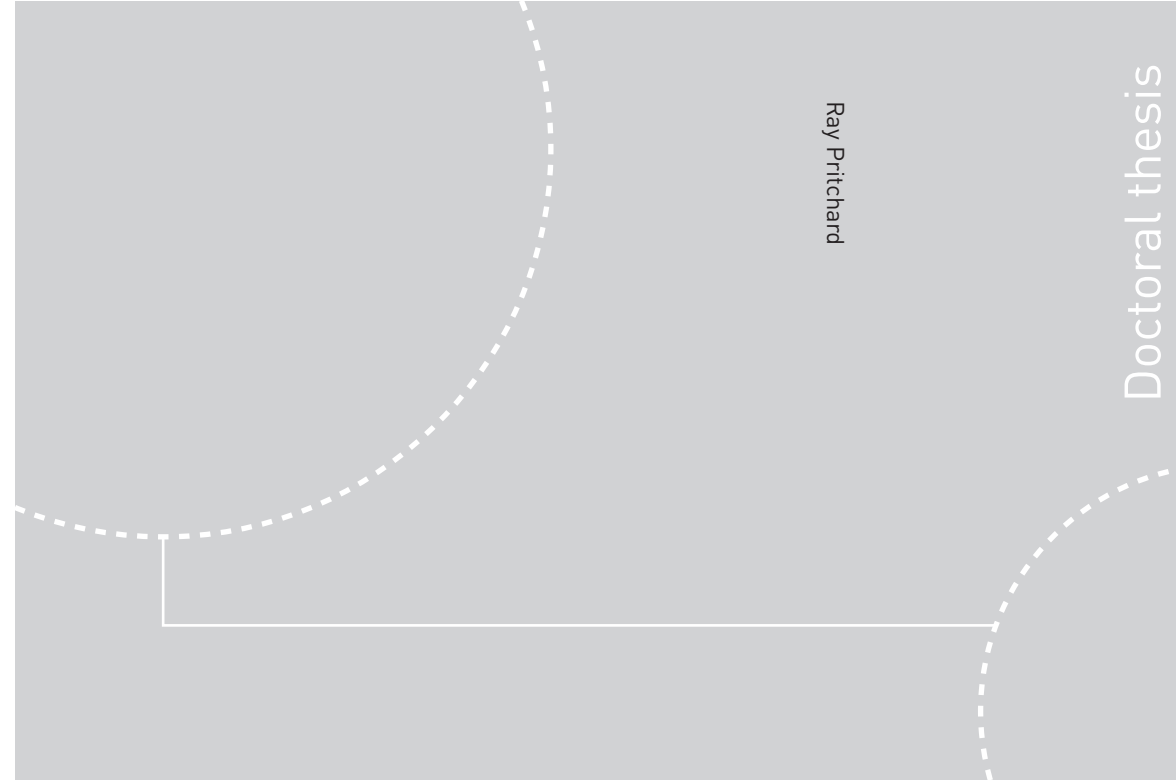


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Thesis for the Degree of Philosophiae Doctor

Trondheim, August 2019

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## Summary

The prioritisation of bicycle-friendly infrastructure is now on the agenda of many policymakers seeking to capitalise on the advantages of cycling for transport.

This thesis focusses upon how the improved availability, quality, and connectivity of infrastructure suitable for cycling can influence cycling behaviour at the city and neighbourhood level.

Two key elements are necessary to understand the local-scale impact of bicycle infrastructure: the decision to bicycle in preference of other transport modes and the choice of route on the transport network. This thesis first addresses bicycle mode and route choice independently of each other before analysing the interaction between these elements in the context of bicycle infrastructure interventions.

This article-based thesis is comprised of five research papers: four empirical studies and one literature review. Three of the empirical cases are based in the Norwegian city of Trondheim and the fourth is based in Oslo. Paper I addresses the modal shift of employees following a workplace relocation. Papers II and III are focused on bicycle route choice – firstly as a review of methods and then in connection with student route preferences. The two final papers, Papers IV and V, integrate both mode and route choice elements for the detailed analysis of neighbourhood scale effects resulting from the installation of bicycle lanes in Trondheim and Oslo respectively.

The research uses a mixed methods approach, with a focus on empirical data to address the objectives of the thesis. Before and after travel surveys, web-based maps and GPS are the main means of data collection. Comparative analyses are performed using a Geographic Information System (GIS).

Findings suggest that the decision to bicycle is to a significant extent determined by trip and spatial characteristics of the destination (Paper I). Route substitution is witnessed in both intervention studies (Papers IV and V), whilst significant changes ( $p < .05$ ) in the modal share of cyclists is only witnessed in

one (Paper IV), suggesting that it is mostly changes of route rather than mode that contribute to an individual intervention street's change in bicycle volumes.

Bicycle-specific infrastructure appears to be generally valued by all types of road users, however, the evidence suggests that public transport users and pedestrians are more willing to change their mode of transport assuming the only changes made are to the bicycle infrastructure (Papers I and IV). This suggests that much of the increase in the use of new bicycle infrastructure is the result of a reduction in the use of other sustainable transport modes. Many of the benefits associated with increased cycling are the result of reduced private car use, but for this to be achieved, it appears that initiatives beneficial for cyclists alone are insufficient.

The means by which different transport infrastructure attributes can be researched and are valued by users are discussed by Papers II and III respectively. Paper II is a systematic review summarising the means through which revealed preference bicycle route choice data can be collected whilst Paper III evaluates four different Bicycle Level of Service (BLOS) methods for determining bicycle route choice. The latter study reveals that empirically founded BLOS methods with the most explanatory infrastructural attributes correspond best with actual route choices of university students. Of the tested BLOS methods, the Bicycle Compatibility Index is found to correspond best with actual route choice.

Developing an understanding of the impacts of bicycle infrastructure can assist the prioritisation of limited city budgets towards the promotion of sustainable mobility behaviour. This research attempts to advance the state of the art for bicycle route choice research whilst also addressing the decision to bicycle for transportation purposes.

## Sammendrag

Sykkelvevlig infrastruktur blir i økende grad prioritert av både byplanleggere og politikere for å utnytte fordelene med sykkel som transportmiddel. Denne avhandlingen setter søkelys på hvordan forbedret tilgjengelighet til og framkommelighet på sykkelinfrastruktur kan påvirke sykkelatferd både på by- og nabolagsnivå.

To nøkkelelementer for å forstå den lokale påvirkningen av sykkelinfrastruktur er valg av sykkel som reisemiddel og rutevalg blant sykkelbrukerne.

Avhandlingen starter med å undersøke sykkelreisemiddelvalg og rutevalg uavhengig av hverandre, før den samlede effekten av disse blir analysert i lys av intervensjoner i sykkelinfrastrukturen.

Denne artikkel-baserte avhandlingen omfatter fem vitenskapelige publikasjoner, hvorav fire er empiriske casestudier og en artikkel er en litteraturgjennomgang. Tre av de empiriske casestudiene henter sine data fra Trondheim, den fjerde fra Oslo. Artikkel I beskriver endringer i reisemiddelvalg i forbindelse med flytting av en kontorbedrift i Trondheim. Artikkel II og III fokuserer på sykkelrutevalg – der artikkel II gir en oversikt over metoder for datainnsamling mens artikkel III ser på studenters preferanser i sykkelrutevalg. De to siste artiklene, IV og V, kombinerer både reisemiddel- og rutevalg for en detaljert analyse av lokale effekter av opparbeidelsen av en sykkelveg og et sykkelfelt i henholdsvis Trondheim og Oslo.

Det er benyttet flere ulike metoder i dette forskningsarbeidet, og det er lagt vekt på å adressere forskningsspørsmålene ved hjelp av empiriske data. De primære metodene for datafangst har vært reisevaneundersøkelser før og etter tiltak, samt registrering av reisemønstre ved hjelp av GPS eller nettbaserte kart. Geografiske informasjonssystemer (GIS) har vært brukt for å gjennomføre komparative analyser.

Funnene tyder på at valget om å gjøre arbeidsreisen med sykkel i stor grad er påvirket av egenskaper ved selve reisen samt egenskaper knyttet til arealbruk

ved arbeidsstedet (artikkel I). Ruteendring er påvist i begge intervensjonsstudiene (artikler IV og V), mens signifikante endringer i sykkelandelen ( $p < .05$ ) bare er funnet i artikkel IV. Dette antyder at det er ruteendringer i større grad enn reisemiddelendringer, som bidrar til endringer i antallet syklistene i gatene når det blir gjort endringer i sykkelinfrastrukturen.

Sykkelspesifikk infrastruktur viser seg å være verdsatt av alle typer brukere, men kollektivreisende og fotgjengere er i større grad villig til å endre reisemiddelvalget sitt dersom endringene er avgrenset til sykkelinfrastruktur (artikkel I og IV). Dette tyder på at mye av økningen observert langs ny sykkelinfrastruktur er et resultat av redusert bruk av andre bærekraftige reisemidler. Mange av fordelene assosiert med økt sykling er koblet til redusert personbilbruk, men for at dette kan realiseres, virker det som at tiltak som er knyttet kun til infrastruktur for syklistene er utilstrekkelig.

Hvordan egenskaper ved transportinfrastrukturen kan bli forsket på, og hvordan de verdsettes av sykkelbrukere, er diskutert i henholdsvis artikkel II og III. Artikkel II er en systematisk litteraturgjennomgang som oppsummerer datainnsamlingsmetoder for faktiske, eller «revealed preference», sykkelrutevalg. Artikkel III evaluerer fire ulike «Bicycle Level of Service» (BLOS) metoder som brukes for å estimere sykkelrutevalg. Den sistnevnte studien viser at BLOS metoder som er basert på empiriske data og med flest attributter koblet til sykkelinfrastrukturen stemmer best med faktisk rutevalg blant universitetsstudenter – der Bicycle Compatibility Index har den beste matchen.

Å framskaffe kunnskap om påvirkningen av sykkelinfrastruktur kan gi et bedre grunnlag i prioriteringen av begrensede byutviklingsmidler til bærekraftig mobilitet. Forskningen i denne avhandlingen bidrar til økt kunnskap angående sykkelrutevalg og adresserer samtidig sykkelreisemiddelvalg til nytteformål.

## 摘要

自行车友好型基础设施的优先性已列入许多政策制定者的议程，以最大化利用自行车作为交通方式的益处。对此，本研究着重探讨提升后的基础设施的可用性、质量、以及连通性如何影响城市及周边地区自行车使用者的骑行行为。

以下两点对理解自行车基础设施的局部效应是必要的：选择自行车而非其他交通方式和交通路线的选择。在分析两者在自行车基础设施干预下的相互关系之前，本研究首先分别探讨自行车出行方式和路线的选择。

本博士学位论文基于已发表及待发表的五篇研究论文撰写而成，其包括四篇实证研究和一篇文献综述。其中三个实证研究是针对挪威城市，特隆赫姆，另一个则基于奥斯陆。论文一探讨某工作地点变动后员工们出行方式的改变；论文二和三重点关注自行车路线的选择——首先系统综述了研究路线选择的不同方法，进而关联到学生骑行路线的偏好。最后两篇论文则集交通方式和路线选择为一体分别详细分析在特隆赫姆和奥斯陆这两个城市自行车道的设立对所在社区市民出行方式的影响。

本研究使用混合的研究方法，主要利用基于实证数据探析本论文的研究目的和对象。在出行方式问卷调查之外，网络地图和 GPS 是主要的数据采集渠道。所涉及的对比分析是利用地理信息系统(GIS)进行的。

研究显示对自行车出行的选择在很大程度上取决于出行和目的地空间特征(论文一)。路线替代在两个干预研究(论文四和五)中均有出现，但自行车出行分担率的显著改变只出现在其中的一个干预研究(论文四)中。这暗示基础设施的调整主要引起的是骑行路线的改变，而不是影响单个街道自行车通行流量的改变。

提升后的自行车基础设施受到所有道路使用者的青睐，而研究显示，只有公共交通使用者和行人在仅有自行车基础设施改变的情况下更愿意改变他们的出行方式(论文一和论文四)。这表明自行车基础设施使用率提高的很大部分是其他可持续出行方式分担率降低的结果。然而，大量与提高自行车出行使用率相关的益处来源于私家车出行分担率的降低，要实现这一点，仅实施有利于骑行者的措施是不够的。

不同交通基础设施属性的研究方式和这些属性被使用者重视的程度在论文二和三中分别作了讨论。论文二是一个系统性的综述，总结了基于实证的偏好路线选择研究收集数据的方式，论文三则评估了四种不同的决定自行车路线选择的自行车服务水平(BLOS)方法。后者揭示了基于实证研究建立并包含最具解释力的基础设施属性的 BLOS 方法与大学生们实际骑行路线的实证结果最为匹配，其中，自行车兼容性指标在两种情形下，显示了最佳的匹配结果。

城市用于促进可持续出行行为的预算往往非常有限，建立对自行车基础设施影响效应的理解有助于优化该预算的分配。本研究尝试提升关于自行车出行路线选择研究的前沿性，同时为不同城市就关于将自行车提升为一种交通出行工具的决策提供依据。

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I am glad to have had the company of two other PhD candidates on my doctoral journey, Petr Pokorny and Miroslav Vasilev, who have been addressing similar topics at the Department of Civil and Environmental Engineering. I have gained a lot personally and professionally from our frequent discussions both in and outside of work.

A word of thanks is extended to the NTNU Department of Architecture and Planning for enabling me to undertake a PhD in a field I am deeply passionate about. The additional financial support from the Directorate of Public Roads (Vegdirektoratet), the Nordic Road Association (Nordisk vegforum – NVF), and Norges tekniske høgskoles (NTH) fund have also been highly appreciated.

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## List of Abbreviations

AADT: Annual Average Daily Traffic
API: Application Programming Interface
App: (Smartphone) Application
BSL: Bicycle Stress Level
BLOS: Bicycle Level of Service
BCI: Bicycle Compatibility Index
CI: Confidence Interval
DiD: Difference in Differences
EU: European Union
GDPR: General Data Protection Regulation
GIS: Geographic Information System
HCM6: US Highway Capacity Manual 6 <sup>th</sup> edition
ID: Identification (number)
LOS: Level of Service

LTS: Level of Traffic Stress

M: Mean

NNTS: Norwegian National Travel Survey

NPRA: Norwegian Public Roads Administration

NSD: Norwegian Centre for Research Data

NTP: Norwegian National Transport Plan

NVDB: Norwegian National Road Database (Nasjonal Vegdatabanken)

OD: Origin-Destination

OSM: OpenStreetMap

OSRM: Open Source Routing Machine

RP: Revealed Preference

PT: Public Transport

SE: Standard Error

TRID: Transport Research International Documentation

TRB: Transportation Research Board

URL: Uniform Resource Locator

VKT: Vehicle Kilometres Travelled

## List of Papers

### **Paper I – Adresseavisen office relocation**

Pritchard R, Frøyen Y (2019). *Location, location, relocation: how the relocation of workplaces from suburbs to the inner city impacts commuting on foot and by bike*. European Transport Research Review 11(14):1-20. doi: [10.1186/s12544-019-0348-6](https://doi.org/10.1186/s12544-019-0348-6)

*Contribution of each author: Ray Pritchard co-conceptualised the study (together with Tor Medalen), organised the data collection, performed statistical and comparative analyses and wrote the paper. Yngve Frøyen performed GIS analyses and created OD cost matrices for travel time and distance.*

### **Paper II – Literature review (methods)**

Pritchard R (2018). *Revealed Preference Methods for Studying Bicycle Route Choice—A Systematic Review*. International Journal of Environmental Research and Public Health 15:1–30. doi: [10.3390/ijerph15030470](https://doi.org/10.3390/ijerph15030470)

### **Paper III – SiT student route choice**

Pritchard R, Frøyen Y, Snizek B (2019). *Bicycle Level of Service for Route Choice—A GIS Evaluation of Four Existing Indicators with Empirical Data*. ISPRS International Journal of Geo-Information, 8:1–20. doi: [10.3390/ijgi8050214](https://doi.org/10.3390/ijgi8050214)

*Contribution of each author: Ray Pritchard conceptualised the study, organised the data collection, co-performed GIS analyses, performed the comparative analysis of BLOS methods and wrote the paper. Yngve Frøyen performed map-matching and lead the GIS analyses. Bernhard Snizek programmed the mapping API used for data collection and managed the database with participant responses.*

### **Paper IV – Trondheim intervention**

Vasilev M, Pritchard R, Jonsson T (2018). *Trialing a Road Lane to Bicycle Path Redesign—Changes in Travel Behavior with a Focus on Users' Route and Mode Choice*. Sustainability 10(12):1-18. doi: [10.3390/su10124768](https://doi.org/10.3390/su10124768)

*Contribution of each author: Miroslav Vasilev lead the investigation, performed statistical analyses and wrote the majority of the paper. Ray Pritchard conceptualised and co-developed the investigation, performed GIS analysis, created visualisations and wrote the sections pertaining to the historical context and route choice. Thomas Jonsson was the primary supervisor and performed statistical analysis.*

***Paper V – Oslo intervention***

Pritchard R, Bucher D, Frøyen Y (2019). *Does new bicycle infrastructure result in new cyclists? A longitudinal GPS study in Oslo*. Journal of Transport Geography 77:113-125. doi: [10.1016/j.jtrangeo.2019.05.005](https://doi.org/10.1016/j.jtrangeo.2019.05.005)

*Contribution of each author: Ray Pritchard conceptualised the study, organised the data collection, performed GIS and statistical analyses and wrote the first draft of the paper. Dominik Bucher developed the technical aspects of data collection including management and map-matching and co-wrote the methodology section of the paper. Yngve Frøyen conducted GIS analyses.*





## 1. Introduction

*The cure for congestion is not more facilities for congestion.*

*– Lewis Mumford, 1955.*

To develop an understanding of the impact of bicycle infrastructure on travel behaviour requires consideration of both the mode and route choices of users. In other words, the decision to cycle in preference of another mode and the subsequent route choice when the bicycle mode is selected. Study of bicycle usage requires these two elements at a minimum in order to understand the dynamic of user preferences between different modes of transport and between alternative routes or destinations.

Bicycle mode and route choice are employed as the cornerstones of this thesis, and the research builds up from these two elements. The decision to bicycle is typically the main motivating factor for the development of most bicycle infrastructure, either directly as a means to promote change in bicycle modal share or indirectly through addressing traffic safety concerns (Dill & Carr, 2003). Knowledge on bicycle route choice meanwhile is critical for the introduction and development of regional transport demand models with cycling (Handy, van Wee, & Kroesen, 2014).

One could also argue that induced travel demand is also a key element of bicycle infrastructure's influence on travel behaviour since the provision of facilities enables the creation of trips that would not otherwise be performed (Næss, Andersen, Nicolaisen, & Strand, 2014). However, separating induced traffic from route, destination and mode choice changes (collectively referred to as generated traffic) is a challenge, especially since longitudinal data on cycling is limited (Díez-Gutiérrez, Andersen, Nilsen, & Tørset, 2018). Most research on induced traffic is connected to modelling and measurement of vehicular traffic, and the adaption to cycling infrastructure is not a topic area directly addressed in this thesis.

Data on modal choice is widely collected in national travel surveys and is thus readily obtainable, however, data on route choice has been mostly collected in relation to research studies and has been largely excluded from national travel surveys (Bohte & Maat, 2009). It is for this reason that the focus in this thesis has been directed more towards route choice than mode choice. Bicycle route choice is thematically represented across all five papers that make up this thesis (although it is not the primary focus of Paper I), whilst mode choice is actively discussed in three of the papers (I, IV and V).

### **1.1. Research Questions**

Bicycle mode and route choice form the starting point for this thesis and are initially addressed as two separate research questions, each with one empirical study. The third overarching research question integrates the mode and route choice questions in the context of changes in bicycle infrastructure, referred to in this thesis as bicycle infrastructure interventions. Research question three is addressed within two empirical studies. The thesis is structured around the thematic categories defined by the research questions which are answered in the final chapter.

The thesis formally addresses the following three research questions:

1. In what manner can the accessibility of urban areas influence the decision to bicycle?
2. How does the quality of bicycle infrastructure impact route choice preferences?
3. What is the effect of new bicycle infrastructure in terms of route and mode choice?

Research question 1 deals with how such trip factors as destination accessibility, distance and travel time together with the provision of bicycle infrastructure can affect the modal choice of cycling. This question starts at a broad level, establishing the context regarding the decision to bicycle in favour

of other modes and providing the background for subsequent research questions.

Research question 2 addresses the interaction between bicycle route choice and bicycle infrastructure quality. The likelihood to make a detour from the shortest path between trip origin and destination is one of the primary elements evaluated – testing the hypothesis that safe and separated infrastructure can induce a greater degree of detour from the shortest path.

The final research question brings together the two initial research questions in the context of isolated upgrades to the bicycle infrastructure network. The effect of these changes, or interventions, is considered at the neighbourhood scale in terms of both cycling uptake and preferred choice of route.

An overview of the contributions of the five papers to the research questions is displayed in Figure 1 below. The order of the thesis' constituent papers follows that of the research questions and is approximately chronological in terms of data collection. The full paper titles are available in the List of Papers and in Appendix: Papers. The research questions are arranged in ascending order of importance: research question 1 is the broadest in scope whilst research question 3 has the most specific focus. Due to overlap in the research questions, they are answered collectively in the concluding chapter rather than at the end of their corresponding chapters.

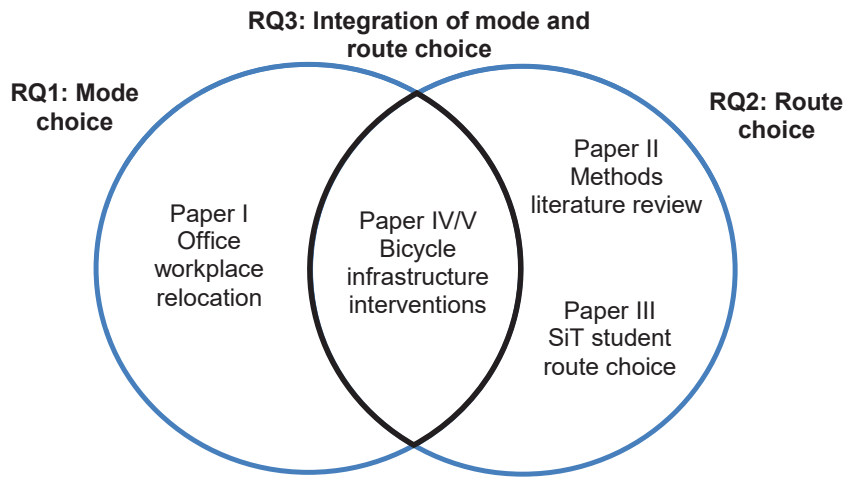


Figure 1. The organisation of the research questions and papers.

In Table 1 below, the connections between the papers, research questions, objectives and methods are highlighted. The two rightmost columns provide an overview of the primary contribution of the paper to the thesis' two foundation elements of route and mode choice.

Table 1. Thematic contributions and objectives of the papers according to research question

Paper	Research question	Objective	Sample, City [test]	Methods	Route choice	Mode choice
I	1 Mode choice	Mode choice effects of office relocation	Adresseavisen employees, Trondheim [change of destination]	Before and after travel survey	modelled route change	YES
II	2 Route choice	Literature Review – data collection approaches	N/A	N/A	YES	N/A
III	2 Route choice	Evaluate existing Bicycle Level of Service (BLOS) metrics with empirical route data	University students, Trondheim [5 origin-destination pairs]	Mapping survey	YES	NO
IV	3 Intervention (route & mode)	Mode and route effects of lane reduction and bi-directional bike path	Users of Innherredsveien, Trondheim [1 bicycle path]	Before (retrospective) and after mapping survey	YES	YES
V	3 Intervention (route & mode)	Mode and route effects of contraflow bicycle lane	Users of Markveien, Oslo [1 bicycle lane]	Before and after GPS, traffic counts	YES	YES

## 1.2. Structure of the thesis

This thesis is article-based, consisting of five separate publications published or submitted to scientific journals that address different aspects of bicycle route and mode choice. The thesis text serves the purpose of integrating the five

papers into a collective work, addressing the research questions and challenges associated with the research. The three research questions are used to structure the papers and are answered collectively in the conclusions chapter.

This thesis is divided into seven main Chapters:

Chapter 1: Introduction

Chapter 2: Background

Chapter 3: Research methods and theory

Chapter 4: Mode choice – the decision to bicycle

Chapter 5: Route choice – where to bicycle

Chapter 6: Infrastructural interventions combining route and mode choice

Chapter 7: Conclusions of the research questions and suggestions for further work

Chapter 1 introduces the topic, research design, research questions and structure of the thesis.

Chapter 2 presents the background and theory for the research conducted, together with the knowledge gaps.

Chapter 3 details the research methods applied throughout the five articles that comprise the thesis.

Chapter 4 addresses research question 1 regarding mode choice or the decision to bicycle. A summary of Paper I on the commuter travel impacts of a newspaper publisher's relocation is provided in this chapter together with a discussion of the mode choice theme in general.

Chapter 5 attempts to answer research question 2 concerning bicycle route choice. Papers II and III are summarised in Chapter 5. Paper II reviews the data collection methods used for bicycle route choice and Paper III discusses bicycle route choice of students' in connection with Bicycle Level of Service (BLOS).

Chapter 6 addresses the third research question in which both route and mode choice are considered in the context of the before and after effects of bicycle infrastructure interventions on cycling behaviour. Papers IV and V are summarised in this chapter, on the effects of a bi-directional separated bicycle path in Trondheim and a contraflow bicycle lane in Oslo respectively.

The thesis is concluded in Chapter 7 which seeks to address all three research questions with a summary of the results and conclusions from each. Recommendations for further research based on the challenges encountered in Chapters 4 to 6 are also provided in the concluding chapter.

### **1.3. Contributions**

The primary aim of this thesis is to develop an empirical understanding of the influence of transport infrastructure (and especially bicycle-specific infrastructure) on bicycle travel behaviour. As the research towards this objective developed, a number of additional research contributions were achieved. These contributions include:

- A systematic literature review of existing approaches to the collection of revealed preference data for bicycling
- A comparison of the effect of Norwegian office workplace relocation on commuter cycling and walking mode choice
- A semi-automated GIS-based approach to map-matching
- The evaluation of four existing BLOS methods in connection with whole-journey route choice data
- A novel methodological approach to establish the empirical willingness to detour from the shortest path
- Detailed infrastructure intervention analysis using a longitudinal panel and passive GPS tracking



#### **1.4. Scope and limitations**

Transportation research on mode choice and route choice are both substantial fields of research, even when considering the urban cycling context. In order to keep within the reasonable boundaries of a PhD thesis, the following limitations to scope were applied:

- The built environment influences considered are limited to those directly connected to the transport infrastructure network, with a focus on bicycle infrastructure
- Travel behaviour analyses are limited to mode and route choice, whilst induced travel behaviour and change of destination is not included
- Qualitative interviews concerning travel behaviour and urban planning are not included
- The thesis does not seek to create new transport demand or route choice models
- Traffic safety is not considered directly but is an underlying factor influencing mode and route choice for cycling

## **2. Background and theory**

*What is the hardest part about learning to ride a bicycle?*

*The ground.*

### **2.1. Utility maximisation theory**

There exists a great multitude of theories concerning travel behaviour choices, and none can claim to completely explain choices connected to cycling for transport (or most other human behaviour for that matter). One of the more common theories or concepts applied to cycling research, particularly in relation to infrastructure or modelling of behaviour, is utility maximisation (also called optimisation) (Handy, 2005; McFadden, 1974). Utility maximisation is one of the core principles in microeconomics in which actors always make optimal decisions. The assumption of utility maximisation theory is that people make rational decisions which offer a level of utility (or satisfaction) that is greater than or equal to any other option open to them.

For bicycle travel behaviour, utility maximisation theory suggests that the selected route or the decision to bicycle must provide the greatest possible benefit for the bicycle user amongst the available routes or modes. The benefit is typically a combination of factors including but not limited to time, costs, safety, energy expenditure, attractiveness and comfort (CROW, 2016). Since the importance of these factors is different for different people, the theory is extended upon in Random Utility Maximisation (RUM) models through the addition of a stochastic component to represent the sum of unobservable variations in attitudes and unobserved traits of the choices (Handy, 2005) (see further discussion in sub-chapter 2.2).

When considering how bicycle infrastructure can impact travel behaviour, this thesis seeks to test the idea that improvements to the factors mentioned above will result in an increased likelihood that the new piece of infrastructure is used. The utility maximising approach suggests that new bicycle infrastructure will only result in changes to route or mode provided it results in a more attractive

route compared to existing alternatives. This approach, therefore, suggests that should bicycle infrastructure be developed near to competing routes, the marginal utility can be expected to be reduced (Broach, 2016). The thesis tests this idea through checking for route substitution versus mode substitution in Papers IV and V. It does not otherwise seek to quantify the relationship between infrastructure and travel behaviour but adds to the empirical knowledge base concerning the direction and scale of changes.

