Examining the association between cycling infrastructure exposure and physical activity: A Natural experiment study in Victoria, Canada

A thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of Master of Science in Kinesiology

By

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Abstract

Background: Most Canadians are not meeting physical activity guidelines. Physical inactivity is an epidemic related to alarming rates of preventable disease and economic burden. Health benefits ensue from modest increases in physical activity (i.e., 5 minutes daily). Despite the health benefits, there is limited evidence about interventions to increase physical activity at the population level. Built environment interventions, like bicycle infrastructure, are one understudied intervention with the potential to increase total population physical activity. The purpose of this study was to examine the physical activity impacts of bicycle infrastructure.

Intervention: The intervention studied is the All Ages and Abilities (AAA) Cycling Network in Victoria, BC. This network of bicycle infrastructure is a $7.75M commitment. In 2018, a 5.4km grid of protected cycle tracks was built downtown.

Research Design: Adults were recruited in Victoria who ride bicycles at least monthly. Baseline activity data were recorded in 2017 (n = 281) using surveys, Global Positioning System (GPS), and accelerometer data, with a follow-up data collection in 2019 (n = 315). The primary outcome was moderate to vigorous physical activity (MVPA), assessed via accelerometer data.

Hypothesis: Exposure to new active transportation infrastructure will be associated with increased MVPA over time.

Analysis: I calculated exposure measures to the AAA Cycling Network using GPS and Geographic Information System using intersections. I used regression models to examine the associations between exposure to new infrastructure and total location-based physical activity levels, controlling for confounders.

Results: In the multilevel models analyzing the interaction between exposure and wave with covariates, wave two, compared to wave one, saw a non-statistically significant increase in

MVPA of 0.93 minutes per week [CI = -5.28, 7.14]. Comparing the models with and without covariates suggests that the wave one and wave two comparisons were highly confounded by individual and weather covariates.

General Summary

Most Canadians are not physically active. Physical inactivity is related to alarming rates of preventable illness. The INTErventions, Research and Action in Cities Team (INTERACT), aims to advance research on the design of healthy and sustainable cities for all. My study is a sub-project of INTERACT, collecting location and activity data from participants in Victoria, BC. The objective of my study was to examine the association between new cycling infrastructure and MVPA. I hypothesized that exposure to the All Ages and Abilities (AAA) network would increase MVPA. In wave one, 281 people were recruited in 2017: with 149 participating in mobile sensing data collection for ten days. Wave two occurred in 2019 and involved 315 people: with 153 participating in mobile activity sensing. I calculated exposure to the new cycling infrastructure during wave one and wave two by counting the number location points that are within a buffer of the new bike lanes. After analyzing the interaction between exposure and wave with covariates, wave two, compared to wave one, saw a non-statistically significant increase in MVPA of 0.93 minutes per week [CI = -5.28, 7.14]. Implementing the AAA cycling network using separated, safe bike lanes, street beautification, and linking neighbourhoods with new activity spaces may increase MVPA in the city of Victoria.

Keywords: Bicycle lane, active transportation infrastructure, population physical activity, cycling.

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As a member of the INTErventions, Research, and Action in Cities Team (INTERACT), I had the exciting opportunity to contribute to a massive population health natural experiment. Working with a Pan-Canadian team of researchers has provided invaluable skills for my future career. I owe a huge thank you to everyone at team INTERACT for allowing me to play my part in increasing population physical activity and building healthy cities. This project would not have been possible without the incredible support and understanding from my supervisor Dr. Daniel Fuller. In addition to Dr. Fuller, Dr. Meghan Winters and Dr. Fabien Basset were kind enough to provide me with valuable feedback and support when it was needed most during my masters. Thank you to my committee; without you, this entire thesis would not be possible. With innovation and adaptability from team INTERACT, all my work was completed remotely.

Lastly, a big thank you to all primary health care providers, essential services workers, and the public health team in Newfoundland and Canada. We were all able to stay safe thanks to

those on the front lines during the pandemic that we are experiencing. I am inspired by all these people to become a primary care physician and continue with population health research.

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List of Abbreviations

Abbreviation:	Meaning:
AAA	All Ages and Abilities Cycling Network
GPS	Global Positioning System
INTERACT	INTErventions, Research and Action in Cities Team
HMM	Hidden Markov Model
GIS	Geographic Information System
MVPA	Moderate to Vigorous Physical Activity
PR	Prompted Recall
NN	Neural Network
BBN	Bayesian Belief Network
ArcGIS	Geographic Information System software
SVM	Support Vector Machine
VERITAS	Visualization, Evaluation and Recording of Itineraries and Activity Spaces
IPAQ	International Physical Activity Questionnaire
R language	Computer programming language
GGIR	Accelerometer data analysis package

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Chapter 1: Introduction

Urban centers are home to 82% of the Canadian population, where physical inactivity is endemic.[1,2] In Canada, self-report data suggest that 60% of the population meet physical activity guidelines of 150 minutes of moderate to vigorous physical activity per week.[3] The global cost of physical inactivity is $67.5 billion, with an estimated 13.4 million disability-adjusted life years lost.[4] Physical inactivity is the world's fourth greatest risk factor for non-communicable disease, responsible for 9% of premature mortality and 6-10% of coronary heart disease, diabetes, and breast and colon cancers.[5,6] Canadian urban centers are presently car-centric, lacking safe and equitable access to cycling infrastructure.[5,7–9] Bicycle to work mode share among Canadians living in urban areas has increased slightly from 1.2% in 1996 to 1.6% in 2006.[10] While this upward trend is encouraging, this statistic does not account for unemployed or rural populations.[10,11] Evidence is needed from research examining the impact of urban form interventions on Canadians' physical activity. Building safe, accessible cycling infrastructure can increase daily physical activity levels,[12–17] which can have important population-level health and economic benefits.[4,18,19]

One health improvement strategy is facilitating the uptake of active transportation in our urban centers. Countries with the lowest prevalence of chronic conditions have high active transportation-related physical activity levels.[20,21] Existing knowledge from currently available research was primarily conducted in Australia, the United Kingdom, or the United States.[14–16,22–25] Karmeniemi and colleagues reviewed 21 prospective cohort studies and 30 natural experiment studies related to built environment interventions and physical activity. Of the 51 studies included in the review five studies used accelerometer data and nine used GPS.[13] Natural experiments allow the investigation of health outcomes based upon exposure to new active transportation infrastructure over time.[26,27] A strength of natural experiments is observing physical activity without direct alteration or manipulation by the experimenter.[15,23,28,29] The review supports that new infrastructure, aesthetics, and safety were significant determinants of physical activity.[13] The high-quality evidence identified in the study showed that changes in the built environment were associated with increased physical activity. Overall, the results showed positive associations between new infrastructure and cycling participation in nine studies, while six studies showed no association, and one study found a negative association.

Here I review in detail the studies that have been published examining a natural experiment and using accelerometer or GPS data. Examples of specific studies using GPS and accelerometer data include Dill et al. and Heesch et al.[30,31] Dill and colleagues[24] evaluated the effect of installing new bicycle boulevards on physical activity levels. GPS and accelerometer data is best used in combination because these data provide both information on the intensity of physical activity and the location where activity took place. The Oregon-based team used GPS and accelerometer data to measure physical activity change but did not identify increased active transportation or physical activity levels.[24] Dill et al.[24] found a negative correlation between total cycling minutes and exposure to new infrastructure. This finding may be because the participants' exposure to the new cycling infrastructure created a more direct route for downtown commuting, potentially explaining the negative association.[24] Heesch and colleagues[25] studied a new bicycle boulevard in Australia via a planned natural experiment study. GPS and survey data suggest that cyclists using the shared path travelled longer distances per trip and increased cycling-related physical activity.[25] The population with the most important change in cycling was primarily adult males, which indicates that the intervention did not attract a greater diversity of people to cycling.

There has been limited research examining the association between new cycling infrastructure and physical activity using GPS and accelerometer data. These studies suggest that when using GPS and accelerometers, several limitations require consideration. First, researchers should measure more prolonged periods of activity and track participants for more extended periods after completing the intervention. For example, Dill et al.,[24] only measured activity for five days and measured behaviour within months after the intervention was complete. Second, researchers should aim to collect representative samples of the cycling community. For example, Heesch et al.,[31] obtained GPS data from Strava[32], limiting the study population to those using this application. Finally, researchers should consider the type of infrastructure. Dill et al. found a negative association between the infrastructure and physical activity because of shortened commute times. Heesch et al.[31] interventions included a longer path designed for uninterrupted trips. The nature of these different infrastructures should be considered when evaluating the effect of new infrastructure on physical activity. These limitations are addressed in the present study, using a comprehensive bicycle network suited to all ages and abilities.

1.2 Relationship between thesis and larger research project

Current evidence, found in three recent systematic reviews, supports a positive relationship between cycling infrastructure interventions and physical activity.[13,15,33] Increases in physical activity reduce premature death and economic burden from excess healthcare expenses.[6] However, there is limited evidence evaluating the potential population physical activity change resulting from building new cycling infrastructure in Canadian cities, particularly from natural experiment longitudinal research using GPS and accelerometers. This study incorporates and builds upon lessons learned from research in these non-Canadian countries. I am contributing to filling this gap in the literature with a sub-study of a larger research project called The

INTErventions, Research and Action in Cities Team (INTERACT). INTERACT is a $2M Canadian Institutes of Health Research funded project.[29,34] INTERACT has the goal of advancing research on the design of healthy and sustainable cities for everyone.[29] My study examined whether building new cycling infrastructure is associated with changes in MVPA in a Canadian city. Specifically, I assessed whether new infrastructure additions to the All Ages and Abilities (AAA) Cycling Network in Victoria, BC, are associated with changes in residents' MVPA over three years.[29] The AAA Cycling Network[35] is a $7.75M project of separated cycling infrastructure connecting a 5.4km grid in the downtown core.[29]

1.3 Purpose

The purpose of this study was to examine the interaction between exposure to new infrastructure, time, and physical activity. This interaction was examined to understand how MVPA changes throughout the AAA Victoria natural experiment. Specifically, the first objective was to determine if exposure to the new Pandora Avenue, Fort Street, Wharf Street, and Johnson Street bicycle lanes increased physical activity levels. The second objective was completing a time-based comparison of the interaction between exposure to safe cycling infrastructure and the wave of data collection. Exposure was defined as the percentage of participants' GPS points within a 70-meter buffer of the four intervention bicycle lanes. The interaction between exposure to new infrastructure and wave was examined to understand how physical activity level changed throughout the AAA Victoria natural experiment.

1.4 Research Hypothesis

I hypothesized that the active transportation infrastructure would increase MVPA due to increased active transportation engagement associated with exposure to new sections of the AAA

Cycling Network. I hypothesize a net increase in physical activity (minutes of moderate to vigorous physical activity (MVPA)) compared to baseline data from wave one analysis in 2017.

1.5 Thesis Format

My thesis proposal follows a chapter style format, as outlined by the Memorial University Thesis Guidelines revised in 2020. This thesis presents five chapters. Chapter 1 provides a brief overview of the literature, research questions, and hypotheses. Chapter 2 is a complete literature review. Chapter 3 provides the methods for the thesis. Chapter 4 presents the results. Chapter 5 presents the discussion, contributions, and limitations to the thesis. The bibliography and appendices are included are all chapters. The writing format follows the American Medical Association (11th edition) style.

Chapter 2: Literature Review

2.0 Introduction

This literature review focused on learning from and improving upon currently available studies with similar methods to the present sub-study. Studies investigating new active transportation infrastructure, using natural experiments or longitudinal cohort design, and collecting activity data by GPS and accelerometer were reviewed. Despite a lack of studies in Canadian cities, there is a solid knowledge base to indicate effective study methods regarding built environment interventions and physical activity level. Many themes have emerged, grouped into exposure studies and their methods, empirical results from infrastructure studies, methods for studying physical activity, and GPS data processing. Lessons learned from these categories provided the necessary information to employ a robust study design and analysis plan in this sub-study.

There are a number of different types of bicycle infrastructure that might be counted as a built environment intervention with the potential to increase cycling. These include, bike paths, cycle tracks, multi-use paths, or bicycle boulevards. A bike path is a paved path separated from motorized traffic (i.e., not on street) dedicated to cycling. A cycle track, sometimes called separated bike lane or protected bike lane, is exclusive to bicycles and is located on or next to a road. A multi-use path, sometimes called shared-use path or mixed-use path, is infrastructure that supports recreation and transportation opportunities, including walking, bicycling, and wheelchair use. A bicycle boulevard is a low speed street which has been optimized for bicycle traffic. Bicycle boulevards discourage often have low speed limit (e.g., 20km/h, have speed bumps and other measures to slow vehicle traffic, and limit all but local vehicles entering.

