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Planning for Human Wellbeing: New Research Evidence in Built Environment, Travel Behavior,
and Physical Activity

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Abstract

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This dissertation is a collection of research on built environment, travel behavior, and physical activity, with an emphasis on understudied populations, behaviors, and urban spaces.

It consists of three studies. The first study assessed how transit stop amenities (e.g. shelter, real-time information system, etc.) as combinations of design elements, affect stop-level ridership using a quasi-experiment design and conditional inference tree models. The second study constructed and validated a state-wide walkability index and an estimated percentage of walking for all K-8 schools in Washington State using student travel survey. The third study examined whether income relates to the wealth of where people walk using Global Positioning System (GPS), accelerometry, and travel diary data.

The three studies tackle important yet unresolved domains in built environment, travel behavior, and physical activity studies, including:

- *the collinearity of built environment elements,*
- *the interaction between different populations and built environment, and*
- *the measurement of exposure to built environment.*

As a whole, this dissertation adds to the understanding of the environment-behavior relation and generates evidence that supports equitable urban design and planning interventions targeting mobility and wellbeing.

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DEDICATION

To Xiaomei and Mingshan.

CHAPTER 1. Introduction

1.1 Problem Statement

1.1.1 Built Environment, Travel Behavior, and Physical Activity

Physical inactivity has been a major health challenge in the U.S. for decades due to its high prevalence and causal relationship with a series of medical complications, such as cardiovascular diseases and diabetes (Bhaskaran et al., 2014; Tobias et al., 2014). Daily travel that involves active transportation, such as that by walking and public transit, constitutes an important source of physical activity needed for otherwise non-active individuals and has the potential to increase physical activity at the population level (Blacklock et al., 2007; Pucher et al., 2010; Davis, 2010, 2014; Sinnett et al., 2011). It has been well-accepted that engaging in walking trips is associated with more physical activity and lower body weight (Faulkner et al., 2009). Similarly, public transit users engage in more daily physical activity than nonusers and are more likely to meet physical activity recommendations, from active travel to and from transit stops (Freeland et al., 2013; Saelens, Moudon, et al., 2014). In addition, as these travel modes do not entail major investments at the individual level, they have significant meaning for low-income and minority groups (Besser & Dannenberg, 2005).

A wide range of factors have been identified to influence people's daily travel, including the socio-political environment (e.g. social support and media coverage), personal factors (e.g. age, gender, and employment), the natural environment (e.g. weather and slope) and the built environment (e.g. street connectivity and land use) (Wang et al., 2016). As many have noted, increasing attentions have been drawn to the role of built environment on travel behavior and

physical activity, with the recognition of its sustained nature, broad reach, and the potential to bring substantial behavioral changes at the population level (Smith et al., 2017).

A rich literature exists that converges on the objectively measurable physical characteristics of the environmental determinants of walking. For utilitarian walking, the agreement is that it takes place in areas with higher development density, more destinations clustered together, and smaller street blocks that ensure route directness between a trip origin and its destination (Frank et al., 2008; Saelens & Handy, 2008). For recreational walking, the activity occurs in more scenic areas, along bodies of water, and where there are views (Kang et al., 2017; C. Lee & Moudon, 2006b). For public transit use, higher ridership is observed in areas similar to that of utilitarian walking (Gan et al., 2020).

The diagram in Figure 1.1 summarizes the conceptualization of the relation between built environment, travel behaviors, and physical activity in existing literature. Travel behaviors (i.e. travel mode, route, duration, time etc.) are often understood as the result of the interplay between personal factors and the built environment. As laid out in Table 1.1, the temporal scale of this relation could be as micro as momentary responses (e.g. physiological responses to environmental triggers such as traffic signals) or accumulatively (e.g. shopping trip routines for residents living in walkable neighborhoods) or across the lifespan (e.g. influence from experiences in childhood). So is the spatial dimension, in that the built environment of interest could be at the micro-scale (e.g. accessible ramp and lighting), neighborhood-scale (e.g. street connectivity, transit access), or as macro as the urban spatial structure (e.g. multi-centric cities). The spatiotemporal scale which many urban design and planning interventions on mobility and wellbeing target are the neighborhood scale and accumulated behaviors over time. Accumulated behaviors here refer to routine and habitual behaviors that are a result of personal conditions

interacting with the physical and social environment over a period of time (Clark, 2000).

Planners aim to shift people's travel habits (e.g. enabling them to take more walking trips or to practice active commuting) by making neighborhood environment more supportive of such behaviors.

Environmental exposure, which is the contact between people and their immediate environment, is another important concept in this relation (Lioy & Smith, 2013). It is the direct result of moving through space or taking trips. It in turn influences the experience of travel and the trips taken immediately after (e.g. walkability and transit access at previous trip destination may impact the mode choice for the trip after) (Chaix et al., 2016). In addition to impacts on travel, the environment people are exposed to as part of their daily mobility also impacts other aspects of wellbeing, such as access to food, parks, and opportunities to socialize (Krieger et al., 2003; Scully et al., 2019; O. T. Stewart, Moudon, et al., 2016). Therefore, the exposure to built environment also has broader implications on health and health equity.

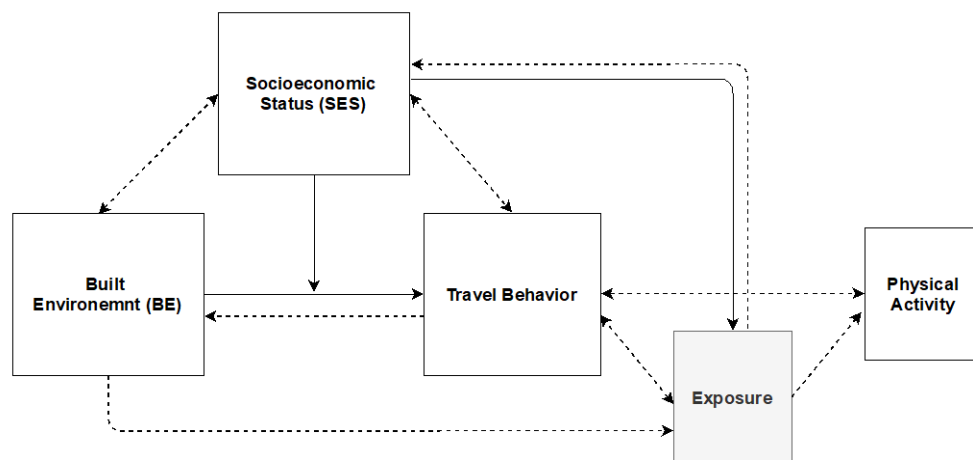


Figure 1.1 Concepts Structuring the Relation of Built Environment, Travel Behavior, and Physical Activity

Note: solid arrows show relations examined in this dissertation.

Table 1.1 Spatiotemporal Scale of Built Environment-Travel Behavior Relation

	Spatial scale	Temporal scale
Micro	• Design features <i>e.g. accessible ramp and lighting</i>	• Momentary <i>e.g. physiological responses to environmental triggers such as traffic signals</i>
Meso	• Neighborhood characteristics <i>e.g. street connectivity, transit access</i>	• Accumulative <i>e.g. grocery shopping trip routines</i>
Macro	• Urban spatial structure <i>e.g. multi-centric cities</i>	• Life-course <i>e.g. influence from experiences in childhood</i>

1.1.2 Domains of Study

This dissertation contributes to the existing body of literature on the relationship between built environment, travel behavior, and physical activity, with a particular focus at the neighborhood level and on accumulative behaviors formed overtime. The focus is on the following three domains: (1) collinearity of built environment elements, (2) interaction between different populations and built environment, and (3) measurement of exposure to built environment. The definition for each domain and the motivations for tackling them are explained as follows.

The first domain is the *collinearity of built environment elements*. Collinearity refers to the existence of linear relations between two or more independent variables, usually in a regression-type analysis (García et al., 2015). Built environment elements, whether at the neighborhood-scale (e.g. residential density, land use mix) or more micro-scale (e.g. pedestrian infrastructure, street trees) are often correlated in everyday environment (Leal et al., 2012; Moudon et al., 2019). For example, places with higher residential density also tend to have more

destinations and transit access (C. Lee & Moudon, 2006a; Mooney et al., 2020). It is difficult to single out the effect of one individual element on health and wellbeing or to change only one single element at a time. The change to one built environment element (e.g. residential density) is often followed by changes in others (e.g. number of transit stops, number of restaurants). Some interventions targeting built environments are also bundled, for example the improvement of sidewalk paving, addition of traffic signals, and accessible ramp are often planned at the same time. Treating built environment elements as if they were independent from each other results in biased estimates of the effect size and unreliable statistical significance (Huang, 2014). A number of studies begin to test methods to address the collinearity of built environment features, such as the use of principle component analysis (S. Lee et al., 2020), which create uncorrelated latent variables based on existing built environment variables. Other methods include those using different variable selection techniques to exclude variables with high correlation (Mooney et al., 2017, 2020; Moudon et al., 2019). However, the cases are still limited and the pros and cons of each method in the setting of built environment studies have not been compared and synthesized.

The second domain is how *different populations*, especially disadvantaged populations, *interact with the built environment*. Much of the current consensus on walking environment and research findings used to inform relevant interventions are based on evidence drawn from adult middle- to upper-income population that dominates the bulk of existing studies. In the last two decades, there is growing evidence on other populations (e.g. children and people of lower income), with an increased recognition that they may experience and interact with built environment differently from what the mainstream literature has captured. However, despite the increasing number of studies, much of the understanding of differences between population groups is still scant in the area of built environment and physical activity. There is only one

systematic review published to date that has considered the difference in relation with built environment by socioeconomic status (SES) (Schüle & Bolte, 2015), which found mixed results and noted the challenge to conduct any quantitative review due to the limited study number and heterogenous study designs. Researchers also report observing more inconsistencies in studies on physical activity and active travel for children, partially due to the limited evidence base (Smith et al., 2017). Transit users are another group that are less studied. Existing transit studies have focused primarily on system efficiency and system-level factors (i.e. service frequency, pricing) and much less from the users' perspective on how they experience and interact with the transit system, such as at the transit stops and on the bus (Brown et al., 2006; J. Y. Kim et al., 2020; Talbott, 2011).

The third domain is the *measurement of exposure to built environment*. There have been two approaches commonly used in public health and geography research to measure environmental exposure. One is the “place-based” approach, which use home neighborhood (e.g. buffer around home address or the administrative boundary where home address locates in) to proximate the environment that a person is exposed to. This approach is easy to compute yet does not consider exposure beyond home neighborhood, which may lead to overlooking the variations in exposure (Kwan, 2018; Matthews & Yang, 2013) and overestimate the effect size of intervention targeting home neighborhoods (Chaix et al., 2017b). With the development of Global Positioning System (GPS), a “people-based” approach has become popular in the past decade, which capture behaviors and environmental exposure beyond home by tracking time, location, and path of movement (Chaix, 2018, 2020; Hurvitz et al., 2014a). When adopting these two approaches to measure the exposure to built environment in urban planning studies, two issues emerged. The first is the lack of a conceptual distinction between studies using the “place-

based” approach versus planning studies targeting specific locations for intervention development, such as studies on improving school environment and workplace. The second is the lack of planning and design interventions directly built upon “people-based” studies. These issues have not been explicitly discussed and examined.

1.2 Objectives

The objective of this dissertation is to add research evidence to the relation between built environment, travel behavior, and physical activity via the three domains identified above. First, it explores methodologies to address the collinearity of built environment elements. Second, it investigates the interactions between built environment and travel behavior among understudied population groups including transit riders, children, and low-income people. Thirdly, it applies the concept and measurement of environmental exposure to the study of built environment for walking and active travel. Jointly, the dissertation intends to add to the understanding of the environment-behavior relation and generates evidence that supports equitable urban design and planning interventions targeting mobility and wellbeing.

1.3 The Three Cases

The first study presented in Chapter 2 assessed how transit stop amenities (e.g. shelter, real-time information system etc.) as combinations of design elements, affect stop-level ridership. Transit stops are the first point of physical contact between users and transit systems and influence overall transit experiences. However, compared to system-level factors (e.g service frequency and pricing, etc) and external factors (e.g.: neighborhood residential density), the effect of transit stop amenities on ridership is rarely studied. This is likely due to the difficulty of collecting stop amenity data and a lack of interest in doing so. Unlike other service attribute such

as scheduling and ridership counters, stop amenities do not have an integrated data collection process and are often managed by multiple jurisdictions. As a result, data on stop constructions are not always readily available and may have inconsistency across jurisdictions. There is also a lack of interest in documenting stop amenity changes compared to more noticeable system-wide changes such as upgrading to new vehicles or increasing service frequency. In addition, the correlated nature of stop amenities makes it hard to model their effects using traditional regression methods (Brakewood et al., 2015; Mucci & Erhardt, 2018; Tang & Thakuriah, 2012; Taylor et al., 2009). The lack of quantification of the impact of stop amenities on transit ridership brings challenge to estimate the return of stop amenity investment during funding allocations, making it hard to compete with other capital investments or system-wide upgrades in transportation planning (Brown et al., 2006; J. Y. Kim et al., 2020; Talbott, 2011). Tree-based models, which have been used in statistics to model correlated variables, provide unbiased estimates of correlated stop features and are easy to interpret. The objective of this study was to provide empirical evidence on transit micro-environment and tests the use of tree-based models to study bundled micro-level built environment elements.

The second paper presented in Chapter 3 focused on the walking environment for active travel to school and developed a walkability index specific for children in Washington State. Walkability indices are often used to capture and compare walking environments across regions and populations. Regional and local active school transport promoting programs, such as Safe Route to School programs, could benefit from such information to assess school walking environment across a state and to help prioritize limited resources. So far, three studies have developed walkability indices specific for children (Christiansen et al., 2014a; Giles-Corti et al., 2011; S. Lee et al., 2020). They were based on a small number of schools in similar urban

contexts, and the results may not be applicable to a larger geographical scale. The objective of this study was to provide empirical evidence on a less studied population and a useful tool for regional and state-level programs targeting children.

The third paper presented in Chapter 4 used GPS, accelerometer, and travel log data to measure the wealth of walking environment for people with different socioeconomic status, with a focus on those with lower-income and on walking trips beyond home neighborhood. The intention is to examine whether there might be inequities in daily walking and specifically whether disadvantaged and minority populations might disproportionately access similarly disadvantaged environments while walking. Walking is considered a promising means of acquiring health-enhancing levels of physical activity (Berke et al., 2007; Frank et al., 2004). Under the premise that anyone able to walk should be able to do so anywhere, encouraging everyone to walk would fail to be equitable if where walking took place was restricted based on the socioeconomic characteristics of the walkers. Prior studies show that low-income and Hispanic populations typically reside in neighborhoods that are low in support for active lifestyle, suggesting they may also walk in less-favorable environments. However, these studies focus only on the home neighborhood environment, ignoring the significant amount of activities people take outside. The advent of Global Positioning Systems (GPS) and the collection of data on actual walking paths enables the examination of the entire environment people are exposed to throughout the day, thus may reveal hidden differences and disparities experienced by disadvantaged groups in their daily walking environment.

Each one of the three chapters is a standalone paper formatted for peer-reviewed publication. Jointly, they contribute to research evidence on the topic of built environment, travel behavior, and physical activity and adds to our understanding of unresolved domains of study

using innovative data and methodology. Chapter 5 analyzes and synthesizes the main findings and contributions from the three papers, lessons learned, and provides suggestions for future research.

CHAPTER 2. Does Improving Stop Amenities Help Increase Bus Rapid Transit Ridership? Findings Based on a Quasi-Experiment

Originally published in Transportation Research Interdisciplinary Perspectives (Shi et al., 2021)

2.1 Background

Public transportation serves multiple functions in American cities, including providing mobility (Jiao & Dillivan, 2013), combating traffic congestion (Choi, Jiao, and Zhang 2017), and supporting walking and active commute choices (Huang et al., 2017; Saelens, Vernez Moudon, et al., 2014; Sun et al., 2018, p.). Yet the use of public transportation remains lower than desired and national transit ridership has declined by 7% over the past decade (Mallett 2018). This study built upon literature and methodologies from transportation, public health, and urban design to understand the factors that influence public transportation ridership. The results not only inform transit agencies and operators develop cost-effective strategies to increase ridership, but also aim to encourage collaborations between the aforementioned fields in understanding the impact of micro-urban environment on travel behavior with machine learning methods.