This thesis takes an open approach to utility maximisation theory insofar as factors that are not easily quantifiable such as perceived safety are still considered as being optimised in balance with traditional monetary and time-related costs. At the same time, it is acknowledged that utility maximising theory has some weaknesses, particularly due to its limited ability to account for three key factors (Anable, Lane, & Kelay, 2006; Kremers et al., 2006; Salon, Conway, Wang, & Roth, 2019; Schwanen, Banister, & Anable, 2012):

1. Decision-maker knowledge regarding the options available is often imperfect;
2. Humans do not always make linear and predictable rational choices;
3. The social context with respect to attitude and behaviour formation and execution is largely ignored.

This thesis has not addressed these weaknesses, however many other theories such as the theory of planned behaviour, social learning theory, ecological models and behavioural economics address such aspects (Bamberg, Ajzen, & Schmidt, 2003; Klöckner & Blöbaum, 2010; Krizek, 2019). Whilst utility maximisation theory does not account for all variation in travel behaviour, the competing theories possess similar issues, and attempting to resolve the disparities between all theories is beyond the scope of this work.

## **2.2. Transport modelling and generalised travel cost**

Within the field of travel demand forecasting, the four-step transport planning model is widely applied. The four steps are comprised of trip generation, trip

distribution, modal split and trip assignment (Cervero, 2006). The two first stages produce a trip matrix based on the numbers of residences and attractions in the various zones of a transport model. It is the two final elements of the four-step model that are of relevance for this thesis. Modal split as discussed above allocates trips to different transport modes, whilst the trip assignment stage involves path estimation (or route choice) and ultimately provides approximate volumes of different transport modes that can be expected on any transport link in the network.

The four-step model is mostly applied to motorised traffic, and rarely outside of some research applications is it applied to cycling (Ehrgott, Wang, Raith, & Van Houtte, 2012). Existing national transport models that do take account of cycling, such as the one used in Sweden, rely nearly exclusively on travel time (van Wee & Börjesson, 2015). A key underlying assumption behind this model is the concept of generalised travel cost (GTC) (Ehrgott et al., 2012). The goal of most transport models is to minimise this cost, which is comprised of both the monetary costs (such as vehicle operating cost) and non-monetary costs (such as travel time). The processing of minimising generalised costs can be seen as an integral part of the utility maximisation concept discussed in sub-chapter 2.1. For example, the goal of minimising costs such as the risk of traffic injury or travel time is equivalent to the goal of maximising safety and efficiency, both of which are key elements of the broadly defined 'utility' to the cyclist.

For application to cycling, monetary costs are minimal and multiple non-monetary factors such as traffic safety, pleasantness (noise, greenery etc.) and energy exertion become important explanatory variables together with travel time (Dill & Carr, 2003; Jensen, 2007; Kärmeniemi, Lankila, Ikäheimo, Koivumaa-Honkanen, & Korpelainen, 2018; Parkin & Rotheram, 2010). The development of bicycle infrastructure has typically the greatest influence on traffic safety by offering separation from other vehicles, thereby increasing the comfort level for many cyclists. By performing safety improvements through the development of bicycle infrastructure, the comfort level of the network is increased, effectively opening new possibilities for infrequent users who

perceive cycling to be a highly unsafe travel mode in traffic (Hood, Sall, & Charlton, 2011; Rowangould & Tayarani, 2016).

Two assumptions of many discrete mode and route choice models are the Independence of Irrelevant Alternatives (IIA) assumption and Random Utility Maximisation (RUM) assumption (Habib, 2018). The IIA assumption suggests that preferences between any two non-zero probability alternatives are independent of the introduction or removal of a new alternative. This necessarily applies to all other existing alternatives in the choice set. In reality however, the alternatives are not always completely independent. For example, alternative bicycle routes often overlap and cannot, therefore, be considered as distinct choice alternatives. The IIA problem has been addressed in multiple ways, for route choice often through the use of path size logit models which account for overlap (Broach, Dill, & Gliebe, 2012; Hood et al., 2011; Menghini, Carrasco, Schüssler, & Axhausen, 2010), whilst for mode choice, IIA is often addressed through the use of nested logit models which collect or 'nest' related alternatives (Hood, Erhardt, Frazier, & Schenk, 2014; Rayaprolu, Llorca, & Moeckel, 2018; Shakeel, Rashidi, & Waller, 2016).

The second assumption of most discrete choice models concerns decision making and is called Random Utility Maximisation (RUM) (Habib, 2018). The RUM assumption finds optimum solutions in the choice set on the basis of maximum randomised utility, in which the random element is a stochastic parameter which accounts for unknown additional factors, such as the elements that are not traditionally assigned utility described in sub-chapter 2.1 (Chen, Shen, & Childress, 2017). RUM models typically require explicit enumeration of all feasible alternatives (the route or mode consideration set) (Zhu & Levinson, 2015). The RUM assumption requires choice set specification and accounts for unknown or un-modellable factors through the addition of a randomised parameter. The IIA assumption meanwhile addresses correlated alternatives. The four-step discrete choice modelling approach, by considering both assumptions, can thus be seen as an advancement of utility maximisation theory.

This thesis does not seek to modify or replicate the four-step model, however Paper III performs an evaluation of existing Bicycle Level of Service (BLOS) models in application to whole journey bicycle route choice. BLOS is used in Paper III to capture the effect of multiple parameters known to influence bicycle travel behaviour (mostly connected to perceived safety). Energy exertion is also addressed in the third paper through the travel time parameter which is influenced by both length, intersections (increased chance of stoppage) and the bicycle network's underlying topography.

### **2.3. The transportation and land use connection**

From a transport planning perspective, increasing numbers of cities are seeking to mitigate the adverse impacts of transport, typically through a shift from private car use to a combination of walking, cycling and public transport (Buehler, Pucher, Gerike, & Götschi, 2016; Federal Ministry of Transport Building and Urban Development, 2012; Samferdselsdepartementet, 2017). Bicycle promotion for transportation purposes is widely recognised as having a diverse range of indirect societal benefits such as improvements in public health, air quality, traffic safety, and community sociability (Macmillan et al., 2014; Schepers et al., 2015). At the same time, a switch from motorised transport modes to cycling can mitigate congestion whilst reducing the need for road capacity expansions, local air pollution, and greenhouse gas emissions (Wahlgren & Schantz, 2012). For these reasons and others, many cities are searching for measures to stimulate increased bicycling and walking as part of an active lifestyle (Mason, Fulton, & McDonald, 2015).

Key to the selection of the bicycle as a transport mode is the competitiveness it has with alternative transport modes, which is influenced by a multitude of factors including geographical, social and economic factors (Heinen, Maat, & Van Wee, 2011; Hunt & Abraham, 2007; Rietveld & Daniel, 2004; C. H. Wang, Akar, & Guldmann, 2015). Density and connectivity of the transport infrastructure network and its integration with transport-generating land uses are especially important factors influencing travel behaviour (Ewing & Cervero,

2010; Næss et al., 2014; Piatkowski, Marshall, & Krizek, 2019). These factors have direct consequences on accessibility, defined here as “the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)” (Geurs & van Wee, 2004).

Urban density has been found to be positively correlated with bicycle modal use for adults and older children but insignificant or even slightly negative for younger children (Salon et al., 2019). As density increases, the average distances needed to be travelled to reach common destinations including homes, workplaces, and services is reduced (Schneider & Stefanich, 2015).

With reduced distance comes an improvement in accessibility since the ease of accessing common destinations is enhanced whilst the number of destinations reachable in a given period of time is increased. For young children, traffic safety considerations such as overall exposure to vehicular traffic are likely of greater importance than accessibility, potentially explaining why density is not positively associated with bicycle use for this group.

If the transportation connectivity within a city is improved, for example through the connection of adjacent no-through roads, the accessibility of the neighbourhood is correspondingly improved (Akar & Clifton, 2009). Connectivity can also be considered in terms of how various land uses are placed in relation to the central nodes and axes of a transport network. Colocation of transport-intensive land uses such as office workplaces, most consumer retail, and public services with the central axes of the transport network improves the accessibility of an area (Strømmen, 2001).

Changes in the relative competitiveness of one transport mode over another are needed to create change in the transport modal split of an urban area (Levinson & Krizek, 2017). One of the main intentions of integrated land use and transportation policies is to facilitate the everyday transport demands of users in a manner that attempts to minimize the total amount of travel required (Sim, Malone-Lee, & Chin, 2001). Whilst the concepts discussed refer to changes in

the built environment, cycling behaviour can equally be influenced by changes in the monetary or time-based competitiveness of alternative modes of transport. Examples include public transport service frequency, connectivity and ticket pricing, road pricing, paid parking, taxes and speed limits (Cervero & Landis, 1995; Ewing & Cervero, 2010; Litman & Burwell, 2006; Moore, Thorsnes, & Appleyard, 2007).

It should be noted that despite this thesis' focus on the influence of transport infrastructure, it is increasingly considered to have a greater effect in combination with so-called 'soft' or market-based initiatives (Gössling, 2013; Piatkowski et al., 2019; Pucher, Dill, & Handy, 2010; Scheepers et al., 2014). Soft measures focus on voluntary travel behaviour change through changing attitudes and perceptions through initiatives such as promotional events, marketing campaigns, and individualised travel planning (Bamberg, Fujii, Friman, & Gärling, 2011). A review of 141 studies using such behaviour change techniques demonstrates an average increase in the non-car modal share from 39% to 46% (Möser & Bamberg, 2008). In addition, economic motivators such as tolls, taxes and subsidies have been demonstrated to have a considerable impact on travel behaviour including the decision to cycle (Scheepers et al., 2014). The influence of the soft and market-based spectrum of policy measures related to urban bicycle use is not addressed in this thesis.

#### **2.4. Cycling context in Norway**

Norway has a relatively low bicycle modal share of 4.5% compared to its Nordic neighbours Sweden (10%), Denmark (16%), and Finland (9%) (Buehler et al., 2016; Hjorthol, Engebretsen, & Uteng, 2014). This low modal share is associated with many factors, and in terms of infrastructure, Norwegian cities (where most of the cycling occurs) tend to have a low network density and connectivity (Pokorny, Pritchard, & Pitera, 2018). The cycling infrastructure in Norway is also of a lower standard compared to its neighbouring countries, typically represented by shared paths or bicycle paths with footpaths along suburban arterials outside the city centre which, with few exceptions, become



bicycle lanes in more central areas where bicycle infrastructure can be found. The comparatively low level of bicycle infrastructure development in Norway provides an interesting situation for planners and researchers alike as the question remains: how to most efficiently achieve a well-functioning bicycle network?

Historically, the development of separate infrastructure for cyclists began primarily in response to increasing traffic deaths following the growth in private car ownership in the decades after the second world war. The first efforts to separate different groups of road users involved the development of shared pedestrian and cycling paths in the 1970s. In 1978, a new traffic rule came into place allowing cyclists to use the footpaths provided they did not cause “danger or a hindrance” for pedestrians. Whilst this initiative may have improved the traffic safety for cyclists at the time, it has in hindsight been seen by some planners as an “excuse” by policymakers for not further developing separated bicycle-specific infrastructure in the decades that followed. It has also been met with resistance from organisations representing the interests of pedestrians – especially the blind or physically handicapped. The regulation did not completely remove conflicts with cars either, since cycling on the road was still permitted and zebra crossings in Norway do not give cyclists right of way unless they dismount. A modification to the traffic rule came into place in 1998, additionally specifying that cycling on footpaths is permitted on the condition that pedestrian traffic is low, and in the case of overtaking manoeuvres, occurs with a reasonable passing distance at walking speed. The modified rule changed little in practice, and in Europe today, Norway together with Iceland are the only two countries that still permit footpath cycling for all age groups (Sørensen, 2013).

In addition to shared paths, bicycle lanes were built in some areas, and gradually became a standard infrastructure choice in more recent years. They are today recommended on streets with 30-50 km/h speed limits and over 4000 AADT and are delineated from car lanes with striped white road markings, a demarcation also used in Sweden (Spilsberg, Børrud, Myrberg, & Nordgård,

2008). In suburban areas when more than 15 pedestrians can be expected per hour during peak times, bi-directional bicycle paths with a curb-separated footpath are now recommended in the NPRA bicycle planning handbook, limiting the conflicts between pedestrians and bicycle users (Vegdirektoratet, 2014). It has also become increasingly common to use a dark red colouring to emphasise bicycle infrastructure from other traffic groups – either with paint, thermoplastic or asphalt blends similar to those widely used in the Netherlands. This is however not yet stipulated in any NPRA manuals for bicycle infrastructure planning and therefore holds no jurisdictional value separate from that of uncoloured bicycle infrastructure.

There are some solutions common in other northern European countries that are rare in Norway. Bicycle streets in which bicycles have priority over car traffic travelling in the same direction are not recognised as standard infrastructure in Norway, but can be found in Sweden, Denmark, Germany, Belgium and the Netherlands. Physical separation of bicycle lanes (with bollards or raised curbs) from adjacent road lanes is virtually unseen in Norway and is not discussed in the bicycle planning handbook. Road intersections do not have continuous bicycle infrastructure in Norway (such as the blue bicycle lanes in Copenhagen, Denmark). The NPRA bicycle planning handbook is however reviewed approximately every ten years and there is increasing willingness from both municipalities and the NPRA to trial non-standard bicycle infrastructure. Thus, it can be expected that future bicycle infrastructure projects may be more in line with best practice elsewhere in Europe.

### **2.5. The Norwegian Zero Traffic Growth Goal policy context**

Many urban regions are today experiencing congestion and other externalities that stem from private car use. In Norway, the government has introduced 'nullvekstmålet' or the Zero Traffic Growth Goal (hereafter referred to as the zero-growth goal) for the nine largest urban areas in an attempt to reduce these externalities (Samferdselsdepartementet, 2017). The goal seeks to stop the growth in Vehicle Kilometres Travelled (VKT) by private cars travelling to, from

or within each of the nine city regions: Oslo, Bergen, Trondheim, Stavanger-Sandnes, Kristiansand, Drammen-Kongsberg, Skien-Porsgrunn, Fredrikstad-Sarpsborg and Tromsø (Samferdselsdepartementet, 2017, p. 164). The zero-growth goal was first introduced in the Norwegian National Transport Plan (NTP) 2014-2023 following the second parliamentary Agreement on Climate Policy 'Klimaforliket 2012' (Det Kongelige Miljøverndepartement, 2012).

Policy initiatives to curb traffic growth in Norwegian cities have existed for some years, however, in order to meet the zero-growth goal, the nine largest cities are now reviewing their integrated transport and land use plans via so-called City Growth Agreements or 'byvekstvtaler' which have zero traffic growth as their principal aim. City Growth Agreements stem from a variety of other transport policy initiatives: City Packages 'bypakkene', the Reward System 'belønningsordningen', City Development Agreements 'byutviklingsavtalene', and City Environment Agreements 'bymiljøavtalene' as illustrated in Figure 2 (Samferdselsdepartementet, 2018). Smaller cities outside of the nine largest urban areas are not currently affected by these agreements, and through-traffic, freight and service vehicles are excluded from the VKT measurement (Samferdselsdepartementet, 2013b). The implication of the limitation to private car traffic in the nine largest cities is that all other forms of traffic can continue to grow.

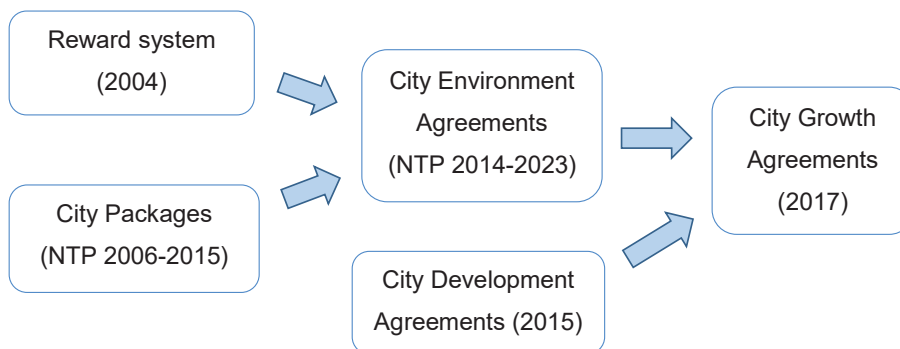


Figure 2. Governmental policy initiatives focused on urban transportation. Year of first mention from the Department of Transportation or National Transport Plans (NTP) in parentheses (adapted from Samferdselsdepartementet, 2013a, 2018).

Importantly the City Growth Agreements include financial incentives for city regions to facilitate the necessary changes from present transportation trends. This includes the national government covering half of the costs of initiatives that promote walking, cycling and public transport. The Norwegian Public Roads Administration (NPRA) has also conducted city evaluations or 'byutredninger' which project the impacts of various transport policy packages that cities must utilise in order to achieve zero-growth in car Vehicle Kilometres Travelled (VKT) (Statens Vegvesen, 2018). The city evaluations consider many initiatives that reduce the competitiveness of car transport such as road pricing, stricter parking policies, compact city development, and reduced road capacity. At the same time, measures that promote cycling, walking, and public transport have been modelled in the evaluations, which demonstrate that a combination of initiatives is necessary to meet the zero-growth goal.

Modelling results from the City Evaluation of the Trondheim region 'Byutredning Trondheimsområdet' show that improvements for cyclists, pedestrians and public transport patrons are not sufficient to achieve the zero-growth goal (Norwegian Public Roads Administration, 2017). To achieve zero-growth, three policy alternatives have been proposed, and all involve improvements to the pedestrian and bicycle infrastructure, service improvements to the public transport system together with driving cost increases (through a combination of parking and toll charges). Considering that the zero-growth goal effectively acts as the overarching transportation target in Norway's largest urban areas, the development of cycling infrastructure can be thought of as being one requisite part of the total initiative package.

To understand more about the context for zero-growth in car traffic, we should first consider the historical transportation trends in Norway using national travel survey data. This data, collected approximately every four years between 1985 and 2014, is plotted in Figure 3 below and survey years are represented by the vertical grey bars. The y-axis illustrates the general increased demand for mobility over the survey time horizon (presented as daily trips taken in Norway), and this is mostly the result of population growth since the number of trips per

person remains relatively stable. The car modal share increases from 58% of all trips in 1984 to 63% in 2014, although the percentage of car passenger trips falls (Hjorthol et al., 2014).

Figure 3 additionally illustrates the projected mobility in 2023 based on the Norwegian National Transport Plan (NTP) 2014-2023 in combination with population growth expected by Statistics Norway (1.05% annual growth). The modal split is assumed to follow NPRA policy documents connected to the NTP which outline specific goals for growth in cycling (8% bicycle modal share by 2023) and walking (number of people to take at least one walking trip each day to increase from 35.5% in 2009 to 50% in 2023) together with the zero traffic growth goal (which applies to the nine largest cities). It is assumed that the number of trips per person per day remains unchanged in 2023, which gives the net result that public transport will decrease in patronage when projecting forward. This is of course not a policy goal but illustrates a lack of communication between different policy makers within the transport sector.

It can be seen in Figure 3 that the bicycle modal share has declined from a peak of 6.5% in 1992 to a minimum of 4.2% in 2009. The ambition of achieving an 8% bicycle modal share within ten years can be found already in NTP 2006-2015. Despite this target remaining in all subsequent NTPs, it remains far from being met. The most recent national travel survey from 2013/2014 reveals a bicycle modal share of 4.5% (compared to the minimum of 4.2% in 2009). The ambition to achieve an 8% bicycle modal share in ten years means a near-doubling of bicycle trips is required. This means that a compound year-on-year growth rate in the numbers of bicycle trips of 7.8% is required.

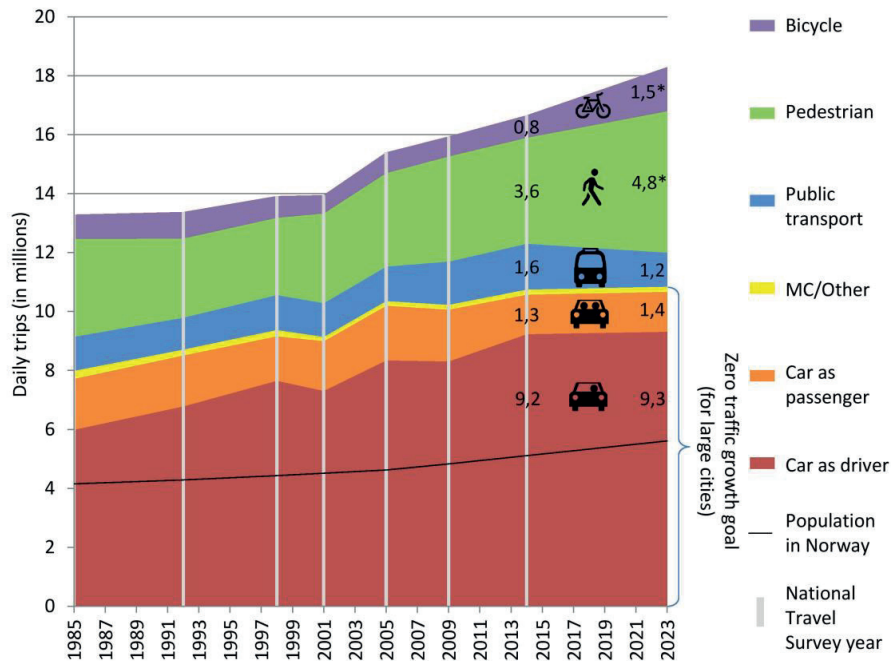


Figure 3. Historical national travel survey data (Hjorthol et al., 2014) together with projected annual growth for the period of the National Transport Plan 2014–2023 (Samferdselsdepartementet, 2013b). \*Projected growth in bicycle and pedestrian journeys based on the NPRAs national walking (Berge, Haug, & Marshall, 2012) and cycling strategies (Espeland & Amundsen, 2012).

Figure 3 does not illustrate trip lengths, but these have been increasing across all transport modes whilst travel time has increased at a slower rate. In the period from 1992 to 2014, the average trip length averaged across all modes increased by 41% from 10.3km to 14.5km whilst the average trip time increased by 26% from 19 to 24 minutes (Hjorthol et al., 2014, p. 20). The difference in the rate of increase indicates improvements to average accessibility (greater average speed). The combination of an increased number of trips due to population growth, increasing car modal share and longer average trip length means that VKT increases at a much greater rate than is shown above. The total vehicle kilometres travelled per person per day in 1992 was 32.1km which increased to 47.2km in 2013/2014 (Ibid., p.20). When combined with the

population increase over the same time period from 4.3 to 5.1 million people, the Norwegian national VKT increased by 58%. This highlights the challenge of achieving zero traffic growth.

Since cycling and walking trips are so much shorter than car and public transport trips, they have a comparatively small role to play in terms of their contribution for VKT stabilisation, even in countries with high levels of cycling. However bicycling can also function as an effective access/egress mode for public transport. The bicycle-public transport combination works synergistically, extending the service area for public transport services compared to walking. Thus designing bicycle infrastructure with this in mind offers a potential which should not be ignored when attempting to capture all projected growth in mobility with non-car means (Kager, Bertolini, & Te Brömmelstroet, 2016).

## **2.6. Knowledge Gaps**

In a review of the academic literature related to the study of bicycle route choice, it was found that most studies are focussed upon the travel behaviour of current cyclists, with these findings often extrapolated to the population at large (Pritchard, 2018). In such countries as the UK and USA, most cities have relatively low rates of cycling, and the attributes of current cyclists is rather unlike non-cyclists, both demographically and behaviourally (Aldred, Elliott, Woodcock, & Goodman, 2017; Misra & Watkins, 2018; Sener, Eluru, & Bhat, 2010). Cyclists in both contexts are more likely to be male and younger than the population at large, which is thought to be the result of differences in acceptable perceived risk (Misra & Watkins, 2018). Similar trends exist to a lesser degree in Norway: 44% of cyclists are female, and young adolescents are overrepresented amongst the cycling population (Hjorthol et al., 2014).

There is some evidence to suggest similarities in the preferences of frequent and infrequent cyclists, especially with regards to separation from motorised traffic (Epperson, 1994), however cycling acceptance (and presumably therefore willingness) has been shown to vary significantly in relation to both gender and age (Parkin, Wardman, & Page, 2007). Developing bicycle

infrastructure can change the risk perception and thus acceptance of cycling. Stated preference studies suggest that this has the greatest potential to influence especially those users with the least cycling experience (Hood et al., 2011; Rowangould & Tayarani, 2016).

In the interests of understanding the travel preferences of the target group of infrequent cyclists, this PhD has been focused on users of all transport modes. This provides data that can be useful for both mode and route choice analyses and broadens the knowledge base concerning particularly route choice preferences amongst a more representative sample of the population.

The third and summarising research question in this PhD attempts to address a knowledge gap concerning the extent to which new bicycle infrastructure results in new or rerouted cyclists – and does so through the utilisation of interventions. Interventions are underutilised within bicycle research, and bicycle infrastructure interventions are no exception (Handy et al., 2014).

Through the analysis of two infrastructure interventions in Papers IV and V, this thesis contributes to an empirical foundation concerning the effect of intervention size on the nature of travel behaviour change. The two interventions are of differing magnitude and are used to test the hypothesis that change of transport mode to cycling requires a greater magnitude intervention than a change of bicycle route (based on the assumption that utility differences between alternate routes are smaller than the differences between competing modes). This hypothesis is additionally based on findings that suggest transport modal choice has a low elasticity (Börjesson & Eliasson, 2012; Krizek, Handy, & Forsyth, 2009).





### **3. Research methods**

*Why couldn't the bicycle stand up for itself?*

*Because it was two-tyred.*

This PhD explores the topic area in two main ways. First, to understand the influences on and the interactions between bicycle route and mode choice and secondly, to reflect on the topic area within the Norwegian context. The broad nature of the problems examined in this thesis encourages the application of multiple research methods. Table 2 overleaf provides an overview of the methods applied in this thesis, data sources, analysis approaches and objectives. Specific methods are selected for a more detailed description in the remainder of this chapter.

Table 2. Table of methods, data sources, analytical approaches

Paper	Type of study	Data source	Analytical approach	Objective
I	Literature Review (1)	Grey literature, NTNU library, Norwegian transport institutes	Case comparison (Norwegian context)	Identify contextual information and comparable Norwegian relocation cases for analysis of mode choice effects
II*	Literature Review (2)	Scopus, TRID databases	Systematic literature search	Summary of bicycle route choice data collection approaches
I	Online questionnaire	Travel survey (longitudinal)	GIS, descriptive statistics, regression analysis	Commuter mode choice. Impact of new route (following workplace relocation)
III	Online questionnaire	Travel survey with map (single time point)	GIS, descriptive statistics	Variation in route choice on common origin-destination pairs
IV	Online questionnaire	Travel survey with map (longitudinal)	GIS, descriptive statistics	Route and mode choice in association with bicycle path opening
V	GPS tracking	Smartphone GPS application	GIS, descriptive statistics	Route and mode choice in association with bicycle lane opening
V	Observation	Video and radar-based traffic counting	Descriptive statistics (as supplementary source)	Comparative data for GPS route choice analysis

\* Literature reviews were also performed for the other studies; however, these were not the primary output as was the case for Paper II.

### **3.1. Literature review**

A systematic literature review (Paper II) was performed to explore the variety and frequency of different methods used for gathering bicycle route choice data. This was helpful in subsequent empirical studies when determining the method to be used to collect data. There are many alternative approaches that can be used for developing a literature review paper, with a wide variation in criticality, type of synthesis and quantity of literature reviewed (van Wee & Banister, 2016). The search strategy used for Paper II follows guidelines outlined in the PRISMA statement, which is widely used in the medical and health sciences and attempts to make the review procedure as reproducible as possible (Moher, Liberati, Tetzlaff, & Altman, 2009). An overview of the databases and filtering strategy used is displayed in Figure 4 below, taken from Paper II. Search terms are described in the paper.

The primary contribution of the other four empirical papers is principally empirical rather than literature based. However, as for all scientific papers, a brief literature review is conducted for each topic to describe the state of the art and to provide a contextual position for the corresponding paper (Avni et al., 2015). Utilising existing review papers can help to create a concise, yet sufficiently detailed review and this approach is used for Papers I, III, IV and V.

