Evaluating and utilizing crowdsourced data and population surveys in bicycling safety research

by

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Abstract

Increased population level bicycling would benefit society by improving health outcomes and reducing fossil fuel emissions. A main factor preventing increased bicycling is concerns regarding safety. Traditional sources of bicycling safety data (police, hospital or insurance data) underreport incidents and are biased. Alternative sources of bicycling safety data, including crowdsourcing and population surveys, are untested and rarely utilized. Crowdsourced data will include incidents that go unreported to traditional sources, but the nature of any systematic biases in these data are poorly understood. Population surveys represent the only means of collecting detailed individual-level information regarding road users, but there is little consideration by researchers of how survey design choices may affect measured outcomes. When combined with spatial data, population surveys can contribute to understanding associations between rarely studied characteristics of road users and perceived or objective safety. In this thesis, I evaluate alternative sources of bicycling safety data, and contribute to different dimensions of bicycling safety knowledge, by evaluating bicycling safety data collection methods and identifying correlates of perceived and objective bicycling safety. Specifically, the chapters in this thesis address gaps in our understanding of (i) biases in crowdsourced bicycling safety data, (ii) the relationship between personal characteristics, infrastructure, and overall perceived bicycling safety, (iii) the impacts of survey design on measurements of bicycling behaviour, and (iv) bicycling crash risk for different sociodemographic characteristics, social environments (including attitudes and social norms), and neighbourhood-built environment features. In this thesis I provide two broad contributions: (i) showcasing the potential for crowdsourced data and population surveys to compliment traditional bicycling safety data and, provide answers to applied question in bicycling safety research; (ii) underscoring the value of linking a-spatial survey data to a geographic location to be able to assign measurements of a participants built environment and, be able to consider different scales of influence on the outcome. Future research in this area should focus on creating a linked crash database of self-report, crowdsourced, police, hospital and insurance data, as well as on the collection and integration of spatially resolved exposure estimates in travel surveys.

Keywords: Bicycling; Safety data; Crowdsource; Exposure; Study design

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List of Acronyms

BC	British Columbia
BMI	Body Mass Index
CI	Confidence Interval
GPAQ	General Physical Activity Questionnaire
IBICCS	International Bikeshare Impacts on Cycling and Collisions
ICBC	Insurance Corporation of British Columbia
IQR	Interquartile Range
IRR	Incident Rate Ratio
MICE	Multivariate Imputation through Chained Equations
NDVI	Normalized Difference Vegetation Index
OR	Odds Ratio
PASTA	Physical Activity Through Sustainable Transport Approaches
US	United States of America
VGI	Volunteered Geographic Information

Chapter 1.

Introduction

1.1. Background

Bicycling for transport has been promoted as a strategy to improve population health, while also reducing carbon emissions and mitigating climate change (Maibach *et al.* 2009, Woodcock *et al.* 2009, Lindsay *et al.* 2011). Consistent bicycling can provide physical activity which has been shown to reduce the risk of several chronic diseases including heart disease, diabetes, stroke, and certain cancers (Götschi *et al.* 2016). The potential physical activity benefits associated with increased population level bicycling has consistently been found to outweigh potential costs, such as injuries from crashes, and exposure to air pollution (de Hartog *et al.* 2010, Mueller *et al.* 2015, Götschi *et al.* 2016). Replacement of motor vehicle trips with bicycling trips could also serve to reduce green house-gas emissions, as well as air and noise pollution caused by motorized transport modes (Woodcock *et al.* 2007, 2009, Lindsay *et al.* 2011).

Despite the societal benefits of bicycling, in many countries only a relatively small proportion of trips are made by bicycle. Bicycling for transportation is multi-faceted, and dependent on the confluence of a person's individual characteristics (e.g., socioeconomic, demographic, attitudinal, habits, normative influences) and their physical environment (e.g., the built environment, topography, weather/climate, broader bicycling culture) (Heinen *et al.* 2010, Schepers *et al.* 2014). As a part of this broad suite of factors, a key deterrent is a concern of being injured while bicycling, especially in areas that lack bicycling specific infrastructure (Heinen *et al.* 2010, Willis *et al.* 2015). The perceived and objective safety of bicycling for a specific place and time is governed by the interaction between road users, their vehicles and the broader road environment (Haddon 1980, Cho *et al.* 2009, Teschke *et al.* 2012, Winters *et al.* 2012). Concerns regarding the safety of bicycling are generally in alignment with the objective risks of bicycling, in the sense that fatality rates tend to be higher for bicyclists than for motorists (Beck *et al.* 2007, Teschke *et al.* 2013, Scholes *et al.* 2018).

In Figure 1 I present a conceptual framework which outlines the underlying relationships between the road system, perceived and objective safety, bicycling mode share and ultimately improved pollution and population health outcomes that underpin the larger motives behind this thesis. For a given time and place within the road network, there is an unmeasured level of safety for bicyclists, which will vary based on the interaction between the different elements of the road system. The elements of the road system include the road environment, vehicle characteristics and road user characteristics. The perceived and objective safety of bicycling are key factors for determining the amount of bicycling in a region (mode share), which can then influence the pollution levels and positive population health outcomes associated with both switching from driving to bicycling, and the physical activity benefits of bicycling. In this framework, improving the perceived and objective safety of bicycling is vital to unlocking the net benefits of increased population level bicycling.

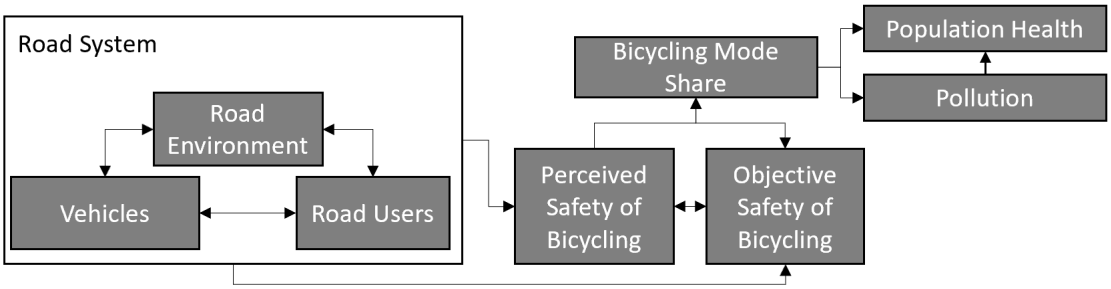

Figure 1. The conceptual framework outlining the rationale for this thesis

In the next sections I will review the literature on the empirical evidence regarding objective and perceived bicycling safety, including: (i) why bicycling is perceived as unsafe (ii), the interdependence of perceived safety, mode share and objective safety and (iii) the role of bicycling infrastructure in perceived safety and mode share. The empirical evidence section will then be followed by a review of methodological and data considerations in road safety research, including: (iv) epidemiological approaches in road safety research, (v) traditional sources of data for road safety research, and (vi) alternative sources of road safety data.

1.2. Empirical evidence

1.2.1. Why is bicycling perceived as unsafe?

The perception that bicycling is unsafe is largely driven by the fact that, unlike cars or trucks, bicycles do not offer physical protection from injury in the event of a crash. In the event of a crash, the risk of serious injury or fatality increases with the weight of the other vehicle, and, with the speed of traffic/impact (Bíl *et al.* 2010, Moore *et al.* 2011, Kaplan *et al.* 2014). Concerns regarding the risk of a serious injury or death are exacerbated in the many motorized regions throughout the world, where there is an expectation that bicyclists share road space with motorized vehicles (Pucher and Buehler 2008, Pucher *et al.* 2011). Sharing road space with motor vehicles as a bicyclist is typically perceived to be a life threatening endeavour by both bicyclists and motor-vehicle drivers (Kaplan and Prato 2016) and, unsurprisingly, a major deterrent to bicycling (Winters and Teschke 2010, Winters *et al.* 2011, Aldred, Elliott, *et al.* 2016, Misra and Watkins 2018).

While crashes that result in severe and fatal injuries play a large role in broader perceptions of bicycling safety (Macmillan *et al.* 2016), the role of crashes that result in minor or no injury or near miss events are often overlooked. Incidents that result in minor or no injury, as well as near misses, are far more numerous than the fatal and non-fatal severe injuries (Veisten *et al.* 2007, Aertsens *et al.* 2010, de Geus *et al.* 2012, Sanders 2015, Aldred 2016). The exact definition of a near miss can vary based on methodological approaches (Aldred and Goodman 2018), but may be interpreted here as a narrowly avoided collision. Fatal and non-fatal severe injuries that are captured by official sources such as police, insurance or hospital data are only the “tip of the iceberg” in terms of traffic safety incidents (Hyden 1987, Svensson and Hydén 2006).

The notion that the frequency and severity of traffic incidents are inversely related is illustrated by the conceptual framework known as the “Safety Pyramid”. The safety pyramid posits that the total distribution of interactions between road users (analogous to the concept of a Bernoulli trial) can be portrayed as a pyramid, divided into sections based on the severity of the interaction. At the base of the pyramid is a section that includes undisturbed passages, on top of which is a section including potential and slight conflicts, then serious conflicts (near misses), and finally crashes at the tip of the

pyramid. Crashes can be further decomposed into those that result in no injury, injury or fatality (Figure 2). The severity of a conflict (near miss) is based on how close in time and space a road user comes to being involved in a crash. Potential conflicts can be conceptualised as two road users who are on a collision course at some point in time and space, but avoid the collision with ample time. A more severe conflict is when two road users come closer in space and time to a collision (Svensson and Hydén 2006). The implication of the safety pyramid is that for every serious or fatal crash that occurs there are many times more minor crashes or near miss events.

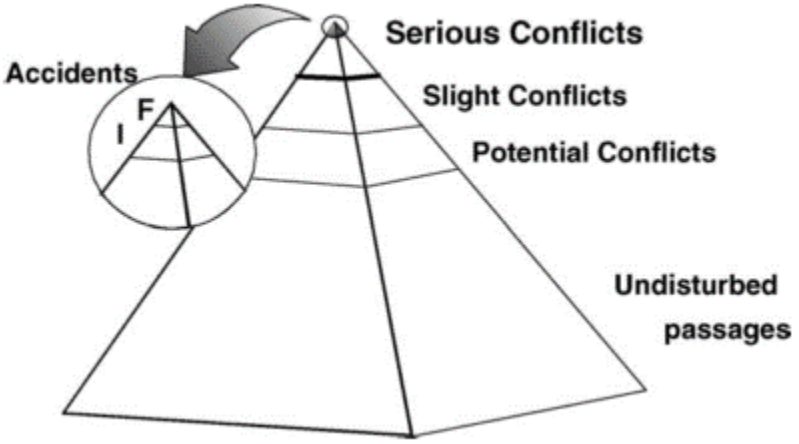

Figure 2. The road safety pyramid. Here the distribution of interactions between road users can be described as divided into different categories of severity ranging from undistributed passage to fatal crash *(Svensson and Hydén 2006)*. Here "I" refers to an accident that resulted in injury, while "F" refers to an accident that resulted in a fatality. The implication of this framework is that as severity of outcome increases its relative frequency decreases.

These less severe types of incidents, such as near misses or crashes resulting in minor injury, are not inconsequential due to the sheer volume at which they occur. On a per crash basis, minor crashes do have significant economic costs in the form of indirect costs, lost leisure time and direct non medical costs, which can add up to significant overall economic costs (Aertsens *et al.* 2010, Palmer *et al.* 2015). There is also a hypothesis that non-injury crashes and near miss events can play an insidious role in depressing bicycling rates as a result of their ubiquity in the everyday bicycling experience (Aldred and Crosweller 2015, Sanders 2015, Aldred 2016). This hypothesis suggests that since minor collisions and near miss events are a source of constant emotional distress, they could lead to systemic avoidance of bicycling within the broader

population (Aldred 2018), as a result of people that stop bicycling, or bicycle less frequently. If this is the case than it would then also be likely that there are significant costs in terms of unmaterialized benefits of physical activity associated with bicycling, given that the time that would have been spent bicycling is not replaced by other physical activities.

1.2.2. The interdependence of perceived safety, mode share and safety

Perceptions of bicycling risk are vital to understand as they are a primary deterrent to uptake. Improving the perception of the safety of bicycling may have a disproportionately positive effect on modal share (Noland 1995). For example, one model suggested that 10% increase in bicyclist comfort would result in a greater than 10% increase in bicycle modal share (Noland 1995). There is also substantial evidence that suggests that routes with greater numbers of bicyclists are safer (Elvik and Bjørnskau 2017, Elvik and Goel 2019). This phenomenon, whereby areas that experience a greater volume of bicyclists have reduced bicyclist collision rates, is often referred to as the “safety in numbers” effect.

The safety in numbers effect has been observed in a number of studies throughout the world at varying spatial scales, ranging from the intersection and roadway level (Brüde and Larsson 1993, Gårder *et al.* 1998, Schepers *et al.* 2011, Kaplan and Giacomo Prato 2015, Elvik and Bjørnskau 2017, Elvik and Goel 2019), to larger scales such as municipality or country (Jacobsen 2003, Robinson 2005, Elvik and Bjørnskau 2017, Elvik and Goel 2019). While it is not known whether the relationship between bicycling volume and increased safety is causal, the prevailing theory is that greater volumes of bicyclists results in a modification of motorists’ behavior, as a result of both an increased expectation of encountering bicyclists and because motorists are more likely to cycle themselves (Jacobsen 2003, Johnson *et al.* 2014).

1.2.3. The role of bicycling infrastructure in perceived safety and mode share

There is strong evidence that potential bicyclists have a preference for using bicycle-specific infrastructure compared to bicycling in mixed-traffic (Heinen *et al.* 2010,

Winters and Teschke 2010, Winters *et al.* 2011, Aldred, Elliott, *et al.* 2016). There is an established link between facilities that offer greater separation of bicyclists from motorized traffic, an increased willingness to use bicycling as a mode of transport, as well as an increased perception of safety (Winters and Teschke 2010, Winters *et al.* 2011, National Institute for Transportation and Communities 2014, Aldred, Elliott, *et al.* 2016). Both women and elderly have been found to be more sensitive to safety concerns that arise from bicycling in mixed traffic than young men (Aldred, Elliott, *et al.* 2016). This is likely a key reason that young men are disproportionately represented among commuter bicyclists in cities with low bicycling mode share (Garrard *et al.* 2008, Aldred, Woodcock, *et al.* 2016).

The preference for bicycling specific infrastructure is congruent with the fact that availability of bicycling specific infrastructure is correlated with greater numbers of bicyclists at a variety of spatial scales. Comparative analyses of national bicycling data suggest a positive relationship between bicycling mode share, availability of bicycle-specific facilities and overall bicyclist safety, meaning that a greater availability bicycle-specific facilities is associated with both lower injury and fatality rates, as well as higher bicycle mode share (Pucher and Buehler 2006, 2008). The positive association between provision of bicycle specific facilities and bicycling mode share has also been found at the municipal level in North America and Europe. Studies that investigated the variability in bicycling mode share between different North American cities found that after controlling for factors such as land use, climate, topography, socioeconomic indicators, among others, the availability of bicycle-specific facilities are a statistically significant predictor of bicycling mode-share (Dill and Carr 2003, Buehler and Pucher 2012). In Europe, an analysis comparing mode share to bicycling network density found a positive, non-linear relationship (Mueller *et al.* 2018). In this analysis, the authors suggest that the length of the bicycling network alone is responsible for mode shares of up to 24.7% (Mueller *et al.* 2018). These cross-sectional studies provide non-causal evidence of a positive relationship between bicycling and bicycling infrastructure (Buehler and Dill 2016), while results from the few longitudinal studies of specific infrastructure interventions have been mixed (Panter and Ogilvie 2015, Heesch *et al.* 2016, Panter *et al.* 2016, Prins *et al.* 2016, Crane *et al.* 2017, Pritchard *et al.* 2019). Though general causality is not established, there is some evidence to suggest that bicycling infrastructure can encourage bicycling.

1.3. Methodological and data considerations

Applied road safety research is largely concerned with relating features of various components of the road system to safety outcomes. To advance our understanding of these relationships we need to consider both the methods used to analyse data, as well as the data sources themselves.

1.3.1. Epidemiological approaches to road safety

Epidemiology is the study of how often and why disease occurs within different populations (Aschengrau and Seage III 2014). Epidemiological approaches relate disease frequency to a population at risk for that disease over a certain period of time, and assessing how the disease frequency differs through time, between different places, and/or between groups of people. Epidemiological methods as applied to road safety have been used in both a descriptive capacity, where patterns of crashes and injuries by time, place and populations are investigated, as well as in a more analytic capacity where, the association between potential risk factors and outcomes are tested in a more rigorous manner. Epidemiological studies that quantitatively assess the different factors that affect risk of crash involvement and injury severity are a vital first step in the development of road safety policy (Elvik *et al.* 2009).

Descriptive epidemiology is concerned with describing the occurrence of disease by person, place and time (Aschengrau and Seage III 2014). In the context of road safety, studies that take this approach seek to describe the occurrence of crashes and/or injury severity by road user and vehicle characteristics, road environments characteristics, and also how their frequency may change over time. Studies of this nature can discover patterns within crash and travel data to determine what localities, time periods, or groups of people are associated with higher or lower rates of crashes, which may provide insight into potential causal factors.

Crash rates can be generally defined as the number of crashes within a specified time period divided by the population at risk within a specified time period. There are two main purposes for developing crash or injury incidence rates: 1) to make meaningful comparisons of risk, and 2) to gain insight into potential risk factors (Hauer 1995). The denominator in the crash rate, also commonly called “exposure”, refers to some measure

of the intensity of traffic participation. Crash rates are analogous to the concept of disease incidence, which refers to the number of new cases of a disease within a population at risk over a given period of time. Descriptive epidemiological approaches to road safety are therefore generally concerned with calculating various types of crash rates (varying based on the choice of numerator and denominator data) and comparing how they differ between different categories of road user, vehicle, or road environment characteristics (Massie *et al.* 1995, Aultman-Hall and Kaltenecker 1999, Beck *et al.* 2007, Broughton 2008, McCartt *et al.* 2009, Mindell *et al.* 2012, Minikel 2012, Teschke *et al.* 2013, Lusk *et al.* 2013, Santamariña-Rubio *et al.* 2014, Castro *et al.* 2018). These approaches may also compare how rates differ between different geographic regions (Hakkert and Braimaister 2002, Vandenbulcke *et al.* 2009, Yiannakoulias *et al.* 2012) or how they change through time (Oster and Strong 2013).

There are two fundamental data requirements for epidemiological studies of crash incidence: crash data and exposure data, which are, essentially, measures of the occurrence of crashes and the size of the population at risk. In practice, descriptive crash studies are based on the conflation of existing databases that describe the frequency of crashes/injuries, and the amount of traffic participation within a given region and time period. Systematically collected crash data are generally available from police or insurance records, while data on traffic participation are normally available in the form of population censuses, vehicle registration, or travel surveys (Hautzinger *et al.* 2007). Provided these data sources have common attributes (e.g., gender, age), the sum of both crashes and exposure within these strata can be combined to calculate their respective crash rates.

1.3.2. Traditional sources of bicycling safety data

Traditional bicycling safety data relies on administrative records such as police, insurance or hospital records. Commonly, these types of data are combined with population level surveys on travel habits to generate the epidemiological measures of crash risk (e.g Castro et al., 2018). These traditional sources suffer from two main issues: 1) traditional sources of crash data severely under-report crashes for bicyclists and, are biased towards certain types of crashes, and 2) only aggregate analyses are possible, limited by the number of common variables between the safety data (number of crashes) and the travel survey data (exposure).

The traditional sources of crash data consist of three primary agencies that systematically collect crash data: police, insurance companies, and hospitals (Elvik *et al.* 2009). In most countries, official records of traffic crashes are based on police reported incidents, but there are some jurisdictions where they may be based on insurance records (Winters and Branion-Calles 2017). Police reported incidents will miss all traffic crashes in which police were not required at the scene. Furthermore, police data under report non-fatal bicyclist crashes (Elvik and Mysen 1999, Stutts and Hunter 1999, Cryer *et al.* 2001, Langley *et al.* 2003, Amoros *et al.* 2006, Meuleners *et al.* 2007, Veisten *et al.* 2007, de Geus *et al.* 2012, Juhra *et al.* 2012, Watson *et al.* 2015), have higher rates of under reporting for bicyclist crashes of decreasing injury severity (Elvik and Mysen 1999, Amoros *et al.* 2006, Veisten *et al.* 2007) or if a motor vehicle is not involved (Stutts and Hunter 1998, Langley *et al.* 2003, Juhra *et al.* 2012). Insurance agencies will only record crashes in which an insurance claim is made, and in some instances, only if a motor vehicle is involved (Winters and Branion-Calles 2017). Hospital data do not tend to be used as “official” sources of crash data, but often are used in studies to gauge a more complete picture of bicyclist crashes in a region as they will include a broader range of crash types, such as single-bicycle crashes (falls) (Elvik and Mysen 1999). Hospital data are also unlikely to be complete, as they require a baseline level of injury severity to be recorded, and will fail to capture crashes that resulted in no injury or injury treated by a general practitioner (Elvik and Mysen 1999, Juhra *et al.* 2012). Hospital data are generally more difficult to obtain than police or insurance data, while integrating data from multiple hospitals within a jurisdiction can introduce additional complexity. The extent to which any one source captures the entirety of bicycling crashes in a region is not known, but when comparing police to hospital data, police data tend to capture less than 30% of crashes (Elvik and Mysen 1999).

In addition to under-reporting, the use of traditional safety data combined with population travel surveys to obtain estimates of epidemiological crash risk is limited by the number of common variables between them. For example, if we wished to understand differences in risk between people who have different perceptions of safety, then we would need to know the total number of crashes that occurred amongst people who believe bicycling is safe versus unsafe, as well as the number of trips, total hours or total distance travelled within those groups. Comparisons of population groups by such in-depth characteristics is not possible when using these secondary data sources, as

they tend to be limited to very general sociodemographic or locational attributes such as age strata and sex (Beck *et al.* 2007) or broad classification of classes of roads (Elvik *et al.* 2009) or large geographic regions (Hakkert and Braimaister 2002, Yiannakoulias *et al.* 2012, Castro *et al.* 2018).

1.3.3. Alternative sources of bicycling safety data

Given these issues with traditional datasets, there has been a movement toward using novel approaches for collecting bicycling safety data, such as through anonymous crowdsourced data or population surveys.

Crowdsourcing

Recent advances in web-mapping and smart-phone technology have widened the scope of available bicycling incident and exposure data through crowdsourcing (Ferster *et al.* 2018). Crowdsourced data refers to data that have been collected by ordinary citizens typically via mobile applications or web-mapping interfaces (Elwood 2008, Ferster *et al.* 2018). When the data are tied to a specific location they are often referred to as Volunteered Geographic Information (VGI). Increasingly VGI are available for bicycling safety and exposure (Nelson *et al.* 2015, Jestico *et al.* 2016, Roy *et al.* 2019). Websites and mobile apps collect bicycling safety VGI by providing a web-mapping platform for individuals to report details and locations of incidents they experience in traffic (Nelson *et al.* 2015, Jestico *et al.* 2017) or by passively collect data on bicycling exposure through fitness apps (Jestico *et al.* 2016, Roy *et al.* 2019). Crowdsourced incident data may be able to help collect data that go unreported to police, insurance or hospital data such as minor crashes, non-injury crashes and near miss experiences (Mannering and Bhat 2014, Nelson *et al.* 2015). Contributions to crowdsourced data are often anonymized, thereby not allowing for person-level safety analyses.

Few studies have been conducted to understand the information content of crowdsourced bicycling safety data. One of the main barriers to utilizing crowdsourced traffic safety data is concerns regarding its quality and representativeness (Ferster *et al.* 2018), for example, whether there are systematic biases in terms of who are reporting certain types of incidents, and in what built environment or traffic conditions.

Furthermore, little is known about how different these data are compared to official sources such as police or insurance data.

Population surveys

Population surveys can be an important tool for collecting road safety information as they can allow for the simultaneous collection of crash and exposure data at the individual level, as well as much more detailed information about each individual including sociodemographic, attitudinal, social and built environment characteristics. Survey data can also be linked to “objective” measures of the built environment by conflating disparate geospatial datasets (e.g., road network, bicycling network, building density etc.) through locational information participants provide in surveys. Typical locational information includes geocoded postal code or address, of a participants home, work or travel locations, or self-reported trip-diary route data, or GPS traces (Dons *et al.* 2015, Gerike *et al.* 2016, Romanillos *et al.* 2016). A population survey approach can generate a comprehensive individual-level dataset including both self-reported crash, exposure, sociodemographic, attitudinal, social and built environment information. Such data can be used to not only compare crash rates between different groups, but also to statistically adjust for other factors using regression analyses. Very few studies have been able to collect data in this manner and analyse disaggregated crash risks.

Similarly, population surveys can also be used to understand perceptions of bicycling safety. As previously discussed, bicycle-specific facilities are preferred over bicycling in mixed traffic, and within a given jurisdiction the availability of bicycle-specific facilities is positively correlated with higher ridership. However, most studies that compare the perceived safety of different bicycling environments tend to focus on how specific route characteristics influence perceived safety. Typically these studies have compared the perceived safety of different infrastructure by asking bicyclists to rate the safety (or risk) of different network features through video-clips (Parkin *et al.* 2007), intercept surveys at specific locations (Møller and Hels 2008, National Institute for Transportation and Communities 2014) or recall of a bicyclists route (Winters *et al.* 2012, Manton *et al.* 2016). These studies are important to understanding how detailed route characteristics are related to perceptions of safety, but do not provide information on how existing infrastructure may be associated with a bicyclist’s general perceptions of overall bicycling safety within their locality. For example, a population survey with spatial

data (e.g., geocoding of addresses or estimates of route data) could be used to investigate how existing real world-built environment conditions may be associated with perceived safety. Individual information on perceived risk derived from surveys could be combined with location data, which would also enable statistical adjustment of potentially confounding variables such as exposure and sociodemographic factors.

Collecting crash and exposure data in population surveys

Population surveys allow some flexibility in collecting crash and exposure data (Vanparijs *et al.* 2015). For example, a cross-sectional design asks questions at one point in time about past exposure and crashes (Aultman-Hall and Hall 1998, Aultman-Hall and Kaltenecker 1999, Bacchieri *et al.* 2010, Heesch *et al.* 2011, Palmer *et al.* 2014). Such a study would typically ask participants about factors at that point in time (e.g., current age, gender, perceptions of safety etc.), as well as questions on past bicycling behaviour and whether they were involved in any crashes within a certain period of time (Aultman-Hall and Hall 1998, Aultman-Hall and Kaltenecker 1999, Bacchieri *et al.* 2010, Heesch *et al.* 2011, Palmer *et al.* 2014). A prospective study may capture the same information, but would follow the same cohort of participants over time, thereby obtaining repeat measurements of both exposure and crash data through time (de Geus *et al.* 2012, Tin Tin *et al.* 2013a, Poulos *et al.* 2015a). Prospective collection of both crash and exposure data over time presumably will reduce recall bias, and allow for more precise estimates of long-term bicycling behaviour (exposure).

Irrespective of the approach, bicycling exposure can be measured in three different units: duration, distance or number of trips. Within a population survey, exposure can be extrapolated from a range of approaches, from detailed travel diaries complete with route data, to simple frequency questions with no spatial component (Heesch *et al.* 2011, Tin Tin *et al.* 2013a, Palmer *et al.* 2014, Degraeuwe *et al.* 2015, Dons *et al.* 2015, Poulos *et al.* 2015b, 2015a). In addition to choosing a survey instrument and unit(s) of measurement, researchers also need to decide the time-frame (e.g., a week, month year), and whether to measure using direct-recall (e.g., minutes of bicycling in the past week or number of bicycling trips in the previous day etc.) or to measure using recall of “typical” behaviour (e.g., minutes of a bicycling in a *typical* month). Direct-recall aims to reduce desirability bias, while the use of shorter time periods aims to reduce recall bias (Brenner and DeLamater 2014). Often, choices of

survey instrument, units of measurement, time frame and typical versus direct-recall are correlated due to considerations of participation burden and bias. For example, a travel diary that maps the routes taken by each individual can measure all three units (distance, duration and number of trips) at the same time, but are typically restricted to a short period of time (e.g., 1 day) to reduce participation burden, and recall bias (Gerike *et al.* 2016).

Measuring bicycling accurately has been identified as a key research need (Handy *et al.* 2014). The extent to which measured bicycling is biased as a result of measuring once, versus multiple times, is not known. There is very little research available to provide researchers or practitioners practical knowledge for making informed decisions in survey design.

1.4. Research gaps

Based on the literature synthesized above, there is a need to address the safety risks, both real and perceived, that ultimately limit the broader uptake of bicycling. There are gaps in data and knowledge on bicycling safety, including on the information content of novel data collection sources, the impact of study design on measurement of bicycling, and the relationship between more detailed sociodemographic characteristics, infrastructure, and perceived and objective risk. In Figure 3 I show how survey design (including the source of data collection and the study approach) influences measurements of objective safety, perceived safety and the road system components. In this thesis I aim to address gaps in data and knowledge on bicycling safety, by drawing on novel data types, and research designs to (i) understand biases in emerging sources of bicycling crash data, (ii) understand the relationship between detailed sociodemographic characteristics, infrastructure, and perceived safety, (ii) provide guidance on how to measure bicycling behaviour more accurately, and (iv) to identify risk factors for a bicycling crash, including detailed sociodemographic characteristics, social environments, and built environment features.

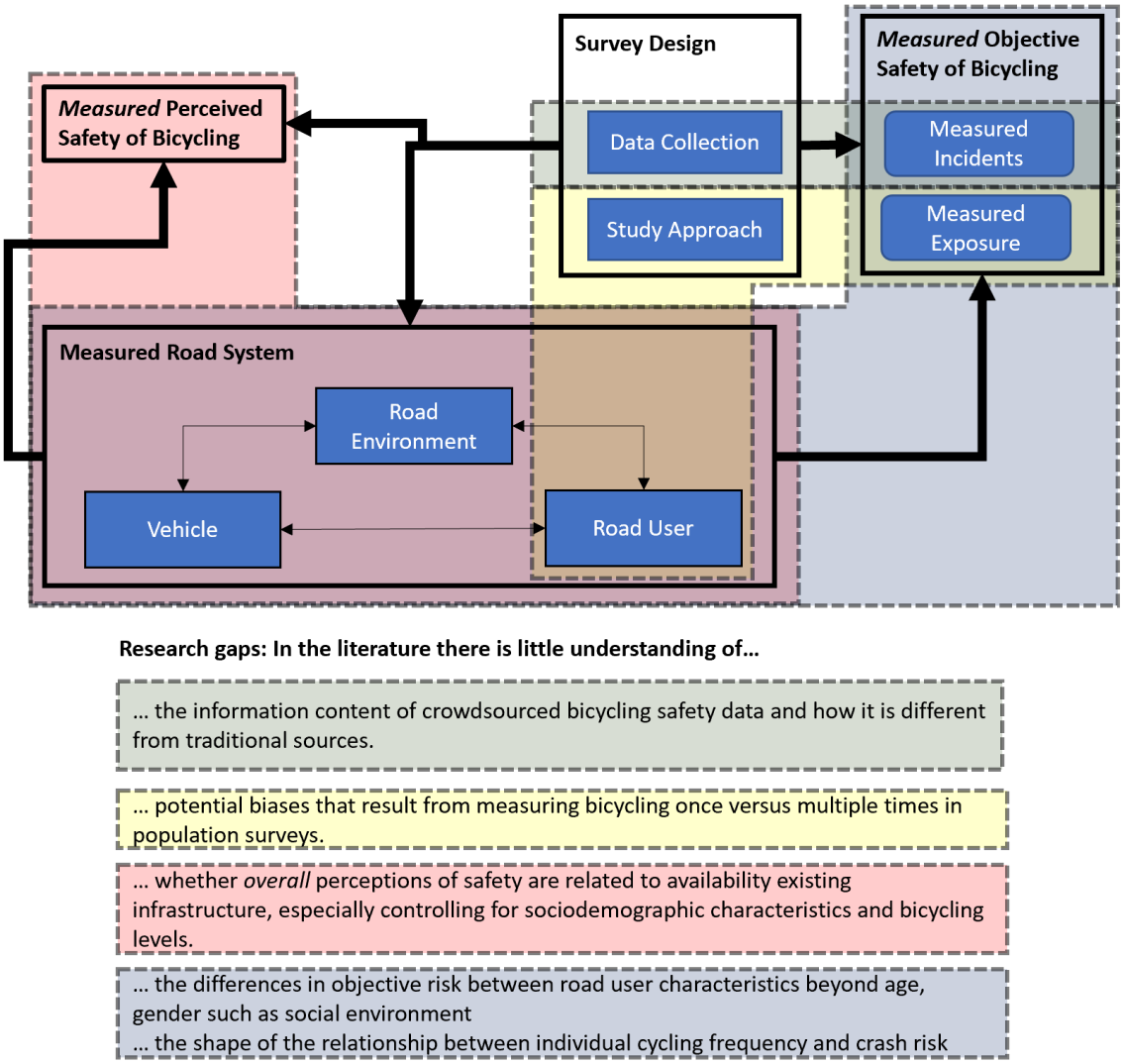

Figure 3. Diagram outlining the relationship between survey design, the road system, perceived safety and objective safety of bicycling, with the corresponding research gaps that are addressed in this thesis.