2.1.1 Influences on Transit Ridership

Previous studies have categorized factors influencing the ridership of public transport systems into external and internal factors (Taylor et al., 2009). External factors are those that are beyond the control of transit systems and agencies, such as residential and employment density as well as sociodemographic characteristics of local potential users. Internal factors include system-level factors, such as level and quality of transit service, the location and distance between stops, and fare price, as well as stop-level amenities (El-Geneidy et al., 2006; Fabbiani

et al., 2018; Furth & Rahbee, 2000; Kikuchi & Miljkovic, 2001; Mucci & Erhardt, 2018).

Research to date has mostly focused on the effects of external factors (Chung, 1997; Gomez-Ibanez, 1996; Gutiérrez et al., 2011; Kain & Liu, 1999) and system-level internal factors (Brakewood et al., 2015; Mucci & Erhardt, 2018; Tang & Thakuriah, 2012; Taylor et al., 2009), rather than on stop amenities. Yet improving amenities, whether those essential to riders with mobility related disabilities such as ADA-compliant sidewalk or those making riding experience more pleasant such as shelters, is a relatively inexpensive way to upgrade transit services and it is popular among transit users and local agencies.

We are aware of only few peer reviewed studies and technical reports with direct quantitative evidence that stop amenities affect ridership in the US context. One study (Miao et al., 2019) revealed that having bus shelters mitigated ridership reduction under extreme hot, cold, and heavy rainfall conditions in the Salt Lake City metropolitan area. Another study (J. Y. Kim et al., 2020) using propensity score matching found that bus stops with improved amenities were associated with a significant increase in ridership in Salt Lake County; possible differences in impact by amenity type were not assessed. In North Carolina, Brown et al.'s team (Brown et al. 2006) created a Bus Stop Index to score amenities including signs, shelters, schedules, lighting, and paved landings, and found that the index was positively related to ridership. Finally, a multi-city study (Talbot, 2011) observed correlations between ridership and the presence of amenities in several cities; however, the absence of confounding variables in the analyses hindered the ability to make causal inferences.

2.1.2 Possible Effects of Added Stop Amenities

Although we know of few studies exploring amenity impacts on ridership, there is evidence that stop amenities influence many aspects of the transit use experience including

safety, accessibility, and thermal and visual comfort (Zhang, 2012). In particular, stop amenities may affect the perception of time spent waiting for transit and feelings of safety (Fan et al., 2016). The presence of shelters, benches, and mature trees at stops was found to significantly lower the perceived waiting time reported by passengers (Lagune-Reutler, Guthrie, Fan, & Levinson, 2016). In another study, the presence of shelters was found to be associated with higher crime incidence within 100 m of stops (Moudon, Bassok, & Kang, 2018). Real-time information system (RTIS) displays have been reported to reduce perceived waiting time (Dziekan & Vermeulen, 2006) and bring higher customer satisfaction (Science Applications International Corporation, 2003) in selected European and U.S. cities (Dziekan & Kottenhoff, 2007). In a survey of 749 transit passengers in Los Angeles County, they ranked transit stops being well-lit at night as one of the most important factors in their decision to use transit among 16 attributes of stops, while having a place to sit or buy food were ranked as least important (Iseki & Taylor, 2010).

2.1.3 Research Needs

Overall, few studies rigorously examined the impact of stop amenities on ridership, with most existing studies focusing on other service attributes such as frequency, travel time, and price. This is partially due to difficulties in collecting stop amenity and ridership data at fine spatial and temporal scales. It may also be that stop amenities are not changed or upgraded frequently enough and are often considered as inferior to other service attributes.

Studies exploring the effects of stop amenities have typically used additive models (Brown et al., 2006; Cervero et al., 2010; Fan et al., 2016; Lagune-Reutler et al., 2016), under the assumption that the impacts of individual amenities are independent and statistically identifiable (Hernán & VanderWeele, 2011). However, this assumption may not hold given that stop amenities are

typically installed in combinations (i.e., a shelter is added along with a new bench and a litter receptacle). From the experiential perspective, the effect of individual amenities may be difficult to isolate: sitting on a bench under a shelter is qualitatively different than the sum of standing under a shelter and sitting on an unsheltered bench. The bundling of stop amenity installations, which is commonly observed in real-world practice, presents a challenge to the traditional additive model approach. Moreover, in the literature we reviewed, except for Kim et al.’s study (2020), studies of bus stop amenities used cross-sectional data. The absence of more sophisticated research designs has hindered the inference of causal relations. Additionally, prior studies either focused solely on boardings or counted boardings and alightings jointly, thereby missing the opportunity to explore possible differences in the effect that amenities may have on boardings versus alightings as distinct behaviors.

This study addresses empirical gaps by examining the effect of upgrading transit stops with different sets of amenities on ridership following the conversion of regular bus routes to BRT service, which served as a quasi-experiment. As such, the study contributes to understanding the impact of stop-level internal factors on ridership. It also combines the use of the conditional inference tree (CIT) method with regression models to address the problem of correlated design features.

2.2 Methods

2.2.1 Study Setting

King County Metro, the regional transit authority, began implementation of its “RapidRide” branded BRT service in King County, Washington, in October 2010. The service replaces conventional bus service with all new diesel-electric hybrid high-occupancy vehicles

(HOV) operating on Business Access and Transit (BAT) lines (King County Metro Transit, 2019) and adds or upgrades amenities at each stop. Metro operates six RapidRide lines, named A through F. The two most recently converted lines, the E and F lines, were selected as the focus of this study. For both lines, the upgraded service was accompanied by substantial improvements to stop amenities made at similar time, which allowed us to use a quasi-experimental research design. The lines started operating on February 15th, 2014 and June 7th, 2014, respectively. The E line is 12.5 miles long and has 75 stops. The F Line is 12.8 miles with 59 stops.

The two lines serve different cities and neighborhoods (Figure 2.1) and replaced bus service that differed markedly. The E line operates along 3rd Avenue in Downtown Seattle, the state's largest employment center, and along Aurora Avenue North, a state highway lined with retail services, ending at the Aurora Village Transit Center, a suburban node. The route passes through neighborhoods with an average residential density of 18.3 units/ hectare, excluding the Downtown area. E line buses run throughout the day and every day of the week, with service headways as low as 5 min during peak hours and as high as 65 min around 4:00 a.m. (King County Metro Transit, 2019). Prior to the E line opening, Standard Metro Route 358 served this corridor and was the County's second busiest route, with an average of 11,730 riders on weekdays during the last month before the implementation of the Rapid Ride system (Lindblom, 2014).

In contrast, the F line operates between the City of Burien and 'The Landing' Center at Renton via Tukwila International Blvd Link Station and Renton Transit Center. It runs through neighborhoods with an average residential density of 7.08 units/ha and operates from 4:45 a.m. to midnight on weekdays and 6:00 a.m. to midnight on weekends. Service headways on the F line range from 10 min at peak hours to 30 min late at night (King County Metro Transit, 2019).

Prior to RapidRide service, Metro lines 110 and 140 serviced the route and carried 3,500 riders on an average weekday.

2.2.2 Study Design

Conversions to RapidRide were accompanied by the installation of new or upgraded stop amenities. The new amenities included RTIS, shelters, pedestrian lighting, benches, litter receptacles, and bike hoops (Table 2.1). Prior research has suggested that ridership increased overall in the E and F lines relative to the previously existing traditional bus service along these routes (O. T. Stewart et al., 2017). The current study explores whether stop-level amenity improvements further explain increases in ridership in addition to the effect of conversion to BRT. The installation of amenities in anticipation of the BRT service serves as a quasi-experiment, which adds to the rigor of assessment compared to cross-sectional studies. Stops included in the study all experienced the same level of upgrade in BRT service, which included the introduction of new vehicles. The only difference between stops was the types of amenities installed. Therefore, by comparing stops with different types of amenities being added or upgraded, we were able to assess the effect of stop amenity changes while controlling for other system factors such as service quality and frequency.

Amenities were installed between May 20, 2013 and the opening of the E line on February 15th, 2014 and the F line on June 7th, 2014. The dates at which changes were made were recorded for each individual amenity. We used data collected in the fall of 2012 and 2014 to capture ridership before and after the addition of amenities. Amenities were mostly installed in groups. King County Metro Transit Facilities Guidelines (King County Metro, 2018) recommend that benches be installed in all shelters, and shelters and bike hoops be installed with RTIS.

Therefore, we expected to observe high correlations between the different types of amenity changes.

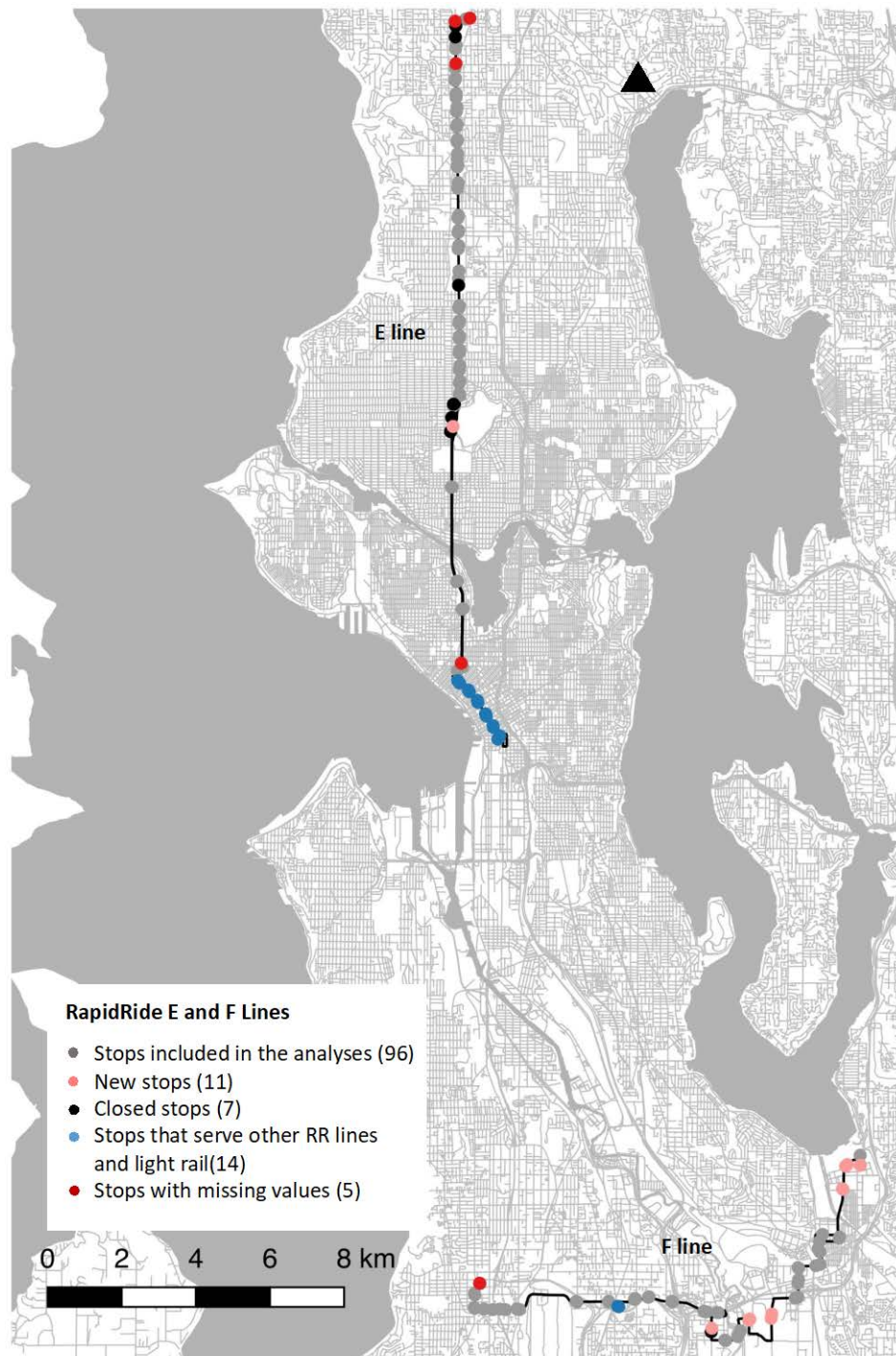


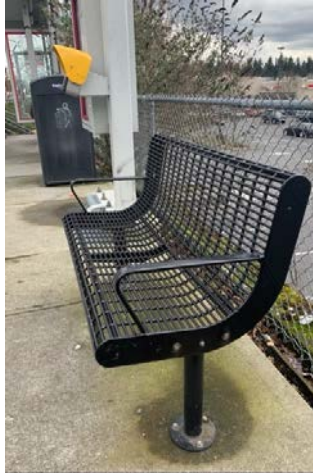
Figure 2.1 Map of RapidRide E and F Lines

Table 2.1 Types of Amenities

Amenity	Photos
Real Time Information System (RTIS) display provides up-to-the-minute estimates of incoming King County Metro bus arrival times.	
Shelter Either new RapidRide branded shelters are installed or conventional shelters are replaced with RapidRide branded shelters, which are cleaner and easier to spot. Left: conventional shelter Right: RapidRide shelter	
Lighting Pedestrian lighting illuminates the pedestrian walkway and is typically mounted 12 -14 feet above the sidewalk.	

Bench

Benches can be either installed in the shelter or outside of the shelter.



Litter Receptacles

35-gallon litter receptacles are commonly installed at shelters.



Bike Hoops

Bicycle hoops near RapidRide stops.



2.2.3 Study Sample of Stops

We used individual transit stops as the units of analysis. The study sample included all the stops along the E and F lines that were active (n=96) in fall, 2012 (before the E and F line launch, where existing traditional bus service had stops) and fall, 2014 (after the E and F lines

were in BRT service) (Figure 2.1). We excluded new stops (n=11) added to the lines, stops that were permanently closed (n=7) due to the change in service, and stops that were temporarily closed (n=1) due to construction during the study period. New stops were not considered to be replacements or relocations of closed stops because all opened and closed pairs were more than 1.5 km apart, with the one exception of a pair that was 340 m apart. We also excluded stops that shared service with other existing RapidRide lines (n=9) or light rail stations (n=5) because we expected their ridership to be affected by their connection to these other higher capacity transit options. Stops that had served other traditional bus services were retained. Five stops were removed due to missing amenity change documentation.

2.2.4 Data

Ridership

Ridership was the dependent variable in the analyses. Data included the average weekday daily boardings and alightings at each stop. King County Metro provided stop-level count data obtained by using the Automatic Passenger Counter system, which uses infrared sensors at doors of buses to count the number of passengers that enter and exit at every transit stop (Hallenbeck et al, 2017). Ridership data have been collected for each unique stop three times a year in spring, summer, and fall on one weekday since early 2000. We used fall 2012 and fall 2014 ridership data to represent the two closest time points respectively before and after the installation/upgrade of the amenities. Using ridership collected in the same season of a year helps to control for regular seasonal variations commonly observed in ridership.

Ridership was measured as the difference in boardings or alightings between 2014 and 2012 for one set of analyses; and as a continuous measure of 2014 boardings or alightings for the second set of analyses.

Amenity Changes

Amenity change for each stop was the predictor variable. Tabular data on the types of amenities and the dates when they were installed came from King County Metro. We enhanced these data using Metro's master maps for E and F lines, which included more detailed information on benches, bike hoops and litter receptacles for each unique stop than was contained in the tabular data.

Binary variables were created for each type of amenity that was added or upgraded (shelters were the only amenity that was potentially upgraded): *RTIS*, *shelter*, *lighting*, *bench*, *litter receptacle* and *bike hoop*. Except for *shelter*, 1 denotes the addition of one or more of the new amenities and 0 denotes no change. For *shelter*, 1 denotes either new shelter(s) or an upgrade of existing shelter(s), and 0 denotes no change. New (n=22) and upgraded (n=40) shelters were coded identically because many of the existing shelters exhibited wear and tear suggesting that installing new or larger shelters with distinct RapidRide design would bring significant improvements to the stops in terms of visual appearance and sanitation.

