:** Spatial clustering techniques can identify high and low risk areas for physical activity and obesity. Although covariates significantly differed inside and outside the clusters, patterns of differences were mostly inconsistent. The findings from these spatial analyses could eventually facilitate the design and implementation of more resource-efficient, geographically targeted interventions for both physical activity and obesity.

4.2 Background

High rates of physical inactivity and the obesity epidemic continue to pose major public health burdens that not only influence children and adults, but also affect older adults in developed countries such as the United States [1, 3, 141]. Despite the health benefits of physical activity [1], U.S. national data collected objectively with accelerometers showed that older adults attained the lowest levels of physical activity among all age groups[3]. Furthermore, a U.S. national survey from 1999-2008 on the prevalence of obesity among adults indicated that 37% of men (≥ 60 years; highest among all age groups) and 34% of women (≥ 60 years) were obese [142]. Among older adults, weight gain is associated with declines in functional performance and daily abilities, which in turn can lead to more sedentary lifestyles [143].

To address these issues, the U.S. Department of Health and Human Services [1] and the World Health Organization [144] have strongly emphasized the importance of physical activity-friendly environments [145] and neighborhoods with better access to healthy foods [5]. The influence of environmental exposures on individual health may increase with age as older adults spend longer periods of time in or near residential areas [146]. A review of the neighborhood influences among older adults indicated that neighborhood environments can affect the older population's health and functioning [147]. The majority of the literature indicates that there are positive relationships between neighborhood built environment characteristics (e.g., LUM, population density, street connectivity, and access to recreational facilities) and physical activity among older adults [18, 76-78]. Certain characteristics of neighborhood environments (e.g., a higher density of fast-food restaurants) are positively associated with obesity [22, 75] and body weight [148]. In contrast, neighborhood walkability (i.e., describing the extent to which an environment is conducive to walking and an active lifestyle) and LUM are negatively associated with obesity [78], body mass index (BMI) [149], and body weight [148] among older adults. However, results from other studies indicate null associations of neighborhood walkability, green spaces, street connectivity, and urban sprawl with BMI [150, 151] and obesity [146, 151, 152] among older adults.

The majority of the studies cited above utilized geographically referenced data (e.g., participant's geocoded home address) in the analyses. If participants in a given study live close to each other, their corresponding environmental characteristics would tend to be more similar [95]. Thus, relationships between the built environment and physical activity and obesity are clearly embedded in a spatial context [95]. However, most built environment studies have not taken these spatial relationships into consideration in the analysis.

Spatial analytic techniques are needed to better understand the geographic patterns of physical activity and obesity in relation to the built environment. Spatial clustering analysis, which tests for unusually concentrated areas with high or low prevalence of specified outcomes, is one technique that can be used to investigate spatial patterns of physical activity and obesity. Spatial clustering techniques have been applied in studies of chronic diseases, such as certain cancers [105-107, 153-156] and type II diabetes [27], in order to identify specific geographic areas where public health professionals may need to increase disease screenings and other prevention-related activities.

Recently, researchers have begun to apply spatial clustering techniques to physical activity [23, 24, 110] and weight-related outcomes, such as obesity [24, 111, 112, 114] and BMI [28, 113]. Spatial clusters were consistently identified across these studies despite differences in cluster detection methods, participant characteristics, and geographic areas [23, 24, 28, 110-114]. Collectively, these studies demonstrate the utility of spatial clustering techniques for studying physical activity and obesity.

Nevertheless, these spatial clustering studies [23, 24, 28, 110-114] have certain limitations. First, adjustment for the geographic distribution of covariates, sometimes referred to as spatial confounders, has been limited to age [23, 28, 111] and race [28]. Failure to examine other covariates (e.g., education and income), is a key limitation since the geographic distribution of these factors could account for spatial clusters. Additionally, only one study examined differences in participants' built environment attributes inside and outside spatial clusters of transportation-related physical activity [23]. Lastly, investigators have not yet tested for clusters of physical activity and obesity among older adults, a population known to be at greater risk for physical inactivity [157] and obesity [158]. Therefore, the objectives of this study were to: 1) determine whether or not meeting recommended levels of physical activity and obesity were spatially clustered among older women in California, Massachusetts, and Pennsylvania; 2) examine whether the geographic distribution of demographic and health-related variables account for spatial clusters; and 3) compare demographic, health-related, and built environment attributes for participants living inside and outside spatial clusters.

4.3 Methods

4.3.1 Participants

The Nurses' Health Study (NHS) is an ongoing cohort study that began in 1976 with 121700 female registered nurses (ages 30-55 years at recruitment, 97% Caucasians) from 11 states. Currently NHS participants live in all U.S. states. The initial focus of the NHS study was to prospectively examine risk factors for chronic diseases, such as cardiovascular disease and cancer [159]. Participants are mailed follow-up questionnaires biennially, which assess potential risk factors and health outcomes. The current study builds on an exploratory study of NHS participants in California, Massachusetts, and Pennsylvania that involved developing objective built environment measures and testing associations with physical activity and obesity [121]. Thus, the current study involved 22,599 NHS participants from these three states who completed the 2004 NHS survey and met the following criteria: 1) had a geocoded home address; 2) had complete information on physical activity, body weight, and walking limitations; 3) reported they were able to walk; and 4) did not live in a nursing home. All procedures for this study were approved by the Institutional Review Boards at Purdue University, West Lafayette, Indiana, and the Human Subjects Committee at Brigham and Women's Hospital, Boston, Massachusetts.

4.3.2 Physical Activity and Obesity

Participants reported their average time per week engaged in walking for exercise or to work during the previous year. Participants were also asked to provide their walking pace (i.e., easy/casual [< 2.0 mph]; normal/average [2.0-2.9 mph]; brisk [3.0-3.9

mph]; and very brisk [≥ 4.0]). Consistent with previous NHS studies using physical activity data, walking metabolic equivalent (MET) minutes/week was calculated by multiplying duration by the assigned MET value based on reported walking pace. A binary physical activity outcome was created indicating whether the participant met the current U.S. physical activity recommendation of 500 MET minutes/week of activity via walking (i.e., equivalent to 150 minutes/week of moderate-intensity activity) [1]. Self-reported height in 1976 (last time reported by NHS participants) and weight reported in 2004 were used to calculate BMI = (weight in kg)/(height in m^2). Obesity was defined as a BMI≥30.0. Underweight (BMI<18.5) participants were excluded from all analyses (n=473). The reproducibility and validity of the physical activity [117] and weight [160] variables have been shown previously.

4.3.3 Built Environment

Eleven objective built environment variables were created using ArcGIS 9.3 software (ESRI, Redland, CA) and employed methods described more fully in earlier work [121]: population density, intersection density, diversity of facilities, and eight facility density variables. Built environment variables were created within 1200 meter line-based road network buffer (i.e., residential buffer) that extended from the geocoded home address of each participant [121]. In the previous work by this group, they created both 800 meter and 1200 meter buffers and found that differences in built environment variables for two buffer sizes were negligible [121]. Population density was calculated as the number of persons per square kilometer of area within the buffer using Landscan data [161]. Intersection density was computed by dividing the number of 3-way or greater intersections by the total length of roads [123] within the buffer using StreetMapUSA [162]. A 2006 InfoUSA™ facility database, containing North American Industrial Classification System (NAICS) codes and longitude and latitude for each facility [163] was used to create the diversity of facilities and facility density variables within each buffer. Using five categories of facilities (food, retail, services, cultural/educational, and physical activity), diversity of facilities was calculated with an entropy formula [133, 140] that estimates the mixture of facility types. Possible scores range from 0 (no diversity) to 1 (maximum diversity). Eight facility density variables were created for retail (e.g., book store), services (e.g., post office), cultural/educational (e.g., school), physical activity (e.g., gym, golf course), as well as the density of food facilities further classified into four different types of densities, including fast-food restaurants, full-service restaurants (e.g., table-service restaurant), convenience stores, and grocery stores (e.g., supermarkets). These variables were calculated by dividing the number of facilities by kilometers of road within each 1200 meter buffer.

4.3.4 Covariates

A number of socio-demographic and health-related factors were examined as potential spatial confounders. For each covariate, values were averaged for all participants in a given county, resulting in one aggregate value for the county. Individual-level socio-demographic variables included age and both nurse's and husband's education (only assessed in 1992). At the census tract level, socio-demographic variables included proportion of the population without a high school education and median family income. Health-related variables consisted of physical activity (yes/no: meeting or not meeting physical activity recommendations), obesity (yes/no: obese or not obese), walking limitations (yes: limited a lot or a little for walking from one to several blocks; no: not limited at all), smoking status (past, current, never), history of chronic diseases (yes/no; had heart disease, cancer, diabetes), and the Alternate Healthy Eating Index (AHEI assessed in 2002, a higher value indicating healthier eating), which estimates adherence to U.S. dietary guidelines [126]. The four continuous covariates, including age, proportion of the population without a high school education, median family income, and AHEI, were expressed as quintiles. Quintiles are defined as a five-level categorical covariate. These percentile ranges are: 0-20, 20.1-40, 40.1-60, 60.1-80, and 80.1-100.

4.3.5 Statistical Analyses

A spatial scan statistic [115, 116] based on the Bernoulli model was used to separately test for county-level spatial clustering of women meeting current physical activity recommendations and obesity. Unadjusted tests for clustering were conducted separately for participants in each of the three states. The null hypothesis was that no spatial clusters of physical activity and obesity would be detected [115, 116]. If the null hypothesis was rejected, this was interpreted to mean that participants inside of the cluster have a higher or lower likelihood of meeting physical activity recommendations or being obese, compared to participants outside of clusters. A relative risk (RR) was generated for each cluster along with a radius of the cluster. Calculations of the sizes and locations of the clusters were based on the centroids of each county. Tests for clustering were then conducted adjusting for the geographic distribution of one covariate at a time, including demographic and health-related covariates (i.e., test for spatial confounding). This analytic approach was used due to the challenge of interpreting clustering results when more than one covariate was included. In other words, in cases where a cluster was altered by covariate adjustment, it would not be possible to determine which covariate was affecting the cluster (e.g., its size or location). This approach is consistent with the recent clustering research on active transportation and obesity [23, 28]. Age, nurse's and husband's education, educational attainments and median household income at the census tract level, walking limitations, previous chronic disease and obesity were included as covariates in physical activity analyses. For obesity analyses, covariates were age, nurse's and husband's education, educational attainments and median household income at the census tract level, walking limitations, previous chronic diseases, AHEI, smoking status, and physical activity. Since potential effects of the neighborhood built environment on weight-status may take longer to appear than the effects on physical activity behaviors, obesity analyses were restricted to women who had lived at their address ≥ 4 years (N = 19,448). Obesity analyses with the full sample were also performed. However, the differences in locations and sizes of the clusters were minor.

Monte Carlo testing was utilized to determine statistical significance of clusters. Statistical significance of the clusters was defined as a p-value less than 0.05 [115, 116]. To better understand the characteristics of physical activity and obesity clusters, socio-demographic, health-related, and objective built environment characteristics of participants were compared inside and outside the clusters using t-tests for continuous variables and chi-square tests for categorical variables. Socio-demographics, health-related factors, and built environment attributes were compared between participants living inside and outside clusters. Analyses were conducted with SaTScan^{TM} version 9 and SAS version 9 for UNIX. Maximum window sizes were tested from 10-50% (in 10% increments) of participants at risk. Since these different window sizes did not affect the results, all reported results were based on the 30% maximum window size.

All analyses were carried out at the county level to maximize available cases and controls. According to SaTScan guidelines [109], if cases or controls are missing in a given row of data within a county, that row of data must be deleted to properly run SaTScan. To avoid further missing data caused by using finer geographic scales, the county boundary was used. Missing data at a finer scale would reduce the analytic sample and might distort the development of a spatial cluster due to artifacts of the missing data [109].

4.4 Results

4.4.1 Participants Characteristics

The average age of participants in 2004 was 69.9 ± 6.8 years and was similar for women living in Massachusetts, Pennsylvania, and California. Overall, 23% of the women met current physical activity recommendations via walking (25.6% in California, 24.0% in Massachusetts, and 20.2% in Pennsylvania). Approximately 21% of participants were obese (16.8% in California, 21.8% in Massachusetts, and 24.4% in Pennsylvania).

4.4.2 Spatial Clusters of Physical Activity

Spatial clusters of women meeting physical activity recommendations via walking were identified in California and Massachusetts, but not in Pennsylvania. In California, four statistically significant spatial clusters of physical activity were identified (Table 4.1 and Figure 4.1).

Participants inside clusters 1 and 2 had a 51% (RR = 1.51, p = 0.0024) and 17% (RR = 1.17, p = 0.035) higher likelihood of meeting physical activity recommendations, respectively, as compared to participants outside of clusters. In contrast, participants inside clusters 3 and 4 had a 58% (RR = 0.42, p = 0.0027) and 29% (RR = 0.71, p = 0.047) lower likelihood of meeting recommendations, respectively, relative to women living outside of clusters. Separately, participant's and husband's education, and obesity fully accounted for both clusters 2 and 4. Adjusting for other covariate adjustments, the size or location of the clusters changed. For instance, when adjusting for age, husband's education, and obesity, cluster 1 became larger and cluster 3 became smaller. When adjusting for walking limitations, cluster 2 became smaller and the location moved to somewhat north in the San Francisco Bay Area. Adjusting for previous chronic diseases had little effect on the size or location of the clusters 1–3 in California.

In Massachusetts, one statistically significant cluster of physical activity and two borderline statistically significant clusters were detected (Table 4.1 and Figure 4.2). Participants inside clusters 5 and 6 had 39% (RR = 1.39, p = 0.0003) and 48% (RR = 1.48, p = 0.053) higher likelihood of meeting recommendations, respectively, compared to women outside of clusters. Participants inside cluster 7 had a 14% (RR = 0.86, p = 0.060) lower likelihood of meeting physical activity recommendations compared to participants outside the cluster. Adjusting for covariates had no effect on the three spatial clusters of physical activity in Massachusetts.

Table 4.1 Characteristics of spatial clusters of physical activity in California and Massachusetts and obesity in Pennsylvania

	Area: Counties	Radius (km)	Participants	Cases[a]	Relative risk	P-value
Physical activity clusters in California						
Cluster 1	Coastal area: San Luis Obispo, Santa Barbara	96.74	232	88	1.51	0.0024
Cluster 2	Bay Area: San Francisco, Santa Clara, Santa Cruz, Alameda, San Mateo, Marin, Contra Costa	73.19	1837	527	1.17	0.035
Cluster 3	South inland: Tulare, Kern Kings	121.09	129	14	0.42	0.0027
Cluster 4	North inland: Lassen, Shasta, Tehama, Plumas, Butte, Glenn, Sierra, Yuba, Nevada, Placer, Sutter, El Dorado	139.21	385	71	0.71	0.047
Physical activity clusters in Massachusetts						
Cluster 5	Cape Cod: Barnstable, Dukes, Nantucket	50.67	427	138	1.39	0.0003
Cluster 6	Boston: Suffolk	0[b]	122	43	1.48	0.053
Cluster 7	Central/Western Massachusetts: Berkshire, Franklin, Hampshire, Hampden Worcester	117.08	1432	306	0.86	0.06
Obesity clusters in Pennsylvania						
Cluster 8	Western Pennsylvania: Allegheny, Armstrong, Beaver, Butler, Cambria, Clarion, Forest, Indiana, Jefferson, Lawrence, Venango, Washington, Westmoreland	82.93	2424	657	1.17	0.029
Cluster 9	Near Philadelphia: Montgomery, Chester, Delaware	36.54	1335	268	0.8	0.01

[a] Cases are defined as participants meeting physical activity recommendations and as obese participants.
[b] Since Suffolk County was the only county identified as cluster 5, the radius was 0.