1.5. Specific aims

Based on the identified research gaps, the chapters in this thesis are organized around one of the following four specific aims:

1. To gain a better understanding of the information content of crowdsourced bicycling safety data and compare it to a traditional insurance-based source (Chapter 2)

2. To examine the association between availability of bicycle infrastructure, individual characteristics, and perceptions of bicycling safety (Chapter 3).

3. To understand the impacts of measuring cross-sectionally (at one time) versus longitudinally on estimates of bicycling exposure (Chapter 4)

4. To explore determinants of bicycling crash risk using longitudinally collected crash and exposure data (Chapter 5)

1.6. Datasets

Several different datasets are used in this thesis. In the following sections broad introductions are given to each. These datasets are not used in combination with one another, but rather are each individually a main data source used to evaluate the aims within Chapters 2 to 5.

1.6.1. Bikemaps.org

BikeMaps.org was launched in October 2014 and is a global web-mapping application that enables the collection of incidents bicyclist experience in traffic, including collisions, falls, and near misses (Nelson *et al.* 2015). The application is supported by mobile apps for Android and iPhone devices, as well as over a web-browser (Figure 4) (Nelson *et al.* 2015, Ferster *et al.* 2018). The website was explicitly created to collect both under-reported incidents in official sources such as minor collisions or falls, as well as completely unreported incidents such as near misses. Citizens are able to identify the location of a given incident by navigating to the location at which the incident occurred on a web map and clicking “add a new marker”. After pinning the location of an incident, a menu appears wherein the user can answer a series of questions surrounding the incident through pull-down options. Citizens can decide to report either a collision, near miss, bicyclist hazard or a bike theft, the choice of which will guide the subsequent questions which were designed with the purpose of researching bicycling injury determinants (Ferster *et al.* 2018). Questions were designed to illuminate three types of attributes: incident details, conditions, and personal details of the person reporting. All reports are anonymous. This new crowdsourced data type is used in Chapter 2 of the thesis to examine information content of crowdsourced bicycling safety data including

similarities and differences between personal, trip and built environment characteristics of the crowdsourced near miss reports, crowdsourced collision reports, and official insurance reports

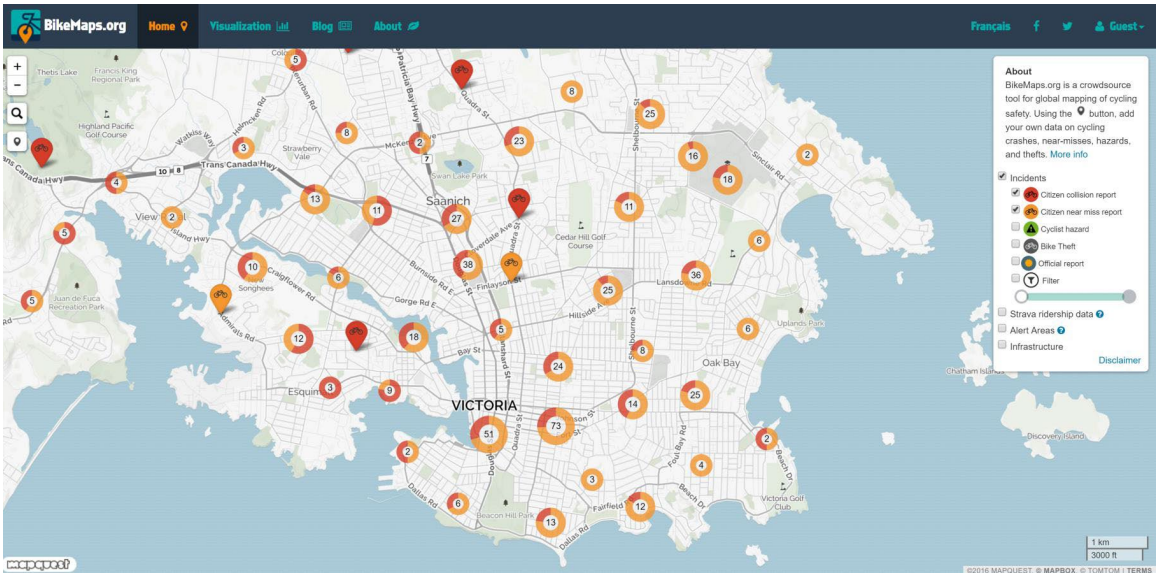

Figure 4. Bikemaps.org interface on the website

1.6.2. The International Bikeshare Impacts on Cycling and Collisions Study (IBICCS)

The International Bikeshare Impacts on Cycling and Collisions Study (IBICCS) was designed to use population surveys to understand the health impacts of public bike share systems in a Canadian and US context (Fuller *et al.* 2014). Three cross-sectional surveys were conducted for citizens in eight different Canadian and US cities in the fall of 2012, 2013, and 2014. A pooled total of 23,901 participants were sampled in New York City, Toronto, Vancouver, Montreal, Boston, Chicago, Detroit and Philadelphia. The questionnaire consisted of questions regarding each participant's self-reported health, physical characteristics, physical activity questions, and perceptions of bicycling safety. Respondents could choose to answer the questions in either English, Spanish or French. While historical crash data were collected, the manner in which they were collected would not allow for a calculation of crash rates as it did not allow for the possibility of multiple crashes per person. Participants were asked if they were involved in a crash in the past 3 months and could answer yes or no, but there was not a question about how many incidents. Participants were also asked for postal/zip code information of their homes, in order to enable each survey to be geolocated. Data from this study is

used in Chapter 3 of the thesis to examine the association between availability of bicycle infrastructure, individual characteristics, and perceptions of bicycling safety

1.6.3. The Physical Activity through Sustainable Transport Approaches (PASTA) project

The Physical Activity through Sustainable Transport Approaches (PASTA) project is a longitudinal cohort study of participants from seven European cities over two years (Dons *et al.* 2015, Gerike *et al.* 2016). The purpose of this study was to better understand how physical activity in terms of walking and bicycling was integrated into the everyday lives of the citizens of these cities. The study was designed to have a long and detailed baseline survey, with short and frequent follow-up surveys. Specifically, the baseline survey collected detailed information on personal characteristics, social and built environment characteristics; travel behaviour, a 1-day travel diary. Short follow-up questionnaires sent every 13 days to collect data on travel behaviour, levels of physical activity and traffic safety incidents in the time since the previous survey using simple frequency questions. Every third follow-up survey was a longer follow-up with a 1 day travel diary included. Data from this study is used in Chapters 4 and 5 of the thesis, to: (i) understand the impacts of measuring bicycling behaviour cross-sectionally versus longitudinally (Chapter 4) and (ii) explore determinants of bicycling crash risk using longitudinally collected crash and exposure data (Chapter 5).

1.7. Thesis outline

This manuscript-based thesis presents four stand-alone chapters, bookended with introductory (Chapter 1) and concluding (Chapter 6) chapters. Each chapter contributes to the thesis as follows:

- **Chapter 1** reviews the background research underpinning this thesis, outlines the specific aims of each chapter and describes the different datasets that I used to meet these aims.

- **Chapter 2** uses logistic regression models to gain a better understanding of the information content of crowdsourced bicycling safety data generated from BikeMaps.org by comparing the personal, trip and built environment

characteristics of the crowdsourced near miss reports, crowdsourced collision reports, and official insurance reports, using the cities of Victoria and Vancouver which were pilot cities for the Bikemaps.org project. This chapter has been published in Transportation Research Record: Journal of the Transportation Research Board (Branion-Calles *et al.* 2017).

- **Chapter 3** uses multinomial regression to examine the association between availability of bicycle infrastructure, individual characteristics, and perceptions of bicycling safety using IBICCS survey data across 6 major cities in the US and Canada. This chapter has been published in Transportation Research Part A: Policy and Practice (Branion-Calles, Nelson, *et al.* 2019).

- **Chapter 4** explores the impacts of measuring bicycling behaviour once versus multiple times through a variety of methods using PASTA survey data that samples from 7 European cities. This chapter has been published in the Journal of Transport & Health (Branion-Calles, Winters, *et al.* 2019).

- **Chapter 5** uses negative binomial regression to examine crash risk amongst bicyclists across the 7 European cities sampled within the PASTA cohort. This chapter has been published in Accident Analysis & Prevention (Branion-Calles *et al.* 2020).

- **Chapter 6** synthesises the findings from this thesis and outlines directions for future research.

Chapter 2.

Comparing crowdsourced near miss and collision bicycling data and official bike safety reporting

2.1. Introduction

Bicycling as means of transport is associated with a variety of personal and environmental health benefits (de Hartog *et al.* 2010). In recent years and in many regions throughout the world, increased commuter bicycling has been promoted as a means of both increasing population health and reducing the negative environmental impacts associated with motor vehicle traffic (Pucher *et al.* 2010). Perceptions of the safety of bicycling have been found to be a main factor for individuals choosing whether to cycle and/or where to cycle (Winters *et al.* 2010, 2011). In North America, the perceived risks of bicycling are not entirely misplaced, as fatality rates per trip are higher for bicyclists than for motor vehicles (Beck *et al.* 2007, Teschke *et al.* 2013).

Official crash data, usually police or insurance records, form the basis of bicycling safety research. These official sources under-represent the number of non-fatal bicyclists crashes (Elvik and Mysen 1999, Stutts and Hunter 1999, Cryer *et al.* 2001, Langley *et al.* 2003, Meuleners *et al.* 2007, Veisten *et al.* 2007, de Geus *et al.* 2012, Tin Tin *et al.* 2013b, Watson *et al.* 2015), and are disproportionately composed of both bicycle-motor vehicle collisions and severe injury outcomes (Stutts and Hunter 1998, Elvik and Mysen 1999, Langley *et al.* 2003, Amoros *et al.* 2006, Veisten *et al.* 2007, Tin Tin *et al.* 2013b). In fact, of injured bicyclists attending emergency departments only a minority are injured in collisions with motor vehicles; estimates range from 21% to 34% in studies from the United States(Stutts and Hunter 1999), England (Davidson 2005), Australia (Meuleners *et al.* 2007, De Rome *et al.* 2014), France (Amoros *et al.* 2011) and Canada (Teschke *et al.* 2014).

In response to data limitations, there is increasing interest in the use of surrogate measures of collisions, such as conflicts, to evaluate road safety (Tarko *et al.* 2009, Sayed *et al.* 2013). Surrogate measures are predicated on the idea that in traffic there are interactions between road users that would have led to a collision had evasive action

not taken place. These “near miss” events are thought to be similar to collisions in the pre-crash phase and possibly predictive of the occurrence of future collisions (Tarko *et al.* 2009). Near miss events occur much more frequently than collisions themselves, thereby enabling the collection of larger samples of data, in much shorter time periods, than available from officially reported collision data (Tarko *et al.* 2009). Due to effort it takes to collect surrogate measures, either through human observers or automated video analysis, surrogate measures have been used for site specific evaluations (Sayed *et al.* 2013), but not for surveillance across broad geographic areas. Access to surrogate safety data for region-wide analyses could enable the identification of high-risk areas more quickly than with collision data alone, facilitate timely interventions to increase road safety and provide a mechanism for ongoing surveillance and change detection.

Crowdsourcing (obtaining data through volunteers via the internet) represents a promising new means for supplementing official collision data, as well as collecting region-wide surrogate collision data using self-reported near miss events (Nelson *et al.* 2015). BikeMaps.org is a global online mapping tool that allows users to record the location and the details of bicycling incidents they experience, including collisions, falls and near misses (Nelson *et al.* 2015). BikeMaps.org represents a means for collecting bicycling safety incidents that may not have been reported to official sources.

In order to utilize crowdsourced bicycling safety data in surveillance, it is important to understand the subset of incidents it represents, and to identify any potential systematic differences in the conditions in which different incident types are reported. For example, more novice bicyclists may be more likely to report near miss events than more experienced bicyclists. Identifying the factors that affect the frequency of near miss reporting has important implications for safety evaluations. For instance, if younger bicyclists were more likely to report near miss events than older bicyclists, the use of near miss data in dangerous intersection identification would be biased towards sites along routes with a higher proportion of younger bicyclists. It is important understand how crowdsourced collision data may be different or similar to the conditions in which collisions are reported to official sources to better assess how crowdsourced collision data may be best used in bicycling safety surveillance. Understanding these differences is a first step in being able to tap into the full potential of data for road safety practice.

The goal of this research is to gain a better understanding of the information content of crowdsourced bicycling safety data generated from BikeMaps.org by comparing the personal, trip and built environment characteristics of the crowdsourced near miss reports, crowdsourced collision reports, and official insurance reports. Our objectives are to assess similarities and differences in 1) near misses and collisions reported to BikeMaps.org; and 2) collisions reported to BikeMaps.org and to an official insurance dataset.

2.2. Materials and methods

2.2.1. Study area

We used data from two cities in southwestern British Columbia (BC), Canada, Victoria and Vancouver, where there has been substantial promotion of BikeMaps.org. Victoria has a population of ~80,000 and a bicycling mode share of ~10.6%, while Vancouver has a population around ~600,000 and a bicycling mode share of ~4.3% (Statistics Canada 2013a, 2013b). These cities have mild climates that allow for year round bicycling, as well as municipal governments which have made increasing both the mode share and safety of bicyclists a major policy priority (City of Vancouver 2012, City of Victoria 2016a).

2.2.2. BikeMaps.org: crowdsourced collision and near miss data

BikeMaps.org is a global online mapping tool developed specifically for the purpose of collecting citizen generated reports of bicyclist collisions and near misses (Nelson *et al.* 2015). The mapping tool allows the website user to pin the locations of a collision or near miss they have experienced. Users' complete follow-up questions regarding the incident, including crash circumstances, the road and weather conditions as well as demographic questions (see Nelson et al (2015*)* for full list of attributes collected). We use data from BikeMaps.org that were reported to have took place between May 2014 and April 2016 within the cities of Victoria and Vancouver. These data consist of 404 reported incidents (24% are collisions or falls, 76% are near misses).

2.2.3. Insurance Corporation of BC: official collision data

The Insurance Corporation of British Columbia (ICBC) is the only motor vehicle insurance company in the province of BC, and is the official source of collision data for safety evaluations within the province (Wei and Lovegrove 2013). The dataset includes only bicyclist crashes with motor vehicles where an insurance claim is made, and thus it misses collisions that result from interactions with other road users (e.g.,, bicyclists or pedestrians) or single-bicycle crashes (e.g.,, a collision with a stationary object). Many motor vehicle crashes go unreported, especially where motor vehicle damage is limited.

We used the most recent ICBC data available (2013), which included 599 bicycle-motor vehicle collisions reported within Vancouver and Victoria with information on the road network location and time of the incident. ICBC data has no other descriptors, for example, no information on injury severity. All ICBC crash locations are assigned to an intersection or mid-block location prior to release (Colleen Woodger, personal communication).

2.2.4. Built environment and weather data

We compiled built environment and weather spatial datasets for factors that influence both perceived and real bicycling risk (sources, variables, and categories in Table 1). To each BikeMaps.org and ICBC incident we assign the following variables based on the location and/or time at which they occurred: 1) Road Location; 2) Road Classification; 3) Number of Lanes; 4) Time of Day; 5) Truck Route Presence; 6) Bicycle Facility Presence; 7) Lighting Conditions; and 8) Weather Conditions. The levels for each of these variables are in Table 1. We expect that ICBC data will have a greater proportion of severe injury outcomes than BikeMaps.org based on the fact that ICBC data are composed entirely of bicycle-motor vehicle collisions, which are known to have more severe injury outcomes than bicycle collisions with other road users or falls (Loo and Tsui 2010, Kaplan *et al.* 2014, Cripton *et al.* 2015). Variables were selected based on documented associations with risk perceptions, as well as associations with injury risk, or injury severity (Table 2).

Table 1. List of spatial datasets and variables for bicycling incidents for Vancouver and Victoria, BC, and trip and built environment characteristics

Source	Data Type	Variable	Levels	Operationalization
BikeMaps.org	Points	Incident Type	Near Miss Collision	Users report either a near miss or collision that they have experienced
		Bicyclist Age	< 30 31-40 40-50 >50 NA	Users have option to provide age with their report
		Bicyclist Gender	Male Female NA	Users have option to provide gender with their report. Two reports identified gender as Other. We randomly assigned the two reports to either Male, Female or NA.
		Trip Purpose	Commute Other	Users have option to detail the purpose of their trip. 7 users had no response and were grouped into "Other" category.
Insurance Corporation of British Columbia	Points	Collision		Collisions with motor vehicles with approximate location and time and no additional attributes
BC Digital Road Atlas(GeoBC 2016)	Street Network	Road Location	Intersection Non-Intersection	Each incident was assigned to intersection or non-intersection based on overlay with street network.
		Classification of Road	Arterial Collector Local	Each incident was assigned to road class based on overlay with street network. For incidents at intersections with multiple road classes, the highest class in the street hierarchy road was used.
		Number of Lanes	1-2 3-6	Each incident assigned a number of lanes on the road based on overlay with street network. For incidents at intersections with multiple values, the highest value was used.
VicOpen(City of Victoria 2016b); VanOpen(City of Vancouver 2016a)	Truck Route Network	Truck Route Presence	Yes No	Truck route networks integrated with digital road network. Each incident was assigned value based on overlay with street network.
Capital Regional District; VanOpen(City of Vancouver 2016a)	Bicycle Facility Network	Bicycle Facility Presence	No Facility Facility Present	Bicycle facility networks standardized and integrated from Victoria and Vancouver. Each incident was assigned value based on overlay with bicycle network.

Source	Data Type	Variable	Levels	Operationalization
BikeMaps.org ; ICBC	Time and Location of Incident	Lighting Conditions	Night Daytime	R package *RAtmosphere* (Biavati 2014) was used to calculate sunrise and sunset for each bicycling incident based on the location, date and time of day. If the incident took place between sunrise and sunset it was assumed to have taken place during daylight hours.
Environment Canada	Environment Canada Weather Station Data	Weather Conditions	Clear or Cloudy Precipitation or Fog	R package *weatherData* (Narasimhan 2014) was used to extract the weather conditions from Environment Canada weather stations at Victoria (YYJ) or Vancouver international airports (YVR) based on reported time, and classified.
BikeMaps.org ; ICBC	Time of Incident	Time of Day	Off-Peak Peak Hours	Peak hours were defined as 6-9 AM or 3-6PM from Monday to Friday. Incidents were classified based on reported time.

Table 2. Rationale for personal, trip and built environment variables associated with likelihood of reporting a near miss compared to a collision to BikeMaps.org as well as their potential impact on reporting a collision to BikeMaps.org, as compared to reporting to Insurance Corporation of British Columbia (ICBC).

Variable	Effect on Risk Perception	Hypothesized Relationship to Near Miss reporting	Effect on odds of bicycle-motor vehicle crash and/or odds of a major injury	Hypothesized Relationship with Collision/ Injury Outcome	Hypothesized Result on Reporting Source
Age Category	Age has been found to have an affect on perceptions of risk and the rate at which near misses are reported (Joshi *et al.* 2001, Parkin *et al.* 2007).	Higher frequencies of near miss reporting within the youngest and oldest age categories compared to middle-aged categories.	NA	NA	NA
Gender	Females may have increased propensity to report near misses in traffic (Joshi *et al.* 2001, Aldred and Crosweller 2015) and a greater aversion to risk when bicycling than males (Parkin *et al.* 2007, Garrard *et al.* 2008, Chataway *et al.* 2014).	Higher frequencies of near miss reporting for females compared to males.	NA	NA	NA
Trip Purpose	Route choices and timing of trips likely related to whether a bicyclist is travelling for utilitarian or recreational purposes.	Higher frequencies of near miss reporting for commuter trips.	NA	NA	NA

Variable	Effect on Risk Perception	Hypothesized Relationship to Near Miss reporting	Effect on odds of bicycle-motor vehicle crash and/or odds of a major injury	Hypothesized Relationship with Collision/ Injury Outcome	Hypothesized Result on Reporting Source
Collision or Near Miss Partner/Object	Concerns regarding the safety of interacting with motor vehicle traffic are consistently found to be one of the top influences on bicycling frequency and route preferences (Parkin *et al.* 2007, Winters and Teschke 2010, Chataway *et al.* 2014).	Higher frequencies of near miss reporting when interacting with motor vehicles compared to other road users or road surface/infrastructure features.	NA	NA	NA
Road Location (Intersection or Non-Intersection)		Higher frequencies of near miss reporting at intersections compared to non-intersections.	The odds of a collision with motor vehicles have been found to be increased at intersections(Romanow *et al.* 2012); However, odds of a major injury have also been found to be increased at non-intersection locations (Kaplan *et al.* 2014)	At non-intersection locations, compared to intersections, we expect: ↓ odds of bicycle motor vehicle crashes ↑ odds of a major injury	↑ or ↓ Odds of reporting to BikeMaps.org
Classification of Road		Higher frequencies of near miss reporting on arterial roads compared to collector or local roads.	Greater number of vehicles (e.g.,, higher level in the hierarchy of road class, greater number of lanes and trips during peak vehicle traffic hours) means greater number of opportunities for bicycle motor vehicles collisions(Romanow *et al.* 2012); multi-lane roads associated with increased odds of a major injury(Kaplan *et al.* 2014). Bicycle motor vehicle crashes are more likely to result in major injuries than single vehicle or bicycle-bicycle injuries (Kaplan *et al.* 2014, Cripton *et al.* 2015).	At both intersection and non-intersection locations with a greater number of lanes and are higher in the street class hierarchy (e.g.,, arterial) during peak traffic hours we expect: ↑ odds of bicycle motor vehicle crashes	↓ Odds of reporting to BikeMaps.org
Number of Lanes		Higher frequencies of near miss reporting on 3-6 lane roads compared to 1-2 lane roads.			
Time of Day		Higher frequencies of near miss reporting during peak-hours compared to off-peak hours,			

Variable	Effect on Risk Perception	Hypothesized Relationship to Near Miss reporting	Effect on odds of bicycle-motor vehicle crash and/or odds of a major injury	Hypothesized Relationship with Collision/ Injury Outcome	Hypothesized Result on Reporting Source
				↑ odds of a major injury	
Truck Route Presence		Higher frequencies of near miss reporting on roads designated as truck routes compared to those that are not.	Increased exposure to heavy vehicles associated with greater chance of being involved in a collision with greater odds of a more severe injury outcome (Kaplan *et al.* 2014, Kaplan and Giacomo Prato 2015).	On road segments and intersections which are designated truck routes we expect: ↑ odds of bicycle motor vehicle crashes ↑ odds of a major injury	↓ Odds of reporting to BikeMaps.org
Bicycle Facility Presence	Bicycle specific infrastructure (e.g.,, signed bike routes on local roads, painted lanes, separated lanes) has been found to be associated with a higher perception of safety compared to bicycling in mixed traffic (Parkin *et al.* 2007, Winters and Teschke 2010, Winters *et al.* 2011, Chataway *et al.* 2014).	Lower frequencies of near miss reports on streets with bicycling facilities compared to streets without bicycling facilities.	Bicycle facilities are associated with decreased risk of motor vehicle collisions (Reynolds *et al.* 2009, Kaplan and Giacomo Prato 2015, Park *et al.* 2015); Bicycle facilities are known to be associated with decreased probability of major injuries (Thomas and De Robertis 2013, Kaplan and Giacomo Prato 2015).	On road segments and intersections with bicycle facilities we expect: ↓ odds of bicycle motor vehicle crashes. ↓ odds of major injuries	↑ Odds of reporting to BikeMaps.org

Variable	Effect on Risk Perception	Hypothesized Relationship to Near Miss reporting	Effect on odds of bicycle-motor vehicle crash and/or odds of a major injury	Hypothesized Relationship with Collision/ Injury Outcome	Hypothesized Result on Reporting Source
Lighting Conditions	Concerns regarding bicycling when there is darkness has been found to be a significant deterrent to bicycling (Winters *et al.* 2011).	Higher frequencies of near miss reporting at night compared to during the day.	There are conflicting results in studies reviewed here. Darkness has been associated with both decreased probability of major injury in Europe(Kaplan *et al.* 2014) and increased odds of major injury in Australia (Boufous *et al.* 2012).	After the sun has set (i.e. when it is dark) we expect: ↓↑ odds of major injuries	↑ or ↓ Odds of reporting to BikeMaps.org
Weather Conditions	Concerns regarding the bicycling when the road surface is wet or icy found has been to be a significant deterrent to bicycling (Winters *et al.* 2011).	Higher frequencies of near miss reporting when there is rain/snow or fog compared to clear or cloudy conditions.	Inclement weather associated with greater probabilities of a major injury (Kim *et al.* 2007, Kaplan *et al.* 2014)	When there is precipitation we expect: ↑ odds of a major injury	↓ Odds of reporting to BikeMaps.org

NOTE: We do not have personal characteristics of bicyclists involved in ICBC reports and thus these are not included in our analysis. Since ICBC to captures only bicycle-motor vehicle collision, and these are more likely to be serious injuries, we consider variables that have been associated with increased odds of a bicycle-motor vehicle crash and/or increased odds of a major injury.

2.2.5. Statistical analysis

The frequency of BikeMaps.org reported near miss events may be influenced by perceptions of risk. We can gain insights into the role of risk perceptions through investigation of differences in the frequency with which near misses are reported relative to collisions across personal, trip and built environment conditions. Furthermore, comparing the relative frequency of BikeMaps.org reported collisions to ICBC reported collisions within different trip and built environment conditions can help to reveal the general differences in reporting conditions between crowdsourced and official collision data.

We implement logistic models to identify the personal, trip and built environment conditions which contribute to relative odds of reporting a near miss compared to collisions in BikeMaps.org crowdsource data, as well as crowdsource collision reports to insurance reports. In the first analysis we model the odds of near misses relative to collisions reported to BikeMaps.org (1=Near Miss, 0=Collision), by personal, trip and built environment variables that influence perceptions of risk. In the second analysis we model the odds of collisions reported to BikeMaps.org relative to collisions reported to ICBC (1= BikeMaps.org collision report, 0=ICBC collision report), by trip and built environment variables that influence the risk of a bicycle-motor vehicle collision and/or greater injury severity outcomes. We do not include personal characteristics of the bicyclist in the second analysis as ICBC reports do not include bicyclist characteristics. In both approaches we first examine the bivariate relationship between the outcome and each explanatory variable. Second, we assess their influence in an adjusted model using a stepwise procedure. The stepwise procedure involved fitting a global model that included all explanatory variables and evaluating each variable's effect on the outcome using a Wald test. The variable with the largest p value was removed and the model re-fit with the remaining explanatory variables. This process was repeated until each variable in the model was significant at $p < 0.05$. All modelling was performed in R 3.2.3 (R Core Team 2015).

2.3. Results

There were 404 near misses and collisions reported to BikeMaps.org within the cities of Victoria and Vancouver between May 2014 and April 2016. Table 3 shows the distribution of personal characteristics and incident circumstances. In BikeMaps.org, demographic questions are optional. Age, gender and bicycling frequency were incomplete in approximately one third of reports. Overall, trends suggest more reports are made by males (46.8%), those between the

ages of 31-50 (39.4%), and those who cycled at least once a week (71.3%). Most incidents took place while commuting to work or school (70.3%) and involved a motor vehicle (88.6%).

Table 3. Distribution of personal characteristics and incident circumstances of near misses (n=309) and collisions (n=95) recorded within the cities of Victoria and Vancouver in British Columbia by BikeMaps.org between October 2014-April 2016 (n=404)

		Near Miss		Collisions		Total	
Characteristics		**n**	**%**	**n**	**%**	**n**	**%**
Age Category	30 and under	43	13.9	17	17.9	60	14.9
	31-40	98	31.7	22	23.2	120	29.7
	41-50	28	9.1	11	11.6	39	9.7
	>50	33	11.4	13	13.7	46	11.4
	No response	107	34.4	32	33.7	139	34.4
Gender	Male	146	47.2	43	45.3	189	46.8
	Female	66	21.4	23	24.2	89	22.0
	Other	0	0.0	2	2.1	2	0.5
	No response	97	31.4	27	28.4	124	30.7
Cycle once a week	Yes	221	71.5	67	70.5	288	71.3
	No	1	0.3	3	3.2	4	1.0
	Don't know	0	0.00	1	1.1	1	0.2
	No response	87	28.2	24	25.3	111	27.5
Trip purpose	Commute	221	71.5	63	66.3	284	70.3
	Other	83	2.6	30	31.6	113	27.9
	No response	5	1.6	2	2.1	7	1.7
Type of Incident	With moving object or vehicle	293	94.8	72	75.8	365	90.3
	With stationary object or vehicle	16	5.2	6	6.3	22	4.2
	Fall	0	0.0	17	17.9	17	4.2
Collision or Near Miss Partner/Object	Motor Vehicle	292	94.5	66	69.5	358	88.6
	Other Road User (Pedestrian, other bicyclist, or animal)	3	1.0	19	20.0	22	5.4
	Road / Transportation Infrastructure	14	4.5	10	10.5	24	5.9

Table 4 shows the distributions of trip and built environment conditions of collision and near miss incidents recorded by BikeMaps.org (n=404) and ICBC reports (n=599). Most BikeMaps.org reports took place during the day (79.5%) at peak traffic hours (61.4%), in clear or cloudy weather (84.9%), and at intersections (58.9%) of roads with 2 or less lanes (65.6%), designated as truck routes (65.3%) and with bicycle facilities present (66.6%). Most ICBC reports took place during the day (79.0%), at off-peak hours (59.8%), in clear or cloudy weather (83.0%), at intersections (91.8%), on arterial roads (49.4%), roads with 2 or less lanes (51.6%), roads designated as truck routes (51.9%), and roads with bicycle facilities present (54.9%).