Covariates

External and internal factors have been identified in the literature as influencing ridership in addition to stop amenity changes. These factors included neighborhood residential density and the number of transit routes served at each stop. Change in residential density (count of residential units per hectare) was used to approximate change in local demand for transit service

(O. T. Stewart et al., 2017). Data came from SmartMaps (Hurvitz et al., 2014a), raster layers storing residential density within an 800 m radius of each 30 m*30 m cell (800 m capturing an area reachable within an approximately 10 minute walk). Data came from the 2012 and 2014 King County Assessor's property and land use data.

The number of transit routes served at each stop was a count variable representing how many different bus lines, including E, F, and conventional lines, were served at each stop. More bus lines may bring more riders transferring from other lines. The data came from King County Metro.

We also controlled for nearby new stops and nearby closed stops, and being on the E line. Since some stops were closed and new ones opened during the conversion to RapidRide, we developed two binary variables, *nearby new stops* and *nearby closed stops*, to capture the potential shifts of riders between these stops and the stops included in the sample. A new stop nearby had the potential to draw riders away from the studied stop, thus resulting in lower ridership while holding other conditions constant. Similarly, a closed stop nearby was hypothesized to add riders to the studied stop thus leading to higher ridership. Nearby new stops indicated, for a given stop in the sample, if any new stops opened within 1/2 mile on the same route direction, with 1 denoting at least one new stop and 0 denoting none. Nearby closed stops indicated, for a given stop, if there were any stops closed within 1/2 mile along the same route direction, with 1 denoting at least one closed stop and 0 denoting none. The 1/2 mile distance was used as a proxy for a 10 minute walk (Nabors et al., 2008). Finally, the binary variable E line or not, with 1 denoting stops on E line and 0 denoting stops on F line, accounted for the substantial differences in service frequency and coverage between the two lines.

All variables were processed using QGIS 2.18.5, PostgreSQL 9.6 with PostGIS 2.4, and R version 3.6.0 (R Core Team, 2019).

2.2.5 Statistical Analysis

Descriptive statistics (mean, standard deviation, range, or percentage) were provided for all variables at each stop. Change in ridership 2012-2014 is presented as absolute change and as percentage change relative to 2012.

Following King County Metro Transit Facilities Guidelines (2018) recommendations to install combinations of amenities at stops, we hypothesized that amenities were added in a non-random way, with several types of amenities being added together at given stops. This was consistent with prior studies (Talbot, 2011) and was confirmed by Pearson correlation analyses showing that many amenity changes co-occurred and that, as a result, single amenities would be unlikely to have an independent association with the outcome. We concluded that assessing the effect of individual amenities would not be appropriate and proceeded to only estimate the effects of combinations of amenity changes on ridership.

To address the great variations in the groups of amenities installed at individual stops, we used the conditional inference tree (CIT) method, a tree based recursive binary splitting algorithm (Hothorn et al., 2006). It has been used in other transportation contexts with similarly correlated predictors, such as highway design features affecting collisions (Das et al., 2009; Li et al., 2014), or locational and behavioral factors affecting consumer shopping trips (Hounwanou et al., 2018). The algorithm identified key amenity changes based on their association with change in boardings between 2012 and 2014. We then grouped stops based on whether they included the identified key amenities. Unique combinations of amenities by stop were then sorted into a smaller number of groups of stops, defined as amenity combinations, which were then treated as

predictors of ridership in subsequent models. Compared with traditional clustering methods, tree-based methods require fewer assumptions about data distribution and allow more robust statistical inference. It was also preferred in this study for its ease of interpretation and application in applied research and in the policy context.

Negative binomial multivariate regression models, which have been commonly used to model count data, served to estimate the associations between amenity combinations and ridership. The dependent variable was the counts of boardings or alightings after BRT conversion in 2014. Ridership before conversion (2012) was one of the control variables, and groups of amenity combinations identified using CIT was the predictor of interest. Additional controlled covariates included change in residential density, number of transit routes served at each stop, nearby new stops, nearby closed stops, and being on the E line or not. The choice of negative binomial regression model over Poisson model was based on the observed over-dispersion in the outcome variable (Hilbe, 2011; White & Bennetts, 1996). The analysis process is visualized in Figure 2.2.

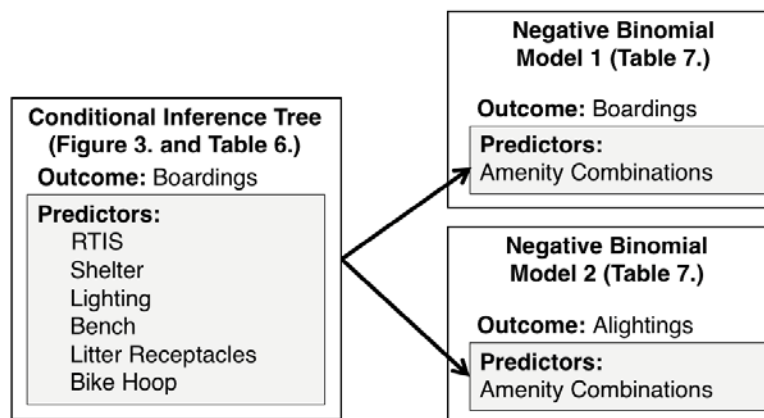


Figure 2.2 Statistical Analysis Diagram

2.3 Results

2.3.1 Descriptive Statistics

Mean, standard deviation, and range of boardings and alightings, before and after amenity installations of all stops are shown by E and F line separately (Table 2.2). Overall, average weekday boardings were similar to alightings. Both mean boardings and alightings increased from 2012 to 2014 at a similar rate, 139.9% for boardings and 138.2% for alightings. Mean boardings and alightings at stops along the E line were higher than those at stops on the F line, but the percentages of increase on the F line were higher than on the E line.

Table 2.2 Boarding and Alightings at E and F line stops in 2012 and 2014

Lines	N	2012 (Before Change)		2014 (After Change)		Change, 2012-2014	
		Mean (SD*)	Range	Mean (SD)	Range	Absolute	Percentage
Boardings							
E	52	125.9 (104.9)	13 - 459	215.4 (226.2)	16 - 1222	89.5	63.6%
F	44	77.1 (150.0)	0 - 702	111.3 (163.2)	6 - 871	34.3	234.3% [†]
Total	96	103.5 (129.2)	0 - 702	167.7 (205.5)	6 - 1222	64.2	139.9% [†]
Alightings							
E	52	117.2 (84.1)	0 - 422	179.7 (120.7)	11 - 555	62.5	59.5% [†]
F	44	63.1 (99.8)	0 - 432	93.9 (120.3)	11 - 594	30.8	233.8% [†]
Total	96	92.4 (95.1)	0 - 432	140.4 (127.2)	11 - 594	48.0	138.2% [†]

* SD = standard deviation

[†]For percentage change, stops with 0 ridership in 2012 were removed from calculation: 2 stops on F line for boardings, 1 stop on E line and 2 stops on F line for alightings.

Amenity changes within this period show that benches, shelters, and litter receptacles were the most common amenities being added or changed (Table 2.3). There were differences between the E and the F line, with fewer lighting, bike hoops, and RTIS amenities being added at the F line stops. On average, stops on the E line had more amenity changes (3.46 per stop,

SD=1.61) than those on F line (1.98 per stop, SD=1.30). Table 2.4 shows the unique combinations of amenity changes present among the 96 stops in the sample. There were in total 21 unique combinations, with the two most frequent combinations being only new benches (n=22 stops) and new shelters, benches and litter receptacles (n=25 stops). Among these 21 unique combinations, 15 were added to fewer than 5 stops. Due to the presence of sparse combinations, further grouping was needed to reduce the dimension and variance for statistical modeling.

Table 2.3 Amenity Changes

	Total Stops (n = 96)		E line (n = 52)		F line (n = 44)	
	<i>Count</i>	<i>Percentage</i>	<i>Count</i>	<i>Percentage</i>	<i>Count</i>	<i>Percentage</i>
RTIS	34	35.4%	28	53.9%	6	13.6%
Shelter	62	64.6%	42	80.8%	20	45.5%
Lighting	16	16.7%	14	26.9%	2	4.5%
Litter Receptable	55	57.3%	37	71.2%	18	40.9%
Bench	83	86.5%	45	86.5%	38	86.4%
Bike Hoop	17	17.7%	14	26.9%	3	6.8%
Average per stop	2.78 (SD=1.65)		3.46 (SD=1.61)		1.98 (SD=1.30)	

Table 2.4 Unique combinations of amenity changes at stops (n=21)

Number of changes	Number of stops	RTIS	shelter	lighting	bench	litter receptacle	bike hoop
0	3						
1	22				√		
	3		√				
	3	√					
	1						√
2	4		√		√		
	1				√	√	
	1			√	√		
	1		√			√	
3	25		√		√	√	
	2	√	√		√		
	1		√	√	√		
4	5	√	√		√	√	
	2	√			√	√	√
	1	√		√	√	√	
	1	√	√	√		√	
	1	√	√			√	√
	1	√	√		√		√
5	6	√	√	√	√	√	
	6	√	√		√	√	√
6	6	√	√	√	√	√	√

√ indicates addition of amenities

Among control variables (Table 2.5), the number of routes sharing each stop ranged from 1 to 7, with an average of 2.19 lines. On average, F line stops had more routes passing each stop than E line stops. Residential density (units per ha) within an 800-meter radius of RapidRide transit stops on both lines increased slightly from 2012 to 2014 (2.00% for E line and 0.1% for F line) and the E line had higher residential density than the F line at both time points. There were

12 stops on E line (23.1%) and 2 stops on F line (4.5%) with closed stops nearby. One stop on the E line (1.9%) and 9 stops on F line (20.5%) had new stops that opened up nearby existing stops.

Table 2.5 Control Variables

	Total Stops (n = 96)		E line (n = 52)		F line (n = 44)	
	<i>Mean (SD)</i>	<i>Range</i>	<i>Mean (SD)</i>	<i>Range</i>	<i>Mean (SD)</i>	<i>Range</i>
Residential Density (units/ha)						
2012	12.72 (9.93)	0.03 - 63.65	17.47 (10.96)	7.61 - 63.65	7.11(3.95)	0.03-13.47
2014	13.92 (10.39)	0.03 - 67.45	17.82 (11.59)	7.61 - 67.45	7.11(3.97)	0.03-13.64
Number of Bus Routes Sharing the Stop	2.19 (1.66)	1 - 7	1.71 (1.35)	1 - 6	2.75(1.83)	1-7
	<i>Count</i>	<i>Percentage</i>	<i>Count</i>	<i>Percentage</i>	<i>Count</i>	<i>Percentage</i>
Nearby new stops	10	10.4%	1	1.9%	9	20.5%
Nearby closed stops	14	14.6%	12	23.1%	2	4.5%

2.3.2 Amenity Combinations Using Conditional Inference Tree (CIT)

To group the unique combinations of amenity changes, we applied conditional inference tree methodology, using change in boardings as the dependent variable and all 6 types of amenity changes as binary predictors. Figure 2.3 is the tree structure plot, which shows key amenities (the strongest predictors of change in boardings in CITs) in the three circles labeled 1, 2, and 3 and new groups of amenity combinations represented by one of the four box plots. These combinations thus represent a mutually exclusive and collectively exhaustive partitioning of the amenity changes that best predicted changes in boardings. From the boxplots, combination 3 and 4 have higher average increases in boardings than the other two combinations.

Table 2.6 shows the four classified combination groups and their corresponding unique amenity change combinations. In general, the four combination groups had an increasing number of new installations. Combination group 1 consisted of 22 stops with only new benches, 3 stops without any new amenities and 2 stops with new lighting and litter receptacles. None of them had any changes in the key amenities: shelter, RTIS or bike hoops. This combination group represented the stops with the smallest number of total new amenities. Combination group 2 contained stops with new shelters but none of them had new RTIS or new bike hoops. They may have had new benches, lightings, and litter receptacles, but those were less important for predicting boarding increases compared to having shelters. Combination group 3 were stops with new RTIS but no new bike hoops. They tended to also have other new amenities installed, but again those were less important than having RTIS. Combination group 4 included stops with a new bike hoop. They tended to have other amenities as well but those were not important as having bike hoops. A categorical variable was constructed based on which combination of amenities each stop had.

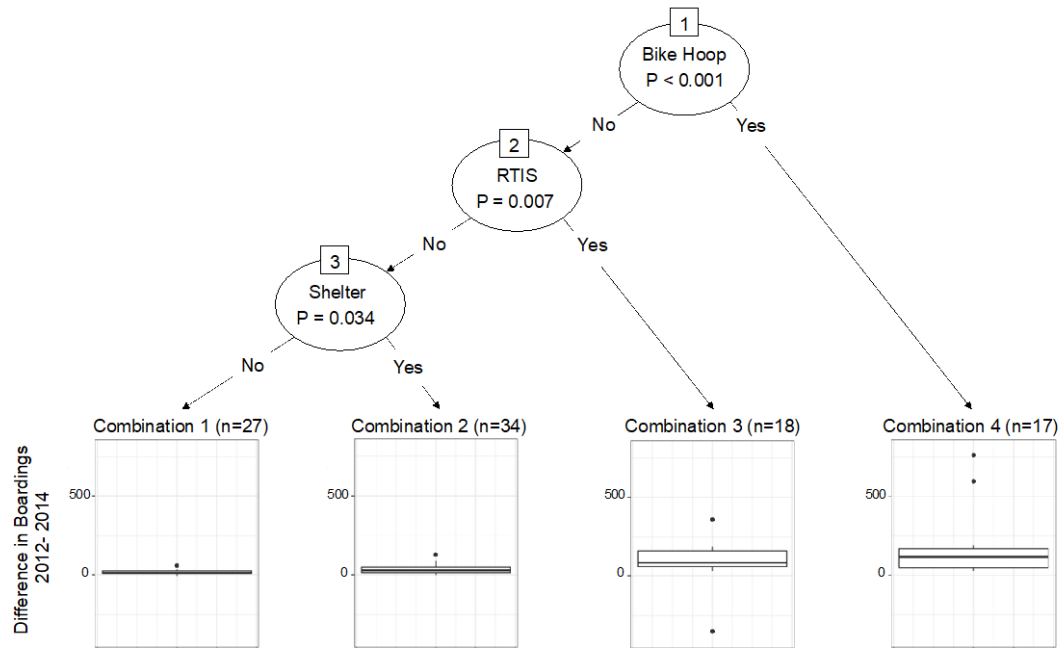


Figure 2.3 Conditional inference tree plot with boardings

Table 2.6 Summary of Combinations of Changes in Amenities (n=96)

Combination	N	Description	mean count of changes	RTIS	shelter	lighting	bench	litter receptacle	bike hoop	# of stops
1 No key amenity change	27	all without changes in any of the 3 key amenities (shelter, RTIS or bike hoops)	0.96							3
							√			22
							√	√		1
						√	√			1
2 Shelter as key amenity change	34	all with new or improved shelter but without new RTIS or new bike hoops	2.68		√					3
					√			√		1
					√		√			4
					√		√	√		25
					√	√	√			1
3 RTIS as key amenity change	18	all with new RTIS but without new bike hoops	3.72	√						3
				√		√	√	√		1
				√	√		√			2
				√	√		√	√		5
				√	√	√		√		1
				√	√	√	√	√		6
4 Bike hoop as key amenity change	17	all with new bike hoops	4.88						√	1
				√			√	√	√	2
				√	√			√	√	1
				√	√		√		√	1
				√	√		√	√	√	6
				√	√	√	√	√	√	6

Legend: √: addition of key amenities; √: addition of the other amenities

2.3.3 Amenity Combinations and Ridership

Table 2.7 shows the negative binomial regression results for 2014 boardings and alightings, testing the effect of the combination groups of amenity changes, along with covariates including the 2012 corresponding boardings and alightings. Odds ratios (OR) and 95% Confidence Interval (CI) were reported for each variable. Using combination group 1 as reference, combination group 2 was positively associated with more boardings (OR=1.814, $p<0.001$). Also significantly associated with more boardings were combination group 3 (OR=2.991, $p<0.001$) and group 4 (OR=3.035, $p<0.001$), but no significant difference was found between these latter two combinations ($p=0.926$). None of the combination groups were found to be significantly associated with more alightings in 2014 relative to combination group 1. Among the control variables, a stop being on the E line (OR=1.704, $p<0.001$) and the number of routes served at the stop (OR=1.084, $p=0.015$) were associated with more alightings. A sensitivity analysis using CIT and negative binomial regression testing amenity change combinations with the change in alightings yielded results that were not significant.