4.4.3 Spatial Clusters of Obesity

Two statistically significant s Two statistically significant spatial clusters of obesity were identified in Pennsylvania (Table 4.1 and Figure 4.3), whereas no obesity clusters were identified in Massachusetts and California. Participants inside cluster 8 had a 17% (RR = 1.17, p = 0.029) higher likelihood of obesity and in cluster 9, a 20% (RR = 0.80, p = 0.010) lower likelihood of obesity, as compared to participants outside of clusters. None of the covariate adjustments accounted for the two spatial clusters of obesity in Pennsylvania, nor did these adjustments affect the size or location of the two clusters, except for four cases. For instance, when adjusting for age, the proportion of the population without a high school education, median family income, and AHEI, cluster 9 became slightly smaller, but was at the same location.

4.4.4 Comparison of Demographic and Health-Related Factors Inside and Outside Clusters

In California there were several statistically significant differences in demographic and health-related factors. However, the magnitude of the differences in some (e.g., age) was relatively small and no consistent patterns in the covariates were observed, except for median family income at the census tract level (Table 4.2). The two low physical activity clusters 3 and 4 in California had lower family income than did areas outside the clusters.

In Massachusetts, there were statistically significant differences in demographic and health-related factors (Table 4.3). For example, educational attainments at the census tract level was significantly greater inside high physical activity cluster 5, compared to outside this cluster; and it was significantly lower in clusters 6 and 7, compared to outside these clusters. The results are inconsistent that higher education might contribute to the development of high physical activity cluster 5, but not in cluster 6. Census tract level median family income was significantly lower inside high and low physical activity clusters 5–7.

In Pennsylvania, there were statistically significant higher percentages of participants in high obesity cluster 8 with walking limitations and chronic diseases, a higher percentage of participants who never smoked, as well as lower family income, compared to areas outside of clusters (Table 4.4). Both individual and census tract educational levels and AHEI were significantly higher in the lower obesity cluster 9 compared to outside the cluster.

4.4.5 Comparison of Built Environment Factors Inside and Outside Clusters

4.4.5.1 Physical Activity Outcome

In California and Massachusetts, women living in two of the four higher physical activity clusters 2 and 6, respectively, had statistically significant higher population density (e.g., 2252 versus (vs.) 2003 persons/km2), intersection density (e.g., 6.08 vs. 4.01), and diversity of facilities (e.g., 0.77 vs. 0.52) and facility density (consistent with higher walkability), compared to outside of clusters. Alternatively, the values for these built environment characteristics were significantly lower for women in three lower physical activity clusters (clusters 3 and 4 in California and cluster 7 in Massachusetts).

Figure 4.1 Spatial clusters of higher and lower likelihood of women meeting physical activity recommendations in California. The red color represents higher physical activity levels (clusters 1 and 2), whereas blue represents lower physical activity levels (clusters 3 and 4). All clusters are from unadjusted tests. Since the analyses were conducted at the county-level, clusters were visualized using a county boundary. The radius for each cluster was reported in Table 1.

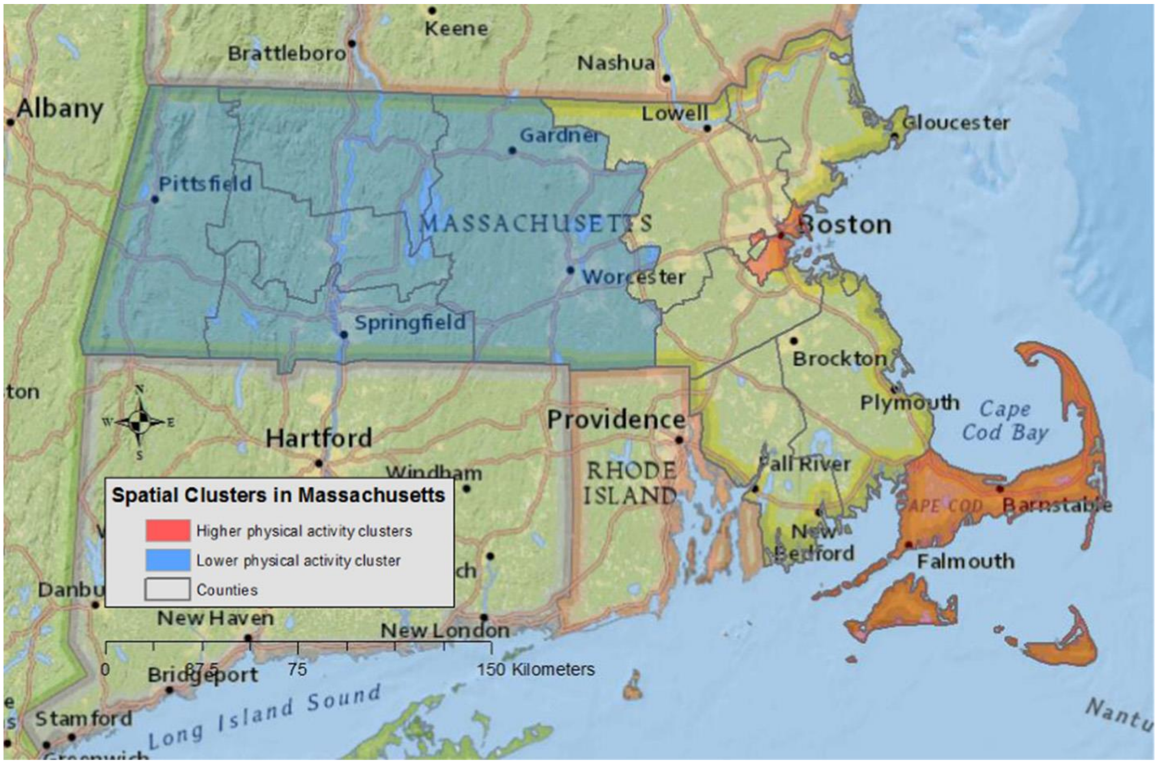

Figure 4.2 Spatial clusters of higher and lower likelihood of women meeting physical activity recommendations in Massachusetts. The red color represents higher physical activity levels (clusters 5 and 6), whereas blue indicates a lower physical activity level (cluster 7). All clusters were from unadjusted tests. Since the analyses were conducted at the county-level, clusters were visualized using a county boundary. The radius for each cluster was reported in Table 1.

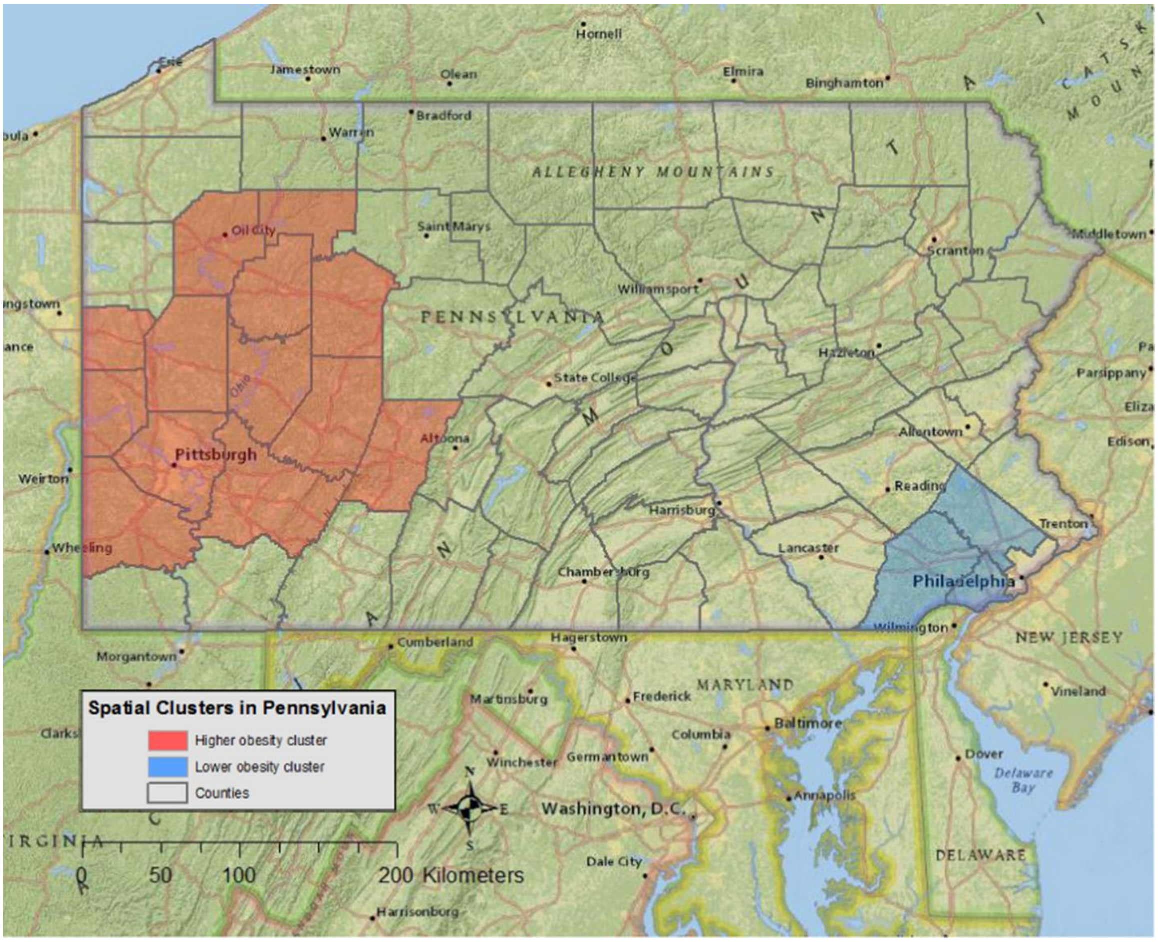

Figure 4.3 Spatial clusters of higher and lower likelihood of obesity in Pennsylvania. The red color represents a higher obesity level (cluster 8), whereas blue indicates a lower obesity level (cluster 9). Both clusters are from unadjusted tests. Since the analyses were conducted at the county-level, clusters were visualized using a county boundary. The radius for each cluster was reported in Table 1.

Table 4.2 Participant characteristics inside and outside of recommended levels of physical activity clusters in California (N = 7153)

Factors	Higher recommended levels of PA clusters		Lower recommended levels of PA clusters		Outside clusters
	Cluster 1 (n = 232)	Cluster 2 (n = 1837)	Cluster 3 (n = 129)	Cluster 4 (n = 385)	(n = 4570)
Socio-demographics					
Individual level					
Age, %[a]					
57.5 – 64.9 years	15.95	21.94**	17.05	17.92	19.67
64.9 – 69.4 years	23.71	21.45	20.16	22.6	18.84
69.4 – 73.5 years	23.28	19.22	20.16	18.96	19.89
73.5 – 78.1 years	19.4	18.56	20.16	22.6	20.18
78.1 – 85.4 years	17.67	18.84	22.48	17.92	21.42
Nurse's education, %					
RN degree	61.64	52.42	55.81	58.44	53.26
Bachelors	22.41	29.01	26.36	27.01	26.87
Graduate degree	8.19	11.7	6.98	8.83	11.9
Missing	7.76	6.86	10.85	5.71	7.96
Husband's education, %					
High school graduate or less	28.88	22.81**	28.68	29.09	26.37
Bachelors	27.16	24.93	18.6	28.83	24.86
Graduate degree	25.43	29.23	23.26	23.12	25.73
Missing	18.53	23.03	29.46	18.96	23.04
Census tract level					
Proportion of population without high school education, %[a]					
0 – 20%	4.74***	33.86***	2.33***	13.25***	16.24
20.1 – 40%	28.02	26.84	5.43	14.03	17.79
40.1 – 60%	24.57	17.15	17.83	26.23	20.46
60.1 – 80%	31.47	14.53	26.36	28.83	20.72
80.1 – 100%	11.21	7.62	48.06	17.66	24.79
Median family income, %[a]					
$18917 – 50034	18.10***	2.67***	54.26***	41.30***	24.25
$50034 – 61942	35.34	7.57	27.91	37.92	22.47
$61942 – 76251	29.31	16.82	10.85	7.01	22.21
$76251 – 94702	13.36	28.31	3.88	9.61	18.32
$94702 – 200001	3.88	44.64	3.1	4.16	12.76

Health-related factors					
Walking limitations, %					
Yes	25.43*	26.29***	37.21	32.73	33.13
No	74.57	73.71	62.79	67.27	66.87
Previous chronic diseases, %					
Yes	31.47	28.91***	34.11	33.77	34.42
No	68.53	71.09	65.89	66.23	65.58
Walking MET min/wk, mean (SD)	533.40 (607.40)***	431.50 (586.10)***	216.60 (339.20)***	331.60 (505.00)	374.40 (540.10)
BMI, mean (SD)	25.64 (4.27)	25.59 (4.73)*	26.60 (4.99)	26.18 (5.21)	25.89 (4.75)
Built environment, mean (SD)					
Population density[b]	1218.90 (812.00)***	2252.40 (1768.20)***	1358.50 (942.30)***	743.50 (748.30)***	2003.20 (1335.80)
Intersection density[c]	3.98 (1.11)*	4.41 (0.89)***	3.73 (1.21)***	3.22 (1.23)***	4.14 (1.04)
Diversity of facilities[d]	0.47 (0.34)**	0.59 (0.29)***	0.46 (0.34)**	0.28 (0.33)***	0.55 (0.31)
Facility density (total)[e]	1.31 (1.56)*	1.89 (2.25)***	0.90 (0.97)***	0.64 (1.21)***	1.59 (1.82)
Retail	0.42 (0.60)***	0.70 (0.98)***	0.29 (0.40)***	0.22 (0.49)***	0.59 (0.80)
Services	0.08 (0.15)	0.09 (0.15)***	0.04 (0.07)***	0.03 (0.10)***	0.07 (0.14)
Cultural/educational	0.31 (0.31)	0.36 (0.32)***	0.21 (0.21)***	0.14 (0.22)***	0.29 (0.27)
Physical activity	0.05 (0.09)	0.08 (0.10)***	0.04 (0.05)***	0.03 (0.06)***	0.06 (0.09)
Fast-food restaurants	2.48 (3.77)*	4.20 (7.68)***	1.43 (2.09)***	1.00 (2.58)***	3.14 (5.33)
Full-service restaurants	0.88 (1.49)	0.88 (1.47)***	0.87 (1.59)	0.41 (1.52)***	1.04 (1.66)
Convenience stores	0.21 (0.42)	0.21 (0.42)	0.28 (0.45)	0.16 (0.45)**	0.23 (0.43)
Grocery stores	0.37 (0.67)	0.41 (0.72)**	0.17 (0.37)***	0.13 (0.46)***	0.35 (0.65)

Note: P-values are based on the t-test for continuous variables and chi-square test for categorical variables. The values are compared between participants in a specific cluster and those outside the cluster. SD = standard deviation. PA = physical activity. $*p < 0.05$; $**p < 0.01$; $***p \leq 0.001$.

[a] A five-level categorical covariate expressed as quintiles.

[b] Population density (number of persons per km^2 of area within residential buffer) was averaged inside and outside of clusters.

[c] Intersection density (number of intersections divided by total road length within residential buffer) was averaged inside and outside of clusters.

[d] Diversity of facilities within residential buffer (ranging from 0 [no diversity] to 1 [max diversity]) was averaged inside and outside of clusters.

[e] Facility density (number of facilities divided by kilometers of road within residential buffer) was averaged inside and outside of clusters.