Table 4. Built environment and weather conditions of collision and near miss events recorded within the cities of Victoria and Vancouver in British Columbia, by both BikeMaps.org (n=404, May 2014-April 2016) and ICBC (n=599, January 2013 - December 2013)

		BikeMaps.org: Collisions		BikeMaps.org: Near Misses		BikeMap.org: Total		ICBC: Collisions	
		n	%	n	%			n	%
Location	Non-Intersection	30	31.6	124	40.1	154	38.1	49	8.2
	Intersection	58	61.1	180	58.3	238	58.9	550	91.8
	Off-road	7	7.4	5	1.6	12	3.0	0	0.0
Road Class	Arterial	27	28.4	100	32.4	127	31.4	296	49.4
	Collector	34	35.8	106	34.3	140	34.7	151	25.2
	Local/Off-road†	34	35.8	103	33.3	137	33.9	152	25.4
Number of Lanes	0 – 2[a]	64	67.4	201	65.0	265	65.6	309	51.6
	3 – 6	31	32.6	108	35.0	139	34.4	290	48.4
Time of Day	Off Peak Hours	38	40.0	118	38.2	156	38.6	358	59.8
	Peak Hours	57	60.0	191	61.8	248	61,4	241	40.2
Truck Route	Yes	34	35.8	106	34.3	140	34.7	311	51.9
	No	61	64.2	203	65.7	264	65,3	288	48.1
Bicycle Facility	No Bicycle Facility	20	21.1	115	37.2	135	37.2	270	45.1
	Facility Present (Local street bikeway/ painted bicycle lanes/ separated cycle track)	75	78.9	194	62.8	269	66.6	329	54.9
Lighting	Day	248	80.3	73	76.8	321	79.5	473	79.0
	Night	61	19.7	22	23.2	83	20.5	126	21.0
Weather	Clear or Cloudy	78	82.1	265	85.8	343	84.9	497	83.0
	Rain or Fog	17	17.9	44	14.2	61	15.1	102	17.0

[a] Categories into which the 12 incidents reported to BikeMaps.org (7 collisions, 5 near misses) which occurred in an off-street location (e.g., multi-use trails) and were grouped.

2.3.1. Comparison of near misses and collisions reported to Bikemaps.org

Table 5 provides results of logistic regression models comparing near misses to collisions reported to BikeMaps.org for personal, trip and built environment characteristics. Three variables were included in the final parsimonious model: trip purpose, collision or near miss

partner/object, and presence of a bicycle facility. Bicyclists who reported travelling for non-commuting purposes (e.g.,, social, recreational, leisure) were found to have significantly lower odds of reporting a near miss than bicyclists travelling for commuting purposes (OR=0.58; 95% confidence interval [CI]=0.34,1.00). Incidents not involving a motor vehicle (e.g., instead with a pedestrian, other bicyclist, surface feature) had lower odds of being reported as a near miss, than for incidents involving a motor vehicle (OR=0.14; CI=0.07, 0.27). Finally, there were lower odds of reporting a near miss at locations with bicycling facilities present compared to locations without any bicycling facilities (OR=0.51; CI=0.28,0.89).

Table 5. Comparison of personal, trip and built environment characteristics for BikeMaps.org near miss reports and BikeMaps.org collision reports

Variable	Levels	n Near Miss	n Collisions	Unadjusted Odds Ratios (95% CI)	Adjusted Odds Ratios (95% CI)
Age Category	>30	43	17	1.00	
	31-40	98	22	1.76 (0.84, 3.64)	
	41-50	28	11	1.01 (0.41, 2.51)	
	>50	33	13	1.00 (0.43, 2.38)	
	NA	107	32	1.32 (0.66, 2.61)	
Gender	Male	146	44	1.00	
	Female	66	24	0.83 (0.47, 1.49)	
	NA	97	27	1.08 (0.63, 1.88)	
Trip purpose	Commute	221	63	1.00	
	Other/NA	88	32	0.78 (0.48, 1.29)	**0.58 (0.34, 1.00)**
Collision or Near Miss Object	Motor –Vehicle	292	66	1.00	
	Other Road User/ Infrastructure or Surface Feature	17	29	**0.13 (0.07, 0.25)**	**0.14 (0.07, 0.27)**
Location	Non-Intersection	124	30	1.00	
	Intersection	180	58	0.75 (0.45, 1.23)	
	Off-Road	5	7	**0.17 (0.05, 0.58)**	
Road Class	Arterial	100	27	1.00	
	Collector	106	34	0.84 (0.47, 1.49)	
	Local/Off-Road[a]	103	34	0.82 (0.46, 1.45)	
Number of Lanes	0-2[a]	201	64	1.00	
	3-6	108	21	1.11 (0.68, 1.82)	
Time of Day	Off-peak hours	118	38	1.00	
	Peak hours	191	57	1.08 (0.48, 1.29)	
	Yes	106	34	1.00	

Variable	Levels	n Near Miss	n Collisions	Unadjusted Odds Ratios (95% CI)	Adjusted Odds Ratios (95% CI)
Truck Route	No†	203	61	1.07 (0.66, 1.72)	
Bicycle Facility	No Bicycle Facility	115	20	1.00	
	Facility Present (local street bikeway/ painted bicycle lanes/ separated cycle track)	194	75	**0.45 (0.26, 0.76)**	**0.51 (0.28, 0.89)**
Lighting	Day	248	73	1.00	
	Night	61	22	0.82 (0.47, 1.44)	
Weather	Clear or Cloudy	265	78	1.00	
	Rain or Fog	44	17	0.76 (0.42, 1.44)	

We ran bivariate and multivariable logistic regression for n=404 BikeMaps.org incidents reported from May 2014-April 2016.
NA Not Available
CI Confidence Interva
[a] Categories into which the 12 incidents reported to BikeMaps.org (7 collisions, 5 near misses) which occurred in an off-street location (e.g., multi-use trails) and were grouped.
Bold $p<0.05$.

2.3.2. Comparison of collisions reported to Bikemaps.org and those reported to ICBC

Table 6 provides results of logistic regression models comparing BikeMaps.org collision to ICBC collisions, for selected trip and built environment characteristics. Three variables were included in the parsimonious model: incident location (non-intersection or intersection), time of day (peak traffic hours or off-peak traffic hours), and bicycle facility presence. The odds of a collision report to BikeMaps.org relative to a collision report to ICBC were lower at intersections compared to non-intersections locations (OR=0.10; CI=0.06,0.19), higher during peak traffic hours compared to off-peak traffic hours (OR=2.14; CI=1.32,3.51), and higher at locations with bicycle specific facilities compared to locations without bicycle specific facilities (OR=4.31; CI=2.41,8.14).

Table 6. Comparison of trip and built environment characteristics for BikeMaps.org collision reports and ICBC collision reports.

Variable	Levels	n BikeMaps Collisions	n ICBC Collisions	Unadjusted Odds Ratios (95% CI)	Adjusted Odds Ratios (95% CI)
Location	Non-Intersection	30	49	1.00	
	Intersection	58	550	**0.17 (0.10, 0.29)**	**0.10 (0.06, 0.19)**
Road Class	Arterial	27	296	1.00	
	Collector	34	151	**2.47 (1.44, 4.27)**	
	Local	27	152	**1.95 (1.10, 3.40)**	
Number of Lanes	0-2	57	309	1.00	
	3-6	31	290	**0.58 (0.36, 0.92)**	
Time of Day	Off-Peak	36	358	1.00	
	Peak	52	241	**2.15 (1.37, 3. 40)**	**2.14 (1.32, 3.51)**
Truck Route	Yes	34	311	1.00	
	No	54	288	**1.72 (1.09, 2.73)**	
Bicycle Facility	No Bicycle Facility	20	270	1.00	
	Facility Present (local street bikeway/ painted bicycle lanes/ separated cycle track)	68	329	**2.79 (1.68, 4.82)**	**4.31 (2.14, 8.14)**
Lighting	Day	68	473	1.00	
	Night	20	126	1.10 (0.63, 1.86)	
Weather	Clear or Cloudy	73	497	1.00	
	Rain or Fog	15	102	1.00 (0.53, 1.77)	

We ran bivariate and multivariable logistic regression for n=674 collisions reported to either ICBC or BikeMap.org from January 2013 to April 2016. We did not include the 7 collisions that took place in an off-road location in this analysis.

CI Confidence Interval

Bold $p<0.05$.

2.4. Discussion

Given the gaps that exists in bicycling safety data, there has been increasing interest in using crowdsourcing tools to generate more comprehensive data (Jestico *et al.* 2016). The utility of crowdsourced data in bicycling safety have not been previously examined. In particular, tapping into near miss data as a proxy for collisions brings potential value since near misses are reported more often than collisions with approximately three misses for every collision reported to BikeMaps.org. Our first analyses revealed that there are no differences in near miss reporting relative to collision reporting across personal characteristics, but that certain trip and built environment conditions are associated with near miss incidents, including commute trips,

incidents with motor vehicles, and a lack bicycle specific infrastructure. This finding may be in part due to a higher sense of perceived risk in these circumstances. Our second analyses revealed that there are certain trip and built environment conditions that are associated with an increase in crowdsource reporting, relative to reporting to official collisions. We suggest that crowdsourced sources may be able to fill in some gaps in official sources, especially at non-intersection locations which appear to be under represented in the ICBC data.

It is important to consider the characteristics of the bicyclists who report incidents to BikeMaps.org in order to contextualize the results of our analyses. BikeMaps.org reports were primarily made by commuter bicyclists who cycle more regularly than the general bicycling population. Previous research has estimated that within the Metro Vancouver Region (larger than our study area) 56% of all bicycling trips were for commuting (TransLink 2013), and only 8% of current and potential bicyclists cycled at least once a week (Winters and Teschke 2010). In contrast, 70% of incidents reported to BikeMaps.org occurred on commuting trips and 71% of respondents indicated they cycled at least once per week. The large proportion of incidents reported to BikeMaps.org by commuter bicyclists reflects the initial marketing of BikeMaps.org to bicycling advocacy groups and their members.

2.4.1. Differences in personal, trip and built environment conditions in crowdsourced near miss and collision reports

We found that personal characteristics such as age and gender were not associated with reporting near misses, relative to collisions. This contrasts with previous research that captured near miss reporting through travel diaries (Joshi *et al.* 2001, Aldred and Crosweller 2015). Joshi et al. (2001) examined the travel diaries of road users in the United Kingdom and found that that females had a higher rates of near miss reporting than males per distance travelled. Aldred and Crosweller (2015), analyzed bicyclists' travel diaries in the United Kingdom, and also found that women had higher rates of near misses, which they suggest is due to the fact that women generally ride at slower speeds and take shorter trips than men. The authors also found that bicyclists over the age of 55 reported lower rates of near misses than younger bicyclists (Aldred and Crosweller 2015). Our finding that gender and age were not associated with near miss reporting may be explained in part by the fact that BikeMaps.org contributors are dominantly commuter bicyclists, who may be less risk averse and ride faster for longer than the general bicycling population, irrespective of gender and age status. It is also worth noting that ~31% of reports had no data on gender, as this question is optional on the site.

We found that incidents reported on commuter trips were more likely to be near misses than collisions. This may result from differences in the built environment characteristics between commute and non-commute trips. For example, a study of regular commuter bicyclists in Portland, Oregon found trip purpose influenced route choices (Broach *et al.* 2012). Bicyclists making a non-commute trip (e.g., social reasons or errands) placed a higher value on using bicycle specific facilities than bicyclists making a commute trip (Broach *et al.* 2012). We suggest that BikeMaps.org users making commute trips may be more willing to use routes with higher perceived risk than users travelling for non-commute purposes, such as routes with increased traffic volume. The decreased odds of reporting a near miss relative to collision on non-commute trips may in part be explained by the idea that commute trips may be more likely to take place in heavy traffic areas in the urban core, while social, personal or recreational trips may have more discretionary routing.

The effect of bicycling infrastructure on near miss reporting has not yet been widely explored. Our results indicate that the presence of bicycle specific infrastructure results in lower odds of reporting a near miss relative to a collision, suggesting that risk perception may be playing a role in near miss reporting. Previous literature has shown that bicyclists of varying experience levels perceive bicycle specific infrastructure as safer than bicycling in mixed traffic (Parkin *et al.* 2007, Winters and Teschke 2010, Winters *et al.* 2011, Chataway *et al.* 2014). The lower odds of near misses on roads and intersections with bicycling facilities in this study could be interpreted as bicyclists' sense of security being higher when they are bicycling facilities. Alternatively, it may be that perceptions of risk are higher than observed risk on facilities without bicycling infrastructure.

The greatest influence on reporting a near miss versus a collision was the object with which a bicyclist has a near miss or collision. In our models, adjusted for trip purpose and bicycle facility, for every collision reported there were ~ 7 times as many near miss incidents involving motor vehicles reported compared to incidents not involving motor vehicles. This might be explained by the differences in perceptions of risk in the 'other' objects (e.g., road surface features, pedestrians, other bicyclists). Previous research suggests that interactions with motor vehicles are much more threatening and "scary" when compared to other interactions that do not involve motor vehicles (Aldred and Crosweller 2015).

Our analyses of similarities and differences in crowdsourced near miss and collision data suggests that for road safety studies that aim to do geographic surveillance of bicycling safety,

use of near miss and collision data (combined) would tend to highlight locations with characteristics associated with higher odds of near miss reporting relative to collisions. Specifically, routes with higher interactions with motor vehicles; and routes with no bicycling infrastructure. Relative increases in near miss reporting may be associated with differential levels of perceived risk.

2.4.2. Differences in trip and built environment conditions in crowdsourced reported collisions and insurance reported collisions

In our second analyses we assessed similarities and differences in crowdsourced and insurance reported collisions, to better inform how crowdsourced data may compliment bicycling safety research that relies on official data sources. We found that the time of day, presence of bicycle specific infrastructure and location on the street network were associated with the odds of a collision being reported to BikeMaps.org relative to ICBC.

Based on previous literature ((Romanow *et al.* 2012), as per Table 2), we had hypothesized that there would be a decrease in the odds of reporting a collision to BikeMaps.org relative to ICBC during peak hours, based on the idea that there would be more motor vehicles on the road at this time and more collisions with motor vehicles (which are reportable to insurance claims). Our results indicate the opposite effect, that during peak traffic hours, there are two times more collision reports to BikeMaps.org relative to ICBC collisions compared to off-peak hours. This is likely related to the fact that BikeMaps.org contributors are largely commuters. We suspect that the BikeMaps.org contributors are more likely to ride during this peak traffic times than the general bicycling population, and may underrepresent trips made in off-peak hours.

A large difference between the crowdsourced and insurance reports was that BikeMaps.org reports had far lower odds (1/9th) of being at an intersection, versus non-intersection locations. In part this may be a manifestation of data processing: ~92% of ICBC reports were attributed to intersections. Previous research of injured bicyclists admitted to emergency departments in Canada indicates that the proportion of bicyclist crashes at intersections is actually much lower, with 31% of total crashes and 53% of crashes with bicycle-motor vehicle collisions occurring at intersections (Teschke *et al.* 2014). While bicycle motor vehicle collisions may be more likely to occur at intersections compared to non motor vehicle collisions (Romanow *et al.* 2012), the proportion of ICBC incidents reported to have occurred at

intersections appears too high to explained by this alone. The data processing of ICBC crash locations may account for the disproportionately high number of collisions recorded as occurring at intersections, which requires that all collisions be assigned to the nearest intersection or mid-block location prior to their release. About two thirds of collisions reported to BikeMaps.org occurred at intersections; lower than the ICBC data, but still higher than the study of injured bicyclists reporting to emergency departments. BikeMaps.org appears to have potential to fill in this gap, as it captures non-motor vehicle collisions which have been shown to be more likely to occur at non-intersection locations than bicycle-motor vehicle collisions (Romanow *et al.* 2012).

Our comparison of crowdsourced and insurance reported collisions shows that crowdsourced data may be complimentary, but also may be impacted by the subset of the bicycling population contributing data. As noted above, BikeMaps.org captures non-motor vehicle crashes while ICBC data does not. However, currently BikeMaps.org incidents are contributed by mainly commuter bicyclists. Crowdsourced collision data may help to identify high-risk areas more quickly than with official data alone, especially those areas characterized by higher proportions of non-motor vehicle incidents and less severe injury outcomes which are typically underrepresented in official sources.

2.5. Limitations

This is a novel study which aims to characterize the potential of crowdsourced data for bicycling safety surveillance. However, we also acknowledge study limitations. First, our variables describing traffic conditions are general, and may encompass a wide range of traffic conditions. For example, our model uses both road classification and number of lanes as a proxy for traffic volume, however, traffic counts by road class have shown considerable variation in previous work (Setton *et al.* 2005). Second, our results are specific to the time period and study area. ICBC data was not available more recent than 2013. BikeMaps.org data is contributed predominantly by regular bicyclists, as might be expected given that regular bicyclists have more exposure. We are continuing BikeMaps.org promotions with broader populations with the aim to reach more occasional bicyclists, and will continue to analyze incident circumstances as more data is contributed. Given the relatively recent launch of BikeMaps.org we anticipate that patterns of near miss and collision reporting will become more representative of the broader bicycling experience over time, as BikeMaps.org becomes better known to a diverse bicycling population with increased outreach and promotion to bicyclists at non-bicycling advocacy events (e.g., street festivals, annual community events). Moreover, we

compare ICBC records to BikeMaps.org collisions in differing time periods. We are aware of several spot improvements (City of Vancouver 2016b), and speed limit changes on a select few roads (City of Victoria 2014) between the two periods, which could in part contribute to observed differences. Third, this study does not address whether reported near misses are predictive of crashes at specific locations, but instead represents a first step towards understanding the differences between the two types of safety data. A recent study of 3994 incidents in the United Kingdom suggests that the behavioural factors contributing to near misses are similar to minor injury events, and thus may be reasonable proxies (Aldred 2016). Further research will be need to test if this holds at the site specific level. Fourth, in about one third of the crowdsourced incidents no personal information was provided. These questions are optional to reduce user burden: in collecting crowdsourced data a balance needs to be struck between detailed data and enabling quick and easy reporting in order to reduce the burden and encourage reporting. BikeMaps.org has four required questions regarding the incident circumstances and 14 optional questions regarding the incident circumstance and personal information of the user; this balance may change with experience over time.

2.6. Conclusion

Crowdsourcing represents a new data collection method for supplementing official collision data, as well as collecting region wide surrogate collision data using self-reported near miss events. Near miss events occur much more often than collisions (Sanders 2015) and their collection may enable the identification of unsafe locations in much shorter time periods than use of collision data alone, however, further research is needed on the relationship between near misses and collisions at the site specific level. Given the identified differences in the crowdsourced data from BikeMaps.org and official insurance data from ICBC, we suggest that these data are complementary. The future use of crowdsourced data in conjunction with official sources could allow for timely bicycling safety surveillance and the identification of dangerous locations, especially for non-motor vehicle incidents.

Chapter 3.

Associations between individual characteristics, availability of bicycle infrastructure, and city-wide safety perceptions of bicycling: A cross-sectional survey of bicyclists in 6 Canadian and U.S. cities

3.1. Introduction

Research indicates that there are significant societal benefits for bicycling, primarily due to health benefits of increased physical activity (de Hartog *et al.* 2010, Mueller *et al.* 2015, Götschi *et al.* 2016). Within cities in Canada and the United States (US), bicycling uptake is generally low, with only 1.3% and 0.6% of workers reporting that they commute by bicycle to work, in Canada and the US respectively (Statistics Canada 2013c, McKenzie 2014). Ridership levels in European cities are much higher than in Canada and the US (Pucher and Dijkstra 2003, Bassett *et al.* 2008, Pucher and Buehler 2008), suggesting there is substantial potential for increased bicycling.

Safety concerns are a primary deterrent to bicycling (Heinen *et al.* 2010, Willis *et al.* 2015). Previous research has shown that the perceived safety of bicycling varies by age, gender and bicycling experience, across a range of different bicycling environments (Hels and Orozova-Bekkevold 2007, Parkin *et al.* 2007, Møller and Hels 2008, Lawson *et al.* 2013, Chataway *et al.* 2014, Bill *et al.* 2015, Manton *et al.* 2016). Bicycling environments that provide bicycle infrastructure tend to be perceived as safer than those that require bicycling in mixed traffic (Parkin *et al.* 2007, Winters *et al.* 2011, Chataway *et al.* 2014, Manton *et al.* 2016). Increasing access to bicycle infrastructure has been promoted as a potentially effective means of increasing bicycling mode share in cities with low bicycling uptake (Dill and Carr 2003, Pucher and Buehler 2006, 2008, Buehler and Pucher 2012). Implementing bicycle infrastructure has the potential to increase trips from new bicyclists, as well as existing (Noland 1995, National Institute for Transportation and Communities 2014).

Studies of the association between bicycling environments and perceived safety tend to focus on comparing different infrastructure or routes within the road network. These studies are important for understanding how specific infrastructure designs may improve perceived personal

safety at a specific time and place, but do not provide insight into their associations with general perceptions of bicycling safety. More generalized perceptions of bicycling safety across a larger geographic context (e.g.,, across a neighbourhood or city) may be associated with individuals bicycling, or how often they bicycle (Lawson *et al.* 2013). In this study we aim to examine the associations between individual characteristics, bicycling infrastructure availability, and city-wide perceptions of bicycling safety across 6 major cities in the US and Canada. We use survey data from the International Bikeshare Impacts on Cycling and Collisions Study (IBICCS) (Fuller *et al.* 2014) to measure perceived safety and individual characteristics, and Bike Lane Score, a component of the Bike Score Index (Winters *et al.* 2016), to measure bicycle infrastructure availability.

3.2. Materials and methods

3.2.1. IBICCS

IBICCS was designed to evaluate the health impacts of public bicycle share programs. The study protocol is published elsewhere (Fuller *et al.* 2014). Briefly, it included three repeat, cross-sectional online panel surveys (in fall of 2012, 2013, and 2014) of residents across eight cities: Montreal, Toronto, Boston, New York, Vancouver, Chicago, Detroit and Philadelphia (n=23,901). Each survey collected information on sociodemographic characteristics, health and travel behaviour, safety perceptions, and residential and work locations (post codes). The study aimed to survey participants within a defined sampling area, which were generally smaller subsets of the city proper based on where public bike share stations were (or potentially would be) implemented (see Fuller et al., 2014 for details). In this analysis we include all participants living within the city boundaries. The IBICCS data collection was approved by the Research Ethics Committee of the Centre Hospitalier de l'Université de Montréal.

3.2.2. Study area

Our study area includes the six IBICCS cities for which we have comparable data on bicycle infrastructure: Boston, Chicago, New York, Montreal, Toronto and Vancouver (Figure 5). In 2012 each city had a low bicycling rate, with between 0.8 to 4.4% of workers reporting that they commute by bicycle (Table 7).

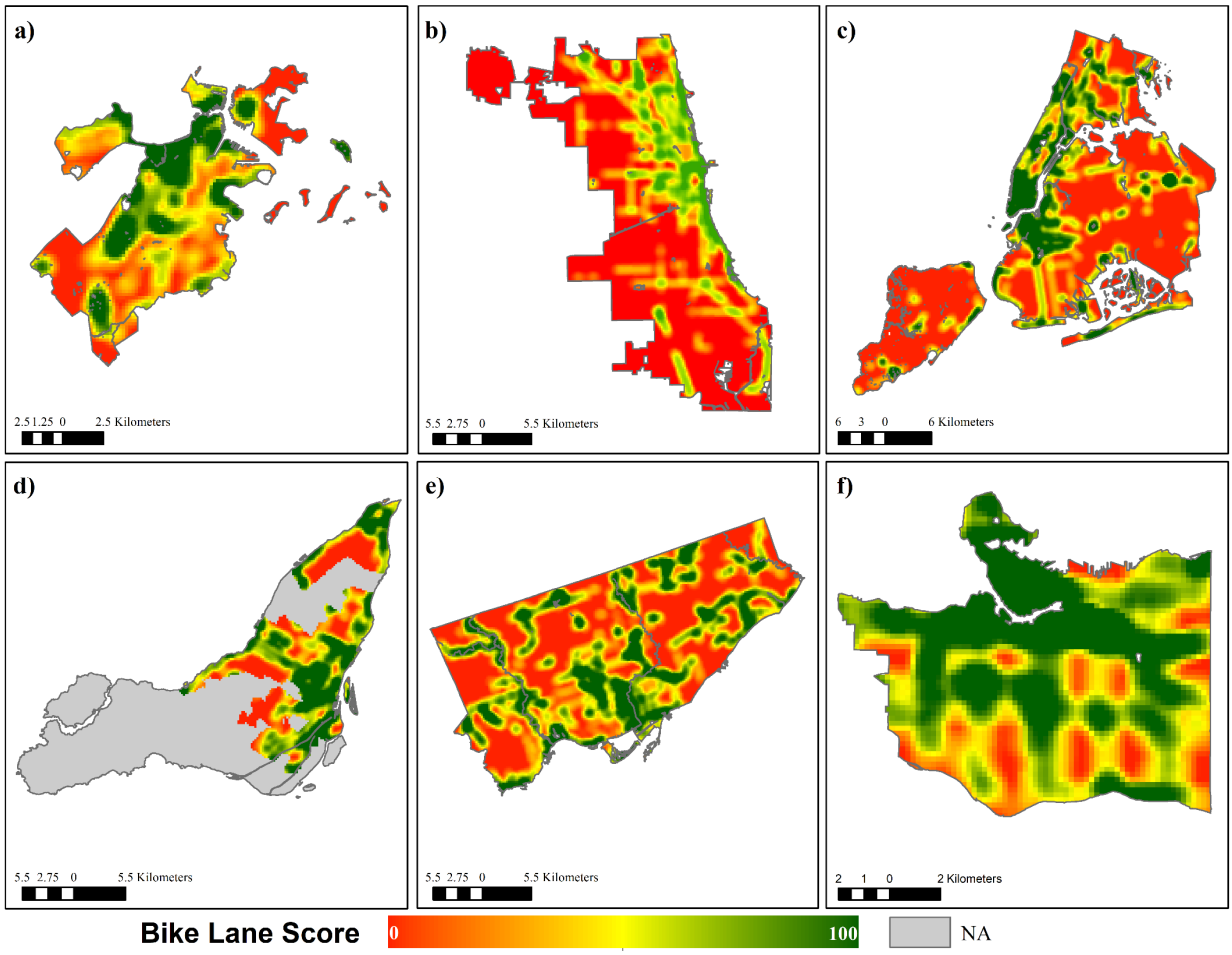

Figure 5. **IBICCS study area boundaries and the spatial distribution of bicycle infrastructure, using Bike Lane Score as a proxy. The study areas include the cities of: a) Boston, b) Chicago, c) New York, d) Montreal, e) Toronto, f) Vancouver. Bike Lane Score can range from 0-100, where 100 indicates close proximity, or greater availability of bicycle infrastructure and 0 indicates no bicycle infrastructure within 1-km. NA indicates an area where Bike Lane Score data were not available. Note that cities are of different geographic extents as indicated by scale bars.**

Table 7. **Descriptive information regarding city populations, bicycling mode shares, and distributions of Bike Lane Score for 6 cities IBICCS participants were recruited.**

City	Boston	Chicago	New York	Montreal	Toronto	Vancouver
Area (km^2)	125.1	589.3	783.5	366.4	630.6	114.9
Total population[a]	619,662	2,702,471	8,199,221	1,649,519	2,615,060	603,502
Working population[b]	317,930	1,213,901	3,685,786	727,455	1,174,610	294,790
Proportion who commute by bicycle[b]	1.7%	1.3%	0.8%	3.2%	2.2%	4.4%
Average fatalities per million bicycle to work trips (2007-2012)[c]	1.16	1.38	2.94	0.60	NA	1.10
City-wide Bike Lane Score (2012)						

City	Boston	Chicago	New York	Montreal	Toronto	Vancouver
Mean	46	20	29	56	39	68
Median	40	6	11	61	30	74
Q1	14	0	0	1	1	44
Q3	78	33	54	100	72	100
IQR	64	33	54	81	71	56
Range	0-100	0-100	0-100	0-100	0-100	0-100

[a] Boston, Chicago and New York, based on 2008-2012 American Community Survey 5-year estimates (US Census Bureau 2017a), Montreal, Toronto, Vancouver, based on Census 2011 (Statistics Canada 2012a, 2012b, 2012c).
[b] Boston, Chicago and New York, based on 2008-2012 American Community Survey 5-year estimates (US Census Bureau 2017b), Montreal, Toronto, Vancouver statistics are based on 2011 National Household Survey (Statistics Canada 2013d, 2013e, 2013a).
[c] Based on previous study which, for Canadian cities compiled fatality and exposure data directly from the cities, and for American cities obtained data from National Highway Traffic Safety Administration Fatality Data (Urban Systems 2015).
NA Not Available

3.2.3. Measures

Safety perceptions

Only those participants who reported bicycling in the previous month were asked their perceptions of bicycling safety. Bicycling safety perceptions were measured based on a question which asked bicyclists “Overall, how safe do you think bicycling is in your city?” Respondents could answer based on a 5-point scale: 1-“Very Safe”, 2- “Somewhat safe”, 3-“Neutral”, 4-“Somewhat dangerous” and 5-“Very Dangerous.” We collapsed these responses into a 3-point scale consisting of “Safe” (1+2), “Neutral” (3) and “Dangerous” (4+5).

Bicycling infrastructure

We use a component of the Bike Score index, called Bike Lane Score, to measure the availability of bicycling infrastructure at a given location within the study area (Figure 5). Bike Lane Score (2012, 100 m grids) was provided by RedFin Real Estate and represents the only internationally available standardized infrastructure dataset at the time the IBICCS survey data were collected. Bike Lane Score is a normalized index of a location’s proximity to bicycle infrastructure. Bicycle infrastructure data used in this index were provided by municipal governments, and includes the following: on-street painted bicycle lanes, off-street trails, separated bicycle paths, and neighbourhood bikeways (Winters *et al.* 2016). To compute Bike Lane Score for a given location, the length of all infrastructure nearby were summed and weighted based on a distance decay function where infrastructure outside 1 kilometre were weighted 0. Infrastructure types that are separated from traffic are weighted double compared to those that are not. The raw weighted lengths were then normalized to a score between 0-100,

with higher Bike Lane Scores indicating greater availability of bicycle infrastructure and a Bike Lane Score of 0 indicating no infrastructure within 1 kilometre. Past work shows that Bike Lane Score is positively correlated to journey-to-work bicycle mode share in 24 Canadian and US cities (Winters *et al.* 2016).

The distribution of Bike Lane Scores within each city indicated that many areas still lacked bicycle infrastructure. The median Bike Lane Score within each city ranged from a low of 6 to a high of 74 (Table 7). Chicago, New York and Toronto had lower median Bike Lane Scores as compared to Boston, Montreal or Vancouver, but the spatial extent of Bike Lane Score in these cities was much greater (Figure 5). Each city tended to have higher Bike Lane Scores in the core area as compared to the surrounding area. Survey participants were assigned a Bike Lane Score based on the location of their residence as derived from postal codes.

Covariates

Potential confounders were identified a priori based on sociodemographic characteristics that could influence both choosing to live in bicycling supportive areas, as well as to differences in the perceived safety of bicycling. Selected variables were based on a consideration of individual level confounding variables previously used in research on the effect of proximity to bicycle infrastructure and bicycle use (Krizek and Johnson 2006) and include age (continuous), gender (male or female), having young children (yes or no), income (under $50 K, $50-100 K, over $100 K, refuse), education (high school or less, or any college/university), and ethnicity (White/Caucasian or Asian / Insular of the Pacific or Black/African/African-American or Hispanic/Latino/Spanish or Other).

We calculated average daily bicycling frequency as a measure of individual bicycling exposure. Specifically, participants were asked to recall the average number of days per week in the last month they used a given mode for at least 10 minutes at time to go from place to place, and then how much time they usually spent on one of those days using that mode. An average daily bicycling frequency measure was calculated for each participant, and outliers (n = 56) were truncated to a maximum of 3 hours per day.