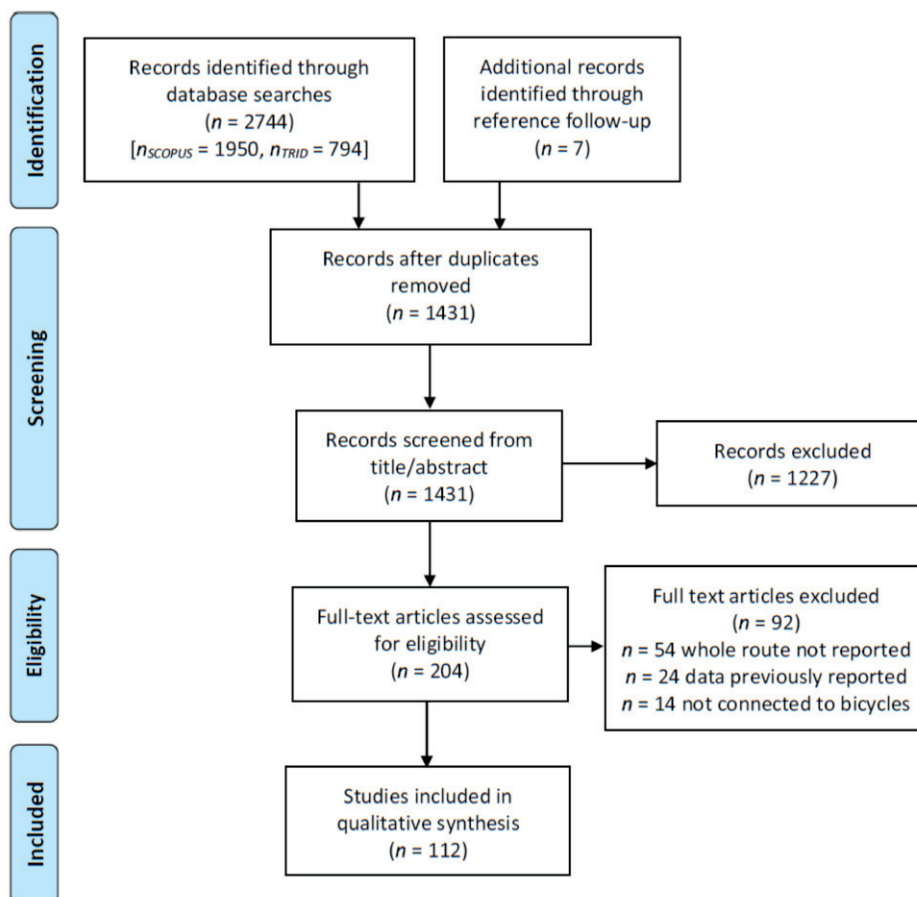


Figure 4. Systematic search strategy applied to Paper II on data collection methods for bicycle route choice.

### 3.2. Selection of cases

The structure of the research papers in this thesis was not clear at the outset of the work, and this led to a variety of different cases being selected. It became apparent when looking for knowledge gaps that before and after interventions connected to cycling (both infrastructural and behaviour change initiatives) were gaining attention as an underdeveloped area that offered significant room for new research designs. The relatively small amounts of existing intervention literature concerning bicycle infrastructure projects made this an area of interest

for the PhD research. This led naturally to the next phase of finding suitable cases to research.

Although not a classic bicycle infrastructure intervention, the relocation of the newspaper office Adresseavisen occurred at an opportune time when planning Paper I in that it was public knowledge well in advance of the moving date. The Adresseavisen case is an atypical relocation example in that it published its intended relocation through its main business arm – media creation, likely as a form of self-promotion. Most company relocations are however seldom public knowledge until after the move has occurred. Whilst this is not a requirement for all study designs, it is critical for the before-after travel survey study design performed in Paper I, an approach which is also used in Paper V.

Two main potential case types were considered for assessing the route choice preferences of different users: large destinations (such as workplaces in Paper I) and large origins (such as residential apartment complexes). In Paper III the later was targeted, and through contacting the Student Welfare Organization in Trondheim, it was possible to distribute a survey to five clusters of university student residences. The ease of access makes the targeting of university populations for cycling behaviour research relatively common (Akar & Clifton, 2009; Kang & Fricker, 2018; Nankervis, 1999).

Papers IV and V address bicycle lane interventions in Innherredsveien in Trondheim and Markveien in Oslo respectively. The selection of these cases was connected both to the availability of appropriate research methods and the appropriate timing of a project to analyse. For Paper IV, case selection was less time-dependent since prior and current travel behaviour was elicited in the same post-intervention travel survey. For Paper V however, the longitudinal Global Positioning System (GPS) based study design required close collaboration with infrastructure developers to be able to collect data before and after the bicycle lane completion whilst also avoiding the winter low-season. In the Municipality of Trondheim, plans for the building of new bicycle

infrastructure were not as detailed as for the City of Oslo, and therefore Oslo was selected for Paper V.

Many other potential bicycle infrastructure intervention cases were considered during the course of this PhD, for example in connection with the Norwegian Public Road Administration's (NPRA) pilot bicycle project scheme. The pilot scheme had confirmed implementation sites for previously untested initiatives (in the Norwegian context) as early as the beginning of 2017 (Berger, 2017) however, the lack of timeline made these cases impractical for the intended before and after study design proposed in Paper V.

### **3.3. Online travel surveys**

The four empirical papers are based upon or utilise variations of travel surveys, querying most recent or typical travel behaviour in addition to basic questions on users' demographics. For Papers I, III and IV, the primary method of data collection is a form of web-based travel survey. Papers I and III used freely available commercial survey tools Survey Monkey<sup>1</sup> and Jotform<sup>2</sup>, whilst Paper IV made use of a customisable survey platform developed by Emotional Maps<sup>3</sup> (Pánek & Benediktsson, 2017). For Papers III and IV, the survey was conducted only once, whilst for Paper I, two surveys were conducted with an interval of one year. Whilst Paper I also could have been performed as a single survey in which participants are asked to recall travel behaviour, the intention of repeating the survey was to avoid recall bias for former travel behaviour (Mertens et al., 2017).

A travel survey built in Jotform was also used to recruit participants for the Oslo study (Paper V). In this case, the survey was very brief and was used principally as a means of gathering interest and creating a list of potential participants who could be sent invites to the primary Global Positioning System (GPS) data

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<sup>1</sup> <https://www.surveymonkey.com>

<sup>2</sup> <https://www.jotform.com/>

<sup>3</sup> <https://www.emotionalmaps.eu/>

collection (which required users to begin tracking their activity at the same time).

### **3.4. Norwegian National Travel Survey data**

Reference data from the most recently published 2013/2014 Norwegian National Travel Survey (NNTS) was used in the empirical Papers I, IV and V (Hjorthol et al., 2014). The NNTS records the travel behaviour of 61400 individuals across Norway, with a higher weighting in city regions financed by the NPRA and regional authorities. In the City of Trondheim, the sample size consisted of 2002 people from a population of 175000 (in 2014), whilst in the City of Oslo it contained 6515 of 629000 residents. Raw NNTS trip data is valuable for making comparisons of population and study sample travel behaviour, since data is aggregated to Statistics Norway's relatively small geographical tracts known as Basic Statistical Units (BSU) or 'grunnkrets'. There are approximately 14000 BSUs in Norway, which are intended to be as stable as possible to allow the comparison of these zones between successive NNTSs or other statistical releases (Hartvedt, 2018). To give an illustration of size, 17 BSUs were used as the recruitment target area for Paper IV, highlighted in Figure 5 below. Eleven of these are immediately adjacent to the 1.8km long intervention section of Innherredsveien (shown in dark blue).



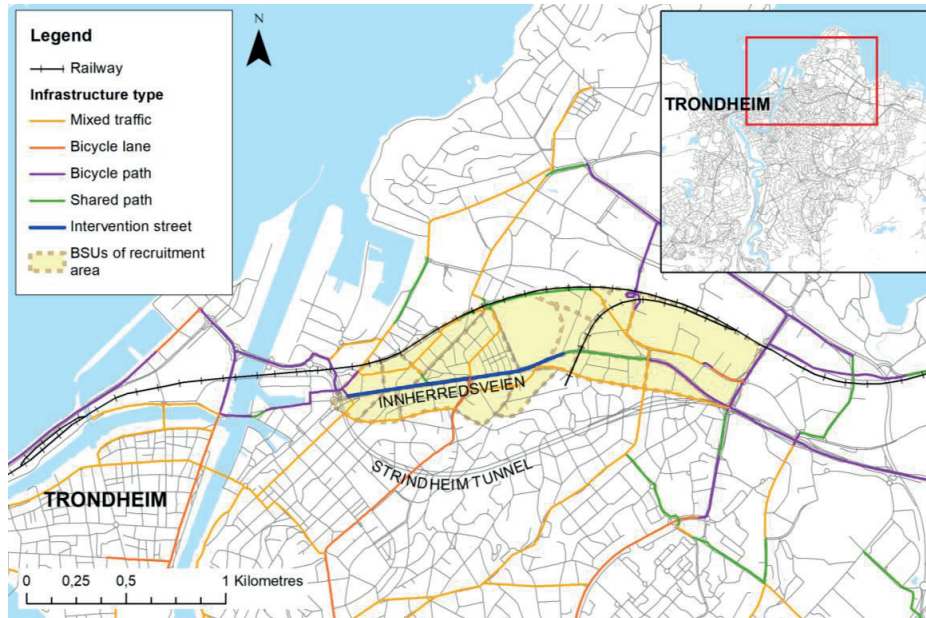


Figure 5. Contextual map of the bicycle path intervention in Innherredsveien, Trondheim (reported on in Paper IV) illustrating the 11 Basic Statistical Units (BSUs) whose residents were invited to participate in a survey.

### 3.5. Intervention study design

The building and evaluation of bicycle infrastructure is a key element of many cities' work with bicycle promotion. However, in many cases, the evaluation is limited to traffic counts, which risks oversimplifying the reality of changes in bicycle use. This is because regardless of whether a new piece of bicycle infrastructure causes a positive or negative effect on cycling, there is always the question of what has happened to those who changed behaviour. A new bicycle lane may double the number of cyclists, but if these "additional" cyclists have only changed their choice of street, the net effect is very different to a doubling in the number of cyclists due to change of transport mode. In other words, it is important to understand whether an infrastructural initiative causes route substitution or mode substitution and for the latter case, which transport modes are substituted to/from cycling. Testing the extent of route and mode

substitution following a bicycle infrastructure intervention is the primary aim of the third research question, addressed in Papers IV and V.

Intervention study designs, such as longitudinal panel studies, are widely used in the medical sciences and public health domains to assess the impacts of treatments (Kärmeniemi et al., 2018). In the context of cycling, using an intervention approach provides a means of measuring the impacts of a specific bicycle mobility promoting initiative as free from the influence of confounding factors as possible (Yang, Sahlqvist, McMinn, Griffin, & Ogilvie, 2010). This is typically done by investigating the travel behaviour of the same group of participants (a panel) before and after the intervention to provide a time order of cause and effect.

In addition to time-order, intervention research seeking to determine causality should also attempt to fulfil three other factors: association or covariance, non-spuriousness, and causal mechanism (Handy, Cao, & Mokhtarian, 2005). Association is the first step which identifies specific factors which can potentially have an influence on travel behaviour. Cross-sectional study designs are often used to identify statistically significant causal associations with travel behaviour (Heesch, Giles-Corti, & Turrell, 2015). Non-spuriousness is ensured by isolating the impact of an intervention from other possible causal factors, for instance through the inclusion of a control group which is unaffected by the intervention (Benton, Anderson, Hunter, & French, 2016). Thus once some associations have been identified, a proper experimental study should randomly assign participants to the intervention and control groups, to ensure that the association is nonspurious (Krizek, Handy, et al., 2009). Causal mechanism refers to a theoretical justification for the observed outcome and has not been the focus of very much existing research concerning travel behaviour – with most research focussing instead on association (Handy et al., 2005). Following a study design like this allows more conclusive statements to be made about the overarching effects of interventions in terms of route substitution (change of route) versus change of mode.

Bicycle infrastructure interventions are used in this thesis to refer to infrastructural changes such as the development of bicycle lanes or closure of a street to vehicular traffic whilst maintaining cycling access (filtered permeability) (Aldred, 2015). Such initiatives are seldom able to be independently shaped by researchers, meaning that the study of such initiatives is often done in parallel with a planned project, something often referred to as a natural experiment (Heinen, Panter, Mackett, & Ogilvie, 2015). Travel behaviour is a function of many causal influences beyond infrastructure such as travel costs, marketing, social norms, safety, convenience, and reliability, and these factors can be controlled for in bicycle infrastructure intervention studies.

Achieving all four criteria for determining causality is recognised as being challenging in the travel behaviour research domain (Handy et al., 2005; Krizek, Handy, et al., 2009). Indeed, even amongst those active travel intervention studies using control groups, there is a significant risk of bias, due to inadequate control sites, poor control of confounding variables and limited precision with the measurement of the outcome (Benton et al., 2016).

When the measured outcome is the level of cycling, the selection of control groups is relatively straightforward, with the main criteria being independence from the intervention and in an otherwise similar context. When route choice is the measured outcome of a bicycle infrastructural intervention, the selection of control sites becomes challenging, since the entire neighbourhood of a control area should be similar to the intervention area in order to represent a comparable route choice environment. A potential solution to this issue is to use distance or separation from the intervention as a control variable (Krizek, Handy, et al., 2009). This approach is adopted in Paper V in which a quasi-control group is formed of participants who did not use the intervention street in the post-construction data collection period.

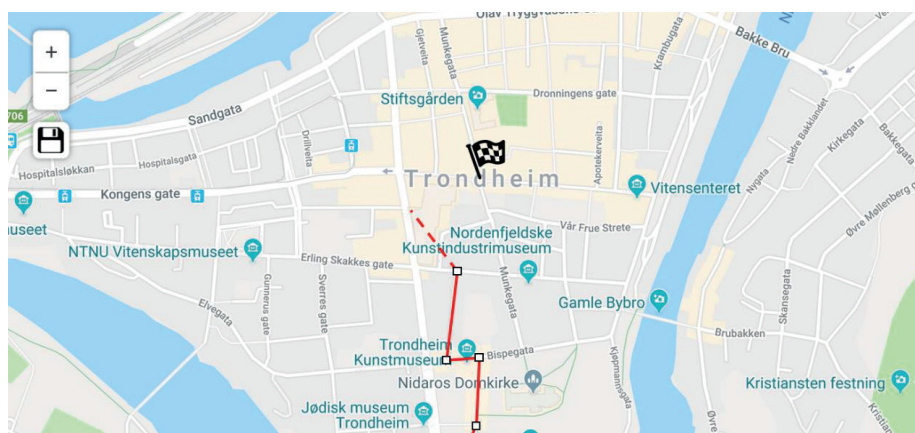
### 3.6. Web-based mapping data collection

This thesis uses web-based Geographic Information Systems (GIS) to integrate online travel surveys with the geographic mapping of user knowledge, an approach sometimes referred to as SoftGIS (Kahila & Kytta, 2009). This is done through a mapping Application Programming Interface (API), which allows the drawing of polylines (points or polygons are also possible) in an online map in the area of interest (Shakeel et al., 2016). Papers III and IV use this approach, with the advantage of reaching the same potential number of participants as any other short web-based survey. User's digitally drawn routes can thereafter be directly imported into GIS.

In terms of survey preparation, mapping API creation requires more planning than conventional travel surveys. For Paper III, the mapping API was built on a Google Maps platform using the same approach as in Snizek et al. (2013) and subsequently linked to the online survey platform Jotform<sup>4</sup> where the non-mapping survey responses were gathered. Jotform contains the option to redirect participants upon survey completion to a webpage of the creator's choosing as an alternative to a "thank you" page. Data from Jotform, such as a user identification number (ID), can be sent to the second webpage via the HTTP POST request method, which is explained in more detail in Paper III. Although the survey and mapping responses were collected separately, the existence of the common ID made the connection of these datasets straightforward.

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<sup>4</sup> <https://www.jotform.com/>



*Figure 6. Google Maps based mapping API used to collect participant responses on bicycle route choice in Paper III.*

For Paper IV, the survey was built in and hosted on a single online platform called Emotional Maps<sup>5</sup>. The requirements for the paper were similar to Paper III, except that multiple routes (before and after the bicycle path intervention) now needed to be drawn in separate maps. This allowed the participants to reflect upon their experiences prior to the intervention, around one year earlier, with the present situation. In principle, the mapping API element was very similar to the Google Maps API used in Paper III, but was instead based on an OpenStreetMap (OSM) basemap. Technical information on the API and data collection approach is detailed in Pánek and Benediktsson (2017). The main difference to Paper III was that the survey questions and mapping API were integrated on a single highly customisable platform, allowing the display of multiple maps between survey questions.

### **3.7. GPS data collection – passive smartphone application**

Global Navigation Satellite System (GNSS) is a collective term for positioning and navigation systems based upon signals sent from a network of satellites

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<sup>5</sup> <https://www.emotionalmaps.eu/>

orbiting the Earth. The NAVSTAR Global Positioning System, or GPS, has become the most widely used GNSS, with receivers integrated into a wide variety of civilian navigation products including smartphones, which are owned by 91% of the Norwegian population as of 2017 (Vaage, 2018).

For the final study, Paper V, a passive GPS-based smartphone application was used as the primary data collection means to consider the route and mode choice of study participants. The methods review article, Paper II, provides details of the existing research designs utilised, broadly categorised as either passive or active smartphone applications (apps). Passive apps record all travel behaviour and are therefore well-suited to studies that seek to consider mode choice in addition to route choice (Laube, 2014). Active apps on the other hand, typically require the user to start and stop GPS tracking on their phone in connection with the start and end of journeys (Ibid.). This is more commonly used for studies of a single transport mode due to the increased participant burden and is the more commonly used approach amongst existing smartphone-based bicycle research (Pritchard, 2018).

The app used for data collection resulted from a collaboration with a member of the ETH Zurich research project *GoEco!*, which had developed a passive smartphone tracking technique to study the effects of gamification on travel behaviour change (Bucher et al., 2016). The *GoEco!* team developed an app called *GoEco! Tracker*<sup>6</sup>, which extracts routes tracked in a second, freely available app called Moves® (shut down in July 2018) (Evenson & Furberg, 2017). Moves® passively monitors GPS in combination with accelerometer readings to estimate outdoor physical activity, and an in-built algorithm classifies movement into categories: walking, bicycling, running or transport. The accelerometer assists greatly in identifying the transport mode used due to typical “signature” vibration patterns for each mode, discussed also in Paper II. Moves® enables third-party developers to build on data collected in the app

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<sup>6</sup> [www.goeco-project.ch](http://www.goeco-project.ch)

through a robust API library (Evenson & Furberg, 2017). Processed GPS tracks from multiple participants can then be automatically collated to a secure server by the *GoEco!* Tracker app. *GoEco!* Tracker reclassifies the journeys categorised as 'transport' into their separate motorised modes, mostly importantly breaking down private vehicular use from different forms of public transport (metro, rail, tram, bus, ferry and plane), assisted largely by the comparison of GPS traces with General Transit Feed Specification (GTFS) data from Oslo's public transport operator Ruter. Participants are required to download both apps and authorise the transfer of data from Moves® to *GoEco!* Tracker, through an Application Programming Interface (API).

The comparative user-friendliness (in programming terms) of the integrated API in Moves® was the reason for its selection over other physical activity monitoring apps. In particular, the ease with which individuals can grant permission to access their data in the app made Moves® highly versatile for purposes other than physical activity registration. Prior to shutdown in 2018, Moves had more than 50 officially "connected" partner apps (and many more non-official apps including *GoEco!* Tracker) which made use of Moves data for other purposes. More detailed information on the data collection protocol can be found in the methodological paper from the *GoEco!* project (Bucher et al., 2016).

### **3.8. Bicycle counting for route choice decision making**

In Papers IV and V, bicycle traffic counts are used as a supplementary data source to provide an indication of intervention impact. In Paper IV, both manual and video counts were commissioned by the project owner NPRA, although route choices were not considered.

In Paper V, bicycle count data was collected with the specific intention of considering route choice and utilised both video and radar-based traffic counting techniques. Both techniques involved the temporary installation of measuring equipment for a period of at least three consecutive days both before and after the completion of the bicycle lane intervention. A telescopic Miovision



Scout camera<sup>7</sup> of the same type shown in Figure 7 was installed overlooking a forked intersection leading into the intervention street. The intersection was chosen as the fork is a natural decision point for cyclists who must choose one of two alternative routes when cycling towards the city centre (see also the contextual map in Figure 21). Cyclist volumes between the three polygons shown in the camera view in Figure 8 were semi-autonomously processed by Miovision (with  $\geq 85\%$  accuracy) using their proprietary Traffic Data Online bicycle counting service<sup>8</sup>.

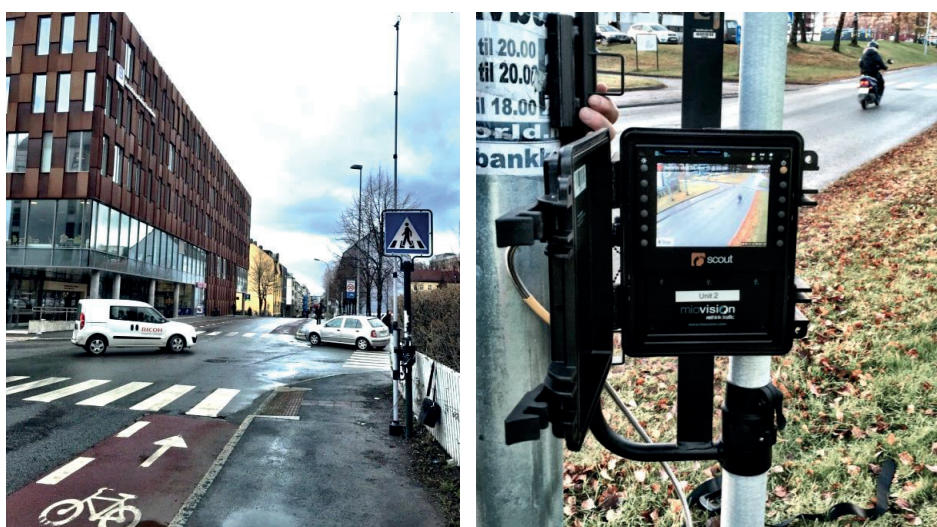


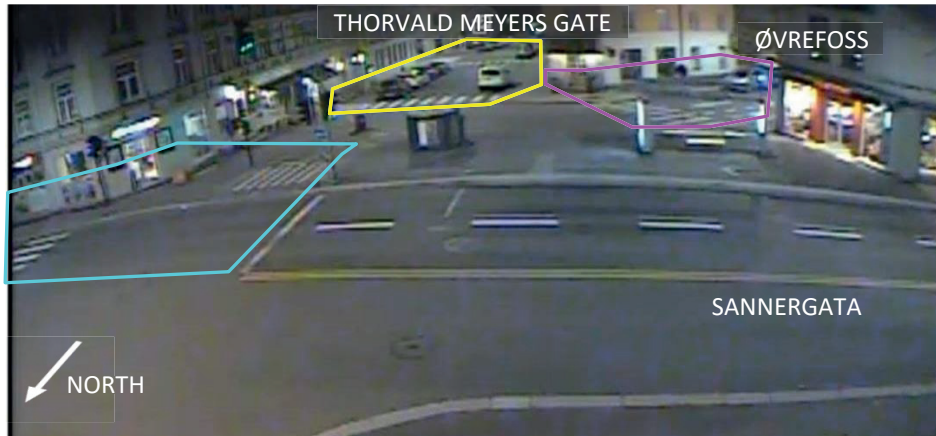
Figure 7. Miovision Scout camera set-up in Trondheim (photo: Petr Pokorny).

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<sup>7</sup> <https://miovision.com/scout/>

<sup>8</sup> <https://miovision.com/datalink/traffic-data-processing/>



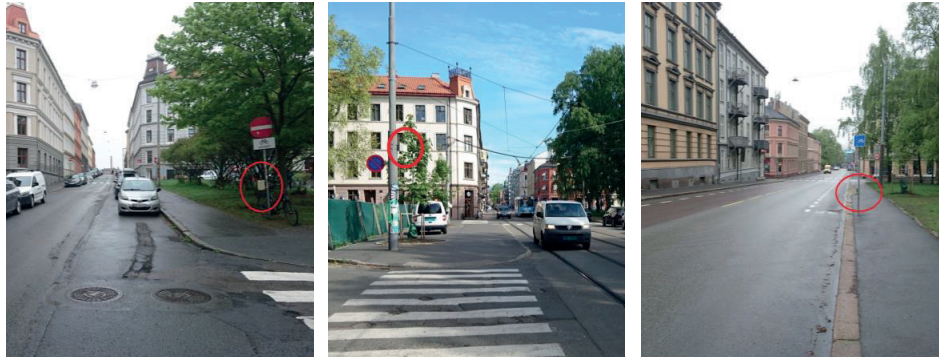


*Figure 8. Camera perspective over the forked intersection in Oslo. The pink counting zone records bicycle movements on Øvrefoss, a short street that leads into the intervention street Markveien.*

In addition to the single video camera location, radar-based ViaCountII mobile traffic counters<sup>9</sup> were simultaneously installed at three locations including the intervention street and the two nearest parallel alternative streets for one week of counting before and after the street was modified. The microwave-based radar counters work on the Doppler principle, measuring reflections of moving vehicles and cyclists to determine both speed and length, which is used to classify the type of road user in addition to the counting itself. The counting devices are typically deployed in connection with traffic evaluation studies (Ryus et al., 2014), and the installation of equipment was provided by ProxII, a traffic systems subcontractor to the City of Oslo operations division.

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<sup>9</sup> <https://www.viatraffic.de/en/products/viacount-ii-traffic-counter/>



*Figure 9. Radar traffic counters installed on Markveien, Thorvald Meyers gate and Toftes gate in Grünerløkka, Oslo (left to right).*

### **3.9. Data preparation and map-matching**

For the three studies in which detailed route choice data was collected (Papers III, IV and V), some data preparation was required before the data could be analysed or presented. Individually drawn or GPS-tracked routes are not easily analysed as raw data, as attributes of the street network are not easily transferred to raw routes and the extent of overlap or similarity between routes is not quantifiable using standard GIS procedures. For this reason, this thesis makes use of post-collection map-matching to ‘snap’ routes to the underlying street network.

The mapping API based studies (Papers III and IV) exhibited imperfect route tracing which required the manual removal of routes for cases in which the participants’ selected street or path was inconclusive (due to general imprecision or lack of sufficient vertices or waypoints). For some routes, the route choice appears relatively clear, yet the match with the underlying street network remains poor (for example when crossing a bridge for which there are no nearby alternatives). In these cases, routes were manually edited to improve the closeness of match with the underlying network without changing the route selection. This meant the addition and/or relocation of some vertices. This was a necessary step for the following map-matching operation (see below).

Following the data filtering and cleaning phases, the route traces could be map-matched. There exist many approaches to perform map-matching, however, few are user-friendly for the non-programmer (Dalumpines & Scott, 2011; Schuessler & Axhausen, 2009; Schweizer, Bernardi, & Rupi, 2016). The chosen approach was based on GIS, using ArcMAP 10.6 to conduct a shortest path search for each origin-destination (OD) pair on the transport network contained within a 50m buffer around the user-drawn route. The transport network available was dependent on the mode of transport (such that cyclists could not be matched to a busy highway where cycling is forbidden).

The process of finding a single route match was performed in ArcMAP Model Builder, as shown in Figure 10 below. The four first blue boxes are derived from the user-drawn routes prior to starting the Model Builder operation. The sequence was then looped after each iteration allowing the map-matching to be automated for the full dataset. The Model Builder script had a processing time per route of approximately 5 to 10 seconds (running on a Windows laptop with above-average specifications in 2017). This time requirement was acceptable for Papers III and IV for which less than 1000 routes were used as input data.

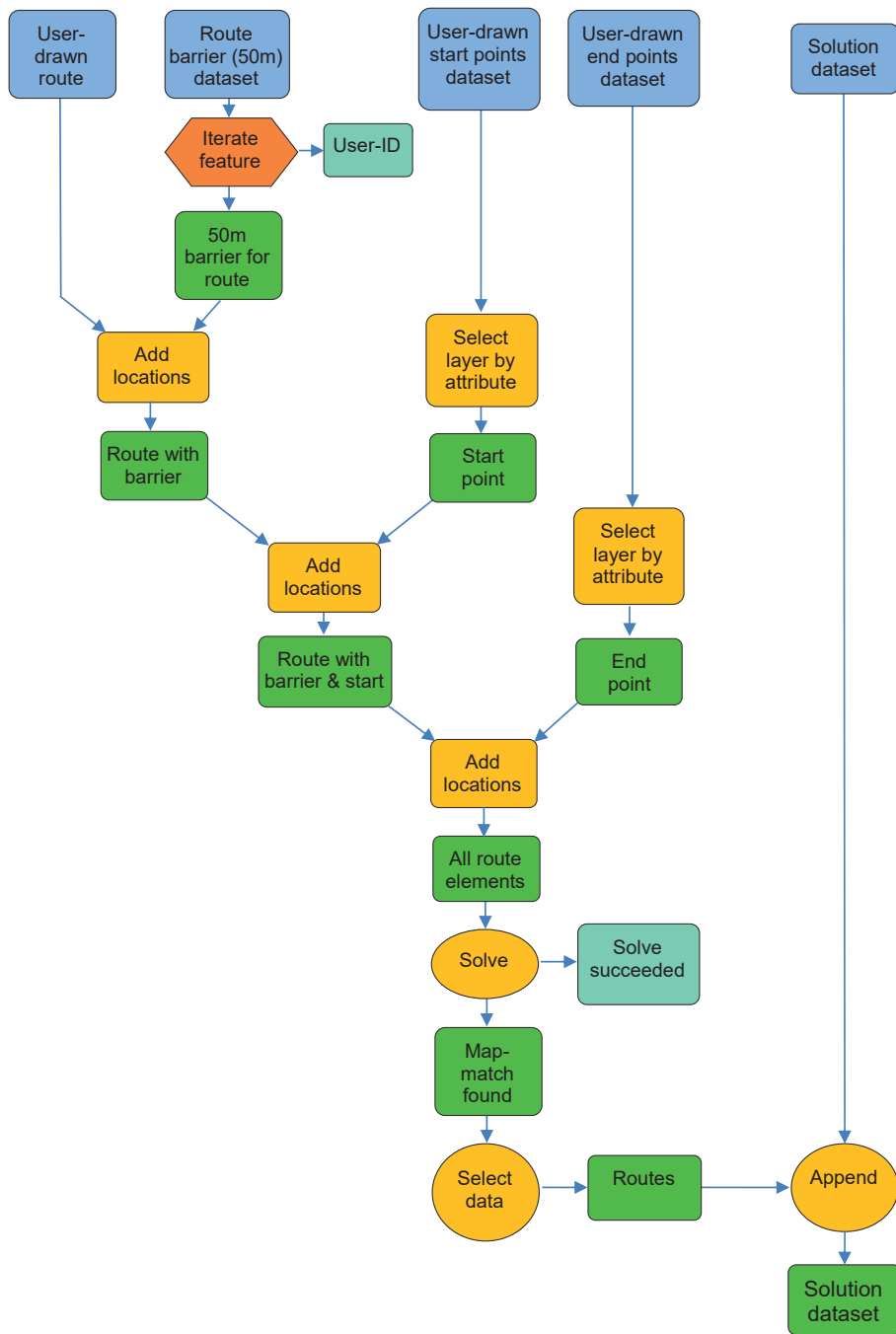


Figure 10. The ArcMAP 10.6 Model Builder algorithm used for map-matching of filtered and cleaned routes in Papers III and IV.