Table 2.7 Negative Binomial Regression Results with Amenity Combinations (n=96)

	Model 1-Boardings fall 2014		Model2-Alightings fall 2014	
	<i>Odds Ratio (95% CI*)</i>	<i>P value</i>	<i>Odds Ratio (95% CI)</i>	<i>P value</i>
Boardings/Alightings 2012	1.004 (1.003, 1.006)	<0.001	1.007 (1.006, 1.008)	<0.001
Combination				
1 - other	<i>Reference</i>		<i>Reference</i>	
2 - shelter	1.814 (1.392, 2.360)	<0.001	1.036 (0.815, 1.313)	0.779
3 - RTIS	2.991 (2.137, 4.195)	<0.001	1.109 (0.838, 1.468)	0.485
4 – bike hoop	3.035 (2.146, 4.324)	<0.001	0.936 (0.697, 1.261)	0.673
Nearby new stop	0.903 (0.558, 1.522)	0.688	1.043 (0.680, 1.699)	0.650
Nearby closed stop	1.146 (0.774, 1.765)	0.519	1.056 (0.628, 1.375)	0.816
Change in Residential Density	1.084 (0.894, 1.335)	0.409	0.915 (0.879, 1.250)	0.661
E Line	1.195 (0.938, 1.522)	0.145	1.704 (1.351, 2.51)	<0.001
Number of Routes Served	1.029 (0.961, 1.105)	0.413	1.084 (1.016, 1.158)	0.015
Log-likelihood	-500.4		-491.5	

*CI=Confidence Interval

2.4 Discussion

Between 2012 and 2014, King County Metro added amenities to transit stops along RapidRide E and F lines. Taking into account the practice of bundling amenity installations, the study showed that compared with boardings at stops that had the smallest number of amenity changes, boardings at stops with new bike hoops were 203.5% higher; boardings at stops with new RTIS were 199.1% higher; and boardings at stops with new or improved shelters were 81.4% higher. Thus bike hoops, RTIS, and shelters appeared to be key amenities that, combined with other amenities as was frequently done in practice, could affect transit ridership. Because this quasi-experimental design accounts for ridership increases due to within-line factors such as service increases, present findings suggest that the improved stops either attract new riders or encourage existing riders to take transit more and/or shift to stops with improved amenities. These findings and the estimated effect of amenities are consistent with prior studies; in Kim et al.'s study (2020), an average of 141% increase in boardings was observed for stops with amenity improvement, compared to those without. Also, in Brown et al. (2006), a one unit increase in Bus Stop Index (ranging from 0 to 8 units) was associated with a 31% increase in total boardings and alightings. Importantly, the present study adds to this body of literature by estimating the strength of the effect of specific key amenities and combinations thereof on ridership.

No prior studies have examined the impact of stop amenities on alightings. In our analyses, none of the combinations of new amenities was associated with changes in alightings, suggesting that transit users may be more sensitive to stop environments where they spend more time (i.e., while waiting for transit). This is consistent with prior studies on traveler satisfactions (Abenzo et al., 2019; Susilo & Cats, 2014), where researchers found that in multi-modal trips,

access and egress trip stage satisfaction were most impacted by the primary trip, which was often defined using trip leg duration. The APC data in our study did not distinguish between egress trips and alighting at transfer stops. The latter may also be impacted by stop amenities, the effect of which could be further studied using person level smartcard transaction data.

The CIT method applied in this study is a robust alternative to using traditional multivariate linear models when studying such highly correlated variables as the combinations of amenities installed at stops. This study is among the first to use CIT to assess the impacts of correlated microscale features of the transit environment on behavior. The approach could be adapted to other contexts and to analyze the role of the urban environment in health, urban planning, and transportation studies.

The study has limitations. The results may only be generalizable to metropolitan areas with sociodemographic and public transportation infrastructure that are similar to those of King County. Because King County Metro's mandate is to allocate amenity improvements to maximize public benefit, we cannot rule out that association between amenities and boarding increases were due to stops being upgraded based on anticipated ridership increases; we attempted to control for that possibility by including changes in residential density surrounding the stops. Longitudinal amenity change data and research based on data from other metropolitan areas are needed to further validate causal inferences. Also, the increase in boardings could be due to new riders attracted to RapidRide or to existing riders taking transit more and/or shifting to stops with improved amenities or a combination of all. It should be noted that “amenity,” if conceptualized as a desired but not necessary feature, is a bit of a misnomer as some of the amenities examined are critical to universal design and to supporting a more inclusive environment that improves access to transit for all riders. Finally, the stop level APC data

distinguish between boardings and alightings but do not provide information on transfers when stops serve multiple lines: the same transfer riders who are alighting one bus will be boarding another bus, thus affecting stop-level analyses. The use of smart card data would help collect data that more precisely distinguishes between boardings and alightings at stops serving multiple lines. To this end also, local and regional transportation agencies may benefit from systematically collecting and managing stop-level amenity and ridership data over time to guide future infrastructure investments.

In addition to carrying out longitudinal analysis with systematic amenity data collection, future research could examine the interplay between stop amenities and other factors internal and external to the public transportation system. For example, the importance of shelters and benches may differ by weather and frequency of service. The longer-term effect of stop amenity changes should also be investigated to pinpoint the time span after which boardings cease to increase. In summary, this study adds to the understanding of how bus stop features and amenities affect transit use at the stop level. It is among the first to quantitatively evaluate this relationship per amenity type, using a quasi-experiment design with tree-based methods to treat correlated amenity features. As a less expensive capital investment option compared to other system improvement such as vehicle purchase or service area expansion, amenities at bus stops provide the first impression of the transit services and thus affect users' attitudes and experience towards the service. The study demonstrates the importance of amenities on improving service quality and system efficiency. Enhancing stop-level amenities, especially focusing on a set of more impactful amenities, can be a cost-effective strategy of system improvements to increase transit ridership and improve travel experience.

CHAPTER 3. Benchmarking Students Walking to School: A Walkability Index and the Percentage of Students Who are Likely to Walk to School

3.1 Introduction

Active school travel (AST) has multipronged benefits. It reduces the number of vehicular trips and thus improves transportation system efficiency by reducing traffic congestion and the associated environmental burdens of air pollution and carbon emission (Rabl & de Nazelle, 2012). In addition, it reduces the risk of child obesity by increasing daily physical activity (Lubans et al., 2011b; O. Stewart, 2011) and help children establish a healthy living style in their future adulthood (H. J. Kim & Heinrich, 2016). Despite these perceived benefits, not many children are walking, with only 16% of children in U.S. walk to school at least once a week in 2017 (Omura et al., 2019).

State and local governments as well as community groups have been actively developing school-based programs, such as Safe Routes to School programs (SRTS), to promote active travel, with program types ranging from engineering, educational, to safety enforcement interventions. Most programs have been proven to significantly increase the percent of children walking and biking (Chillón et al., 2011). From a planning and engineering perspective, the effectiveness of the programs depends on transportation staff and policy makers to have the appropriate tools to identify and prioritize the allocation of funding and resources (National & Center of Safe Routes to School, 2015). This is particularly important as funds remain scarce and need to be targeted to the right type of projects in places most in need (O. Stewart et al., 2014).

Composite scores built on multiple criteria, such as walkability indices, have been shown to be effective tools to assist project prioritization and to benchmark progress (Pineo et al.,

2018). Many studies have devised walkability scores for adults (C. Lee & Moudon, 2006a; Rundle et al., 2019), such as Walk Score[®], which ranks neighborhood from 1 to 100, where scores of 90 to 100, are referred as “walker’s paradise,” 70 to 89 are “very walkable,” 50 to 69 somewhat walkable, and 0 to 49 “car dependent”. Regarding children and youth, there is a rich literature on their travel characteristics (Everett Jones & Sliwa, 2016; Pang et al., 2017; J. R. Panter et al., 2008), but as far as we know, only three studies measured walkability for children, whose walking behavior and perceptions are different from adults (Baslington 2008). The three walkability indices targeted at children have mainly been applied to and verified in a limited number of schools in urban areas and across a small geographical extent, including 25 schools from metropolitan Perth in Australia (Giles-Corti et al., 2011), 14 schools from southern Denmark (Christiansen et al., 2014a), 18 schools in Seattle and 4 schools in Houston (S. Lee et al., 2020).

The lack of school walkability indices hinders the understanding of trends and disparities in children’s walking environment, especially at the larger scale, across regions or states. The reason for the dearth of walkability indices may come from the lack of large extent children walking data, which prevents verification. Inconsistent built environment data on schools and their surrounding neighborhoods also hinders the development of walkability indices across geographical regions. Because of this lack of data, there have been very few studies examining factors associated with rates of walking at the school level (Braza et al., 2004; Falb et al., 2007; Jones, 2016). Braza et al (2004) studied factors influencing rates of walking and biking for 34 schools in California and Jones et al (2016) studied rates of walking and biking for 577 schools nationwide. Neither comprehensively examined built environment elements. Aside from these two studies, other studies focused on predicting individual child travel mode choice but not on

estimating school level outcomes (Lovasi et al., 2008; Yelavich et al., 2008). Yet, predicting school-level AST rates still has practical importance as conditions for walking are local and the targeted interventions on active school travel need to be at the school level.

Washington State is among the few states that conduct statewide longitudinal student travel surveys (Finch & Smith, 2011). Together with Department of Health (WSDOH), the Washington State Department of Transportation (WSDOT) has been collecting a Student Travel Survey bi-annually since 2014 with data now available for 2014, 2016, and 2018 (Washington State Department of Transportation, 2015, and 2017). The objective of the surveys is to understand how students in Washington State travel to and from school and to explore the barriers to taking active transport modes. In this study, we utilized this unique survey data and available built environment data in Washington State to construct a walkability index applicable to a multi-school, statewide, and large-extent setting. We then used the walkability index together with student and school socioeconomic information to predict the percentage of children walking for all Washington State K-8 schools. The index and the predicted walking rates developed in this study serve to support the future allocation of funds to promote AST and to benchmark project progress.

3.2 Methods

3.2.1 Study Setting and Sample

Washington State Office of Superintendent of Public Instruction tallied 1610 schools in Washington State with K-8 students enrolled in the year of 2016, including regular, special education, and alternative schools. Each school day, nearly 1.1 million students in Washington State travel to and from school, with walking or bicycling as one of three main modes of travel,

added to travel by school bus and private vehicle (Washington State Department of Transportation, 2017).

WSDOH and WSDOT 2016 student travel survey data included 11,421 respondents from 242 schools, comprising about 10% of the state students (Washington State Department of Transportation, 2015 and 2017). Among them, 69 schools are located in King County. The schools were selected randomly proportional to size. School districts used a secure portal to provide phone number lists of the parents or guardians of all the students enrolled in grades K–8th at participating schools. Within each school, phone numbers were randomly selected by grade and a trained interviewer contacted parents and administered the survey via phone.

The final sample for this study was all K-8 schools with complete built environment and social environment data (as detailed in section 2.2) in Washington State. Among all the 242 schools included in the 2016 Student Travel Survey, 17 were removed because of missing values in either built environment or socioeconomic variables. A total of 66 schools in King County and 159 schools in other counties in Washington State were included in the statistical analysis. The findings were then applied to 1,610 schools with complete built environment data in Washington state to calculate a Walkability Index and to 1,338 schools with complete built environment and socioeconomic data to predict the percentages of walking (as detailed in section 2.3).

3.2.2 Variables and Data

The **main outcome of interest** was the percentage of students walking at each school. For schools included in the student travel survey, it was calculated as the number of surveyed participants reporting student walk to or from school, divided by the total number of parents surveyed at each school. The survey question corresponding to this variable was phrased as “on

most school days, how does your child usually get to school?”. For schools not included in the survey, the outcome was the estimated percentage of student walking at each school derived from the developed models.

The **built environment factors** identified from prior literature to influence the walkability around school and thus may influence student walking included *road connectivity*, *vehicular traffic exposure*, *residential density*, *sidewalk prevalence*, and *collision* (Everett Jones & Sliwa, 2016; Pang et al., 2017; J. R. Panter et al., 2008). The presence or improvements in pedestrian infrastructure, such as sidewalk, was found to be associated with more or increase in active travel to school (Ewing et al., 2004; Zhu & Lee, 2009; H. J. Kim & Heinrich, 2016). Higher route safety, measured using vehicular traffic or collisions, as well as higher residential density and street connectivity were also found to be associated with higher levels of walking or cycling to school (Christiansen et al., 2014b; Giles-Corti et al., 2011). The measurements of these variables were consistent with Giles-Corti et al.’s (2011) and Kaplan’s (2016) study. *Road connectivity* was the ratio of street length in the two km network buffer area around school to street length in the two km Euclidian buffer area. *Vehicular traffic exposure* was the ratio of street length of major streets (collectors, minor arterials, principal arterials, and freeways) to street length of local streets (pedestrian path, alley, trail etc.) within two km network buffers around school. Both variables were constructed in ArcGIS environment using OpenStreetMap data. *Residential density* was the number of residential units divided by two km network buffer area (residential units per km²), obtained using census data. *Sidewalk prevalence* was the ratio of the length of streets with a complete sidewalk at least on one side to the length of all streets within the two-km network buffer around school. The data was created and managed by Urban Form Lab at the University of Washington. *Collisions* was pedestrian-motor vehicle collision

counts within the two-km network buffer of a school, obtained from Washington State Department of Transportation (WSDOT). The complete data sources and availability of data were documented in Table 3.1.

Based on prior studies, **social environment factors** hypothesized to influence children walking included the *percentage of male students* surveyed at each school, the *percentage of surveyed children graded from kindergarten to 4th grade* (age between 5 to 10 years old), the *percentage of children living within one mile of the school*, the *percentage of free and reduced meal enrollment*, the *percentage of surveyed participants considering that the school encouraged children walking*, and *total enrollment*. The percentage of free and reduced meal enrollment at each school was a proxy measure for family income. Lower family income and older age were found to be associated with more AST (H. J. Kim & Heinrich, 2016; Mota et al., 2007).

Unsurprisingly, distance between home to school was found to be a significant predictor of travel behavior in all studies, with those who had shorter journey distances being more likely to walk to school (Cole et al., 2007; Merom et al., 2006; Schlossberg et al., 2006). There were mixed results on the effect of school size and student gender on AST (Braza et al., 2004; Ewing et al., 2004; Lubans et al., 2011a). We also included total enrollment, which was the total number of enrolled students from kindergarten to 8th grade at each school, to control for the effect of school size.

The data sources and availability of data are documented in Table 3.1. Free lunch enrollment and total enrollment for each school were obtained from the Washington State Office of Superintendent of Public Instruction (OSPI). For schools included in the survey, the others socioeconomic factors came from student and school information collected in the survey.

Not all data for the above identified variables were available for all schools in all counties in Washington State. Table 3.1 showed the availability of the above variables at each

geographical scale. As noted, all the data were available for 66 of the King County schools covered in the student travel survey. For the 159 surveyed schools in other counties, all data were available except for sidewalks. The remaining schools in Washington State were not included in the survey and hence did not have data on student travel, student's distance to school, and parent's perspective towards school policy regarding AST. For schools not included in the survey, the percentage of male students and the percentage of students in lower grades were obtained from OSPI. These remaining schools did have data for four of the five school built environment variables; only sidewalk data was not available.