3.2.4. Sample

Overall 16,864 of 23,901 IBICCS survey participants lived within the boundaries of the six cities, and these participants were assigned post-stratification weights based on comparing

the age and sex distribution of each city as defined by census data, to the age and sex distribution of our sample within each city. We removed participants that did not have a valid Bike Lane Score (n=374; weighted n = 356) and those that reported spending a combined total of greater than 16 hours per day using any form of transportation (n=53; weighted n=55). Of the remaining participants, those who report bicycling in the past month had responses for bicycling safety perceptions and were eligible to be studied (n=3,561; weighted n = 3,608). Finally, participants that had missing data on sociodemographic characteristics apart from income were removed (n=113; weighted n = 111). We maintained those who refused to provide income (n=243; weighted n = 238). Our final sample of bicyclists included 3,446 participants, representing a weighted population of 3,493.

3.2.5. Statistical analysis

Weighted descriptive statistics were generated for all variables, overall and stratified by city. Weighted multinomial logistic regression was used to analyze the association between bicyclists' spatial access to bicycling infrastructure (as represented by Bike Lane Score) and perceptions of bicycling safety (ie., safe, neutral, dangerous), controlling for sociodemographic characteristics. We included a fixed effect for city which is appropriate when adjusting for clustering with small numbers, allowing us to pool our sample rather than run city-specific models (Cerin 2011). Modeling was done using Proc SURVEYLOGISTIC (SAS 9.4) with link=GLOGIT to specify a multinomial outcome. We applied post-stratification weights. We fit individual models for each covariate, followed by an adjusted model containing all variables, with 'Neutral' set as the reference category. Each exponentiated coefficient represents the within-city effect of a variable on the odds of rating bicycling as neutral compared to safe, or dangerous compared to safe. We tested all two-way interaction effects between Bike Lane Score and sociodemographic variables and found no significant interactions.

We plotted the marginal effects of each covariate to visualize the predicted relationship between each covariate and perceived bicycling safety. Here we define marginal effects as the adjusted model's prediction of perceived safety over the range of values for a specific covariate, when other covariates are held to a representative value (mean or mode). These plots can be conceptualized as the predicted effect of a given variable on the perceived safety of bicycling for an *average* bicyclist.

Since infrastructure availability is a readily modifiable factor, we create a scenario to quantify the predicted effect of increasing the bicycling infrastructure availability on perceptions of bicycling safety. In this scenario we first defined a hypothetical sample of bicyclists where each individual was characterized by a unique combination of the levels of the independent variables in the adjusted model (including gender, age, bicycling frequency, income, education, having children, ethnicity, and city of residence). We then used the adjusted model to predict the probability that each bicyclist in this sample perceived bicycling in their city to be safe, neutral and dangerous if they resided in an area with no bicycling infrastructure available within 1 kilometre (Bike Lane Score of 0) and also if they resided in an area with high quality bicycling infrastructure available nearby (Bike Lane Score of 100). We then subtract the predicted probabilities of safe, neutral and dangerous when Bike Lane Score is 0, from when Bike Lane Score is 100, for each individual. This difference represents the predicted effect that increasing Bike Lane Score from 0 to 100 would have on perceived bicycling safety, where a positive value represents an increase in probability of a given perceived safety rating, and a negative value a decrease. The absolute difference in probabilities when Bike Lane Score is 100 versus 0, is repeated across all individuals in our hypothetical sample and plotted in a boxplot to visualize the predicted effect of increasing the availability of bicycling infrastructure of an area. All plots were created in R 3.4.1(R Core Team 2017).

3.3. Results

3.3.1. Sample characteristics

Across the six cities, most bicyclists were male (61.1%), employed full-time (57.7%), had at least some post-secondary education (90.9%), and did not have any children aged 17 years or under (74.4%) (Table 8). A majority of bicyclists had a driver's license (87.8%), as well as had access to a motor vehicle (69.4%). Most had cycled 1-2 days per week in the previous month (56.6%) (Table 8). Compared to the full IBICCS sample (bicyclists and non-bicyclists) bicyclists were disproportionately male (61.1% compared to 47.7% of full sample) and under the age of 55 (81.0% compared to 69.6% of full sample) but otherwise were similar in sociodemographic characteristics. Overall, 22.1% report bicycling in the past month; 20.8% in Boston, 22.9% in Chicago, 23.4% in Montreal, 20.3% in New York, 22.6% in Toronto, and 22.2% in Vancouver.

Table 8. Weighted values for sociodemographic characteristics of the subsample of respondents from the IBICCS sample who reported bicycling in the previous month.

		Boston	Chicago	New York	Montreal	Toronto	Vancouver	Overall
	Weighted Total (n)	**222**	**785**	**715**	**467**	**887**	**417**	**3493**
		% of n	**% of n**	**% of n**	**% of n**	**% of n**	**% of n**	**% of n**
Safety Perception	Safe	45.3	61.7	55.7	56.7	52.7	73.2	57.9
	Neutral	14.2	12.5	14.4	15.2	17.4	16.5	15.1
	Dangerous	40.5	25.8	29.8	28.0	29.8	10.4	27.0
Residential Bike Lane Score	25 or under	4.4	33.2	12.4	16.1	30.6	11.1	21.5
	26 - 50	20.4	28.5	16.8	12.2	22.0	11.0	19.7
	51 - 75	11.0	22.5	20.7	18.1	16.8	19.0	19.0
	75-100	64.3	15.8	50.0	53.6	30.6	58.8	39.8
Gender	Female	45.2	37.1	40.5	39.8	38.2	36.4	38.9
	Male	54.8	62.9	59.5	60.2	61.8	63.6	61.1
Age	18-24	13.1	25.0	23.3	14.8	22.8	24.4	21.9
	25-34	14.4	19.2	24.3	30.3	22.3	23.9	22.8
	35-44	15.8	17.9	20.0	16.9	19.3	16.9	18.3
	45-54	18.1	17.2	17.3	21.9	17.6	17.1	18.0
	55 or older	38.5	20.7	15.0	16.2	18.0	17.8	19.0
Income	Under $50 K	21.4	33.8	29.7	40.4	30.9	31.1	32.0
	$50-100 K	33.5	35.8	34.0	37.5	33.3	37.2	35.0
	Over $100 K	38.0	25.6	30.4	14.6	27.4	24.1	26.2
	Refuse	7.1	4.8	5.9	7.5	8.4	7.6	6.8
Ethnicity	White/Caucasian	78.3	68.5	64.6	83.5	71.2	58.0	69.8
	Black/African/African-American	7.3	12.2	9.9	1.9	2.6	0.8	6.3
	Hispanic/Latino/Spanish	4.3	9.4	11.3	2.1	2.0	5.1	6.1
	Asian / insular of the Pacific	9.3	8.8	12.1	7.4	17.6	30.9	14.2
	Other	0.9	1.1	2.1	5.0	6.7	5.1	3.7
Children Under 18	Children	17.0	23.7	29.6	23.1	26.4	28.2	25.6
	No Children	83.0	76.3	70.4	76.9	73.6	71.8	74.4

		Boston	Chicago	New York	Montreal	Toronto	Vancouver	Overall
	Weighted Total (n)	**222**	**785**	**715**	**467**	**887**	**417**	**3493**
		% of n	**% of n**	**% of n**	**% of n**	**% of n**	**% of n**	**% of n**
Education	Any College or University	97.2	92.0	92.2	88.9	91.2	85.2	90.9
	High School or Less	2.8	8.0	7.8	11.1	8.8	14.8	9.1
Employment	Full-Time	65.9	59.0	57.5	51.0	59.2	56.1	57.7
	Part-Time	7.6	9.5	9.4	7.1	9.9	11.8	9.4
	Self-employed	5.4	6.9	12.3	11.5	9.9	7.1	9.3
	Student	8.6	10.3	11.9	13.1	8.9	10.2	10.5
	Unemployed/Retired /Other	12.6	14.1	8.6	17.3	11.8	14.6	12.8
	Refuse	0.0	0.2	0.2	0.0	0.4	0.2	0.2
Driver's License	Yes	96.6	89.7	84.6	83.3	87.8	90.0	87.8
	No	3.4	9.8	15.2	16.6	11.9	9.6	11.9
	Refuse	0.0	0.5	0.3	0.1	0.3	0.3	0.3
Access to Motor Vehicle	Yes	77.1	76.7	54.4	63.3	70.1	82.9	69.4
	No	22.8	22.3	45.2	36.3	29.0	16.7	29.9
	Refuse	0.1	1.0	0.4	0.4	0.8	0.4	0.6
Average Days per Week Cycled in Previous Month	1 to 2	59.2	60.8	57.0	48.0	55.7	58.2	56.6
	3 to 5	30.0	31.5	36.3	44.4	33.6	33.7	34.9
	6 to 7	10.8	7.7	6.7	7.7	10.7	8.1	8.5
Average Daily Bicycling Minutes in Previous Month	15 minutes or less	49.7	48.4	43.4	48.0	47.8	45.5	46.9
	15-30 minutes	31.2	23.4	24.8	26.5	21.3	25.1	24.3
	30-60 minutes	14.4	17.0	18.1	16.6	21.4	19.4	18.4
	>60 minutes	4.8	11.3	13.7	8.9	9.4	10.0	10.4
	Mean (minutes)	23.5	28.2	31.7	27.3	29.0	28.0	28.7
	Minimum (minutes)	0.1	0.1	0.1	0.3	0.3	0.1	0.1
	Maximum (minutes)	180.0	180.0	180.0	180.0	180.0	180.0	0.0

A Bike Lane Score lower than 50 indicates minimal bike infrastructure was available near a bicyclists' residence (Walk Score 2018). A considerable proportion of bicyclists (41.2%) had a Bike Lane Score lower than 50, with variability by city. Toronto and Chicago had the highest proportion of bicyclists with limited access (52.6 % and 61.7% with a Bike Lane Score lower than 50, respectively), while the remaining cities had similar proportions ranging between 22.1% and 29.2%.

Overall, most bicyclists perceived bicycling in their city to be safe. Specifically, 57.9% of bicyclists reported bicycling in their city as safe, 15.1% as neutral, and 27.0% as dangerous (Figure 6). A larger proportion of bicyclists in Boston perceived bicycling to be dangerous (40.5%) and Vancouver was perceived as safer (73.2%) (Figure 6).

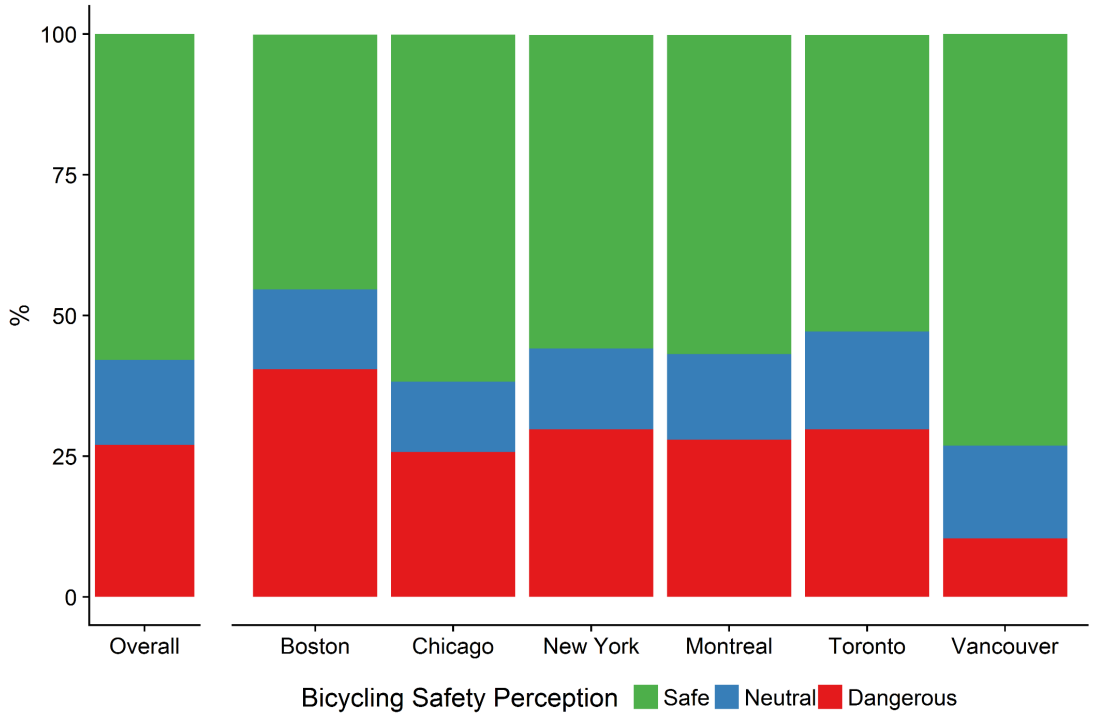

Figure 6. Weighted distribution of perceived bicycling safety, overall and by city.

3.3.2. Bicycling infrastructure and perceived bicycling safety

Within the six cities, bicycling infrastructure availability was significantly associated with the perceived safety of bicycling in that city (Table 9). For every 10-unit increase in Bike Lane Score the odds of rating bicycling as safe compared to neutral increased by 6% (OR = 1.06,

95% confidence interval (CI): 1.02 to 1.10), and the odds of rating bicycling as dangerous compared to neutral were estimated to increase by 4% (OR = 1.04, 95% CI: 1.00 to 1.08).

Table 9. Results of multinomial logistic regression models estimating associations between Bike Lane Score (proxy for spatial access to bicycle infrastructure around one's residence), sociodemographic characteristics, and perceived safety of bicycling among 3493 IBICCS respondents reporting having cycled in the previous month.

Variable	Outcome	Unadjusted OR[a] (95% CI)	Adjusted OR[b] (95% CI)
Residential Bike Lane Score			
	Safe	**1.05 (1.01, 1.09)**	**1.06 (1.02, 1.10)**
10 unit change	Neutral	Reference	
	Dangerous	**1.06 (1.02, 1.11)**	1.04 (1.00, 1.08)
Gender [ref=Female]			
	Safe	0.81 (0.63,1.03)	0.82 (0.64, 1.04)
Male	Neutral	Reference	
	Dangerous	**0.57 (0.43, 0.74)**	**0.57 (0.44, 0.74)**
Age			
	Safe	0.95 (0.85, 1.05)	0.94 (0.84, 1.04)
10 year change	Neutral	Reference	
	Dangerous	**1.29 (1.15, 1.44)**	**1.21 (1.08, 1.35)**
Income [ref=<50 K]			
	Safe	0.94 (0.69, 1.28)	0.88 (0.64, 1.22)
50k – 100 K	Neutral	Reference	
	Dangerous	**1.42 (1.01, 1.99)**	1.07 (0.75, 1.52)
	Safe	1.01 (0.73, 1.42)	0.88 (0.62, 1.26)
>100 K	Neutral	Reference	
	Dangerous	**1.84 (1.29, 2.62)**	1.21 (0.82, 1.78)
	Safe	**0.60 (0.38, 0.96)**	**0.57 (0.35, 0.93)**
Refuse	Neutral	Reference	
	Dangerous	0.82 (0.50, 1.36)	**0.54 (0.31, 0.92)**
Ethnicity [ref = White/Caucasian]			
	Safe	**0.68 (0.48, 0.97)**	**0.62 (0.44, 0.88)**
Asian / insular of the Pacific	Neutral	Reference	
	Dangerous	**0.42 (0.29, 0.62)**	**0.52 (0.35, 0.77)**
	Safe	0.74 (0.44, 1.24)	0.66 (0.38, 1.14)
Black/African/African-American	Neutral	Reference	
	Dangerous	**0.30 (0.16, 0.55)**	**0.36 (0.19, 0.68)**
	Safe	0.92 (0.54, 1.57)	0.78 (0.47, 1.31)
Hispanic/Latino/Spanish	Neutral	Reference	
	Dangerous	**0.33 (0.17, 0.63)**	**0.47 (0.24, 0.89)**
	Safe	1.24 (0.61, 2.54)	1.08 (0.51, 2.27)
Other	Neutral	Reference	
	Dangerous	1.02 (0.46, 2.24)	1.19 (0.52, 2.72)
Have Children Under 18 [ref = None]			
At least 1	Safe	**1.77 (1.34 2.35)**	**1.86 (1.40, 2.48)**

Variable	Outcome	Unadjusted OR[a] (95% CI)	Adjusted OR[b] (95% CI)
	Neutral	Reference	
	Dangerous	0.85 (0.63, 1.16)	0.99 (0.72, 1.36)
Education [ref = Highschool or Less			
	Safe	1.34 (0.87, 2.04)	1.38 (0.90, 2.12)
Post-Secondary	Neutral	Reference	
	Dangerous	**3.07 (1.85, 5.08)**	**2.43 (1.43, 4.10)**
Average Daily Bicycling in Previous Month			
	Safe	1.17 (0.94, 1.47)	1.18 (0.94, 1.47)
1 hour change	Neutral	Reference	
	Dangerous	**0.61 (0.46, 0.80)**	**0.67 (0.50, 0.90)**

[a] Unadjusted refers to a model consisting of the variables + City Term
[b] Adjusted refers to a model consisting of all variables + City Term
Bold $p<0.05$

The marginal effects plot visualises the estimated relationship between bicycling infrastructure availability and perceived bicycling safety (Figure 7a). Model predictions indicate that with larger Bike Lane Score values, there is an increase in the predicted probability that the average bicyclist perceives bicycling as safe, a decrease in the probability they perceive bicycling to be neutral, and virtually no effect on the probability they perceive bicycling to be dangerous (Figure 7a).

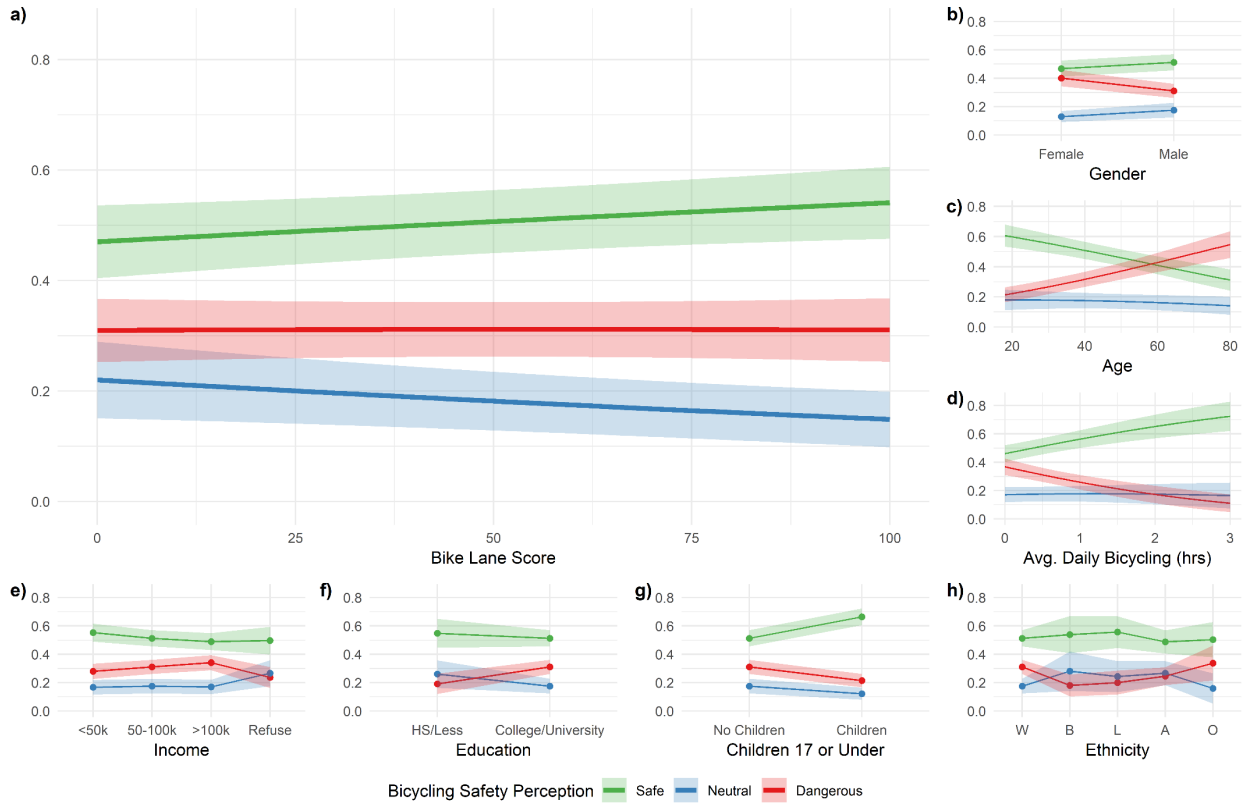

Figure 7. Marginal effects plots visualize the predicted probability that a bicyclist perceives bicycling in their city as safe, neutral, or dangerous across different values for each variable, when all other independent variables are held to their mean or mode. Each plot describes how the perception of bicycling safety would be expected to change given a particular variable's value was changed for bicyclists who, in all other aspects, are average with respect to sociodemographic characteristics within the sample. For example, in 3b) the average female bicyclist is less likely to rate bicycling as safe or neutral and more likely to rate bicycling as dangerous, when compared to the average male bicyclist. HS: High School education; W: White/Caucasian; B: Black/African/African-American; H: Hispanic/Latino/Spanish;A: Asian/insular of the Pacific; O: Other.

The predicted effect of increasing bicycling infrastructure availability for a hypothetical sample of bicyclists, such that the Bike Lane Score increases from 0 to 100, suggests that perceptions shifted from neutral to safe, but the perception of bicycling as dangerous was virtually unchanged (Figure 8). The hypothetical sample were, on average, 7.8% more likely to perceive bicycling as safe (predictions ranged between a 2.4% and 12.7% increase), 7.7% less likely to perceive bicycling as neutral (predictions ranged between a 2.0% and 13.0% decrease) and 0.1% less likely to perceive bicycling as dangerous (predictions ranged between 2.2% decrease and 3.1% increase).

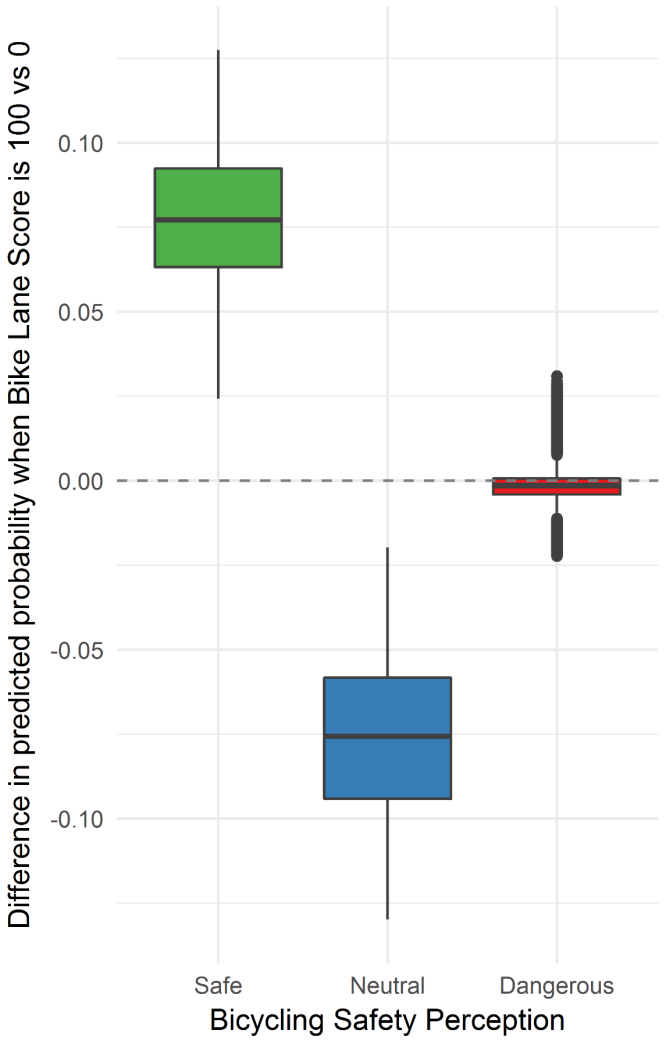

Figure 8. The distribution of the predicted change in probability of perceiving bicycling as safe, neutral and dangerous for a hypothetical sample of bicyclists when the bicycle infrastructure availability was increased such that the Bike Lane Score went from 0 to 100.

3.3.3. Sociodemographic characteristics and perceived bicycling safety

Adjusted models indicate that sociodemographic characteristics are statistically associated with bicycling safety perceptions (Table 9). Bicyclists who are male, younger, lower income, have young children, have a high-school education, and bicycle more frequently are predicted to be more likely to perceive bicycling in their city to be safe (Figure 7b-d, Figure 7f-h). Ethnic background does not appear to be associated the likelihood with perceive bicycling as safe, but rather the likelihood that bicycling is rated neutral or dangerous, with non-Caucasian bicyclists being more likely to rate bicycling as neutral compared to dangerous (Figure 7e).

3.4. Discussion

In this study, we examined the association between perceived bicycling safety and spatial access to bicycle infrastructure accounting for sociodemographic characteristics, amongst over 3,000 bicyclists across 6 geographically diverse major Canadian and US cities, including Boston, Chicago, New York, Toronto, Montreal and Vancouver. These cities covered a wide range of bicycling conditions and safety contexts with mode share ranging from 0.8% to 4.4% of commuters who travel by bicycle (Statistics Canada 2013e, 2013a, 2013d, US Census Bureau 2017b), bicyclist fatality rates varying between 0.60 to 2.94 deaths per million bicycle trips (Urban Systems 2015) and the proportion of bicyclists who perceive bicycling to be safe between 45.3% to 73.2%. In multinomial regression analyses, bicycle infrastructure was positively associated with the likelihood of perceiving bicycling as safe compared to neutral. Bicyclists who are male, younger, lower income, have young children, have a high-school education, and bicycle are predicted to be more likely to perceive bicycling in their city to be safe. Our adjusted model indicated that increasing the availability of bicycling infrastructure such that the Bike Lane Score increased from 0 to 100, would result in a 7.8% average increase in the probability a bicyclist perceives bicycling to be safe. These results highlight that amongst a population that report bicycling, the availability of nearby bicycle infrastructure, in combination with individual sociodemographic characteristics, plays a role in shaping overall perceptions of bicycling safety.

Our findings support the hypothesis that bicycling infrastructure around one's residence is associated with more favourable perceptions of bicycling safety. The finding that greater availability is associated with a greater likelihood of rating bicycling as safe is consistent with previous research which suggests that at the network level, bicyclists perceive bicycle facilities to be safer than bicycling in mixed traffic (Parkin *et al.* 2007, Møller and Hels 2008, Winters *et al.* 2012, Manton *et al.* 2016). Bike Lane Score is a generalized metric of bicycling infrastructure availability, and thus our work complements this past work investigating how perceived safety varies for specific route characteristics (Parkin *et al.* 2007, Møller and Hels 2008, Winters *et al.* 2012, Manton *et al.* 2016). Our results show a positive relationship between availability of bicycle infrastructure around one's residence and perceiving bicycling as safe in one's city, but no difference in perceiving bicycling as dangerous. This result suggests that increasing the availability of bicycling facilities may lead to improved safety perceptions amongst those who

feel neutral, but may not be effective way to improve perceptions of bicycling safety for those who already consider bicycling to be dangerous.

Implementing bicycle infrastructure may also be a means of promoting gender equity in a traditionally male dominated activity, at least in cities with low ridership levels (Garrard *et al.* 2008, Aldred, Elliott, *et al.* 2016). In our sample, females are underrepresented as only 38.9% of bicyclists are female compared to 52.3% of participants in our full sample. The sex imbalances often found in bicycling populations within low bicycling contexts are often attributed to differences in risk aversion where women are more likely to perceive bicycling to be a risky mode of a transport and choose not to bicycle (Garrard *et al.* 2008, Heinen *et al.* 2010). Our research indicates that after controlling for confounders such as bicycling frequency, that there are still significant differences in perceptions of bicycling safety between males and females who already bicycle (at least once a week in the previous 30 days). Previous research has shown that female bicyclists, when compared to males, are more likely to perceive bicycling on specific routes to be too unsafe to bicycle on (Parkin *et al.* 2007), consider various situations while bicycling in traffic to be more risky (Møller and Hels 2008, Chataway *et al.* 2014, Bill *et al.* 2015), and report that road segments along their commute are dangerous (Manton *et al.* 2016).

In cities where bicycling prevalence is low, not only do bicyclists tend to be disproportionately male, but they are also generally much younger (Aldred, Woodcock, *et al.* 2016). We find a similar pattern in our sample with participants over the age of 55 years make up only 19.0% of bicyclists but 30.4% of our full sample. Similar to that of the gendered trends, the literature suggests that older adults are underrepresented in low bicycling environments due to a higher aversion to bicycling in mixed traffic, combined with more limited physical abilities (Aldred, Elliott, *et al.* 2016, Aldred, Woodcock, *et al.* 2016). Our sample is limited only to those persons that already report bicycling, but still shows that younger bicyclists are still more likely to perceive bicycling as safe, compared to older bicyclists, even after controlling for bicycling regularity and the bicycling environment. Previous research has found mixed results on the associations between age and perceptions of bicycling safety within bicycling populations in Western Europe. Some research has indicated that older bicyclists are less likely to perceive bicycling as safe compared to their younger counterparts in Ireland and Denmark (Møller and Hels 2008, Lawson *et al.* 2013), while others have found that older age was associated with an increased likelihood of perceiving bicycling as safe in Ireland and the United Kingdom (Parkin *et al.* 2007, Manton *et al.* 2016). We contribute to the literature in that we provide evidence that in

a Canadian and US context, older bicyclists tend to perceive bicycling to be less safe than younger bicyclists.

Perceptions of safety may inform transportation choices (Heinen *et al.* 2010, Aldred 2016), but safety perceptions don't necessarily align with observed safety (Winters *et al.* 2012). We were not able to assess observed safety (e.g., a measure of injuries or crashes per unit of exposure), as spatially and temporally resolved crash data are not readily available across municipalities. At the city level, there is no correlation between the proportion of bicyclists who perceive bicycling to be dangerous in our sample and city-wide bicycling fatality rates. For example, Boston and Vancouver have similar bicyclist fatality rates, but Boston had the highest proportion reporting bicycling to be dangerous in our study, and Vancouver the lowest. Overall perceptions of bicycling safety are likely influenced not only by fatal and serious injuries that occur in a city, but also by minor injuries and near miss events which occur much more frequently and can be formative negative experiences (Sanders 2015, Aldred 2016, Branion-Calles *et al.* 2017).

Our study has various strengths and limitations. The IBICCS study provided a large sample of spatially located survey data over diverse contexts in six large Canadian and US cities, and used a standardized a measure of the bicycle environment, shown to be associated with bicycling (Winters *et al.* 2016). We also use an outcome with three levels to measure perceived safety (safe vs neutral vs dangerous), rather than a binary category (safe vs dangerous), which enables a more nuanced understanding of the association between access to bicycle infrastructure and perceived safety. Bike Lane Score is a standardized measure that captures the availability of bicycle infrastructure, and was the best available proxy for bicycle infrastructure consistent across cities at the time of the study. The development of Bike Score, including the weighting and decay functions, were informed by research but led by a private company. Bike Score uses a proprietary distance decay function to weight nearby infrastructure higher than distant infrastructure, but the score does not provide the distance to nearest infrastructure, a metric is often used in research studies (Panter *et al.* 2016). To note, the methodology of Bike Score has recently changed, and the description in this paper differs from the Redfin website (Walk Score 2018). Motor vehicle traffic volumes may also play a role in safety perceptions (Parkin *et al.* 2007, Winters *et al.* 2012), but standardized, spatially resolved data on traffic volumes was not available. Of note, the administrative city boundaries vary in terms of the geographic extent with some cities covering a much larger area (e.g., New York,

Chicago). The IBICCS sample was an online panel survey, and both a large sample size and use of post-stratification weights on age and sex improve the generalizability of our results.