The high degree of manual filtering and editing of routes used for the mapping API studies was not practical for the much larger GPS dataset described in Paper V with 36000 raw routes to match across all modes. The map-matching approach adopted for Paper V was based on code developed by the Open Source Routing Machine (OSRM) Project (Project OSRM, 2018). OSRM is based on a Hidden Markov Model, and the open source code was modified for the purposes of matching to different modes identified by *GoEco!* Tracker. GPS traces are typically imperfect with respect to data frequency or horizontal accuracy. This makes the Hidden Markov process suitable since it is adapted for applications with hidden or missing data (such as waypoints) in combination with a probability function which for this application can take horizontal GPS accuracy as an input variable (Ibid.). For bicycle journeys, the matching profiles were adapted by the *GoEco!* Tracker developers to allow matching to both bicycle-specific and generic routes within OpenStreetMap (OSM), whilst opening up for matching to links deemed 'unavailable' (such as one-way) in OSM. This was done to reflect the actual behaviour of cyclists in which traffic regulations are not always followed. This is particularly important in the Norwegian context since cyclists are permitted to ride on the footpath, meaning that there are in practice very few network restrictions for bicycles. In many cases there were sections of GPS traces with a vertex frequency too low for map-matching. For those sections of trips with large gaps (more than three kilometres), a shortest path routing algorithm was applied between the vertices adjacent to the gap (Huber & Rust, 2016). The matching and routing process are described in more detail in Paper V.

### **3.10. Geographic Information System (GIS) analysis**

The Geographic Information System (GIS) software ArcMAP 10.6 was used in the analysis stages of the empirical studies in this thesis (in addition to map-matching described in Section 3.9). GIS software assists in the presentation and study of spatial or geographic data and is therefore widely used in transportation and urban planning. Layers in a GIS model such as streets, land use zoning, water bodies and buildings can be added to analyse the

relationship between bicycle activity (represented by polylines) and built environment factors. For this thesis, the primary uses of GIS are for map-matching (Papers III and IV), identifying overlapping routes/route segments (Papers III, IV and V), route optimisation based on Bicycle Level of Service characteristics (Papers I and III) and OD cost matrix generation for identifying the distance and travel time of different modes of transportation (Paper I). The spatial join functionality is used to graphically illustrate route choice preferences through the creation of heat maps displaying frequency of use for different routes.

### **3.11. Data privacy**

When researching human travel behaviour, and especially when gathering data on precise location at specific points in time, it is important to ensure user anonymity. All four empirical studies in this PhD have sought and received the approval of NSD – the Norwegian Centre for Research Data. Applications to NSD are required for all Norwegian research projects which may access personal data. For all articles, study participants were informed of the type of data being collected and the manner in which it would be handled and processed. Participants were ensured that their responses would not be traceable back to them based on any of the published information.

For studies I, III and IV, users were required to self-report their travel behaviour – giving them control over the quantity and precision of data they choose to provide. However, to avoid concerns about data privacy, names and home addresses were not registered in any of the travel surveys, and instead, the nearest road intersection was requested of users in Papers I and III. Email details were however collected in Paper III and V in order to be able to contact users regarding clarifications to their responses – and this data is required by NSD to be anonymised at the end of the project.

For Paper V, GPS methods were used to register all travel behaviour over a period of several weeks before and after a bicycle lane was built in the neighbourhood of users. Because both origin, destination, route and time are

revealed in the dataset, this paper required special consideration with respect to data privacy. All GPS data was maintained on secure servers with restricted access and stored separately from demographic information about users (which was collected via a travel survey).

In May 2018, the EU Regulation 2016/679, also known as the General Data Protection Regulation (GDPR) came into effect with the aim to harmonise privacy legislation and ensure consistent high-level data protection of citizens' privacy (European Union, 2016). The primary intention is to regulate how data-related services use the information collected from citizens and to grant individuals rights over the data that is collected about them through such platforms as digital subscriptions, social media and internet search engines amongst others. The GDPR states that further processing of personal data is only allowed where it is compatible with the purposes for which it was originally collected. In other words, the GDPR provides a presumption that research is compatible with the purposes for which the data was obtained, so long as this is made clear to participants.

The data for the empirical studies in this thesis was collected prior to 2018 and was therefore not influenced by the GDPR. However future studies of a similar nature to the ones performed in this thesis should be aware of the implications it has including improved rights for user access to data, restricted consent to data use (to the extent allowed by the stated intentions) and deletion of collected data. This has implications for subsequent research purposes that are beyond the stated intention and can potentially impact data sharing across country borders or open data publication. Improved user knowledge about their rights could potentially also affect response rates when sensitive information is collected.

## 4. Bicycle mode choice – the decision to bicycle

*To bicycle, or not to bicycle, that is the question.*

*– Shakespeare's Hamlet, who was (at least) 200 years before his time*

### 4.1. Research question 1

This thesis adopts a structure in which the research questions are arranged in order of ascending importance and increasing specificity. Research question 1 serves as an introduction to the subsequent research questions by starting at a broad level:

*In what manner can the accessibility of urban areas influence the decision to bicycle?*

The question holds relevance for urban planners given the increasingly common goal for local authorities to stimulate physical activity and mitigate traffic congestion through changes to the built environment. Subsequent research questions begin to focus on narrower problem areas – covering bicycle route choice as a separate entity in research question 2 before research question 3 combines both mode and route choice in the context of infrastructural interventions for the promotion of cycling. Since the three research questions overlap, they are answered collectively in the conclusions in Chapter 7.

Paper I, in which the effects of company relocation on bicycle and walking mode choice are investigated, is the main study which addresses research question 1 in its entirety. Therefore, the main role of this chapter is to summarise the results from Paper I, whilst elaborating on the challenges faced through the discussion. The other role of this chapter is to briefly summarise the academic literature relevant to the research question. Integrated land use and transportation planning and the Norwegian context have been introduced already in the background and theory chapter. This chapter, therefore, starts by providing a brief overview of the various factors influencing bicycle mode



choice. Mode choice is also a key element of Papers IV and V, however, this is discussed in the context of intervention changes in research question 3 in Chapter 6.

#### **4.2. The bicycle as a transport mode**

Whilst cycling is often associated with childhood and recreational use, it is estimated to be the primary mode of transportation for 6% of trips worldwide (Mason et al., 2015). In countries such as Sweden, Finland and Germany, the modal share of bicycles is 10%, 9% and 13% respectively, whilst Denmark and the Netherlands have an even higher percentage of trips made by bicycle at 16% and 29% each (Buehler et al., 2016).

Norway, despite the many similarities it shares with its neighbouring countries, has a considerably lower bicycle modal share of 4.5% (Hjorthol et al., 2014). Low population density, a cold climate and challenging topography are examples of factors that negatively influence Norway's bicycle modal share (Mathisen, Annema, & Kroesen, 2015; Moura, Magalhães, & Santos, 2017; Schneider & Stefanich, 2015). With the possible exception of urban density (through land use development policies), these factors are largely beyond the realm of transportation planners' traditional sphere of influence. But even when excluding the impact of such factors, a large degree of the variation in bicycle friendliness or 'bikeability' of an urban region can be explained by accessibility and transportation-related policies (Vaismaa et al., 2012).

Whilst many cities in traditionally cycling-friendly nations (such as the Netherlands and Denmark) have had a long history of developing bicycle-appropriate infrastructure, most of the global urban population has an incomplete or non-existent bicycle network (Koglin & Rye, 2014; Macmillan et al., 2014; Mason et al., 2015). These contexts with comparatively disconnected or low-density bicycle networks have been demonstrated to have lower rates of cycling in cross-sectional studies comparing multiple urban areas (Buehler & Pucher, 2012; Dill & Carr, 2003; Schneider & Stefanich, 2015).

Mounting evidence suggests that bicycle-friendly built environments are a critical element in facilitating increased bicycle usage (Cervero, Denman, & Jin, 2019; Goodman, Sahlqvist, & Ogilvie, 2013; M Winters, Brauer, Teschke, & Fuller, 2016). Bicycle infrastructure, a key element of such environments, has been demonstrated to promote cycling's competitiveness in terms of travel times and comfort (Börjesson & Eliasson, 2012).

Bicycle infrastructure is widely considered to be a necessary part of enabling a modal shift to cycling but is not necessarily a sufficient condition for a modal shift (Song, Preston, & Ogilvie, 2017). Whether or not infrastructure is sufficient for achieving modal shift is debated, however there is mounting evidence to suggest that the effect of infrastructure can be enhanced through combination with market-based measures (such as tolls, taxes and subsidies) and 'soft' policy measures (such as campaigns and promotional events) (Gössling, 2013; Piatkowski et al., 2019; Pucher et al., 2010; Scheepers et al., 2014). A review of 141 studies on soft policy measures (also called programmatic interventions) revealed a mean increase in the active and public transport modes from 39% to 46% (Möser & Bamberg, 2008). However, a review of evidence specific to cycling suggests that such programs (typically focussed on reduced car use) have a greater effect on transferring vehicle trips to public transport and walking than to bicycling (Pucher et al., 2010). This suggests that the competition between walking, cycling and public transport is not to be ignored within the overarching aim of reducing journeys by private car. This chapter considers only the impacts of transport infrastructure (for both cycling and competing modes) and the effects of changes in infrastructural offering on urban bicycle modal share.

Neighbourhood land use variables such as accessibility, job/housing mix, population density and access to parks are frequently shown to be relevant factors upon individuals' decision to cycle (Ewing & Cervero, 2010; Krizek, Forsyth, & Baum, 2009). Some of these urban form factors including density, connectivity, destination concentration and public transport accessibility are additionally captured by so-called bikeability metrics (Lowry, Callister, Gresham,

& Moore, 2012; Nielsen, Olafsson, Carstensen, & Skov-Petersen, 2013; Nielsen & Skov-Petersen, 2018). This thesis focuses mostly on variables related to transport infrastructure provision, although land use factors contribute to some of the Bicycle Level of Service methods evaluated in Paper III. Additionally, land use variables can also play a role in minimising trip distances, thereby making walking and cycling more competitive (Sardari, Hamidi, & Pouladi, 2018).

### **4.3. Summary of Paper I**

Paper I uses a comparative case study method. Employee travel surveys were conducted before and after the July 2015 relocation of the main case study - the editorial office of the newspaper Adresseavisen in Trondheim, Norway.

Adresseavisen relocated from the urban periphery (Heimdal) approximately 9 kilometres south of the centre of Trondheim to an area immediately east of the city centre (Solsiden). The follow-up survey was performed one year after relocation to ensure stability and comparability of the commuting behaviour (especially relevant given seasonal variations in Norway) (Hjorthol et al., 2014). The intention of Paper I is to assess the relationship between the accessibility and transport characteristics of the former and present office locations with the employees' commuting mode of transport, with a focus on bicycling and walking.

Figure 11 below illustrates the study design of the case study through two online travel surveys: pre- and post-relocation. Respondents' home locations were registered, and GIS was used to model the approximate route, distance and travel time with different modes to the old and new workplace locations (in addition to stated responses from employees). In order to test the influence of the bicycle-related attributes on the commuting route to work before and after relocation, a form of Bicycle Level of Service called Level of Traffic Stress is adapted and applied to the modelling of routes (Cervero et al., 2019; Furth et al., 2016).

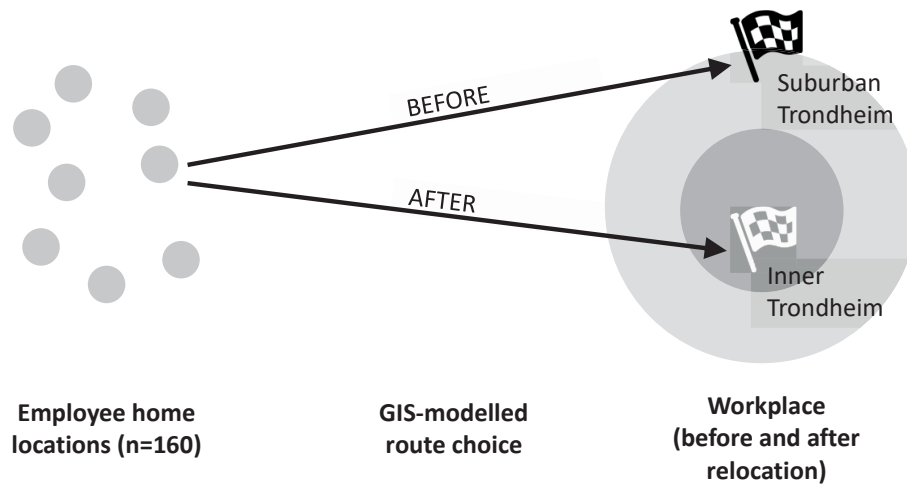


Figure 11. Graphical illustration of Paper I study design. Data was gathered from a before and after travel survey with Adresseavisen employees.

Three other Norwegian relocation cases were found in the Norwegian literature to compare with Adresseavisen: the headquarters of insurance firm Gjensidige in Oslo (Christiansen & Julsrud, 2014), and two public offices in Trondheim: Statens Hus (Meland, 2004) and Trondheim Municipality (Paulsen, Kvidal, & Strømmen, 2008). The transport-related attributes of the four cases are comparable due to the similarity of workplace function: all are offices with a limited visiting customer function. Anonymised travel data on commuting from the 2013/2014 Norwegian National Travel Survey (NNTS) was used for comparison of the neighbourhood travel behaviour with both the Adresseavisen and Gjensidige relocations (which occurred in 2015 and 2013 respectively).

For the Adresseavisen relocation, a Pearson's chi-squared test revealed significant changes ( $p < .001$ ) in the transport modal share (walking, cycling, public transport, car/motorcycle) following the relocation. Modal shares before and after relocation are presented in the two leftmost data columns in Table 3. A multinomial logit model for the participants' travel mode choices was also created, revealing that commute distance, access to a bicycle, access to a car and the existence of paid parking are significant explanatory variables for the

choice of transport mode ( $p < .01$ ). The model suggests that shorter distances, access to a bicycle and paid parking all promote the selection of the bicycle over alternative transport modes. Having a child under the age of 10 years or having regular access to a car was associated with a decreased likelihood of cycling.

During the creation of the logit model, many additional built environment and land use characteristics were tested but were found to be not statistically significant. These variables include: gender, age, education, response year, provision of bicycle infrastructure along the shortest path, number of toll ring crossings, working time, perceptions of bicycle safety, self-reported mode sensitivity to additional trips, number of changes required on the fastest public transport commute (from one bus to another) and travel times with different modes of transport. Some of these variables are correlated with the model covariates (for example travel times with distance), resulting in their exclusion from the final model. Model results are further detailed in Table 1 of Paper I.

In Table 3 below, the transport modal share of Adresseavisen employees is displayed on the left whilst NNTS travel survey data (for commuting journeys) from the same neighbourhoods as Adresseavisen's former and current locations is presented on the right for the survey year 2013/2014. This comparison of case study data from 2015 and 2016 with NNTS data from 2013/2014 relies on the assumption that the commuting transport modal split for a selected neighbourhood is relatively stable from year to year. The table demonstrates that although the mix of workplace functions (e.g. retail, public service, private office) in the NNTS dataset is significantly different from the Adresseavisen office, the difference in commuting behaviour between the neighbourhoods is relatively similar (see the final column 'factor change' in each dataset).

Table 3. Commuting modal shares for employees before and after Adresseavisen relocation (left) and comparison with the (static) commuting modal share from the Norwegian National Travel Survey (NNTS).

	Adresseavisen			NNTS 2013/14 (commuting)		
	Heimdal (2015)	Solsiden (2016)	Factor change	Heimdal area	Solsiden area	Factor difference
Walking	6%	15%	2.5	10%	26%	2.6
Cycling	10%	28%	2.8	7%	18%	2.6
Public transport	11%	28%	2.5	13%	29%	2.2
Car/motor- cycle	73%	29%	0.40	70%	27%	0.39

Table 3 demonstrates that the cycling modal share increased by a factor of 2.8 for Adresseavisen, and the factor change for the same neighbourhoods a year earlier was 2.6 (for all commuting registered in the NNTS). An alternative Difference in Differences (DiD) approach is used to approximate the change in average modal share trends. DiD is often applied for the analysis of pre and post-intervention data in combination with control groups (Dill, McNeil, Broach, & Ma, 2014). The DiD treatment effect is shown in the equation below where  $\bar{y}$  is mean bicycle modal share given the conditions in subscript. The first term in parentheses is therefore the change witnessed for the intervention – Adresseavisen, whilst the second bracketed term represents the change in the control group – in this case, NNTS comparative commuting data. The DiD approach effectively normalises the observed changes with respect to the NNTS comparison data, giving an indication of changes that are not the result of location.

$$DiD = (\bar{y}_{Solsiden,Adr.} - \bar{y}_{Heimdal,Adr.}) - (\bar{y}_{Solsiden,NNTS} - \bar{y}_{Heimdal,NNTS})$$

Hence for cycling modal share, the 'normalised' treatment size is given by  $DiD = (28 - 10) - (18 - 7) = 7\%$ . This suggests that the relocation of

Adresseavisen lead to more cycling than the comparison between the corresponding NNTS neighbourhoods ( $DiD = 7\%$ ) but less walking ( $DiD = -7\%$ ) whilst public transport and car usage was comparable ( $DiD = -1\%$  and  $1\%$  respectively). This inverse walking/cycling relationship could reflect the greater geographical spread of Adresseavisen employees than the average workplace surveyed in NNTS (due to relatively high specialisation). The land use attributes such as similar costs of car parking may explain the similarity in levels of driving, although these can also be affected by other factors such as education level (Hansen & Nielsen, 2014).

The potential for cycling to work in relation to the shortest bicycle friendly (LTS minimised) commute distance for employees before and after relocation is shown in Figure 12. The employees stated that they would be willing to cycle to work if the distance was less than 6km, which is displayed as a vertical line in the figure. A similar threshold for maximum walking distance of 1.5km was used based on median walking commutes in the NNTS for Trondheim. The change in the potential to walk or cycle to work can be considered as the difference between the curves at a given distance. This reduced distance greatly improves cycling accessibility. The number of employees within cycling distance of Adresseavisen can be seen to triple from 18% to 54% following the relocation.

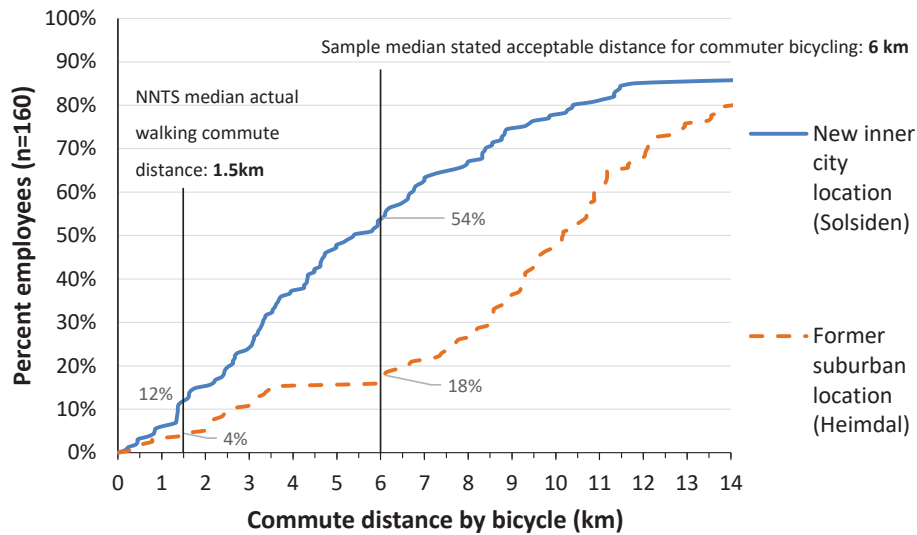


Figure 12. Cumulative distribution of commute distance from unique Adresseavisen employee addresses to the former and present location. Distances are calculated from a GIS operation minimising the bicycle Level of Traffic Stress.

The potential for bicycling to work can be approximated by taking the percentage of employees within cycling distance (54%) and subtracting those who live within walking distance (12%) to give 42%. There is, however, variability in the length people are willing to walk or cycle, meaning some bicycle and walking trips will be found on both sides of the 1.5km commuting distance. A better approximation could be achieved had the participants been individually asked about their walking distance tolerance to produce the same thresholds at the individual level and compare this with their commute distance. The cycling potential (42%) is greater than the actual post-relocation cycling modal share from Table 3 (28%). This may be the result of a number of different factors:

- spatial attributes inhibiting the uptake of cycling and walking (such as poor infrastructure)
- trip-chaining amongst some employees which can positively influence the selection of a motorised mode



- the threshold distances (1.5km and 6km) not being representative of the sample's true willingness to walk or bicycle to work
- external factors related to other transport modes (e.g. parking)

Transport modal splits for Adresseavisen and the two other comparative cases in Trondheim reveals that the relocation of office workplaces towards inner Trondheim lead to a reduction in average commute distances and an increase in cycling levels. The Gjensidige case in Oslo revealed a reduction in car use similar to the Trondheim cases, however, bicycle modal share was unchanged following relocation to the inner city. The stability in cycling levels was potentially due to the unchanged average commute distance for employees after the relocation. The majority of Gjensidige's employees live to the west of Oslo, meaning that the centroid of employees' home locations (i.e. the point from which the cumulative distance to all homes is minimised) is also to the west of the city centre. This potentially explains why the relocation did not reduce commuting distances (this assumes that the before and after locations were equidistant from the centroid of employee locations). It should be emphasised that workplace relocation towards the city centre did lead to increased public transport usage and walking together with a reduction in driving to work for all four cases.

A statistically significant increase in the number of additional trips taken on the way to or from Adresseavisen was observed (from 0.8 to 1.3 trips per person per day). This may reflect the greater opportunities associated with having a workplace near to non-work destinations (such as cinemas, restaurants and shops) – a key factor contributing to increased accessibility. Whilst the association between the relocation and number of additional trips is identified, it is unclear how this may be related to modal choice. Mode choice may influence additional trips, but the desire for additional trips may also influence mode choice (particularly for recreational purposes).

Research suggests that creating a modal shift away from cars is difficult, especially from groups that have become car dependent (Keall, Chapman,

Shaw, Abrahamse, & Howden-Chapman, 2018). The workplace relocation studies all result in significantly reduced car competitiveness which reflects the improved travel times (and thus accessibility) for all modes except car. This is shown to be highly effective at reducing car commuting. Replicating a similar modal shift at the city level is much more demanding both politically and infrastructurally. The competition between different modes is key to the selection of the bicycle as the primary commute mode, and this applies especially to the cost of car parking and public transport in combination with factors that directly affect the cycling experience (Heinen, Maat, & van Wee, 2013). The Gjensidige case had few changes in the cycling experience given an unchanged average distance to work and similar infrastructural conditions before and after relocation, suggesting that the latter point from Heinen et al. may be a necessity to achieve increased cycling modal share.

#### **4.4. Challenges with researching bicycle mode choice**

Online survey data collection for Paper I was relatively straightforward compared to the other studies conducted in this PhD since the survey link was distributed via internal employee email giving a relatively high response rate 160 of approximately 300 employees in total. In addition, the traditional travel survey design meant that the data provided by participants was volunteered by participants who had full control over what they wished to disclose. These respondent advantages translate also to travel surveys concerning route choice. Response rates (discussed also in Chapter 6) should be considered for future work, especially when statistical tools require large numbers of participants or responses in relevant predictor variable categories.

A multinomial logit model was developed in SPSS for Paper I to summarise the impacts of various transport-related factors on the choice of commuting transport mode. This is a commonly utilised approach for bicycle mode choice studies that seek to develop an understanding of explanatory factors (Manaugh, Boisjoly, & El-Geneidy, 2017; Mitra & Buliung, 2015; Sprumont, Viti, Caruso, & König, 2014; Zhao, Nielsen, Olafsson, Carstensen, & Meng, 2018). Multinomial

logistic regression typically requires large sample sizes in order to create meaningful results with many predictor variables, and the usable sample size of 195 responses (from both time periods) appeared to be close to the lower limit for small samples. Multiple model configurations were tested including some which considered only the responses before or after relocation. This, however, resulted in unreasonably high standard errors, particularly when the number of predictor variables was maintained. Peduzzi et al.'s Monte Carlo based rule-of-thumb for logistic regression finds that there are no major problems associated with sample size if 10 or more events per predictive variable are used (Peduzzi, Concato, Kemper, Holford, & Feinstein, 1996). For Paper I, the predictive variable (cyclists and pedestrians combined) had 57 responses, suggesting that 5.7 variables may be used. The study ultimately used 5 covariates in the multinomial logistic regression model: distance, availability of bicycle or car, young child/ren in the household, and paid parking.

The ideal situation for statistical analysis would have allowed separate models to be created for the before and after respondent categories – preferably in the form of a panel study. This would have allowed consideration of further predictors; however, the sample size restricts the opportunities to perform such tests. The sample size is, therefore, a critical consideration if such questions are to be explored – and can be potentially increased through the use of alternative data sources such as national travel surveys or the targeting of larger workplaces (Schneider & Stefanich, 2015).

Paper I additionally attempted to test the importance of bicycle infrastructure attributes on the decision to bicycle, since the relocation of the office workplace also results in a near-complete change in the route to work. The bicycle network was extracted from a merger of the Norwegian National Road Database (NVDB) with OSM data<sup>10</sup>. This network data was used as a foundation for creating a Level of Traffic Stress (LTS) optimised route in which participants are

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<sup>10</sup> <https://github.com/vegvesen/Sykkeldata>

routed to a weighted bicycle network using Dijkstra's shortest path algorithm in ArcGIS. This routing operation was performed due to lack of empirical data about preferred bicycle route or perceptions associated with respondents' bicycle commute – which would be preferable for future work.

The weighting of the network was performed by multiplying segment length by impedance values for roads which are inversely rated to their suitability for cycling using the method described by Cervero et al. (2019). An acceptable detour rate or diversion factor was critical therefore to allocating an appropriate impedance. The paper uses a detour rate of 1.20, or an additional length of 20% that cyclists are considered willing to ride in order to use a high-quality bicycle path compared to a poor quality path, based on route choice modelling results from Portland suggesting commuter cyclists are willing to travel 19% further to use a bicycle path compared to a regular road (Broach et al., 2012). The 1.20 detour rate is allocated as a link-length multiplier to those links with LTS 4, the highest Level of Traffic Stress, and is linearly reduced to 1.00 for LTS levels 3, 2, and 1 (i.e. no change in perceived length for LTS 1). However, different sources suggest substantially different values for typical detour rate from as little as 6% (Hyodo, Suzuki, & Takahashi, 2000) to as much as 67% (Krizek, El-Geneidy, & Thompson, 2007). It appears that the detour rate is highly contextual, and this should therefore be considered in future studies. Paper III addresses the same problem and attempts to find the optimal detour rate for the context of Trondheim, Norway based on empirical route choice data and four Bicycle Level of Service (BLOS) models, including LTS used in Paper I.

OpenStreetMap (OSM) data receives inputs from many sources, and when combined with NVDB data, was found to cause parallel links and nodes in the transport network. OSM data is topologically correct, making it suitable for routing tasks. However, due to the multitude of additional 'false' nodes in the dataset used (a single intersection in Trondheim can have as many as 15 non-existent nodes!), issues were uncovered when attempting to allocate an impedance for cycling through intersections. In GIS, the negative effect of road

intersections for cycling can be overlaid upon the transport segments (represented by polylines) using a link penalty approach proposed by Cervero et al. (2019), however, the effect becomes over-inflated due to the large numbers of false nodes. As a result, Paper I uses only attributes connected to the transport links in the network but not the nodes – a simplification of the reality, even when considering only transportation attributes.

Future research that seeks to use a similar intersection penalty approach to Cervero et al. (2019) to quantify the impact of intersections on the mode choice of cycling should therefore consider the steps necessary to clean OSM data from false nodes or alternatively use a separate transport network (which may be publicly available from regional or national road authorities). It should also be mentioned that Paper I did not fully explore the opportunities associated with GIS methods – since empirical data on route choice was not collected. Revealed preference route choice data of cyclists is, however, addressed in the four other articles in this thesis. In particular, Paper III makes use of the same approach as Paper I with a different transport network and was therefore also able to include intersection impedance into consideration for bicycle route choice (but not mode choice).