All datasets were joined using the unique school IDs except for the free and reduced lunch data from OSPI, where school ID was catalogued differently, and text matching by school name was used.

3.2.3 Study Design and Statistical Analysis

Figure 3.1 summarize the study design and statistical analysis for the study, with each step explained in detail below.

Develop and verify the walkability index

We first used best subset regression to select the built environment variables needed to predict walking and estimated their coefficients. Best subset regression is a common variable selection and model building method that aims to find the subset of independent variables that best predict the outcome. We kept social environment factors since they did not present strong correlations and only performed best subset selection on built environment variables. All variables in the models were standardized to z-score in order to obtain the corresponding

coefficients. The resulting walkability index algorithm was the sum of variables selected using best subset regression multiplied by their estimated coefficients.

We performed the same set of procedures described above using the 66 King County schools in the survey (i.e. training dataset) under two different data availability scenarios: scenario 1 – all data are available; scenario 2 - sidewalk prevalence not available. The performance was measured using Pseudo R squared, BIC, and Spearman’s rank correlation. The Spearman’s Rank correlation coefficients served to measure the similarity between the predicted percentage of walking and the actual walking data from the survey, with higher coefficients indicating higher similarity between the two, as used in the previous study (S. Lee et al., 2020).

We used the 159 other counties schools in the survey (i.e. test dataset) to verify the model performance, again, using Spearman’s Rank Correlation Coefficients. Testing algorithms against a new sample (i.e. test dataset) is referred to as cross-validation, which was considered as the golden standard for verification.

Develop and verify the predictive model for the percentages of walking

Similarly, the prediction models were first estimated using the 66 King County schools under two data availability scenarios: 1- when all data were available; 2-when school encouragement and distance to school were not available. The two models were then tested using the rest 159 schools, with Spearman’s rank correlation reported.

Application to all Washington State schools

For the final objective of constructing a walkability index and predicting rates of walking for schools where actual walking data were not available, the regression models verified in 2.3.1 and 2.3.2 were then applied to all schools in the Washington State.

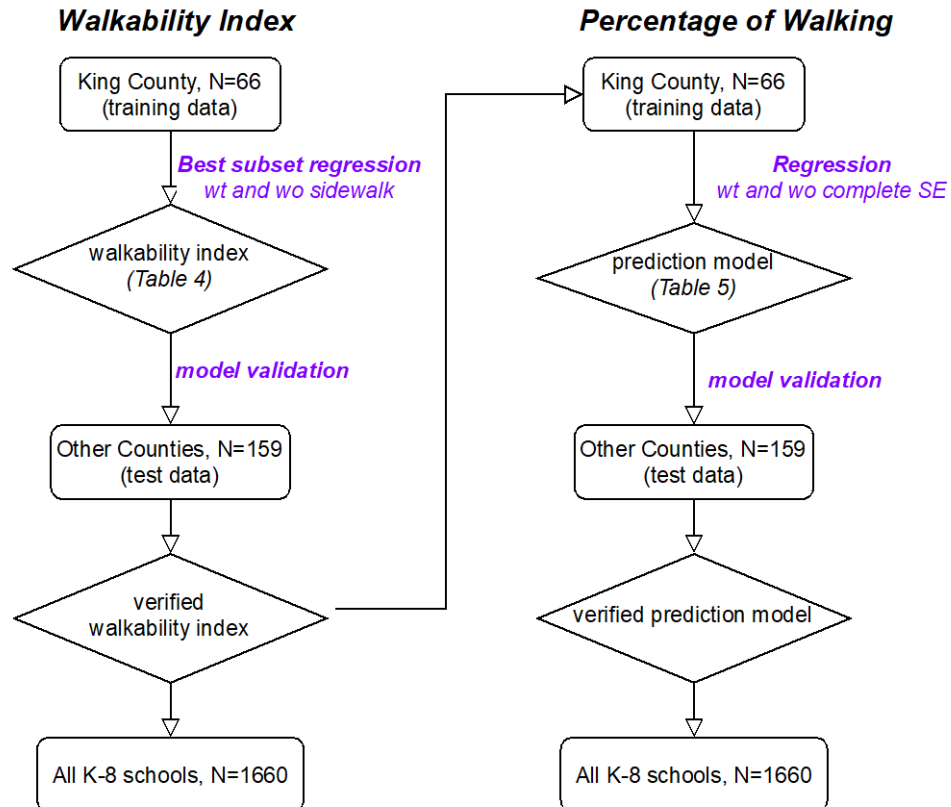


Figure 3.1 Study Design and Statistical Analysis Flow Chart

Table 3.1 Summary of Variables and Data Availability

Domains	Variable	Description	Data Source Indicate date of data used	Data Availability		
				King County N=66	Other Counties N=159	Washington State N=1610
Outcome	<i>Percentage of Children Walking to School</i>	Percentage of participants reporting their children walking at each school	WA survey	✓	✓	Not available
Built Environment Factors	<i>Road Connectivity</i>	Ratio of 2 km street network buffer area around school to 2 km Euclidian buffer area	OpenStreetMap	✓	✓	✓
	<i>Vehicular Traffic Exposure</i>	Ratio of major streets (collectors, minor arterials, principal arterials, and freeways) to local streets (local arterials) within 2 km network buffers around school	OpenStreetMap	✓	✓	✓
	<i>Residential Density</i>	Number of residential units in the 2 km network buffer and divided by buffer area	Census	✓	✓	✓
	<i>Sidewalk Prevalence</i>	Ratio of the length of streets with sidewalks at least one side to the length of all streets within 2 km network buffer around school	Urban Form Lab	✓	Not available	Not available
	<i>Collisions</i>	Pedestrian-motor vehicle collision counts within 2 km network buffers	WSDOT	✓	✓	✓
Social Environment Factors	<i>Total Enrollment</i>	Number of K-8 enrollments at each school	OSPI	✓	✓	✓
	<i>Male</i>	Percentage of male children in school	WA Survey, OSPI	✓	✓	✓
	<i>Low Grade</i>	Percentage of students at each school reporting grade from kindergarten to 4 th (age under10)	WA Survey, OSPI	✓	✓	✓
	<i>Free Lunch</i>	Percentage of free and reduce meal at each school	OSPI	✓	✓	✓
	<i>Distance (<1 mile)</i>	Percentage of participants at each school reporting distance less than 1 mile	WA Survey	✓	✓	Not available
	<i>School Encouragement</i>	Percentage of participants think school encouraging AST	WA Survey	✓	✓	Not available

3.3 Results

3.3.1 Descriptive Statistics

The surveyed schools were located in neighborhoods with a diverse range of built environment characteristics and had on average 22% of the surveyed students reporting walking to or from school (Table 3.2). Street connectivity around schools, which was the ratio of street length in network buffer versus in Euclidian, ranged between 0.13 to 0.67, with a mean of 0.44. Traffic exposure, measured as the length of arterial versus local road ranged from 0.06 to 1, with a mean of 0.33. Residential density ranged between 45 units/km to 2414 units/km. The percentage of streets with sidewalks ranged from 0% to 91%, with a mean of 22%. The number of collisions reported ranged between 0 to 731 incidents.

Of the 1610 K-8 schools in Washington State at the time when the survey was conducted, all had the geographic coordinates information needed to retrieve built environment information (Table 3.3). These schools had a mean street connectivity of 0.39 and a mean vehicular traffic exposure of 0.34. The average percentage of male student was 52% and the percentage of low-grade student was 60%. Among them, 1338 had complete social environment data (i.e. including data on free lunch program enrollment) needed to predict the percentage of children walking to school. For these 1338 schools, the free lunch enrollment was 47%.

Table 3.2 Characteristics of Schools included in 2016 Survey

Domains	Variables	Units	N (Schools)	Mean	SD	Min	Max
Outcome of Interest	<i>Percentage of Children Walking</i>	%	225	22%	16%	0	78%
Built Environment Factors	<i>Street Connectivity</i>	Ratio	225	0.44	0.13	0.13	0.67
	<i>Vehicular Traffic Exposure</i>	Ratio	225	0.33	0.18	0.06	1.00
	<i>Residential Density</i>	unit/km	225	745	415	45	2415
	<i>Sidewalk Prevalence</i>	Ratio	66 [†]	0.52	0.22	0.00	0.91
	<i>Collisions</i>	Count	225	37.1	98.05	0	731
Social Environment Factors	<i>Total Enrollment</i>	Count	225	510	175	85	1176
	<i>Male</i>	%	225	51%	8%	0%	73%
	<i>Low Grade</i>	%	225	61%	36%	0%	100%
	<i>Free Lunch</i>	%	225	50%	26%	2%	100%
	<i>Distance (<1 mile)</i>	%	225	38%	18%	0%	85%
	<i>School Encouragement</i>	%	225	33%	21%	2%	98%

Note: [†]Sidewalk data are only available for schools in King County (N=66)

Table 3.3 Characteristics of all Washington State K-8 Schools

Domains	Variables	Units	N (Schools)	Mean	SD	Min	Max
Built Environment Factors	<i>Street Connectivity</i>	Ratio	1610	0.39	0.14	0.05	0.77
	<i>Vehicular Traffic Exposure</i>	Ratio	1610	0.34	0.42	0	2.87
Social Environment Factors	<i>Total Enrollment</i>	Count	1610	450	220	10	1436
	<i>Male</i>	%	1610	52%	4.5%	0%	100%
	<i>Low Grade</i>	%	1610	60%	35%	0%	100%
	<i>Free Lunch</i>	%	1338 [†]	47%	26%	0%	100%

Note: [†]1338 out of all Washington State K-8 schools have complete lunch enrollment data.

3.3.2 Walkability Index

Based on the sample of 66 King County schools, Table 3.4 shows the built environment variables selected for constructing the walkability index using best subset regression under different data availability scenarios. When all data were available, street connectivity and sidewalk prevalence were selected (Model 1). When sidewalk data was not variable, street connectivity together with traffic exposure were selected (Model 2). Multiple model performance measurements, including pseudo R squared, BIC, and the Spearman's Rank correlation between the fitted values and the survey outcomes, all showed that there were few differences between the scenario where all data are available and that where sidewalk data was not available. This indicated that built environment variables selected using best subset regression (traffic exposure and connectivity) were good approximations and substitutions for sidewalk data.

Model 2 was then applied to the rest of the schools included in the survey (test dataset, N=159) to test the model performance. The Spearman's Rank correlation between the fitted value using Model 2 and the actual observed value was 0.84. This showed that the selected built environment factors and the estimated coefficients in Model 2 also performed well for schools outside of King County and hence at a larger geographical scale.

Based on the above verification results, the index was developed as the sum of all variables multiplied by their coefficients as estimated in Model 2 ($-0.16 \times \text{z-street connectivity} - 0.06 \times \text{z-traffic exposure}$). It was applied to all 1610 schools. The index varied from -1.78 to 0.48 with a means of 0 and SD of 0.12.

Table 3.4 Selecting Built Environment Variables for Walkability Index: Results of Best Subset Regression

		Model 1	Model 2
Model Performance	Geographical Region	King County	King County
	N (school)	66	66
	BIC	-92.56	-90.51
	Pseudo R squared	67.23%	67.47%
	Spearman's Rank Correlation (N=66)	0.77	0.77
	Spearman's Rank Correlation (N=159)	0.84	0.84
Built Environment Factors	z-Street connectivity	0.10	0.16*
	z-Traffic exposure	<i>Not selected</i>	-0.06
	z-Residential density	<i>Not selected</i>	<i>Not selected</i>
	z-Sidewalk prevalence	0.14	<i>Without available data</i>
	z-Collision	<i>Not selected</i>	<i>Not selected</i>
Social Environment Factors	Male	1.35	1.18
	Low Grade	-0.68*	-0.71*
	Free Lunch	0.75**	0.73*
	Distance (<1 mile)	3.00***	3.10***
	School Encouragement	1.45***	1.42***
	Total enrollment	0.0004	0.0003

Note: * P < 0.05, ** P < 0.01, *** P < 0.001

3.3.3 Prediction Model for Percentage of Walking

The resulting walkability index was then combined with other socioeconomic factors to develop prediction models for school-level percentages of children walking under the different data availability scenarios (Table 3.5). The prediction model was first developed using the 66 schools in King County and was then applied to schools in other counties (N=159) for cross-validation. The prediction model with complete data performed very well, with a pseudo R squared of 67.48% and a Spearman's Rank correlated of 0.77 between the predicted percentage of walking and the actual observed value at each school (Model 3). When school encouragement

and distance to school data were not available, the Spearman's Rank Correlation remained significant yet drops to a fair value of 0.43 (Model 4).

Under both scenarios, namely when all data were available and when distance to school and school encouragement were not available, the walkability index was significantly associated with the percentage of student walking. When these social environment factors were missing, the association between the walkability index and the outcome was stronger (Model 4).

When applying the two models to the remaining 159 schools, the Spearman's Rank Correlation was 0.83 for Model 3 and 0.38 for Model 4. This showed that the models performed consistently for schools in King County and when applied to a large geographical extent.

Table 3.5 Prediction Model for School-level Percentage of Walking

		Model 3	Model 4
Model Performance	Geographical Region	King County	King County
	N (school)	66	66
	BIC	-94.70	-56.87
	Pseudo R squared	67.48%	36.44%
	Spearman's Rank Correlation (N=66)	0.77	0.43
	Spearman's Rank Correlation (N=159)	0.83	0.38
Built Environment Factors	Walkability Index	1.00**	2.35***
Social Environment Factors	Male	1.18	0.53
	Low Grade	-0.71*	-0.12
	Free Lunch	0.72**	Without available data
	Distance (<1 mile)	3.09***	0.25
	School Encouragement	1.42***	Without available data
	Total enrollment	0.0003	0.0005

Note: 1-* P < 0.05, ** P < 0.01, *** P < 0.001

3.3.4 Application to all Washington State schools

The walkability index developed in Model 2 was applied to all K-8 schools in Washington State. The calculated walkability indices ranged between -1.78 and 0.48 with a mean of 0 (Table 3.6). Figure 3.2 shows the geographic distribution of the school walkability indices in Washington State. Model 4 was used to predict the percentage of walking for all K-8 schools. The predicted percentage ranged from 0% to 55.2% with a mean of 27.3%, with the geographic distribution shown in Figure 3.3.

Table 3.7 shows the number of schools by quartiles in the walkability index and the percentage of children walking to school. Overall, 4.5% of the schools (N=60) had a below average walkability index but still had an above average rate of children walking to school, while 5% of the schools (N=67) had an above average walkability but a below average rate of walking.