3.5. Conclusions

Our results show that within six major Canadian and US cities, greater availability of bicycle infrastructure as represented by the Bike Lane Score of a bicyclist's residence, is associated with greater odds of perceiving the broader city-wide bicycling environment as safe. We suggest that municipalities who wish to expand their bicycling network, thereby increasing spatial access to bicycle infrastructure, could see the perceived safety of bicycling in their city increase amongst bicyclists. These findings can be complemented by natural experiment studies which track changes in perceived safety as bicycle networks are expanded.

Chapter 4.

Impacts of study design on sample size, participation bias, and outcome measurement: a case study from bicycling research

4.1. Introduction

Measuring bicycle behaviour is critical to surveillance of bicycling and its outcomes, including health benefits and crash risks (Götschi *et al.* 2016). Many population studies rely on indirect measures of bicycle use (e.g.,, self-reports) as these have low participation burden, are practical to implement, and represent a cost-effective means of collecting a large amount of data (Dishman *et al.* 2001). As a result, self-report data can facilitate large sample sizes to address myriads of research questions on bicycling behaviour, such as identifying correlates of bicycling or bicycling safety (Vanparijs *et al.* 2015, Kerr *et al.* 2016) or quantifying the effect of interventions (Hosford *et al.* 2018).

Self-reported bicycling can be measured through survey questionnaires or travel diaries (Krizek *et al.* 2009). These may measure duration or distance of bicycling, or physical activity more broadly (de Geus *et al.* 2012, Dons *et al.* 2015, Sylvia 2015, Hosford *et al.* 2018). There is no single instrument to measure bicycling behaviour; rather, there are many variations ranging from simple frequency questions to elaborate travel diaries. Instruments may use different units (e.g.,, time and/or distance) over different time periods (e.g.,, a day, week or a month)(de Geus *et al.* 2012, Tin Tin *et al.* 2013a). Furthermore, surveys may be based either on a participants' recall of their bicycling in a specified time period (e.g., in the week prior to the survey) or based on their perception of their average long-term behaviour (e.g., in a "*typical" or "usual"* week). As temporal and seasonal fluctuations are strong for active transportation (Yang *et al.* 2011, Tin Tin *et al.* 2012), the timing implied in questions may contribute to variation in bicycling behaviour estimates.

A common study design question in bicycling research and practice is whether to measure participants' bicycling behaviour once (cross-sectional) or multiple times (longitudinal). A cross-sectional approach can be more cost effective with lower burden, enabling wider participation and larger sample sizes. It also does not alter participant's bicycling behaviour.

However, given the seasonal variations in bicycling, it may not capture long-term behaviour. Repeated measures, as in a longitudinal study, may provide more accurate measurement of long-term bicycling behaviour as they follow participants through time (including various fluctuations with seasonality, weather, life changes, etc.). This may be especially true for individuals who are sporadic or infrequent bicyclists and may have less accurate recall of their typical behaviours, relative to those that either never bicycle or bicycle routinely (Prince *et al.* 2008).

4.2. Research aim

To guide future studies, our aim was to investigate the impacts of study design on the measurement of bicycling behaviour. Specifically, we explored a common question facing both researchers and practitioners: should they collect data once (cross-sectional) or multiple times (longitudinal)?

We capitalized on the Physical Activity through Sustainable Transport Approaches (PASTA) project, a longitudinal cohort study of participants from seven European cities over two years (Dons *et al.* 2015). We used PASTA data as a case study to investigate how measuring once or multiple times impacted three major factors: a) sample size b) participation bias and c) accuracy of bicycling behaviour estimates. To do so we compared two scenarios: i) as if only the baseline data were collected (the cross-sectional approach) and ii) as if the baseline plus repeat follow-ups were collected (longitudinal approach). The different scenarios, the population samples and analysis approaches for each are outlined in Table 10.

Table 10. Research questions to understand the impacts of study design choices: collecting data once (cross-sectional) or multiple times (longitudinal)

Question	PASTA Subset	Approach
1. Sample size		
1.1 How many participants completed the baseline survey on bicycling compared to subsequent follow-ups?	All PASTA participants that complete the baseline survey (n=7,704).	Total the number of participants that completed baseline self-report and subsequent follow-ups. Calculated the percent change in number of participants (attrition) after each follow-up survey.

Question	PASTA Subset	Approach
2. Participation bias		
2.1. How do geographic, sociodemographic, attitudinal and bicycling behaviour vary between the participants who complete the baseline relative to those that also complete a follow-up?	Participants that complete the baseline survey (n=7,704) versus those that complete at least one follow-up (n=5,806).	Compared geographic, sociodemographic, attitudinal and bicycling behaviour characteristics between each approach using the ratio of relative frequencies. Assessed significant differences through bootstrapped confidence intervals.
2.2. How does the amount of bicycling compare between those who report more follow-ups relative to those that complete less?	Participants that complete at least one follow-up and report some bicycling (n =3,511).	Calculated each participant's average 7-day bicycling behaviour in minutes over all follow-ups completed. Modeled participants' average 7-day minutes of bicycling as a function of the number of follow-ups they completed using a GAM.
3. Accuracy of bicycling behaviour estimates		
3.1 Are binary bicycling behaviour (yes or no) estimates consistent from baseline to follow-ups when calculated from i) typical weekly bicycling at baseline and ii) repeated measures of bicycling in last 7 days?	Participants in the longitudinal study (n=5,806).	Categorized participants' bicycling status (yes/no) at baseline, and over each follow-up. Generated a confusion matrix for bicycling status.
3.2. Are bicycling behaviour estimates similar when calculated from i) typical weekly bicycling at baseline and ii) repeated measures of bicycling in last 7 days?	Participants who provided non-zero estimates of bicycling duration at baseline and who completed at least 1 follow-up (n = 2,635)	Modeled the absolute difference between average follow-up bicycling behaviour and baseline typical bicycling behaviour using a GAM to understand magnitude and directionality of errors.

GAM Generalized Additive Model.

4.3. Materials and methods

4.3.1. Study design

Data were collected as part of the PASTA project, funded by the EC under FP7-HEALTH-2013-INNOVATION-1. Data from a longitudinal web-based survey of residents of Antwerp, Barcelona, London, Örebro, Rome, Vienna and Zürich (Dons *et al.* 2015) were collected between November 2014 (April 2015 in Örebro) and December 2016. Participants could enter the study at any time and were able to access the surveys through an internet browser across a range of devices (e.g., mobile phones, desktop computers, tablets etc.). The study employed an opportunistic sampling approach, although a portion of participants in

Örebro were recruited through random sampling. The same standards for recruitment were used in all cities, including press releases and editorials, integrated promotional materials, collaboration with local stakeholders networks to distribute information, promotion of the study through social media and participation incentivization though a prize lottery (except for Örebro where lotteries were not legally permitted) (Gaupp-Berghausen *et al.* 2019). All promotional materials and automated questionnaires were translated into local languages by native speakers. A custom survey platform sent up to three automatic reminder emails to complete questionnaires. Participants were 18 years or older, except for in Zürich, where the minimum age was 16 years. Bicyclists were oversampled in order to have sufficient samples in cities with a low bicycling mode share (Raser *et al.* 2018).

The surveys consisted of a comprehensive baseline questionnaire followed by repeated frequent short and long follow-up surveys (Figure 9). The baseline questionnaire collected data on sociodemographic characteristics, travel behaviour, physical activity, locational information (home, work and school), as well as attitudes toward transportation. Physical activity questions included a modified version of the Global Physical Activity Questionnaire (GPAQ) aimed at estimating the duration and frequency of bicycling (Gerike *et al.* 2016). The entire baseline survey was designed to take 30 minutes to complete (Dons *et al.* 2015). Following the baseline survey, a short follow-up survey was sent out every 13 days to collect measurements of physical activity and travel behaviour in the previous 7 days. This was designed to take 5 minutes to complete (Dons *et al.* 2015). A long follow-up survey was sent out every third follow-up; which was identical to the short follow-up but with the addition of a 1-day travel diary. The long follow-up was designed to take 10 minutes to complete (Dons *et al.* 2015). At each follow-up, participants were also given the opportunity to report any safety incidents (e.g., crashes) they experienced since their last follow-up.

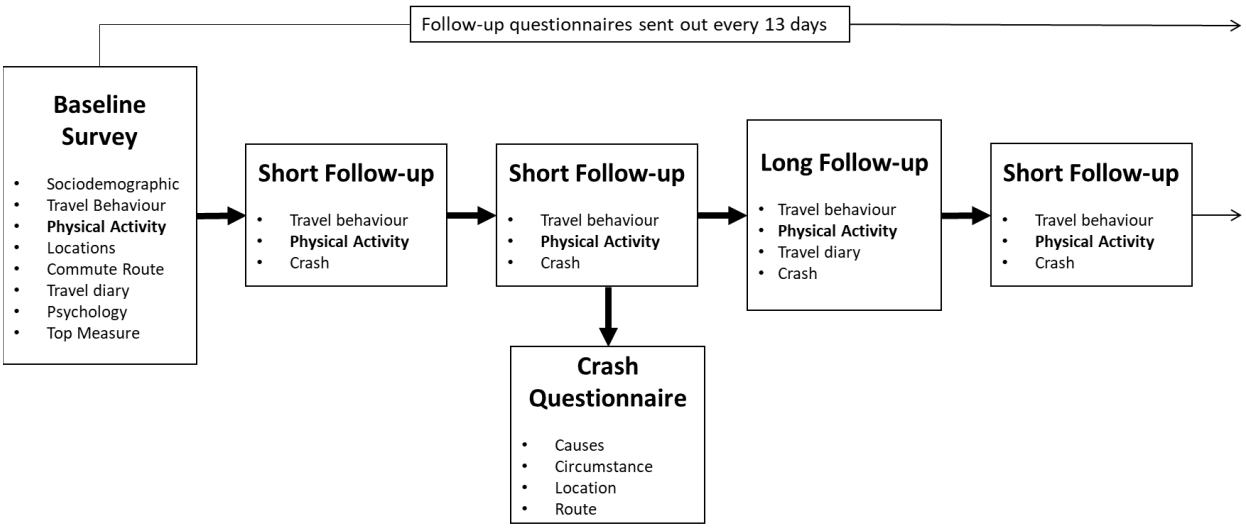

Figure 9. PASTA study design.

In the baseline questionnaire the modified version of the GPAQ asked two questions to estimate long-term bicycling behaviour: 1) “In a *typical* week, on how many days do you cycle for at least 10 minutes continuously to get to and from places? and 2) “Typically, how much time do you spend bicycling on such a day?” The same questions were asked for each follow-up survey, but the time period was framed as the prior seven days, rather than for a typical week.

4.3.2. Data processing and cleaning

Typical and average 7-day recall were calculated for each participant. Typical weekly bicycling was calculated by multiplying the number of days they typically bicycle by the time spent bicycling on those days. Average 7-day recall was estimated by first calculating the time spent bicycling in previous 7-days for each follow-up, and then taking the average over follow-ups.

We removed all participants affected by a proposed intervention (“top measures”) within the broader PASTA project, as survey administration differed for this group. These participants were identified a priori as “exposed” to an urban form change or participation in a program within the study period, and were placed into a “hibernation period” before the planned intervention, in which they were not sent new questionnaires (Dons *et al.* 2015).

We then defined the two study design approaches using the PASTA study: cross-sectional and longitudinal. In the cross-sectional approach, we only considered a participant’s baseline-questionnaire, while in the longitudinal approach we considered their follow-ups. The participants within the cross-sectional approach consisted of those that completed the GPAQ

component of the baseline questionnaire and did not provide outlier values. Outlier values were defined as bicycling >8 hours on a given day in a typical week. The participants within the longitudinal approach consisted of the subset from the cross-sectional approach which completed the GPAQ component of at least 1 follow-up survey and did not provide outlier values in any of their follow-ups. Outlier values in the longitudinal approach were defined as reporting bicycling an average of >8 hours on a given day in the past week. A flowchart of the process is presented in Figure 10.

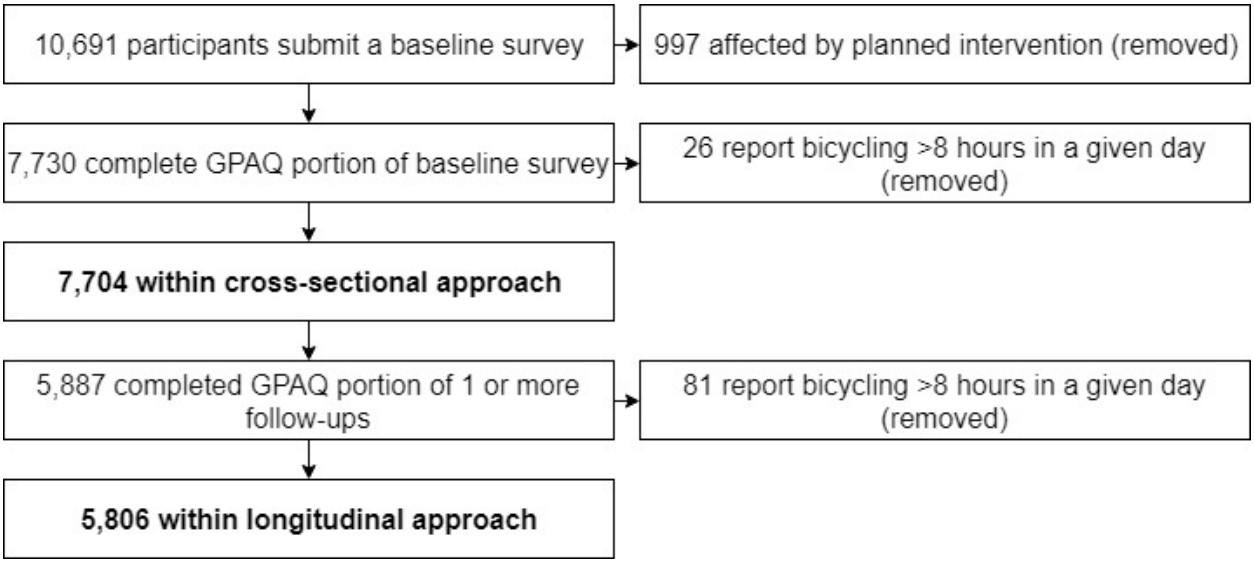

Figure 10. Data cleaning flow-chart to define two study design approaches: the cross-sectional and longitudinal approach.

4.4. Analysis

4.4.1. Sample size

To understand the impact of measuring once versus multiple times on sample size we compared the number of participants who completed baseline self-report to the number who completed subsequent follow-ups (Table 10, Question 1.1). We also calculated the percent change in number of participants after each follow-up survey to understand patterns of attrition. The number of participants who completed the baseline survey represents the sample size for the cross-sectional approach, while the number of participants who completed at least the first follow-up represents the sample size for the longitudinal approach.

4.4.2. Participation bias

We compared the relative frequencies of sociodemographic, attitudinal and bicycling characteristics at baseline between the cross-sectional and longitudinal approaches. Sociodemographic characteristics we included were age, gender, body mass index, education, income, employment, drivers licensing and having young children. Attitudinal characteristics included the participant's level of comfort, and perceived safety of bicycling for transport, as well as how well regarded and common they felt bicycling was in their neighbourhood. Bicycling characteristics included the frequency of bicycling at baseline and whether they typically bicycled in a given a week. We compared the ratio of relative frequencies (RRF) between each level of a given variable of interest (longitudinal approach / cross sectional approach) (Table 10, Question 2.1) (Tin Tin *et al.* 2014). An RRF of 1 corresponds to no change in representation of given characteristic from a cross-sectional to longitudinal approach, while > 1 corresponds to over-representation and <1 under-representation. We constructed a 95% confidence interval around each RRF through bootstrapping with 10,000 replications to assess statistical significance (Tin Tin *et al.* 2014).

Participants within the longitudinal approach completed varying numbers of follow-ups, so we sought to understand if there was an association between the number of follow-ups completed and the average 7-day recall over those follow-ups (Table 10, Question 2.2). To do so, we modeled participants' average 7-day recall (average over all follow-ups) as a function of the number of follow-ups they completed. We restricted this analysis to the subset of participants within the longitudinal approach (i.e., the participants with repeat measurements) who reported some bicycling and considered up to the first 28 follow-up surveys completed (~ 1 year of follow-ups if completed every 13 days). We used a generalised additive model (GAM) with thin-plate spines to estimate the shape of the relationship between participants' overall average 7-day recall and their number of completed follow-ups.

4.4.3. Accuracy of bicycling behaviour estimates

To assess whether accuracy of bicycling status was consistent from baseline to follow-ups, we compared bicycling status derived from typical weekly bicycling to bicycling status from average 7-day recall. We only considered the first 28 follow-ups in calculating average 7-day recall (~ 1 year of follow-ups if completed every 13 days) (Table 10, Question 3.1). Participants were coded as "typical bicyclists" if they provided non-zero values for bicycling duration in a

typical week at baseline. They were coded as “follow-up bicyclists” if they had non-zero values for bicycling in the previous 7 days in any follow-up. We assess consistency of bicycling status between baseline and follow-up by framing this as ‘false negative’ and ‘false positive rates’. In this instance, the false negative rate refers to the proportion of participants who bicycle in follow-ups that were not identified as bicyclists at baseline, while the false positive rate refers to the proportion of participants who were identified as bicyclists at baseline but reported no bicycling in follow-ups.

One-time surveys often ask participants to recall their typical bicycling habits over a period of time to estimate long-term average behaviour. In contrast, when there are repeated measurements researchers may use the averaged value to estimate long-term behaviour. Thus, we sought to understand if estimates of typical weekly bicycling at baseline were similar to average 7-day recall reported over follow-up surveys, quantifying the absolute and relative differences between them (Table 10, Question 3.2). We only considered up to 28 follow-up surveys (~ 1 year of follow-ups if completed every 13 days). For each participant we calculated absolute error by subtracting their typical weekly bicycling at baseline from their average 7-day recall over follow-ups. The shape of the relationship between typical weekly bicycling at baseline and the absolute error was estimated using a generalised additive model with thin-plate splines (Zuur *et al.* 2009).

We visualised the differences between typical weekly bicycling at baseline and average 7-day recall over follow-ups by developing a correction factor (typical weekly bicycling/ the predicted average 7-day recall) for the range of typical weekly bicycling values. Values above 1 indicate the need to correct for under-predictions at baseline and below 1, overpredictions. Since the number of follow-ups may affect the accuracy, we also examined the relationship between number of completed follow-ups and the absolute error.

4.5. Results

4.5.1. Sample size

There were 10,691 participants who submitted a baseline survey but only 7,704 of these completed the GPAQ component. These participants made up the participants within the cross-sectional approach (Figure 11a). Of the participants in the cross-sectional approach 5,806 participants completed the GPAQ component of at least the first follow-up survey and comprise

the participants within the longitudinal approach. This represents an attrition of 24.6% from baseline to the first follow-up (Figure 11b). The attrition rate was highest in the initial follow-ups (10.4% - 16.1% attrition over follow-ups 2-4) and lessened later on (4.3% - 10.8% attrition from follow-up 5-35). Only a small proportion of participants completed 36 or more follow-ups (4.7%), meaning there were larger relative incremental percentage change in sample size in the later follow-ups. Because of rolling recruitment, participants would have needed to have been in the study for over a year to complete more than 30 surveys.

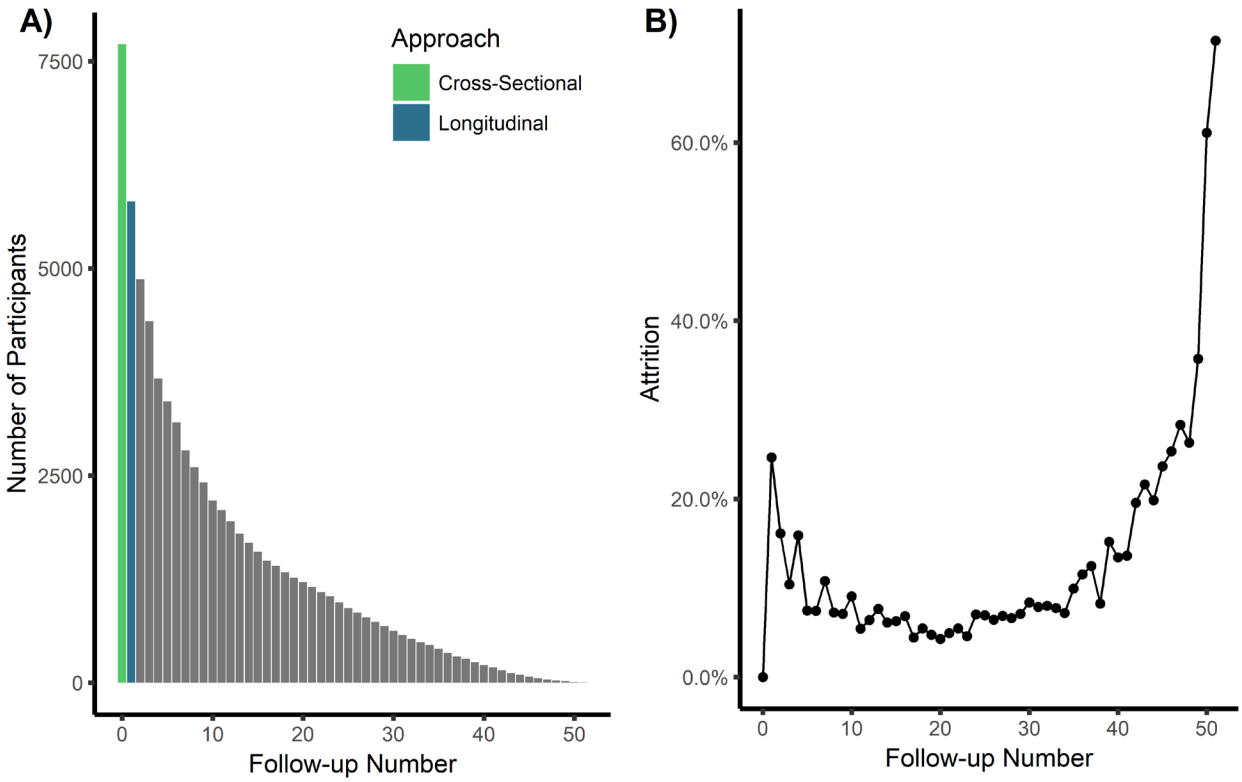

Figure 11. **A) The cumulative number of participants completing GPAQ follow-up surveys. The green column represents participants who, at minimum, complete the GPAQ component of the baseline and comprise the "baseline approach"; the blue those who, at minimum, completed the first follow-up survey and comprise the "longitudinal approach". B) The attrition in total number of participants at each follow-up survey. For example, 24.6% of participants did not complete the first follow-up after the baseline, while 16.1% do not complete the second follow-up after the first.**

4.5.2. Participation bias

How do geographic, sociodemographic, attitudinal and bicycling behaviour characteristics vary between the participants who complete the baseline relative to those that also complete a follow-up?

There were differences in the distribution of geographic and sociodemographic characteristics of participants within the longitudinal approach relative to the cross-sectional. Residents of Zürich were over-represented, while residents of London and Örebro were under-represented (Table 11). Sociodemographic groups that were slightly over-represented in the longitudinal approach included those with a normal body mass index (BMI), the highly educated, middle-income, and those without children 18 years or under. Slightly under-represented groups included students. Participants aged 16-25 years or over 65+ years were also less likely to be within the longitudinal approach. The longitudinal approach had much lower rates of missing data for some sociodemographic characteristics including BMI, education, income, having young children, and perceptions of bicycling in their neighbourhood.

Table 11. Sociodemographic, attitudinal and bicycling characteristics of participants by participation

		Cross-Sectional		Longitudinal		
Variable	**Level**	**Frequency**	**Relative Frequency**	**Frequency**	**Relative Frequency**	**RRF (95 % CI)**
n		7704		5806		
City	Antwerp	884	11.5	705	12.1	1.06 (0.96, 1.16)
	Barcelona	1400	18.2	1073	18.5	1.02 (0.95, 1.09)
	London	1074	13.9	715	12.3	**0.88 (0.81, 0.96)**
	Örebro	560	7.3	355	6.1	**0.84 (0.74, 0.96)**
	Rome	1512	19.6	1087	18.7	0.95 (0.89, 1.02)
	Vienna	1132	14.7	896	15.4	1.05 (0.97, 1.14)
	Zürich	1142	14.8	975	16.8	**1.13 (1.05, 1.22)**
Age (years)	16-25	1186	15.4	826	14.2	0.92 (0.85, 1.00)
	26-35	2301	29.9	1731	29.8	1.00 (0.95, 1.05)
	36-45	1816	23.6	1401	24.1	1.02 (0.96, 1.09)
	46-55	1485	19.3	1153	19.9	1.03 (0.96, 1.10)
	56-65	666	8.6	528	9.1	1.05 (0.94, 1.17)
	65+	248	3.2	165	2.8	0.88 (0.72, 1.07)
	Missing	2	0.0	2	0	1.33 (0.00, 5.31)
Gender	Female	4061	52.7	3073	52.9	1.00 (0.97, 1.04)
	Male	3643	47.3	2733	47.1	1.00 (0.96, 1.03)
BMI	<25	5197	67.5	4044	69.7	**1.03 (1.01, 1.06)**
	25-30	1741	22.6	1315	22.6	1.00 (0.94, 1.07)
	30+	547	7.1	395	6.8	0.96 (0.84, 1.09)
	Missing	219	2.8	52	0.9	**0.32 (0.23, 0.42)**
Education	No degree	24	0.3	11	0.2	0.61 (0.27, 1.22)
	Primary education	93	1.2	67	1.2	0.96 (0.69, 1.30)
	Secondary/further education	2006	26.0	1498	25.8	0.99 (0.94, 1.05)
	Higher/university education	5320	69.1	4200	72.3	**1.05 (1.02, 1.07)**

Variable	Level	Cross-Sectional Frequency	Cross-Sectional Relative Frequency	Longitudinal Frequency	Longitudinal Relative Frequency	RRF (95 % CI)
	Missing	261	3.4	30	0.5	**0.15 (0.10, 0.21)**
Income (€)	<10,000	711	9.2	492	8.5	0.92 (0.82, 1.02)
	10,000 - 24,999	1222	15.9	937	16.1	1.02 (0.94, 1.10)
	25,000 - 49,999	1837	23.8	1473	25.4	**1.06 (1.00, 1.13)**
	50,000 - 74,999	1150	14.9	950	16.4	**1.10 (1.01, 1.19)**
	75,000 - 99,999	527	6.8	413	7.1	1.04 (0.92, 1.18)
	100,000 - 150,000	291	3.8	251	4.3	1.14 (0.97, 1.35)
	>150,000	113	1.5	90	1.60	1.06 (0.80, 1.39)
	Missing	1853	24.1	1200	20.7	**0.86 (0.81, 0.92)**
Employment	Full-time employed	4437	57.6	3410	58.7	1.02 (0.99, 1.05)
	Part-time employed, or casual work	1280	16.6	1021	17.6	1.06 (0.98, 1.14)
	Student / In training	1142	14.8	790	13.6	**0.92 (0.84, 1.00)**
	Home duties / Unemployed / Retired / Sickness leave / Parental leave	661	8.6	462	8	0.93 (0.83, 1.04)
	Missing	184	2.4	123	2.1	0.89 (0.70, 1.11)
Has Driver's License	Yes	6737	87.4	5128	88.3	1.01 (1.00, 1.02)
	No	967	12.6	678	11.7	0.93 (0.85, 1.02)
Has Children Under 18 years	Yes	2452	31.8	1884	32.4	1.02 (0.97, 1.07)
	No	4715	61.2	3684	63.5	**1.04 (1.01, 1.06)**
	Missing	537	7.0	238	4.1	**0.59 (0.50, 0.68)**
Bicycling for transport is comfortable	Agree	4398	57.1	3369	58	1.02 (0.99, 1.05)
	Neutral	1715	22.3	1262	21.7	0.98 (0.92, 1.04)
	Disagree	1591	20.7	1175	20.2	0.98 (0.92, 1.05)
Bicycling for transport is safe with regards to traffic	Agree	1586	20.6	1165	20.1	0.97 (0.91, 1.04)
	Neutral	1779	23.1	1343	23.1	1.00 (0.94, 1.06)
	Disagree	4339	56.3	3298	56.8	1.01 (0.98, 1.04)

Variable	Level	Cross-Sectional Frequency	Cross-Sectional Relative Frequency	Longitudinal Frequency	Longitudinal Relative Frequency	RRF (95 % CI)
In my neighbourhood bicycling is well regarded	Agree	3327	43.2	2564	44.2	1.02 (0.98, 1.06)
	Neutral	2605	33.8	2010	34.6	1.02 (0.98, 1.07)
	Disagree	1606	20.8	1232	21.2	1.02 (0.95, 1.09)
	Missing	166	2.2	0	0	
In my neighbourhood bicycling is common	Agree	2646	34.3	2040	35.1	1.02 (0.98, 1.07)
	Neutral	2340	30.4	1801	31	1.02 (0.97, 1.07)
	Disagree	2517	32.7	1965	33.8	1.04 (0.99, 1.09)
	Missing	201	2.6	0	0	
Typical Bicycling	Never	1903	24.7	1365	23.5	0.95 (0.89, 1.01)
	< once per month	1044	13.6	782	13.5	0.99 (0.91, 1.08)
	1-3 days per month	760	9.9	571	9.8	1.00 (0.90, 1.11)
	1-3 days per week	1233	16.0	935	16.1	1.01 (0.93, 1.09)
	Daily or almost daily	2711	35.2	2122	36.5	1.04 (0.99, 1.09)
	Missing	53	0.7	31	0.5	0.78 (0.48, 1.19)
Baseline weekly bicyclist	Yes	3461	44.9	2692	46.4	1.03 (0.99, 1.07)
	No	4243	55.1	3114	53.6	0.97 (0.94, 1.00)

[a] 95% bootstrapped confidence intervals with 10,000 replications
RRF Ratio of Relative Frequencies
BMI Body Mass Index
Bold statistical significance at 95% confidence.

How does the amount of bicycling compare amongst those who report more follow-ups relative to those that complete less?

Participants with the fewest follow-ups tended to report more minutes of bicycling in their 7-day recall (Figure 12). The predicted average 7-day recall was just over 210 minutes for bicyclists who completed one follow-up, compared to 135 minutes/week for those who completed 15 follow-ups: a 75-minute difference.

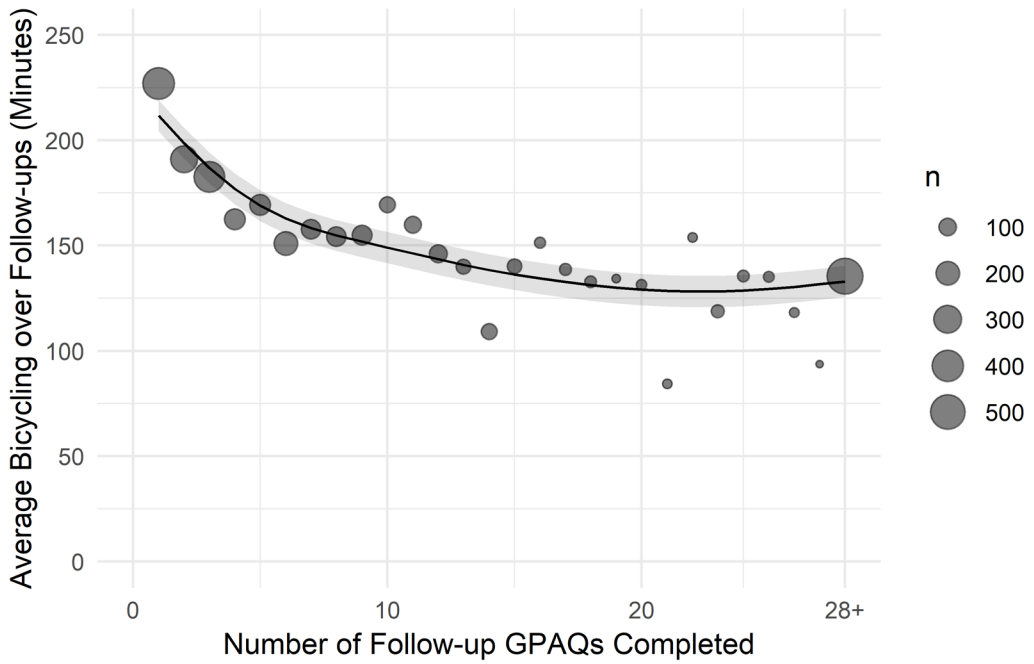

Figure 12. The relationship between the average 7-day recall over follow-ups amongst bicyclists and the number of follow-ups completed. Fitted trend line on the raw data (not plotted) using a simple generalized additive model.