The philosophy behind the Level of Traffic Stress methodology is that different users have different thresholds for acceptable traffic risk (Furth et al., 2016). Combining this approach with the routing approach described in Papers I and III can give an estimate of the extra detour required to be able to ride between two points within a particular risk threshold and thereby account for the needs of a group of potential cyclists. The logic here is that the cycling infrastructure is of high quality if the network can accommodate the travel needs of most users without unacceptably long detours from the shortest path. The OD cost matrix approach used in Paper I to calculate distances and travel times with different modes can then be extended to understanding the competitiveness of the bicycle (for groups with different risk adversity) against other travel modes.

## 5. Bicycle route choice – where to ride

*Two bicycle paths diverged in a wood, and I—  
I gathered data on the one less travelled by,  
And that has made all the difference.*

*– misquoted from Robert Frost, 'The Road Not Taken'*

### 5.1. Research question 2

The second research question takes a narrower focus than the first research question in considering bicycle route choice. Research question 2 considers which routes cyclists may prefer to ride upon and what kind of detour is considered acceptable for cycling on a chosen route:

*How does the quality of bicycle infrastructure impact route choice preferences?*

As for the first research question, research question 2 is answered together with the other research questions in this thesis' conclusions in Chapter 7. This chapter seeks to briefly summarise the state of research within bicycle route choice, discuss the results from Papers II and III before addressing some of the challenges and recommendations for future research in this area. Paper II addresses the methods used for collecting empirical bicycle route choice data whilst Paper III examines the association between bicycle route choices of students in Trondheim with four bicycle suitability metrics.

### 5.2. Bicycle route choice

An individual's choice of cycling route can be both a behaviour shaped by habit or an instantaneous decision in response to environmental factors. In either case, the exact route along which people choose to cycle is not generally a direct goal of planners but can be symptomatic of a well-planned versus a poorly planned transport network. Cyclists are highly sensitive to travel time and distance, so observing detours from the shortest OD path gives an indication of the lower suitability of the shorter route (Cervero et al., 2019; Larsen & El-

Geneidy, 2011; Lu, Scott, & Dalumpines, 2018; Misra & Watkins, 2017). Travel time and distance alone are not sufficient to explain the route choice of cyclists, given such additional inter-related factors as comfort, attractiveness, network coherence, and safety (CROW, 2016). GPS-based research has found that travel time-based cost functions or shortest distance measures cannot adequately capture the route choice preferences of cyclists (Casello, Nour, Rewa, & Hill, 2011).

Much of the existing bicycle route choice research is focussed on the behaviour of specific groups of present cyclists (Handy et al., 2014; Pritchard, 2018). There is increasing recognition that the oversampling of such groups provides results that cannot easily be transferred to infrequent cyclists. It is not unreasonable to think that the very absence or seldom appearance of some users within the bicycle modal category suggests that one or more aspects of their bicycle travel options are unsatisfactory to their needs (Parkin et al., 2007; Schoner, Cao, & Levinson, 2015; Meghan Winters & Teschke, 2010). Given the heterogeneity in cycling route choice preferences, the opinions of those who are occasional or recreational-only users are likely to be different to those who have extensive cycling experience (Aultman-Hall et al., 1997; Li, Wang, Yang, & Ragland, 2013; Meghan Winters & Teschke, 2010). One consistent element throughout this PhD work has been the recruitment of both infrequent and frequent cyclists concerning their use of and preferences towards different types of bicycle infrastructure (including routes), although differences between groups with different levels of cycling experience is not a focus of the thesis.

Understanding the bicycle route choice preferences of different kinds of users can assist in the prioritisation of bicycle infrastructure spending to suit a community's needs (Gustafsson & Archer, 2013; Jestico, Nelson, & Winters, 2016; Milakis & Athanasopoulos, 2014). For example, different infrastructure characteristics are important for young children compared to cargo bicycle users. For young children, a high degree of separation from motorised traffic (at crossings and on paths) is generally considered to be a prerequisite (Ghekiere et al., 2015), whilst wide entrances at access points to bi-directional shared

paths (often limited by bollards or gates to inhibit car entry) may be a necessary criterion for cargo bicycles.

Although bicycle route choice has received some attention from the modelling research domain, it remains under-investigated and is relatively crudely (if at all) integrated into the few national transport models that do take cycling into account (van Wee & Börjesson, 2015). Research has found that travel time-based cost functions cannot adequately capture the route choice preferences of cyclists alone (Casello et al., 2011). Early route models sourced data mainly from surveys with hand-drawn routes (Aultman-Hall et al., 1997; Hyodo et al., 2000; van Schagen, 1990), but the advent of GPS enabled a boom in this research (Broach et al., 2012; Casello & Usyukov, 2014; Khatri, Cherry, Nambisan, & Han, 2016; Menghini et al., 2010; Montini, Antoniou, & Axhausen, 2017; Shen, Chen, Schmiedeskamp, Bassok, & Childress, 2014; Zimmermann, Mai, & Frejinger, 2017). The route choice modelling research requires the definition of alternative route choices that can be considered and ranking of these based on attributes of the rider/s. Whilst this approach can quantify the value of various route choices to the rider, it does not necessarily provide an indication of ridership levels on any particular link (Buehler & Dill, 2015).

Bicycle Level of Service (BLOS) methods have been developed with the primary aim of rating individual road links, and have been adapted from similar methodologies for car traffic (Dowling et al., 2008). BLOS methods can also be used to consider the performance of bicycle networks (Lowry et al., 2012; Zolnik & Cromley, 2007). Since the earliest BLOS models were created in the 1980s, there have been many stepwise improvements, most importantly through the refinement of variable coefficients through regression testing against empirical route choice data (Harkey, Reinfurt, & Knuiman, 1998; Jensen, 2007; Landis, Vattikuti, & Brannick, 1997; Majumdar & Mitra, 2018). Paper III uses the network BLOS approach to assessing the influence of four existing BLOS indicators on bicycle route choice in combination with varying importance of travel time. It does not develop new route choice models, seeking instead to



evaluate how known transport attributes in BLOS can be used to estimate bicycle route choice.

### **5.3. Summary of Paper II**

Paper II is a systematic literature review that makes a comparison of the relative strengths and weaknesses of methods that have been applied to assess the whole journey route choices of bicyclists. The paper uses the following search string in the Scopus and Transport Research International Documentation (TRID) databases: “route choice” OR “naturalistic” OR “revealed preference” AND (bicycl\* OR bik\* OR cycl\*). In total 112 empirical studies were reviewed in terms of methods applied to gather bicycle route choice data. In total seven families of methods are identified: GPS devices, smartphone applications, crowdsourcing, participant-recalled routes, accompanied journeys, egocentric cameras and virtual reality. More detailed descriptions of the data collection approaches used within each family are summarised in Paper II. The paper does not assess analytical approaches to bicycle route choice.

GPS technology is used in over two-thirds of the research papers collected through the systematic review. However, except for some studies in which user responses are gathered via a user interface, the decision-making process behind the route choice is not typically revealed through this approach (Dill & Gliebe, 2008). This is a common limitation of revealed preference studies, where the primary contribution is in showing the preference made rather than demonstrating the reasoning behind the route preference.

To understand more about the decisions being made by bicyclists, the other methods can be used. Follow-up interviews or surveys as part of GPS-based studies have been demonstrated to provide attitudinal parameters (Montini et al., 2017; Plazier, Weitkamp, & Berg, 2017). Cameras can also be used to inform reasons for bicycle route choice, but these are limited to reasons that can be visually identified in the camera field of view (Simpson, 2017). The final method family of virtual reality, which was addressed in two papers, allows testing of past, current or future scenarios, limited only by the time needed to

create the virtual test environment (de Leeuw & de Kruijf, 2015; Hirose & Kitamura, 2015).

Paper II illustrates a trade-off in the quality of route choice data obtainable and the typical number of participants – most likely reflecting the effort necessary on the part of the researcher to gather the data. Crowd-sourced datasets such as those provided by the cycling tracking app Strava can be obtained nearly instantaneously, but the data lacks individual route details in the interests of protecting participant privacy (Sun, Du, Wang, & Zhuang, 2017). Meanwhile, the highest quality data with good spatial and qualitative information for every participant typically involves a combination of two or more of the following methods: interviews, ride-along interviews or GPS-tracking techniques, thereby significantly increasing the data-gatherer's workload for each participant (Van Duppen & Spierings, 2013).

#### **5.4. Summary of Paper III**

Paper III is the main empirical study to consider how different environmental attributes of the bicycle network influence bicycle route choice. Rather than checking for association between route preferences and potentially relevant environmental factors individually, four aggregate Bicycle Level of Service (BLOS) indicators are compared with the empirical route choice data:

1. Bicycle Compatibility Index (BCI) (Harkey et al., 1998)
2. Bicycle Stress Level (BSL) (Sorton & Walsh, 1994)
3. 6<sup>th</sup> edition US Highway Capacity Manual Bicycle Level of Service (HCM6) (Dowling et al., 2008; Transportation Research Board, 2016)
4. Level of Traffic Stress (LTS) (Furth et al., 2016; Furth, Putta, & Moser, 2018)

BLOS indicators are typically comprised of anywhere between three and fifteen factors known to influence the cycling quality, as summarised in Paper III's review of 12 BLOS methods. BLOS methods are used in this thesis as a proxy

for bicycle infrastructure quality since they combine multiple factors found to be important for cyclists. Since cycling quality is a function of both link-level infrastructure and network connectivity, Paper III aims to expand the application of BLOS to full origin-destination journeys, taking into account both intersections and links in the bicycle network.

The four BLOS indicators listed above are chosen for their relevance to urban mixed traffic environments and relative ease of application to the city of Trondheim, Norway. The factors comprising these four methods and their direction of impact on Level of Service (where higher BLOS corresponds to better cycling conditions) are detailed in Table 4 below. The table shows that certain factors are common to all the selected BLOS methods such as Annual Average Daily Traffic (AADT), speed and width of bicycle facility/outside lane. The full version of the table in Paper III has 12 methods and 19 factors.

Table 4. Bicycle Level of Service (BLOS) methods evaluated in Paper III. Factors that positively influence BLOS are indicated with a “P” whilst negative effects are indicated with a dash.

Method Name	Bicycle Stress Level	Bicycle Compatibility Index	6 <sup>th</sup> edition US Highway Capacity Manual	Level of Traffic Stress	
Acronym	BSL	BCI	HCM6	LTS	
Factor	Reference	(Sorton & Walsh, 1994)	(Harkey et al., 1998)	(Dowling et al., 2008)	(Mekuria, Furth, & Nixon, 2012)
AADT	-	-	-	-	
Bicycle facility width/presence		P	P		
Bicycle separation from traffic		P			
Driveways			-		
Kerb height/presence			-		
Land use intensity		-			
Number/type of traffic lanes		P	P	-	
On-street parking		-	-		
Percentage of heavy vehicles			-		
Shoulder			P		
Speed	-	-	-	-	
Surface quality			P		
Width of outside lane (inc. bike lane/shoulder)	P	P	P	P	

The component elements of the BCI, BSL, HCM6 and LTS methods were collated in attribute tables in ArcMAP 10.6 from which network maps for each method were created for the study area. The BCI network map for Trondheim is shown in Figure 13 below as an example. Paper III then describes a procedure for using each network map to generate routes between a given origin and destination using a link penalty-based approach in which links with poor BLOS are allocated higher impedance, further developing the method used by Cervero et al. (2019) for LTS discussed in Chapter 4 (Paper I). The procedure developed for Paper III additionally iterates the detour rate used for route generation between 1.00 and 1.50. Whilst detour rate was previously defined in this thesis as the ratio of actual to shortest distance, in Paper III, the detour rate

is now the independent variable which is stochastically modelled to recreate the observed route choices. Thus, a detour rate of between 1.00 to 1.50 corresponds to a 0 to 50% additional distance cyclists are considered willing to travel relative to the shortest path. This is done in order to vary link impedance and thus generate alternate routes.

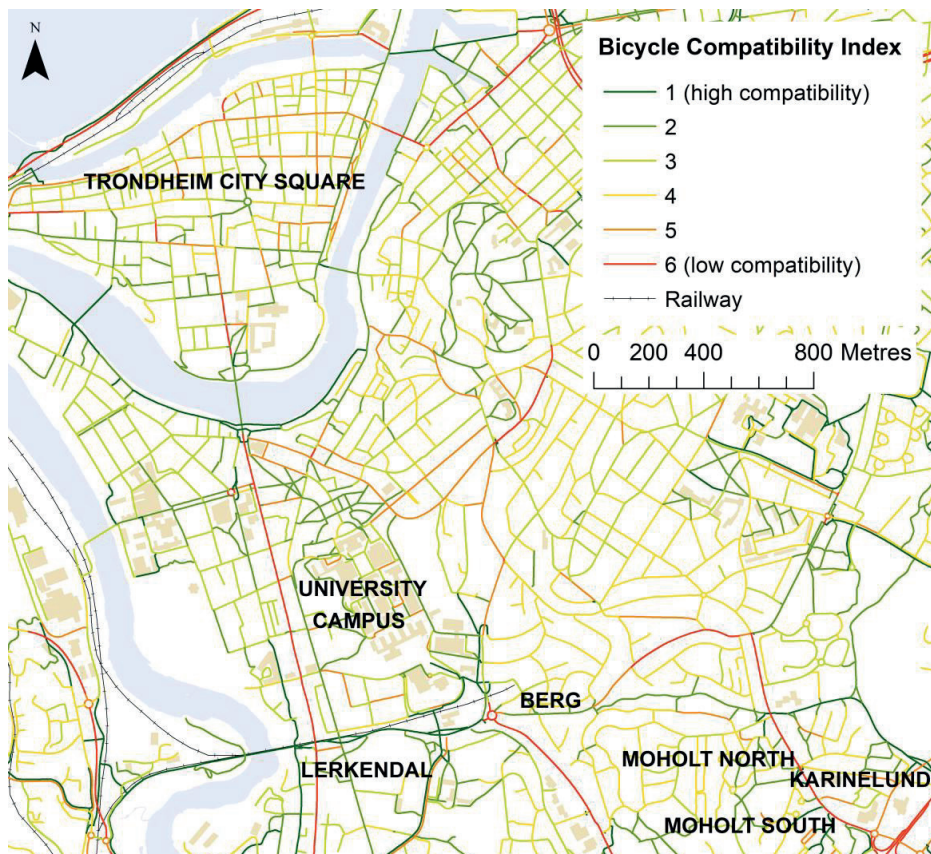


Figure 13. Bicycle Compatibility Index for Trondheim together with the five student residence locations of respondents at the bottom of the map.

The origins and destinations for route generation in Paper III are the midpoints of five student residence clusters shown in Figure 13 above which were surveyed regarding bicycle route preferences. A total of 467 students provided usable responses via the web-based mapping survey which asked students (all of whom lived in one of the five residential clusters) to draw their preferred

bicycle route between their place of residence and the Trondheim City Square. The empirical route data was then compared with the generated routes, allowing for an assessment of the four different BLOS methods. Figures illustrating the empirical data and the best routes generated are shown in Paper III. The data collection approach used in Paper III is seldom applied to studies of travel behaviour but provides a level of detail uncommon in most studies of route choice. Only one similar data collection effort was found in the 112 articles reviewed in Paper II in which 21 cyclists used an instrumented bicycle on one OD pair (Allemann & Raubal, 2015).

The results conclude that BCI is the best performing of the BLOS methods, achieving the highest match with empirical route data in all five origin-destination pairs. This was closely followed by HCM6 which produced the equal best match for four of the OD pairs. The coefficients for both methods have been empirically determined and are comprised of eight and nine individual variables respectively. BSL and LTS perform somewhat worse and share common traits of having fewer variables (three and four respectively) and variable coefficients that are not empirically founded. It is also shown that both BCI and HCM6 generate double as many route alternatives compared to BSL and LTS through the iteration of detour rate (16 compared to 8).

Two different approaches were used to determine the optimum detour rate for the route generation approach. The first approach considered the average impact of detour rate across the four BLOS methods and five OD pairs, as illustrated in Figure 14 below. The polynomial line of best fit suggests that the global maximum is reached at a detour rate of approximately 15%, however, the match percentage is relatively low, so the same procedure would need to be repeated should further improvements to the route generation approach be made. Given the trend in Figure 14 is less clear for the individual methods, an alternative means of comparing detour rates was performed by averaging the detour rate for each OD pair's best route (independent of BLOS method). Although there are only 5 OD pairs, there are 11 combinations of BLOS method and detour rate which provide the optimum result, and the mean of the 11

detour rates is 21% (additional length). Interpretation of the detour rate optimisation and suggestions for improvements to the route generation procedure are detailed in the discussion in Paper III.

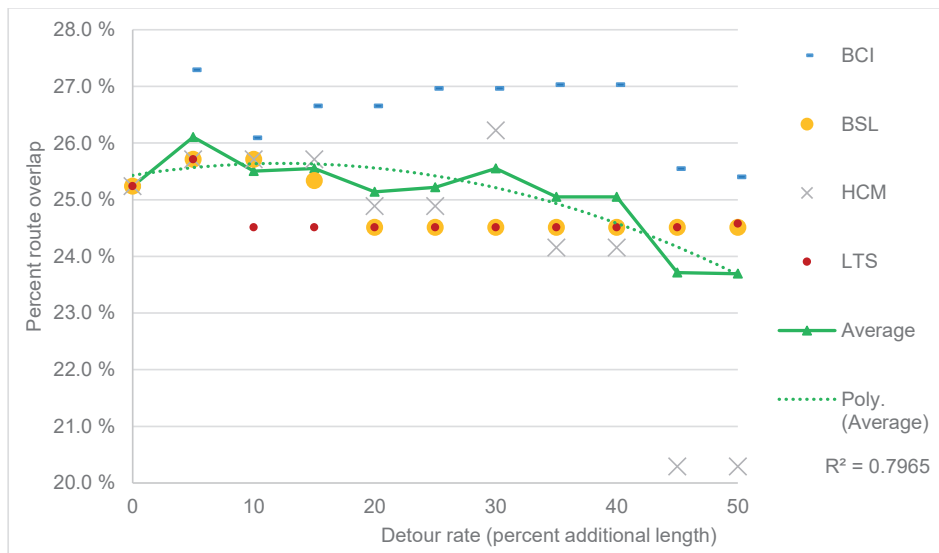


Figure 14. Percentage route overlap between empirical and generated routes for the four tested BLOS models

### 5.5. Challenges with researching bicycle route choice

Data quality is of critical importance to enable many of the desired study designs for bicycle route choice. For most revealed preference bicycle route choice studies, the researcher needs to know the combination of streets, paths and open spaces the participant used in the area of interest. The resolution of route choice data is discussed at length in Paper II – in which it is found that there can be quality concerns with most methods except for camera or accompanied journey techniques: GPS may lose signal in urban canyons, precision of hand-drawn routes may be low or participants' poor familiarity with maps may not allow them to accurately recall their route.

There are many alternative sources for bicycle route choice data, however many of the potential data providers such as the cycling tracking app Strava<sup>11</sup> aggregate data to the route level in the interests of users' privacy (see discussion on data privacy in Chapter 3.11). Some of the potential data sources considered early in this PhD include the European Cycling Challenge<sup>12</sup>, Bike Data Project<sup>13</sup> and the Dutch and Belgian Fietstelweek<sup>14</sup> bicycle tracking initiatives. Additionally, bikeshare networks with GPS are becoming increasingly common. Most bike-share systems register only a single bicycle's dock out and dock in times, but this is changing. The establishment of the Platform for European Bicycle Sharing & Systems (PEBSS)<sup>15</sup> by the European Cycling Federation in 2017 offers promise for bicycle route choice researchers with one of the aims to "promote a Big Data-based framework to urban mobility and bicycle sharing systems planning." Some studies have already begun to use dockless bicycle data for origins and destinations, with the potential of gathering locations of the bicycle fleet once per minute (He, Zhang, Chen, & Gu, 2018). At such a frequency, many of the bicycle route choice details are lost, as was found in Paper V, which had a comparable point frequency. In such cases, route choices must be estimated with the assistance of combined matching and routing algorithms such as those employed in Paper V.

Concerning case selection for bicycle route choice research, one seemingly straightforward method of recruitment is via large residential apartment complexes, since many people live at the one address. Whilst looking for a case for Paper III, it was found that contacting the residents of large apartment complexes is not always simple – the post boxes of most apartments are inside buildings with restricted access and obtaining approval to distribute participant

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<sup>11</sup> <https://metro.strava.com>

<sup>12</sup> <http://www.cyclingchallenge.eu>

<sup>13</sup> <http://bikedataproject.com>

<sup>14</sup> <http://fietstelweek.nl/data/> and <https://fietstelweek.be>

<sup>15</sup> <https://ecf.com/community/platform-european-bicycle-sharing-systems-pebss>



invitations was found to be troublesome. Attempts were also made during the study design to have surveys distributed through the Trondheim Housing Cooperative 'Trondheim og Omegn Boligbyggelag' without success, despite the assurance of respondent anonymity. An easier alternative can be the targeting of destinations such as workplaces for the distribution of travel surveys, as was performed in Paper I with Adresseavisen. Since employees live at different addresses however, the data privacy must be maintained if gathering location-specific trip data.

In Paper III, participants from five student residence complexes were required to provide their preferred bicycle route to the centre of Trondheim. Several issues were uncovered. Since around 60% of the sample had moved to Trondheim in the six months prior to the survey, their knowledge of the area was in some cases limited – leading to the selection of bus routes not appropriate for cycling for example. Methodologically, Paper III required participants to complete the mapping task online through a Google mapping API. It was quickly found that many students (41%) responded via touchscreen devices (mostly mobile phones) in which map navigation and route drawing proved to be troublesome tasks as indicated by the poor spatial quality of some raw routes in Figure 15 below. Those students who provided their contact details and a low-quality route were specifically requested to redraw their route choice on a personal computer using a user-specific URL. The net result after both rounds of data collection were merged was that 467 routes were able to be map-matched from 518 respondents (see sub-chapter 3.9 for more information on map-matching).



Figure 15. Raw route choice data provided by students for Paper III.

Alternative mapping Application Programming Interfaces (API) to the one utilised in Paper III were not known to the authors at the time of conducting the survey in late 2015. At the time of writing this thesis, at least two commercial platforms are known to be able to outperform the data collection methodology utilised in Paper III: ArcGIS online<sup>16</sup> and Maptionnaire<sup>17</sup>. These are both forms of participatory GIS and enable the collection of mapped data and survey data within a single platform. Open source alternatives are also in development with Umap<sup>18</sup>, part of the OpenStreetMap (OSM) initiative.

Once data was collected, there were analytical challenges associated with determining a suitable approach for measuring the correlation between drawn routes (polylines) in GIS. This is because polylines that have similar but non-identical spatial characteristics may be significantly different in terms of cycling suitability (Stewart, 2017). The approach used in Paper III considered the percentage of identical overlap between generated routes and empirical routes

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<sup>16</sup> <https://www.arcgis.com/home/index.html>

<sup>17</sup> <https://maptionnaire.com/>

<sup>18</sup> <https://umap.openstreetmap.fr/en/>

(after map-matching). It is not certain whether this is the best approach for measuring the geographic similarity between polylines, however, and at least two alternative approaches were considered for how best to portray the spatial correlation between alternative routes (but were not pursued):

1. Accumulate indicator variables (such as the number of metres or minutes of level A standard street for instance) for each route. Repeat for different BLOSs and perform regression analyses on the results.
2. Considering the user routes from each OD pair as a choice set, develop a list of decision nodes in the network where a route choice option appears. Regression analysis can subsequently be performed to assess the association between the characteristics of the alternatives at each decision node and the frequency of their selection.

The route generation approach adopted in Paper III combined link and intersection impedance based on the work of Cervero et al. (2019) in application to BLOS methods. Paper I also attempted to use this method for routing of bicycle journeys, however, the hybrid NVDB-OpenStreetMap network was unsuitable for intersections as detailed in sub-chapter 4.4. However, impedance arguably also comes at the origins and destinations depending on other factors such as the provision of secure bicycle parking and changing rooms (Heinen et al., 2013). Metrics that collectively consider such origin and destination effects in combination with BLOS indicators are sometimes referred to as bikeability metrics (Lowry et al., 2012; Nielsen & Skov-Petersen, 2018). BLOS is thus only one approach to the study of bicycle route choice with collective measures of bicycle suitability and the development of new indicators following procedures similar to BLOS remains an area with considerable potential.

One of the aims of Paper III was to iterate the detour rate in the route generation procedure to find an optimum match with empirical data. This showed that the best matches were achieved for routes generated using a detour rate of between 15 and 21% (see Figure 14 and associated discussion in the previous sub-chapter). Existing empirical research on willingness to deviate

from the shortest path suggests that detour rates should typically lie between 10 and 21% (Aultman-Hall et al., 1997; Broach et al., 2012; Hulleberg, Flügel, & Ævarsson, 2018; Segadilha & Sanches, 2014), however, it is uncertain whether this similarity has statistical significance. The detour rate appeared to generate fewer routes than expected with only 23 unique routes created across the 5 OD pairs – or approximately four unique routes per OD pair (using all four BLOS methods). Furthermore, none of the generated routes in Paper III exhibit more than 5% difference in total length, thus encountering a known problem in the literature with limited variation in routes generated (Bovy, 2009; Prato, 2009). A potential means of overcoming this problem is to generate routes using link-elimination or k-shortest path algorithms (Ton, Duives, Cats, & Hoogendoorn, 2018; Yen, 1971).



## **6. Infrastructural interventions combining mode and route choice**

*A bike lane, a footpath and a bus lane walk into a bar. They spot their old friend parking lane slumped over the end of the counter. Rumours have been flying about the parking lane's dependence on government handouts. They wake the parking lane and who squints at them groggily.*

*The bike lane steps closer.*

*"This is an intervention. We're here to help you become one of us."*

### **6.1. Research question 3**

The third research question considers the interaction of the two previous research questions with both mode and route choice elements. This is taken in the context of bicycle infrastructure interventions, in which a change to the bicycle infrastructure network is analysed in close detail before and after the implementation:

*What is the effect of new bicycle infrastructure in terms of route and mode choice?*

Research question 3 wraps up elements of the two first research questions and is answered together with the other research questions in the final chapter, Chapter 7.

Transport infrastructure has been shown in the two previous chapters to influence the mode and route choice of cycling. These two elements can be studied in a variety of different ways. This chapter summarises Papers IV and V which use two different approaches to observe revealed preference travel behaviour before and after each paper's respective bicycle infrastructure intervention. This offers in-depth insights into the impact of single infrastructural initiatives whilst minimising the confounding factors associated with cross-sectional study approaches.

## 6.2. Bicycle infrastructure interventions

The intention of most urban bicycle infrastructure initiatives is the same: to promote increased bicycle usage in everyday life by designing attractive routes to suit the needs of a larger proportion of the population. This is typically done through improving a combination of comfort, attractiveness, access (including directness and network coherence), and safety of the streets and paths available for bicycle users (CROW, 2016).

In a 2017 systematic review of built environment intervention effects on physical activity and active transport, 11 of 28 reviewed articles had levels of cycling as a specific outcome (Smith et al., 2017). Intervention types found to have a positive impact on cycling include combined pedestrian and bicycle access bridges and boardwalks (Goodman, Sahlqvist, & Ogilvie, 2014), urban trails (Fitzhugh, Bassett, & Evans, 2010), traffic calming (Morrison, 2004) and complete streets (Shu, Quiros, Wang, & Zhu, 2014). Positive effects have also been found for a number of additional types of interventions such as on-road bicycle lanes (Parker et al., 2013) and separate bicycle paths (Heesch, James, Washington, Zuniga, & Burke, 2016; Rissel, Greaves, Wen, Crane, & Standen, 2015). Only one of the 11 bicycle-related intervention studies assessed by Smith et al. (2017) showed negative effects; specifically concerning cross-sectional cycling levels in response to the development of bicycle boulevards (traffic calmed low-volume streets) (Dill et al., 2014).

Regarding route choice effects of interventions, evaluations from the 1970s and 1980s of the Dutch cities Tilburg and The Hague demonstrate greatly increased cycling volumes along routes which received bicycle infrastructure (140% and 76% respectively) (van Goeverden, Nielsen, Harder, & van Nes, 2015). Corridor bicycle volumes meanwhile (the combination of intervention streets and the streets serving approximately the same destinations) observed only a 10-20% increase for both cities. Changes to the corridor volumes indicate a shift in the modal use of bicycles, whilst the difference between corridor volume and intervention volume can be assumed to be the result of route substitution (from

nearby streets in the corridor to the intervention route). Thus, the Dutch cases demonstrate a much greater route shift than modal shift. Changes of a similar nature (significantly larger volume changes in intervention than corridor) have been observed in before-after studies in Davis, California, (Lott, Tardiff, & Lott, 1978), New Orleans, Louisiana (Parker et al., 2013) and San Francisco, California (Fitch, Thigpen, Cruz, & Handy, 2016).