Table 3.6 Walkability Index and Predicted Percentage of Walking for all Washington State Schools

	N	Mean	SD	Min	Max
Walkability Index	1610	0	0.12	-1.78	0.48
Percentage of Children Walking to School	1338	27.3%	6.9%	0%	55.2%

Table 3.7 Number of Schools by Walkability Index and Percentage of Walking Quartile

Walkability Index	Percentage of Walking			
	<21%	21%-26%	26%-33%	>33%
[-1.78, -0.123]	274	59	2	0
(-0.123,0]	63	213	56	2
(0,0.13]	1	65	224	44
(0.13,0.48]	0	1	56	278

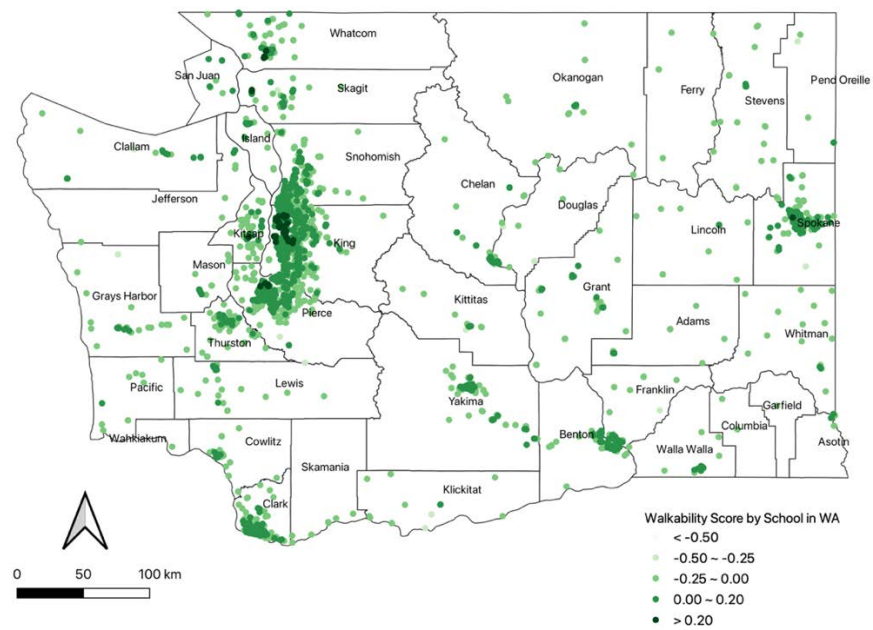


Figure 3.2 Geographic distribution of schools by Walkability Score (n=1610)

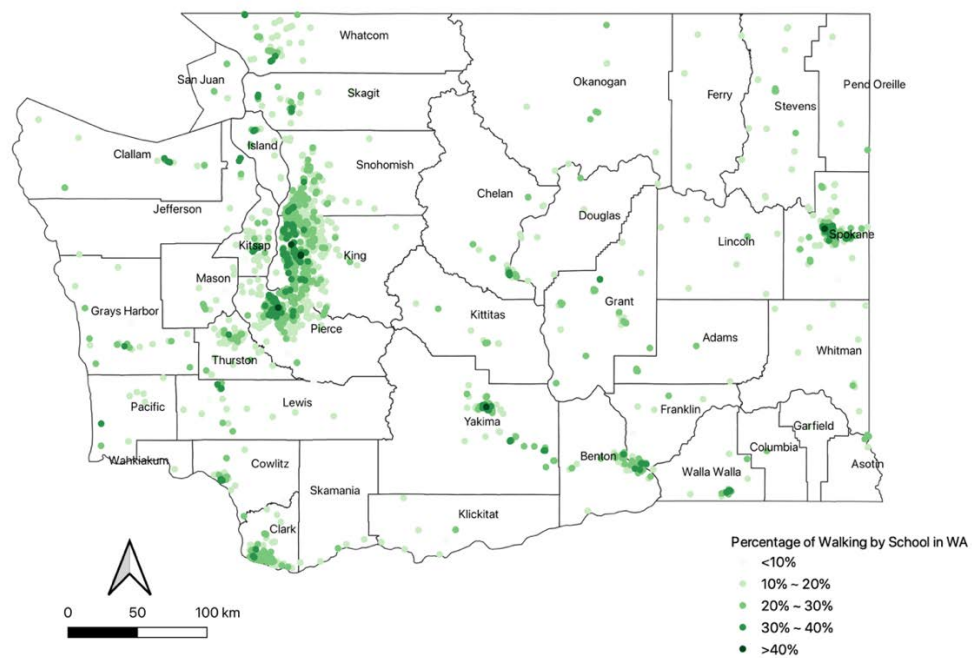


Figure 3.3 Geographic distribution of schools by estimated percentage of children walking(n=1338)

3.4 Discussion

3.4.1 Findings

The 2016 Washington State student survey included K-8 schools in Washington, that represented the range of school built and social environment characteristics. The study took advantage of this survey and of the readily available statewide data on the built environment around schools and on the characteristics of the schools and their population, to produce verified algorithms that (1) create walkability indices and (2) estimate the percentage of children walking to school. Significantly, both the walkability index and the estimation of walking are obtained at a fine grain, the individual school level, but for a large area extent, the entire State of Washington. Best subset regression and cross-validation were used to develop and verify the algorithms, both of which performed well under different availability scenarios and were stable when upscaled from King County to Washington State.

The study found that publicly available GIS data on built environment features (i.e. street connectivity and traffic exposure measured using OpenStreetMap) were sufficient for measuring school walkability across the state. OpenStreetMap (OSM) is an open source and volunteered geographic information source with worldwide coverage. Its major benefits include the easy access, wide geographical span, and detailed coverage on local street networks (e.g. tertiary roads, paths, and tracks) not available in many public datasets (rural areas in particular). The downside of using OSM is its lack of systematic quality check throughout the map yet this has been compensated by the enormous amount of contributors (Boeing, 2021).

Other built environment variables impacting AST, including residential density, collision, and sidewalk were also examined but were not retained in the final model as they did not

significantly add more information than what had already been captured by street connectivity and traffic exposure. This is likely due to the correlated nature of built environment elements that support walking. For example, denser neighborhoods also tend to have higher street connectivity and more streets with sidewalks as well as other pedestrian infrastructure (C. Lee & Moudon, 2006a; Leal et al., 2012; Moudon et al., 2019). As a result, these built environment features also capture the other micro-environment features for which secondary data are not readily available.

Free and reduced lunch enrollment were a proxy for student family income, which typically cannot be obtained, and yet was found to have a significant association with percentage of walking at the school level. We did not find readily available and effective substitutes for the two variables of students' travel distance to school and school policy towards AST, both of which were significant determinants for student travel mode to school. Without these two variables, the model generated only fair estimations for school-level percentages of walking. In the future, this information should be collected by proponents of AST.

The two-step verification process used, where models were developed using samples in King County and were then verified using samples in other counties in Washington State, showed that the models on walkability and percentage of student walking were stable when scaled up from King County to entire Washington State. This result indicated that data from a county may be applied to a larger geographical scale. Since for many states, only a limited number of schools or school districts have actual walking data, this information is helpful for those that plan to develop their own walkability index and predictions.

The walkability index and predicted rates of walking revealed schools in need of resource support as well as schools with opportunities for change to improve AST in Washington State. Around 5% of the schools in Washington State had high walkability school environment yet very

low rate of children walking to school. These are the schools with potentials to encourage more student walking and could benefit from AST educational programs. About another 5% of the schools in Washington State had low walkability environment yet high rate of children walking to school. These schools tend to have more students with low family income, measured using free and reduced lunch enrollment in this study, who have limited access to alternative modes of travel to school such as private car (Dargay, 2001; Mota et al., 2007). Programs need to prioritize funding for such schools with less walkable environments but with more students who rely on walking due to low household income.

3.4.2 Strengths and Limitations

Each school day, nearly 1.1 million students in Washington State travel to and from school, with walking or bicycling as one of three main modes of travel (Washington State Department of Transportation, 2017). The developed walkability index and estimations of school-level percentage of walking serve to benchmark those trips and the environment where those trips took place.

The walkability index can be applied to a large spatial extent such as at the municipal, regional, or state level. It measured attributes of urban environments, such as density, street connectivity, traffic exposure, and sidewalk prevalence at the neighborhood level. It did not capture finer environmental features, such as street trees and lighting, which could be measured using other methods such as fieldwork and street audit (S. Lee et al., 2020). However, it offered a cost-efficient method to measure and compare school walkability across a large geographical area, which is useful for regional and state AST promoting programs. The same goes for the predicted school-level percentage of walking. It is most suited for comparing spatial and

temporal changes in AST rate across counties and could be complementary to existing survey data.

The methods used to develop these indices and predictions can be replicated in other jurisdictions. Scholars and decision makers outside Washington State who want to use the findings from this study for their own region need to be cautious to the unique data availability scenarios, especially student and school information, in their region. The variables retained in the index and the value of their coefficients may only be generalizable to regions with sociodemographic that are similar to those of Washington State. However, the methods used to develop the index and estimations of walking rate can serve as a protocol workflow for other regions or states to develop child-specific walkability indices and school-level predictions using their own data.

CHAPTER 4. Is Income Related to the Wealth of Where You Walk?

4.1 Introduction

Walking is a popular and convenient activity that has the potential to increase physical activity at the population level (Blacklock et al., 2007; Pucher et al., 2010). Encouraging more walking is a promising health promotion strategy. It is equitable because the activity does not entail major investments at the individual level—among those able to walk, it can be performed in regular clothing and without special equipment; and it is cost-effective for the public sector because the activity can and does occur in many parts of the existing public space, including parks, streets, trails, and sidewalks, thus requiring little if any infrastructure investment beyond that that has been made (Davis, 2010, 2014; Sinnett et al., 2011).

People generally walk for either utilitarian or recreational purposes. These two types of walking typically occur in different built environments. Knowing the characteristics of where people walk and for what purpose is essential in order to devise targeted and effective built environmental interventions that support walking (Sallis et al., 2006; Saelens & Handy, 2008; J. Panter et al., 2019). A rich literature already exists that converges on the objectively measurable physical characteristics of the environmental determinants of walking. For utilitarian walking, the agreement is that it takes place in areas with higher development density, more routine destinations clustered together, and smaller street blocks that insure route directness between a trip origin and its destination (Frank et al., 2008; Saelens & Handy, 2008; O. T. Stewart, Vernez Moudon, et al., 2016). For recreational walking, the activity occurs in more scenic and green areas, along bodies of water, and where there are views (C. Lee & Moudon, 2006b; Kang et al., 2017; Christian et al., 2017).

Compared with the relation between built environment and walking purposes and the related issue of what is a walkable environment, less is known about differences in walking environments experienced by walkers of different sociodemographic status such as income and race. Studies in major US cities have found that low-income and Hispanic populations typically reside in neighborhoods that are low in support for active lifestyle, have lower levels of street and sidewalk maintenance, less tree shade, fewer concentrations of healthy food outlets, and higher rates of felony complaints and vehicular crashes (Zhu & Lee, 2008; Neckerman et al., 2009; Yu, 2014). This evidence suggests that disadvantaged and minority groups may also walk in less-favorable environments (Sallis et al., 2011). However, most of the aforementioned research has focused on the home neighborhood environment, which may not be the main exposure for people walking. People spend considerable amount of time away from home. Some studies show that 40% to 50% of moderate-to-vigorous physical activity happen outside of home neighborhoods (Hurvitz & Moudon, 2012), suggesting the need to further examine the characteristics of environments that walkers are exposed to throughout the day (Chaix et al., 2017a; Kwan, 2018; Matthews & Yang, 2013) .

The examination of where walking takes place, whether inside or outside of the home neighborhood has been greatly facilitated by the advent of Global Positioning Systems (GPS) and the collection of data on actual walking paths (Chaix, 2020). GPS-derived objectively measured individual activity data can serve to map exposure to environments in space and time. It opens opportunities to match and compare the socioeconomic characteristics of individuals or groups and those of the environments they are exposed to. It can help assess the extent to which walking is equitably accessible as a means to be physically active and to achieve better health. Under the premise that anyone able to walk should be able to do so anywhere, encouraging

everyone to walk would translate into an equitable health promotion strategy (Keith et al., 2016; Thomas, 2017). But the strategy would fail to be equitable if where walking took place was restricted based on the socioeconomic characteristics of the walkers.

In this study, we investigate the variations in the socioeconomic characteristics of environments where walking takes place by people with different socioeconomic characteristics. The intention is to examine whether there might be inequities in daily walking and specifically whether disadvantaged and minority populations might disproportionately access similarly disadvantaged environments while walking.

We use residential property values to capture the socioeconomic dimension of environments where walking occurs. Property values have been used in previous health studies to quantify the socioeconomic status or relative wealth of neighborhoods. These objective data are location-based at a fine level of resolution (the tax parcel) and regularly maintained and updated by tax assessors (Jiao et al., 2016; Rehm et al., 2012; Vernez Moudon et al., 2011). The spatial distribution of residential property values has been shown to reflect socioeconomic gradients spanning from population wealth to deprivation and to stand-in for relative economic security and a range of life-course resources (Diez Roux, 2004; Krieger et al., 2003). Property values have been positively associated with an area's resources such as access to transit and jobs (Golub et al., 2013; McKenzie, 2013); with aspects of walkability such as street connectivity, proximity to retail, social and recreational locations (Connolly et al., 2010; Diao & Ferreira Jr, 2010; Drewnowski et al., 2014; Fone et al., 2006; Guo et al., 2016); and with the presence of street trees (O'Neill Marie S et al., 2003; Theebe, 2004). They also correlate with an area's maintenance expenditure and frequency of policing (Connolly et al., 2010; Fone et al., 2006; Rehm et al., 2012).

However, areas of greater wealth also come with negative characterizations. They present barriers for, and are often perceived as unfriendly and inaccessible by low-income populations, racial/ethnic minorities, and others experiencing stigmatization and oppression (Lang and Rothenberg, 2014; Rigolon and Nemeth, 2018; Nemeth 2007). In addition, increases in property values can have negative connotations because they have been linked to gentrification processes whereby outsiders of higher means than local residents threaten and displace them (Guerrieri et al., 2013).

The study uses household income as the main measure of participants socioeconomic status. Walking is measured objectively in space and time using walking activity bouts derived from accelerometers and GPS in a Geographic Information System (GIS) environment. Analyses focus on walking that is tracked outside of the home neighborhood. This reduces the self-selection effect because people have more limited choice as to where they travel outside of their home neighborhood on a daily basis, especially for utilitarian walking. The study examines how high or low income status is associated with walking for utilitarian or recreation purposes in areas of varying wealth.

4.2 Method

4.2.1 Study Setting and Participants

This study used individual-level data collected for the Travel Assessment and Community (TRAC) study, which was a three-wave longitudinal study on the effect of a newly built light rail line on the physical activity of the population in King County, Washington. TRAC participants were older than 20 years of age in 2009 and were able to walk unassisted for at least 10 minutes. An equal number of participants resided less than one mile (exposed) and

more than one mile (unexposed) from a light rail stop. Both groups lived in built environments that had similar development densities, mixed uses, access to transit, and sociodemographic characteristics (Moudon et al., 2009).

Participants were instructed to wear an accelerometer (ActiGraph GT3X), set to collect at 15 second epochs but aggregated to 30-second intervals for analysis, and a global positioning system (GPS) data logger (QStarz BT-1000XT) configured to collect at 30-second intervals for 7 consecutive days. Subjects were also directed to record locations in a place-based travel diary for the same time period. Data collected using these three instruments were matched by common time stamps (Kang et al., 2013), which generated time-indexed tables including data from all three instruments. Participants also completed surveys about their demographic and socioeconomic information. This analysis was limited to participant travel data collected between May 1, 2012 and August 30, 2013 (TRAC study, wave 3) in order to take advantage of an updated GPS technology (QStarz BT-1000XT) that contained satellite information that could be used to determine whether subjects were indoors or outdoors (Tandon et al., 2013). The Institutional Review Board at the Seattle Children's Research Institute approved the project.

4.2.2 Walking Bouts

Walking activity was identified using an algorithm published previously (Kang et al., 2013). Briefly, a physical activity bout was defined as a ≥ 5 min interval of sustained accelerometer counts ≥ 500 counts per 30-s epoch (cpe), or ≥ 7 min, allowing for up to 2 min of activity outside the 500 cpe threshold to account for short breaks, such as waiting at traffic signals. Among all activity bouts, walking bouts were identified based on either the GPS-recorded speed and point patterns consistent with walking or a reported overlap with a walking

or other trip (e.g., transit trip, with the assumption that walking was included as part of these other trips) recorded in the travel diary. For this study, we included only walking bouts with at least 1 GPS point within the study area, defined as the King County Urban Growth Area (UGA, the 1200 km² urbanized area around the City of Seattle).

To reduce exposure related to home neighborhood self-selection, we excluded bouts that were completely within participants' home neighborhood (defined as a 400 m Euclidean buffer around their geocoded home address). Bouts that crossed the buffer were truncated so that only the portion occurring outside of the 400 m buffer was retained. Also, in order to explore time of day as a covariate, bouts that spanned two times of day (see full description of variable, below) were recorded as two separate bouts such that each portion was appropriately classified by their relevant time period. Any bout truncated by the 400 m buffer whose remaining portion had a duration shorter than 2 minutes were excluded from the analysis because they were not long enough to represent the experience of walking. Finally, bouts from participants without a complete survey and bouts without any property value data were removed from the sample.