2.1 Exposure to Safe Active Transportation Infrastructure

Evidence from urban environments and health research indicates the built environment plays an essential role in increasing population levels of physical activity, which may have a more important role than genetic and biological variables.[6,36,37] Perception of risks associated with cycling is a deterring factor, but analyses have compared the health benefits of bicycling to its dangers. Bicycling injuries are the main risk for cyclists. Overall, the benefits outweigh the risks.[38] In a review of 30 studies assessing varied benefits and consequences, the median benefit-to-risk ratio was 9 (range: 2-360).[39] To put this in context, in transportation decision-making, a ratio of 2 is considered a good value for money.[40] In urban areas, cycling is an accessible travel choice, as the majority of trips taken are of reasonable distances,[41] and cycling trips can be time-competitive with driving. The potential for increasing active transportation via cycling is underscored by the difference in cycling rates between North American and European cities with similar climates and demographics (1-2% of trips versus 15-40% of trips, respectively).[42,43] Further, cycling can be an accessible and equitable transportation mode that provides mobility to individuals of all ages and economic circumstances.

Recent evidence provides a framework for urban planners and policymakers to take meaningful steps to improve public health using built environment interventions.[44,45] At a national and regional level, the evidence clearly shows that areas with more cycling infrastructure have higher cycling and physical activity behaviours.[6,12,23,37,44,46] As well, countries with the lowest prevalence of chronic conditions have the highest active transportation-related physical activity levels.[20,21] For example, Buehler & Pucher[12] used regional level data from 90 American cities to examine the association between cycling infrastructure and cycling. The results (R^2 =.65; p <.05) indicate that cities with a higher supply of bike lanes have significantly greater bike commute rates.[12] A study examining national travel data suggests that considering the high prevalence of walking and cycling in Germany, active transportation is common for meeting daily physical activity recommendations.[47] Research from other countries provides evidence to inform and inspire the future implementation of equitable cycling infrastructure in Canadian urban centers.

Existing knowledge from current research was primarily conducted in Australia, the United Kingdom, and the United States.[14–16,22–25] There is limited evidence that new cycling infrastructure is associated with cycling in Canada. Given the substantial investment required to develop cycling infrastructure, municipal decision-makers across Canada require clear evidence to guide program and policy development effectively. The questions they need to answer are: "Does total cycling increase? Do those who participate in cycling change? What strategies offer the most promise? What are the benefits to cities if they succeed in increasing cycling levels?" [48]. Without such evidence, cities risk misallocating scarce resources or continuing the Canadian paradigm with minimal provision for cyclists: deterring those who might otherwise cycle,[49] and placing those who do cycle at unnecessarily high risk.[50]

While country or city-level analyses are essential, they do not provide specific evidence on the impact of particular cycling-related policies in given cities. Also, country or city-level studies cannot quantify newly constructed cycling infrastructure usage and whether that infrastructure is associated with physical activity changes. For example, weaknesses of the Buehler and Pucher[12] study are not using GPS and accelerometer data to record real-time location and physical activity and a lack of a specific ability to guide the health impacts of local cycling infrastructure investments.[12] As a result of these limitations, and the specific Canadian context, I reviewed the literature focusing on GPS and accelerometer-based research examining the impact of new cycling infrastructure on physical activity. This literature review will determine the best practices for analyzing the AAA Cycling Network's potential impact on physical activity.

2.2 Empirical results from cycling infrastructure studies

Cycling infrastructure provides opportunities for individuals to be physically active and reduce sedentary transport modes.[35,44] Based on the currently available literature, I reviewed five studies that used natural experiments to evaluate physical activity levels after new infrastructure interventions. Natural experiments allow the investigation of health outcomes based upon exposure to new physical activity infrastructure over time.[26,27] A strength of natural experiments is observing physical activity levels without direct alteration or manipulation by the experimenter.[15,23,28,29] Four studies used GPS data to measure physical activity, with three studies using GPS and accelerometer data. One study used surveys to measure physical activity pre-and post-intervention. Various statistical analysis methods were used including Difference in Differences, Hidden Markov Models, multivariate regression, linear regression, and paired sampled *t*-tests. Below these methods are reviewed in more detail with the findings from each study.

In a natural experiment of bicycle boulevard urban form interventions in Portland, Oregon, the team used GPS and accelerometer data on a sample of adults with children ($n = 353$) to assess physical activity changes over time.[24] The study used a data collection period of five days using a longitudinal approach occurring at two-time points.[24] There are few statistical methods used to calculate effect size including difference in differences using multivariate regression models. This is consistent with other natural experiments investigating physical activity levels.[15,16,23,24,28] The study did not show an increase in active transportation-related physical activity after the bicycle infrastructure intervention, which researchers explain in part by the short data collection period of 5 days.[24]

Pritchard et al (2019) in Oslo, Norway, investigated if new bicycle infrastructure resulted in new or rerouted cyclists using a planned natural experiment.[23] The study recruited 113 adult participants to use a smartphone app with GPS for 28 days pre and post-intervention. In the natural experiment, both exposed and unexposed groups experienced an increase in total cycling.[23] The researchers used a difference in differences approach to estimate the new infrastructure's impact on new cycling. They estimated a treatment effect of a 4.7% change in bicycle modal share (95% CI [-0.065, 0.159]) using a difference in differences. Difference in differences is a valuable tool in this case for its ability to mimic experimental research approaches using observational study data by comparing a defined treatment (or exposed) group to a control (or non-exposed) group.[51]

Brown and colleagues[9] found similar results when using accelerometers and GPS to collect one week of physical activity data from adult participants (n = 536) after installing new bicycle and complete streets infrastructure in Salt Lake City, Utah. They found that participants cycling increased on new cycling infrastructure from 18.51 minutes (SD = 54.96) to 22.55 minutes (SD = 49.95), but these results were not statistically significant (SD = 49.95; t(203) = 0.99, p = 0.32). A limitation of this study that may lead to non-significant results is that the researchers focused on non-cyclists (n = 434) in comparison to previous cyclists (n = 102). Non-cyclists comprised over three-quarters of the participant sample, which may contribute to the non-significant findings. Another important factor to consider is the cycling network's placement and the amenities accessible by infrastructure users. Cycling networks connected with mixed land use allow cyclists to perform bicycle trips for multiple purposes, contributing to greater overall cycling.[30]

Heesch et al (2016) evaluated a new bicycle highway in Brisbane, Australia using a cell phone-based GPS tracking application combined with GPS bicycle counts over four years.[31] Although finding a significant increase in cycling and GPS tracking users, many problems arose. The study employed a passive GPS data collection of a homogenous participant sample (n=78,325). The big data approach involved 90% males, primarily aged 35-44.[31] The generalizability of this study is very low, with sacrifices to internal validity. Of note, heat maps were used to define exposure, and there was no analysis of individual-level cycling data. As a result, this study did not examine individual level behaviour change, rather it measured changes in population averages. The population-level analysis leaves a large margin for error and limited generalizability. Based on these reviewed studies' results, individual-level data analysis will provide the greatest strength of evidence in my research.

Goodman et al.[37] analyzed new cycling routes using linear regressions to assess how proximity to the new infrastructure predicted changes in physical activity measured with accelerometers. This study did not include GPS data. The study population included (n=1796) adult residents in three U.K. municipalities at baseline, with 1465 participating in follow-up data collection in 2012.[37] The team determined that the use of active transportation infrastructure was associated with baseline physical activity levels. Proximity effects were significant at a 2-year follow-up. The results demonstrate an increase in physical activity of 15.3 minutes per week per kilometre (CI = 6.5, 24.2) closer to the intervention. The team found that in the short term, new local routes displaced walking and cycling trips, and in the long-term new trips were generated.

Studies examining associations between new cycling infrastructure and physical activity show that infrastructure tends to be associated with increased physical activity. These associations appear to depend on the type of infrastructure and the length of time data are collected post-intervention. Of note, there are no intervention studies in Canadian cities. The literature shows that there are also considerable differences in the data processing and analysis methods for GPS and physical activity data, which make replication and comparison of different studies challenging.

2.3 GPS and Physical Activity Methods

Accelerometers measure the change of velocity over time and report acceleration in terms of multiples of gravitational force. Unprocessed acceleration data is often referred to as raw acceleration data. To develop measures of different movement types (e.g., sitting, lying down, walking/running at different intensities), physical activity researchers have typically used research grade accelerometers placed on the hip or worn on the wrist.[52] Raw data are typically converted into cut points to predict human movement from smartphones at known wear locations.[53] A cut-point approach uses a single summary measure of acceleration (e.g., counts) and applies thresholds, known as cut-points, to define categories of movement types or physical activity intensity. For example, the Freedson cut-points define physical activity intensities as sedentary (<99 counts), light (100-759 counts), moderate intensity (760-5724 counts), and vigorous (5725-max counts).[54] Data collection with GPS devices is an affordable and accurate method to collect movement data that improve the error-prone travel diaries, interviews, travel surveys, mail surveys, and prompted recall surveys.[55] GPS data collection is useful and accurate for recording time and location, but it is challenging to discern trip mode or purpose.[55,56] There are no generalizable methods to imputing trip mode using the INTERACT data. Combining GPS and GIS methods, it is possible to accurately determine whether the physical activity occurred on or near the new or existing cycling infrastructure.[9,25,57–60]

2.5 Research Question and Hypothesis

Studies examining the association between new cycling infrastructure and physical activity using GPS and accelerometer show that new infrastructure is associated with greater physical activity. However, several literature gaps remain pertaining to Canadian data, sample representativeness, length of measurement, and GPS and accelerometer processing methods. My study is designed to build upon previous research and contribute to filling current gaps in the literature.

Does exposure to new active transportation infrastructure among adults in Victoria, BC, change physical activity? That is the question I seek to answer in this thesis. I hypothesized that exposure to the AAA Cycling Network would be associated with an increase in MVPA among residents of Victoria. My sub-study of the large natural experiment in Victoria, BC, can provide empirical evidence for urban planners and future researchers to understand healthy city design and its effects on MVPA.[29]

Chapter 3: Methods

3.0 Overview

The INTErventions, Research and Action in Cities Team, a Canadian Institutes of Health Research funded project, seeks to advance research on the design of healthy and sustainable cities for all.[29] INTERACT is a pan-Canadian collaboration of scientists, urban planners, and citizens uncovering the impact of urban changes on health and equity.[34] INTERACT is currently studying urban form interventions in four Canadian cities: Vancouver and Victoria, British Columbia, Saskatoon, Saskatchewan, and Montreal, Quebec. In Victoria, the AAA is being examined. The study is taking place in three waves in each city over five years. In each wave, approximately 300 participants were recruited. Participants have multiple options for participation, but all participants completed an online survey and had the option to participate in further data collection opportunities. My portion of the project examined the association between exposure to the first phase of the AAA Cycling Network in Victoria on overall physical activity levels. I analyzed the first and second waves of data collection. These waves examine the completion and exposure of the Pandora Avenue protected cycle track, Johnson Street bridge, Wharf Street protected cycle track, and the Fort Street cycle track. This project is important because it examined the effects of the interventions over two years, compared to the baseline effects of the AAA Cycling Network. The natural experiment design addresses limitations found in previous experiments, where it has taken greater than one year for significant uptake of usage for new infrastructure. Results from my project can help inform the Bicycling Master Plan currently being developed by the City of St. John's in Newfoundland. Using INTERACT study data, small cities lacking cycling infrastructure like St. John's can have a clear path to become healthy, sustainable, and equitable.

3.1 Study Design and Intervention

This study is a prospective cohort study with the planned evaluation of a natural experiment analyzing exposure to the new AAA Cycling Network on active transportation physical activity levels. Victoria's AAA Cycling Network introduced protected cycling infrastructure across the city, starting with the implementation of a 5.4 km grid in the downtown core in 2018.[29] The construction phase includes five years (2018 through 2022), connecting all of downtown Victoria with active transportation infrastructure.[61] Figure 1 shows the study timeline.