Table 4.3 Participant characteristics inside and outside of recommended levels of physical activity clusters in Massachusetts (N = 5329)

Factors	Higher recommended levels of PA clusters		Lower recommended levels of PA clusters	Outside clusters
	Cluster 5 (n = 427)	Cluster 6 (n = 122)	Cluster 7 (n = 1432)	(n = 3348)
Socio-demographics				
Individual level				
Age, %[a]				
57.5 – 62.4 years	12.88***	22.95	19.41**	20.91
62.4 – 66.4 years	17.8	19.67	17.6	21.21
66.4 – 70.7 years	21.55	20.49	19.76	20.13
70.7 – 75.7 years	23.19	18.03	20.95	19.27
75.7 – 83.4 years	24.59	18.85	22.28	18.49
Nurse’s education, %				
RN degree	65.11	56.56	71.37***	65.29
Bachelors	18.74	21.31	11.8	17.89
Graduate degree	8.43	9.02	8.45	8.99
Missing	7.73	13.11	8.38	7.83
Husband’s education, %				
High school graduate or less	25.29	22.13	38.06***	30.35
Bachelors	25.53	25.41	22	25.81
Graduate degree	23.42	24.59	17.04	20.58
Missing	25.76	27.87	22.91	23.27
Census tract level				
Proportion of population without high school education, %[a]				
0 – 20%	29.51***	12.30***	8.10***	24.07
20.1 – 40%	27.87	5.74	14.46	22.1
40.1 – 60%	20.61	18.03	17.81	20.58
60.1 – 80%	17.33	22.13	30.03	16.16
80.1 – 100%	4.68	41.8	29.61	17.08
Median family income, %[a]				
$17246 – 55125	47.31***	34.43***	36.59***	8.87

$55125 – 64456	39.58	21.31	27.3	14.22
$64456 – 73101	6.32	21.31	19.27	21.54
$73101 – 86110	6.79	9.84	12.02	25.96
$86110 – 191062	0	13.11	4.82	29.42
Health-related factors				
Walking limitations, %				
Yes	32.79	30.33	37.57***	32.5
No	67.21	69.67	62.43	67.5
Previous chronic diseases, %				
Yes	33.72	31.15	28.84	29.48
No	66.28	68.85	71.16	70.52
Walking MET minutes/wk, mean (SD)	474.90 (600.50)***	484.60 (591.60)*	338.80 (516.90)	364.90 (515.70)
BMI, mean (SD)	25.92 (4.53)**	26.62 (5.67)	26.87 (5.13)	26.63 (5.02)
Built environment, mean (SD)				
Population density[b]	396.70 (294.00)***	5530.70 (7422.20)***	813.60 (879.70)***	1214.90 (1271.30)
Intersection density[c]	4.14 (0.95)*	6.08 (1.13)***	3.38 (1.30)***	4.01 (1.34)
Diversity of facilities[d]	0.35 (0.35)***	0.77 (0.09)***	0.44 (0.36)***	0.52 (0.33)
Facility density (total)[e]	0.69 (1.08)***	4.21 (4.75)***	0.97 (1.14)***	1.22 (1.36)
Retail	0.21 (0.42)***	1.22 (1.22)***	0.30 (0.42)***	0.41 (0.54)
Services	0.04 (0.09)***	0.24 (0.38)***	0.06 (0.11)***	0.08 (0.12)
Cultural/educational	0.13 (0.18)***	0.91 (1.05)***	0.25 (0.28)*	0.27 (0.28)
Physical activity	0.04 (0.07)***	0.12 (0.14)***	0.04 (0.07)***	0.06 (0.09)
Fast-food restaurants	1.44 (3.00)***	15.69 (27.58)***	1.53 (2.68)***	2.20 (3.52)
Full-service restaurants	0.26 (0.72)***	1.70 (2.13)***	0.53 (0.96)	0.53 (1.10)
Convenience stores	0.27 (0.64)***	2.43 (2.35)***	0.44 (0.81)	0.48 (0.76)
Grocery stores	0.14 (0.38)***	0.57 (1.02)***	0.15 (0.43)***	0.21 (0.52)

Note: P-values are based on the t-test for continuous variables and chi-square test for categorical variables. The values are compared between participants in a specific cluster and those outside the cluster. SD = standard deviation. PA = physical activity. *$p < 0.05$; **$p < 0.01$; ***$p \leq 0.001$.

[a] A five-level categorical covariate expressed as quintiles.

[b] Population density (number of persons per km^2 of area within residential buffer) was averaged inside and outside of clusters.

[c] Intersection density (number of intersections divided by total road length within residential buffer) was averaged inside and outside of clusters.

[d] Diversity of facilities within residential buffer (ranging from 0 [no diversity] to 1 [max diversity]) was averaged inside and outside of clusters.

[e] Facility density (number of facilities divided by kilometers of road within residential buffer) was averaged inside and outside of clusters.

Table 4.4 Participant characteristics inside and outside of obesity clusters in Pennsylvania (N = 8598)

Factors	Higher obesity cluster Cluster 8 (n = 2424)	Lower obesity cluster Cluster 9 (n = 1335)	Outside clusters (n = 4839)
Socio-demographics			
Individual-level			
Age, %[a]			
57.5 – 62.4 years	19.93	21.42	19.05
62.4 – 66.8 years	19.60	19.40	20.40
66.8 – 71.1 years	21.16	18.50	19.98
71.1 – 76.2 years	20.13	19.78	20.40
76.2 – 83.5 years	19.18	20.90	20.17
Nurse's education, %			
RN degree	69.6	66.37***	72
Bachelors	13.78	14.38	12.69
Graduate degree	6.64	10.19	5.95
Missing	9.98	9.06	9.36
Husband's education, %			
High school graduate or less	41.46	30.04***	42.28
Bachelors	20.87	25.47	20.15
Graduate degree	15.35	21.57	16.28
Missing	22.32	22.92	21.29
Census tract level			
Proportion of population without high school education, %[a]			
0 – 20%	21.95***	49.66***	11.94
20.1 – 40%	25.95	23.07	17.23
40.1 – 60%	22.81	11.69	20.56
60.1 – 80%	18.81	8.46	22.42
80.1 – 100%	10.48	7.12	27.84
Median family income, %[a]			
$10461 – 42667	22.57**	1.12***	23.25
$42667 – 50341	25.70	2.77	21.49
$50341 – 58152	21.20	10.94	22.32
$58152 – 70096	18.65	22.25	20.79
$70096 – 200001	11.88	62.92	12.15
Health-related factors			
Walking limitations, %			
Yes	35.60**	30.71	32.32
No	64.4	69.29	67.68
Previous chronic diseases, %			
Yes	33.25**	31.69	29.68
No	66.75	68.31	70.32
Healthy Eating Index, %[a]			
22.5 – 44.5	18.89	17.30*	19.74
44.5 – 50.8	19.64	17.30	19.22
50.8 – 56.8	19.35	19.25	18.43
56.8 – 63.8	19.02	18.43	18.64
63.8 – 93.8	16.67	22.25	18.43
Missing	6.44	5.47	5.54
Smoking status, %			
Previous smoker	47.73*	44.42*	49.37
Current smoker	43.19	47.34	43.36

Never smoked	8.99	8.09	7.11
Missing	0.08	0.15	0.17
Walking MET min/wk, mean (SD)	309.40 (492.90)	300.60 (460.60)*	331.90 (513.90)
BMI, mean (SD)	27.41 (5.32)	26.47 (5.16)***	27.18 (5.28)
Built environment, mean (SD)			
Population density[b]	941.60 (997.40)***	1253.70 (913.20)*	1174.90 (1525.60)
Intersection density[c]	3.90 (1.54)***	3.69 (1.16)***	4.07 (1.59)
Diversity of facilities[d]	0.50 (0.34)***	0.53 (0.35)**	0.56 (0.33)
Facility density (total)[e]	0.97 (1.08)***	1.17 (1.16)	1.18 (1.24)
Retail	0.30 (0.43)***	0.39 (0.49)	0.37 (0.47)
Services	0.06 (0.10)***	0.08 (0.13)	0.08 (0.11)
Cultural/educational	0.27 (0.26)***	0.28 (0.23)***	0.32 (0.30)
Physical activity	0.04 (0.07)	0.05 (0.08)***	0.04 (0.06)
Fast-food restaurants	1.65 (2.68)***	1.92 (2.47)**	2.20 (4.65)
Full-service restaurants	0.66 (1.26)*	0.59 (1.16)***	0.73 (1.25)
Convenience stores	0.30 (0.54)***	0.32 (0.52)***	0.46 (0.64)
Grocery stores	0.16 (0.39)***	0.26 (0.55)	0.26 (0.59)

Note: P-values are based on the t-test for continuous variables and chi-square test for categorical variables. The values are compared between participants in a specific cluster and those outside the cluster. SD = standard deviation. *$p < 0.05$; **$p < 0.01$; ***$p \leq 0.001$.

[a] A five-level categorical covariate expressed as quintiles.

[b] Population density (number of persons per km^2 of area within residential buffer) was averaged inside and outside of clusters.

[c] Intersection density (number of intersections divided by total road length within residential buffer) was averaged inside and outside of clusters.

[d] Diversity of facilities within residential buffer (ranging from 0 [no diversity] to 1 [max diversity]) was averaged inside and outside of clusters.

[e] Facility density (number of facilities divided by kilometers of road within residential buffer) was averaged inside and outside of clusters.

Contrary to expectations, higher physical activity cluster 1 in California and cluster 5 in Massachusetts had built environment characteristics that indicated lower walkability, in comparison to the areas outside of clusters. In the California cluster 1, which encompassed San Luis Obispo and Santa Barbara counties, values for several variables, such as population density (i.e., 1219 vs. 2003 persons/km2), intersection density (i.e., 3.98 vs. 4.14), and diversity of facilities (i.e., 0.47 vs. 0.55) were significantly lower than outside of clusters. This pattern existed despite the fact that women in the cluster had 159 more MET minutes/week of walking than those outside the clusters (Table 2). In Massachusetts, participants in cluster 5 (Cape Cod area) had statistically significant lower values for most built environment attributes (i.e., the differences were in unexpected directions), yet women in this cluster had 110 more MET minutes/week of walking than outside the clusters (Table 3).

4.4.5.2 Obesity Outcome

In Pennsylvania, the values for built environment characteristics inside obesity clusters tended to be lower compared to outside the clusters, regardless of whether or not it was a higher or lower obesity cluster (Table 4). In the higher obesity cluster 8, values for built environment characteristics, such as population density (i.e., 942 vs. 1,175 persons/km2), intersection density (i.e., 3.90 vs. 4.07), diversity of facilities (i.e., 0.50 vs. 0.56) and most facility density variables were significantly lower than outside the cluster. Among eight statistically significant differences in built environment characteristics inside and outside the lower obesity cluster, differences in three attributes were in the expected direction was lower inside the cluster compared to outside (e.g., fast-food facility density; 1.92 vs. 2.20).

4.5 Discussion

The present study applied spatial scan statistics to identify spatial clusters of physical activity and obesity among approximately 20,000 older women in California, Massachusetts, and Pennsylvania. High and low physical activity clusters were identified in California and Massachusetts, while none were identified in Pennsylvania. High and low obesity clusters were detected only in Pennsylvania. The majority of the adjustments for demographics and health-related factors did not fully account for physical activity and obesity clusters, suggesting that other factors may be contributing to the development of these spatial clusters. Although some statistically significant differences in demographic and health-related characteristics inside and outside of clusters were found, not all patterns in differences were consistent. Furthermore, built environment characteristics inside and outside clusters of physical activity and obesity generally showed statistically significant differences. In a number of cases, higher physical activity clusters had higher values of population density and intersection density, expected to be associated with higher walkability. This finding is supported by a previous study on spatial clustering of active transportation in California [23]. However, in several other cases, built environment factors typically associated with higher neighborhood walkability were lower in high physical activity clusters, particularly along coastal areas in California and Massachusetts.

Identification of higher physical activity clusters in areas adjacent to the ocean in California and Massachusetts is generally consistent with findings from two previous U.S. studies [23, 114]. In a recent investigation of active transportation in California, researchers detected clusters of higher transportation-related walking near coastal areas around Long Beach and Santa Monica in Los Angeles County [23]. Another study, using data from the Behavioral Risk Factor Surveillance System (BRFSS) from 2000-2006, showed higher physical activity clusters in parts of the San Francisco Bay Area, northwest coastal states (Washington and Oregon), and by Lake Michigan [114]. Collectively, the results from these recent U.S. studies [23, 114], earlier studies in Australia, which indicated a positive influence of coastal areas on physical activity [164, 165], and the present study, suggest that living near large bodies of water has a positive relationship with physical activity. However, since all of this evidence is from cross-sectional studies, the direction of these effects cannot be determined. A plausible alternative explanation is that more active, outdoor-oriented, and health conscious adults, including older adults such as those in the present study, seek to live in areas closer to lakes and oceans.

The detection of higher and lower obesity clusters among participants in western and eastern Pennsylvania contrasts findings from two recent U.S. studies that used BRFSS data [28, 114]. In one study of U.S. adults, ages 22 to 74 years, researchers applied the spatial scan statistic to data from 1999 to 2003 and detected clusters of high and low BMI prevalence in southern (e.g., Louisiana) and western (e.g., California) states of the U.S., respectively [28]. However, they found no clusters of high or low BMI prevalence in Pennsylvania [28]. In another study of U.S. adults (aged ≥18 years) investigators used the local Moran's *I* to identify clusters using BRFSS data from 2000 to 2006 [114]. They found significantly low obesity clusters in mountain regions of the U.S. (e.g., Colorado) and in some New England (e.g., Massachusetts) states as well as high obesity clusters in southern states (e.g., Texas) [114]. However, they did not detect significant clusters of obesity in Pennsylvania [114]. The present study's findings may vary from these previous investigations due to differences in sample characteristics (e.g., older adults, women only, predominantly white), use of different spatial analytic techniques, the geographic scope of the study area (i.e., three states vs the entire U.S.), and the scale differences for the analyses (i.e., individual's and census tract level variables at county level analyses for each state vs. county level variables for the analyses at the entire U.S.).

Although a number of socio-demographic and health-related factors were examined as spatial confounders in the current study, there was limited evidence that these covariates accounted for spatial clusters of physical activity and obesity. The issue of spatial confounding has received little attention in previous cluster analyses of physical activity and weight status. In two investigations of active transportation and BMI, only participants' age [23, 28] and race [28] were evaluated as potential confounders. In these studies, there was mixed evidence that age was a spatial confounder. In one study adjusting for age fully accounted for a lower BMI cluster (i.e., disappearance of the cluster after adjustment), but only partially accounted for a higher BMI cluster (i.e., size of the cluster became larger, and location moved further south) [28]. However, in a study of active transportation clusters in San Diego County in California, age adjustment did not account for clusters [23]. Race fully explained spatial clusters of high and low BMI detected in the U.S.[28]. The limited investigation of spatial confounders suggests the need for testing other types of factors that might account for spatial clusters of physical activity and obesity. For example, these studies could include psychosocial variables (e.g., social support, self-efficacy, psychosocial hazards) that have been assessed in recent built environment studies [22, 56, 57, 166, 167] as well as eating behaviors (e.g., eating habits in the past year, eating-out behavior since it is hypothesized that obesity would be influenced by an individual's past eating behaviors or habits) [22, 166].

To the best of this group's knowledge, this study is only the second one to compare objective built environment characteristics inside and outside of spatial clusters of physical activity and the first to do so with obesity. Generally, a mixed pattern of differences in built environment characteristics was found, in some cases consistent with what would be hypothesized (e.g., higher connectivity in higher physical activity clusters) and in others contradicting these expectations. In contrast to the present study, Huang and colleagues found a consistent and expected pattern of built environment differences inside and outside clusters, for example, where inside high active transportation clusters the values of population density and intersection density index were higher than in areas outside of clusters in Los Angeles and San Diego counties in California [23]. The findings from the present study highlight the complexity of built environment and physical activity relationships, resulting in consistent and inconsistent patterns in the built environment factors.

There were consistent patterns in the built environmental attributes in the two high physical activity clusters 2 and 6 in California and Massachusetts, respectively. The majority of the built environment variables, including population density, intersection density, diversity of facilities, and most of facility densities, were consistently higher compared to outside of clusters. These two clusters were located in more populous areas (San Francisco Bay Area and Boston) compared to the other two high physical activity clusters 1 and 5. In contrast, low physical activity clusters 3, 4, and 7 were located in inland California and middle to western Massachusetts, and most of the built environment values for these clusters were consistently lower than outside of clusters. Inconsistent patterns of built environment factors across the clusters were also found, for example, the average level of walking for participants in higher physical activity cluster 1 in California with lower built environment values, including population density, intersection density, diversity of facilities and some densities of facilities (i.e., hypothetically less favorable for walking) was 102 MET minutes/week higher than for women in higher physical activity cluster 2 with higher built environment values. One possible explanation for these findings is that certain unmeasured built environment characteristics, such as availability and condition of sidewalks, aesthetics, outdoor recreational facilities including trails and parks, or neighborhood safety (e.g., crime rates), may account for the differences in walking between these two clusters. Future analyses of physical activity clusters should examine a more comprehensive list of both perceived and objective built environment variables.