This chapter addresses research question 3 by merging the two elements of bicycle mode and route choice through the evaluation of two newly built bicycle infrastructure initiatives. For both empirical studies, reported on in Papers IV and V, mode and route changes are considered by gathering data on travel behaviour before and after the respective intervention was completed.

### **6.3. Summary of Paper IV**

Paper IV evaluates how the replacement of two road lanes in Innherredsveien, Trondheim with a separated 1.8km bi-directional bicycle path influences the route and mode choice of different road users. The bicycle path connects two existing bicycle paths (separated from road traffic), thereby completing a route leading into Trondheim from the east. The case is an example of a complete street intervention, in which the interests of all users is maintained. Car drivers were prohibited from driving through one intersection at the intervention's mid-point, however, a tunnel beneath the intervention site completed four years prior served the needs of drivers travelling through the area. Car journeys starting or ending near to the intersection were the most affected in terms of their accessibility, however alternative streets nearby provided sufficient connectivity for residents affected by the ban on through-driving on Innherredsveien. Public transport services meanwhile were unchanged, but the waiting area for patrons was greatly improved on the northern side of the road, where two road lanes were converted into space for vulnerable road users. The bicycle path was separated from traffic with a combination of concrete barriers and metre-wide road markings as illustrated in Figure 16 below.





*Figure 16. The intervention in Innherredsveien, Trondheim used two forms of separation: painted horizontal lane markings and concrete barriers (photo: pbb/Mapillary <sup>19</sup>, licensed under CC BY-SA 4.0 <sup>20</sup>).*

An online survey was conducted approximately one year after intervention completion in which integrated maps allowed respondents, mostly residents in the neighbourhood, to draw their choice of route before and after the intervention. The origins and destinations were not specifically required of participants for this study in the interests of obtaining higher resolution data in the corridor of the intervention (by reducing participant burden to draw full routes). The study design is graphically illustrated in Figure 17 below.

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<sup>19</sup> <https://www.mapillary.com/map/im/Ho0mq2xFH73byGRs-Gct-g>

<sup>20</sup> <https://creativecommons.org/licenses/by-sa/4.0/>

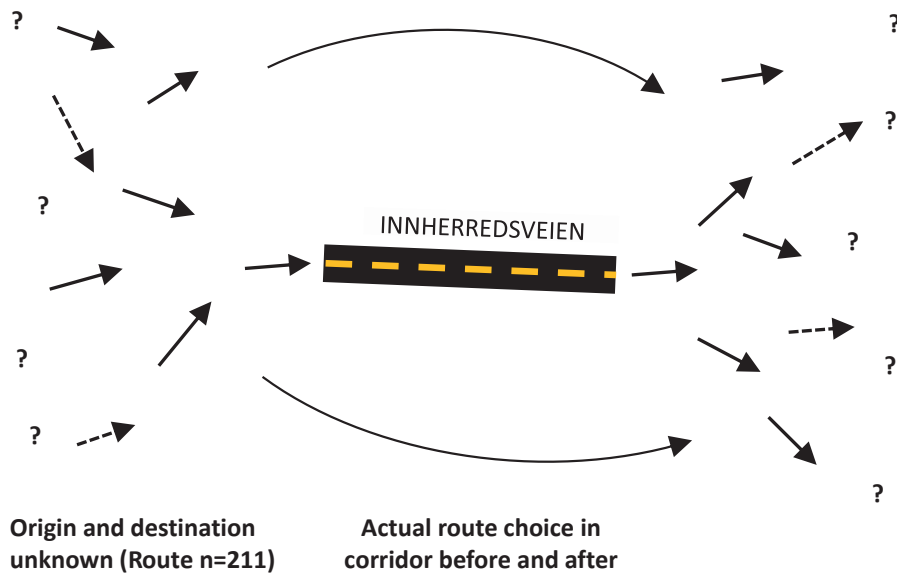


Figure 17. Graphical illustration of Paper IV study design. Route preferences (for all modes) were gathered from neighbourhood residents one year following the street's redesign and respondents were additionally requested to recall pre-intervention route preference.

Recruitment was focused on residents in the neighbourhood surrounding the intervention street through the distribution of 5000 flyers in June 2018 (nearly one year following the intervention completion) containing a link to the online survey. Alternative forms of recruitment included distribution via various social media websites connected to the area of interest, together with the intranet of the nearby university college campus. The survey attracted higher rates of cyclist responses than NNTS data suggests is typical for the neighbourhood area of interest. This can be related to two known issues: participant self-selection (since the study was a post-intervention evaluation) and social media sampling that was overly focussed on cyclist interest groups (in part due to the weak presence of interest groups for other modes). The survey collected 719 responses, however, only 211 of these drew sufficiently precise network-matchable routes with at least one bicycle trip (see procedure outlined in Figure

10) for both the pre- and post-intervention phases to allow route choice panel analysis.

A modal shift to cycling was witnessed amongst participants' most common journeys in the neighbourhood (from 42 to 54%), but this came mostly at the expense of public transport patronage rather than car usage. 6.7% of the respondents switched from public transport to bicycling whilst 4.5% switched from driving and 4.2% switched from walking. This corroborates economic studies which demonstrate a higher cross-elasticity between public transport and cycling than car use and cycling (Börjesson & Eliasson, 2012). In addition, nearly half of the users who reported using a bicycle at least once per month (272 of 577) reported an increase in their frequency of cycling as a result of the trial project implementation. Whilst younger residents were more inclined to change their frequency of cycling in Innherredsveien, the lack of significant other explanatory demographic or attitudinal variables to explain changes in bicycle frequency suggests that the intervention was equally appealing to all user groups.

The modal shift to cycling and increased cycling frequency is also reflected through bicycle counts performed in June and September 2017 in the three traffic light-controlled intersections along Innherredsveien. The average peak hour bicycle volumes (between 7-9am and 3-5pm) increased from 261 to 564, or by 105% (averaged from three days of peak hour counts). Bicycle traffic counts for Trondheim as a whole, however, showed negligible change between 2016 and 2017 (Rambøll AS, 2018).

Changes in bicycle route choice are best summarised in Figure 18, taken from Paper IV. The figure illustrates the difference in the number of bicycle users for journeys made in the area around Innherredsveien drawn by the panel respondents (n=211) before and after the intervention. Note that each user could only their single most typical route in the area, irrespective of the frequency of such trips. This means that the numbers in the legend of Figure 18 do not reflect changes in number of trips, but rather a change in most common

bicycle route for each of the 211 users who drew at least one bicycle trip. Red lines indicate declining popularity amongst cyclists whilst green indicate growth. Since there were more bicycle journeys drawn after than before (a modal shift to cycling), the scales for increases and decreases in cycling volumes are not equal. The study found that cycling participants' average utilisation of the intervention section of Innherredsveien increased significantly ( $p < .0005$ ) from 550m to 929m for their most common journey in the neighbourhood. This is to say that although distances cycled were unchanged, the amount of the average cyclist's path that coincided with the initiative in Innherredsveien nearly doubled.

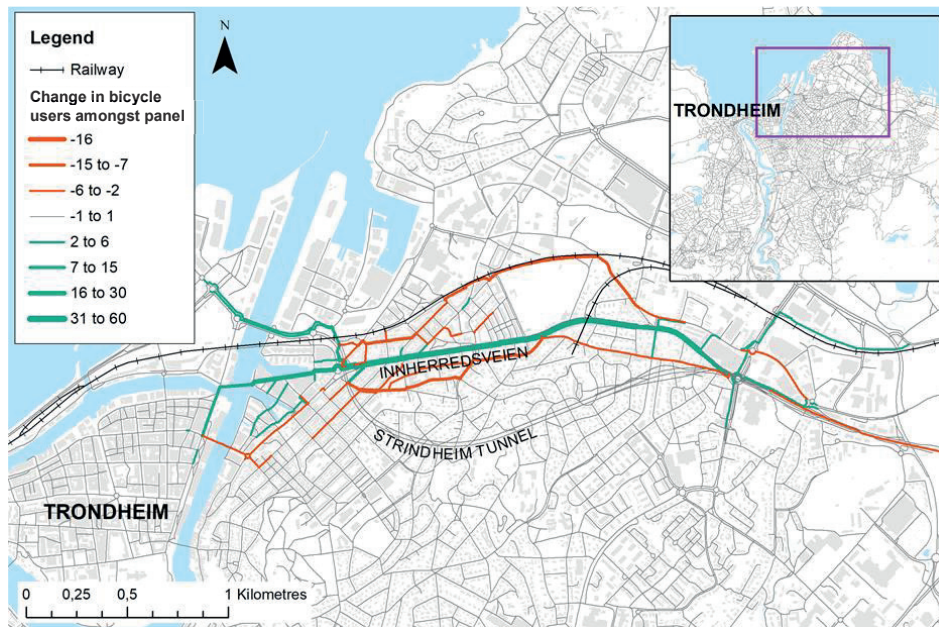


Figure 18. Map showing the change in numbers of bicycle users on each street segment made by the route choice panel respondents ( $n = 211$ ).

Paper IV demonstrates changes to both route and bicycle mode choice following the intervention performed in Innherredsveien in Trondheim. This can be attributed to a combination of factors: increased physical separation from other road users, reduced car volumes and the connection made by the

intervention between two existing bicycle paths. Paper IV corroborates existing evidence which suggests that the combination of enablers of active transport and deterrents of undesirable competitors (through reduced car accessibility in the intervention street) is most effective at encouraging modal shift to active modes (Piatkowski et al., 2019). The study revealed changes in bicycle route preference (towards the intervention), increased cycling frequency amongst participants and a modal shift to cycling.

#### **6.4. Summary of Paper V**

The Oslo intervention study is described in Paper V. This study tracked the mobility behaviour of a panel of residents from the northern suburbs of Oslo who were exposed to a red asphalt bicycle lane constructed in Markveien, Grünerløkka in the second half of August 2017. The bicycle lane intervention was on one side of Markveien, against the flow of one-way southbound vehicular traffic (contraflow). The 400m long intervention replaced parked cars on the eastern side of the street, whilst the driving lane became marginally wider. Unlike Innherredsveien, the initiative was only partially connected to existing bicycle infrastructure (on the northern side at Øvrefoss), whilst a gap of one city block without bicycle infrastructure exists to the south of the intervention.

Participants were recruited through multiple means, including invitational letters in the neighbourhood of interest, a local newspaper advertisement, flyers, posters and social media groups connected to the area of interest. The main method used to collect route data was a GPS-enabled passive smartphone application (app) which participants (n=113) were required to download. The methodology used is described in more detail in sub-chapter 3.7 and in Bucher et al. (2016). The study design is graphically displayed in Figure 19 below.

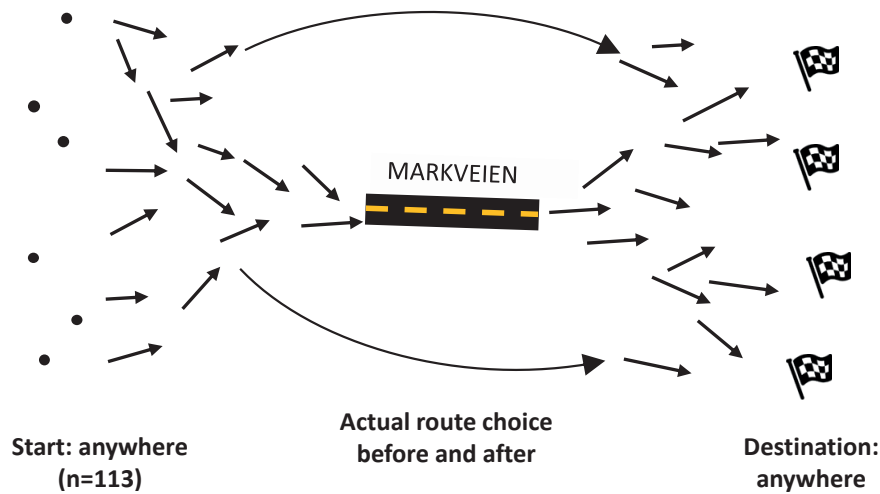


Figure 19. Graphical illustration of Paper V study design. Smartphone GPS route traces were provided by neighbourhood residents and users of Markveien both before and after the street's redesign (in which a parallel parking lane was substituted with a contraflow bicycle lane).

Apart from the different means of data collection, an important difference in the study design with Paper IV is the longitudinal panel approach in which data was collected before and after the bicycle lane was constructed amongst the same group of respondents. The smartphone app recorded journey data over two four-week periods in May/June and September/October 2017. The other difference to Paper IV was to avoid any references to the intervention or specific objectives of the study, in the interest of reducing self-selection response bias (Envall, 2007, p. 164; Stigell, 2011, p. 72). The study purpose was instead generically described as being related to seasonal travel behaviour variation in the local environment.

Given the cool climate of Oslo, an explicit aim of the study design was to avoid data collection during the winter months. The data sampling in the Spring and Autumn avoided large seasonal variations in cycling levels, as can be observed in the left panel of Figure 20 below. Figure 20 also shows how cyclists and

pedestrians in the GPS panel are overrepresented in relation to the Oslo population, whilst car drivers and public transport users are underrepresented.

The sampling strategy used in Paper V could also be applied in other contexts with seasonal variation to limit the number of confounding factors that can influence bicycle mode or route choice. For this thesis, the other route choice studies (Papers III and IV) used recalled route preferences, meaning that the seasonal effect was not as important.

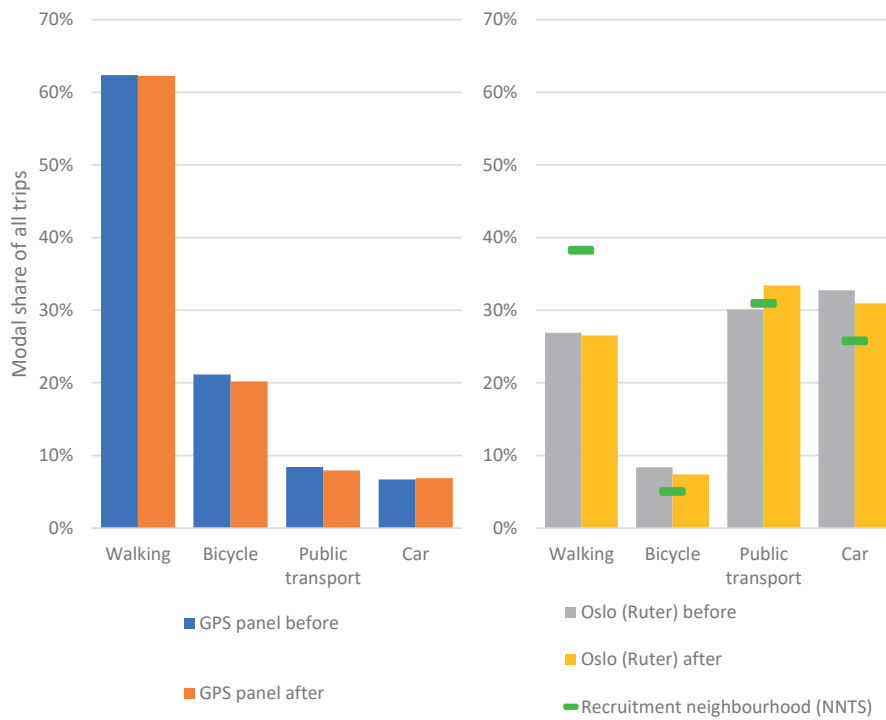


Figure 20. Transport modal share for the GPS panel (left panel) relative to the general Oslo population for the before and after data collection intervals (right panel). Seasonal travel data from Oslo is sourced from Ruter's Market Information System travel survey (Angell, 2018), whilst recruitment neighbourhood data comes from the NNTS (Hjorthol et al., 2014).

For bicycle trips taken on the intervention street, the mean deviation from the shortest path (the difference between the chosen route and the shortest path between origin and destination) increased significantly ( $p < .05$ ) from 171 to 221m. This suggests that the 'catchment area' of the street increased since more users were taking larger detours from the shortest path in order to use the intervention. This quantifies the shift in route to the new bicycle lane. The change in preference is clearly illustrated in Figure 21 below. The intervention street Markveien clearly increased in popularity amongst the panel, as indicated by the thick turquoise line representing an increase in bicycle volumes. At the same time, the neighbouring streets Toftes gate, Thorvald Meyers gate and the riverside shared path all experience a reduction, visualised in orange indicating a decrease in bicycle volumes. Although some smaller changes to the cycling infrastructure were made in Sandakerveien and Toftes gate during approximately the same time interval as Markveien, mixed results are observed in these streets.



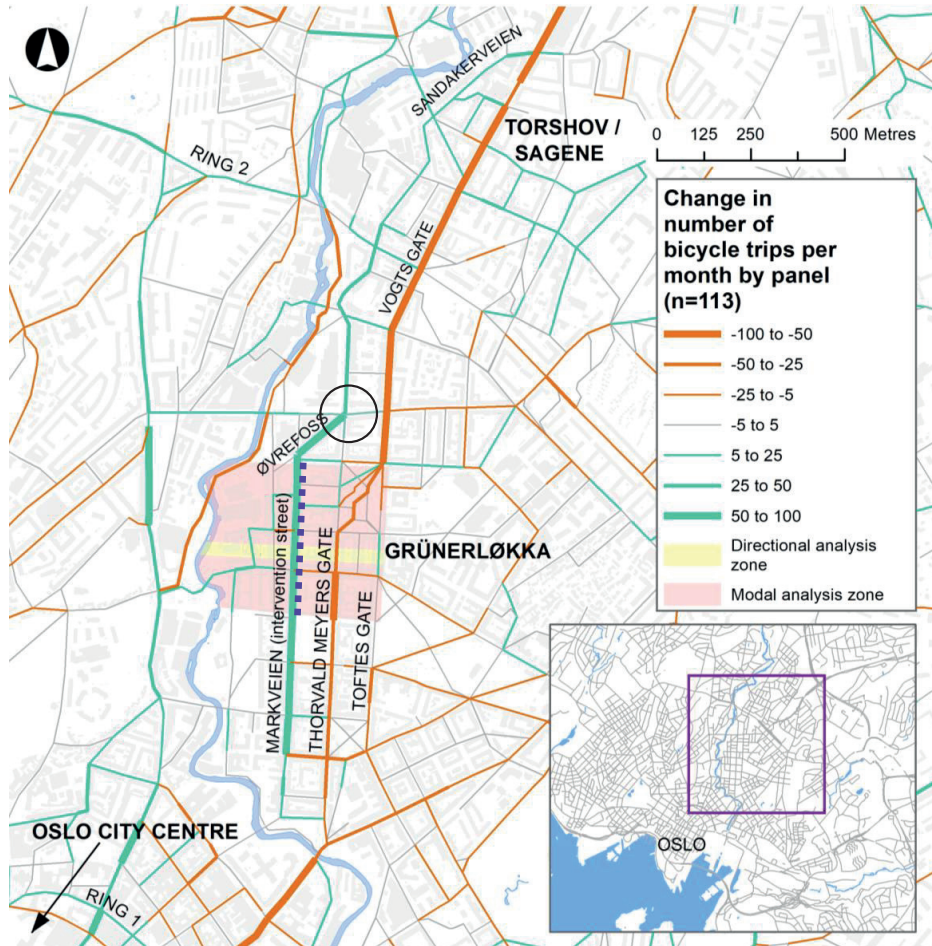


Figure 21. Change in the panel's (n=113) number of monthly recorded bicycle trips taken before and after the 400m long contraflow bicycle lane was installed in Markveien (indicated by the dashed violet line).

A supplementary means to check the GPS route observations was to use video observation to track cyclist choices over the forked intersection of Øvrefoss and Thorvald Meyers gate (as indicated by the black ring in the figure above). This method is described in sub-chapter 3.8. This intersection forms a natural decision point for cyclists travelling in the direction to or from the suburb of Torshov in the Sagene district (see Figure 21). In Table 5 below the percentages of cyclists choosing either of the forks is shown and compared with

the GPS panel counts on the same two streets. It should be noted that not all traffic along the intervention goes through the forked intersection, and therefore it is only indicative of changes that occur in the intervention. The table demonstrates that the GPS panel was strongly attracted to the intervention whilst a weaker attraction in the same direction is observed for the population. The comparison demonstrates that the scale of the intervention changes for the video observations is much less than the GPS panel. Whilst both streets have the same starting ratios (43% choosing the intervention), this increases to only 47% for the video observations after, whilst for the GPS panel, it increases to 70%.

*Table 5. Average daily number of observed trips taken by bicycle*

Time period	GPS panel (n=113)		Video observation (population)	
	Intervention 'tributary' (Øvrefoss)	Thorvald Meyers gate	Intervention 'tributary' (Øvrefoss)	Thorvald Meyers gate
Pre- intervention	4.19 (43%)	5.60 (57%)	374 (46%)	439 (57%)
Post- intervention	5.69 (70%)	2.41 (30%)	563 (50%)	566 (50%)

The discrepancies in the results above may be due to an incorrect assumption that changes on the intervention street will be reflected by changes at the forked intersection. The GPS panel was considered to have used the intervention if they cross the intervention mid-point whilst the video observations were made at the forked intersection 250m away. There were also differences in the time periods used for data registration (several days of video counting versus two month-long periods of GPS registration).

For the purpose of identifying whether or not any modal shift had occurred, a modal analysis zone was created in GIS to count all GPS journeys that utilise the intervention street and the four nearest parallel alternative streets (north-

south) in the intervention neighbourhood. This is indicated by the light pink region in Figure 21. To determine the impact of the intervention, the participant panel was split into an exposure group (n=39) and a quasi-control (not exposed) group (n=47). In addition, one further group that did not meet the criteria for inclusion to either the exposed or control groups was formed (n=27).

The exposure group was comprised of participants who had used the intervention street during the after period (not including those who had crossed it, since the bicycle lane is not very apparent at the intersection). The modal share for this group was calculated based on the 2032 trips they made (with all modes) in the modal analysis zone in both periods. The exposure group had a higher bicycle modal share in the after period (M=0.499, SE=0.056), than the before period (M=0.422, SE=0.053), and the difference, -0.077, 95% CI [-0.166, 0.012] was weakly significant,  $t(38) = -1.743$ ,  $p=.089$ . The modal shares above are presented as decimal values but indicate the percentage of all trips taken by bicycle: 42.2% before and 49.9% after for the exposure group.

The quasi-control group for the modal analysis is the subset of the panel that was not exposed to the intervention according to the definition above but still performed at least one trip in the modal analysis zone in both the before and after periods. For the quasi-control, the modal share is calculated based on the 1193 trips they made in the modal analysis zone in both periods. They had a higher bicycle modal share in the after period (M=0.342, SE=0.058), than the before period (M=0.312, SE=0.053), however the difference, -0.030, 95% CI [-0.11, 0.05] was not significant  $t(46) = -0.728$ ,  $p=.471$ .

As with Paper I, the Difference in Differences (DiD) approach is used as an alternative means of measuring the changes above (see sub-chapter 4.3 or Paper V for further details on this method). The exposed-control pre-intervention difference of 11.0% is subtracted from the post-intervention difference of 15.7% giving a 'normalised' treatment effect of 4.7% change in bicycle modal share ( $p=.676$ ). This DiD measure should be taken cautiously however since it is not certain that the control and exposure groups satisfy the

parallel trend assumption. This assumption states that both groups would follow the same trends in bicycle usage by the equivalent (net not percentage) amounts had no treatment taken place. This does not necessarily correspond with alternative theories for travel behaviour change such as the market segmentation approach in which there are distinct groups which can have different behavioural responses to the same intervention (Li et al., 2013).

This analysis shows that whilst the quasi-control group increased its bicycle modal share from 31 to 34%, the exposure group increased its bicycle modal share by more than double this amount, from 42 to 50% ( $p < .10$ ). The relatively small scale of the intervention in Oslo compared to Trondheim makes this a noteworthy finding, although to be more certain of the impact would require a larger sample size. The difference in cycling levels can be reasonably attributed to the significantly improved conditions for northbound cyclists given the few other infrastructural changes in the immediate vicinity. At the same time, the street has low importance for car traffic and public transport through the neighbourhood (since Markveien is one-way driven and the one-way direction changes midway along the street). This reduces potential exposure to the initiative.

Paper V provides clear evidence of route substitution from nearby streets and paths following the bicycle lane completion. It also suggests that there may be some degree of modal change witnessed in the panel exposed to the intervention, although this finding is based on few participants. The difference in strength of the route and mode change findings lend weight to the notion that small behavioural changes (such as route for existing cyclists) have a higher elasticity than larger changes (change of mode in this case). Direct comparison of the significance of the route and mode changes is not possible with the techniques presented in this paper, nor in Paper IV. However, Paper IV's demonstration of route and mode changes following a much larger intervention is also compatible with the idea of route changes having a lower 'inertia' or resistance to change than modal changes. This is because bicycle modal changes (from 42 to 50%) are weakly significant amongst a small selected

population (n=39) exposed to the (minor) intervention for Paper V, whilst the whole sample (n=719) in Paper IV had a greater bicycle modal shift (42 to 54%) in response to the (major) intervention in Trondheim. It should be mentioned, however, that exposure to the intervention was almost guaranteed in Trondheim due to Innherredsveien's role as a major arterial and public transport axis (and widely publicised closure to through-traffic).

### **6.5. Challenges with bicycle infrastructure intervention research**

Concerning the case of Innherredsveien in Trondheim (Paper IV), it was public knowledge from as early as November 2016 that the long-proposed four to two lane reduction project had reached political agreement, after an extended debate between politicians. Despite alerting contacts within Trondheim Municipality and the Norwegian Public Roads Administration (NPRA) of the intended before-after study on this street, the exact date for the implementation was not apparent before it had already begun. As a result, the study was performed in the summer following project completion. A weakness of such post-intervention evaluation is inaccuracy in recalled travel behaviour (in Paper IV for travel behaviour from one year earlier) and self-selection bias towards participants who are highly supportive of the initiative (since the initiative of interest was explicitly stated in the flyers and advertisements used for recruitment to the study).

From 5000 distributed flyers, targeted recruitment through social media and electronic mailing lists, Paper IV achieved 719 valid responses. Whilst these recruitment methods are not known to have high response rates, it is worth noting that the trend is becoming more and more challenging for researchers. Response rates have been declining for the telephone-based Norwegian National Travel Survey (NNTS) from 77% when first performed in the 1984/1985 to only 20% at the last NNTS in 2014 (Hjorthol et al., 2014). This is potentially a reflection of increased requests to participate in consumer surveys (for marketing purposes) but also a general increase in exposure to surveys conducted online.

The recruitment issue is greater again for study designs like Paper V due to the additional factor of data privacy concerns (from GPS tracking). For Paper V, 3000 letters were mailed, from which approximately 15% were returned to sender (presumably due to the use of an out-of-date address database from postal services provider Bring). 152 responses were received to the online pre-GPS survey. Of these, 51 provided data in both rounds of the GPS study and were thus eligible for inclusion in the panel of 113. This gives a response rate of approximately 2% (for full study participation).

In addition to mailed invitations in Paper V, recruitment was performed through the distribution of 1000 flyers given to businesses and people travelling in the neighbourhood, social media, a local newspaper advertisement and the display of 50 posters on public community noticeboards. Apart from social media (in which interest groups specific to the neighbourhood were targeted), the recruitment process was randomised. However, it was apparent that the participants recruited through mailed invitations had very different travel behaviour compared to those recruited through either flyers or social media (see *Figure 22*). Note that the responses in *Figure 22* are to a short pre-study survey intended to collect expressions of interest and contact information for the subsequent GPS panel. Not all respondents participated in both rounds of GPS data collection which accounts for the smaller final panel size of 113.

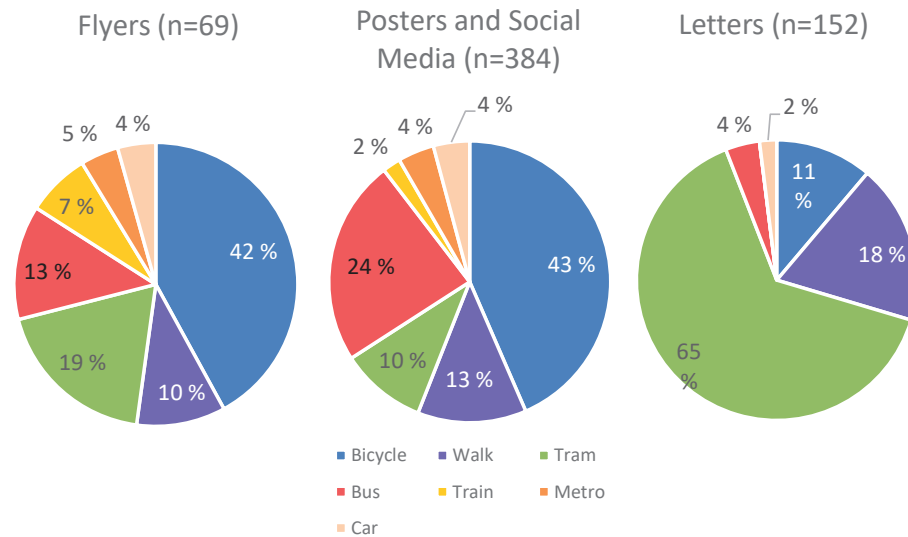


Figure 22. Type of recruitment to Oslo study's expression of interest phase (pre-GPS) and primary self-reported transport mode

Whilst low response rates result in more time and effort required on behalf of the research team, it also causes challenges in terms of representativeness. For example, a study of GPS bicycle behaviour in Portland, USA found that participants were “slightly older, were more likely to have a college degree, had higher incomes, and were more likely to have full-time jobs than other regular cyclists” (Dill & Gliebe, 2008). A possible means to overcome this issue is weighting samples based on demographics, or specifically targeting under-represented groups, as is performed for the NNTS (Hjorthol et al., 2014).