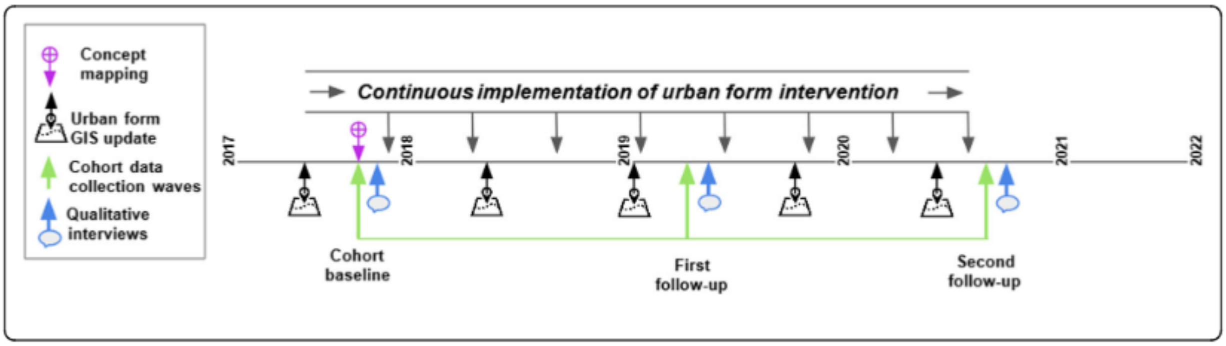

Figure 1. INTERACT AAA Victoria timeline

The AAA Cycling Network is in the median stage of construction in downtown Victoria, BC.[34] The first phase of this project is a 5.4km grid located in the downtown core with protected bike lanes for high traffic volume streets and neighbourhood bikeways for lower volume areas.[29] This phase concluded with the completion of the Pandora Avenue protected cycling path.[61] By 2019, Fort Street, Johnson Street bridge, and Wharf Street were complete and open during the data collection period. These new additions can be seen in Figure 3 below.[61] It is visually apparent from Figure 3 that there is a significant increase in exposure areas for cyclists in Victoria in 2019 compared to 2017. The actual exposure areas were calculated using a 70-meter buffer around the four sections of the AAA Cycling Network. Forecasted for completion in the year 2022, the AAA network will connect every neighbourhood in Victoria for a total of thirty-two kilometres of safe bicycle infrastructure.[61] The AAA Cycling Network is designed to provide equitable access for everyone in the community. It is designed to reduce active transportation barriers, including cycling efficacy, access, and safe activity spaces.[29,34]

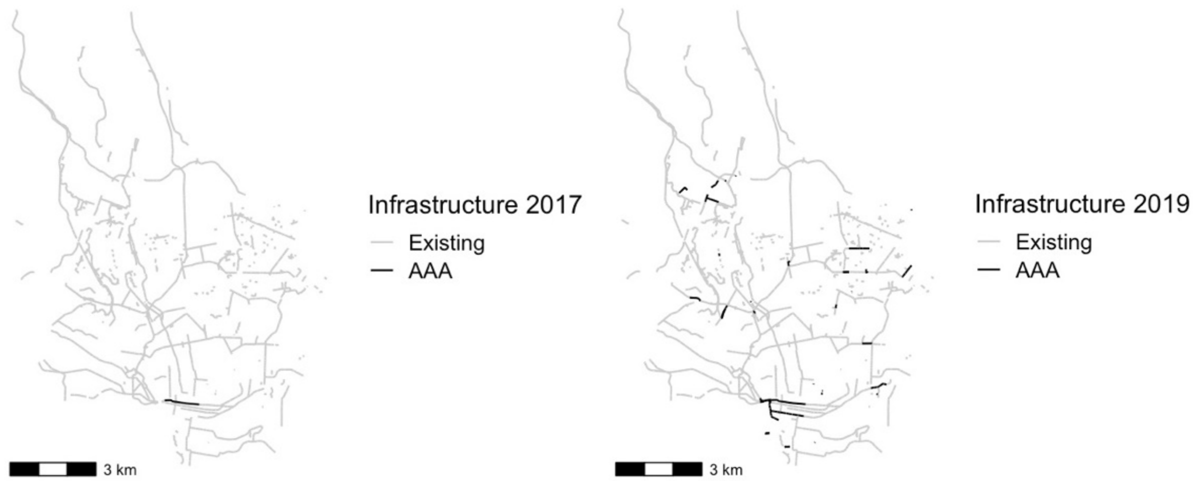

Figure 3. Victoria AAA Cycling Network Implementation Maps in 2017 and 2019

3.2 Data Collection Protocol

Two methods of data collection[29] were employed for the AAA study online surveys (See Appendix B) and activity sensing tools in each of the two waves. Figure 2 shows a flow diagram of participation options for the study. The data from the two data collection waves were combined for analysis. Participants were asked to wear a mobile sensing device (SenseDoc).[62]

3.2.0 Online Survey

All participants were asked to complete an INTERACT online survey.[63] The survey was divided into several categories. Initially, participants were asked questions about their demographic information. The next section included questions about their health and well-being. Questions in

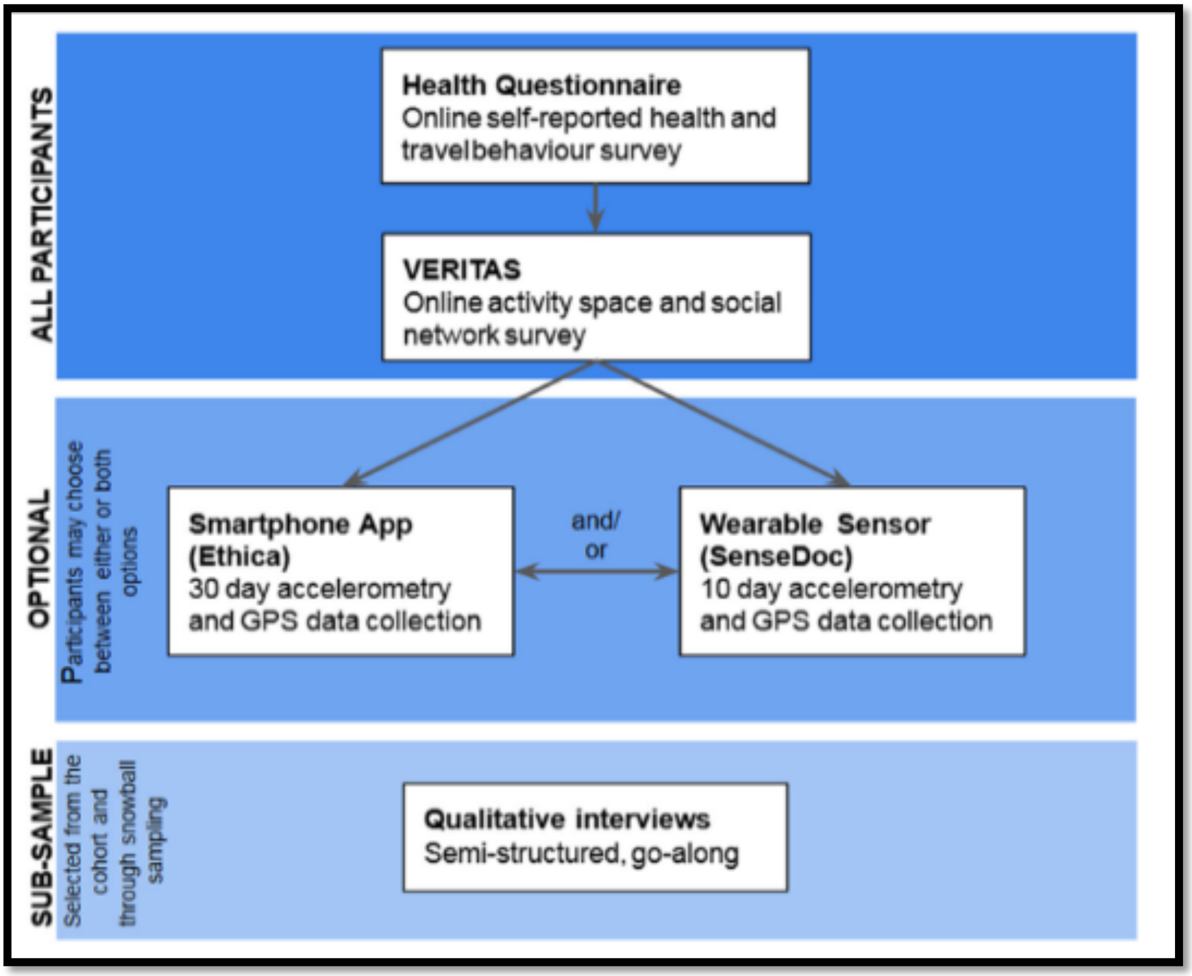

Figure 2: Team INTERACT data collection methods

the next sections were related to activity level, asking participants about the types of transportation modes, their physical activity levels, and their time spent sitting. Participants were then asked if they use activity trackers to measure their physical activity. To understand barriers to using digital tools, questions were asked regarding any concerns with data security. Sense of community and neighbourhood belonging questions followed in the next section. Finally, participants were asked if they use and have knowledge of the AAA Bicycling Network.

3.2.1 Activity Sensing Tool

For the activity sensing portion of the study, participants had the opportunity to use a wearable activity sensing tool called a SenseDoc for ten days.[64] A SenseDoc is a research-grade GPS and accelerometer device.[62] SenseDoc collects physical activity and location data continuously, as long as the device is on. For this study, I analyzed the SenseDoc data to determine participant physical activity levels and locations. During data analysis, I calculated location-based MVPA and used location data to calculate exposure to the AAA network during each wave of data collection using methods consistent with other INTERACT sites and waves.[55,56,65]

3.2.2 Data Collection Period

Wave one data collection was completed from May 2017 to November 2017. The data collection for wave two of this study took place from May 2019 to August 2019.

3.2.3 Ethics

Ethics approval for the greater team INTERACT project was received from the ethics boards of Simon Fraser University, the University of Saskatchewan, the *Centre de Recherche du Centre Hospitalier de l' Université de Montréal,* and Memorial University of Newfoundland. For my Master of Science in Kinesiology thesis, I have obtained sub-project ethics approval before beginning data analysis (ICEHR # 20211696-HK – See Appendix A).

3.3 Sample, Measures, and Exposure

3.3.0 Sample

In Victoria, 315 participants were recruited for the second wave of data collection. We attempted to recruit a representative sample from those in the population who fit the inclusion criteria accounting for age, gender, and socioeconomic status. The inclusion criteria for participants included living in the Capital Regional District and bicycling at least once a month in the City of Victoria. Participants were excluded if they under 18 years old, unable to read or write English well enough to complete an online survey, and had any intentions of moving out of the region in the next two years.[29] Not everyone participating had access to the internet, had a mobile phone or a computer. These individuals could participate in the survey either in person with a research assistant or over the phone.[29] These individuals also had the opportunity to wear a SenseDoc, making study participation equitable. No participants used the in person or over the phone option. All the 315 participants completed the online survey, and 123 participants chose to wear a SenseDoc to collect data on their physical activity and spatial location data.

Recruitment involved street marketing, attending community events, postering campaigns, email campaigns, snowball marketing, some traditional media, and social media. Street marketing included handing out cards or stickered lollipops to people on bikes at street lights and bike racks. We attended numerous community events with either a table or assisting with a bike valet. Events were general, such as community festivals, and also directed to the bicycling community (e.g., Bike to Work Week). In addition to attending over 20 events, we created two pop up events specifically to recruit for INTERACT. One morning we engaged with Crystal Pool patrons over coffee in the lobby to let them know about INTERACT. On another occasion we handed out free lemonade and popsicles on the Galloping Goose Regional Trail in order to engage potential participants for a longer than possible with street marketing tactics. To reinforce our branding, we put up 100 posters in coffee shops, libraries, on campus, at work place bike lockers, and in some bike stores in all neighbourhoods of the city. In some locations such as bike shops, we also had small buckets of lollipops that were stickered with our branding.

3.3.1 Measures

3.3.1.0 Outcome

The primary outcome variable for this analysis is MVPA. Physical activity was measured through validated device-based measures collected using the SenseDoc device.[66] This study analyzed the total minutes of moderate and vigorous physical activity. I calculated minute-by-minute location-based physical activity levels using existing methods.[9,14,29,79] Physical activity data analysis was done in a number of steps. First, raw accelerometer data were converted to counts using published methods and custom-developed Python code. Vertical axis counts were then used for wear detection. The well-validated Choi algorithm was used to calculate device wear and non-wear.[80] Following wear/non-wear detection, physical activity cut-points developed by Troiano for the vertical axis were to classify sedentary, light, moderate, and vigorous physical activity.[81] The resulting analysis classified every minute of activity as either sedentary, light, moderate, or vigorous. I then created a variable that indicated if a minute was either sedentary or active, meaning it was either light, moderate or vigorous activity. Both the Choi algorithm and the Troiano cut-points are well-validated and commonly used in physical activity research.[82,83] Minutes of physical activity were summed per day.