The present study has several limitations. The findings may not be applicable to more diverse groups of older women in the U.S., since the sample is predominantly Caucasian, moderately well-educated, and generally aware of health issues due to their background in nursing. The walking measure did not differentiate between walking for leisure and transportation. If separate measures of walking for recreation and transportation had been available, different clusters might have been detected and patterns in built environment characteristics inside and outside of spatial clusters might have been different for the two types of walking. Thus, inconsistencies in built environment characteristics might have been observed in this study. This study examined clustering at the county level and the actual spatial clustering of physical activity and obesity may not coincide with geo-political boundaries [168, 169]. Obesity estimates may be biased since self-reported height from 1976 was used to calculate BMI, resulting in misclassifying some participants as either obese or non-obese. As individual level income was not available, median family income at the census tract level was used in the analyses. Since the geographic distribution of individual level income would differ from the distribution of median family income, this scale difference may influence the existence of the physical activity and obesity clusters. A scan statistic based on the Bernoulli model restricts the type of the covariate adjustment to only categorical variables. In the present study, continuous covariates (e.g., median family income) were categorized into quintiles. Depending on arbitrary categories for these covariates, the assessment of the spatial clusters may be impacted with respect to the size or location, or disappearance of the cluster. The results from covariates expressed as binary and quartiles were compared to those of quintile covariates. However, the differences in results were minor.

4.6 Conclusions

The present study contributes to the sparse literature on spatial clustering of physical activity and obesity among older women, including the limited assessments of spatial confounders, and comparisons of built environment characteristics inside and outside of clusters. Although spatial clusters of physical activity were detected, the majority of the spatial confounders examined did not explain the identified clusters. The patterns of the built environment values inside and outside of clusters revealed complex relationships. Higher street connectivity was consistently found in higher physical activity clusters 2 and 6, whereas inconsistent patterns even among high physical activity clusters 1 and 2 were found (i.e., a higher level of walking for cluster 1 with unsupportive built environment characteristics, compared to cluster 2). These findings were not fully consistent with existing built environment literature. The spatial clustering methods and findings have implications for future directions in public health research and practice. For example, the findings from this study and others [23, 28] suggest that further examination of factors that contribute to the development of spatial clusters of physical activity and obesity is needed. One way to address this gap would be to examine space-time clustering of physical activity and obesity, which may have the potential to shed new light on determinants, including neighborhood built environment factors. In terms of public health practice, where surveillance data on physical activity and obesity are available along with geographic identifiers, public health officials could take advantage of existing cluster detection software, such as SaTScan™ [170], to identify clusters. Results of these spatial analyses could facilitate the design and implementation of more geographically targeted, resource-efficient interventions for both physical activity and obesity.

CHAPTER 5. ACCELEROMETER AND GPS ANALYSIS OF TRAIL USE AND ASSOCIATIONS WITH PHYSICAL ACTIVITY

5.1 Abstract

Purpose: To examine associations between trail use and physical activity and sedentary behavior and to quantify on-trail physical activity using accelerometers only and a combination of accelerometer and global positioning system (GPS) data. Methods: Participants (N = 141, 53% female, 19-78 yr), who were recruited on five trails in Massachusetts, wore accelerometer and GPS units concurrently for one to four days. Total physical activity (daily mean activity counts·min^{-1}), and daily minutes of light, moderate, or vigorous physical activity, and sedentary behavior were derived from accelerometer counts. A trail use day was defined as a day on which a participant engaged in a minimum of two consecutive minutes of activity on a trail. Mixed models were used to examine whether trail use was associated with light, moderate, or vigorous physical activity, and sedentary behavior. Intensity of activity on trails was quantified in two ways: using accelerometer counts only and using a combination of counts and GPS speed. **Results:** In multivariable models, trail use had statistically significant positive associations with total physical activity, moderate, and light physical activity. Minutes of vigorous physical activity on trails increased by 346% when accelerometer and GPS data were used to define intensity, compared to using accelerometer counts only.

Alternatively, on-trail minutes of light, moderate, and sedentary behavior decreased by 15%, 91%, and 85%, respectively, when accelerometer and GPS data were used to classify intensity. On three linear trails where bicycling was a more common activity, vigorous physical activity minutes increased between 786% and 1015%. **Conclusions:** This study demonstrated that adults accumulated more total physical activity, moderate, and light physical activity on days when they used study trails, indicating the importance of these outdoor facilities for supporting regular activity. Exploratory analyses indicated that the combination of GPS and accelerometer data may be useful for classifying intensity of physical activity, particularly on trails where individuals are likely to be bicycling. Keywords: Exercise, sedentary behavior, geographic information system.

5.2 Introduction

Recent U.S. national guidelines for physical activity indicate that adults should engage in 150 minutes/week of moderate-intensity physical activity; or 75 minutes/week of vigorous-intensity physical activity or some combination of the two [1]. Well-demonstrated health benefits of moderate-to-vigorous intensity physical activity (MVPA) include reduced risks for heart disease, some cancers, stroke, diabetes, hypertension, and psychological issues [1]. Beyond the focus on MVPA, there has been increasing interest in examining the protective effects of light-intensity physical activity on individual health [171]. Recent studies have shown that independent of MVPA, light physical activity is positively associated with physical health [172], such as biomarkers of cardiometabolic health [173, 174] and psychosocial health [172, 175].

Over the past two decades, social ecological frameworks that emphasize the use of environmental and policy approaches to increase physical activity have been embraced by researchers and practitioners [145]. Numerous studies have shown beneficial relationships between the neighborhood built environment, including a greater mix of residential and commercial land uses, street connectivity, access to parks and open spaces, and physical activity [18, 76-78]. One specific component of the built environment, community trails, has received growing attention as an important resource for supporting physical activity among adults [79, 80]. For instance, studies have shown that new community trails were positively associated with physical activity [81, 82]. Another study demonstrated that a park with a trail was more likely to be used for physical activity than parks only [83]. Finally, a study examining physical activity levels among trail users in the U.S. indicated that individuals who used trails at least once a week were twice as likely to meet physical activity guidelines, compared to those who rarely or never utilized trails [84]. Despite evidence for the physical activity benefits of trail use, there are two key limitations in this research area. First, the majority of trail studies have relied on self-report surveys [176]. These measures are limited by recall [36] and social desirability bias [177]. Although some studies have utilized infrared counters to objectively measure trail use [178, 179], these methods are not designed to quantify activity at an individual level; instead they provide aggregate measures of trail traffic at different locations and times. Another limitation of the current evidence on trails is that self-report measures have focused on assessing MVPA [85]. Given the growing evidence that light physical activity may have positive health effects, examining how trails may also support light physical activity is important to explore.

Simultaneous use of accelerometers and GPS units could be used to quantify physical activity occurring on trails and thereby provide a better understanding of how community trails can support regular physical activity [38, 132]. To date, researchers have concurrently used these devices to objectively assess how much physical activity occurs at home and school [30, 31], in parks and recreational facilities, and in open spaces [30-34]. One recent study used accelerometer and GPS monitoring with adults to demonstrate that bouts of daily MVPA were greater on days when participants visited a park [132]. Although this is a rapidly emerging research area, to our knowledge no studies have examined the association between trail use and light, moderate, vigorous physical activity, and sedentary behavior measured through simultaneous accelerometer and GPS monitoring. Therefore, the primary aim of this study was to examine associations between trail use and light, moderate, vigorous physical activity, total physical activity, and sedentary behavior among a sample of Massachusetts adults. A secondary aim was to objectively quantify physical activity and sedentary behavior occurring on-trail, using two approaches--the first using accelerometer counts only and the second using both accelerometer counts and GPS speed data.

5.3 Methods

5.3.1.1 Participants and Trail Characteristics

The sample for this study was recruited from 1194 adults who completed brief intercept surveys at five trails in Massachusetts during the fall of 2004 and the spring/summer of 2005. The trails were: 1) Cutler Reservation (suburban conservation land with about two mile circular dirt path, highly wooded and water views); 2) Franklin

Park (500 acre urban park with three mile circuit of trail paths); 3) Minuteman Bikeway (11 mile suburban rail-trail, asphalt); 4) Nashua River Rail Trail (12 mile rural rail-trail, mostly asphalt); and 5) Southwest Corridor (five mile urban linear park, asphalt). Survey respondents who reported having used a trail at least four times in the past four weeks were asked to participate in a second study that involved wearing an accelerometer (Actigraph™ Model 7164) and global positioning system (GPS) unit (GeoStats Wearable GeoLogger™) for a four-day period (two weekdays, two weekend days). Of 294 individuals who initially provided contact information, 178 wore the two devices. Recruitment procedures were described in detail in a prior study [88]. All procedures were approved by the Institutional Review Boards at Purdue University and the Human Subjects Committee at the Harvard School of Public Health. Participants provided written informed consent and were told that the main purpose of the study was to assess how much of their activity occurred while they were on a trail or at other places.

5.3.1.2 Data Collection

Research staff met participants at public places (e.g., libraries) to deploy and pick up equipment. Staff instructed participants how to wear the two devices and provided daily log sheets to record time-on and time-off for both devices. Participants were instructed to wear the accelerometer at all times for four days, with exceptions for periods of sleeping, bathing, or swimming. The Actigraph was initialized to collect data using one-minute epochs. Participants were also instructed to wear the GPS device when they were outside irrespective of being active, driving a car, or taking a bus. Data were collected at five-second intervals.

5.3.1.3 Data Processing

The data processing procedures were described previously [88]. GeoStats software was used to download raw data from the GPS receivers. For each participant, a research analyst evaluated the GPS data for the four-day period to identify outlying points that may be due to poor GPS signals. These points were subsequently removed from the database. GPS points were then aggregated to one-minute intervals, which had latitude and longitude for both the starting and ending points of each minute.

Accelerometer data were downloaded using Actigraph software. GPS and accelerometer data were merged by using their respective date and time stamps. A valid monitoring day was defined as having a minimum of 40 minutes with GPS readings [88] and ≥ 600 minutes of valid accelerometer wear time [3, 127]. Among 178 participants, 147 met both GPS and accelerometer criteria and had at least one valid monitoring day. Of these 147 participants, four were excluded due to not residing in Massachusetts and two had no demographic data, leaving a final sample of 141 individuals. These participants had 429 person-days of observations; a mean number of valid monitoring days = 3.1 days (± 1.1) per person. To examine associations between trail use and physical activity, two datasets were used: one using only monitoring minutes where accelerometer counts were linked to actual GPS readings (N = 60,342). The other dataset included all accelerometer monitoring minutes (N = 460,744), both with and without GPS coordinates. For statistical analyses, minutes in each dataset were aggregated to the person-day level.

5.3.1.4 Physical Activity and Sedentary Behavior Outcomes

Using cut-points developed by Matthews, each monitoring minute was classified as sedentary behavior (i.e., 0-99 counts), light (100-759), moderate (760-5724), or vigorous (≥5725) [128, 129]. Light, moderate, vigorous physical activity, and sedentary behavior were expressed as mean minute/day. Additionally, total physical activity was defined as daily mean activity count/minute.

5.3.1.5 Determination of Monitoring Minutes On Trails

A variable indicating whether participants were on one or off one of the five study trails (1 = on-trail, 0 = off-trail) was initially created by a GPS vendor (Westat, Rockville, MD: https://www.westat.com/). The vendor used automated procedures (.NET Framework v1.1.) to define trips as sets of GPS points grouped in time and space. To verify the on/off-trail classification created by the vendor, we manually inspected all the GPS monitoring minutes by overlaying the data on publicly available aerial photography and other GIS data sources (i.e., Open Street Map (https://www.openstreetmap.org) using ArcGIS 10.2 (ESRI, Redlands, CA)

Visual checks of monitoring minutes to determine the location as on- or off-trail were performed by the lead author. To be categorized as on-trail, a minimum of two consecutive monitoring minutes needed to occur on the trail. This criterion excluded isolated GPS points that were classified as on-trail when a participant may have happened to cross a trail, for example, when traveling along a road that intersects a trail [132]. Each monitoring minute was examined concurrently with the preceding and following minutes to assess whether any spatial or temporal discontinuity of activity existed. These procedures involved examination of the following: average speed for each minute, distance covered during a given minute, and accelerometer counts for each minute. Average of 5 - 10 minutes for each participant per day were spent to assess these procedures above.

After visually inspecting each minute, we compared the on-trail classifications from the vendor to our trail classification using Cohen's kappa statistic. Among all monitoring minutes (N = 60,342), 16% (n = 9625 minutes) were classified as on-trail and 80.9% (n = 48,794) were classified as off-trail by both the vendor and our classifications. The vendor classified 1.7% (n = 1017) of all minutes as on-trail, whereas our group classified these as off-trail. Similarly, the vendor classified 1.5% (n = 906) as off-trail and we reclassified these minutes as on-trail. Based on Landis and Koch's classification of kappa statistics [130], the coefficient was 0.89 (p-value = 0.011), indicating "almost perfect" agreement between the vendor's classification and ours.

The following four cases were most commonly observed during the reclassification process. First, some monitoring minutes that occurred in parking lots adjacent to trails were initially classified by the vendor as on-trail. Based on our visual checks, these minutes were reclassified as off-trail. Second, we reclassified some minutes as on-trail that the vendor initially classified as off-trail due to an average speed of 0 MPH for the minute despite geographic proximity to a trail. In the third case, some monitoring minutes were misclassified by the vendor as on-trail since the GPS points occurred in close proximity, but not directly on a trail. For example, the participant was using a sidewalk or road that closely paralleled a trail segment. After our visual checks, these minutes were reclassified as off-trail. Fourth, some minutes initially classified as on-trail had high average speeds, low accelerometer counts, and covered long distances. Our group reevaluated these minutes and determined that they would not be considered on-trail. They appeared to occur while the participant was driving a car on roads either parallel to the trails or on roads that crossed a trail. Since the visual inspection of monitoring minutes had almost perfect agreement with the original classification, the on-trail variable for this study was based on our classification.

5.3.1.6 Classification of Intensity of Activity On-Trail Using GPS and Accelerometer Data

We explored two approaches to classifying intensity of activity on trails, one using accelerometer counts only (using cut-points) and one using a combination of counts and GPS speed. For the second approach, intensity of activity was classified based on average speed from the GPS device for a given minute, the metabolic equivalent (MET) value for bicycling at that speed [131], and activity counts from accelerometer data. If the average speed for a minute was ≥ 9.52 mph (i.e., MET = 6.0 for bicycling [131]), then the activity was classified as vigorous. If the average speed for the minute was ≥ 2.5 mph and < 9.52 mph (i.e., MET = 3.0 – 5.9) and the activity count was < 5725, then the activity for a given minute was classified as moderate. Light intensity and sedentary behavior were classified based on the Matthews cut-points described previously [128, 129].

5.3.1.7 Trail Use Days

A binary variable was created to indicate whether or not a participant used any of the five study trails on a given day (1 = yes, used trail, 0 = no, did not use trail). To be defined as a trail use day, at least two consecutive minutes had to occur on-trail. This operational definition is analogous to one used in a recent study of parks in which researchers defined a park visit day as one where the user was in the park for ≥ three consecutive minutes [132]. Since several trails in our study are used for bicycling and a relatively long distance can be covered in two minutes, we decided to use a lower threshold for defining trail use.

5.3.1.8 Covariates

The following variables were included in multivariable models: age, gender, race (white or non-white), and education (undergraduate degree or less, some graduate school or more). In addition, several other variables were included as covariates since they might confound relationships between trail use and physical activity and sedentary behavior. These included: first time using a study trails (< three years, ≥ three years), origin when using trails (home or other), usual reason for using trails (exercise/recreation, transportation, both exercise/recreation and transportation), trail sites (Cutler Reservation, Franklin Park, Minuteman Bikeway, Nashua River Rail Trail, Southwest Corridor), and weekday versus weekend use [180].