The data collection approach used in Paper IV gave a relatively low usable number of drawn trips in both time periods (211 of 719). This limits the possibility of panel travel behaviour comparisons for the other modes (which were not as numerous as cyclists shown in Figure 18). It is unclear precisely why this number was so low, but it was in part due to poor precision in route drawing, a non-compulsory question type (respondents could skip the question) and potentially low familiarity with the survey area in map-form. This can be



potentially avoided by allowing alternative means of describing route choice – such as full-text responses of waypoints (J. Y. T. Wang, Mirza, Cheung, & Moradi, 2012) or through follow-up interview techniques (Meghan Winters, Teschke, Grant, Setton, & Brauer, 2010).

Papers IV and V differ in their study design in terms of the control group. Whilst control groups are considered to be a key element of a good practice intervention study (see Section 3.5), they are challenging to identify for studies of route choice. Paper IV had no control group, partly due to this difficulty of finding an appropriate target group. For Paper V, an attempt was made to develop an independent control group through recruiting participants in Tøyen, a neighbouring suburb to the intervention area. Tøyen is similar to the Grünerløkka intervention neighbourhood in terms of distance from the Oslo city centre, and shares similarities in terms of land use, grid-based street network and population density. The recruitment efforts were, however, insufficient to acquire an adequate number of respondents to the intervention neighbourhood (11 participated in the GPS study). The intention as with other control groups was to check if there were any changes in route or mode behaviour that have causes external to the intervention (although this was not expected). Whilst this could not be done due to the limited sample size, a quasi-control was instead made by splitting the existing respondent group according to exposure to the intervention as described in the previous sub-chapter. This was done to observe potential modal changes; however, route analyses of the control and exposure sub-groups were not performed as a part of this study.

In Paper V, the primary data source is route tracking from the passive smartphone app Moves®. The problem with this and many other passive apps is high battery use and a low GPS sampling rate. Whilst the GPS sampling rate is deliberately reduced Moves® for the purposes of conserving battery, multiple respondents reported that this was a major disadvantage of the application, and that reported that they needed to charge more frequently as a result of their participation in the study. The low sampling rate, with adjacent waypoints typically separated by two to five minutes, meant that whilst walking journeys



were reasonably well represented, faster-moving modes of transport had large distances between geo-located points. Moves® was created for the purpose of providing feedback on the total amount of activity performed in a day and therefore did not specifically target high route quality. Tailor-made commercial travel survey applications such as the Trivector AB TRaveIVU app<sup>21</sup> or free fitness apps such as Endomondo<sup>22</sup> may provide a better resolution without sacrificing further battery reserves, although these were not tested as a part of this study. An overview of the available smartphone apps used in bicycle-related research published in 2017 or earlier can be found in Paper II.

Mode-classification algorithms are required for all passive GPS data collection and for the combination of Moves® data with additional mode classification from *GoEco!* Tracker, the correct mode was identified in approximately 80% of cases (Bucher et al., 2016). Whilst smartphones utilise accelerometer data together with waypoints, this information is not always connected to the route trace data when exported from the app. This should be a consideration for studies that seek to perform their own mode-classification such as the one performed by the *GoEco!* Tracker research team.

Amongst the supplementary methods used in Paper V to compare with GPS data, radar counting (described in sub-chapter 3.8) had considerable issues with reliability for classification and directional counting. The use of radar counting technologies is seldom reported in the academic literature, however, existing experiences did not suggest that there should be significant problems with data reliability (Ryus et al., 2014). Microwave-based radar counting is used by the City of Oslo for assessing traffic and bicycle flows as part of its planning and evaluation routine. The post-intervention radar data collection in Markveien revealed an 83% decrease in volumes of northbound cyclists despite the contraflow bicycle lane specifically providing for this group (and evidence from

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<sup>21</sup> <https://en.trivector.se/it-systems/travelvu/>

<sup>22</sup> <https://www.endomondo.com>

the GPS and video data sources showing that this was an unreliable value). Directional data, whilst not obviously inconsistent in the two parallel streets could therefore not be used. After data analysis, the producers of the microwave radar counter Via Traffic Controlling GmbH were contacted concerning the data quality who claimed that their device was not suitable for inner city environments due to reflection from buildings, parked cars and due to the sensitivity of radar beam interruption by pedestrians. This information is not disclosed in the product specifications<sup>23</sup>. Ultimately this made the radar count data effectively unusable even though the device can theoretically provide reliable counts and classify modes based on length of traced object and speed.

A means of achieving higher quality counting data is to use pneumatic tube counting due to the low error rate. These were deemed unsuitable for the study in Paper V due to high installation costs and the presence of trams in Thorvald Meyers gate, one of the comparison streets to Markveien (meaning two separate counters would need to be installed on each side of the street). Alternative supplementary counting methods include strategically placed cameras, as used in Paper V, or Bluetooth or Wi-Fi sensors (Ryeng, Haugen, Grønlund, & Overå, 2016). Mode identification can be troublesome for such sensors meaning that they are better suited to single streams of traffic such as separated bicycles paths. For camera footage, there are several computer-vision based solutions for mode identification and route tracing<sup>24</sup>, however, the error rates are unknown, and the solutions often have exacting requirements regarding acceptable camera footage making them unsuitable for the existing footage recorded in Oslo.

The mode effect of interventions should be expected to be small, especially when considering individual infrastructure projects that are not of a great scale. This is because transport mode choice – and in particular driving – are relatively

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<sup>23</sup> <https://www.viatraffic.de/en/products/viacount-ii-traffic-counter/>

<sup>24</sup> For example: <http://datafromsky.com>, <https://viscando.com/en/>, <http://www.almere.co.uk/almere-technology/>

inelastic and achieving modal shift requires substantial changes in utility (Krizek, Handy, et al., 2009; Madsen, 2013). Larger infrastructural changes such as Innherredsveien in Paper IV offer better chances of being able to measure changes in bicycle route and mode choice. Paper IV was able to demonstrate clear changes in mode choice resulting from installation of a 1.8km bidirectional separated bicycle path in lieu of two car lanes in combination with a restriction to the through movement of cars. Paper V meanwhile provides less rigorous evidence of modal shift, which is unsurprising given the difference in magnitude to Paper IV: a 400m contraflow bicycle lane (principally affecting one direction of bicycle traffic). These two papers suggest that the sample size and the degree of detail for recorded travel behaviour are critical to being able to make conclusive statements regarding the (oftentimes) small changes in travel behaviour resulting from individual bicycle infrastructure interventions. There are additional suggestions that the period of time between pre and post bicycle intervention measurements needs to be longer than the one month used in Paper V. This applies particularly for the consideration of modal shift and for “infrastructure change[s] that may not appear as a major change for some residents” (Dill et al., 2014).

## **7. Conclusions of the research questions and suggestions for further work**

*"Bicycling is a big part of the future. It has to be. There's something wrong with a society that drives a car to work out in a gym."*

– Bill Nye

The primary objective of this thesis is to improve understanding of the influence of urban transport infrastructure on bicycle route and mode choice. The thesis addressed this aim through three research questions:

1. In what manner can the accessibility of urban areas influence the decision to bicycle?
2. How does the quality of bicycle infrastructure impact route choice preferences?
3. What is the effect of new bicycle infrastructure in terms of route and mode choice?

The research questions are addressed through four empirical studies and a systematic literature review, which are summarised by this thesis and presented in full in the aAppendix: Papers. Key findings from the studies and the manner in which they respond to the research questions are briefly summarised in the following sections. As previously noted, the research questions are arranged in ascending order of importance for the overall thesis objective – such that research questions 1 and 2 provide background information for the final and most important research question 3.

### **7.1. Research question 1: bicycle mode choice**

*In what manner can the accessibility of urban areas influence the decision to bicycle?*

Research question 1 was primarily addressed in Chapter 4 – where the influence of an office relocation in Trondheim on commute mode choice (including cycling) was considered. The primary case was also compared with

three similar office relocations in Norway. The bicycle mode choice aspect associated with infrastructure interventions is discussed further in Chapter 6.

Although the sample size for the primary case study of Adresseavisen restricted the statistical analyses, the regression analysis reveals that participants' travel mode choices are strongly influenced by commute distance, access to a bicycle, access to a car and the existence of paid parking. For cycling, short distances, access to a bicycle and paid parking are all associated with higher probabilities of choosing to ride to work, together with limited car access. Whilst access to different vehicles were supply variables that did not change as a result of relocation, distances and parking did, contributing to the increase in bicycle modal share from 10 to 28%. This corroborates existing findings from the literature concerning supply variables. In addition, having a child under the age of 10 years was associated with a decreased likelihood of cycling.

The number of employees cycling to Adresseavisen increased by 2.8 times following relocation, which correlates well with the 3 times increase in the number of employees who live within the median stated acceptable cycling distance of their workplace following relocation (6km). The potential for cycling, when considered as the difference in the number of employees within cycling distance and walking distance, increased from 14% to 42%. That the actual post-relocation cycling levels did not meet the potential cycling levels suggests that the threshold distances used may require adjustment, however, the concept is shown to demonstrate the importance of commute distance (according to a traffic-stress weighted shortest path calculation).

The two comparison cases in Trondheim exhibited many similarities to Adresseavisen in terms of bicycle modal share in relation to change of office location, with all three cases significantly increasing in numbers of cyclists. In addition, strong similarities are shown between the commuting modal splits for Adresseavisen and Gjensidige with the equivalent neighbourhoods in the Norwegian National Travel Survey (NNTS). NNTS commuting data is for all workplace types, so the similarity of modal splits demonstrates the importance

of location attributes on travel behaviour. This approach does not pinpoint specifically which characteristics influence the decision to bicycle but provides further evidence for the association between travel behaviour and the destination environment.

Bicycle accessibility is a measure of the ability of land-use and transport systems to enable individuals to achieve their daily transport needs by bicycle. The 20% reduction in the average cycling-optimised distance to work amongst Adresseavisen employees represents a substantial improvement to the bicycle accessibility that resulted from relocation. This is reflected by a tripling in the number of employees living within cycling distance of their workplace. Although rates of cycling are determined by a combination of factors, the tripling in the actual numbers of cyclists suggests that change in destination distance is a major factor. Therefore, accessibility promoting policies that reduce distances through densification can be seen as highly beneficial for the goal of increasing bicycle modal share.

## **7.2. Research question 2: bicycle route choice**

*How does the quality of bicycle infrastructure impact route choice preferences?*

The influence of transport network design on bicycle route choice was the focus of Chapter 5. In this chapter, empirical route choice preferences from university students were used to test the relative usefulness of four composite Bicycle Level of Service (BLOS) indicators in estimating the whole journey. In addition, a systematic literature review assessed 112 empirical articles for the approaches that have been used for collecting bicycle route choice data. Route choice is also a central theme of the final research question with respect to interventions.

The review of the literature demonstrated strong growth in research production on bicycle route choice – with only one of the seven method families present in literature prior to 2007. This method family, participant recalled route choices (through interviews or surveys), is the least technology dependent group of

methods together with accompanied journeys. Two-thirds of the research fell under three method families that utilised GPS signals as the primary means of finding route choice, which has become by far the dominant means of collecting route choice data. The review illustrates a trade-off in the quality of route choice data obtainable and the typical number of participants, although all methods can provide some indication of route choice.

The study of student route preferences in Paper III provided a unique route choice dataset whilst at the same time further developing an approach through which BLOS methods can be applied to route choice generation. The results show that BCI provides the highest match with empirical route data in all five origin-destination pairs, closely followed by HCM6. These two best-performing methods share several common traits relative to the two other methods BSL and LTS, most notably that they have more explanatory variables and use empirically tested coefficients. The routing approach finds an optimal route along the BLOS-weighted OD pairs whilst incrementally increasing the value of detour rate – a measure of willingness to deviate from the shortest path. Two alternative approaches for determining the optimum detour rate suggest that the best match with modelled BLOS routes is achieved between 15 and 21% (additional length) although the route generation approach requires further development before conclusions can be drawn regarding detour rate.

BLOS methods are used in this thesis as a proxy for bicycle infrastructure quality since they combine multiple factors known to be important for cyclists. This thesis extends the application of BLOS from link-level evaluation to full origin-destination journeys, taking into account both intersections and links in the bicycle network. The link-penalty based route generating approach used did not create routes with greatly differing lengths, however, conceptually demonstrates that the best performing BLOS methods are those which cover the greatest number of factors and are empirically founded. The best match with observed route preferences averaged across the five OD pairs was approximately 27%, however, the method created fewer alternative routes than expected, suggesting that additional procedures may need to be added such as

link-elimination. The findings suggest that BLOS methods do represent observed bicycle preferences in Norway and that the rigour of the method is reflected in the percentage match with empirical observations. Quality of the bicycle infrastructure can, therefore, be said to be an influential factor on bicycle route choice, however, the method used must be refined in order to better replicate the choice set observed.

### **7.3. Research question 3: bicycle infrastructure intervention effects on mode and route choice**

*What is the effect of new bicycle infrastructure in terms of route and mode choice?*

The influence of both route choice and mode choice was brought together in Chapter 6. Two case study bicycle infrastructure interventions in Trondheim and Oslo are reported on in this chapter – and their effects on bicycle travel behaviour are considered in terms of both route and mode choice.

The Trondheim intervention required participants to recall their preferred route before and after the intervention occurred. The intervention was a form of complete streets initiative in which especially the cycling situation was improved without unacceptably compromising the accessibility of other transport modes. With a 1.8km stretch of two road lanes converted to a separated bicycle path and the implementation of a no-through driving intersection for cars, the level of vehicular traffic in the intervention street dropped, whilst the safety and comfort for cyclists (and pedestrians) was greatly improved. Results showed that the large change to the built environment in Trondheim resulted in a near doubling of peak hour cycling volumes. Evidence is found to show that route substitution of existing bicyclists' routes had occurred, together with an increase in cycling frequency and a modal shift towards bicycle use on the most common journeys taken in the neighbourhood (from 42% to 54%,  $p < .05$ ). The study may have been influenced by self-selection bias given the high rates of cycling observed compared to the NNTS data for the same area of around 11%.



The Oslo intervention meanwhile was much less substantial in terms of impact on bicyclists and other road users. A 400 metre stretch of a one-way street with parallel parking on both sides had one parking lane replaced by a contraflow red asphalt bicycle lane. The driving lane became marginally wider as a result, but no other changes were made for drivers or pedestrians. The methodological approach differed from the Trondheim intervention in that GPS recorded travel behaviour was collected for a one month period both before and after the bicycle lane construction. Despite the very different scale of the intervention, the route substitution effect was very clear for the panel of participants.

Supplementary video counts of bicyclists meanwhile suggest that there was some degree of route substitution, but not to the same extent as the GPS data. Given that the intervention was much smaller than the Trondheim case, a subset of the exposed participants was considered for measuring modal shift impacts of the intervention. Amongst this sub-group of participants, a weakly significant ( $p < 0.1$ ) modal shift was observed, from 42% to 50%.

The results of the two intervention studies suggest that whilst route substitution can be an expected effect even for a relatively minor intervention, mode substitution appears to be less pronounced in the short term. Mode changes may be more evident after a longer period of time has elapsed since intervention or may be simply a function of intervention scale (the larger the intervention, the more evident the change). Further research will be necessary to confirm which aspects of larger interventions are most likely to cause a modal shift to cycling. Lastly, the data collected in the studies addressing research question 3 (and in particular the GPS data from Paper V) is by no means fully analysed and offers opportunities for further research in such fields as transport demand modelling and cost-benefit analysis which has not been performed as a part of this thesis.

#### **7.4. Recommendations for further study**

When studying bicycle mode choice, this thesis has focussed on changes in the built environment and their effect on the modal split (through destination

relocation and infrastructural interventions). Changes in bicycle mode choice resulting from such environmental influences are typically relatively small. Therefore, to witness significant changes requires either a large dataset or a large intervention. Large datasets assist in isolating covariates from each other in regression analyses, allowing the identification of factors that influence the decision to cycle. Large interventions can be expected to produce a larger change in travel behaviour and can therefore demonstrate changes with multiple study types and a range of sample sizes.

Increasing the sample size or studying more extensive (preferably isolated) changes would be a possible means by which future research could gather more from this thesis' research approach. An example of a change that could be considered is a longitudinal or cross-sectional observation of travel behaviour over a longer time period (one or more years for example). In this example, changes to the transport infrastructure can be subsequently cross-checked with changes in the likelihood of riding a bicycle. It should be noted also that short-term and long-term effects are rarely measured, which provides an opportunity for future studies to evaluate both types of effects.

Studies of bicycle route choice can similarly benefit from having a larger sample. The relative strengths and weaknesses of different data collection approaches for bicycle route choice preferences are covered in Paper II (together with a discussion of sample size). Analytically, assessing the associations between route choice preferences and the built environment offers a number of challenges that future research could seek to focus upon. Similar but non-coincident routes are not interpreted by the GIS methods used in this thesis as having any similarity. Future studies may consider the applicability of modelling approaches such as path size logit models to consider the similarity between route choices.

Whilst bicycle route choice is increasingly being studied in travel behaviour research, it is often tackled from either a quantitative or qualitative perspective. Where this thesis has been focussed mostly on quantitative revealed

preference travel behaviour, other studies consider qualitative aspects concerning why people behave the way they do or how urban planners approach the task of bicycle network development. A hybrid of these two methodological approaches can provide more in-depth contextual information whilst also revealing quantitative insights both of which can be of use to transport modellers and planners.

Bicycle travel behaviour is a function of many variables and is not limited to changes in the destination or infrastructural offering. Promotional measures such as marketing, electric bicycle subsidies, traffic safety training for school children and ride-to-work events also influence the likelihood of cycling. Future studies may wish to consider the impact of some of these additional factors and their relative importance compared to transport infrastructure.

Much of the research focussed on urban cycling behaviour does not attempt to quantify the benefits and costs of promotional efforts from cities. In particular, the quantification of benefits for both infrastructural projects and other promotional measures is associated with a high degree of uncertainty. Health benefits from cycling often assume that any increases in cycling comes in addition to existing physical activity levels and does not substitute it. This is a hypothesis which demands further investigation due to the importance of the health benefits in many of today's cost-benefit analyses.

Similarly, in the field of travel demand modelling, bicycles remain a fringe mode and are rarely considered in terms of both route and mode choice aspects in practice. The development of further studies which focus on both route and mode choices in urban environments should create opportunities for modelling researchers to better integrate cyclists and pedestrians into existing transport models.

## 8. References

- Akar, G., & Clifton, K. J. (2009). Influence of Individual Perceptions and Bicycle Infrastructure on Decision to Bike. *Transportation Research Record: Journal of the Transportation Research Board*, 2140(2140), 165–172. <https://doi.org/10.3141/2140-18>
- Aldred, R. (2015). Adults' attitudes towards child cycling: a study of the impact of infrastructure. *European Journal of Transport and Infrastructure Research*, 15(2), 92–115.
- Aldred, R., Elliott, B., Woodcock, J., & Goodman, A. (2017). Cycling provision separated from motor traffic: a systematic review exploring whether stated preferences vary by gender and age. *Transport Reviews*, 37(1), 29–55. <https://doi.org/10.1080/01441647.2016.1200156>
- Allemann, D., & Raubal, M. (2015). Usage Differences Between Bikes and E-Bikes. In F. Bacao, M. Y. Santos, & M. Painho (Eds.), *AGILE 2015, Geographic Information Science as an Enabler of Smarter Cities and Communities*. (pp. 201–217). Cham, Switzerland: Springer International Publishing Switzerland AG. [https://doi.org/10.1007/978-3-319-16787-9\\_12](https://doi.org/10.1007/978-3-319-16787-9_12)
- Anable, J., Lane, B., & Kelay, T. (2006). Review of public attitudes to climate change and transport: Summary report. *The UK Department for Transport*, (July), 32. <https://doi.org/10.1016/j.tim.2005.10.004>
- Angell, T. (2018). Nasjonal RVU og Ruters MIS RVU – ulikheter og vurdering av sambruk (utkast) {National Travel Survey and Ruter's MIS Travel Survey - differences and evaluation of compatibility (unpublished)}. Oslo.
- Aultman-Hall, L., Hall, F., & Baetz, B. (1997a). Analysis of bicycle commuter routes using geographic information systems: implications for bicycle planning. *Transportation Research Record*, (970168), 102–110. Retrieved from <http://trb.metapress.com/index/67L8N01117256723.pdf>
- Aultman-Hall, L., Hall, F. L., & Baetz, B. (1997b). Analysis of bicycle commuter routes using geographic information systems: implications for bicycle planning. *Transportation Research Record: Journal of the Transportation Research Board*, (970168), 102–110. Retrieved from <http://trb.metapress.com/index/67L8N01117256723.pdf>
- Avni, A., Burley, P., Casey, P., Cherney, J., Christiansen, L., Daly, J. S., ... Yu, H. (2015). Literature Searches and Literature Reviews for Transportation Research Projects. How to Search, Where to Search, and How to Put It All Together: Current Practices. *Transportation Research Circular*. Transportation Research Board. Retrieved from <http://www.trb.org/Main/Blurbs/172271.aspx>
- Bamberg, S., Ajzen, I., & Schmidt, P. (2003). Choice of Travel Mode in the

Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action. *Basic and Applied Social Psychology*, 25(3), 175–187. [https://doi.org/10.1207/S15324834BASP2503\\_01](https://doi.org/10.1207/S15324834BASP2503_01)

- Bamberg, S., Fujii, S., Friman, M., & Gärling, T. (2011). Behaviour theory and soft transport policy measures. *Transport Policy*, 18(1), 228–235. <https://doi.org/10.1016/j.tranpol.2010.08.006>
- Benton, J. S., Anderson, J., Hunter, R. F., & French, D. P. (2016). The effect of changing the built environment on physical activity: a quantitative review of the risk of bias in natural experiments. *International Journal of Behavioral Nutrition and Physical Activity*, 13(1), 107. <https://doi.org/10.1186/s12966-016-0433-3>
- Berge, G., Haug, E., & Marshall, L. (2012). Nasjonal gåstrategi. Strategi for å fremme gåing som transportform og hverdagsaktivitet {National Walking Strategy. Strategy for the promotion of walking as a transport form and everyday activity} NPRA Report 87, (87), 1–180. Retrieved from [https://www.vegvesen.no/\\_attachment/528926/binary/851213?fast\\_title=Nasjonalgåstrategi.pdf](https://www.vegvesen.no/_attachment/528926/binary/851213?fast_title=Nasjonalgåstrategi.pdf)
- Berger, M. (2017). Tester ut nye sykkeltiltak i en rekke byer i Norge [Testing out new bicycle initiatives in a host of cities in Norway]. *Vegnett*. Retrieved from <https://vegnett.no/2017/02/tester-ut-nye-sykkeltiltak-i-en-rekke-byer-i-norge/>
- Bohte, W., & Maat, K. (2009). Deriving and validating trip purposes and travel modes for multi-day GPS-based travel surveys: A large-scale application in the Netherlands. *Transportation Research Part C: Emerging Technologies*, 17(3), 285–297. <https://doi.org/10.1016/j.trc.2008.11.004>
- Börjesson, M., & Eliasson, J. (2012). The value of time and external benefits in bicycle appraisal. *Transportation Research Part A: Policy and Practice*, 46(4), 673–683. <https://doi.org/10.1016/j.tra.2012.01.006>
- Bovy, P. H. L. (2009). On Modelling Route Choice Sets in Transportation Networks: A Synthesis. *Transport Reviews*, 29(1), 43–68. <https://doi.org/10.1080/01441640802078673>
- Broach, J. (2016). *Travel Mode Choice Framework Incorporating Realistic Bike and Walk Routes* (Doctoral thesis). Portland State University. <https://doi.org/10.15760/etd.2698>
- Broach, J., Dill, J., & Gliebe, J. (2012). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice*, 46(10), 1730–1740. <https://doi.org/10.1016/j.tra.2012.07.005>
- Bucher, D., Cellina, F., Mangili, F., Raubal, M., Rudel, R., Rizzoli, A. E., & Elabed, O. (2016). Exploiting Fitness Apps for Sustainable Mobility - Challenges Deploying the GoEco! App. In *4th International Conference on*

- ICT for Sustainability (ICT4S 2016)*. Atlantis Press. Retrieved from <https://pdfs.semanticscholar.org/16c7/ba4702ec81529d2410ac30468ecce61cfbbe.pdf>
- Buehler, R., & Dill, J. (2015). Bikeway Networks: A Review of Effects on Cycling. *Transport Reviews*, (August 2015), 1–19. <https://doi.org/10.1080/01441647.2015.1069908>
- Buehler, R., & Pucher, J. (2012). Cycling to work in 90 large American cities: New evidence on the role of bike paths and lanes. *Transportation*, 39(2), 409–432. <https://doi.org/10.1007/s11116-011-9355-8>
- Buehler, R., Pucher, J., Gerike, R., & Götschi, T. (2016). Reducing car dependence in the heart of Europe: lessons from Germany, Austria, and Switzerland. *Transport Reviews*, 1647(May), 1–25. <https://doi.org/10.1080/01441647.2016.1177799>
- Casello, J., Nour, A., Rewa, K. C., & Hill, J. (2011). Analysis of Stated-Preference and GPS Data for Bicycle Travel Forecasting. In *Transportation Research Board 90th Annual Meeting* (pp. 1–18). Washington D.C., USA. Retrieved from <http://trid.trb.org/view/1093054%0A>
- Casello, J., & Usyukov, V. (2014). Modeling Cyclists' Route Choice Based on GPS Data. *Transportation Research Record: Journal of the Transportation Research Board*, 2430(2430), 155–161. <https://doi.org/10.3141/2430-16>
- Cervero, R. (2006). Alternative Approaches to Modeling the Travel-Demand Impacts of Smart Growth. *Journal of the American Planning Association*, 72(3), 285–295. <https://doi.org/10.1080/01944360608976751>
- Cervero, R., Denman, S., & Jin, Y. (2019). Network design, built and natural environments, and bicycle commuting: Evidence from British cities and towns. *Transport Policy*, 74, 153–164. <https://doi.org/10.1016/j.tranpol.2018.09.007>
- Cervero, R., & Landis, J. (1995). The Transportation-Land Use Connection Still Matters. *ACCESS Magazine*, 1(7), 2–10.
- Chen, P., Shen, Q., & Childress, S. (2017). A GPS data-based analysis of built environment influences on bicyclist route preferences. *International Journal of Sustainable Transportation*, 0(0), 1–14. <https://doi.org/10.1080/15568318.2017.1349222>
- Christiansen, P., & Julsrud, T. E. (2014). *TØI report 1344/2014. Effekter av Gjensidiges omlokalisering fra Lysaker til Bjørvika [Effects of Gjensidiges relocation from Lysaker to Bjørvika]*. Oslo: Institute of Transport Economics. Retrieved from <https://www.toi.no/getfile.php?mmfileid=38240>
- CROW. (2016). *Design manual for bicycle traffic*. Ede: Centre for Research and Contract Standardization in Civil and Traffic Engineering C.R.O.W.