3.3.1.1 Exposures

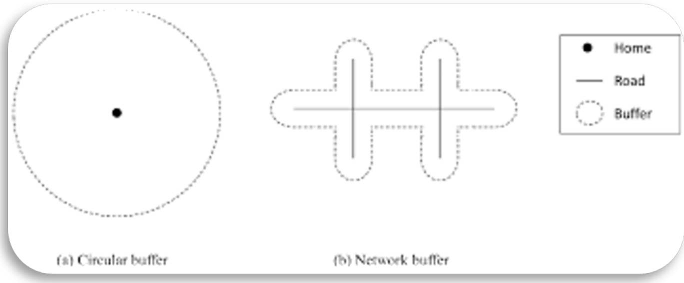

Figure 4: Buffer zone examples adapted from Lee and Kwan[76]

Exploring causation is a primary objective in epidemiological studies.[67] If a chosen method's assumptions are met, exposure measures can provide causal claims about observational studies.[56,68] GPS data from each participant were analyzed to determine their level of exposure to the intervention (AAA Cycling Network).[29] I calculated individual exposure to the AAA network using GPS and GIS using a method known as daily path mobility.[55] Daily path mobility can be used effectively in natural experiments using GPS, provided the networks are not overly dense with limited overlapping of same-purpose infrastructure.[69] Daily path mobility has been used to relate environmental contexts along a participant's GPS route and is helpful in defining exposure.[69] For my AAA Cycling Network sub-study, I applied network daily path mobility in my GPS data analysis to confirm that participants used the AAA network. I created a 70-meter buffer around the AAA network(s) of interest in 2017 and 2019 and calculated in a GPS point was either inside or outside of the buffer. I chose a 70-meter buffer because this buffer size selects the road network and adjacent building but minimizes the chance that another road adjacent to the road of interest will also be measured. After determining participant exposure, participants were assigned according to their level of exposure. Comparisons of the different exposure levels of participants were performed during data analysis. To test the potential sensitivity of my analysis to buffer size, I also compared my existing 70-meter buffer zones with 50- and 100-meters buffer zones and compared the results.

For the exposure estimates, I remove participants who had more than 500 minutes (~8 hours) of absolute exposure per day and participants who had more than 40% of their daily time spent within the buffers. I assume these people live or work near the bike lanes. Minutes of absolute and relative exposure were calculated per day. Relative exposure refers to the proportion of GPS points inside the buffer zone divided by the Sensedoc wear time per day. This metric is useful for estimating exposure while studying only the physically active periods of the day. The absolute exposure refers to the proportion of GPS points inside the buffer zone per day.

3.4 Statistical Analysis

3.4.0 Causal Model

Figure 5 below illustrates the causal model for this study. I believe there is a direct effect between the exposure variable (new active transportation infrastructure) and the outcome variable (MVPA). The exposure to infrastructure featured above in Figure 3 displays the new sections of the AAA Cycling Network that were completed during the 2017 and 2019 waves of data collection, respectively. The study has confounding variables, including age, gender, weather, and socioeconomic status (income).[49,70,71]

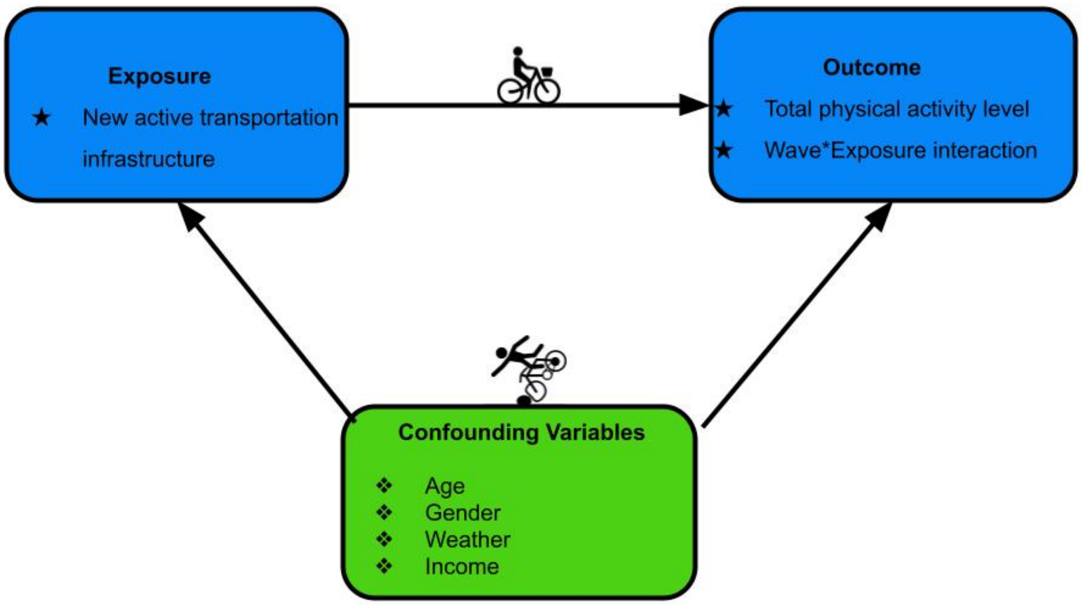

Figure 5. Causal Diagram

3.4.1 Confounding

The literature review process has allowed me to identify several confounding variables that have occurred repeatedly in similar studies. Confounding is defined as a distorted exposure-disease association attributable in part or whole to the influence of factors other than the exposure of interest.[27,72] This study is investigating population physical activity levels in response to an urban form intervention. Identifying and controlling for confounding improves the ecological validity of the study and contributes to unbiased results.[15] Confounders are variables that meet all of the following criteria: (1) has an association with the outcome; (2) is associated with the exposure, for instance, a variable that is unequally distributed between study groups; and (3) is not a part of the causal pathway.[73] Potential confounders identified in this sub-study include age, gender, ethnicity, socioeconomic status, habitual activity level, and bicycle access.[15,33,44,74] Appendix B contains the specific survey questions addressing each of the potential confounding variables.[63] In my data analysis, I have controlled for confounding using multivariate regression analysis.

3.4.2 Data Analysis

My data analysis approach consists of four primary steps: 1) descriptive statistics, 2) physical activity calculation, 3) exposure estimation, and 4) intervention effect estimation. Data analysis was conducted reproducibly using R and R Studio.[29,75,76] The primary outcome for this study is MVPA. Descriptive statistics were calculated for the total sample and the Sensedoc subsample for each wave. For all samples, I calculated descriptives for gender, ethnicity, income, marital status, health status, having children, and access to a car. Income was re-coded from 11 categories to five categories. The descriptive statistics of the wave one and two participant samples, including physical activity, exposure, and confounders, have been analyzed for normality.[77] The sample was not representative of the general population of Canada, and data on cyclists living in Victoria are not currently available. As a researcher and member of team INTERACT, I am committed to open, reproducible science and will post all code and analyses online.[78]

3.4.3 Intervention Effect Estimation

After calculating physical activity and creating exposure measures, additional methods are required to determine if the infrastructure intervention was associated with physical activity level over time. In the AAA Cycling Network study, the intervention's effect size is estimated by combining baseline data (2017) to wave two data (2019) into one dataset. As a longitudinal study with two time points to date, the difference in differences method was used to measure the impact of the AAA Victoria intervention.[29] The primary outcome of the study is MVPA at the minute level. The exposure was either absolute (number of minutes) or relative (% of total daily minutes spent) near the AAA network each day. The intervention was the 2017 or 2019 AAA network. The data are nested, with minutes of physical activity, nested within days, nested within participants. Multilevel linear models were used to estimate the impact of the intervention accounting for the nested structure of the data and including covariates of weather, wave, gender, income, and age.

In my literature review, it has become apparent that no methods are refined enough to be universally accepted in GPS location-based physical activity research. After reviewing the literature, difference in differences[84] is the method that I decided to adopt to provide consistent and reproducible results.[51,84–86] With the INTERACT dataset, it is also possible to use interrupted time series analysis using weekly rather than individual-level data. Using these methods allows for a greater understanding of any effects the AAA Cycling Network has on MVPA.

Chapter 4: Results

4.0 Total Sample

The total sample size for this study was 596 participants. This sample is divided into two waves during the data collection periods of the natural experiment. In 2017 (wave one) and 2019 (wave two) respectively, there were n = 281 and n = 315 participants. See Table 1 for participant demographic information for each wave of data collection. To summarize, participants' mean age was 44.7 years old (SD = 13.2). Just over half (51.6%) of the sample were women (n = 293), and eight participants identified as trans or gender non-binary (1.4%). Most participants (73.5%, n = 438) identified as Caucasian. Most participants (74.4%, n = 444) had incomes greater than $50,000 per year. Over two-thirds (68.6%, n = 409) were currently married or common law and

9.4% (n = 56) were separated or divorced. Most participants (71.2%, n = 424) ranked their health status as either very good or excellent.

4.1 Sensedoc Subsample

A subset of our sample (n =278) wore a Sensedoc for ten days which collected GPS and accelerometer data (Table 1). One group of participants (n=149) wore the Sensedoc during the first wave of data collection, with a second group (n = 129) wore the device in the second wave of data collection. The sociodemographic characteristics of these participants did not differ substantially from the entire sample. The demographic data for each group are presented in Table 2. Since there are no differences between participants who wore the device at Wave 1 and Wave 2, the total sample was be used when discussing the data collected using the survey.

The total sample for the combined demographic and Sensedoc data included 1264068 minutes, nested within 345 days (across 2017 and 2019), nested within 245 participants. Thirthy three participants data was removed due to missing data on covariates. Data cleaning resulted in removing 6029 days of activity (0.5%) where absolute exposure was greater than 500 minutes per day. For relative exposure, 39594 days were removed (3.1%) were more than 40% of the participants recorded time was spend exposed to the intervention.

Table 1. Participant demographics from the INTERACT cohort, a sample of residents who cycled at least once per month in Victoria, BC, Canada

	Wave one (2017, N = 281)	Wave two (2019, N = 315)
Age		
Mean (SD)	44.2 (13.4)	45.6 (13.0)
Range	(20, 79)	(23, 81)
Gender		
% Women	51.9	51.4
% Men	46.9	38.1
% Trans or gender non-binary	1.1	1.7
Ethnicity		
% Caucasian	86.8	80.0
% Aboriginal	1.4	2.2
% Asian	6.4	5.1
% Latin American	1.4	0
% Middle Eastern	0.3	0.6
% Unknown	3.5	1.9
Born in Canada		
% Yes	74.4	72.7
% No	25.6	18.4
Income		
$49,999 or less	16.4	10.6
$50,000 to $99,000	38.1	28.9
$100,000 to $149,999	23.1	25.1
$150,000 or more	15.3	18.7
I do not know/ Prefer not to say	7.1	8.0
Marital Status		
Married (or common-law)	71.9	65.7
Separated or divorced	8.2	10.5
Single (never married)	19.2	14.6
Widowed	0.7	0.3
Health Status		
Poor/Fair/Good	26.2	22.2
Very good	49.1	43.2
Excellent	24.5	25.7
Children		
% Yes	53.7	51.1
% No	46.3	40.0
Car Access		
% Yes	90.7	85.4
% No	6.4	3.5

Table 2: Participant demographics from the Sensedoc subsample, a sample of residents who cycled at least once per month in Victoria, British Columbia, Canada

	Wave one (2017, N = 129)	Wave two (2019, N = 153)
Age		
Mean (SD)	45.7 (13.7)	44.6 (14.5)
Range	(22, 79)	(23, 79)
Gender		
% Women	51.6	50.0
% Men	47.0	49.3
% Trans or gender non-binary	**	**
Ethnicity		
% Caucasian	88.6	89.5
% Aboriginal	1.3	2.7
% Asian	7.4	4.0
% Latin American	0.7	0
% Middle Eastern	0	0.9
% Unknown	2.0	2.0
Born in Canada		
% Yes	70.5	83.6
% No	29.5	16.3
Income		
$49,999 or less	16.8	16.7
$50,000 to $99,000	34.9	29.9
$100,000 to $149,999	24.8	27.9
$150,000 or more	15.4	18.9
I do not know/ Prefer not to say	8.0	6.6
Marital Status		
Married (or common-law)	74.8	73.6
Separated or divorced	8.0	9.0
Single (never married)	14.8	17.4
Widowed	1.3	0
Health Status		
Poor/Fair/Good	23.5	23.9
Very good	47.6	46.5
Excellent	28.8	29.6
Children		
% Yes	53.0	50.4
% No	46.9	49.6
Car Access		
% Yes	92.5	91.1
% No	7.5	4.9

Note: ** Excluded from regression analysis due to small sample size

4.2 Physical Activity

The average minutes of moderate to vigorous physical activity were 36.1 (SD = 35.1) per day across both waves. During wave 1, the average physical activity was 35.1 (SD = 35.2) minutes. During wave 2, the average physical activity was 37.4 (SD = 35.0) minutes. Figure 6 the histogram of minutes per day of moderate to vigorous physical activity. Figure 7 shows the daily minutes of physical activity over time for each wave. Both Figures 6 and 7 are what is typical for physical activity measures using accelerometers. Figure 6 shows that many participants engaged in little to no MVPA per week, while Figure 7 shows variation in activity by participant and over the seasons. There is a gap in Figure 7 in August when no participants were recording data using Sensedoc. This was due to a staff shortage for our team in Victoria during that 2 week period.