5.3.2 Statistical Analysis

Descriptive statistics were performed to summarize all study variables. Linear mixed models (PROC MIXED in SAS) were used to estimate relationships between trail use and total physical activity (counts/minute/day); mean daily minutes of light, moderate, vigorous physical activity, and sedentary behavior. Two datasets were used to analyze these relationships: one with accelerometer data linked to GPS coordinates (N=60,342), and the other with all accelerometer data (N= 460,744). The unit of analysis was a person-day (daily minutes of activity were aggregated to the person-day level). The data structure was hierarchical, representing that person-day observations (level 1) were nested within an individual (level 2). For all outcomes, an intraclass-correlation coefficient (ICC) with an intercepts-only model was used to assess the extent to which the total proportion of variability in each outcome came from the variability between participants, as compared to the variability within participants. Using accelerometer data linked to GPS coordinates, the ICC ranged from 0.12 to 0.39 indicating that 12-39 % of the total variability in each outcome was due to the variability between participants. In turn, using the larger accelerometer dataset, the ICC ranged from 0.17 to 0.46. Models were fully adjusted for age, gender, race, education, trail site, and time of week. Sedentary time was adjusted for light, moderate, and vigorous physical activity outcomes, while minutes of physical activity was adjusted for in models for sedentary behavior. Based on the Akaike's Information Criterion for model selection, trail use variables such as first time using trail, origin when using the trail, and usual reason for using trail were not included in the fully adjusted models. All analyses were performed with SAS version 9.3 (Cary, NC, See Appendix A for SAS code).

5.4 Results

5.4.1 Participants' Characteristics

The average age of participants was 44.1 ± 13.0 years (Table 1). Slightly over half (53.2%) were women; the majority (72.3%) were white, 20.6% were African-American or black, and 7.1% were Asian, Native Hawaiian, or other Pacific Islander. The majority had at least undergraduate degrees (95%).

Approximately 48% of the participants (n=68) had four valid monitoring days with accelerometer data linked to GPS coordinates; 21% (n=30) had three days; 18% (n=25) had two days; and 13% (n=18) had one day. There were 231 participant-monitoring days with trail use and 198 days without. Mean monitoring minute/day was 155.1 ± 87.3 on days with trail use and 140.7 ± 91.5 on days without trail use ($p = 0.0945$). Daily mean counts/minute were higher on days with trail use (1707.8 ± 1151.9), compared to days without trail use (1186.0 ± 1542.9, $p <.0001$). Average moderate physical activity minutes/day was higher on days with trail use (65.5 ± 43.9), compared to days without use (35.3 ± 35.8, $p < .0001$). No statistical differences were found for average vigorous physical activity minutes/day on trail use (6.1 ± 13.9) and on non-trail use days (5.6 ± 15.9, $p = 0.7290$), and average light physical activity minutes/day with trail use (49.0 ± 52.3) and without trail use (41.9 ± 44.1, p =0.13.16). Average sedentary behavior minutes/day was lower on days with trail use (72.4 ± 134.7), compared to days without trail use (66.7 ± 90.6, $p = 0.6035$).

Table 5.1 Participants' demographic and trail-use characteristics, overall and by trail (N=141)

	Overall *N = 141*	Cutler Reservation *n = 20*	Franklin Park *n = 35*	Minuteman Bikeway *n = 33*	Nashua River Rail Trail *n = 20*	Southwest Corridor *n = 33*
Age, mean (SD)	44.1 (13.0)	42.0 (9.2)	46.5 (12.9)	42.2 (12.6)	49.1 (16.2)	41.8 (13.0)
Gender, n (%)						
Female	75 (100)	10 (13.3)	12 (16.0)	16 (21.3)	12 (16.0)	17 (22.7)
Male	66 (100)	10 (13.5)	23 (31.1)	17 (23.0)	8 (10.81)	16 (21.6)
Race, n (%)						
White	102 (100)	17 (16.7)	3 (2.9)	31 (30.4)	20 (19.6)	31 (30.4)
African-American or Black	29 (100)	0 (0)	28 (96.6)	0 (0)	0 (0)	1 (3.5)
Others	10 (100)	3 (30.0)	4 (40.0)	2 (20.0)	0 (0)	1 (10.0)
Education, n (%)						
Some college or less	7 (100)	0 (0)	5 (71.4)	0 (0)	2 (28.6)	0 (0)
Undergraduate degree	73 (100)	9 (12.3)	23 (31.5)	11 (15.1)	10 (13.7)	20 (27.4)
Some graduate or graduate degree	61 (100)	11 (18.3)	7 (11.5)	22 (36.1)	8 (13.1)	13 (21.3)
First time using trail, n (%)						
< 12 months	13 (100)	2 (15.4)	2 (15.4)	2 (15.4)	3 (23.1)	4 (30.8)
1 - 3 years	39 (100)	10 (25.6)	5 (12.8)	6 (15.4)	8 (20.5)	10 (25.6)
> 3 years	89 (100)	8 (9.0)	28 (31.5)	25 (28.1)	9 (10.1)	19 (59.4)
Origin when using trail, n (%)						
Home	111 (100)	14 (12.6)	29 (26.1)	28 (25.2)	18 (16.2)	22 (19.8)
Work	8 (100)	4 (50.0)	1 (12.5)	2 (25.0)	0 (0)	1 (12.5)
Home and work	21 (100)	2 (9.5)	5 (23.8)	3 (14.3)	2 (9.5)	9 (42.9)
School	1 (100)	0 (0)	0 (0)	0 (0)	0 (0)	1 (100)
Travel time from home to trail, n (%)						
<15 minutes	111 (100)	12 (10.8)	30 (27.0)	27 (24.3)	12 (10.8)	30 (27.0)

15-29 minutes	15 (100)	3 (20.0)	4 (26.7)	2 (13.3)	5 (33.3)	1 (6.7)
30-120 minutes	6 (100)	1 (16.7)	0 (0)	2 (33.3)	3 (50.0)	1 (0)
Missing	9 (100)	4 (44.4)	1 (11.1)	2 (22.2)	0 (0)	2 (22.2)
Usual reason for using trail, n (%)						
Recreation	99 (100)	20 (20.2)	33 (33.3)	18 (18.2)	20 (20.2)	8 (8.1)
Transportation	21 (100)	0 (0)	0 (0)	3 (14.3)	0 (0)	18 (85.7)
Both recreation and transportation	21 (100)	0 (0)	2 (9.5)	12 (57.1)	0 (0)	7 (33.3)
Trail use, mean number of days (SD)[b]						
Weekdays	0.9 (0.8)	0.4 (0.6)	0.9 (0.8)	1.0 (0.8)	0.7 (0.7)	1.1 (1.0)
Weekend days	0.8 (0.7)	0.6 (0.8)	0.8 (0.7)	0.9 (0.8)	0.8 (0.6)	0.7 (0.8)
Mean $min \cdot d^{-1}$ (SD)[b]						
VPA[c]	5.9 (14.9)	4.9 (9.9)	7.2 (15.2)	8.7 (21.4)	3.6 (9.2)	3.5 (9.6)
MPA[d]	51.6 (43.0)	44.2 (36.9)	51.0 (39.8)	51.3 (42.8)	45.7 (42.5)	61.4 (49.0)
LPA[e]	45.7 (48.8)	32.1 (23.4)	43.4 (38.1)	42.5 (42.6)	78.7 (75.6)	37.3 (43.8)
SB[f]	69.8 (116.4)	60.0 (56.4)	48.1 (58.8)	70.2 (125.1)	66.0 (81.2)	99.8 (178.3)

Note: [a] Others = American Indian, Asian, Native Hawaiian or other Pacific Islander. [b] SD = Standard Deviation. [c] VPA = vigorous-intensity physical activity. [d] MPA = moderate-intensity physical activity. [e] LPA = light-intensity physical activity. [f] SB = sedentary behavior.

Table 5.2 Distribution of physical activity and sedentary minutes on trails based on accelerometer data only (A)[a] and both accelerometer and GPS data (A/G)[b] (N= 10,531)

	Overall minutes on-trail			Cutler Reservation			Franklin Park			Minuteman Bikeway			Nashua River Rail Trail			Southwest Corridor		
	A	A/G	Δ%[c]	A	A/G	Δ%	A	A/G	Δ%	A	A/G	Δ%	A	A/G	Δ%	A	A/G	Δ%
VPA[d]	999	4454	+345.8	94	96	+2.1	546	595	+9.0	195	2061	+956.9	109	1215	+1014.7	55	487	+785.5
MPA[e]	6839	5800	-15.2	670	709	+5.8	2976	3029	+1.8	1618	921	-43.1	742	511	-31.1	833	630	-24.4
LPA[f]	2189	199	-90.9	29	11	-62.1	118	36	-69.5	1109	59	-94.7	679	58	-91.5	254	35	-86.2
SB[g]	504	78	-84.5	27	4	-85.2	42	22	-47.6	130	11	-91.5	284	30	-89.4	21	11	-47.6

Note: [a]A = Accelerometer counts were used to define intensity of activity, using the cut-points: sedentary = 0-99, light = 100-759, moderate = 760 – 5724, and vigorous ≥ 5725). [b] A/G = Accelerometer counts and average GPS speed for each minute were used to define intensity of activity. Definition of vigorous intensity physical activity: If average speed ≥ 9.52 mph, then intensity = vigorous. Definition of moderate intensity physical activity: If average speed = 2.5 mph - 9.51 mph and counts ≤ 5725 then intensity = moderate. The rest of monitoring minutes were based on cut-points for the accelerometer counts above. [c] Percent change = [(A/G - A)/A]*100. [d] VPA = vigorous-intensity physical activity. [e] MPA = moderate-intensity physical activity. [f] LPA = light-intensity physical activity. [g] SB = sedentary behavior.

Table 5.3 Associations between trail use and objective measures of physical activity and sedentary time (N=429 person-days)

	Accelerometer data linked to GPS coordinates[a]				Accelerometer data[b]			
	Age adjusted model[c]		Fully adjusted model[d]		Age adjusted model[c]		Fully adjusted model[d]	
	Beta (95% C.I.)	*p*	Beta (95% C.I.)	*p*	Beta (95% C.I.)	*p*	Beta (95% C.I.)	*p*
TPA[e]	583.17 (338.95, 827.39)	<.0001	522.15 (272.66, 771.63)	<.0001	113.81 (68.55, 159.08)	<.0001	117.87 (71.35, 164.39)	<.0001
VPA[f]	1.88 (-0.29, 4.06)	0.0879	2.05 (-0.13, 4.24)	0.0653	2.25 (-0.30, 4.81)	0.0831	2.44 (-0.16, 5.03)	0.0651
MPA[g]	28.49 (20.49, 36.48)	<.0001	28.29 (19.99, 36.60)	<.0001	31.34 (20.10, 42.58)	<.0001	30.54 (18.99, 42.08)	<.0001
LPA[h]	5.65 (-1.67, 12.97)	0.1283	7.73 (0.35, 15.12)	0.0404	14.05 (-0.68, 27.41)	0.0397	14.09 (1.53, 26.64)	0.0284
SB[i]	-0.32 (-16.53, 15.90)	0.9689	-7.51 (-25.45, 10.42)	0.4069	2.32 (-27.54, 32.19)	0.8773	4.96 (-26.56, 36.48)	0.7550

Note: [a] GPS/Accelerometer data (N = 60,342): accelerometer counts are linked GPS recordings. [b]Accelerometer data (N = 460,774) including GPS recordings (n=60,342), imputed GPS recordings (n=381,084), and missing GPS recordings (n=19,348). [d] Adjusted for age, gender, race, education, trail site, weekday vs. weekends, and sedentary time (for physical activity outcomes, except total PA), and LPA, MPA, VPA minutes (for sedentary outcome). [e]TPA = total physical activity based on daily mean activity counts·min^{-1}. [f] VPA = vigorous-intensity physical activity. [g]MPA = moderate-intensity physical activity. [h]LPA = light-intensity physical activity. [i]SB = sedentary behavior.

5.4.2 Trail Use Patterns

The majority of participants (63.1%, n=89) used one of the study trails for the first time at least three years ago (Table 1). Home was the point of origin for 78.7% of participants (n=111) when they used trails. Approximately 5% of participants (n = 8) came from work and 15% (n = 21) came from both home and work. Most participants (78.7 %, n = 111) traveled less than 15 minutes to the trails and 13.5% (n = 19) traveled 15-44 minutes. Ninety-nine participants (70.2%) reported that they use the trails for recreational purposes, 21 (14.9%) for transportation, and 21 (14.9%) for both recreation and transportation. Most participants reported that walking (n = 50, 35%) or bicycling (n = 45, 31.9%) were their usual activities when they used the trails for recreational purposes. Fifteen-percent reported jogging/running as their usual activity.

5.4.3 Classification of Trail Activity Using Accelerometer Only Versus Accelerometer and GPS

The distribution of light, moderate, vigorous physical activity and sedentary behavior minutes on five study trails differed substantially depending on whether it was based on accelerometer counts only or on the combination of accelerometer and GPS data (Table 2). Overall minutes of vigorous physical activity increased about 346% using a combination of accelerometer and GPS information, while minutes of moderate and light physical activity, and sedentary behavior decreased by 15%, 91%, and 85%, respectively. The percent increase in vigorous physical activity ranged from 2% at Cutler Reservation to 1016% at the Nashua River Rail Trail. The largest percentage increases in vigorous physical activity were found at three linear trails (i.e., Minuteman Bikeway, Nashua

River Rail Trail, and Southwest Corridor). Moderate physical activity minutes increased by 2% at Franklin Park and 6% at Cutler Reservation, whereas moderate physical activity decreased 24 - 43% on the other three trails. Minutes of light physical activity decreased by 62 - 95% on the 5 trails and sedentary behavior decreased 48 - 92%.

5.4.4 Associations between Trail Use and Physical Activity and Sedentary Behavior

Based on accelerometer data linked to GPS coordinates (N=60,342), there were statistically significant positive associations between trail use and physical activity and an inverse association with sedentary (Table 5.3), with a few exceptions for LPA. Trail use was positively associated with total physical activity, though attenuated from $\beta = 587.8$ counts/minute to $\beta = 530.2$ counts/minute in the fully adjusted model. Trail use was positively associated with moderate physical activity (approximately 28 mean minutes/day more compared to no trail use). Trail use was also significantly associated with light physical activity in the fully adjusted model ($\beta = 7.73$ mean minutes/day). However, trail use was not associated with vigorous physical activity and sedentary behavior.

With the use of accelerometer dataset (N=460,744), there were statistically significant positive associations between trail use and total physical activity ($\beta = 117.87$ mean counts/minute) and moderate physical activity ($\beta = 24.48$ minutes/day) in fully adjusted models. In contrast, trail use was not associated with vigorous physical activity and sedentary behavior.

5.5 Discussion

Simultaneous assessment of physical activity with accelerometers and GPS units with 141 trail users in Massachusetts indicated that trail use was positively associated with daily minutes of light, moderate, and total physical activity (daily mean counts/minute). However, trail use was not associated with vigorous physical activity and sedentary behavior. Using a larger dataset with all available accelerometer data (with or without GPS coordinates), positive associations between trail use and total physical activity and moderate physical activity were also found. However, the magnitude of these effects was lower compared to the results from GPS/accelerometer data. No associations were found between trail use and vigorous physical activity and sedentary behavior using this larger dataset that included accelerometer data without locational information.

The amount of vigorous physical activity on study trails changed substantially when it was classified with a combination of accelerometer counts and GPS speed, compared to classification with counts only. Overall on-trail vigorous physical activity minutes increased four to five-fold based when GPS speed data was used. In contrast, on-trail light and moderate physical activity, and sedentary behavior minutes decreased by approximately 15%, 91%, and 85% respectively, when the combination of both accelerometer and GPS data was used to classify intensity of activity. On-trail vigorous physical activity minutes increased from 786% to 1015% on three linear trails where bicycling is a more common activity.