4.2.3 Variables

Outcome: Area Residential Property Value

The main outcome of the analysis was the mean property value of residential units around a walking bout. Property value was calculated as the mean within 400 meters of each GPS point of a walking bout; the GPS point values were then averaged for each bout. We used 400 meters to capture the immediate environment a person was exposed to and the nearby environment that might contribute to walking barriers or support. Property value data came as rasterized *SmartMaps* using King County tax assessor parcel data. Details of this method have been

described elsewhere (Hurvitz et al., 2014a); briefly, each 30 m cell in the SmartMap has a value representing the mean property value of all residential units within 400 m of that cell. By pre-processing the data as opposed to performing GIS analysis for every GPS point, this method allows for efficient measurement of large point data sets. Tax assessor data from 2012 and 2013 matched with the time stamp dates of GPS points.

Main Predictor: Household Income

Self-reported participant annual household income from the survey was the main predictor of interest. The data were collected as a categorical variable with 11 USD levels (<\$10,000, \$10,000-19,999, \$20,000-29,999, \$30,000-39,999, \$40,000-49,999, \$50,000-59,999, \$60,000-69,999, \$70,000-79,999, \$80,000-89,999, \$90,000-99,999, >\$100,000). For the analyses, we recoded income into three levels: below \$50,000, which was consistent with the median household income of \$51,371 in US during the same time (United States Census Bureau, 2013), was considered as low income; medium income fell between \$50,000 to \$100,000; and above \$100,000 was high income.

Secondary Predictors and Potential Effect Modifiers

In addition to income, we were also interested in whether variations in the property values of walking environments were related to participant age, sex, race, purpose, time and day of walking. If they were, we further examined if these factors modified the relation between income and the property value.

Age was collected as a continuous variable and coded as a binary variable with age below 65 as the reference, as previous studies associated age above 65 with a change in daily routine due to sometimes retirement and with increased mobility difficulties (Beurskens & Bock, 2012).

Gender was coded as a binary variable, male, female. None of the participants self-identified with gender other than the two categories. *Race* was categorized as White or non-White. African American, Asian, Native American or Alaska, Hawaiian/Pacific Islander, other, or multiple were combined as non-White because of the low number of observations in these categories. Overall, neighborhoods with predominantly non-White residents have long had unequal access to transit opportunities and other resources (Golub et al., 2013; McKenzie, 2013) and institutional racism has caused significant segregation of public spaces such that many people of color feel unwelcome and even unsafe in many areas (Anderson, 2015). *Walking purpose* was categorized as either utilitarian or recreational. Utilitarian walking bouts were defined as having a destination while recreational walking bouts were defined as “tours” or walking without stops at destinations, based on GPS and travel diary records (Kang et al., 2013, 2017). Details of the method for this categorization of walk bouts are documented elsewhere (Kang et al., 2017). *Time of Day* was categorized into *during daytime* and *during nighttime* based on the timestamps of the accelerometer records. The measure was to test the potential effect of daylight on walking location. Daytime was defined as after sunrise and before sunset (Sunrise and Sunset, 2020). *Weekday or weekend day* were identified based on accelerometer time stamps.

Other Variables

We also included *household size*, reported in the survey as the number of people in the household, including children. Large households tend to have more employed members and therefore higher overall household income, but perhaps lower per person income. Previous literature suggested a nonlinear relationship between household size and basic economic activities such as buying a car and daily expenses (Arbués et al., 2010; Deaton & Paxson, 1998).

It was coded into a binary variable with “small” indicating households with two or fewer members and “large” indicating households with three or more members.

Walking bout duration was introduced as a precision variable. The duration of the bout may influence bout mean property value as longer bouts may have fewer extreme mean values and allow for more opportunities for participants to move through very different environments. Bout duration was calculated in minutes as the difference between the timestamps of the first and last accelerometer records of the bout.

4.2.4 Statistical Analysis

The unit of analysis was the walking bout. We used a hierarchical generalized linear model with participant-level random effects to address the two-level data structure with walking bouts nested within participants, and to account for the fact that participants contributed different numbers of days and walking bouts. The outcome was the mean residential property value exposure of each bout and the main predictor of interest was the household income category. The outcome presented a log-gamma distribution with outliers of large values. To obtain stable model results, we Winsorized the top property values, namely replacing the ones above 95-percentile with the 95-percentile value (Dixon & Yuen, 1974) and assumed log-gamma distribution for the hierarchical model (Malehi et al., 2015). The distribution of bout duration was positively skewed by large values, so it was standardized after log transformation.

To assess if bout property values were related to income and other socioeconomic and walking characteristics, the models included all variables of interest (household income, gender, age, race, purpose of walking) except the time of walking bout. Bout time of day overlapped significantly with utilitarian bouts, with 74.6% (n=771) of the utilitarian bouts occurring during

daytime. Given our interest in accounting for variations in exposure by walking purpose, the time of day variable was not included. Household size and bout duration were introduced as precision variables. Incident rate ratios are reported with the 95% confidence interval.

To assess if the relationship between income and property value exposure differed by age, gender, race, day, and the purpose of walking, we sequentially introduced interaction terms between these potential effect modifiers and household income. Only models with interaction terms significant at $p < 0.05$ level, indicating that the variable modified the relation between income and bout property value, were reported. To visualize the marginal effects of income with interaction terms, we calculated the predicted values for different levels of income with 95% prediction interval while holding all other covariates constant.

All analyses were performed in PostgreSQL 9.6 with PostGIS 2.4, and R version 3.6.0 environment (R Core Team, 2019).

4.3 Results

4.3.1 Characteristics of Participants and Walking Bouts

Of the 567 participants retained in the third wave of the TRAC study, 286 had outdoor walking bouts with GPS information within the study area and contributed a total of 1438 walking bouts. We split the bouts that spanned two time periods (e.g. from daytime to nighttime) into separate bouts, resulting in a total of 1471 bouts. We excluded 14.7% of the bouts ($n=216$) that occurred within participants' home neighborhoods, 13.4% of the bouts ($n=197$) without complete participant socioeconomic data (most common variable missing being household income) and 3.7% of the bouts ($n=55$) without property value information. The final sample yielded a total of 1003 bouts from 234 participants. Each participant contributed between 1 to 19

bouts, with a mean count of 4, and on average 58.5 minutes of accumulated walking outside of home neighborhood per participant.

The final study population had higher percentages of female, people above 65, and had a slightly lower median household income compared to the population of King County in 2013 (United States Census Bureau, 2013). The sample included a higher percentage of people self-identifying as White relative to King County (85.0% vs. 74.1% in King County). There was a balanced number of participants in the low-, medium- and high-income categories. On average, a higher percentage of participants with low household income were above age 65 (25.7%) and self-identified as non-White (21.4%), compared to the medium income population (17.6% > 65yr, 12.9% non-White) and the high-income population (16.5% > 65 yr, 11.4% non-White) (Table 4.1).

As for walking bouts, low-income participants had a higher percentage of utilitarian walking (89.5%) compared to medium- (81.9%) and high-income (83.4%) participants (Table 4.2). We did not observe differences in the number of daytime and nighttime walk bouts by income. High-income participants were on average exposed to higher property value environments (median = \$167,000) than low- (median = \$137,000) and medium- (medium=\$141,000) income participants on their walk outside of the home neighborhood.

Table 4.1 Characteristics of participants by income level (n=234)

	Total (n=234)	Low Income (n=70, 29.9%)	Medium Income (n=85, 36.3%)	High Income (n=79, 33.8%)
Age				
Above 65	46 (19.7%)	18 (25.7%)	15 (17.6%)	13 (16.5%)
Below 65	188 (80.3%)	52 (74.3%)	70 (82.4%)	66 (83.5%)
Gender				
Male	95 (40.6%)	29 (41.4%)	31 (36.5%)	35 (44.3%)
Female	139 (59.4%)	41 (58.6%)	54 (63.5%)	44 (55.7%)
Race				
White	199 (85.0%)	55 (78.6%)	74 (87.1%)	70 (88.6%)
Other	35 (15.0%)	15 (21.4%)	11 (12.9%)	9 (11.4%)
Household Size				
Small	172 (73.5%)	67 (95.7%)	56 (65.9%)	49 (62.0%)
Large	62 (26.5%)	3 (4.3%)	29 (34.1%)	30 (38.0%)

Table 4.2 Characteristics of walking bouts by participant income level (n=1003)

	Total (n=1003)	Low Income (n=353, 35.2%)	Medium Income (n=354, 35.3%)	High Income (n=296, 29.5%)
Purpose				
Utilitarian	853 (85.0%)	316 (89.5%)	290 (81.9%)	247 (83.4%)
Recreational	150 (15.0%)	37 (10.5%)	64 (18.1%)	49 (16.6%)
Time of day				
Daytime	907 (90.4%)	319 (90.4%)	320 (90.4%)	268 (90.5%)
Nighttime	96 (9.6%)	34 (9.6%)	34 (9.6%)	28 (9.5%)
Day				
Weekday	737 (73.5%)	262 (74.2%)	261 (73.7%)	214 (72.3%)
Weekend	266 (26.5%)	91 (25.8%)	93 (26.3%)	82 (27.7%)
Duration (min)				
Mean (SD)	15.3 (17.0)	12.7 (11.9)	13.2 (13.9)	13.6 (14.3)
Median [Min, Max]	9.00 [2, 109]	9.00 [2, 90]	9.00 [2, 156]	9.00 [2, 156]
Property Value (\$1,000/unit)				
Mean (SD)	193 (131)	182 (120)	187 (130)	211 (142)
Median [Min, Max]	147 [13.2, 552]	137 [266, 552]	141 [13.2, 552]	167 [22.8, 552]

4.3.2 Associations between Walking Bout Property Value, Income, and Other Socioeconomic and Walking Characteristics

Table 4.3 Model 1 presented the relationship between the property value around walking bouts and participant income after controlling for socioeconomic and walking characteristics. The average residential property value of walking bouts from participants with low household income was 12.3% lower than that of those from high income households ($p < 0.1$). There was no significant difference in property value exposure between participants with low-income and medium household income. The property value around walking bouts of male participants was 11.8% (95%CI=0.9%-21.5%) lower than that of female participants, and was 16.0% higher for White participants than non-White participants. The value of properties around utilitarian walking bouts was 11.3% (95%CI=2.4%-19.4%) lower than that of recreational walking bouts, and 14.2% (95%CI=6.2%-22.9%) higher around weekend walking bouts than weekday walking bouts. After adjusting for the purpose of walking, day of walking, gender, and income, we did not observe a significant difference in property value exposure by age.

4.3.3 Associations between Walking Bout Property Value and Income, by Race and Purpose of Walking

Table 4.3 Model 2 presented the associations between walking bout property value and household income considering the potential moderation effect by race and purpose of walking. The interaction terms between income and race, income and purpose were significant, indicating that the relation between bout property value and income differed by race and purpose of walking. The difference in bout property value by income was larger for recreational trips than utilitarian trips and was larger for non-White participants than White participants. None of the

other socioeconomic and walking characteristics were found to moderate the relation between income and property value.

Moderating Effects of Race

Figure 4.1(a) showed the predicted property value exposure for each income group by race, calculated based on model coefficients. For both White and non-White participants, as income decreases, the property value of environments around walking also decreases. However, the differences in property value between high- and low-income groups were much larger for non-White participants (\$217,000/unit) than White participants (\$97,000/unit).

Table 4.4 showed the simple main effect of income under each race, namely whether the difference in property value by income and race observed in Figure 1 was statistically significant. The results confirmed that the differences in property value between high- and low-income groups was indeed significantly larger for non-White participants (low-income group being 55% lower than high-income group) than White participants (18% lower).

Moderating Effects of Purpose of Walking

Figure 4.1(b) shows the predicted property value exposure for each income group by the purpose of walking. As income decreases, the property value of walking environments also decreases for recreational walking, but only decreases slightly for utilitarian walking. The simple main effect in Table 4.4 confirmed this finding. There was no significant difference between utilitarian walking trips for low- and medium-income groups and only a small difference between medium- and high-income groups (18% lower).

This association between income and walking bout property value was stronger after considering the moderation effect of race and purpose of walking. The inclusion of interaction terms revealed the relation between income and property value exposure that was not obvious in the base model, possibly masked by the difference related to utilitarian walking.

Table 4.3 Associations of property value around walking bouts with individual socioeconomic and demographic factors and characteristics of walking bouts

		Model 1 (N=1003)			Model 2 (N=1003)		
		DV: property value			DV: property value		
		IRR	95% CI	p	IRR	95% CI	p
<i>Participant Level</i>	Income						
	Low	0.877	0.761-1.003	0.09†	0.353	0.229-0.544	<.001***
	Medium	0.874	0.754-1.020	0.06†	0.597	0.389-0.915	0.02*
	High		<i>Reference</i>			<i>Reference</i>	
	Gender (male)	0.882	0.785-0.991	0.03*	0.905	0.807-1.015	0.09†
	Age (above 65)	1.039	0.897-1.205	0.61	1.014	0.878-1.172	0.015
	Race (White)	1.160	0.985-1.366	0.08†	0.821	0.602-1.121	0.215
	Household Size (small)	0.826	0.716-0.953	0.01**	0.841	0.731-0.968	0.016*
<i>Walking bout Level</i>	Purpose (utilitarian)	0.887	0.806-0.976	0.01*	0.730	0.615-0.867	0.215
	Day (weekend)	1.142	1.062-1.229	<.001***	1.147	1.067-1.233	<.001***
	Duration	1.095	1.060-1.131	<.001***	1.100	1.065-1.137	<.001***
<i>Interactions</i>	Low income*White	-	-	-	1.832	1.226-2.737	0.003**
	Medium income *White	-	-	-	1.328	0.881-2.002	0.175
	Low income * Utilitarian	-	-	-	1.595	1.239-2.053	<.001***
	Medium income* Utilitarian	-	-	-	1.176	0.940-1.470	0.156

***p<0.001 **p<0.01 * p<0.05 †p<0.1

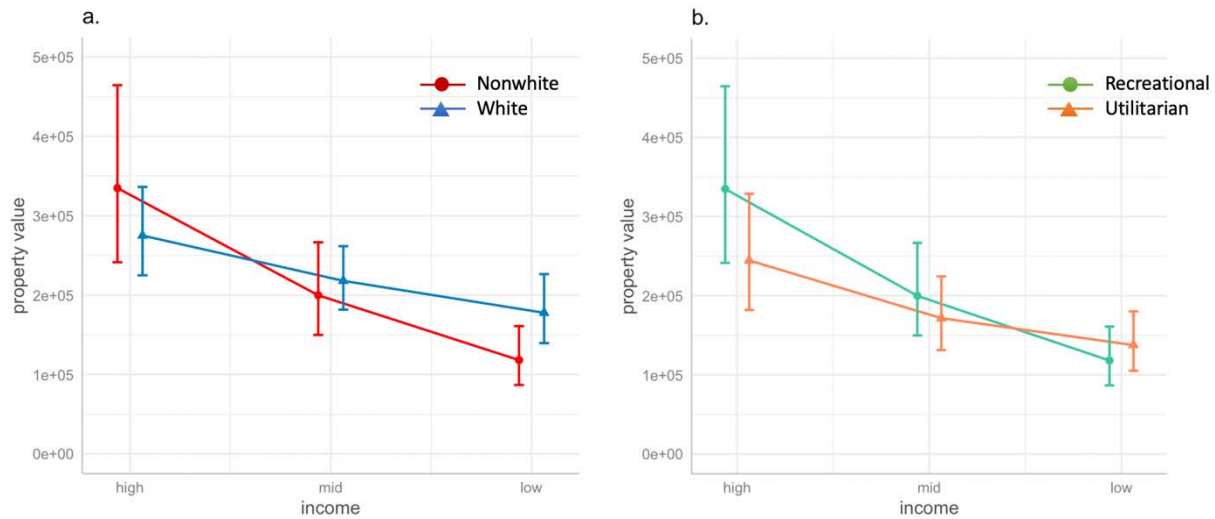


Figure 4.1 Predicted mean property value around walking bouts by individual household income, stratified by race (a) and purpose of walking (b).