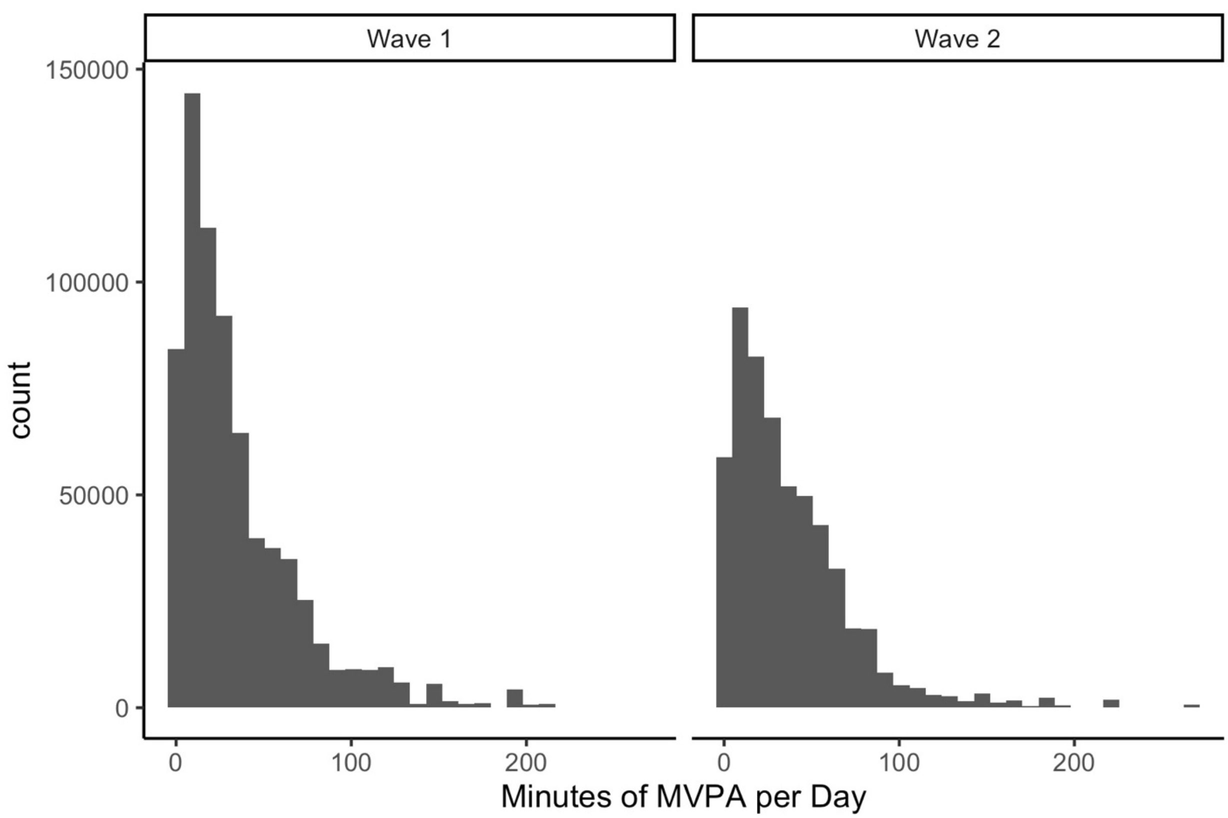

Figure 6. Histogram of Minutes of Moderate to Vigorous Physical Activity per Day in Wave 1 and Wave 2

Wave 1 Wave 2

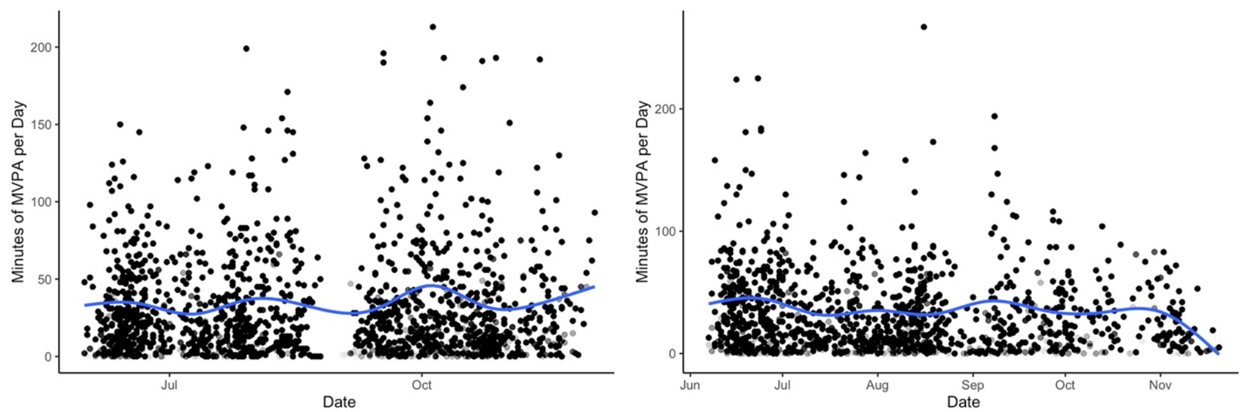

Figure 7. Scatterplot of Minutes of Moderate to Vigorous Physical Activity per Day over time in Wave 1 and Wave 2.

4.3 Exposure Measure

Exposure to the AAA Cycling Network is defined as the proportion of GPS points that fall within a 70-meter buffer around the network. Buffer zones can be used effectively in urban space natural experiments using GPS, provided the networks are not overly dense with limited overlapping of same-purpose infrastructure.[69] Buffer analysis (e.g., 70m) has been used to relate environmental contexts along a participant's GPS route, useful for defining exposure.[69] Exposure to the AAA Cycling Network is illustrated in Figure 8 (Histogram of absolute exposure) and Figure 9 (Histogram of relative exposure) below, and a map is provided in Figure 12.

The mean absolute exposure using the 70-meter buffer was 21.7 minutes while the median was 2.0 minutes, suggesting that over the approximately ten-day study period, participants had little exposure to the AAA bicycle network. Exposure at Wave 1 was on average 14.5 minutes (SD = 48.4, median = 0), while at Wave 2, exposure was 31 minutes (SD = 72.8, median = 7) across the participation period of approximately ten days. The mean relative exposure was 2.53%. Only 2.5% of participants' total GPS points were within a 70-meter buffer of the AAA Cycling Network. Exposure at Wave 1 was on average 1.9 % of time (SD = 5.23, median = 0), while at Wave 2 exposure was 3.4 percent of time (SD = 5.8, median = 1.2) across the participant period of approximately ten days.

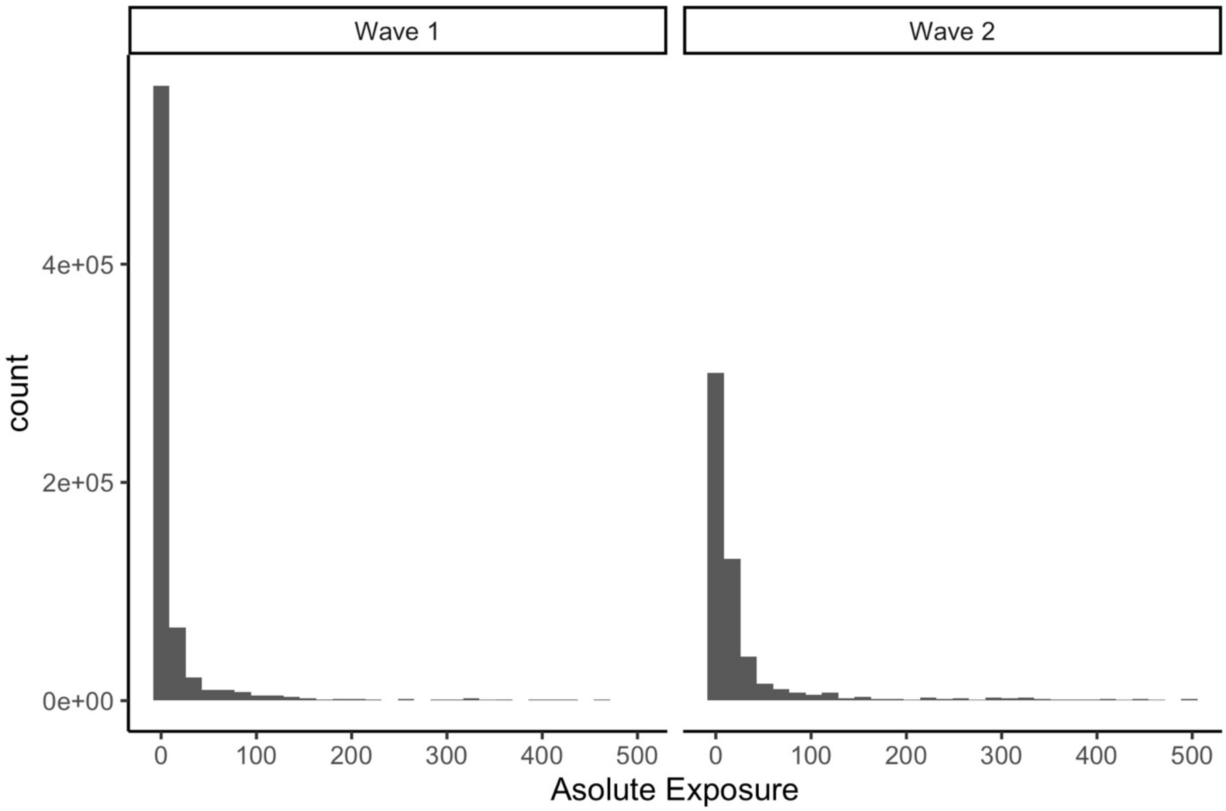

Figure 8. Histogram of absolute exposed to AAA Cycling Network at Wave 1 and Wave 2

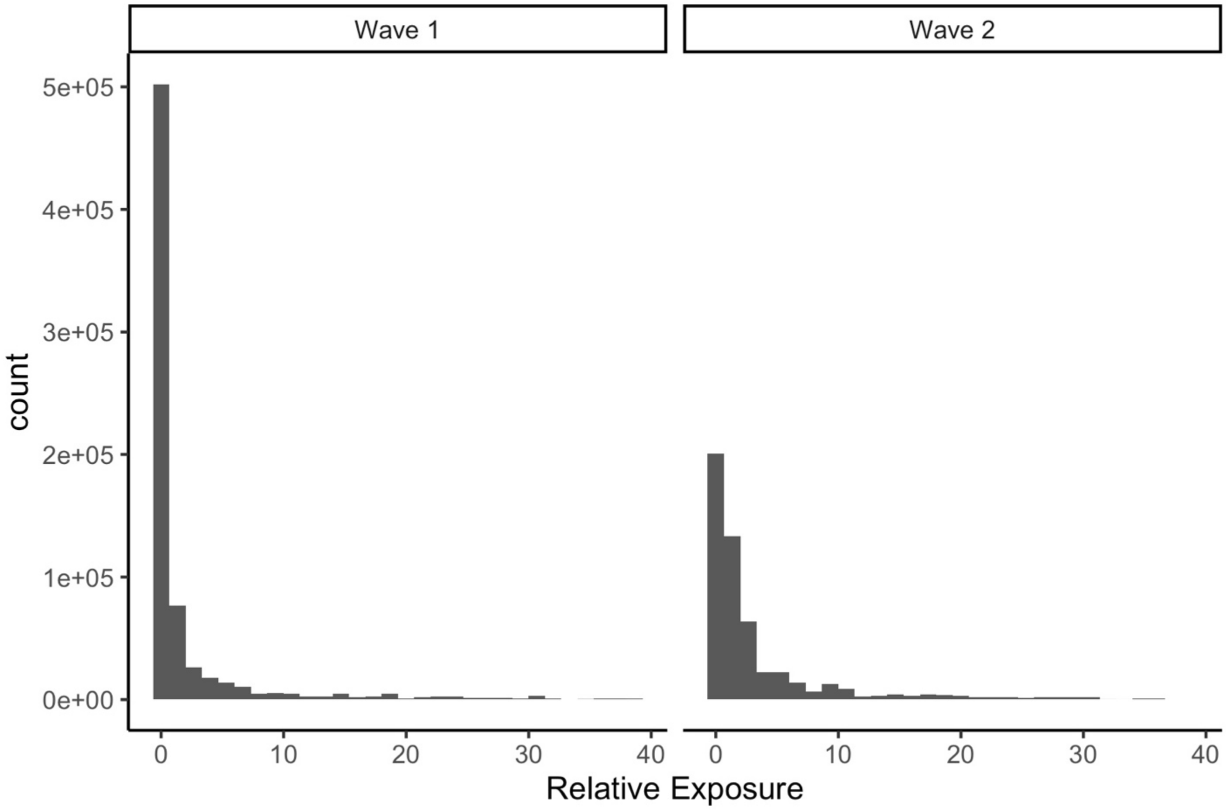

Figure 9. Histogram of relative exposed to AAA Cycling Network at Wave 1 and Wave 2

Figures 10 and 11 show the scatter between MVPA, and absolute and relative exposure, respectively. The scatter plots show that most physical activity occurs at relatively low levels of exposure for both absolute and relative exposure measures. Across waves and definitions exposure, visual inspection of the figures suggests greater MPVA as exposure increases, though this relationship is small.