Our findings of significant positive associations between trail use and total physical activity, vigorous, moderate physical activity were comparable to the results from a recent study by Evenson and colleagues [132] on parks and physical activity in five U.S. states. Using accelerometer and GPS data collected from 218 adult men and women (age ranged from 18-85), researchers found significantly higher levels of total physical activity (343 median counts/minute versus 287) and moderate physical activity (26.4 median minutes/day versus 16.7) on days with a park visit compared to days without a visit [132]. However, there were no significant differences in vigorous physical activity between days when parks were used and days when they were not used. In our study, trail use was associated with 522 counts/minute higher and with 28 minutes/day higher moderate physical activity. These associations were expected since these trails are settings that support moderate physical activity, particularly walking, which is the most common on-trail activity identified by participants. The findings that trail use was not associated with vigorous physical activity may in part be the overall low levels of vigorous physical activity among participants. This low level of vigorous physical activity is consistent with national surveillance data from accelerometers, which showed that adults about four minutes/day of vigorous physical activity or less [3].

Our findings from analysis of a larger accelerometer dataset are generally consistent with the findings for mean counts/minute and moderate intensity physical activity based on the smaller accelerometer dataset linked to GPS coordinates. Consistent with findings from accelerometer data linked to GPS coordinates, trail use was not associated with vigorous physical activity and sedentary behavior. Our findings that a trail use day was positively associated with daily light physical activity and not associated with minutes of sedentary behavior differ from Evenson and colleagues' findings for park visits among adults (age ranged from 18-85) [132]. These researchers found almost the same amount of light physical activity on days with and without a park visit; 167.9 minutes/day and 169.8, respectively [132]. Alternatively, we found almost eight more minutes of light physical activity on days with trail use. On days with a park visit, participants accumulated more sedentary minutes compared to days without a visit (447.5 minutes/day and 430.6, respectively); whereas in the present study trail use was not associated with sedentary time. Parks are often designed with a wide range of amenities that not only support different types of physical activity, but also support sedentary behaviors such as sitting and reading on a bench or having a picnic. Alternatively, trails by their very design are intended to support moving about; in other words, physical activities such as walking, jogging, and bicycling [83].

When we examined associations with the larger accelerometer dataset, trail use was positively associated with light physical activity and was not associated with sedentary behavior. These findings were consistent with those from the smaller dataset linked to outdoor location via GPS and in general seem to bolster the finding that use of trails may be associated with higher levels of light intensity physical activity. A large volume of sedentary behavior in daily activities might dilute associations between trail use and sedentary behavior.

A growing number of studies have applied accelerometer and GPS units to examine relationships between the built environment and physical activity, whereas others focused on classifying modes of activity using accelerometer or GPS data [89, 181, 182]. For example, a recent study examined modes of transportation such as walking, bicycling, driving a car, and taking a bus or train, based on GPS speed only [181]. Another study utilized both GPS speed and accelerometer counts to identify mode of activity [89]. A recent study examined whether routes of activity for transportation-related physical activity can be determined by intensity and speed of activity (i.e., commutes to/from workplace) using GPS, accelerometer, and survey data [182]. These studies have demonstrated that GPS data can be utilized to identify types of activities such as walking, running, bicycling, or driving a car. In contrast, we attempted to classify intensity of activity occurring on-trail by using two approaches, accelerometer counts only, and the combination of accelerometer counts and GPS speed.

On-trail vigorous physical activity minutes substantially increased on three linear trails, the Minuteman Bikeway, Nashua River Rail Trail, and Southwest Corridor, whereas moderate, light physical activity, and sedentary behavior minutes decreased. In contrast, on-trail vigorous physical activity minutes increased on Cutler Reservation and Franklin Park, but to a small extent, compared to the three linear trails. A plausible explanation for these differences is that Cutler Reservation and Franklin Park are circular trails generally used for walking, jogging, and running. Conversely, Minuteman Bikeway, Nashua River Rail Trail, and Southwest Corridor are relatively long, asphalt-surfaced rail-trails and linear parks that experience a high volume of bicycling, in addition to walking, and jogging/running. For example, intercept survey data indicated that more than half of the participants recruited on the Minuteman Bikeway (n = 18 of 33 participants) and the Nashua River Rail Trail (n=17 of 20) reported that their usual activity on the trails was bicycling. In contrast, few participants recruited from the other two trails reported that bicycling was their usual activity. The use of GPS and accelerometer data to classify intensity of physical activity may be better suited to specific outdoor settings such as trails, where researchers can be more certain that faster speeds are indicative of bicycling or in-line skating versus driving a car.

This study has several strengths that further bolster its contribution to the evidence base on trails and physical activity. The use of accelerometer data linked to GPS coordinates allowed us to objectively determine trail use days; a distinct advantage over previous studies which relied almost exclusively on self-reports to identify trail use. Furthermore, as the majority of previous trail studies using survey data focused on MVPA, this study added to limited literature on associations between trail use and objectively measured light physical activity and sedentary behavior. This has public health relevance given the growing evidence that light physical activity may have health benefits and that sedentary behavior has health risks independent of physical activity. Strength of this study was the manual checking and verification of monitoring minutes occurring on- and off-trail. We found almost perfect concordance between a previous vendor’s classification and ours. We reclassified the intensity of activity occurring on-trail based on the combination of GPS and accelerometer data. Using GPS speed data in addition to accelerometer counts may help to improve the classification of intensity of physical activity in such contexts, particularly areas where cycling is a common activity.

This study has several limitations. Participants were generally well-educated, outdoor-oriented, frequently used trails, and their levels of physical activity were greater than those of the representative U.S. population. Therefore, the findings from this study are not necessarily generalizable to adults using other trails in Massachusetts or elsewhere in the U.S. Since only five study trails were used to define trail use day, associations between trail use and physical activity and sedentary behavior may be biased. Several variables including intra-personal (e.g., attitude, enablers, and barriers towards physical activity [82]), interpersonal (e.g., social support [183]), and environmental factors (e.g., weather conditions [176]) in the ecological frameworks, were not included in this study. Some of these variables may confound or moderate the associations between trail use and physical activity and sedentary behavior. For example, attitude toward being physically active among intrapersonal factors is known to be positively associated with physical activity [12]. Social support from families and friends is also related to higher physical activity levels [14]. Furthermore, weather conditions such as temperature and daylight hours are positively associated with physical activity [180]. Thus, the findings from our study could potentially be confounded by individual, interpersonal, and environmental variables.

5.6 Conclusions

Simultaneous use of accelerometer and GPS data allowed us to examine associations between trail use and objective measures of light, moderate physical activity, vigorous, total physical activity, and sedentary behavior. Trail use days were positively associated with light, moderate and total physical activity. These findings are consistent with prior research on the benefits of trails in terms of supporting regular physical activity and further support the Community Preventive Services Taskforce recommendations that creates and enhances accessibility to places for physical activity [79]. In addition, this study provides preliminary evidence that trails may contribute to higher levels of LPA, which in turn might contribute to reducing risk of adverse health outcomes, such as cardiometabolic disease [173, 174]. Finally, this study's findings indicate that combined accelerometer and GPS monitoring may provide an improved method to measure physical activity on trails, particularly those where bicycling is a common activity.

CHAPTER 6. APPLICATION OF ACCELEROMETER AND GPS MONITORING TO EXAMINE RELATIONSHIPS BETWEEN BUILT ENVIRONMENT AND PHYSICAL ACTIVITY

6.1 Abstract

Accelerometer counts linked to global positioning system data were used to estimate associations between the built environment and minute-by-minute physical activity among 141 adults in Massachusetts. Generalized linear mixed models were fitted to examine associations between five built environment variables and MVPA and LVPA. Overall, there were statistically significant positive associations between population density and MVPA and LVPA. Alternatively, street density, LUM, and a walkability index were inversely associated with MVPA and LVPA. These inverse relationships contrast evidence from most built environment studies in adults, though a direct comparison is not possible. Most studies have focused on buffers around home locations, rather than all locations where activity occurs, as was done in the present study.

6.2 Introduction

It is well documented that regular physical activity is beneficial for primary (i.e., risk reduction before the onset of disease) to tertiary prevention of chronic diseases (i.e., reducing impact of diseases) [1]. Over the past two decades, there has been a dramatic shift in strategies for physical activity promotion from one heavily focused on individual or intrapersonal factors, such as self-efficacy, to one emphasizing the influence of neighborhood environmental factors [4, 145]. Systematic reviews on physical activity interventions conducted by the U.S. Community Preventive Services Task Force provided evidence for a creation of improved accessibility to locations for physical activity [184, 185].

The majority of built environment studies have focused on the environment around individuals' homes (i.e., residential areas) in relation to physical activity [29, 86, 186-188]. For example, it has been a common practice to obtain home addresses from study participants, geocode these addresses, and then, using various types of buffering approaches (e.g., circular buffers, line-based road network buffers), quantify different built environment variables within the buffer. One key limitation with this approach is the potential for a spatial mismatch between environmental exposures and locations where physical activity takes place. Adults are generally mobile and engage in daily activities that are not restricted to locations close to their homes. Therefore, relevant built environment exposures for physical activities, such as walking and bicycling, are more spatially dynamic rather than static [86, 187]. An ethnographic study of 10 families who resided in Boston indicated that only 6% of daily activities such as those involving work, education, child care, social services, and food or non-food shopping occurred within their residential census tract, while 21% of these activities occurred within adjacent census tracts and 73% in non-adjacent tracts [189]. Recent time-use surveys have also shown that many adults engage in exercise and sports activities outdoors approximately 25% of the time, 25% of the time at home, 8% at gyms, 3% at work, 36% unspecified, and 3% unusual places [190]. These studies have demonstrated that people frequently engage in daily activities, including physical activity, at places away from where they live [86, 191].

An emerging method in built environment studies involving the simultaneous monitoring of activity with accelerometers and global positioning system (GPS) devices permits researchers to spatially and temporally link built environment exposures to physical activity. A number of recent studies have used GPS units to identify various locations where physical activity occurs, linking geographic coordinates to accelerometer measures of physical activity among children [192, 193] and adults [88, 132]. In one study among youth, neighborhood walkability and intersection density were positively associated with GPS-accelerometer measured walking and bicycling, and were inversely associated with the time spent traveling in a vehicle [192]. Another recent study examining associations between the built environment and MVPA among adolescents indicated that they engaged in more MVPA when they were at school, on sidewalks, and in parks and playgrounds, compared to at home [193]. Only a few studies using both accelerometer and GPS methods have spatially contextualized physical activity and sedentary behavior taking place among adults [88, 132, 194]. One study found that within 1 kilometer buffers around participants' homes, population and intersection density, and LUM were positively associated with MVPA occurring within the buffer, but not with total MVPA (at any location) [88]. Another study assessed physical activity and sedentary behavior occurring in parks and indicated that park visits were associated with more minutes of moderate, MVPA, and sedentary time compared to days without park visits [132].

A couple of studies in youth have spatially contextualized physical activity at a finer scale and examined associations between the built environment and minute-by-minute or 30s samples of physical activity [38, 39]. One such study found that a greater number of MVPA minutes occurred at parks, schools, and in high population density areas, compared to sedentary time [38]. Another study found that children who were exposed to green space for longer than 20 minutes engaged in almost five times more physical activity than those who were not exposed to any greenness [39]. Despite this evidence, there is a lack of built environment studies that have directly linked physical activity to built environment exposures via accelerometer and GPS monitoring, especially among adults. Therefore, the aim of the present study was to examine relationships between built environment variables and MVPA and LVPA linked to locations via GPS coordinates.

6.3 Methods

6.3.1 Study Participants and Data Collection

During the fall of 2004 and spring/summer of 2005, 1194 adults, aged 19-78 years, completed brief intercept surveys while they were engaging in various types of physical activity (e.g., walking, jogging/running, bicycling, or in-line skating) at five trails in Massachusetts. Respondents who reported using a trail at least four times in the past four weeks were recruited to participate in a sub-study and asked to wear an Actigraph™ accelerometer (Model 7164) and a GeoStats-GeoLogger™ (Atlanta, GA) GPS unit for four days (i.e., two weekdays and two weekend days). Among the survey participants, 294 (24.6 %) agreed to take part in this study and provided contact information. However, 116 individuals did not participate due to loss of interest in the study, scheduling conflicts, or could not be contacted. Consequently, two devices were deployed to 178 study participants [88].

Research staff met with participants to instruct them how to wear the accelerometer and GPS units and to provide log sheets for recording when the devices were worn or taken off. Participants were asked to wear the accelerometer unit for four consecutive days, except while bathing, swimming, or sleeping. Participants were instructed to wear the GPS unit during all times spent outside. The Actigraph accelerometer was programmed to collect data using 1-minute epochs. The GPS unit was programmed to collect data at 5-second intervals.

6.3.2 Data Processing

Data processing procedures for the accelerometer and GPS data were described in more detail previously [88]. A research analyst downloaded the raw GPS data using GeoStats software (Atlanta, GA). To identify improbable points or locations, the analyst manually reviewed GPS points over the monitoring period for each participant. GPS points were aggregated to one-minute intervals with latitude and longitude for both starting and ending points of each minute.

Accelerometer data were downloaded using Actigraph software. By using the date and time stamps in the accelerometer and GPS unit, data from the two devices were merged. Each minute of GPS recordings was linked to the corresponding accelerometer count for that minute. A valid monitoring day for the accelerometer was defined as a day with ≥ 600 minutes of valid wear time. [3, 127]. A valid day also required ≥ 40 minutes of GPS data; the rationale for this approach was described in a previous study [88]. One hundred forty-seven out of 178 participants had at least one valid monitoring day based on two criteria. Six participants were excluded either due to not living in Massachusetts (n=4) or not having any demographic information (n=2), resulting in a final sample of 141 individuals. Accelerometer data without GPS points and GPS points without accelerometer data were excluded from the analyses. The unit of analysis was minute-by-minute physical activity (N=60,342).

6.3.3 Study Measures

6.3.3.1 Physical Activity Outcomes

Intensity of activity was classified using activity count cut-points developed by Matthews and Crouter [128, 129]: 0-99 counts = sedentary; 100-759 counts = light; 760-5724 counts = moderate; and ≥ 5725 count = vigorous. Two binary outcomes were created for each monitoring minute: moderate-to-vigorous physical activity (1) versus sedentary-to-light activity (0). The second outcome was light-to-vigorous intensity physical activity (1) versus sedentary (0).

6.3.3.2 Built Environment Variables

Five built environment variables were created: population density, street density, LUM [88], walkability [133], and greenness [134, 135], using the ArcGIS version 10.2 (ESRI, Redlands, CA). These were created using a 50-meter circular buffer around the ending latitude and longitude of each monitoring minute. This approach is consistent with one used in a recent study of adolescents that linked accelerometer data to GPS coordinates [38].

Population density was created using U.S. Census 2000 data at the block group level and was calculated as the number of persons per square km of area within the 50 m buffer [138]. Street density was created using TIGER street files from the U.S. Census 2000 and was calculated by dividing the total length of the street network within the buffer by the total land area within the buffer. LUM was created using Landuse2005 from the Office of Geographic Information in Massachusetts [139]. LUM was calculated with an entropy formula [133, 140] that estimates the mixture of different types of land use within the buffer (i.e., residential, commercial, recreational, and urban public). The possible values for LUM range from 0 (no diversity) to 1 (maximum diversity). A greenness index was created within each buffer based on the mean normalized difference vegetation index (NDVI), which was measured using Landsat satellite images from 2004 and 2005 (downloaded from the U.S. Geological Survey at http://earthexplorer.usgs.gov) [135]. NDVI values range from +1 (i.e., healthy green vegetation) to -1 (i.e., non-vegetated land cover, or water body) [135]. A walkability index was created within the buffer using LUM, population density, and street density variables [133]. A normalized distribution (z-score) for each variable was summed to create the walkability index [133]. Higher values for the walkability index generally indicate that an environment is more conducive to walking and an active lifestyle.

6.3.3.3 Covariates and Moderator

Participant demographics included age, gender, race (White versus Non-White), and education (undergraduate degree or less vs. some graduate courses or graduate degree). Other covariates were included in the models which could confound associations between the built environment and physical activity. These include time related covariates and monitoring minutes occurring on and off trails. Time of week and time of day variables were created based on the GPS and accelerometer time stamps since individuals may change their behavior during weekdays versus weekend days [38]. A time of day variable was created based on minutes occurring at midnight (12 am – 5:59 am), morning (6 am – 11:59 am), afternoon (12 pm – 5:59 pm), and evening (6 pm – 11:59 pm) [195]. An on-trail/off-trail variable (1= on-trail; 0= off-trail) was also included as a covariate since environmental characteristics could be different on trails and off trails. On-trail monitoring minute variable was also tested as a moderator to examine whether the associations between the built environment and physical activity varied. Community trails and paths are regarded as one component of the built environment to increase physical activity [84, 196]. However, it is not well-known what environmental characteristics trails encompass and how trails attract or pull individuals to engage in activities. To date, no studies using both accelerometer and GPS data have explored whether associations of built environment characteristics and physical activity differ by monitoring minutes occurring on- and off-trails.