4.5.3. Accuracy of bicycling behaviour estimates

Are binary bicycling behaviour (yes or no) estimates consistent from baseline to follow-ups when calculated from i) typical weekly bicycling at baseline and ii) repeated measures of bicycling in last 7 days?

At baseline 46.4% (2,692 / 5,806) of participants were classified as typical bicyclists, while over follow-ups 60.5% (3,511/5,806) were classified as follow-up bicyclists (Table 12). Typical bicycling status at baseline was consistent with follow-up bicycling status for just over 4 in 5 participants (4,705/5,806). There was a small chance that if participant was coded as a follow-up non-bicyclist, that they previously reported being a typical bicyclist (6.1% false positive

rate). There was a comparatively higher chance that if a participant reported being a follow-up bicyclist, that they previously reported being a typical non-bicyclist (27.3% false negative rate).

Table 12. Confusion matrix for bicycling status at baseline (cross-sectional approach) or over follow-ups (longitudinal approach).

		7-Day Recall Over Follow-ups (Up to 28)		
		Follow-up Bicyclist	**Follow-up Non-Bicyclist**	**Total**
Baseline Typical Weekly Bicycling (cross-sectional)	**Typical Bicyclist**	2551 (72.7%)	141 (6.1%)	2692
	Typical Non-Bicyclist	960 (27.3%)	2154 (93.9%)	3114
	Total	3511(100%)	2295 (100%)	5806

Are bicycling behaviour estimates similar when calculated from i) typical weekly bicycling at baseline and ii) repeated measures of bicycling in last 7 days?

There were 5,806 participants who provided duration data on bicycling behaviour in both baseline and follow-ups. For this analysis we considered only the 2,692 participants who were coded as a typical bicyclist at baseline and removed 57 participants that reported typically bicycling more than 2 hours daily.

We found that the accuracy of the typical weekly bicycling estimate at baseline varied by how much bicycling was initially reported, as well as based on the number of follow-up surveys a participant completed. Participants who reported bicycling less than 1.5 hours in a typical week at baseline (~13 minutes a day) tended to report higher levels of bicycling in follow-ups (Figure 13a). There was non-linearity in the relationship between typical bicycling at baseline and the average 7-day recall, with greater over-estimation for participants with higher reported typical weekly bicycling at baseline (Figure 13a). We also found that the number of follow-up surveys completed had a small but significant association with the accuracy of the typical bicycling estimate (Figure 13b). The relationship was linear, where the over-estimation at baseline was increased by just under a minute for every follow-up completed, from a 49-minute weekly overestimation for participants who completed 1 follow-up, increasing to 71-minutes for participations who completed 28 follow-ups.

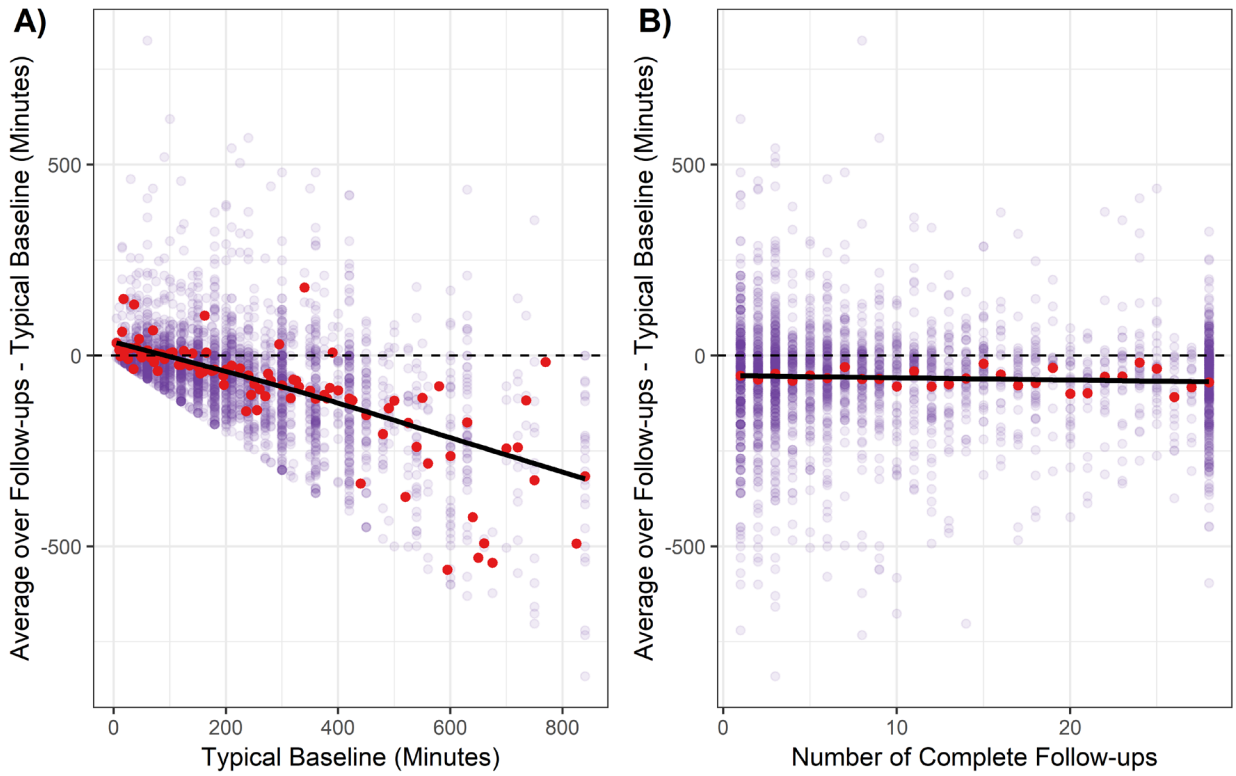

Figure 13. **A) The relationship between typical 7-day bicycling measured at baseline and the difference between average 7-day recall over follow-up surveys (1 or more) and typical weekly of bicycling at baseline. B) The relationship between the number of follow-ups and the difference between the average 7-day recall and typical weekly bicycling at baseline. Points above the dotted-black line indicate an under-estimation of minutes of bicycling at baseline, while points below indicate an over-estimation. Red points indicate the mean difference for a given baseline value or number of follow-ups completed. A generalized additive model was used to visualise the trend in the data.**

The relative difference between the typical weekly bicycling and average 7-day recall indicate that correction factors decrease non-linearly from 4.2 to 0.6 for typical weekly baseline bicycling values between 10 and 840 minutes (Figure 14). The non-linear decrease can be illustrated through the following hypothetical example: if 6 participants report that they bicycle 10, 30, 60, 240 and 600 minutes in a typical week respectively, the model suggests that the first 3 participants under-predict their average 7-day recall by factors of 4.2, 1.8, and 1.2, while the last 3 participants would over-predict their average 7-day recall by factors of 0.8, 0.7 and 0.6.

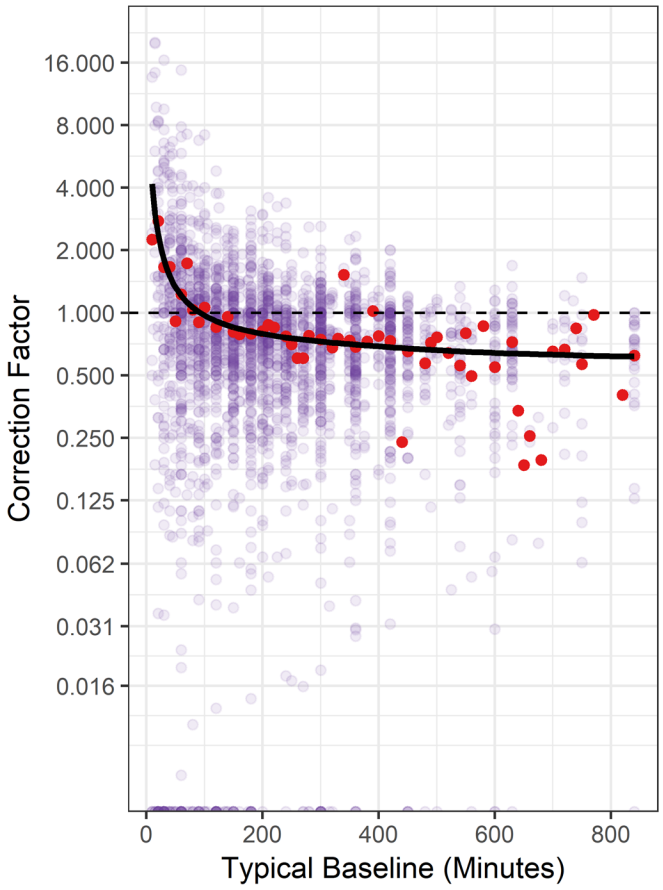

Figure 14. The predicted factor for converting baseline typical bicycling values to the average 7-day recall over follow-ups (black line). A corrective factor above 1 indicates a baseline under-estimation, below 1 an over-estimation. Purple points represent the data, red points the average for a given baseline typical bicycling value.

4.6. Discussion

In this study we used a large longitudinal study with over 10,000 participants in seven European cities to understand the impacts of two study designs (cross-sectional vs longitudinal approaches) on sample size, participation bias and accuracy of bicycling behavior estimates. We found that a cross-sectional approach resulted in a larger overall sample size, and slightly better representation of sociodemographic groups, but inconsistent estimates of long-term bicycling behaviour. In contrast, the longitudinal approach may provide more accurate bicycling behaviour estimates, but suffers from some participation bias, especially the selective drop-out of more frequent bicyclists with greater numbers of follow-up surveys.

Measuring bicycling behaviour accurately is essential for both research and practice. Many studies differentiate between bicyclists and non-bicyclists through self report (Krizek *et al.* 2009). In a cross-sectional study, differentiating between bicyclists and non-bicyclists can involve dichotomizing participants based on a question that asks for typical or usual bicycling habits within a given time frame (e.g., a week) (Moudon *et al.* 2005, Winters *et al.* 2007). To separate participants into bicyclists versus non-bicyclists, our analysis suggests that asking for typical weekly bicycling habits will result in the misclassification of ~1 in 20 bicyclists and ~1 in 4 non-bicyclists. The inconsistency we found could be due to participants having genuinely changed their bicycling behaviour; however, this is unlikely given the short duration of study participation (median time between baseline and follow-up < 5 months for this subset). We suggest it was more likely that the wording of the question itself resulted in the classification issue: participants who may not bicycle in a "typical week" may bicycle in the 7-day recall periods in follow-ups. Questions that ask for direct recall of bicycling for a longer period of time (e.g., in the past 12 months) or use categories (e.g., never, daily, 1-3 days per week, 1-3 days per month, <once per month, etc.) may have better consistency.

We also found that the duration of bicycling derived from self-reported typical weekly bicycling habits was inconsistent with that derived from recall of the past 7-days. When we compared the typical weekly bicycling at baseline to average 7-day recall over follow-ups, we found that bicyclists who reported they typically bicycle frequently (> 90 minutes a week), over-estimated their habits, and those who reported typically bicycling more infrequently (< 90 minutes a week) under-estimated bicycling. Over-estimation is common in self report physical activity as a result of social desirability bias, or recall bias (Sallis and Saelens 2000, Dishman *et al.* 2001, Brenner and DeLamater 2014, Panter *et al.* 2014). Few studies have assessed measurement validity for bicycling. One study of 11 bicyclists in the United Kingdom compared average trip durations derived from GPS data to a questionnaire asking for the "usual" time spent on a bicycling trip and found a mean difference of ~1-minute, and generally good agreement between the methods (Panter *et al.* 2014). Small errors in durations derived from recall of usual habits at the trip level, however, may compound given aggregation to a weekly time period (Panter *et al.* 2014).

The implications of the use of typical weekly bicycling to estimate the amount of bicycling in a cross-sectional approach would depend on the population being sampled. For example, consider a cross-sectional study that sought to quantify population crash rates by asking participants to recall prior crashes (numerator) and assessed bicycling through a question

regarding their typical bicycling habits (denominator). If crashes were distributed equally, and the sample consisted of a larger proportion of infrequent bicyclists relative to frequent bicyclists, we would over-estimate overall crash risk due to the under-estimation of bicycling for infrequent bicyclists. Conversely, a sample with a greater proportion of more frequent bicyclists relative to infrequent bicyclists would result in an under-estimation of crash risks, with an over-estimation of bicycling amongst frequent bicyclists.

Loss to follow-up is a concern for cohort studies, given the potential impacts for biased associations (Greenland 1977, Kristman *et al.* 2004, Tin Tin *et al.* 2014) if both exposure and outcome are related to study participation (Lash *et al.* 2009). Our results suggest that there are only slight differences between a select few sociodemographic variables from baseline to the first follow-up*,* such as people with higher educations, students, middle income earners and people with young children. However, the loss to follow-up did impact bicycling behaviours: we saw a ~75-minute drop in bicycling reported in average 7-day recall for those with 1 follow-up survey, relative to those who completed 15, suggesting a participation bias effect. An alternative explanation for the decrease in bicycling was that it was a short-term effect caused by participation in the study itself (Dishman *et al.* 2001). We explored this possibility in a separate analyses by plotting the average 7-day recall after each follow-up, for a subset of participants who completed at least 15 follow-ups. The average bicycling within the first follow-up was 149 minutes, while the average bicycling within the fifteenth follow-up was 130 minutes, suggesting a short-term study effect was not substantial. In the PASTA study, participants were also asked to complete a detailed 1-day travel diary at every third follow-up (Gerike *et al.* 2016). As such there was differential burden for participants who took more trips. The detailed 1-day travel diary would incur a higher burden on participants with many trips (bicycling and other modes) and potentially lead to increased drop out amongst these participants. We expect that in a similar study which does not include a trip diary, the bias may not be as strong.

The PASTA study is one of the largest mobility studies of its kind, and provided a large sample of longitudinal survey data across seven geographically diverse cities in Europe. While we frame the baseline survey as a cross-sectional sample, PASTA respondents were aware they were signing up for a longitudinal survey and may not be completely representative of an independent cross-sectional sample. A previous analysis found that the PASTA sample was found to be generally representative of gender distribution but tended to be somewhat younger and more educated when compared to census data (Gaupp-Berghausen *et al.* 2019). To facilitate assessing long term outcomes, longitudinal surveys will often have less frequent

follow-ups, spread out over a longer timer period, such as multiple years. The PASTA survey was not designed to specifically evaluate chronic or long-term outcomes and has frequent follow-ups to reduce recall bias of physical activity and bicycling. As a result, some of our results may not be generalizable to all longitudinal designs. The survey structure may have impacted answer quality and quantity, as the PASTA baseline survey was long, and follow-ups were frequent (every 13 days). We used the average 7-day recall to assess the accuracy of typical weekly bicycling, but we did not assess the accuracy of the average 7-day recall itself. The GPAQ has been validated against direct measures of physical activity (Bull *et al.* 2009, Laeremans *et al.* 2017) but the bicycling-specific questions have not been validated. In estimating participation bias, we only compared changes after the first follow-up and a higher threshold may result in different patterns.

4.7. Conclusions

Future studies aiming to derive measures of bicycling behaviour based on repeated measurements must consider the trade-offs between estimating individual bicycling behaviour more accurately, with bias and power. In our case study we found that measuring bicycling once, compared to multiple times, resulted in a larger sample with better representation of sociodemographic groups and bicyclists, but substantially different estimates of long-term bicycling behaviour. We suggest that measuring typical weekly habits at one point in time is not an accurate proxy for measuring bicycling in the past 7-days multiple times. Problems with participation bias and sample size could be resolved in future studies through the use of app-based studies to capture bicycling behaviour (Geurs *et al.* 2015), which, if automated and passively collected over time, may one day enable rich travel data at a lower burden to participants than traditional methods (Prelipcean *et al.* 2017). Further developments are needed for accurate mode detection and privacy considerations (Geurs *et al.* 2015).

Chapter 5.

Bicyclist crash rates and risk factors amongst a prospective cohort in seven European cities

5.1. Introduction

Bicycling for transport has many potential societal benefits. Increased bicycling can improve population health outcomes through increased physical activity (de Hartog *et al.* 2010, Mueller *et al.* 2015, Götschi *et al.* 2016, Rojas-Rueda *et al.* 2016). Bicycling also has potential harms, both real and perceived, that prevent concerned individuals from bicycling. Negative safety perceptions are a main barrier to bicycling (Heinen *et al.* 2010, Willis *et al.* 2015). Bicyclists have higher risks of injury and/or fatality than other road users in highly motorized countries (Beck *et al.* 2007, Mindell *et al.* 2012, Wegman *et al.* 2012, Reynolds *et al.* 2017, Scholes *et al.* 2018).

It is critical to understand risk factors for bicycling crashes to identify potential strategies for interventions. Studies of crash incidence require both crash and exposure data (e.g.,, bicycling distance or duration) for a specified area and time (Vanparijs *et al.* 2015, Götschi *et al.* 2016). Exposure-based studies of bicycling risk are typically conducted by compiling crash and exposure data from different sources, generally police databases (crashes) and travel surveys (exposure) (Hautzinger *et al.* 2007, Castro *et al.* 2018). Comparative studies of crash risk require attributes that are common to both the crash and exposure datasets. When combining crash and exposure data from different sources, common attributes tend to be limited to geography (e.g., countries, provinces, municipalities) and a few general road user characteristics (age and gender strata) (Beck *et al.* 2007, Mindell *et al.* 2012, Blaizot *et al.* 2013, Teschke *et al.* 2013, Santamariña-Rubio *et al.* 2014, Reynolds *et al.* 2017, Scholes *et al.* 2018). As a result, most exposure-based risk studies that combine disparate exposure and crash data are not able to provide detailed explorations of crash risk factors, such as individual user characteristics including bicycling frequency, perception of their social environment, and neighbourhood features. Furthermore, different sources of data also make comparisons across different cities problematic.

Most exposure-based studies of bicycling risk typically use crashes reported to police and/or hospital databases which under report less-serious injuries and crashes without injury (Elvik and Mysen 1999, Langley *et al.* 2003, Amoros *et al.* 2006, Veisten *et al.* 2007, de Geus *et al.* 2012, Juhra *et al.* 2012, Watson *et al.* 2015, Vanparijs *et al.* 2016, Winters and Branion-Calles 2017) and can make comparisons across different regions problematic due to potential differences in reporting practices (Yannis *et al.* 2014). Less severe crashes and crashes without injury are important to capture as they comprise the vast majority of crashes that occur and are a substantial economic cost to society (Veisten *et al.* 2007, Aertsens *et al.* 2010), considering treatment costs, productivity loss or leisure time loss (Aertsens *et al.* 2010). Furthermore, minor crashes and crashes without injury can negatively affect how individuals perceive bicycling safety (Sanders 2015), which may reduce bicycling uptake and therefore minimize the net potential health and other benefits from bicycling.

Prospective cohort studies offer an opportunity to address these limitations by collecting data on a range of crash types, including single bicycle crashes or crashes without injury (de Geus *et al.* 2012, Poulos *et al.* 2012). Furthermore, participant-specific travel behaviour can also be collected concurrently (Vanparijs *et al.* 2015), while also permitting the identification of individual sociodemographic, behavioural, social environment and built environment factors associated with crash risk. As a result, this design can allow for collection of less-severe crash types, more accurate calculation of crash rates and identification of individual level crash risk factors.

The Physical Activity through Sustainable Transport Approaches (PASTA) project was a prospective cohort study that used a longitudinal web survey of over 10,000 individuals residing in seven cities across Europe that collected crash and exposure data simultaneously (Gerike *et al.* 2016). The goal of this study was to use data from the PASTA project to quantify exposure-adjusted crash rates and model crash risk factors, including sociodemographic characteristics, social environment (including attitudes and social norms), and neighbourhood-built environment features.

5.2. Materials and methods

5.2.1. Study area

Our study area includes the cities in which participants were recruited for the PASTA project (Antwerp/Belgium, Barcelona/Spain, London/United Kingdom, Örebro/Sweden, Rome/Italy, Vienna/Austria and Zürich/Switzerland) (Gerike *et al.* 2016). These cities represent a range of environments in terms of size, population characteristics, mode shares, built environment, and culture (Table 13). Örebro and Antwerp have the highest levels of bicycling, with 25% and 23% of trips being made by bicycle, respectively (Mueller *et al.* 2018). Örebro is also the least dense of the cities but is supported by a well maintained hierarchical network of bicycling infrastructure, consisting of high speed regional bicycling corridors that feed into local networks (PASTA Consortium 2018a). Antwerp is a much more dense city than Örebro and is supported by a vast network of cycle paths and an extensive bike share program (PASTA Consortium 2018b). Vienna has the next highest mode share at 6% (Mueller *et al.* 2018). This city is characterised by particularly high dynamics in bicycling promotion. Having started with the active promotion of bicycling not as long ago as some of the other cities in this study such as Antwerp or Örebro, it has today one of the largest bicycling networks amongst the PASTA cities (PASTA Consortium 2018c). Zürich has a modest 4% of trips made by bike (Mueller *et al.* 2018). Historically, other modes of transportation have been prioritized over bicycling in Zürich resulting in an excellent public transportation system along with a high mode share of walking, but a fragmented bicycling network (PASTA Consortium 2018d). London has seen an increase in both investment in the bicycling network and growth in bicycling trips (Aldred and Dales 2017) but still has a bicycling mode share of only 3% (Mueller *et al.* 2018). Similar to London, Barcelona has expanded their bicycling network significantly in recent years and is considered to be an emerging city for bicycling (PASTA Consortium 2018e) but currently only has a mode share of 2% (Mueller *et al.* 2018). Finally, Rome has the lowest bicycling mode share at 1% (Mueller *et al.* 2018), a very limited bicycling network and is considered to be a challenging place to get around by bicycle (PASTA Consortium 2018f).

Table 13. Characteristics of PASTA Cities

City	Antwerp	Barcelona	London	Örebro	Rome	Vienna	Zürich
Country	Belgium	Spain	United Kingdom	Sweden	Italy	Austria	Switzerland
Population[a]	502,604	1,620,943	8,538,689	138,952	2,683,842	1,741,246	398,575
Area (Km^2)[a]	204	102	1,572	1,373	1,285	415	92
Population Density (pop/km^2)[a]	2,464	15,892	5,432	101	2,089	4,196	4,332
Bicycling Mode Share (%)[b]	23	2	3	25	1	6	4
Bicyclists/day[c]	113,509	26,532	235,288	26,538	18,846	75,685	16,416
Mean distance (km)[c]	3.84	3.5	3	3.3	7.7	3.3	2.77
Mean time (mins)[c]	14.4	16.2	22.8	16.2	24	18.6	14.4
Bicycling network km (OSM)[d]	469.17	159.54	969.17	361.35	120.64	715.63	118.36
Street network km (OSM)[d]	1,651.74	1,554.56	16,439.74	3,045.27	8,281.36	3,946.11	1,193.59
Bicycling network / street network[d]	0.28	0.10	0.06	0.12	0.01	0.18	0.10
Fatalities/year[e]	4	3	13	1	4	3	1
Bicycling km/ year[e]	313,625,445	89,663,002	463,174,636	59,361,390	98,362,110	219,430,669	45,048,048
Fatalities/ billion km[e]	13	33	28	17	41	14	22

[a] Data compiled in Gerike et al. (2016) and refer to the year 2012

[b] Data compiled in Mueller et al (2018). Antwerp, Barcelona, London, Örebro, Rome, Vienna and Zürich based on data from 2011, 2012, 2012, 2011, 2014, 2012, 2010, respectively

[c] Data compiled in Mueller et al (2018). Antwerp, Barcelona, London, Örebro, Rome, Vienna and Zürich based on data from 2013, 2006/2015, 2013, 2011, 2014, 2013, 2010, respectively

[d] Data compiled in Mueller et al (2018) from OpenStreetMap as of October 2017

[e] Data compiled in Mueller et al (2018). Antwerp, Barcelona, London, Örebro, Rome, Vienna and Zürich based on traffic fatality data from 2011-2014, 2011-2015, 2014, 2012, 2015, 2010-2015, 2006-2010, respectively.

5.2.2. Study design

Bicycling crash and exposure data were collected as a part of the larger PASTA project (Gerike *et al.* 2016). The project used a longitudinal web-based survey (Dons *et al.* 2015). Data were collected between November 2014 (April 2015 in Örebro) and December 2016, primarily through an opportunistic sampling approach, though some participants in Örebro were recruited through random sampling. Participants were recruited with the same methods across all cities, which included press releases/editorials, consistent design of promotional materials, translation of promotional materials to local languages, close collaboration with local stakeholders networks to distribute information, promotion of the study through social media and participation incentivization through a prize lottery (except for Örebro where lotteries were not permitted) (Gaupp-Berghausen *et al.* 2019). A participant could enter (and leave) the study at any point within the data collection period. Participants were required to be at least 18 years of age, except for Zürich, where the minimum age was 16 years. The survey oversampled bicyclists to ensure sufficient statistical power for analysis in cities with a low bicycling mode share (Raser *et al.* 2018).

The PASTA project consisted of a comprehensive baseline questionnaire followed by follow-up surveys (Figure 15). The baseline questionnaire collected data on sociodemographic characteristics, travel behaviour, physical activity, information regarding locations of their home, work and school, as well as data on attitudes toward transportation. Follow-up survey invitations were sent every 13 days after completion of a questionnaire to collect prospective repeated measurements of travel, physical activity behavior, and safety incidents. Each follow-up survey included a modified version of the Global Physical Activity Questionnaire (GPAQ) aimed at estimating the duration and frequency of bicycling in the previous week (World Health Organization 2019). Every third follow-up included a 1-day travel diary. A custom designed web-survey platform automatically sent reminder emails for participants to complete questionnaires.

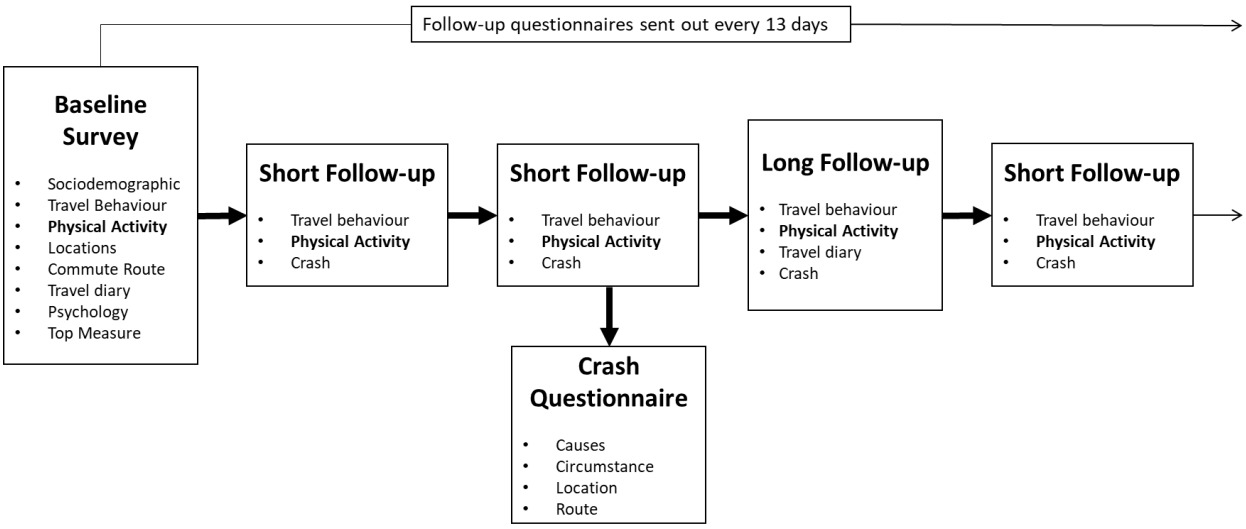

Figure 15. Longitudinal Survey Design for PASTA participants

5.2.3. Bicycling exposure and crash data

We estimated bicycling duration from the modified version of the GPAQ administered in every follow-up survey. The questionnaire consisted of the following two questions: 1) “In the previous 7-days on how many days do you cycle for at least 10 minutes continuously to get to and from places?” and 2) “Typically, how much time do you spend bicycling on such a day?”.

To obtain an estimate of weekly duration of bicycling at each follow-up, we multiplied the number of days cycled by the typical time spent bicycling. To estimate the total bicycling exposure for the study, we multiplied the average of a participants weekly bicycling over all follow-ups by the number of weeks between the date they entered the study and the date of the last follow-up survey they completed.

For capturing safety incidents, each follow-up survey asked, “Since the last time you filled out a questionnaire…, have you experienced any safety relevant incidents (i.e. a collision, fall or near miss as a pedestrian, bicyclists, in public transport or driving)?” If participants had experienced a collision or fall, they were asked to complete a crash questionnaire for each case. This crash questionnaire collected details of circumstances including the crash type (fall, crash with motor vehicle, crash with bicyclist or crash with pedestrian), injury (injury or non-injury) and medical treatment (none, treated without doctor, treated by doctor, brought to hospital, hospitalized). We only include collisions

and falls while bicycling in our analysis (e.g., we removed falls or crashes while using other modes of transport) referred to collectively as crashes in this paper.

5.2.4. Covariates

The PASTA study followed a comprehensive framework to understanding active travel behaviour, and aimed to not only measure sociodemographic characteristics, but also the characteristics of their social and built environments (Götschi *et al.* 2017). For this analysis, we selected the sociodemographic, social and built environment characteristics from the baseline survey that were either previously identified as risk factors in other bicyclist cohorts (Tin Tin *et al.* 2013a, Degraeuwe *et al.* 2015, Poulos *et al.* 2015a, Vanparijs *et al.* 2015), or had a plausible association with crash risk, such as perceptions of traffic safety. Sociodemographic characteristics included age, gender, education, body mass index (BMI), and whether the bicyclist had a driver's license. Perceptions of built and social environments were included as well, where participants rated their level of agreement with whether bicycling for travel was comfortable, whether bicycling for travel was safe with regards to traffic, whether bicycling was well regarded in their neighborhood, and whether bicycling was common in their neighbourhood. For each participant we also generated objective measures of the built environment around a participant's home (300m) including bicycling infrastructure density, building density and a measure of "greenness" the Normalized Difference Vegetation Index (NDVI). These were derived by mapping the participants' residential locations to geospatial data from local partners, and/or open data infrastructure including from the European Environment Agency and OpenStreetMap.

5.2.5. Data cleaning and dealing with missing values

From the over 10,000 participants who completed the baseline questionnaire, we included those who completed at least one follow-up survey in which they were asked about bicycling crashes (n=6,817). We removed participants who reported zero minutes of bicycling (n=2,448), those who reported over 8 hours of daily bicycling in 1 or more follow-ups (n=190), those that were in the study for less than 13 days (n=12), and those who provided incomplete data on crash type and injury (n=62). There were 4,180 participants who fulfilled the inclusion criteria.