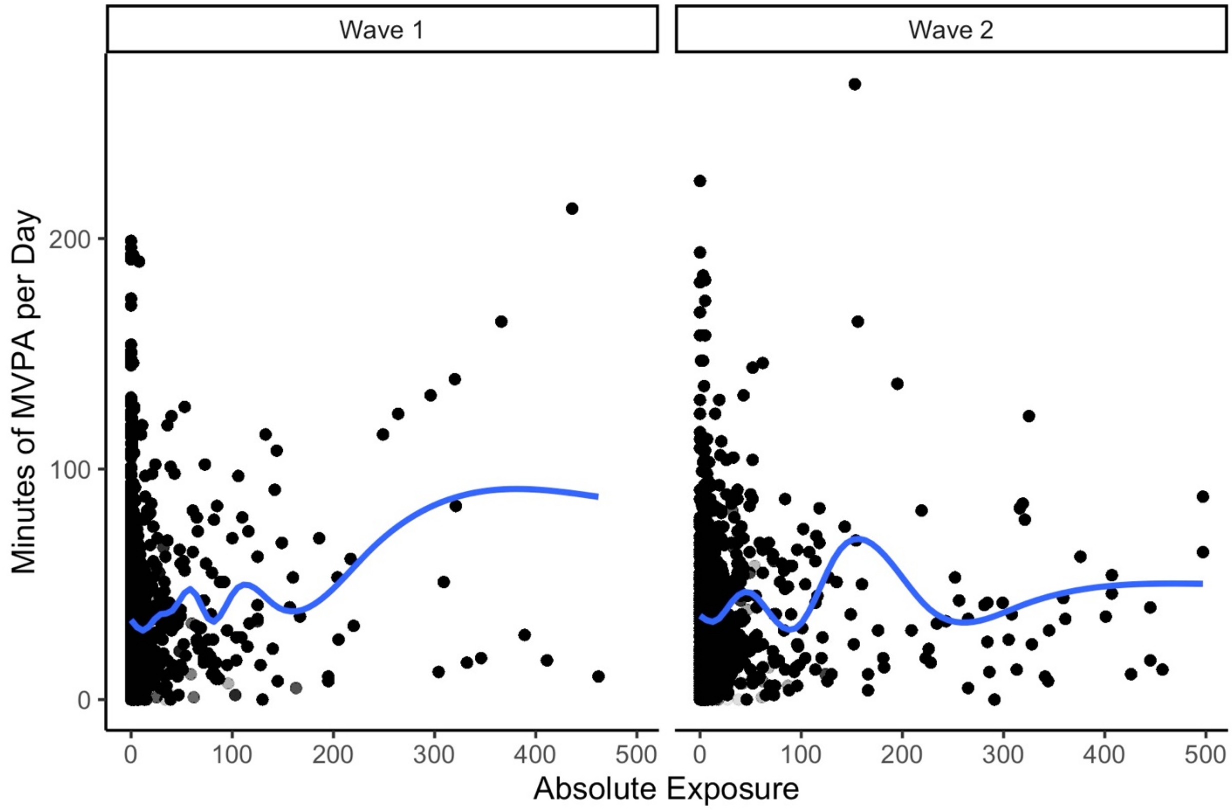

Figure 10. Scatterplot of Absolute Daily Exposure to AAA Cycling Network in Wave 1 and Wave 2

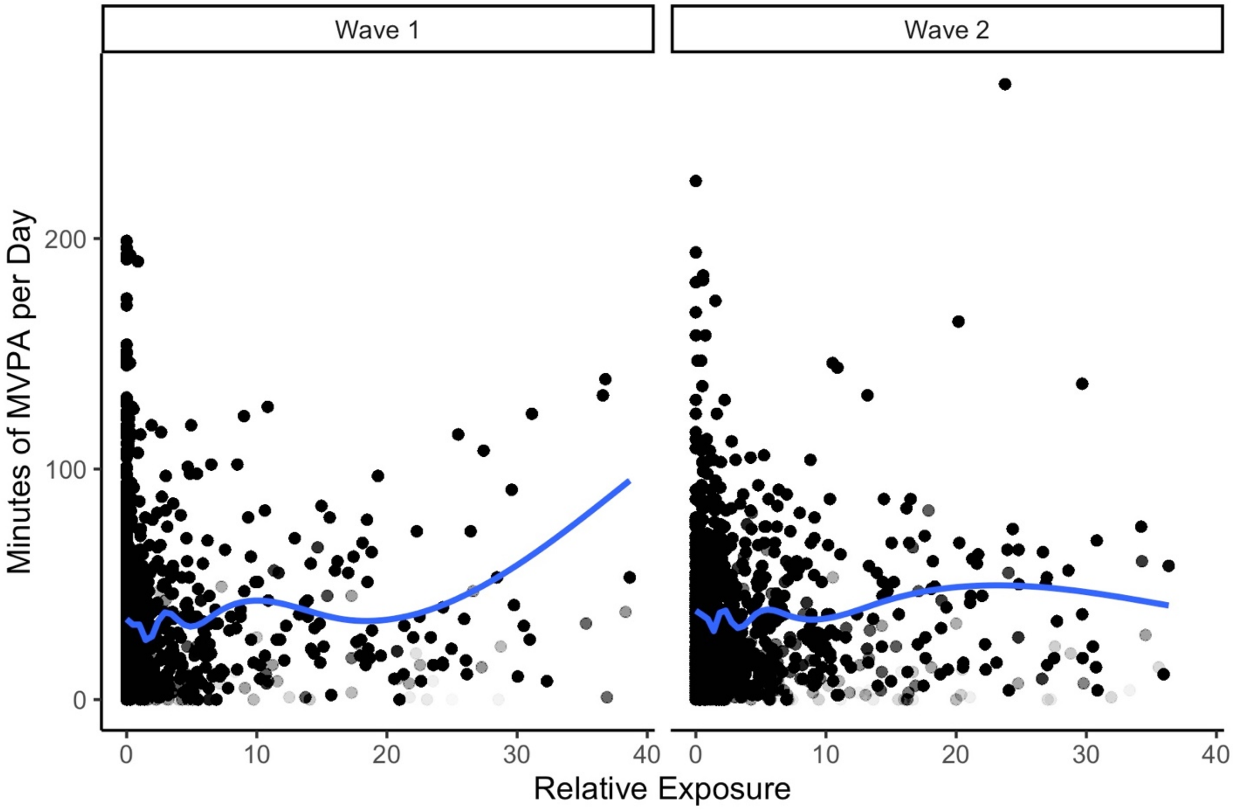

Figure 11. Scatterplot of Relative Daily Exposure to AAA Cycling Network in Wave 1 and Wave 2

Figure 12 shows a map of all GPS points at wave one and wave two. Based on the analysis of the histograms and descriptive statistics for absolute and relative exposure and visual inspection of the maps, it is clear that exposure represents only a small number of total GPS in the sample. The small proportion of GPS points suggests that the intervention effect is likely to be small.

Wave 1 Wave 2

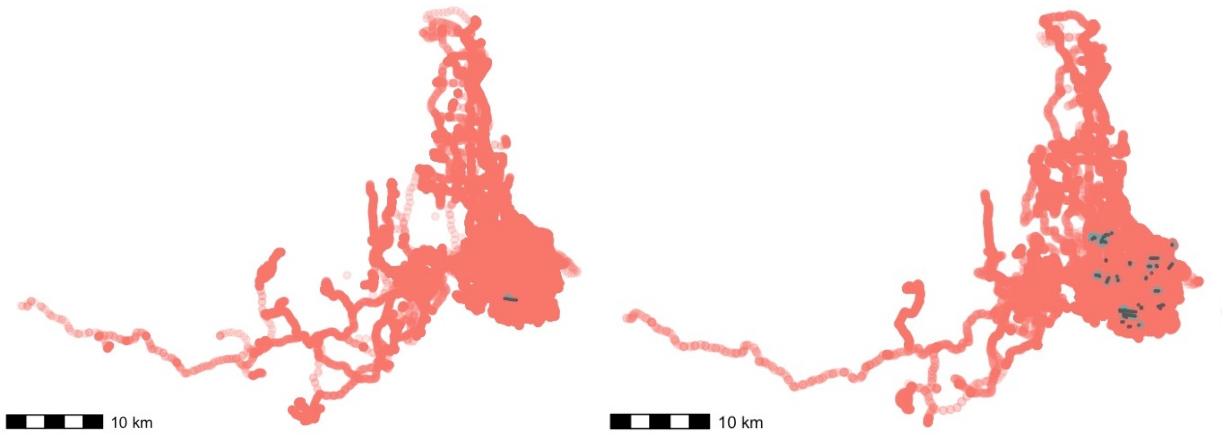

Figure 12. Scatterplot of Absolute Daily Exposure to AAA Cycling Network. Notes. Red points are non-exposed and blue points are exposed. Black lines represent the AAA cycling infrastructure.

4.5 Difference in Differences Multilevel Models

Linear and multilevel regression models were used to examine the association between exposure to the AAA Cycling Network and physical activity (MVPA/day). Models were computed separately for both absolute and relative exposure. The models were run in the following order. First, linear regression models with covariates Second, a three level random intercept models with minutes, nested in days, nested in participants. Third, a three-level random slopes model with a random slope accounts for variation between days within participants and a random intercept for participants. Finally, I include quintiles of exposure and covariates rather than a linear term to examine potential non-linear associations between exposure and physical activity for absolute exposures. Finally, a sensitivity analysis was conducted to investigate possible differences in results between different exposure sizes (50m and 100m) for both relative and absolute exposure) using models with random intercepts at the day and participant level and including covariates.

4.5.1 Absolute Exposure to AAA Cycling Network

Table 3 presents the models for the absolute exposure. The results are consistent across the different model specifications, which suggests that the findings are relatively robust. In model 1, the linear regression with covariates, a one-minute increase in absolute exposure to the AAA network is associated with a small 0.03 (95% CI: 0.03 to 0.03) increase in minutes of moderate to vigorous physical activity. This result is consistent across the different model specifications, with Model 2 and Model 3 estimating small increases in MVPA associated with greater exposure to the AAA network. The interaction term between wave and absolute exposure, the key estimate of interest in difference in differences analysis, shows a negative association between MVPA and greater exposure to the AAA network at Wave 1 compared to Wave 2. This association is estimated to be between -0.01 (95% CI: -0.02 to -0.01, Model 1) and -0.16 (95% CI: -0.16 to -0.15, Model 2).

Table 3. Difference in differences regression analyses examining the association between absolute exposure to the AAA bicycle network and wave with moderate to vigorous physical activity.