6.3.3.4 Variables Accounting for Minute-by-Minute Physical Activity

To account for the temporal data structure of the minute-by-minute physical activity data, two new classification variables were created using the time stamps from the accelerometer and included in statistical models. The first classification variable was an "episode" of activity. An episode was considered a continuous bout of activity where there were no more than five consecutive minutes of missing accelerometer and GPS information. For example, if accelerometer and GPS data were available from 8:00 am to 8:30 am and then were not available until 8:40 am, the first time frame would be considered episode #1 and the second starting at 8:40 would be classified as episode #2. In addition, to investigate the consistency of results based on different discontinuities between minutes of GPS and accelerometer data, a ≥ 10 minute criterion was used to define a new episode. Since the modeling results using the five and ten minute criteria for new episodes were fairly consistent, results using the five minute criterion for a new episode were presented. Sequences of the activity within each episode were numbered to account for correlated data structure. For example, if episode #1 has 30 consecutive minutes from 8:00 am to 8:30 am, then each minute from 8:00 am to 8:30 am was numbered from 1 to 30.

6.3.4 Statistical Analysis

Descriptive statistics were performed on all variables. Associations between built environment variables and MVPA and LVPA were conducted using generalized linear mixed models (GLMM; PROC GLIMMIX in SAS, see SAS code in Appendix B) to handle the multilevel data structure. Minute-by-minute observations (level 1) were nested within each episode of activity for an individual (level 2), and which in turn were nested within an individual (level 3). In addition, due to temporal data (i.e., one minute intervals), we used an autoregressive model to examine the correlation structure of time series data within each episode of activity for an individual. Separately, GLMMs were used to examine relationships between each built environment variable, and MVPA and LVPA, while controlling for age. Subsequently, we fitted GLMMs with the four built environment variables (i.e., population density, street density, LUM, and greenness index) in the model, and controlled for age and race. Since gender, education, time of week and time of day were not statistically significant in any fully adjusted models, these covariates were not included in the final model. Since the walkability index represented the linear combination of population density, street density, and LUM, models were separately estimated for the walkability index in both age and fully adjusted models.

Prior to the stratified analyses, statistical interactions among five built environment variables and the on/off trail variable were examined. Statistically significant interactions were found for all built environment variables ($p < .05$) and associations with MVPA. No statistically significant interactions were found for LVPA. Subsequently, an on-trail variable was used to examine whether the associations between the built environment and physical activity varied.

6.4 Results

6.4.1 Participant Characteristics and Activity Monitoring Patterns

Participants' ages ranged from 19 to 60 years of age, with a mean of 44.0 ± 13.0 years (Table 6.1). Approximately 53% were women, the majority (72.1%) was white, 52% had undergraduate degrees and 43% had some graduate education or more. On average participants had 3.05 ± 1.09 valid monitoring days. Participants wore accelerometers for a daily mean of 892.5 ± 95.8 minutes. Mean accelerometer wear time linked to GPS coordinates was 144.6 ± 65.3 minutes/day. Participants engaged in an average of 52.4 minutes of MVPA per day. Average minutes of light intensity physical activity was 42.9 per day and 42.3 minutes per day for sedentary behavior.

6.4.2 Associations between Built Environment and MVPA and LVPA

Population density had statistically significant positive associations with MVPA and LVPA in fully - adjusted models, but had null associations in age-adjusted models (Table 6.2). In age - adjusted models, street density was inversely associated with MVPA and LVPA. In fully - adjusted models, the associations between street density and MVPA and LVPA were slightly attenuated but still statistically significant, with odds ratios of 0.67 and 0.78, respectively. Similarly, in age-adjusted models, LUM had significant inverse associations with MVPA and LVPA; associations were attenuated, but still significant in fully adjusted models. Greenness index had significant inverse associations with MVPA in fully-adjusted models and with LVPA in age - adjusted model only. In age and fully adjusted models, walkability index had consistent inverse associations with MVPA and LVPA, though the magnitude of effects was small.

6.4.3 Built Environment Associations with MVPA, Stratified by On-Trail and Off-Trail Location

For minutes that occurred both on and off trails, there were statistically significant positive associations between population density and MVPA (Table 6.3). In both cases, the magnitude of associations was relatively small with odds ratios of 1.06 and 1.04, respectively. Street density had a significant inverse association with MVPA for minutes occurring off-trail, but had a null association for on-trail minutes. For monitoring minutes occurring on-trail, there was statistically significant inverse associations between LUM and MVPA, but no association was found for minutes off-trail. Greenness index had a significant inverse association with MVPA for off-trail monitoring minutes, but had a null association for on-trail minutes. For on and off trail locations, there were statistically significant inverse associations between walkability and MVPA, with odds ratios of 0.97 and 0.98, respectively.

6.5 Discussion

This study utilized accelerometer and GPS monitoring of adults in Massachusetts to more directly link built environment exposures to physical activity. In an analysis that examined relationships between built environment characteristics within 50-meter buffers and minute-by-minute measures of physical activity, population density was positively associated with MVPA and LVPA. Alternatively, street density, LUM, and walkability index within these small buffers were inversely associated with MVPA and LVPA. For monitoring minutes that occurred both on and off trails, population density had consistent positive associations with MVPA, while the walkability index was inversely associated

Table 6.1 Participant (N=141) and built environment characteristics

	N
Age, n (%)	
19-29 years	19 (13.5)
30-39 years	37 (26.2)
40-49 years	36 (25.5)
50-59 years	32 (22.7)
≥ 60 years	17 (12.1)
Gender, n (%)	
Female	75 (53.2)
Male	66 (46.8)
Race, n (%)	
White	102 (72.4)
Non-white	39 (27.6)
Education	
Undergraduate degree or less	80 (56.7)
Some graduate or graduate degree	61 (43.3)
Activity, mean min per person (SD)	
MVPA	53.7 (31.5)
Light physical activity	44.1 (35.7)
Sedentary behavior	65.6 (67.1)
Built environment, mean (SD)	
Population density per sq. km	3330.2 (2611.8)
Street density per sq. km	16.2 (3.7)
LUM	0.18 (0.09)
Greenness index	0.21 (0.10)
Walkability index	0.70 (2.98)

Note: * African-American or Black, Asian, Native Hawaiian or other Pacific Islander

Table 6.2 Associations between built environment variables and moderate-to-vigorous physical activity (MVPA) and light-to-vigorous physical activity (LVPA) (N=60,342)

	MVPA				LVPA			
	Age-adjusted models[a]		Fully-adjusted model[b]		Age-adjusted models[a]		Fully-adjusted model[b]	
Covariates	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Built environment characteristics within 50 m buffer around each minute of activity								
Population density (1000 people per sq. km)	1.00	1.00, 1.01	1.04	1.03, 1.05	1.00	0.99, 1.00	1.02	1.01, 1.03
Street density (10 km per sq. km)	0.66	0.63, 0.69	0.67	0.64, 0.70	0.75	0.73, 0.77	0.78	0.76, 0.81
LUM	0.54	0.46, 0.63	0.69	0.59, 0.81	0.54	0.47, 0.61	0.67	0.59, 0.76
Greenness index	0.85	0.70, 1.04	0.59	0.48, 0.73	1.27	1.08, 1.49	0.91	0.77, 1.07
Walkability index	0.97	0.97, 0.98	0.98	0.97, 0.98	0.97	0.97, 0.98	0.98	0.97, 0.98

Note: [a] Each built environment variable was first examined separately in age-adjusted models. [b] One fully-adjusted model included age, race, on-trail monitoring minutes, population density, street density, LUM, and greenness. A second fully-adjusted model included the same covariates and the walkability index. OR = odds ratio. 95% CI = 95% confidence interval.

Table 6.3 Associations between built environment variables and moderate-to-vigorous physical activity by on-trail and off-trail location

	On-trail (n=10,531)		Off-trail (n=49,811)	
Covariates	OR	95% CI	OR	95% CI
Built environment characteristics within 50 m buffer around each minute				
Population density (1000 people per sq. km)	1.06	1.02, 1.10	1.04	1.03, 1.05
Street density (10 km per sq. km)	0.89	0.78, 1.01	0.66	0.63, 0.69
LUM	0.46	0.29, 0.72	0.88	0.74, 1.05
Greenness index	0.84	0.48, 1.48	0.52	0.42, 0.64
Walkability index	0.97	0.96, 0.99	0.98	0.98, 0.99

Note: One fully-adjusted model included age, race, population density, street density, LUM, and greenness. A second fully-adjusted model included the same covariates and the walkability index. OR = odds ratio. 95% CI = 95% confidence interval.

with MVPA. Street density and greenness index were inversely associated with MVPA at off trail locations. In contrast, LUM was inversely associated with MVPA only for activity on trails.

The results from the present study on positive associations between population density and MVPA are consistent with previous studies using accelerometer and GPS data [38, 88, 192]. For example, in a study examining relationships between population density and minute-by-minute MVPA among female adolescents in San Diego and Minneapolis, researchers found that higher population density was associated with 1% and 4% greater odds of MVPA, respectively [38]. Another recent study using accelerometer and GPS units among adolescents indicated that residential density within 1 km of home was positively associated with walking [192]. In addition, an earlier analysis of the same sample of adults used in this study, which took a more home-centric approach, found that residential population density was positively associated with MVPA occurring within 1 km of home and work buffers [88]. The results from the previous studies [38, 88, 192] and our study indicated that those who reside in highly populous areas tend to engage in more MVPA.

In our study street density was inversely associated with MVPA and LVPA, findings that are not consistent with a recent review on influences of the built environment on walking and bicycling within residential areas [197]. Overall the authors of the review study reported that street connectivity or density is positively associated with transportation and recreational walking and transportation bicycling [197]. In contrast, a recent study examining associations of street connectivity with walking patterns among the elderly in Bogota, Columbia, indicated that greater connectivity was inversely associated with walking [198]. The researchers concluded that more intersections and busy streets could be related to a perceived risk of traffic accidents among older adults [198]. Another recent literature review on the built environment and pedestrian safety documented that higher cross-street density is directly related to pedestrian crashes and traffic volumes are consistently associated with higher pedestrian injuries [199]. A possible explanation for the inverse association between street density and physical activity in the present study could be that participants who were physically active may intentionally avoid areas with more intersections and busy streets to engage in physical activity.

LUM showed similar inverse relationships with both MVPA and LVPA. Two review studies reported that associations between LUM and recreational physical activity and walking were generally weak or null [13, 71]. Contrary to the hypothesized direction of effects of LUM on physical activity, a recent study investigating relationships between LUM and transportation physical activity among Brazilian adults showed that greater LUM was negatively associated with bicycling for transportation (OR = 0.52, 95% CI = 0.31 - 0.81) [200]. Additionally, a recent study examined a potential mismatch between perceived and objectively measured LUM and self-reported measures of walking for recreation and transportation among adults in Australia [201]. Researchers found significant discordance between objective and perceived measures of LUM [201]. Among 42% of participants' perceptions of LUM did not agree with objectively measured LUM [201]. They concluded that perceiving high LUM as low walkable environments is significantly related to less walking [201]. Conversely, perceiving low LUM as high walkable environments is associated with higher levels of walking [201]. A possible explanation for the inverse associations found for LUM in the present study might be that participants' perceptions do not align with the objective measures and perceptions may be driving their physical activity behavior.

Our finding on inverse associations of greenness index with MVPA was inconsistent with recent studies with youth that used accelerometer and GPS assessments [39, 202]. These studies found positive associations of NDVI [39] and greenspaces [202] with MVPA. One general assumption with greenness is that the attractiveness of the scenery (e.g., trees, grass) would be conducive to engaging in outdoor physical activity. A possible explanation for these findings may be that some participants might prefer to be near water areas to engage in physical activity. However, areas with water areas are an indication of negative values in the greenness index. In addition, the greenness index is measured using satellite images and these can be influenced by weather conditions when they were taken. These two factors (water bodies and the weather conditions) might account for the inverse relationships between greenness and MVPA.

The results from the present study indicating that walkability is inversely associated with MVPA was inconsistent with a recent review study [203]. This review study indicated that high walkability encourages more MVPA among adults, by factors influencing the walkability index, such as presence or nonexistence of parking, sidewalks, or LUM, community trails or paths, safety, or intersection density [203]. Additionally, a recent study on neighborhood walkability and GPS-derived physical activity among adolescents found that higher walkability was positively associated with walking and bicycling time [192]. In our study, the walkability index was based on the combination of population density, street density, and LUM. Although population density was positively associated with MVPA and LVPA, street density and LUM were negatively associated with MVPA and LVPA. Thus, the combination of street density and LUM might have driven inverse associations of walkability index with MVPA and LVPA.

The strength of the present study is the concurrent use of accelerometer and GPS units to spatially contextualize immediate environments where physical activity takes place. . This dynamic approach addressed one key limitation in built environment research, which is the mismatch between environmental exposures and physical activity. The majority of the built environment studies have focused on an area around residential areas. However, an individual's activity is not limited to locations around home. The present study spatially contextualized any locations where physical activity occurs. This approach has been supported by recent built environment studies [29, 86, 188].

There are several limitations that should be addressed regarding the study sample, and GPS and accelerometer measures in this study. Participants were mostly white and resided in the City of Boston, Massachusetts. Their daily mobility may differ from individuals from rural areas. Thus, the findings from this study are not generalizable to those who live away from urban areas in Massachusetts. Data used in this study only monitoring minutes with GPS coordinates linked to accelerometer counts. It is likely that outdoor monitored minutes in metropolitan areas in Boston, and under tree canopy, as well as indoors may impede GPS satellite signals. Therefore, GPS coordinates would be missing, which may bias the estimated associations. Since only GPS monitoring minutes with geographic coordinates were used in this study, indoor activities occurring at locations such as fitness centers and shopping malls were not included in the analyses.

6.6 Conclusion

Use of accelerometer data linked to geographic coordinates through GPS units allowed us to investigate relationships between objectively measured built environment around GPS points and minute-by-minute physical activity. The results of the present study are consistent with previous studies examining associations between population density and physical activity. However four other built environment variables were inversely associated with physical activity, in contrast to prior evidence. A potential explanation for the contradictory findings may be that adults who frequently used trails and generally engaged in higher levels of physical activity, sought out environments with less dense roads and streets and less commercial activity [199]. Differences in some associations for on and off trail locations indicate that built environment variables may have different relationships with physical activity depending on the specific environmental context. Further research is needed to investigate places where objectively measured physical activity takes place and associations with built environment exposures at those locations.

CHAPTER 7. DISCUSSION

7.1 Summary

The research in this dissertation broadly focused on the built environment and physical activity using three distinct approaches. These included testing for spatial clustering of self-reported physical activity and obesity among older women in three U.S. states, examining relationships between objective measures of trail use and physical activity among Massachusetts adults, and investigating associations between the built environment and minute-by-minute physical activity using a combination of accelerometer, GPS unit, and GIS methods. Collectively, these studies contribute to the area of built environment and physical activity research both methodologically and add to the current evidence base.

The first study demonstrated the utility of spatial clustering analysis for physical activity and obesity among older women in the U.S. Prior to this study, researchers had only tested age and race as variables that could possibly account for spatial clusters of physical activity and obesity. The present study tested additional covariates, such as education, income, and walking limitations that might explain spatial clusters. Most covariate adjustments did not change the size or location of spatial clusters. Further research is needed to better understand socio-demographic factors that might account for the development of physical activity and obesity clusters. In addition, comparisons of the built environment characteristics inside and outside of clusters demonstrated that population density and intersection density were greater in higher physical activity clusters. This finding was consistent with a previous study examining spatial clusters of active transportation among adults in California [1]. Also, application of spatial clustering methods to various population sub-groups (based on age, gender, race and ethnicity) and in more diverse geographic areas within the U.S. may yield better understanding of how physical activity and obesity spatially cluster in relation to built environment characteristics. Finally, given the low prevalence of U.S. adults meeting physical activity guidelines and having a healthy weight, spatial clustering techniques may also have broad applicability for identifying areas where public health resources need to be devoted.