(a): female, below 65, utilitarian, mean duration, weekday

(b): female, below 65, non-White, mean duration, weekday

Table 4.4 Simple Main Effect for Income, Race, and Purpose of Walking

	White		Non-White		Utilitarian		Recreational	
	IRR	P	IRR	P	IRR	P	IRR	P
Low - High	0.82	0.031*	0.45	<0.001***	0.77	0.010*	0.48	0.009**
Low - Medium	0.96	0.605	0.69	0.031*	0.94	0.50	0.70	<0.001***
Medium - High	0.86	0.057†	0.66	0.029*	0.82	0.051†	0.69	0.006**

***p<0.001 **p<0.01 * p<0.05 †p<0.1

4.4 Discussion

4.4.1 Overall Findings

When walking outside of their immediate home neighborhood, low-income participants were generally exposed to environments that had lower property values and, by extension, lower neighborhood wealth than their high-income counterparts. This result provided preliminary

evidence that income disparities may exist not only in residential locations, but also in the non-home environments to which people are exposed within their walking activity space.

We further examined factors moderating the relationship between income and walking environment and found that the relationship was further exacerbated by race. Non-White low-income walkers were more likely to be exposed to lower property value environments than White, indicating that the association between income and the wealth of where people walk was stronger for minorities. This finding was consistent with previous studies on racial and income disparities in environmental exposure and health outcomes in U.S., such as the exposure to neighborhood hazards and mortality (Downey & Hawkins, 2008; McLaughlin & Stokes, 2002; Mode et al., 2016).

Similarly, the relationship was stronger during recreational trips than utilitarian trips. During utilitarian trips, low-income walkers were exposed to environment of similar property value to medium-income walkers, and was only slightly lower than their high-income counterparts. These findings suggested that utilitarian trips had the potential to offer opportunities for people to access walking environments that are not restricted to those matching their own income.

In addition to income, we observed other individual and walking characteristics associated with differences in the wealth of walking environments. Females generally walked in environment of higher property value than males. Recreational and weekend walking, when people were likely to have more choices of where to walk (McGuckin & Srinivasan, 2005), also happened more in environments of higher property value. We did not observe significant differences in the wealth of walking environment by age.

4.4.2 Strength and Limitations

Strengths

Building upon the accumulated body of study on what a walkable environment is, this paper adds to the few studies that have examined whether there were possible inequities between the wealth status of walking locations and the socioeconomic status of the walker. This study recognizes that there is a fundamental difference between a place that is deemed “walkable” in a functional or physical sense and a place where an individual can actually walk, with the latter being the result of complex psychosocial interactions between perceived and actual needs and constraints that are unique to each individual.

This paper extends previous studies examining differences in home neighborhood walking environment by socioeconomic status to beyond home neighborhood and alone people’s actual movement path. It does so by utilizing GPS trajectory data and capture the wealth of walking environment immediately around each GPS point and along walking bouts. Compared with the previous static residence-based environment assessments which approximate the true exposure with home neighborhood environment, this approach greatly improves the accuracy of walking environment assessments (Chaix, 2020; Scully et al., 2019).

Limitations and Future Work

The findings from this observational study described associations observed among different sociodemographic groups, the characteristics of the walk, and property value of the walking environment. It did not permit making inferences about causal relationships. To continue disentangling this complex relation between income and the wealth of where people walk, future studies could further compare the wealth of people’s walking environment with their

own home property value. There may exist differences by income, in that it may be more likely for lower income people to access wealthier environment than having higher income people to access places of lower wealth. Besides, it is also worth exploring the interaction effect between income, home property value, and home neighborhood property value to compare the effect of income and home neighborhood wealth on people's walking environment – whether it matters more to empower people to obtain a higher income or to live in neighborhoods of higher wealth.

Because of the small proportion of participants who self-identified as being non-White, explorations into the more nuanced differences and challenges faced by non-White residents of diverse cultural backgrounds were not possible. Yet the observed differences in walking environment for non-White residents suggested the need for future studies to highlight the potentially varied experiences of those populations.

4.5 Conclusion

There are large variations in people's daily walking environment in terms of neighborhood socioeconomic status. This study is among the first to examine these variations as experienced by people of different socioeconomic status and by types of walking behaviors using objectively measured walking data. The wealth of the place that a person navigates through while walking relates to their income, race, gender, day, and purpose of walking. This study also demonstrates how tracking technologies combined with property value data can be used to obtain an assessment of personal environment exposure at a fine spatial-temporal resolution and to allow the reexamination of spatial and income inequality and opportunities for change.

CHAPTER 5. Lessons Learned

This concluding chapter first summarizes the findings, significance, and recommended future work for each individual study. It then explains and generalizes lessons learned from the three studies on the collinearity of built environment elements, the understudied populations, and the measurement of exposure to built environment. Finally, it gives an overview of the contributions this dissertation made to the study of built environment, travel behavior, and physical activity.

5.1 Summary of Individual Study Findings

Chapter Two examined whether new installations and upgrades of transit stop amenity attracts transit users and increase stop ridership. To capture the variety of combinations of stop amenities, a tree-based model was used to reduce the patterns of amenity combinations that were installed as bundles. The study found that stop amenities mattered for boardings but not alightings, suggesting that transit users may be more sensitive to stop environments where they spend more time (i.e., while waiting for transit). Some amenities (i.e. real-time information system, shelter, and bike hoops) mattered more than others in their association with ridership. The study was among the first to provide empirical evidence on transit micro-environment from the perspective of transit users and to demonstrate the use of tree-based models to assess the impacts of correlated microscale features of the transit environment on behavior. The approach could be adapted to other contexts and to analyze the role of the urban environment in health, urban planning, and transportation studies.

This finding could assist state and local transportation agencies to develop, select, and fund projects to enhance the experience of riders and increase public transit ridership. As a less

expensive capital investment option compared to other system improvement such as vehicle purchase or service area expansion, enhancing stop-level amenities, especially focusing on a set of more impactful amenities, can be a cost-effective strategy of system improvements to increase transit ridership and improve travel experience. Future research could examine the interplay between stop amenities and other factors internal and external to the public transportation system (e.g.: the importance of shelters and benches may differ by weather and frequency of service). The longer-term effect of stop amenity changes should also be investigated to pinpoint the time span after which boardings cease to increase. Local and regional transportation agencies may benefit from systematically collecting and managing stop-level amenity and ridership data over time to guide future infrastructure investments.

The objective of Chapter Three was to develop a school walkability index and an estimated percentage of walking to school for all schools in Washington State. Utilizing the student travel data in Washington State, this study used regression models to construct a walkability index based on student travel data and verified index performance using survey data and cross-validations. The models were then used to estimate the percentage of children walking at the school level for the schools in Washington State where actual walking data were not available. The walkability index and the predictions performed well under different data scenarios and were stable when upscaled from King County to Washington State. The study found that publicly available GIS data on built environment features (i.e. street connectivity and traffic exposure measured using OpenStreetMap) were sufficient for measuring school walkability across the state. In addition, free and reduced school lunch enrollment, a nationwide available dataset (National Education Statistics NES), served as a substitute for unavailable student family economic status, which is an important determinant of student travel to school

mode choice. The developed indices helped to identify schools in Washington State in need of funding and resource support. The methods used to develop these indices and predictions can be replicated in other jurisdictions and states aiming to promote active travel to school.

Chapter Four assessed difference in people's walking environment using GPS and accelerometer data and showed that people of lower income also tended to walk in areas of lower wealth outside of their home neighborhood. In addition, the disparities in walking environment were further exacerbated by race and in particular during recreational trips. During utilitarian trips, low-income walkers were exposed to environments of similar wealth to medium-income walkers, and to environments that were only slightly lower than their high-income counterparts. This chapter revealed income inequalities in exposure to the built environment that extended beyond one's home to environments experienced every day and possibly encompassing conventional economic activities (e.g. work, entertainment) that have been overlooked in prior studies. It also showed that utilitarian trips had the potential to offer opportunities for people to access urban environments that were different from those restricted by their own income.

This finding revealed opportunities for improving inclusive and equitable access to urban spaces for all. Future studies could further examine the walking trips by origins and destination, which could shed light upon locations where people of disadvantaged backgrounds spend a significant amount of time walking in low wealth environments. Targeting these areas for built environment improvement and providing alternative mobility options will likely benefit walkers from economically disadvantaged backgrounds.

5.2 Lessons and Future Work

This dissertation contributed to three unresolved domains in the area of built environment, travel behavior, and physical activity and laid out suggestions for future work: (1) collinearity in built environment elements, (2) understudied populations, and (3) measurement of environmental exposure along movement path.

5.2.1 Collinearity in Built Environment Elements

All three chapters explored built environment features that present collinearity and demonstrated different strategies to tackle it. Chapter Two used the conditional inference tree (CIT) method to group the built environment elements that were correlated (i.e. lighting, shelter, and bike hoops, etc.) and created latent variables that underlie the observed collinear variables (i.e. amenity combinations). It then used the constructed latent variables as explanatory variables. Other methods that have been used in previous studies and that follow the same strategy of constructing latent variables based on existing correlated variables, include principal component analysis (PCA), which creates principal components as explanatory variables and fits regression models using these principal components. Lee et al's study in 2020 used PCA to reduce the large number of correlated street characteristics and pedestrian infrastructure to lower dimensions in order to construct a walkability index. The drawback of PCA is that its results cannot be easily translated into interventions, because the latent variables created using this method are a linear combination of built environment elements, thus no longer correspond to characteristics of the actual built environment in the real world. In contrast, tree-based models, forming new variables based on groupings of existing observations, remain the ease of interpretation.

Chapter Three on school walkability aimed for prediction (rates of walking to school) rather than inference, therefore, the issue of collinearity was less of a problem because it does not impact the predictive power of the model as a whole. However, the best subset model selection used in Chapter Three was indeed another common strategy to treat collinearity, namely using variable selection methods to exclude variables that are highly correlated. Other methods in the same vein either use a combination of model-performance and prior theories or a solely model-performance based approach. Lee et al's study in 2006 is an example of the former (C. Lee & Moudon, 2006a). To select variables correlated with walking, the study first identified clusters of variables with high correlation and then identified from each cluster a central variable based on prior theories and significance in association with walking to be included in the final models. Moudon et al's study in 2019 and Mooney et al's study in 2020 are examples of the latter (Mooney et al., 2020; Moudon et al., 2019). Both teams were working with a high dimensional context (i.e. the number of built environment variables examined are much larger than usual) and based variable selection solely on correlations among variables and model fitness. Chapter Four used a single measurement that captured the multiple inter-related aspects of the built environment (i.e. property value), which had been used in other prior studies (Drewnowski et al., 2015; Vernez Moudon et al., 2011).

In addition to the three genres of methods used in this dissertation, some studies choose to use sampling strategies to isolate the effect of variables of interest. For example, Leal et al's study sampled participants from neighborhoods that differed in only one dimension of the built environment while being similar in other dimensions in order to isolate the effect of certain neighborhood characteristics on body weight. This approach is favored when studies involve primary data collection, which was not the case for this dissertation.

In summary, there is a range of statistical methods available to tackle collinearity issues (Dormann et al., 2013), each with strengths and limitations. For example, while PCA creates latent variables free from collinearity, the results can be sometimes difficult to interpret or to be directly applied to informing interventions. In comparison, the variable selection approach retains interpretability but may suffer from information loss due to omitting variables from the models. Up to now, despite the growing number of studies adopting such methods to address collinearity of built environment elements, limited effort has been expended to compare these different streams of approaches and examine the appropriate context in which they should be applied. In addition to demonstrating the use of CIT method, this dissertation is among the first to provide an overview of some of these different approaches (i.e. latent variable, variable selection, proxy measurement, and sampling) in addressing collinearity in the built environment. More work is needed to systematically review the application of these methods and to communicate the findings to planning scholars, educators, and practitioners.

5.2.2 Understudied Population

As demonstrated in this dissertation, the travel environments of overlooked or disadvantaged populations differ from those of populations who are more privileged. One of the main challenges to generate quantitative evidence specific to the experience of these populations is the lack of systematically collected data on disadvantaged groups as well as on the travel environment they are exposed to. For example, in contrast with information tracking on vehicles and the roadways they use, there is no automated data collection and reporting process for bus stop use, construction, and environmental improvements. Yet transit users spend considerable amounts of time at and near bus stops. Similarly in the case of children, there has been a lack of information related to student travel, such as travel mode to school, distance from home to

school, and school policy towards AST. Yet we know that childhood travel behaviors affect how adults travel later in life. And the lack of exposure to travel by public transit in childhood often leads to ignoring or even fearing that travel mode in adulthood.

This dissertation addressed the above data gap on disadvantaged groups mainly through two channels – (1) data collection and curation; (2) interpolation and/or extrapolation when data was scarce. The former either collects new data or integrates existing yet underused data from various sources. The latter predicts missing values based on existing data. Chapter Two integrated multiple existing datasets from different departments in the regional transportation agency to build a longitudinal record of stop amenity installations, removals, and upgrades. This served as the basis for analyzing transit micro-environments. Chapter Four utilized a unique database of 7-day GPS data of participants from various socioeconomic backgrounds to assess variations in walking environment by income level. On the other hand, Chapter Three addressed the data gap by interpolating and extrapolating using existing student travel survey data to obtain information for schools where actual walking data is no available.

Due to the low percentage of minority population included in the study sample, the examination on walking environment for people of different race and ethnicity was limited. Considering the diverse cultural and personal experiences each individual or group has, future studies should examine such unique experiences and map the resulting differences in their spatial-temporal exposure to built environment.

5.2.3 Measurement of Exposure to Built Environment

Although focused on a specific place (i.e. bus stops and schools), Chapter Two and Chapter Three utilized an approach to study built environment exposure different from the place-based approach commonly practiced in geography and public health studies. To distinguish

between the two concepts, I termed what was used in this dissertation a “*location-based*” approach. The environment exposure measured using the place-based approach is at the individual level and often time, the targeted subjects of intervention are also individuals. For studies using a location-based approach, the target of intervention is the studied place or location itself, such as schools and transit stops. The motivation behind this type of research is to develop findings directly on the target of design and planning interventions – places. For example, in Chapter 2, transit stop, where people interact with stop amenities, is the location of study as well as the target of intervention. The findings drawn from such a study supports further investments in studied places.

Chapter four is among the few studies to apply the people-based exposure measurement to study the wealth of walking environment. Currently, this approach is mainly used to study the relation between built environment, travel behaviors, and exposure at the participant level and has only been used to inform practices such as personalized incentives. One possibility to integrate such studies into urban design and planning interventions in the future is to use such a measurement to identify locations where the most people get the most exposure, and thus could be an optimal location for intervention placement, by introducing location-sensitive variables (i.e. trip origins and destinations). More explorations are needed to establish the link between people-based exposure study and the placed-based interventions commonly practiced in urban design and planning.

5.3 **Conclusion**

In this dissertation, I quantified the association between transit stop design and stop level ridership using a quasi-experiment design and conditional inference tree model. I also developed a state-wide walkability index and a percentage of walking estimation for all K-8 schools in

Washington State. Finally, I quantified the differences in the wealth of people's walking environment by their socioeconomic status and trip characteristics.

Through the above studies, three unresolved conceptual and methodological topics were addressed. First, the studies reviewed and tested methodologies to address the collinearity of built environment elements. Second, they examined interactions between built environment and travel behavior among understudied population groups, including transit riders, children, and people with economically disadvantaged background. Thirdly, a "location-based" approach, unique to urban planning context, was defined and articulated as a concept complementary to the existing placed-based and people-based approaches in the measurement of exposure to built environment.

The dissertation also laid out direction for future work. First, efforts should be made toward reviewing the use of different methodologies to address collinearity of built environment elements and actively incorporate such discussion into research and teaching. Second, studies on transit user and transit stop micro-environment should further examine the interplay between stop amenities and other factors of the public transportation system as well as the longer-term effect of stop amenity changes over time. Third, more studies are needed to reveal the different walking experiences and walking environments for a range of subpopulations, including minority groups. Fourth, built environment studies using the people-based approach to measure exposure should design analyses that can also inform location-based interventions.

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