Across the relevant baseline sociodemographic, social and built environment variables, the percentage of missing data amongst eligible participants ranged from 0 to 16.97%. The specific variables with missing data included age (n=1, <0.1%), BMI (n = 19, 0.5%), education level (n = 8, 0.2%), having young children (n=153, 3.7%), building density within 300 m of residence (n = 65, 1.6%), bike lane density within 300 m of residence (n = 698707, 16.79%), street density within 300m of residence (n = 60, 1.4%), and NDVI within 300 m of residence (n = 65, 1.6%). In total 1,355886 out of 4,180 eligible participants (32.421.2%) had incomplete sociodemographic, social or built environment data.

To address the missing values in sociodemographic, social and built environment variables we took a multiple imputation approach. Specifically, we used the multivariate imputation by chained equations (MICE) technique using fully conditional specification and the default settings of the mice 3.6 package in R (van Buuren and Groothuis-Oudshoorn 2011). Multiple imputation creates multiple plausible versions of a complete dataset by filling in the missing values with reasonable estimates (Azur *et al.* 2011). We used the MICE algorithm to create 20 imputed datasets based on the rule of thumb that the number of imputations should approximate the proportion of incomplete cases (van Buuren 2018).We converted building density, bike lane density, and NDVI to a categorical variable based on quintiles for each imputed dataset after imputation. We then calculated crash rates using the non-imputed data and statistically modelled crash risks using the imputed datasets.

5.2.6. Statistical analysis

Crash rates

Using the non-imputed data, we calculated overall crash rate (number of crashes per 100,000 hours of bicycling) by combining recorded crashes with exposure data. We also calculated crash rates by city and a range of sociodemographic, attitudinal, and built environment characteristics without data imputation. We used bootstrapping with 5,000 replications to generate 95% confidence intervals around crash rates.

To further understand differences in crash rates by city, we also examined crash rates for specific types of crashes based on which road users were involved and the injury severity. Crashes were defined as either involving a motor-vehicle, another

bicyclist, a pedestrian or a fall. There were 9 crashes that involved multiple other road users. These crashes were assigned to a category based on the most dangerous road user involved, where we ranked road users from most to least dangerous as follows: motor-vehicles, another bicyclist, pedestrian, and finally no other road user (i.e. a fall). We also used medical treatment as a proxy for injury severity and assigned a crash as requiring medical treatment if the participant sought any kind of medical treatment, or else not requiring medical treatment.

Crash risk factors

To explore crash risk factors, we analysed the relationship between crash risks, exposure and other individual level factors. We applied this in each of the multiply imputed datasets and combined the results into a pooled model as per Rubin's rules (Azur *et al.* 2011). We used Generalized Linear Models with negative binomial error structures, and logarithmic links to quantify the relationship between the number of crashes a participant reported as a function of exposure, individual level factors, and city (Hilbe 2014). We defined a base crash risk model as the following (Elvik 2009):

$$\hat{E}(Y) = e^{\propto_0} \times EXP^{\propto_1} \times T^{\propto_2} \times e^{(b_1 city_1 + \ldots + b_6 city_6)} \quad (1)$$

Where $\hat{E}(Y)$ is the predicted crashes for a participant, EXP is the average bicycling exposure per month, T is the total months in the study and $city$ is an indicator variable for the city a participant resides in. We used city as an indicator variable to adjust for between city differences in individual crash risk (Cerin 2011). Since participants spent differing amounts of time in the study there is potential for attrition bias. Here, attrition bias refers to the notion that there may be differences in crash risk between participants who participate for different lengths of time (Nunan *et al.* 2018). Therefore, we separated total exposure into two sub-components: average monthly exposure (EXP) and total number of observed months (T). The coefficients $\propto_0$, $\propto_1$, $\propto_2$ and b_i are estimated using maximum likelihood methods. If $\propto_1$ or $\propto_2$ are < 1 it means that the number of expected crashes increases less than proportionally to increases in average exposure or time in the study, respectively. We would expect $\propto_2$ to be ~1 if attrition was non-differential with regards to crash risk.

Each of the specified sociodemographic, social, and built environment characteristics was then initially examined separately by adding each to the base model:

$$\hat{E}(Y) = e^{\propto_0} \times EXP^{\propto_1} \times T^{\propto_2} \times e^{(b_1 city_1 + \ldots + b_6 city_6)} \times e^{(b_7 x_1 + \ldots + b_{(7+k)} x_k)} \quad (2)$$

Where x represented the one additional indicator variable of interest with k levels. We then estimated the incident rate ratio (IRR) for each level of x by exponentiating its coefficient, b. The IRR here represents the change in crash risk from the reference category in a specified sociodemographic, social, or built environment characteristic holding exposure and city-level differences constant. We will refer to these IRR's as "crude".

Finally, we developed a parsimonious crash risk model in a forward stepwise procedure. We added additional variables to the base model one at a time, based on the multivariate Wald statistic, from highest to lowest (van Buuren 2018). A variable was kept in the model if the Wald statistic had a p-value under 0.2. The final parsimonious model is given by:

$$\hat{E}(Y) = e^{\propto_0} \times EXP^{\propto_1} \times T^{\propto_2} \times e^{(b_1 city_1 + \ldots + b_6 city_6)} \times e^{(b_7 x_1 + \ldots + b_n x_n)} \quad (3)$$

Where there are n number of sociodemographic, social or built environment variables that have a p-value under 0.2. We use a high p-value to avoid excluding potentially important variables. We will refer to the IRRs based on this parsimonious model as "adjusted".

5.3. Results

Out of the 10,691 participants in the PASTA study, 4,180 participants provided bicycling exposure data in at least one follow-up and did not provide outlier values or unreliable crash data (Table 14). We will refer to these participants as bicyclists. The bicyclists completed a median of seven follow-up surveys over a median of 7.3 months. At baseline, most reported being daily or almost daily bicyclists (60.3%) and reported bicycling for a median daily average of 16.3 minutes over follow-ups. Relative to other cities, London had the fewest bicyclists (n=355), while Antwerp had the most (n=891). Bicyclists were nearly evenly split between men and women and tended to be young and highly educated. Most bicyclists agreed that bicycling for transport was comfortable (72.9%) but only a minority agreed that it was safe from traffic (28.0%). Most participants agreed that bicycling in their neighbourhood was well regarded (49.5%) and common

(41.9%). About one in ten bicyclists experienced one or more crashes (10.2%) during their time in the study.

Table 14. Baseline characteristics of the bicyclists the PASTA study

Variable	
No. Participants	4180
Months Observed (median [IQR])	7.3 [2.2, 16.6]
Follow-ups Completed (median [IQR])	7.0 [3.0, 17.0]
Total Exposure in Hours (median [IQR])	36.0 [10.5, 114.7]
Average Exposure in Minutes Per Day (median [IQR])	16.3 [6.4, 31.1]
Crashes per person (%)	
0	3752 (89.8)
>=1	428 (10.2)
City (%)	
Antwerp	891 (21.3)
Barcelona	523 (12.5)
London	355 (8.5)
Örebro	590 (14.1)
Roma	594 (14.2)
Vienna	637 (15.2)
Zürich	590 (14.1)
Cycling Frequency at baseline (%)	
Never	138 (3.3)
Less than once per month	247 (5.9)
on 1-3 days per month	370 (8.9)
on 1-3 days per week	893 (21.4)
Daily or almost daily	2522 (60.3)
Missing	10 (0.2)
Age (%)	
16-25 years	483 (11.6)
26-35 years	1313 (31.4)
36-45 years	1049 (25.1)
46-55 years	840 (20.1)
56-65 years	401 (9.6)
65+ years	93 (2.2)
Missing	1 (<0.1)
Gender (%)	
Women	2066 (49.4)
Men	2114 (50.6)
BMI (%)	
<25	2994 (71.6)
25-30	951 (22.8)
30+	216 (5.2)

Missing	19 (0.5)
Education (%)	
No degree/primary education	49 (1.2)
Secondary/further education	930 (22.2)
Higher/university education	3193 (76.4)
Missing	8 (0.2)
Income (%)	
< € 10,000	314 (7.5)
€ 10,000 - € 24,999	628 (15.0)
€ 25,000 - € 49,999	1232 (29.5)
€ 50,000 - € 74,999	799 (19.1)
€ 75,000 - € 99,999	309 (7.4)
€ 100,000 - € 150,000	171 (4.1)
€ >150,000	64 (1.5)
Missing	663 (15.9)
Drivers License (%)	
Yes	3812 (91.2)
No	368 (8.8)
Have Children (%)	
Yes	1460 (34.9)
No	2567 (61.4)
Missing	153 (3.7)
Cycling for transport is comfortable* (%)	
Agree	3047 (72.9)
Neutral	729 (17.4)
Disagree	404 (9.7)
Cycling for transport is safe from traffic* (%)	
Agree	1172 (28.0)
Neutral	1100 (26.3)
Disagree	1908 (45.6)
In my neighbourhood cycling is well regarded* (%)	
Agree	2070 (49.5)
Neutral	1306 (31.2)
Disagree	804 (19.2)
In my neighbourhood cycling is common* (%)	
Agree	1750 (41.9)
Neutral	1194 (28.6)
Disagree	1236 (29.6)
Building density of residence (m^2/km^2), 300 m buffer (%)	
Quintile 1: [0 – 111,080]	823 (19.7)
Quintile 2: (111,080 – 195,283]	823 (19.7)
Quintile 3: (195,283 – 285,409]	823 (19.7)
Quintile 4: (285,409 – 418,375]	823 (19.7)
Quintile 5: (418,375 – 659,249]	823 (19.7)

Missing	65 (1.6)
Bike lane density of residence (m/km²), 300 m buffer (%)	
Quintile 1: [0]	988 (23.6)
Quintile 2: [0.031 – 1,530]	622 (14.9)
Quintile 3: (1,530 – 3,240]	621 (14.9)
Quintile 4: (3,240 – 5,700]	621 (14.9)
Quintile 5: (5,700– 20,400]	621 (14.9)
Missing	707 (16.9)
Street density of residence (m/km²), 300 m buffer (%)	
Quintile 1: [570 – 11,600]	824 (19.7)
Quintile 2: (11,600 – 15,700]	824 (19.7)
Quintile 3: (15,700 – 19,300]	824 (19.7)
Quintile 4: (19,300 – 23,300]	824 (19.7)
Quintile 5: (23,300 – 49,000]	824 (19.7)
Missing	60 (1.4)
NDVI of residence, 300 m buffer (%)	
Quintile 1: [0.122 – 0.271]	828 (19.8)
Quintile 2: (0.271 – 0.360]	826 (19.8)
Quintile 3: (0.360 – 0.474]	815 (19.5)
Quintile 4: (0.474 – 0.595]	828 (19.8)
Quintile 5: (0.595 – 0.874]	818 (19.6)
Missing	65 (1.6)

*Collapsed from 5 category Likert scale, IQR: Interquartile range

5.3.1. Crash characteristics

Of the 4,180 bicyclists in our study, 428 reported a total of 535 crashes (Table 15). Of these, two in five (40.4%) were falls (single bicycle crashes). The remaining crashes involved another road user, either a motor vehicle (35.3%), another bicyclist (17.4%) or a pedestrian (6.9%). Just over half of all crashes resulted in an injury (considered to be a bruise or cramp at minimum) (55.3%). Just over a quarter of crashes required any medical treatment (26.5%), and there were just four hospitalizations (0.7%). Most crashes went unreported in official sources: only 3.9% were reported as recorded by police and 9.3% were reported to an insurance company.

Table 15. Crash characteristics including involvement, injury, and medical treatment

	N Crashes (%)
Total	535 (100)
Bicycling Crash Types	
Fall	216 (40.4)

	N Crashes (%)
Crash with motor vehicle	189 (35.3)
Crash with other bicyclist	93 (17.4)
Crash with pedestrian	37 (6.9)
Injury[a]	
Yes	296 (55.3)
No	239 (44.7)
Medical Treatment	
No	393 (73.5)
Yes, I treated it myself or by another person (no doctor).	80 (15.0)
Yes, I went to a doctor or hospital myself.	47 (8.8)
Yes, from an ambulance at the location of the crash.	0 (0.0)
Yes, I was brought to the hospital for medical treatment but could go home the same day.	11 (2.1)
Yes, I was hospitalized ≥ 1 night.	4 (0.7)
Official police report	
Yes, the police showed up and they officially reported the crash	16 (3.0)
Yes, I reported the crash later to the police (in the station, by phone or online).	5 (0.9)
No, the police showed up but they didn't officially report the crash.	7 (1.3)
No, the police didn't show up and the crash was not officially reported	493 (92.1)
Don't know	14 (2.6)
Reported to insurance company	
Yes	50 (9.3)
No	466 (87.1)
Don't know	19 (3.8)

[a]Defined as physical injury resulting from the crash including bruises or cramps

5.3.2. Crash rates

Across the seven cities the crash rate was 137.9 crashes per 100,000 hours of bicycling (95% CI, 125.2 - 152.1) or 1 crash every 725 hours. London had the highest crash rate with 220.8 crashes per 100,000 hours, while Örebro had the lowest crash rate of 32.8 crashes per 100,000 hours (Table 16, Figure 16). Zürich had the second highest crash rate of 188.6 per 100,000 hours followed by Vienna, Rome, Antwerp and Barcelona with rates of 154.3, 144.9, 136.1 and 134.1, respectively (Table 16, Figure 16). The high crash rate in London was largely driven by its greater number of crashes which involved a motor-vehicle relative to the other PASTA cities, while falls appeared to be a greater issue in Rome compared to other crash types (Figure 17B). When stratifying by whether medical treatment was required or not, there was relatively little difference in the crash rates between cities with the exception of Örebro which had a substantially lower rate requiring treatment (Figure 17C). The overall differences in crash rates between cities appear to be largely driven by crashes that did not require any medical treatment (Figure 17C).

We also examined total crash rates by sociodemographic, social and built environment characteristics of bicyclists. Crash rates decreased with increasing age category, increased with higher BMI category and were higher for men compared to women (Table 16). Crash rates tended to be highest for participants who disagreed that bicycling for travel was comfortable, well regarded in their neighbourhood or common (Table 16). Participants who lived in neighbourhoods with a higher density of bike lanes, higher NDVI or lower building density tended to have lower crash rates (Table 16).

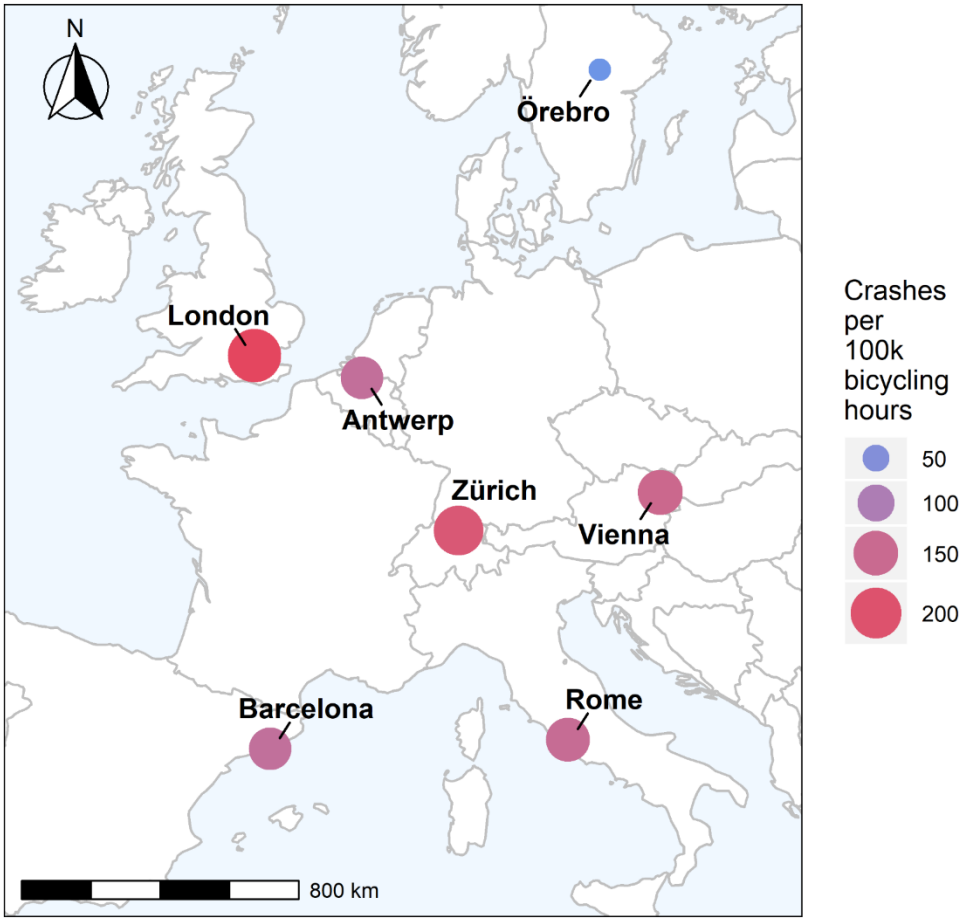

Figure 16. Map of crash rates by city

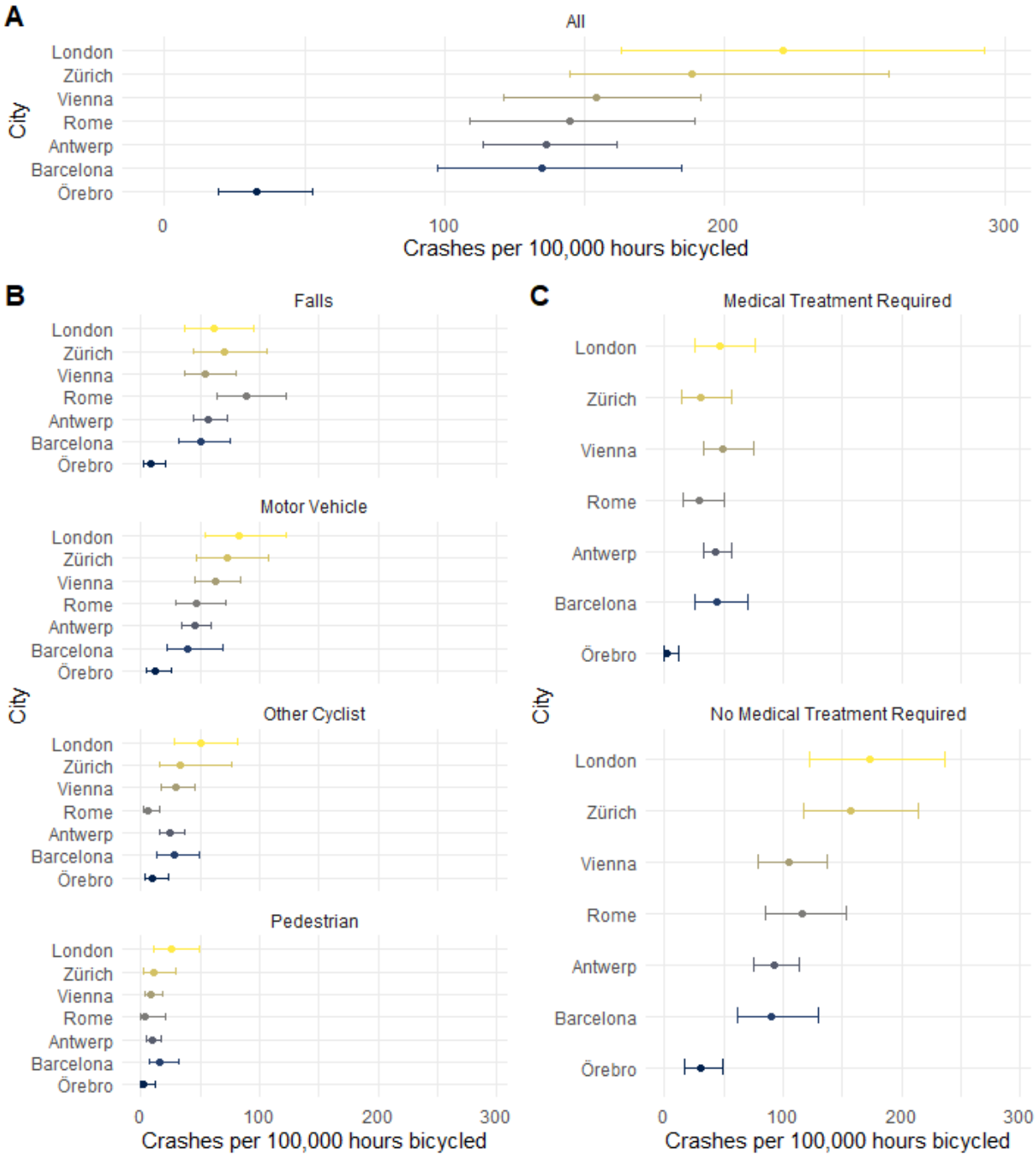

Figure 17. Crash rates by city for A) all crashes B) stratified by other road user involved in the crash and C) by injury severity

Table 16. Crash risk factors by city, sociodemographic, attitudinal, and neighbourhood characteristics.

Variable	Level	% of total n (4,180)	Total Exposure Hours	Total number of crashes	Crash Rate per 100,000 hours (95% CI)[a]	Crude Incident Rate Ratio (95% CI)[b]
Total		100.0	387,968	535	137.9 (125.2, 152.1)	
City	Antwerp	21.3	119,041	162	136.1 (115.6, 162.9)	Referencec
	Barcelona	12.5	43,084	58	134.6 (100.2, 180.7)	0.87 (0.63, 1.22)
	London	8.5	27,630	61	220.8 (164.6, 292.8)	**1.54 (1.09, 2.17)**
	Örebro	14.1	48,721	16	32.8 (19.5, 52.8)	**0.21 (0.13, 0.36)**
	Roma	14.2	51,767	75	144.9 (110.3, 188.6)	1.06 (0.78, 1.45)
	Vienna	15.2	62,198	96	154.3 (122.0, 194.6)	1.03 (0.77, 1.37)
	Zürich	14.1	35,529	67	188.6 (143.1, 256.2)	1.11 (0.80, 1.53)
Age (years)	16-25	11.6	32,140	56	174.2 (124.9, 238.0)	Reference
	26-35	31.4	115,659	167	144.4 (121.2, 172.3)	0.83 (0.59, 1.15)
	36-45	25.1	101,433	146	143.9 (118.4, 175.1)	0.87 (0.62, 1.23)
	46-55	20.1	89,817	117	130.3 (105.3, 157.2)	0.81 (0.57, 1.16)
	56-65	9.6	44,317	45	101.5 (73.8, 138.2)	0.73 (0.47, 1.13)
	65+	2.2	4,497	4	89.0 (20.8, 249.6)	0.53 (0.18, 1.56)
	Missing	0	105	0		
BMI	<25	71.6	277,398	369	133.0 (118.4, 149.9)	Reference
	25-30	22.8	90,476	130	143.7 (114.9, 177.1)	1.19 (0.95, 1.49)
	30+	5.2	18,466	34	184.1 (126.3, 266.9)	1.39 (0.93, 2.09)
	Missing	0.5	1,628	2	122.8 (0.0, 267.6)	
Gender	Women	49.4	166,862	187	112.1 (95.0, 132.5)	Reference
	Men	50.6	221,107	348	157.4 (140.1, 178.5)	**1.42 (1.16, 1.73)**
Education	No degree/Primary	1.2	5,547	6	108.2 (35.7, 216.5)	Reference
	Secondary/further	22.2	79,233	116	146.4 (118.0, 184.5)	1.06 (0.41, 2.76)
	Higher/university	76.4	302,491	410	135.5 (121.7, 151.2)	0.96 (0.38, 2.43)
	Missing	0.2	697	3	430.2 (0.0, 2110.6)	

Variable	Level	% of total n (4,180)	Total Exposure Hours	Total number of crashes	Crash Rate per 100,000 hours (95% CI)[a]	Crude Incident Rate Ratio (95% CI)[b]
Driver's License	Yes	91.2	356,032	483	135.7 (122.5, 150.3)	Reference
	No	8.8	31,936	52	162.8 (117.0, 222.7)	1.16 (0.84, 1.60)
Have Children under 18	Yes	34.9	143,338	176	122.8 (104.3, 145.3)	Reference
	No	61.4	67,299	335	143.2 (126.0, 162.1)	1.09 (0.89, 1.34)
	Missing	3.7	10,664	24	225 (133.8, 360.2)	
Bicycling 'for travel' is comfortable	Agree	72.9	316,507	420	132.7 (119.0, 148.5)	Reference
	Neutral	17.4	53,633	79	147.3 (114.4, 191.9)	0.97 (0.74, 1.27)
	Disagree	9.7	17,828	36	201.9 (136.1, 293.6)	1.17 (0.80, 1.72)
Bicycling 'for travel' is safe (with regards to traffic)	Agree	28	130,021	144	110.8 (91.7, 133.0)	Reference
	Neutral	26.3	109,699	160	145.9 (120.8, 175.5)	1.16 (0.90, 1.49)
	Disagree	45.6	148,248	231	155.8 (134.3, 178.6)	1.10 (0.87, 1.39)
In my neighbourhood is bicycling is well regarded	Agree	49.5	202,584	248	122.4 (106.4, 141.0)	Reference
	Neutral	31.2	108,480	149	137.4 (113.8, 165.8)	1.16 (0.92, 1.46)
	Disagree	19.2	76,904	138	179.4 (146.9, 219.0)	**1.33 (1.03, 1.73)**
In my neighbourhood is bicycling is common	Agree	41.9	159,337	201	126.1 (107.6, 145.9)	Reference
	Neutral	28.6	108,046	137	126.8 (105.7, 151.3)	1.03 (0.81, 1.32)
	Disagree	29.6	120,585	197	163.4 (135.9, 194.2)	1.26 (0.99, 1.62)
Building density (m^2/km^2) within 300 m of residential location	[0 – 111,080]	19.7	82,398	86	104.4 (83.6, 128.0)	Reference
	(111,080 – 195,283]	19.7	83,056	103	124.0 (99.6, 154.2)	0.88 (0.63, 1.22)
	(195,283 – 285,409]	19.7	70,103	92	131.2 (101.3, 169.9)	0.76 (0.54, 1.07)
	(285,409 – 418,375]	19.7	71,501	122	170.6 (138.8, 207.8)	1.09 (0.79, 1.52)
	(418,375 – 659,249]	19.7	75,708	124	163.8 (132.6, 201.3)	1.20 (0.84, 1.73)
	Missing	1.6	5,203	8	153.7 (60.9, 345.0)	
	[0]	23.6	91,284	141	154.5 (127.2, 186.3)	Reference
	[0.031 – 1,530]	14.9	59,303	96	161.9 (124.1, 210.5)	1.03 (0.75, 1.42)

Variable	Level	% of total n (4,180)	Total Exposure Hours	Total number of crashes	Crash Rate per 100,000 hours (95% CI)[a]	Crude Incident Rate Ratio (95% CI)[b]
Bike lane density (m/km^2) within 300 m of residential location	(1,530 – 3,240]	14.9	55,515	80	144.1 (113.0, 180.3)	0.95 (0.68, 1.32)
	(3,240 – 5,700]	14.9	52,456	67	127.7 (96.6, 171.0)	0.97 (0.67, 1.41)
	(5,700– 20,400]	14.9	58,913	57	96.8 (70.8, 129.1)	0.84 (0.58, 1.21)
	Missing	16.9	70,495	94	133.3 (107.5, 163.4)	
Street density (m/km2) within 300 m of residential location	[570 – 11,600]	19.7	92273	98	106.2 (84.2, 132.4)	Reference
	(11,600 – 15,700]	19.7	79,924	99	123.9 (99.0, 153.0)	0.98 (0.71, 1.34)
	(15,700 – 19,300]	19.7	71,207	97	136.2 (108.5, 168.2)	0.98 (0.72, 1.37
	(19,300 – 23,300]	19.7	79,924	129	178.3 (144.5, 219.8	1.26 (0.92, 1.72)
	(23,300 – 49,000]	19.7	71,207	105	155.8 (124.9, 196.9)	1.19 (0.84, 1.70)
	Missing	1.4	72,348	7	145.4 (55.4, 349.7)	
NDVI within 300 m of home location	[0.122 – 0.271]	19.8	72,482	115	158.7 (126.1, 197.4)	Reference
	(0.271 – 0.360]	19.8	72,674	122	167.9 (137.0, 201.5)	0.90 (0.66, 1.22)
	(0.360 – 0.474]	19.5	70,742	108	152.7 (121.6, 194.1)	0.82 (0.59, 1.15)
	(0.474 – 0.595]	19.8	77,777	83	106.7 (83.8, 134.1)	**0.65 (0.45, 0.94)**
	(0.595 – 0.874]	19.6	89,194	100	112.1 (89.8, 136.5)	0.75 (0.51, 1.09)
	Missing	1.6	5,099	7	137.3 (50.0, 323.8)	

[a] Confidence intervals calculated using a bias corrected and accelerated bootstrap method (BCa) with 5,000 replications

[b] Adjusted for average bicycling exposure per month, number of months participated in the study and city

[c] Adjusted for average bicycling exposure per month, number of months participated in the study

Bold Indicates significance at 95% confidence. NDVI = Normalized Difference Vegetation Index.

5.3.3. Crash risk factors

In our parsimonious model, we identified average exposure per month, months of participation, city, gender, perceiving that bicycling is well regarded in their neighbourhood, and building density as important factors affecting crash risk. The final pooled parsimonious model suggests a non-linear relationship between individual bicycling exposure and number of crashes:

$$\hat{E}(Y) = 0.0005 \times EXP_{MonthlyAvg}^{0.58} \times T_{Months}^{0.80} \qquad (4)$$

The exponents for *EXP* and *T* are less than 1, thus while the number of expected crashes for a participant increase with both increased bicycling per month and number of months participated, the risk of a crash (expected crashes per unit of exposure) decreases. In other words crash risk is lower for participants who cycle more frequently as well as those who spend more time participating in the study. The effects are of differing strength, with attrition bias being weaker than the effect of exposure per month.

In the parsimonious model, additional risk factors for a crash included: being a man, living in a neighbourhood of very high building density, and perceiving that bicycling was not well regarded in one's neighbourhood (Figure 18). London and Örebro stood out as the most and least risky cities, respectively. Relative to Antwerp, and holding exposure and other individual factors constant, the crash risk for a participant in London was 1.58 times higher, while in Örebro it was less than a quarter as risky (Figure 18). When we ran a sensitivity analysis with only observations with complete data for all variables, we found very similar results.