	Model 1 Estimate (95% CI)	Model 2 Estimate (95% CI)	Model 3 Estimate*
Intercept	29.86 (29.24 to 30.49)	31.5 (8.1 to 54.9)	-95.93
Absolute Exposure	0.03 (0.03 to 0.03)	0.11 (0.11 to 0.11)	0.07
Wave 1	Reference	Reference	Reference
Wave 2	4.72 (4.48 to 4.97)	0.93 (-5.28 to 7.14)	4.42
Exposure*Wave	-0.01 (-0.02 to -0.01)	-0.16 (-0.16 to -0.15)	-0.13

Notes. Model 1 is a linear model. Model 2 is a multilevel model with random intercepts per day and per participant. Model 3 is a multilevel model with random slopes per day by participant and random intercepts per participant. * It was not possible to estimate Model 3 confidence intervals due to convergence problems. All models include age, gender, household income, average daily temperature, millimeters of daily precipitation, and average daily wind speed as covariates.

Table 4 shows the results of the multilevel model with random intercepts at the day and participant level using quintiles of absolute exposure. The quintile estimates demonstrate no increase in physical activity as exposure quintiles increase. There is also no meaningful effect estimated from the quintile by wave two interaction term.

Table 4. Absolute exposure to AAA Cycling Network with 70m buffer regressed on MVPA without covariates in quintiles.

Predictor Variable	Estimate (minutes MVPA/day)	Standard Error	t-value
Intercept	32.23	12.13	2.66
Quintile 1 Absolute exposure	Reference		
Quintile 2 Absolute exposure	0.010	0.10	0.11
Quintile 3 Absolute exposure	0.018	0.10	0.19
Quintile 4 Absolute exposure	0.029	0.10	0.30
Quintile 5 Absolute exposure	0.036	0.10	0.37
Wave 1	Reference		
Wave 2	-1.70	3.18	-0.54
Quintile 1*Wave 2	Reference		
Quintile 2*Wave 2	0.00	0.24	0.01
Quintile 3*Wave 2	0.01	0.24	0.03
Quintile 4*Wave 2	0.00	0.24	-0.02
Quintile 5*Wave 2	0.00	0.24	-0.00

Notes. Model is a multilevel model with random intercepts per day and per participant. All models include age, gender, household income, average daily temperature, millimeters of daily precipitation, and average daily wind speed as covariates.

4.5.2 Relative Exposure to AAA Cycling Network

Table 5 presents the models for the relative exposure. The results are consistent across the different model specifications, which suggests that the findings are relatively robust. In model 1, the linear regression with covariates, a one percent increase of total time spent in the buffer of the AAA network is associated with a small 0.27 (95% CI: 0.25 to 0.29) minute increase in moderate to vigorous physical activity. This result is consistent across the different model specifications, with Model 1 and 2 estimating small increases in MVPA associated with greater exposure to the AAA network. The interaction term between wave and relative exposure, the key estimate of interest in difference in differences analysis, shows a negative association between MVPA and greater exposure to the AAA network at Wave 1 compared to Wave 2. This association is estimated to be between -0.06 (95% CI: -0.10 to -0.03, Model 1) and -0.35 (95% CI: -0.39 to -0.32, Model 2). The random slopes model that was included in the absolute exposure analysis (Model 3) did not converge with the relative exposure model.[87] Convergence problems are common, and while multiple optimizers were tested, the model still failed to converge.

Table 5. Difference in differences regression analyses examining the association between relative exposure to the AAA bicycle network and wave with moderate to vigorous physical activity.

	Model 1 Estimate (95% CI)	Model 2 Estimate (95% CI)
Intercept	28.16 (27.53 to 28.80)	32.4 (8.55 to 56.28)
Relative Exposure	0.27 (0.25 to 0.29)	0.46 (0.44 to 0.47)
Wave 1	Reference	Reference
Wave 2	4.40 (4.13 to 4.66)	1.06 (-5.32 to 7.45)
Exposure*Wave	-0.06 (-0.10 to -0.03)	-0.35 (-0.39 to -0.32)

Notes. Model 1 is a linear model. Model 2 is a multilevel model with random intercepts per day and per participant. All models include age, gender, household income, average daily temperature, millimeters of daily precipitation, and average daily wind speed as covariates.

Table 6 shows the results of the multilevel model with random intercepts at the day and participant level using quintiles of relative exposure. The quintile estimates demonstrate no increase in physical activity as exposure quintiles increase. There is also no meaningful effect estimated from the quintile by wave two interaction term.

Table 6. Relative exposure to AAA Cycling Network with 70m buffer regressed on MVPA without covariates in quintiles

Predictor Variable	Estimate (minutes MVPA/week)	Standard Error	t-value
Intercept	32.05	12.53	2.56
Quintile 1 Relative exposure	Reference		
Quintile 2 Relative exposure	0.01	0.01	0.11
Quintile 3 Relative exposure	0.02	0.01	0.18
Quintile 4 Relative exposure	0.03	0.01	0.29
Quintile 5 Relative exposure	0.04	0.01	0.36
Wave 1	Reference		
Wave 2	0.263	3.24	0.08
Quintile 1*Wave 2	Reference value		
Quintile 2*Wave 2	0.00	0.24	0.02
Quintile 3*Wave 2	0.01	0.24	0.05
Quintile 4*Wave 2	0.00	0.24	0.00
Quintile 5*Wave 2	0.00	0.24	0.02

Notes. Model is a multilevel model with random intercepts per day and per participant. All models include age, gender, household income, average daily temperature, millimeters of daily precipitation, and average daily wind speed as covariates.

4.6 Buffer Zone Sensitivity Analysis

The statistical analysis in this study relied upon 70-meter buffer zones around the AAA cycling network. The reason for this zone is to capture physical activity while participants are exposed to the AAA cycling network, but to avoid capturing physical activity on adjacent streets and cycle paths. Based on the assessment of the geographical layout of the streets in downtown Victoria, 70-meters was deemed to be an ideal buffer zone to capture exposure. To understand the accuracy of this method, sensitivity analyses were performed using the same covariates and participant data, however, with a 50-meter buffer zone and a 100-meter buffer zone. The results are presented below in Table 7 for the absolute exposure and Table 8 for the relative exposure. There were minor differences between the models with different buffer sizes. For the absolute exposure measures, it appears as though the buffer size increased the estimated effect size for the main effect of exposure. In general, the estimate for the interaction term between wave and exposure was smaller. For the main effect of exposure, the estimated minutes of MVPA increase were 0.12 with 50-meter buffers, 0.12 with 70-meter buffers, and 0.08 with 100-meter buffers. The estimate for the interaction term between exposure using a 50-meter buffer and wave was -0.16 minutes of MVPA and -0.12 for the 100-meter buffer estimate.

Table 7. Absolute exposure to AAA Cycling Network for three different buffer zones regressed on MVPA

Predictor Variable	50-meter Estimate	70-meter: Estimate	100-meter: Estimate
Intercept	31.78	31.5	30.95
Absolute Exposure	0.12	0.12	0.08
Wave 1	Reference	Reference	Reference
Wave 2	0.49	0.93	0.92
Exposure*Wave	-0.16	-0.16	-0.12

Notes. All models are multilevel with random intercepts per day and per participant. All models include age, gender, household income, average daily temperature, millimeters of daily precipitation, and average daily wind speed as covariates.

The effect of the buffer size on relative exposure was less clear. For the main effect of exposure, the estimates are were very similar. For the interaction term between relative exposure and wave, the estimated effects were all negative and ranged from -0.90 for the 50-meter buffer to -0.35 for the 70-meter buffer.

Table 8. Relative exposure to AAA Cycling Network for three different buffer zones regressed on MVPA

Predictor Variable	50-meter Estimate	70-meter Estimate	100-meter Estimate
Intercept	33.06	32.4	32.95
Absolute Exposure	0.42	0.46	0.39
Wave 1	Reference	Reference	Reference
Wave 2	2.52	1.06	2.16
Exposure*Wave	-0.90	-0.35	-0.51

Notes. All models are multilevel with random intercepts per day and per participant. All models include age, gender, household income, average daily temperature, millimeters of daily precipitation, and average daily wind speed as covariates.

Chapter 5: Summary

In this portion of the pan-Canadian team INTERACT natural experiment, the association between new active transportation infrastructure and physical activity was examined. The objective of this thesis was to examine the association between physical activity and exposure to the new sections of the AAA Cycling Network. Four multilevel regression analyses were completed to assess the association between exposure and activity levels.

The hypothesis for this study was that the MVPA for wave two participants would increase as a result of increased exposure to the AAA cycling network. Specifically, by investigating the interaction term of Exposure*Wave, the study evaluated if increased exposure over time resulted in increased MVPA. The results indicate that the null hypothesis cannot be rejected. As seen above, there was a net decrease in MVPA in the interaction term between exposure and wave. The effect size is small, which is to be expected, but the result is consistent across several different modelling approaches. These results are consistent with previous research by Dill and colleagues,[24] who hypothesized that new cycling infrastructure is safer and provides a more direct and uninterrupted route for active commuters. The natural experiment used data from a longitudinal panel of adults with children (n = 353) in Portland, OR. Like the present study, the active transportation outcome was measured with GPS and accelerometers worn for only 5 days in comparison with 10 days in the AAA study. The effect of the treatment was estimated using difference in differences estimation and multivariate regression models.[24] In five of seven models run by the researchers, the interaction term was found non-significant, indicating there was no correlation between being in a treatment area and minutes of moderate and vigorous physical activity.[24]

Brown et al.[9] also found no statistically significant association between new cycling infrastructure and total minutes of moderate to vigorous physical activity. In their study, participants wore accelerometers and GPS measurement devices for one week, pre- and post-construction completion, which is closer to the AAA ten-day collection period. Participants sampled within 2 km of the intervention were in the following group: never cyclists (n=434), continuing cyclists (n= 29), former cyclists, and new cyclists (n=40). Results show that all three cycling groups, as identified by GPS/accelerometry data, expended more estimated kilocalories (kcal) of energy per minute during the monitoring week than those who never cycled during the study. Therefore, the decrease in physical activity seen in the Brown et al.[9] study indicates the possibility of a similar occurrence in Victoria, BC. The AAA Cycling Network may have improved cycling safety and efficiency of travel, which may have led to a decrease in commute times and a decrease in overall physical activity level.

Both cited studies applied methods that are comparable to the present study.[9,24] These two studies used pre and post-data collection periods. However, the current INTERACT study collected data after one cycle path was completed and again when three additional bike lanes were completed (serving as the post-measurement for this study). There will be a third wave of data collection as well after all bike lanes in the AAA Cycling Network are complete. Currently, the present study is most comparable to the previous literature with two waves of data collection. All three studies used GPS for location measurement, an accelerometer to measure physical activity intensity, and survey data to capture more detailed information from participants. Sample sizes for the three studies are comparable, with n=536 in the Brown et al. study, n = 353 in the Dill et al. study, and n = 129 and n = 153 in waves one and two, respectively. A greater variability was seen across studies for data collection duration, ranging from 3 to 10 days. The current study has the smallest sample size of the three but the longest data collection period and greatest total observations. All studies examined new, protected cycling infrastructure within urban centers.

There are many possible explanations for the decrease in MVPA for the participants of wave two compared to wave one. First, there was a significant increase in available infrastructure in downtown Victoria during wave two compared to wave one. One benefit of this increased access to infrastructure is that cycling is safer and more direct. Routes may have been shortened because of the new cycling infrastructure, which results in reduced MVPA. Benefits of this finding include improved safety for motorists and cyclists and the reduction of barriers for more individuals to begin active commuting in Victoria. Next, participants' exposure was measured as the proportion of GPS points within a 70-meter buffer area surrounding the four currently available bicycle lanes that are a part of the AAA Cycling Network. Participants spent 4.3% of their total time along the corridors, which is a small proportion of the total time. Of course, the AAA Cycling Network will not encompass all cycling and physical activity undertaken by participants, and as such, increases in physical activity levels outside of the exposure area are difficult to relate to the new corridors. The AAA Cycling Network connects existing activity spaces and bicycle lanes, possibly increasing activity in non-exposure zones. Third, data collection for wave two was completed in the same cycling season as the opening of the new bike lanes. For the participants in the early study period, this means only days or weeks to uptake cycling of the new lanes. From previous studies, it can take years to uptake cycling of new infrastructure.[44] Data collection for wave three of the AAA Cycling Network may be able to increase our understanding of this observation.

There is currently no standard for defining exposure for new urban infrastructure interventions. In this study, 70-meters was selected based upon the geography of downtown Victoria. The 70-meter buffer zone allows the capturing of physical activity on the new AAA Cycling Network corridors without capturing activity on adjacent streets and bike lanes. To assess the sensitivity of this selected buffer zone, multiple buffer sizes (50-meter, 70-meter, 100-meter) were used to compare to the chosen value. In all three buffer zone analyses, the interaction term between exposure and wave indicated a decrease in MVPA by 9.21, 9.38, and 9.50 minutes per week for the 50m, 70m, and 100m buffers, respectively. The results consistently show that participants completed fewer minutes of physical activity in wave two than wave one regardless of buffer size. The consistent results across three buffers may be explained by GPS accuracy (capturing the same proportion of points for the 50m buffer as the 70m buffer) and decreased usage of non-intervention streets by participants (which would otherwise be captured with the 100m buffer).