The second study examined relationships between objective measures of trail use and physical activity and sedentary behavior using accelerometers and GPS units. The intensity of activity occurring on-trail was also quantified using two approaches, one based on accelerometer counts only and the other based on a combination of GPS speed and count data. Overall, this study demonstrated significant positive associations between trail use and total, vigorous, moderate, and light physical activity and an inverse relationship with sedentary behavior. Findings from this study also indicated that the combination of accelerometer and GPS speed data could be used to refine classification of physical activity intensity on trails since activities such as bicycling would tend to be classified as low intensity if based on accelerometer counts only. Further research is needed to determine the benefits of using accelerometer and GPS output to classify physical activity intensity in specific outdoor settings such as trails.

The findings from this study demonstrate the utility of simultaneous monitoring of physical activity with accelerometers and GPS units in specific outdoor settings such as trails and parks; more specifically this study demonstrated that trail use was positively associated with physical activity. Since most previous trails and physical activity research has relied on self-reported measures, future studies should build on the objective methods used in this study in order to better understand how trails support physical activity.

Using the same data collected for study 2 via accelerometer and GPS monitoring of 141 adults, the third dissertation analysis focused on the relationships between built environment characteristics within small buffers and minute-by-minute physical activity. The finding of positive relationships between population density and physical activity were consistent with previous studies using accelerometers and GPS data [2-4], as well as studies using less-spatially dynamic methods (i.e., those focused on a buffer around home). However, findings of inverse associations between street density, LUM, greenness, and walkability and physical activity outcomes were generally inconsistent with results from previous studies [5-7]. A plausible explanation may be that most previous studies have focused on an area around the home residence and have assumed that most, if not all activity, occurs near home. An individual's daily mobility, however, is not restricted to the area near home. If all locations where people circulate in their environment are studied, the relationships between built environment characteristics and physical activity may be different than what has been traditionally found. The findings from this study seem to provide initial evidence that this be the case.

7.2 Strengths and Limitations

A general strength of this dissertation research is that it expanded upon methods (e.g., spatial clustering analysis, simultaneous monitoring of physical activity with accelerometers and GPS) that have just started to find their way into built environment studies and addressed several unique questions in each of the three studies undertaken. The first study not only identified spatial clusters of physical activity and obesity, but it also attempted to address the question of whether or not built environment characteristics would be different inside and outside clusters. To our knowledge, there was limited research on this topic prior to this study. Findings indicated that certain built environment characteristics, such as population density and intersection density, were higher in some high physical activity clusters, but this depended on the location of the clusters. It has been noted previously that more and more studies are using GPS and accelerometer monitoring to identify locations where physical activity occurs, as well as to examine relationships between the built environment and physical activity. However, in dissertation studies 2 and 3 we expanded the types of questions being addressed in studies using accelerometers, GPS, and GIS methods. A strength of study 2 was that it examined trail use in relation to light physical activity, in addition to moderate and vigorous physical activity. This is significant given the growing evidence that engaging in light physical activity may confer important health benefits, such as cardiometabolic health [8, 9] and psychosocial health [10, 11]. Previous trail studies have used self-reported data and focused on MVPA only. A second strength of this study was classification of intensity of physical activity on-trail, based on a combination of accelerometer counts and GPS speed. Although this approach needs further testing, it could eventually help to better quantify intensity of activity on-trails and other outdoor settings. Also as noted earlier, the majority of previous built environment studies have exclusively focused on residential areas as the relevant areas for built environment exposures, based on the implicit assumption that most physical activity occurs within those areas [12-14]. This dissertation research used accelerometer, GPS, and GIS to avoid this potential spatial mismatch between built environment exposures and physical activity. The third study specifically examined associations between the built environment around each monitoring minute and minute-by-minute physical activity.

There are several limitations in this dissertation research. One of the common issues related to spatial clustering techniques is geographic scale. This research tested for spatial clustering of physical activity and obesity at the county level. However, the actual clustering may not emerge within such a broad geo-political boundary. To better understand how physical activity and obesity spatially cluster, analyses may need to be performed at a finer geographic scale, such as at the census-tract or census-block level. A limitation with studies 2 and 3 is that many accelerometer monitoring minutes did not have GPS data. Missing GPS data could be due to several factors, ranging from running out of battery life, to trees or buildings blocking satellite signals outdoors, to being indoors where signals were blocked completely [15]. The associations between trail use and physical activity (study 2) and between built environment variables within 50 meter buffers and minute-by-minute physical activity may have been biased by these missing data. Future research could incorporate imputed GPS data into analyses to better understand activity occurring at any locations. Future research needs to develop better monitoring devices which could measure both indoor and outdoor activities to overcome these technology-related limitations.

7.3 Implications

The findings from the dissertation have implications for future physical activity and built environment research. Physical activity researchers should consider testing for spatial clustering of physical activity and obesity at finer geographic levels and/or involving diverse populations and study areas. Findings from such studies could be used to design and implement location-oriented interventions to promote physical activity and reduce obesity. Based on the findings of studies 2 and 3, researchers should continue to examine the relationship between objective measures of trail use and physical activity and sedentary behavior using accelerometer and GPS data. Such work would contribute to our understanding of how trails support physical activity. While study 2 did examine how trail use is related to light physical activity, study 3 did not. Given the recent evidence of the protective effects of light intensity activity on individual health [16], future investigations should be conducted to better understand the locations where light intensity physical activity may occur.

Taken together, the three studies reported in this dissertation – examining associations between the built environment and physical activity from analyses of spatial clustering, use of trails, and locations where physical activity takes place – contribute to our understanding of the relationship between the built environment and physical activity. These analyses should be used to inform further research on these topics; and eventually lead to the design and implementation of more effective location oriented physical activity interventions.

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APPENDICES

Appendix A for Study 2

```
/* Outcome and covariates
Participant's ID:
Filename

Outcomes:
Total = Daily mean physical activity count per min per day
Vigorous = Vigorous intensity activity person-day
Moderate = light intensity activity person-day

Covariates:
Age (continuous)
Gender: Male = 1, Female = 0
Race: Whites = 1, Non-whites = 0
Education: Undergraduate degree or higher = 1, less than undergraduate
degree = 0

Ontrail: Monitoring minutes occurring on(=1)or off(=0)trail.

Site: Cutler Reservation, Franklin Park, Minuteman Bikeway, Nashua
River Rail Trail, Southwest Corridor = 6

*/
/* Intercept only model for intraclass correlation coefficient */
proc mixed data = Kosuke_study2 noclprint covtest info method=ml;
class  Filename;
model  Outcome = / s ddfm = bw;
random Intercept / subject=Filename type = un;
run;

/* Age adjusted model */
proc mixed data= Kosuke_study2 noclprint covtest info method=ml;
class  Filename ontrail;
model  Outcome = ontrail age /s ddfm=bw cl ;
random Intercept ontrail /subject=Filename type=un;
run;

/* Fully adjusted model */
proc mixed data= Kosuke_study2 noclprint covtest info method=ml;
class  Filename ontrail gender race education site weekday;
model  Outcome = ontrail age gender race education site weekday/s
ddfm=bw cl;
random Intercept ontrail /subject=Filename type=un;
run;
```

Appendix B for Study 3

```
/*VARIABLES USED IN MODELS
Outcome = MVPA, LVPA
IV:
Population density
Street density
LUM
NDVI_avg
Walkability

Covariates:
Age = age in years
Whites = Whites = 1, Non-whites= 0
Ontrail = monitoring minutes on(=1) and off(=0) trails


Class:
filename = Participant's ID
Episode = Episode of activity nested in participants
Interval = Interval of activity nested in episode, which is nested
within participants
*/

/*Age adjusted model */
proc glimmix data= Kosuke_final;
class Filename Outcome Episode Interval ;
model Outcome(desc) = IV age / distribution=binary link=logit solution
oddsratio ddfm=satterthwaite;
random Interval / subject=Filename*Episode type=ar(1);
run;

/*Fully adjusted model */
proc glimmix data= Kosuke_final;
class Filename Outcome Episode Interval Whites Ontrail;
model Outcome(desc) = IV age Whites Ontrail/ distribution=binary
link=logit solution oddsratio ddfm=satterthwaite;
random Interval / subject=Filename*Episode type=ar(1);
run;

/*Stratified model */
proc glimmix data=Kosuke_final;
class Filename Outcome Episode Interval Whites Ontrail;
by Ontrail;
model Outcome(desc) = IV age whites / dist=binary link=logit solution
oddsratio ddfm=satterthwaite;
random Interval / subject=Filename*Episode type=ar(1);
run;
```

VITA

VITA

Kosuke Tamura

EDUCATION

Doctor of Philosophy in Health and Kinesiology, 2015
Purdue University, West Lafayette, Indiana
Emphasis: Health promotion and health behavior
Advisors: Drs. Philip Troped, Robin Puett, David Klenosky, William Harper, and Hao Zhang

Master of Science in Agricultural Economics, 2008
Purdue University, West Lafayette, Indiana
Emphasis: Health and spatial economics
Advisors: Drs. Raymond Florax and Susan Chen

Master of Arts in International Affairs, 2005
Ohio University, Athens, Ohio
Emphasis: African economic development and environmental economics
Advisor: Dr. Ariaster Chimeli

Bachelor of Laws in Political Science, 2002
Komazawa University, Tokyo, Japan
Emphasis: International relations and development
Advisor: Dr. Motoko Shuto

ADDITIONAL TRAINING

Spatial Econometrics Advanced Institute (non-degree), June 2008
University of Rome, La Sapienza, Rome, Italy

ACADEMIC & PROFESSIONAL HONORS

Fellowship

American Heart Association Predoctoral Fellowship (Midwest Affilitate), 2011 - 2013

Awards

The Judy Kay Black Graduate Student Scholarship Award, 2014
Department of Health and Kinesiology, Purdue University

Physical Activity Special Primary Interest Group Student Abstract Award, 2011
American Public Health Association

Grants

Donald L. Corrigan Professional Development Grant, 2013
Department of Health and Kinesiology, Purdue University

Purdue Graduate Student Government Travel Grant, 2011
Purdue Unviersity

Graduate School Fellowship Incentive Grant, 2011
Purdue University

Donald L. Corrigan Professional Development Grant, 2008
Department of Health and Kinesiology, Purdue University

RESEARCH EXPERIENCE

American Heart Association Predoctoral Fellow, 2011 - 2013
Sponsor: Dr. Philip Troped, Department of Health and Kinesiology, Purdue University

- Examined spatial clusters of physical activity and obesity among the Nurses' Health Study (NHS)

Graduate Research Assistant in Physical Activity and Public Health, 2008 - 2011
Advisor: Dr. Philip Troped, Department of Health and Kinesiology, Purdue University

- Investigated associations between objectively measured built environment factors and both physical activity and obesity among NHS participants from California, Massachusetts, and Pennsylvania
- Examined relationships between perceived neighborhood environmental attributes and physical activity among NHS II participants

Graduate Research Assistant in Environmental Epidemiology, Summer 2010
Advisor: Dr. Frank Rosenthal, School of Health Sciences, Purdue University

- Examined temporal effects of air pollution on myocardial infarction among adults in Finland

Graduate Research Assistant in Spatial Economics, 2006 - 2008
Advisors: Drs. Raymond Florax and Susan Chen, Department of Agricultural Economics, Purdue Univeristy

- Investigated uninsured populations and hospital competitions in the U.S.
- Examined spatial relationships between densities of fast-food and full-service restaurants and body mass index in Marion County, Indiana

PUBLICATIONS

Peer-Reviewed Journal Articles

Published

K. Tamura, R.C. Puett, J.E. Hart, H.A. Starnes, F. Laden, and P.J. Troped. "Spatial clustering of physical activity and obesity in relation to built environment factors among older women in three U.S states." *BMC Public Health*. 2014; 14(1):1322.

H.A. Starnes, M.H. McDonough, **K. Tamura**, P. James, F. Laden, and P.J. Troped. "Factorial validity of an Abbreviated Neighborhood Environment Walkability scale for Seniors in the Nurses' Health Study." *International Journal of Behavioral Nutrition and Physical Activity*. 2014; 11(1):126.

P.J. Troped, H.A. Starnes, R.C. Puett, **K. Tamura**, E.K. Cromley, P. James, E. Ben-Joseph, S.J. Melly, and F. Laden. "Relationships between the built environment and walking and weight status among older women in three U.S. states" *Journal of Aging and Physical Activity*. 2014; 22 (1):114-125.

P.J. Troped, **K. Tamura**, H.A. Whitcomb, and F. Laden. "Perceived built environment and physical activity in U.S. women by sprawl and region." *American Journal of Preventive Medicine*. 2011; 41(5): 473-479

Monograph

K. Tamura and A. B. Chimeli. *The Demand for Solid Waste Collection in Accra: A Willingness to Pay Study*. 2008. Germany: Verlag Dr. Müller. ISBN-10: 3836487519.

CONFERENCE PRESENTATIONS

Oral Presentations (*Presenter)

K. Tamura,* R.C. Puett, H.A. Starnes, J.E. Hart, F. Laden, and P.J. Troped. "Are overweight and obesity clustered? Spatial examination of older women in three U.S. states." The 23rd Congress of the International Society for Environmental Epidemiology, Barcelona, Spain, September 14, 2011.

H. A. Whitcomb,* E. K. Cromley, **K. Tamura**, S. J. Melly, F. Laden, P. James, R. Puett, E. Ben-Joseph, and P. J. Troped. "Validation of a commercial geographic information system database of walking destinations" The 2009 Society for Advancement of Chicanos and Native Americans in Science (SACNAS) National Conference program, Dallas, TX, October 15-18, 2009.

P.J. Troped,* F. Laden, H.A. Whitcomb, **K. Tamura**. “Perceptions of the built environment, walking and BMI in a large cohort of US women.” American College of Sports and Medicine 56th Annual Meeting, WA, May 2009.

S. Chen, **K. Tamura**,* R.J.G.M. Florax, G.H. Avery. “Hospital competition and uncompensated care.” The 2nd World conference of the Spatial Econometrics Association, NYC, NY, November 19, 2008.

S. Chen, **K. Tamura**,* R.J.G.M. Florax, G.H. Avery. “Proximity to uninsured populations and hospital services in the U.S.” Eureka seminar series, the Vrije Universiteit, Amsterdam, the Netherlands, May 18, 2008.

Poster Presentations

K. Tamura, R.C Robin, D.B. Klenosky, W.A. Harper, H. Zhang, and P.J. Troped. “Spatial clustering of objectively measured physical activity in Massachusetts adults: Preliminary findings.” Thematic presentation in the American College of Sports Medicine 61st Annual Meeting, Orlando, FL, May 28, 2014.

K. Tamura, R.C. Puett, J. E. Hart, H. A. Starnes, F. Laden, and P.J. Troped. “Comparisons of built environment characteristics inside and outside spatial clusters of physical activity and obesity in older U.S. women,” Moderated presentation in the Epidemiology and Prevention | Nutrition, Physical Activity and Metabolism 2013, Scientific Sessions, New Orleans, LA, March 20, 2013.

K. Tamura, R.C. Puett, H. A. Starnes, J. E. Hart, F. Laden, and P.J. Troped. “Does physical activity spatially cluster? Preliminary findings from an analysis of older women living in three states.” The 113 American Public Health Association, Washington, D.C., November 2, 2011.

H.A. Whitcomb, P.J. Troped, **K. Tamura**, S. Orstad. “Accelerometer validation of the International Physical Activity Questionnaire among community trail users.” American College of Sports Medicine 57th Annual Meeting, Baltimore, MD, June 2010.

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MANUSCRIPT REVIEWER (Number of times in prentheses if > 1)

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COMPUTER SKILLS

MS-Word, Excel, PowerPoint, SAS, ArcGIS, SaTScan, STATA, R

LANGUAGES

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