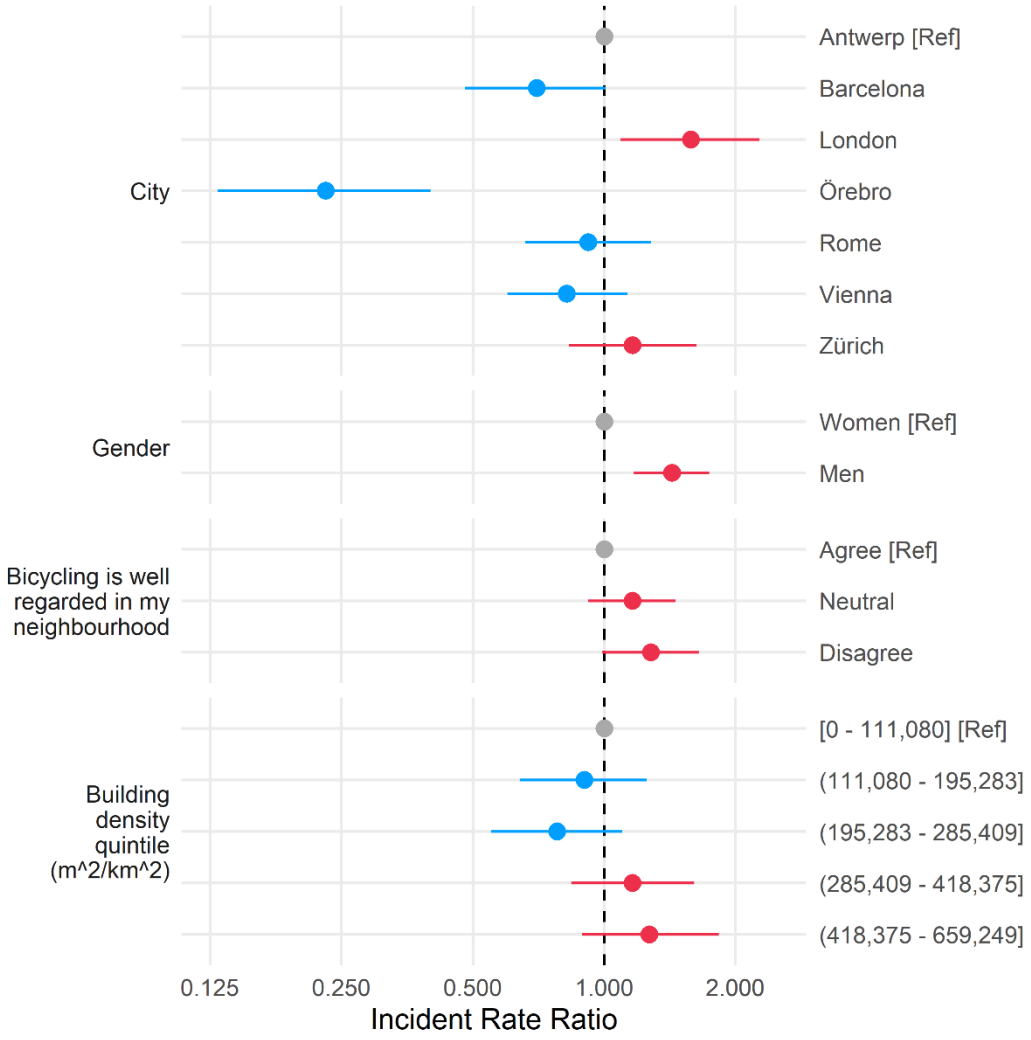

Figure 18. **Adjusted incident rate ratio (IRR) for the variables included in the stepwise model building. The IRR's represent the ratio of expected crashes for a given participant relative to the reference category, adjusting for average exposure per month, number of months participated in addition to the selected variables in the plot (City, Gender, Bicycling well regarded in neighbourhood, and Building density quintile). Holding average exposure and time constant, participants with the highest number of expected crashes are those that live in London, are men, perceive that bicycling in their neighbourhood is not well regarded, and live in a neighbourhood within the highest quintile of building density.**

5.4. Discussion

This study analysed prospectively collected crash data in a cohort of bicyclists across seven geographically diverse European cities, one of the largest studies of its

kind. Of the seven PASTA cities, we found considerable variation in crash risk. Within cities, risk of a crash was highest for less frequent bicyclists, men, those who perceive bicycling to not be well regarded in their neighbourhood, and those who live in areas of very high building density. We show that crash risks differ by city, neighbourhood and individual level factors.

Our findings, like those in the literature, indicate that crash rates vary substantially across cities. Overall, the average crash rate was 137.9 crashes per 100,000 hours, from a low of 32.8 crashes per 100,000 hours in Örebro to nearly 7 times higher in London. There are only two other studies which collected crash and duration-based exposure data simultaneously; one in New South Wales, Australia (Poulos *et al.* 2015a) and one in Belgium (de Geus *et al.* 2012). The Australian cohort had an incidence rate of 606.0 crashes per 100,000 hours (Poulos *et al.* 2015a), while the Belgian cohort had an rate of 89.6 per 100,000 hours (de Geus *et al.* 2012). Difference in rates between these studies may be due to differences in the samples of bicyclists, inclusion criteria for inclusion of crashes, methods in calculating and/or collecting exposure, as well as actual differences in the objective risk of a bicycling crash between these areas. To illustrate, the Australian study included non-injury crashes and a substantial proportion of the cohort (40.1%) were “mainly recreational” bicyclists (Poulos *et al.* 2015a). The Belgian cohort did not include any recreational bicycling and excluded non-injury crashes (de Geus *et al.* 2012). The discrepancy between the crash rate we estimated in Antwerp (136.1 per 100,000 hours) and the crash rate of 75.2 per 100,000 hours for Flanders (a larger region of Belgium in which Antwerp is located) may be partly explained by the crash inclusion criteria. In our study the crash rate for Antwerp drops to 74.8 crashes per 100,000 hours for crashes that resulted in injury and to 43.7 crashes per 100,000 for crashes that required any medical treatment.

When interpreting the differences we found in crash rates and/or adjusted crash risk between PASTA cities, the role of self selection should be considered (Castro *et al.* 2018). Here, self-selection refers to the idea that due to unsafe bicycling conditions, many people may choose not to bicycle at all. Thus, the participants who choose to bicycle in these unsafe conditions may be overly brave and/or exceptionally skillful, the latter possibly having a moderating effect on crash risk (Castro *et al.* 2018). As such, bicycling mode share provides important contextual information when interpreting differences between large geographic units. PASTA cities were selected in part to

introduce variability in the samples in terms of culture, density, built environments, policies, and climates, and thereby cover a wide range of conditions related to bicyclist safety (Dons *et al.* 2015). Our parsimonious model (which adjusted for other factors including exposure, time spent in the study, gender, social environment and neighbourhood building density) indicated that Örebro was the safest city for bicycling, London the riskiest, and the remaining cities similar in terms of safety. Notably, Örebro was the least risky city and has the highest bicycling mode share of our seven cities (25%). Antwerp was riskier than Barcelona, and was similar in risk to Rome, Vienna, and Zürich. Antwerp's population bicycles between 3.8 to 23 times more than Barcelona, Rome, Vienna or Zürich, which suggests that self-selection may play a role in risk differences. For example, Rome is known for highly challenging traffic conditions, reflected in the least extensive bicycling network amongst the seven cities, and the lowest bicycle mode share (1%) (Mueller *et al.* 2018). Despite this, our model suggests a similar level of overall crash risk between participants in Antwerp and Rome. These results should be interpreted with some caution, as they reflected a definition of crashes that include those that resulted in no medical treatment. When we excluded crashes that did not result in an injury that required medical treatment, the differences between cities were much smaller, with the exception that Orebro was still far safer.

Individual level bicyclist crash risk is a complex phenomenon comprised of interactions between individuals and their road environment in both space and time (Schepers *et al.* 2014). At the individual level, we found that crash risks varied based on frequency of bicycling. Those that reported higher bicycling were at a lower risk, compared to those that reported lower rates of bicycling. The non-linear relationship between average bicycling per month and number of expected crashes suggest a "safety in exposure" effect, such as safety from being a more experienced bicyclist. This is consistent with the "safety in numbers" effect observed at aggregated spatial units (Jacobsen 2003, Elvik and Bjørnskau 2017), suggesting an individual level component to this phenomenon. The "safety in numbers" effect has been attributed to behavioural aspects, such as drivers being more used to bicyclists in high bicycling environments, as well as structural aspects, such as safer bicycling infrastructure attracting higher numbers of bicyclists (Götschi *et al.* 2016). Our findings suggest that one contributing factor to "safety in numbers" might be a lower number of inexperienced or infrequent

bicyclists and/or the improvement of safety-relevant bicycling skills with increasing experience/frequency (Elvik and Bjørnskau 2017, Fyhri *et al.* 2017).

Previous research has also found differences in crash risks between different sociodemographic groups, such as between men and women or older and younger adults (Vanparijs *et al.* 2015). In prospective studies, the relationship between gender and crash risk has been mixed, with women having higher crash rates in Belgian (Degraeuwe *et al.* 2015) and Australian cohorts (Poulos *et al.* 2015a), but lower crash rates in a New Zealand cohort (although not statistically significant) (Tin Tin *et al.* 2013a). Women have also been found to be at higher risk for serious or fatal injuries while bicycling using the bike share scheme of London (Woodcock *et al.* 2014), but have similar risks across the United Kingdom (Aldred and Dales 2017). In our study, our parsimonious model suggests that men had a crash risk 1.43 times higher than women. These same cohorts also had mixed results concerning the relationship between age and crash risk, with one study finding that the risk of a minor crash decreases with age (Degraeuwe *et al.* 2015), another that it is lower for the youngest and oldest age groups (Poulos *et al.* 2015a), and another that the directionality depends on whether the collision occurred on-street (risk increases with age) or with a motor vehicle (risk decreases with age) (Tin Tin *et al.* 2013a). In this study we observed that crash risk was lower amongst older bicyclists, but the trend was not statistically significant. The overall sample of PASTA participants (including non-bicyclists) were broadly representative of gender distribution, but tended to be relatively younger compared to city census data (Gaupp-Berghausen *et al.* 2019).

We can only speculate on the reasons behind why certain sociodemographic groups are lower risk than others, but we suggest lower risk is an association between belonging to a given sociodemographic group and a tendency to cycle at lower speeds, and/or engage in fewer risky behaviours (e.g., cycle in safer areas and/or cycle more cautiously). For example, our finding that women and older adults were at lower risk for a crash relative to men and younger adults, may reflect the fact women have been found to cycle at lower speeds than men (Aldred and Crosweller 2015) and have a stronger preference towards using safer infrastructure than men (Aldred, Elliott, *et al.* 2016). Similarly older adults may be more cautious when bicycling compared to younger adults (Bernhoft and Carstensen 2008).

A new contribution of this research is an inquiry on the association between differences in social environment and crash risk. We found that individual perceptions of social norms around bicycling were associated with crash risk, where those who agreed that bicycling was a well-regarded mode of transport in their neighborhood were at lower risk for a crash than those that were neutral (1.16 times higher) or disagreed (1.28 times higher risk). The perception question was asked at baseline, so preceded any reported crashes. We suggest this variable may be in part capturing different built environment conditions, where those participants who think bicycling is well regarded may live and travel in safer areas for bicyclists, within their respective cities. A part of this may also be the safety in numbers effect, where a higher level agreement corresponds to an area with more bicyclists due to the presumably more supportive social environment for bicycling.

Prospective studies such as this one indicate that bicyclist crashes (including non-injury crashes) are more common than would be suggested by more conventional analyses of police or insurance data and travel surveys (Elvik and Mysen 1999, Langley *et al.* 2003, Amoros *et al.* 2006, Veisten *et al.* 2007, de Geus *et al.* 2012, Juhra *et al.* 2012, Watson *et al.* 2015, Winters and Branion-Calles 2017). In this study, we found that on average across the cities, one crash occurs for every 725 hours bicycled. In contrast, a study in France that combined police recorded crashes and travel survey data found 1 crash per 93,023 hours of bicycling (Blaizot *et al.* 2013). Only 3.9% of crashes reported to PASTA were recorded by police, at a rate of 1 per 18,475 hours of bicycling. Of course, police, insurance and hospital data capture more severe (less frequent) events, resulting in lower rates of crashes (Elvik and Mysen 1999, Amoros *et al.* 2006, Veisten *et al.* 2007, Juhra *et al.* 2012, Blaizot *et al.* 2013, Winters and Branion-Calles 2017). While less severe crashes are under-reported in police records, it is likely more severe events are under-reported in the PASTA dataset as it is not possible to self-report a fatality and we cannot ascertain if a participant has dropped out due to severe injury. However, non-injury events may not result in direct healthcare costs, but have important implications for bicycling in terms of perceived safety, and potentially future uptake (Aldred and Crosweller 2015, Sanders 2015, Aldred, Elliott, *et al.* 2016), which consequently may have costs from non-materialized health benefits from prevented bicycling.

Our study has several strengths and limitations. The prospective design enabled the collection of detailed exposure data, as well as data on a range of different crash

types including falls and non-injury events, for a large number of individuals. The data collection was consistent across cities, enabling more valid comparisons. Furthermore, the study design allowed for multivariable analysis to assess impacts of individual factors on crash risks, a refinement over what can be done with aggregate data. The relationships we found between the selected explanatory variables and crash risk should not be interpreted as causal. The extent to which our sample of bicyclists are representative of the broader bicycling population is not known, and results should be interpreted with some caution. PASTA participants are more educated and younger than the general population (Gaupp-Berghausen *et al.* 2019), although recruitment specifically oversampled bicyclists, so there may be better representation of the bicycling populations. The fact that our results show a lower risk of a crash with increasing time in the study may indicate some bias from loss to follow-up. There may be some reporting bias in crashes, although the repeated surveys (as little as 2 weeks apart) was designed to limit recall issues. This study primarily collected non-injury crashes and did not observe many serious injuries and is not able to record fatalities. We did not have traffic condition data to further explain neighbourhood level risks, and limitations to statistical power did not warrant further investigations of crash location attributes. The objective GIS measures of built environment (bike lane density, street density, building density, NDVI) only represent conditions within 300m of a participant's residence and may not reflect the route conditions in which participants typically ride, especially for longer trips. Spatially resolved exposure data would allow for further important analyses, such as risks associated with specific route characteristics, but at the beginning of PASTA large scale collection of spatially resolved route data from participants was not feasible due to limitations of available tracking apps at the time. Passive detection of bicycling routes through mobile tracking apps (Geurs *et al.* 2015) could enable the widespread collection of spatially resolved exposure data and more detailed investigation of policy relevant risk factors in future studies.

5.5. Conclusions

The PASTA design provides comparable crash risks for bicyclists, adjusted for differences in age and gender and other variables, across the diverse set of seven European cities. The large variations in crash risks indicate that bicyclists' safety can still be improved considerably. Longitudinal study designs can provide important insights into

crash risk factors within cities, neighbourhoods, and population groups, in particular for minor crashes. Future research should focus on representative datasets that can integrate the most policy relevant crash risk factors such as route infrastructure and exposure to motorized modes, with individual characteristics and perceptions, benefitting from rapid progress in the collection of spatially resolved exposure data.

Chapter 6.

Conclusions

Increased bicycling for transport has many potential benefits for society - especially if it replaces motor vehicle trips- including improved health outcomes and reduced fossil fuel emissions. One of the main factors preventing greater uptake of bicycling is concerns regarding the safety, especially in cities that are historically dominated by motor vehicle use. For policy makers interested in making bicycling safer within their jurisdictions, there is often a lack of adequate information available to guide their decisions. There remain gaps in our understanding of how to support bicycling as both a comfortable and safe mode of transportation, which has motivated researchers to find new and innovative means to collect relevant data. In particular, traditional sources of bicycling collision data such as police and insurance databases suffer from underreporting and bias, and a lack of information regarding characteristics of the individuals involved in a crash. As a result of the limitations of traditional data sources, and advances in mobile technology, crowdsourced data as well as large scale surveys have been used to try and supplement these data. In this thesis, I used both crowdsourced data and large-scale surveys, representing information on locations and populations over 14 municipalities, 9 countries and two continents. Survey design and data collection methods are often overlooked components of bicycling safety research. In this thesis I explored different aspects of bicycling safety data, and provided contributions to different dimensions of bicycling safety, ranging from an evaluation of bicycling safety data collection methods (Chapter 2 and 4) to applied analyses of identifying correlates of perceived and objective bicycling safety (Chapter 3 and 5).

Specifically, the chapters in this thesis address gaps in our understanding of (i) biases in crowdsourced bicycling safety data (ii) the relationship between personal characteristics, infrastructure, and overall perceived bicycling risk (iii) the impacts of survey design on measurements of bicycling, and (iv) differences in crash risk between cyclists with different sociodemographic characteristics, social environments (including attitudes and social norms), and neighbourhood-built environment features. The chapters are standalone scientific publications, and as a result, the conclusions and implications of results are discussed within each chapter. Below we summarize the

contributions of this body of work to the literature (and practice), discuss the limitations of this work, and directions for overall research.

6.1. Findings

There is little knowledge regarding the nature of systematic bias in crowdsourced safety data, in terms of who are reporting certain types of incidents, what types of incidents, and in what which built environment and/or traffic conditions, and how these biases may be different from official sources such as police or insurance data. In Chapter 2 I investigated the information content of this innovative and largely untested source of road safety data. This study represents one of the first attempts to systematically examine the information content of a novel and increasingly popular method of collecting road safety data. With this chapter I demonstrated there are distinct differences in the personal, trip and built environment conditions in which near misses and collisions are reported to BikeMaps.org, as well as distinct differences in collisions reported to BikeMaps.org compared to collisions reported to ICBC. I found higher numbers of crowdsourced reports of near misses relative to collisions for commute trips, interactions with motor vehicles, and in locations without bicycle-specific facilities. I also demonstrated that there were distinct differences in patterns in terms of where and when collisions are reported to BikeMaps.org compared to official insurance reports. I found that relative to insurance reports, crowdsourced collision reports were associated with peak traffic hours, non-intersection locations, and locations where bicycle facilities were present.

In the bicycling safety literature, there are gaps in the research regarding our understanding of whether existing infrastructure may be associated with bicyclists' perceptions of overall bicycling safety within their area, rather than their perception of specific infrastructure designs. In Chapter 3 I contribute to the literature regarding the association between the built environment and overall perceived bicycling safety by demonstrating that perceptions of overall bicycling safety are influenced by the availability of bicycling infrastructure, even after adjustment for bicycling exposure and sociodemographic characteristics. The more bicycling specific infrastructure close to a bicyclist's home, the greater odds that they perceive bicycling in their city to be safe. I also found bicyclists who were male, younger, lower income, had young children, a high-school education, and bicycle more frequently were more likely to perceive bicycling in

their city to be safe. The findings suggest that increasing the availability of bicycle facilities by expanding bicycling networks may result in increases in perceptions of bicycling safety for existing bicyclists, and that individual characteristics also play a substantial role in bicycling safety perceptions

In the final two chapters (Chapter 4 and 5) I used the same longitudinal dataset which collected data for over 10,000 individuals across seven European cities, to explore two distinct research questions regarding study design and factors affecting crash risk. In Chapter 4, I quantified the impacts of measuring bicycling once (cross-sectional approach) versus multiple times (longitudinal approach) on sample size, participation bias, and outcome measurement, providing vital information to researchers and practitioners who wish to conduct their own surveys. A novel question I studied was the extent to which these study designs resulted in biased measurements of long-term bicycling. I demonstrated that relative to a longitudinal approach, the cross-sectional approach provided a larger sample size and slightly better representation of certain sociodemographic groups, with worse estimates of long-term bicycling behaviour. The longitudinal approach suffered from participation bias, especially the drop-out of more frequent bicyclists. The cross-sectional approach underestimated the proportion of the population that bicycled, as it captured 'typical' behaviour rather than 7-day recall. The magnitude and directionality of the difference between typical weekly (cross-sectional approach) and the average 7-day recall (longitudinal approach) varied depending on how much bicycling was initially reported. Results from this chapter can provide researchers or practitioners practical knowledge for making informed decisions in their future survey designs.

Finally, with Chapter 5, I contributed to the bicyclist crash risk literature by exploring how individual crash risk is influenced by exposure, sociodemographic characteristics, social and built environment factors. Analysis of disaggregated individual-level crash risk factors for bicyclists, including detailed sociodemographic, social and built environment factors, are generally not available in the literature. In this chapter I used a large, disaggregated longitudinal dataset, where crashes and exposure were collected over time, and each individual provided detailed information regarding their sociodemographic characteristics and social environments. Furthermore, these participants' residences were geolocated, allowing for a crash risk model that integrated individual level characteristics with built environment indicators derived from spatial data.

Our results show that there are higher crash risks for less frequent bicyclists, men, those who perceive bicycling to not be well regarded in their neighbourhood, and those who live in areas of very high building density. There were also substantial differences in crash risks between cities, neighbourhoods, and population groups. I also showed that the differences in overall crash rates between cities were driven largely by crashes that did not require medical treatment and that involved motor-vehicles. These results provide novel information on how individual level factors may influence crash risk, while also demonstrating that there are multiple scales of influence, from individual level factors to city-wide.

6.2. Strengths and limitations

Improving the comfort and safety of bicycling is an important aspect of increasing bicycling levels within a given region. This work addressed a wide range of issues in bicycling safety, especially understanding and tapping into novel bicycling safety data sources. This can provide evidence for researchers and practitioners to better understand patterns they might see in crowdsourced data, the impact of survey design decisions on the measurement of bicycling, as well as understanding the association between different parts of the road system (city, built environment, and individual) with overall perceived safety and risk of a minor crash. A great strength of this thesis was that I was able to draw upon large and novel datasets that covered a wide variety of different built environment, climate, and social environment contexts. While each of the papers within this thesis has specific contributions, as a whole the thesis has two overarching contributions. First, it emphasizes the potential utility of crowdsourced data and population surveys to fill large gaps in bicycling safety data to answer applied questions regarding perceived safety and objective safety. Second, it highlights the importance of linking survey data to a geographic location to quantify objective measures of participants' built environments, as well as considering multiple scales (i.e. hierarchies) of influence on outcomes of interest.

While there were important contributions within each paper, a discussion of the limitations is essential to being able to be to interpret their findings. One of the main limitations facing the use of crowdsourced data in safety analyses are questions regarding which crashes get reported, which don't, and why (Ferster *et al.* 2018). My analysis in Chapter 1 provides clues as to how crashes reported to BikeMaps.org are

different from ICBC, but does not, however, directly quantify the overlap between the two databases because the datasets were from differing time periods and could not be linked. Furthermore, even if, at the time, ICBC data were available for a time period consistent with data collected from Bikemaps.org, publicly available ICBC data does not provide any details regarding the individuals involved in the crash, or the crash itself (e.g., gender of bicyclist), precluding the possibility matching a crash reported from that dataset to a crash reported to BikeMaps.org. As a result, it was not possible to provide definitive estimates of bias within each dataset by directly modelling the differences between crashes reported to BikeMaps.org and crashes reported to ICBC. In order to truly understand the bias in crowdsourced data the overlap with other crash datasets needs to be quantified.

While bicycling safety datasets are improving, there are still gaps. A consistent limitation across each of the chapters (with the exception of Chapter 4) is a lack of spatially resolved data for motor vehicle traffic. Motor vehicle traffic conditions contribute significantly to cycling safety outcomes, including objective and perceived safety (Jacobsen 2003, Chataway *et al.* 2014). The inclusion of estimates of motor vehicle traffic volume such as Average Annual Daily Traffic (AADT) as a variable for models within Chapter 1 (at the location of the incident), 2 and 5 (within the neighbourhood of the participants) would have fundamentally strengthened the results and provided key insights. In an ideal world, these models would, in addition to estimates of motor vehicle traffic, contain estimates of pedestrian and bicycling volumes at the location of incidents or within neighbourhoods of participants as well. Obtaining estimates of motor vehicle traffic flow such as AADT, requires extensive data collection efforts, as well as potentially complex methodologies, and are not consistently applied between different countries (Leduc 2008). Estimating equivalent traffic flows for other modes of transportation (e.g., Average Annual Bicycle Traffic) are even more challenging (El Esawey *et al.* 2015). As a result, spatially resolved traffic flow data are rarely publicly available in an immediately useable, consistent format, especially over multiple municipalities and countries.

One of the key data limitations for population survey data in road safety research in general, is that they don't provide data on *where* participants bicycle or crash. In a typical survey participants are asked questions that aim to measure how much they bicycle (e.g "in the last week how many days did you bicycle and how long did you bicycle on those days?") and whether they have been involved in any crashes. Surveys which primarily

aim to measure bicycling duration will result in a dataset with excellent information on how much an individual bicycles (their exposure) and the number of crashes they've experienced, but does not provide any information on *where* they bicycle (e.g., routes they use) or *where* they have crashed. Studies based on population survey data tend to be limited in their ability to understand differences in risk between specific built environment features such as different road designs, due to the fact that the location of where people crash, and where they bicycle, can only be mapped to the home of the individual (via postal code). To fully leverage the potential of population surveys in road safety research, providing a means for participants to map where in the road network they have bicycled and crashed, is essential.

Finally, the research outcomes in each of these chapters are cross-sectional and, as a result, all identified relationships must not be interpreted as causal. Though Chapters 3 and 4 are based on longitudinally collected datasets, they are aggregated to the level of the individual, and analysed in a cross-sectional manner. All findings must be interpreted in terms of statistical associations and cannot provide conclusive evidence of causality.

6.3. Directions and future research

In Canada, there is a distinct need for population surveys to estimate bicycling exposure and provide critical information for bicycling safety (Teschke *et al.* 2015). Many countries, such as the United States and the United Kingdom, have nationally representative trip diary surveys (Beck *et al.* 2007, Mindell *et al.* 2012, Aldred 2018) that are specifically designed to measure transportation habits over a short period of time (e.g 1 week). Canada does not conduct such a survey and as a result, research that seeks to understand risk factors or trends in safety over time have to rely on surveys not designed specifically to measure transportation habits (Teschke *et al.* 2015). A national travel diary survey would provide critical information regarding how much Canadians bicycle and would provide the basis for understanding patterns and trends in bicycling safety. The exposure data collected through a national travel survey could be used in bicycling safety research either as the denominator data in studies that conflate official sources of crash data (e.g., police, hospitals or insurance sources) with exposure data (Beck *et al.* 2007, Teschke *et al.* 2015, Scholes *et al.* 2018), or, in a disaggregated analysis where self-reported crashes are included in the travel diary itself (Aldred 2018). The use of the national travel survey in an aggregated analysis provides a consistent

benchmark for road safety within the country, by providing estimates of crash rates within various strata (e.g., age, gender, region, and whichever variables are common to both the crash data and the travel diary data). If the national travel diary also included questions regarding self-reported crashes, it would enable a disaggregated analysis, and would likely provide more detailed insight into crash risk factors not commonly available such as income level or having a disability (see Aldred, 2018). In lieu of such a national travel survey in Canada, there is opportunity for academics and researchers in Canada to design their own population surveys to fill this data gap, either through longitudinal or cross-sectional designs (Winters *et al.* 2018), although at best this will remain a fragmented picture of bicycling safety.

In general, improved data integration of bicycling safety datasets would provide numerous and fruitful research opportunities in this field, regardless of the jurisdiction being examined. The creation of a linked crash database for a given region of interest would have a variety of useful features, most immediately being that it would give a more comprehensive picture of how many crashes are occurring within a jurisdiction. The ideal linked database would involve matching individual crashes from the range of different crash databases available including police, hospital (both emergency and admissions), ambulance, insurance, crowdsourcing, and/or population surveys. The idea would be to match each record in each database based on the details such as individual characteristics of persons involved in the crash, time of day the crash occurred, the location of crash, etc. (Cryer *et al.* 2001, Clark 2004, Amoros *et al.* 2006, Watson *et al.* 2015). A linked database which integrates crowdsourced data represents a potential solution to the limitations of my analysis of the bias in crowdsourced data outlined in Chapter 2. Although I demonstrated that there were distinct differences in patterns in terms of where and when collisions are reported to BikeMaps.org compared to official insurance reports, I could not directly estimate how reporting to a given source would vary with different characteristics. A linked database would enable researchers to statistically model how likely a crash is to be reported to a given source based on the characteristics of the crash (e.g., time, location, conditions) and individuals involved (e.g., mode of transport, sociodemographic), thereby directly quantifying the bias in each source of data (Watson *et al.* 2015). A linked database that included crowdsourced crashes could enable researchers to provide more definitive answers to fundamental

questions regarding the role of crowdsourced safety data, such as who is more likely to report to crowdsourced data and in what circumstances.

In a similar fashion, future longitudinal studies of crashes could be improved by linking participants to other crash databases, such as police, hospital or insurance reports. This would allow for researchers to know whether any of the participants were involved in a crash that resulted in an injury that was too serious to report through the survey. The linking of these bicycling cohorts to other crash databases wold then allow for a greater ability to understand risk factors for crashes that are unlikely or impossible to self report such as non-fatal serious injuries and fatalities (Tin Tin *et al.* 2013a). This could also provide insight into whether the risk factors for minor crashes are similar or different to risk factors for more severe outcomes. This approach would generally only be useful for a large cohort, followed over a substantial period of time (e.g., several years), due to the fact that serious non-fatal and fatal crashes are rarer relative to minor crashes.

Additionally, future longitudinal studies of bicycling and crash risk could be improved with better methods for collecting exposure and self-reported crash data. In this thesis, I was only able to use exposure and/or crash data that was aggregated to the level of the individual, thereby indicating how many times each person crashed and/or how much they bicycled, but not where they crashed and/or bicycled. As a result, measures of built environment needed to be aggregated to the level of the individual based on where they lived (via postal codes), rather than where they actually bicycled. A longitudinal study that aimed to understand differences in crash risk between different populations of bicyclists would greatly benefit if the a-spatial survey data from participants (e.g., sociodemographic characteristics) could be linked to the spatial locations of where the participants bicycle (rather than just their home location), and, where they crashed. For example, trip-level analyses would be possible if a cohort study collected data on participants' trip routes and where, if any, crashes occurred. A trip-level analyses would provide improved insight into crash risk factors, over a person-level analyses, as it would allow for the incorporation of micro-scale covariates at the trip-level (e.g., route infrastructure used, weather conditions, time of day), in addition to person-level and neighbourhood level factors such as those I used in Chapter 5. This could then, for example, provide estimates of risk for specific route infrastructure types, adjusting for other trip-level factors (e.g., season, weather conditions etc.),

characteristics of the bicyclist (e.g., gender, age, comfort cycling, etc.) and the larger neighbourhood (e.g., average greenness, street density, etc.). This type of study would represent an improvement on the study in Chapter 5, by incorporating finer-resolution information on crash risk for bicyclists through space and time.

Similarly, a study that sought to examine the relationship between overall perceived risk and bicycling infrastructure, such as in Chapter 3, would also benefit from spatially enabled exposure data. In future studies, it would be useful to estimate how much a participant actually uses bicycling infrastructure and integrate that into models of perceived risk. This type of analysis would be able to answer questions regarding whether the *use* of bicycling infrastructure is associated with improved overall perceptions of bicycling safety, rather than whether the simple presence of it is associated with perceptions of bicycling safety.

The main limiting factor for collecting spatially resolved exposure data is a consideration of the trade-offs between the time and effort it takes for individuals to provide that data, and the ability of a study to collect a sufficient quantity of data to be able to detect significant relationships. While it is possible to allow survey participants to manually trace their trip routes on a web-mapping application as a part of a travel diary, such an endeavour is time consuming, and may introduce selection bias (e.g., participants with large numbers of trips may be filtered out) and reduce the sample size (Prelipcean *et al.* 2018). A potential solution would be to integrate surveys with passive detection of bicycling routes through mobile tracking apps, but there are currently ongoing issues with mode detection accuracy and privacy concerns (Geurs *et al.* 2015, Gonder *et al.* 2015, Prelipcean *et al.* 2018). Privacy concerns become more acute with increasingly precise locational information, and a study that seeks to track participants travel habits would need stringent protocols for de-identification and the secure processing of data (Gonder *et al.* 2015). Despite the challenges, spatially resolved exposure and crash data are a necessity to advance the use of longitudinal surveys in bicycling safety and would represent a substantial development in the field, given sufficient quantities of data can be collected.

6.4. Conclusion

The findings of my doctoral research reveal that there is great potential for the use of novel data from new mobile technology and web mapping platforms, either through anonymous crowdsourcing and/or survey techniques. Anonymized, place-based crowdsourced data can supplement traditional sources such as insurance reports and provide new insights into areas that are perceived to be high risk by bicyclists. Furthermore, analysis of large-scale web surveys that link individual survey data to measures of their built environment, demonstrate the importance in considering multiple scales of influence on perceived and objective bicycling risk. These analyses were particularly well placed to differentiate perceived and objective risk between different population groups. Finally, in this thesis I also demonstrate the importance of careful consideration of how exposure data should be collected and the impact that may have on subsequent analyses. Future bicycling safety research should focus on efficient means of collecting spatially enabled exposure data and integrating these data into subsequent analyses.

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