Combining this study with previous research suggests that there is not a defined relationship between new cycling infrastructure and associated increases in MVPA. The present study, Dill et al.[24] and Brown et al.[9] did not show increased physical activity after new infrastructure interventions. It is possible that all studies contribute to increased physical activity outside of the exposure zones, but this is not recorded due to the study design. By allowing more time after the new cycling infrastructure intervention and monitoring physical activity that is augmented by exposure to the intervention, it is possible that the full potential of built environment natural experiments can be realized.

5.2 Limitations

The present study has limitations that can help improve our understanding of urban form interventions using natural experiments. The first limitation is the possibility of reduced generalizability. The study demographic for both waves of the AAA Cycling Network was homogenous. In general, the participants who took part in the study had modest to high incomes (53% of participants had incomes between \$50,000 and \$150,000), identified as Caucasian, and reported either very good (26%) or excellent health (43%). It is difficult to determine if this study sample accurately represents the population of Victoria residents who cycle at least once per month due to lack of information on such a specific group of people. The generalizability of the study suffers because the demographic studied is not generalizable to populations in Canadian cities or Census data. The study sample has a mean age of 45.6 (SD = 13.0) compared to Canada's mean age of 40.7.[88] The ethnicity of our sample was predominantly Caucasian, at 86% for wave one and 80% for wave two compared to Canada's 72%.[88] The health status of our sample was predominantly very good or excellent (78% of the sample), which does not represent the nation's average of 59% reporting very good or excellent health.[89] The sample in this study may be representative of the population of cyclists in Victoria (See Appendix C). However, data on this sub-population is not available. A way to improve upon this limitation is by widening the inclusion criteria. For this study, participants were required to bike at least once a month in the city of Victoria. An attempt to include a greater range of socioeconomic status, ethnicity, and health status could provide a sample with improved external validity.[90]

A second limitation of the study is the data collection period in comparison with the inclusion criteria. The 10-day collection period may have captured zero bicycle days for some participants who met the inclusion criteria (that they previously cycled at least once per month).

Either a more extended data collection period or inclusion criteria that require a greater frequency of cycling could address this limitation.

A third limitation is the Hawthorne Effect, to which no observational study is immune.[91] The Hawthorne effect occurs when a study participant who is being observed acts in a manner that they expect the observers wish to see. In the AAA Cycling Network study, participants were asked to wear a device that collected their physical activity throughout their day. Therefore, it is possible that an individual will be more active while having their physical activity observed than if they were not active at all. The Hawthorne Effect is difficult to control for in any study design due to ethical considerations and the obligation to inform the participants about what they are doing in the study. Blinding or random selection (from mass data collection) are not options in a pre-post natural experiment.

5.4 Contributions

Being a part of team INTERACT has provided me with the opportunity to contribute to the scientific literature in a meaningful way, with evidence backed by a robust natural experiment and research team. My research is necessary because it will assess the impact of the AAA Cycling Network in Victoria on location-based physical activity changes. In collaboration with partners in Victoria and across Canada, this research will provide information about the effectiveness of urban form interventions and their potential for changing physical activity. My analysis will contribute to essential open science products, including code and methodologies available for future research applications. Finally, my research will benefit Canadians with conclusions about addressing current limitations to safe, equitable, and accessible active transportation infrastructure to reduce physical activity barriers in daily life.

5.3 Conclusion

The primary objective of this study was to examine the association between exposure to the AAA Cycling Network and MVPA. The study found that for reasons that required further investigation, the physical activity of participants decreased in wave two compared to wave one. Due to mixed findings in the currently available literature, further studies are needed that address the limitations of current studies. Wave three of the AAA Cycling Network study has the potential to build upon the current study, and current literature because cyclists in Victoria will have adequate time to uptake the use of the new cycling infrastructure. Implementing additional bicycle lanes in the city of Victoria can provide activity spaces for residents to achieve physical activity guidelines as safely as possible.

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Appendix A: Research Ethics Certification

MEMORIAL UNIVERSITY

Interdisciplinary Committee on Ethics in Human Research (ICEHR)

St. John's, NL Canada A1C 5S7
Tel: 709 864-2561 icehr@mun.ca
www.mun.ca/research/ethics/humans/icehr

ICEHR Number:	**20211696-HK**
Approval Period:	April 15, 2021 – April 30, 2022
Funding Source:	
Responsible Faculty:	Dr. Daniel Fuller School of Human Kinetics and Recreation
Title of Project:	*Examining the association between cycling infrastructure exposure and cycling engagement: Wave two natural experiment results from INTERACT Victoria*

April 15, 2021

Mr. Jonathan Slaney
School of Human Kinetics and Recreation
Memorial University of Newfoundland

Dear Mr. Slaney:

Thank you for your submission to the Interdisciplinary Committee on Ethics in Human Research (ICEHR), seeking ethical clearance for your research project. The Committee appreciates the care and diligence with which you prepared your application. The project is consistent with the guidelines of the *Tri-Council Policy Statement on Ethical Conduct for Research Involving Humans* (TCPS2). *Full ethics clearance* is granted for one year from the date of this letter. ICEHR approval applies to the ethical acceptability of the research, as per Article 6.3 of the *TCPS2*. Researchers are responsible for adherence to any other relevant University policies and/or funded or non-funded agreements that may be associated with the project.

The *TCPS2* **requires** that you submit an Annual Update to ICEHR before April 30, 2022. If you plan to continue the project, you need to request renewal of your ethics clearance and include a brief summary on the progress of your research. When the project no longer involves contact with human participants, is completed and/or terminated, you are required to provide an annual update with a brief final summary and your file will be closed. If you need to make changes during the project which may raise ethical concerns, you must submit an Amendment Request with a description of these changes for the Committee's consideration. If funding is obtained subsequent to ethics approval, you must submit a Funding and/or Partner Change Request to ICEHR so that this ethics clearance can be linked to your award.

All post-approval event forms noted above must be submitted by selecting the ***Applications: Post-Review*** link on your Researcher Portal homepage. We wish you success with your research.

Yours sincerely,

Russell J. Adams, Ph.D.
Chair, Interdisciplinary Committee on
Ethics in Human Research
Professor of Psychology and Pediatrics
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RA/bc

copy: Supervisor – Dr. Daniel Fuller, School of Human Kinetics and Recreation

Appendix B: Survey Questions for assessing confounding

In the confounding factors section of this proposal, I identified several potential variables, including age, gender, ethnicity, income, and usual physical activity.

INTERACT Eligibility Survey:

Age:

1. What is your birth date?

DD/MM/YYYY

Gender:

2. How do you describe yourself?

1 Male
2 Female
3 Trans
4 Other

INTERACT Main Online Questionnaire:

Ethnicity:

3. To which ethnic or cultural groups did your ancestors belong? (Check all that apply)

1 Aboriginal
2 Asian
3 Black
4 Caucasian
5 Latin American
6 Middle Eastern
77 I don't know/Prefer not to answer

Income:

4. Which category best describes your annual household income, taking into account all sources of income?

1 No income
2 $1 to $9,999
3 $10,000 to $14,999

4 $15,000 to $19,999
5 $20,000 to $29,999
6 $30,000 to $39,999
7 $40,000 to $49,999
8 $50,000 to $99,999
9 $100,000 to $149,999
10 $150,000 to $199,999
11 $200,000 or more
77 I don't know/Prefer not to answer

5. To what extent does this annual family income allow you to satisfy your household's needs?

1 Very well
2 Decently
3 Not so well
4 Not at all
77 I don't know/Prefer not to answer

Usual Physical Activity:

Part 1: Job-Related Physical Activity
The next questions are about all the physical activity you did in the last 7 days as part of your paid or unpaid work. Do not include unpaid work you might do around your home, like housework, yard work, general maintenance, and caring for your family.

6. During the last 7 days, on how many days did you do vigorous physical activities as part of your work?

Range 1-7 Days per week
0 No vigorous job-related physical activity

7. How much time did you usually spend on one of those days doing vigorous physical activities as part of your work?

Range 0-16 Hours per day
Range 0-60 Minutes per day

Part 2: Transportation
These questions are about how you traveled from place to place, including to places like work, stores, movies, and so on.

8. During the last 7 days, on how many days did you travel in a motor vehicle like a train, bus, car, or tram?

Range 1-7 Days per week
0 No traveling in a motor vehicle

9. How much time did you usually spend on one of those days traveling in a train, bus, car, tram, or other kind of motor vehicle?

Range 0-16 Hours per day
Range 0-60 Minutes per day

Now think only about the bicycling and walking you might have done to travel to and from work, to do errands, or to go from place to place.

10. During the last 7 days, on how many days did you bicycle for at least 10 minutes at a time to go from place to place?

Range 1-7 Days per week
0 No bicycling from place to place

11. How much time did you usually spend on one of those days to bicycle from place to place?

Range 0-16 Hours per day
Range 0-60 Minutes per day

12. During the last 7 days, on how many days did you walk for at least 10 minutes at a time to go from place to place?

Range 1-7 Days per week
0 No walking from place to place

13. How much time did you usually spend on one of those days walking from place to place?

Range 0-16 Hours per day
Range 0-60 Minutes per day

Part 3: Recreation, Sport and Leisure-Time Physical Activity

This section is about all the physical activities that you did in the last 7 days solely for recreation, sport, exercise, or leisure. Please do not include any activities you have already mentioned.

14. Not counting any walking for transportation that you have already mentioned, during the last 7 days, on how many days did you walk for at least 10 minutes at a time in your leisure time?

Range 1-7 Days per week

0 No walking in leisure time

15. How much time did you usually spend on one of those days walking in your leisure time?

Range 0-16 Hours per day
Range 0-60 Minutes per day

16. Think about only those physical activities that you did for at least 10 minutes at a time, not counting any activity for transportation that you have already mentioned. During the last 7 days, on how many days did you do vigorous physical activities like aerobics, running, fast bicycling, or fast swimming in your leisure time?

Range 1-7 Days per week
0 No vigorous activity in leisure times

17. How much time did you usually spend on one of those days doing vigorous physical activities in your leisure time?

Range 0-16 Hours per day
Range 0-60 Minutes per day

18. During the last 7 days, on how many days did you do moderate physical activities like bicycling at a regular pace, swimming at a regular pace, and doubles tennis in your leisure time?

Range 1-7 Days per week
0 moderate activity in leisure time

19. How much time did you usually spend on one of those days doing moderate physical activities in your leisure time?

Range 0-16 Hours per day
Range 0-60 Minutes per day

Appendix C: Comparison between city samples and 2016 Canadian Census data on selected socio-demographic characteristics.

	Victoria n (%)	Victoria Census %
Age		
15-19 years	0 (0%)	5
20-29 years	46 (20%)	13.2
30-39 years	79 (34.3%)	12.8
40-49 years	60 (26.1%)	12.4
50-64 years	26 (11.3%)	22.4
65 and older	19 (8.3%)	21.1
Gender		
Man	131 (46.6%)	-
Woman	146 (51.9%)	-
Trans Man/Woman	4 (1.4%)	-
Genderqueer	0 (0%)	-
Income		
\$0-\$19,999	10 (3.6%)	10.2
\$20,000-\$49,999	36 (12.8%)	24.5
\$50,000-\$99,999	107 (38.1%)	33.5
\$100,000-\$200,000	99 (35.2%)	26.1
\$200,000 and greater	9 (3.2%)	5.8
Prefer not to answer	20 (7.1%)	
Education		
Primary/Elementary	0 (0%)	7.3
Secondary	42 (15.3%)	24.8
Trade/Technical	107 (39.1%)	31.2
University degree	125 (45.6%)	33.8
Graduate degree	0 (0%)	2.1
Prefer not to answer	2 (0.73%)	
Ethnic Groups*		
White	251 (86.9%)	83.6
Asian	19 (6.6%)	10.8
Black	0 (0%)	0.9
Latin American	4 (1.4%)	0.7
Middle Eastern	1 (0.3%)	0.7
Indigenous	4 (1.4%)	6
Ethnic group not included above	0 (0%)	-

* Participants were able to report multiple ethnic identities, therefore the sum of ethnicities exceeds 100% for each city, as each ethnic group represents people who identify alone or in combination with another ethnicity.