- Dalumpines, R., & Scott, D. M. (2011). GIS-based Map-matching: Development and Demonstration of a Postprocessing Map-matching Algorithm for Transportation Research. In S. Geertman, W. Reinhardt, & F. Toppen (Eds.), *Advancing Geoinformation Science for a Changing World* (Vol. 1, pp. 101–120). Berlin, Heidelberg: Springer Berlin Heidelberg. [https://doi.org/10.1007/978-3-642-19789-5\\_6](https://doi.org/10.1007/978-3-642-19789-5_6)
- de Leeuw, G., & de Kruijf, J. (2015). The Act of (Future) Cycling: Testing Urban Designs and Conducting Research in Virtual Reality. In *European Transport Conference* (pp. 1–15). Frankfurt, Germany: Association for European Transport. Retrieved from <https://aetransport.org/public/downloads/3KJvE/4588-56007f730ec5e.pdf>
- Det Kongelige Miljøverndepartement. (2012). Meld. St. 21 (2011–2012) Norsk klimapolitikk, 13.
- Díez-Gutiérrez, M., Andersen, S. N., Nilsen, Ø. L., & Tørset, T. (2018). Generated and induced traffic demand: Empirical evidence from a fixed link toll removal in Norway. *Case Studies on Transport Policy*, (January), 0–1. <https://doi.org/10.1016/j.cstp.2018.11.007>
- Dill, J., & Carr, T. (2003). Bicycle Commuting and Facilities in Major US Cities If You Build Them, Commuters Will Use Them. *Transportation Research Record: Journal of the Transportation Research Board*, 1828(03–4134), 116–123.
- Dill, J., & Gliebe, J. (2008). *Understanding and Measuring Bicycling Behavior: A Focus on Travel Time and Route choice. Report OTREC-RR-08-03*. Portland, OR, USA: Oregon Transportation Research and Education Consortium. Retrieved from [http://pdxscholar.library.pdx.edu/cgi/viewcontent.cgi?article=1027&context=usp\\_fac](http://pdxscholar.library.pdx.edu/cgi/viewcontent.cgi?article=1027&context=usp_fac)
- Dill, J., McNeil, N., Broach, J., & Ma, L. (2014). Bicycle boulevards and changes in physical activity and active transportation: Findings from a natural experiment. *Preventive Medicine*, 69(S), S74–S78. <https://doi.org/10.1016/j.ypmed.2014.10.006>
- Dowling, R., Reinke, D., Flannery, A., Ryus, P., Vandehey, M., Petritsch, T., ... Bonneson, J. (2008). Multimodal Level of Service for Urban Streets. NCHRP Report 616, (616). <https://doi.org/10.3141/2071-01>
- Ehrgott, M., Wang, J. Y. T., Raith, A., & Van Houtte, C. (2012). A bi-objective cyclist route choice model. *Transportation Research Part A: Policy and Practice*, 46(4), 652–663. <https://doi.org/10.1016/j.tra.2011.11.015>
- Envall, P. (2007). *Accessibility Planning: a chimera?* (Doctoral thesis). University of Leeds. Retrieved from <http://etheses.whiterose.ac.uk/id/eprint/11279>



- Epperson, B. (1994). Evaluating Suitability of Roadways for Bicycle Use: Toward a Cycling Level-of-Service Standard. *Transportation Research Record: Journal of the Transportation Research Board*, (1438), 9–16. Retrieved from <http://onlinepubs.trb.org/Onlinepubs/trr/1994/1438/1438-002.pdf>
- Espeland, M., & Amundsen, K. S. (2012). *Nasjonal sykkelstrategi - Sats på sykkel! Grunnlagsdokument for Nasjonal transportplan 2014-2023. {National Cycling Strategy - Focus on cycling! Background document for National Transport Plan 2014-2023} NPRA Road Directorate Report 7*. Retrieved from [https://www.vegvesen.no/\\_attachment/317385](https://www.vegvesen.no/_attachment/317385)
- European Union. General Data Protection Regulation (EU) 2016/679, Official Journal of the European Union § (2016). Retrieved from <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679>
- Evenson, K. R., & Furberg, R. D. (2017). Moves app: a digital diary to track physical activity and location. *British Journal of Sports Medicine*, 51(15), 1169–1170. <https://doi.org/10.1136/bjsports-2016-096103>
- Ewing, R., & Cervero, R. (2010). Travel and the Built Environment. A Meta-Analysis. *Journal of the American Planning Association*, 76(3), 265–294. <https://doi.org/10.1080/01944361003766766>
- Federal Ministry of Transport Building and Urban Development. (2012). *National Cycling Plan 2020 - Joining forces to evolve cycling*. Berlin. Retrieved from <http://edoc.difu.de/edoc.php?id=1U032RD6>
- Fitch, D., Thigpen, C., Cruz, A., & Handy, S. L. (2016). Bicyclist Behavior in San Francisco: A Before-and-After Study of the Impact of Infrastructure Investments. Retrieved from <http://ncst.ucdavis.edu/project/ucd-ct-to-012>
- Fitzhugh, E. C., Bassett, D. R., & Evans, M. F. (2010). Urban trails and physical activity: A natural experiment. *American Journal of Preventive Medicine*, 39(3), 259–262. <https://doi.org/10.1016/j.amepre.2010.05.010>
- Furth, P. G., Mekuria, M. C., & Nixon, H. (2016). Network Connectivity for Low-Stress Bicycling. *Transportation Research Record: Journal of the Transportation Research Board*, 2587(1), 41–49. <https://doi.org/10.3141/2587-06>
- Furth, P. G., Putta, T. V., & Moser, P. (2018). Measuring low-stress connectivity in terms of bike-accessible jobs and potential bike-to-work trips: A case study evaluating alternative bike route alignments in northern Delaware. *Journal of Transport and Land Use*, 11(1), 815–831. <https://doi.org/10.5198/jtlu.2018.1159>
- Geurs, K. T., & van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: Review and research directions. *Journal of Transport Geography*, 12(2), 127–140. <https://doi.org/10.1016/j.jtrangeo.2003.10.005>



- Ghekiere, A., Van Cauwenberg, J., Mertens, L., Clarys, P., de Geus, B., Cardon, G., ... Deforche, B. (2015). Assessing cycling-friendly environments for children: are micro-environmental factors equally important across different street settings? *International Journal of Behavioral Nutrition and Physical Activity*, *12*(1), 54. <https://doi.org/10.1186/s12966-015-0216-2>
- Goodman, A., Sahlqvist, S., & Ogilvie, D. (2013). Who uses new walking and cycling infrastructure and how? Longitudinal results from the UK iConnect study. *Preventive Medicine*, *57*(5), 518–524. <https://doi.org/10.1016/j.ypmed.2013.07.007>
- Goodman, A., Sahlqvist, S., & Ogilvie, D. (2014). New Walking and Cycling Routes and Increased Physical Activity: One- and 2-Year Findings From the UK iConnect Study. *American Journal of Public Health*, *104*(9), e38–e46. <https://doi.org/10.2105/AJPH.2014.302059>
- Gössling, S. (2013). Urban transport transitions: Copenhagen, city of cyclists. *Journal of Transport Geography*, *33*, 196–206. <https://doi.org/10.1016/j.jtrangeo.2013.10.013>
- Gustafsson, L., & Archer, J. (2013). A naturalistic study of commuter cyclists in the greater Stockholm area. *Accident Analysis & Prevention*, *58*, 286–298. <https://doi.org/10.1016/j.aap.2012.06.004>
- Habib, K. N. (2018). A Heteroscedastic Polarized Logit Model to Investigate the Competition of Bicycle for the Bikeable Trips with the Other Modes. *Transportation Research Record*, 1–11. <https://doi.org/10.1177/0361198118796357>
- Handy, S. (2005). Critical Assessment of the Literature on the Relationships Among Transportation, Land Use, and Physical Activity. *TRB Special Report 282*. Retrieved from <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.471.2645&rep=rep1&type=pdf>
- Handy, S., Cao, X., & Mokhtarian, P. (2005). Correlation or causality between the built environment and travel behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, *10*(6), 427–444. <https://doi.org/10.1016/j.trd.2005.05.002>
- Handy, S., van Wee, B., & Kroesen, M. (2014). Promoting Cycling for Transport: Research Needs and Challenges. *Transport Reviews*, *34*(1), 4–24. <https://doi.org/10.1080/01441647.2013.860204>
- Hansen, K. B., & Nielsen, T. A. S. (2014). Exploring characteristics and motives of long distance commuter cyclists. *Transport Policy*, *35*, 57–63. <https://doi.org/10.1016/j.tranpol.2014.05.001>
- Harkey, D. L., Reinfurt, D. W., & Knuiman, M. (1998). Development of the

- Bicycle Compatibility Index. *Transportation Research Record: Journal of the Transportation Research Board*, 1636(1), 13–20.  
<https://doi.org/10.3141/1636-03>
- Hartvedt, H. (2018). Classification of statistical tract and basic statistical unit. Retrieved November 28, 2018, from  
<https://www.ssb.no/en/klasse/klassifikasjoner/1>
- He, B., Zhang, Y., Chen, Y., & Gu, Z. (2018). A Simple Line Clustering Method for Spatial Analysis with Origin-Destination Data and Its Application to Bike-Sharing Movement Data. *ISPRS International Journal of Geo-Information*, 7(6), 16. <https://doi.org/10.3390/ijgi7060203>
- Heesch, K. C., Giles-Corti, B., & Turrell, G. (2015). Cycling for transport and recreation: Associations with the socio-economic, natural and built environment. *Health & Place*, 36, 152–161.  
<https://doi.org/10.1016/j.healthplace.2015.10.004>
- Heesch, K. C., James, B., Washington, T. L., Zuniga, K., & Burke, M. (2016). Evaluation of the Veloway 1: A natural experiment of new bicycle infrastructure in Brisbane, Australia. *Journal of Transport & Health*, 1–11.  
<https://doi.org/10.1016/j.jth.2016.06.006>
- Heinen, E., Maat, K., & van Wee, B. (2013). The effect of work-related factors on the bicycle commute mode choice in the Netherlands. *Transportation*, 40(1), 23–43. <https://doi.org/10.1007/s11116-012-9399-4>
- Heinen, E., Maat, K., & Van Wee, B. (2011). The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. *Transportation Research Part D: Transport and Environment*, 16(2), 102–109. <https://doi.org/10.1016/j.trd.2010.08.010>
- Heinen, E., Panter, J., Mackett, R., & Ogilvie, D. (2015). Changes in mode of travel to work: a natural experimental study of new transport infrastructure. *International Journal of Behavioral Nutrition and Physical Activity*, 12(1), 81. <https://doi.org/10.1186/s12966-015-0239-8>
- Hirose, S., & Kitamura, Y. (2015). Preliminary evaluation of virtual cycling system using google street view. *Persuasive Technology*, 9072, 65–70.  
<https://doi.org/10.1007/978-3-319-20306-5>
- Hjorthol, R., Engebretsen, Ø., & Uteng, T. P. (2014). *TØI report 1383/2014. Den nasjonale reisevaneundersøkelsen 2013/2014 - nøkkelrapport {2013/14 National travel survey – key results}*. Oslo: Institute of Transport Economics. Retrieved from <https://www.toi.no/getfile.php?mmfileid=39511>
- Hood, J., Erhardt, G., Frazier, C., & Schenk, A. (2014). Estimating Emissions Benefits of Bicycle Facilities with Stand-Alone Software Tools. *Transportation Research Record: Journal of the Transportation Research Board*, 2430(2430), 124–132. <https://doi.org/10.3141/2430-13>

- Hood, J., Sall, E., & Charlton, B. (2011). A GPS-based bicycle route choice model for San Francisco, California. *Transportation Letters*, 3(1), 63–75. <https://doi.org/10.3328/TL.2011.03.01.63-75>
- Huber, S., & Rust, C. (2016). Calculate Travel Time and Distance with Openstreetmap Data Using the Open Source Routing Machine (OSRM). *The Stata Journal*, 16(2), 416–423. <https://doi.org/10.1177/1536867X1601600209>
- Hulleberg, N., Flügel, S., & Ævarsson, G. (2018). *TØI Report 1648/2018. Vekter for sykkelinfrastruktur til bruk ved rutevalg i regionale transportmodeller [Empirical based infrastructure weights for bicycle route choice]*. Oslo: Institute of Transport Economics. Retrieved from <https://www.toi.no/getfile.php?mmfileid=48783>
- Hunt, J. D., & Abraham, J. E. (2007). Influences on bicycle use. *Transportation*, 34(4), 453–470. <https://doi.org/10.1007/s11116-006-9109-1>
- Hyodo, T., Suzuki, N., & Takahashi, K. (2000). Modeling of Bicycle Route and Destination Choice Behavior for Bicycle Road Network Plan. *Transportation Research Record: Journal of the Transportation Research Board*, 1705, 70–76. <https://doi.org/10.3141/1705-11>
- Jensen, S. U. (2007). Pedestrian and Bicyclist Level of Service on Roadway Segments. *Transportation Research Record: Journal of the Transportation Research Board*, 2031(1), 43–51. <https://doi.org/10.3141/2031-06>
- Jestico, B., Nelson, T., & Winters, M. (2016). Mapping ridership using crowdsourced cycling data. *Journal of Transport Geography*, 52, 90–97. <https://doi.org/10.1016/j.jtrangeo.2016.03.006>
- Kager, R., Bertolini, L., & Te Brömmelstroet, M. (2016). Characterisation of and reflections on the synergy of bicycles and public transport. *Transportation Research Part A: Policy and Practice*, 85, 208–219. <https://doi.org/10.1016/j.tra.2016.01.015>
- Kahila, M., & Kyttä, M. (2009). SoftGIS as a Bridge-BUILDER in Collaborative Urban Planning. In S. Geertman & J. Stillwell (Eds.), *Planning Support Systems Best Practice and New Methods* (pp. 389–411). Dordrecht: Springer Netherlands. [https://doi.org/10.1007/978-1-4020-8952-7\\_19](https://doi.org/10.1007/978-1-4020-8952-7_19)
- Kang, L., & Fricker, J. D. (2018). Bicycle-Route Choice Model Incorporating Distance and Perceived Risk. *Journal of Urban Planning and Development*, 144(4), 1–8. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000485](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000485).
- Kärmeniemi, M., Lankila, T., Ikäheimo, T., Koivumaa-Honkanen, H., & Korpelainen, R. (2018). The Built Environment as a Determinant of Physical Activity: A Systematic Review of Longitudinal Studies and Natural Experiments. *Annals of Behavioral Medicine*, 52(3), 239–251. <https://doi.org/10.1093/abm/kax043>

- Keall, M., Chapman, R., Shaw, C., Abrahamse, W., & Howden-Chapman, P. (2018). Are people who already cycle and walk more responsive to an active travel intervention? *Journal of Transport & Health*, (xxxx), 0–1. <https://doi.org/10.1016/j.jth.2018.08.006>
- Khatri, R., Cherry, C. R., Nambisan, S. S., & Han, L. D. (2016). Modeling Route Choice of Utilitarian Bikeshare Users with GPS Data. *Transportation Research Record: Journal of the Transportation Research Board*, 2587, 141–149. <https://doi.org/10.3141/2587-17>
- Klöckner, C. A., & Blöbaum, A. (2010). A comprehensive action determination model: Toward a broader understanding of ecological behaviour using the example of travel mode choice. *Journal of Environmental Psychology*, 30(4), 574–586. <https://doi.org/10.1016/j.jenvp.2010.03.001>
- Koglin, T., & Rye, T. (2014). The marginalisation of bicycling in Modernist urban transport planning. *Journal of Transport and Health*, 1(4), 214–222. <https://doi.org/10.1016/j.jth.2014.09.006>
- Kremers, S. P. J., de Bruijn, G. J., Visscher, T. L. S., van Mechelen, W., de Vries, N. K., & Brug, J. (2006). Environmental influences on energy balance-related behaviors: A dual-process view. *International Journal of Behavioral Nutrition and Physical Activity*, 3, 1–10. <https://doi.org/10.1186/1479-5868-3-9>
- Krizek, K. J. (2019). Measuring the wind through your hair? Unravelling the positive utility of bicycle travel. *Research in Transportation Business & Management*, (January 2018), 0–1. <https://doi.org/10.1016/j.rtbm.2019.01.001>
- Krizek, K. J., El-Geneidy, A., & Thompson, K. (2007). A detailed analysis of how an urban trail system affects cyclists' travel. *Transportation*, 34(5), 611–624. <https://doi.org/10.1007/s11116-007-9130-z>
- Krizek, K. J., Forsyth, A., & Baum, L. (2009). *Walking and cycling international literature review: Final report. Department of Transport Victoria Australia*. Melbourne. Retrieved from <http://www.designforhealth.net/techassistance/trec.html.%5Cn???>
- Krizek, K. J., Handy, S. L., & Forsyth, A. (2009). Explaining Changes in Walking and Bicycling Behavior: Challenges for Transportation Research. *Environment and Planning B: Planning and Design*, 36(4), 725–740. <https://doi.org/10.1068/b34023>
- Landis, B. W., Vattikuti, V. R., & Brannick, M. T. (1997). Real-Time Human Perceptions: Toward a Bicycle Level of Service. *Transportation Research Record: Journal of the Transportation Research Board*, 1578(1), 119–126. <https://doi.org/10.3141/1578-15>
- Larsen, J., & El-Geneidy, A. (2011). A travel behavior analysis of urban cycling

- facilities in Montréal, Canada. *Transportation Research Part D: Transport and Environment*, 16(2), 172–177. <https://doi.org/10.1016/j.trd.2010.07.011>
- Laube, P. (2014). *Computational Movement Analysis. SpringerBriefs in Computer Science. Springer, Berlin Heidelberg*. Cham: Springer International Publishing. <https://doi.org/10.1007/978-3-319-10268-9>
- Levinson, D. M., & Krizek, K. J. (2017). *The End of Traffic & the Future of Access: A Roadmap to the New Transport Landscape*. Network Design Lab.
- Li, Z., Wang, W., Yang, C., & Ragland, D. R. (2013). Bicycle commuting market analysis using attitudinal market segmentation approach. *Transportation Research Part A: Policy and Practice*, 47, 56–68. <https://doi.org/10.1016/j.tra.2012.10.017>
- Litman, T., & Burwell, D. (2006). Issues in sustainable transportation. *International Journal of Global Environmental Issues*, 6(4), 331. <https://doi.org/10.1504/IJGENVI.2006.010889>
- Lott, D. F., Tardiff, T., & Lott, D. Y. (1978). Evaluation by experienced riders of a new bicycle lane in an Established Bikeway System. *Transportation Research Record: Journal of the Transportation Research Board*, 683, 40–46. Retrieved from [http://www.john-s-allen.com/research/davis\\_studies/Lott, Tardiff, and Lott.pdf](http://www.john-s-allen.com/research/davis_studies/Lott,Tardiff,andLott.pdf)
- Lowry, M., Callister, D., Gresham, M., & Moore, B. (2012). Assessment of Communitywide Bikeability with Bicycle Level of Service. *Transportation Research Record: Journal of the Transportation Research Board*, 2314, 41–48. <https://doi.org/10.3141/2314-06>
- Lu, W., Scott, D. M., & Dalumpines, R. (2018). Understanding bike share cyclist route choice using GPS data: Comparing dominant routes and shortest paths. *Journal of Transport Geography*, 71(July), 172–181. <https://doi.org/10.1016/j.jtrangeo.2018.07.012>
- Macmillan, A., Connor, J., Witten, K., Kearns, R., Rees, D., & Woodward, A. (2014). The Societal Costs and Benefits of Commuter Bicycling: Simulating the Effects of Specific Policies Using System Dynamics Modeling. *Environmental Health Perspectives*, 122(4), 335–344. <https://doi.org/10.1289/ehp.1307250>
- Madsen, T. (2013). *Transport cycling behavior: Associations between the built environment and transport cycling in Denmark* (Doctoral thesis). *Det Sundhedsvidenskabelige Fakultet*. University of Southern Denmark. Retrieved from [http://findresearcher.sdu.dk/portal/files/88330090/PhD\\_thesis\\_tryk\\_Thomas\\_Madsen\\_final.pdf](http://findresearcher.sdu.dk/portal/files/88330090/PhD_thesis_tryk_Thomas_Madsen_final.pdf)
- Majumdar, B. B., & Mitra, S. (2018). Development of Level of Service Criteria

for Evaluation of Bicycle Suitability. *Journal of Urban Planning and Development*, 144(2), 04018012. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000432](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000432)

Manaugh, K., Boisjoly, G., & El-Geneidy, A. (2017). Overcoming barriers to cycling: understanding frequency of cycling in a University setting and the factors preventing commuters from cycling on a regular basis. *Transportation*, 44(4), 871–884. <https://doi.org/10.1007/s11116-016-9682-x>

Mason, J., Fulton, L., & McDonald, Z. (2015). *A Global High Shift Cycling Scenario: The Potential for Dramatically Increasing Bicycle and E-bike Use in Cities Around the World, with Estimated Energy, CO<sub>2</sub>, and Cost Impacts*. Institute for Transportation & Development Policy. Davis, California. Retrieved from <https://www.itdp.org/2015/11/12/a-global-high-shift-cycling-scenario/>

Mathisen, T. A., Annema, J. A., & Kroesen, M. (2015). The effects of weather and climate change on cycling in Northern Norway. *European Journal of Transport and Infrastructure Research*, 15(15), 261–273.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, 3, 303–328.

Mekuria, M., Furth, P., & Nixon, H. (2012). MTI Report 11-19 Low-Stress Bicycling and Network Connectivity. *Mineta Transportation Institute*.

Meland, S. (2004). *Oppfølging av flytting til Statens hus i Trondheim {Follow-up of relocation to Statens Hus in Trondheim}*. SINTEF Note N-10/04. Trondheim. Retrieved from [https://www.sintef.no/globalassets/upload/teknologi\\_og\\_samfunn/veg-og-samferdsel/n-10-04-oppfolging-av-flytting-til-statens-hus.pdf](https://www.sintef.no/globalassets/upload/teknologi_og_samfunn/veg-og-samferdsel/n-10-04-oppfolging-av-flytting-til-statens-hus.pdf)

Menghini, G., Carrasco, N., Schüssler, N., & Axhausen, K. W. (2010). Route choice of cyclists in Zurich. *Transportation Research Part A: Policy and Practice*, 44(9), 754–765. <https://doi.org/10.1016/j.tra.2010.07.008>

Mertens, L., Compernelle, S., Deforche, B., Mackenbach, J. D., Lakerveld, J., Brug, J., ... Van Dyck, D. (2017). Built environmental correlates of cycling for transport across Europe. *Health & Place*, 44, 35–42. <https://doi.org/10.1016/j.healthplace.2017.01.007>

Milakis, D., & Athanasopoulos, K. (2014). What about people in cycle network planning? Applying participative multicriteria GIS analysis in the case of the Athens metropolitan cycle network. *Journal of Transport Geography*, 35, 120–129. <https://doi.org/10.1016/j.jtrangeo.2014.01.009>

Misra, A., & Watkins, K. (2017). Modeling Cyclists' Willingness to Deviate from Shortest Path Using Revealed Preference Data. *Transportation Research Board 96th Annual Meeting*, 1–17. Retrieved from <http://trid.trb.org/view/1438418>



- Misra, A., & Watkins, K. (2018). Modeling Cyclist Route Choice using Revealed Preference Data: An Age and Gender Perspective. *Transportation Research Record: Journal of the Transportation Research Board*.  
<https://doi.org/10.1177/0361198118798968>
- Mitra, R., & Buliung, R. N. (2015). Exploring differences in school travel mode choice behaviour between children and youth. *Transport Policy*, 42, 4–11.  
<https://doi.org/10.1016/j.tranpol.2015.04.005>
- Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Medicine*, 6(7), e1000097.  
<https://doi.org/10.1371/journal.pmed.1000097>
- Montini, L., Antoniou, C., & Axhausen, K. W. (2017). Route and Mode Choice Models Using GPS Data. In *Transportation Research Board 96th Annual Meeting* (pp. 1–14). Washington D.C., USA. Retrieved from  
<https://www.ethz.ch/content/dam/ethz/special-interest/baug/ivt/ivt-dam/vpl/reports/1201-1300/ab1204.pdf>
- Moore, T., Thorsnes, P., & Appleyard, B. (2007). The transportation land use connection. *APA Planning Advisory Service Reports*, (546–547), 1–409.
- Morrison, D. S. (2004). Evaluation of the health effects of a neighbourhood traffic calming scheme. *Journal of Epidemiology & Community Health*, 58(10), 837–840. <https://doi.org/10.1136/jech.2003.017509>
- Möser, G., & Bamberg, S. (2008). The effectiveness of soft transport policy measures: A critical assessment and meta-analysis of empirical evidence. *Journal of Environmental Psychology*, 28(1), 10–26.  
<https://doi.org/10.1016/j.jenvp.2007.09.001>
- Moura, F., Magalhães, J., & Santos, L. P. (2017). Growing from incipient to large cycle networks in hilly consolidated urban areas: the case of Lisbon. *European Journal of Transport and Infrastructure Research*, 17(1), 170–190.
- Næss, P., Andersen, J., Nicolaisen, M. S., & Strand, A. (2014). Transport modelling in the context of the 'predict and provide' paradigm. *European Journal of Transport and Infrastructure Research*, 14(14), 102–121.
- Nankervis, M. (1999). The effect of weather and climate on bicycle commuting. *Transportation Research Part A: Policy and Practice*, 33(6), 417–431.  
[https://doi.org/10.1016/S0965-8564\(98\)00022-6](https://doi.org/10.1016/S0965-8564(98)00022-6)
- Nielsen, T. A. S., Olafsson, A. S., Carstensen, T. A., & Skov-Petersen, H. (2013). Environmental correlates of cycling: Evaluating urban form and location effects based on Danish micro-data. *Transportation Research Part D: Transport and Environment*, 22, 4044.  
<https://doi.org/10.1016/j.trd.2013.02.017>

- Nielsen, T. A. S., & Skov-Petersen, H. (2018). Bikeability – Urban structures supporting cycling. Effects of local, urban and regional scale urban form factors on cycling from home and workplace locations in Denmark. *Journal of Transport Geography*, 69(October 2017), 36–44. <https://doi.org/10.1016/j.jtrangeo.2018.04.015>
- Norwegian Public Roads Administration. (2017). *Byutredning Trondheimsområdet [City Evaluation of the Trondheim Region]*. Retrieved from [https://www.ntp.dep.no/By/Byutredninger/\\_attachment/2105886/binary/1225320?\\_ts=1606a2cbcc8](https://www.ntp.dep.no/By/Byutredninger/_attachment/2105886/binary/1225320?_ts=1606a2cbcc8)
- Pánek, J., & Benediktsson, K. (2017). Emotional mapping and its participatory potential: Opinions about cycling conditions in Reykjavík, Iceland. *Cities*, 61, 65–73. <https://doi.org/10.1016/j.cities.2016.11.005>
- Parker, K. M., Rice, J., Gustat, J., Ruley, J., Spriggs, A., & Johnson, C. (2013). Effect of Bike Lane Infrastructure Improvements on Ridership in One New Orleans Neighborhood. *Annals of Behavioral Medicine*, 45(S1), 101–107. <https://doi.org/10.1007/s12160-012-9440-z>
- Parkin, J., & Rotheram, J. (2010). Design speeds and acceleration characteristics of bicycle traffic for use in planning, design and appraisal. *Transport Policy*, 17(5), 335–341. <https://doi.org/10.1016/j.tranpol.2010.03.001>
- Parkin, J., Wardman, M., & Page, M. (2007). Models of perceived cycling risk and route acceptability. *Accident Analysis & Prevention*, 39(2), 364–371. <https://doi.org/10.1016/j.aap.2006.08.007>
- Paulsen, K. E., Kvidal, M., & Strømmen, K. (2008). *Endringer i reisevaner etter samlokalisering av kommunal administrasjon i Midtbyen [Changes in travel behaviour after relocation of municipal administration to Midtbyen]*. Trondheim: Trondheim Kommune. Retrieved from <https://153.110.202.34/attachment.ap?id=49199>
- Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstein, A. R. (1996). A simulation study of the number of events per variable in logistic regression analysis. *Journal of Clinical Epidemiology*, 49(12), 1373–1379. [https://doi.org/10.1016/S0895-4356\(96\)00236-3](https://doi.org/10.1016/S0895-4356(96)00236-3)
- Piatkowski, D. P., Marshall, W. E., & Krizek, K. J. (2019). Carrots versus Sticks: Assessing Intervention Effectiveness and Implementation Challenges for Active Transport. *Journal of Planning Education and Research*, 39(1), 50–64. <https://doi.org/10.1177/0739456X17715306>
- Plazier, P. A., Weitkamp, G., & Berg, A. E. Van Den. (2017). “Cycling was never so easy!” An analysis of e-bike commuters’ motives , travel behaviour and experiences using GPS-tracking and interviews. *Journal of Transport Geography*, 65(September), 25–34.



<https://doi.org/10.1016/j.jtrangeo.2017.09.017>

Pokorny, P., Pritchard, R., & Pitera, K. (2018). Conflicts between bikes and trucks in urban areas—A survey of Norwegian cyclists. *Case Studies on Transport Policy*, 6(1), 147–155. <https://doi.org/10.1016/j.cstp.2017.11.010>

Prato, C. G. (2009). Route choice modeling: past, present and future research directions. *Journal of Choice Modelling*, 2(1), 65–100. [https://doi.org/10.1016/S1755-5345\(13\)70005-8](https://doi.org/10.1016/S1755-5345(13)70005-8)

Pritchard, R. (2018). Revealed Preference Methods for Studying Bicycle Route Choice—A Systematic Review. *International Journal of Environmental Research and Public Health*, 15(3), 1–30. <https://doi.org/10.3390/ijerph15030470>

Project OSRM. (2018). Open Source Routing Machine Application Programming Interface documentation v5.15.2. Retrieved September 1, 2018, from <http://project-osrm.org/docs/v5.15.2/api/#match-service>

Pucher, J., Dill, J., & Handy, S. (2010). Infrastructure, programs, and policies to increase bicycling: An international review. *Preventive Medicine*, 50(SUPPL.), S106–S125. <https://doi.org/10.1016/j.ypmed.2009.07.028>

Rambøll AS. (2018). *Evaluering av trafikale effekter av prøveprosjektet i Innherredsveien [Evaluation of traffic effects of trial project in Innherredsveien]*. Retrieved from [https://www.trondheim.kommune.no/globalassets/10-bilder-og-filer/10-byutvikling/byplankontoret/1b\\_off-ettersyn/2018/fv-910-innherredsveien-fra-saxenborg-alle-til-stadsing-dahls-gate-detaljregulering-r20140034/12.--evaluering-av-trafikale-effekter-av-prove](https://www.trondheim.kommune.no/globalassets/10-bilder-og-filer/10-byutvikling/byplankontoret/1b_off-ettersyn/2018/fv-910-innherredsveien-fra-saxenborg-alle-til-stadsing-dahls-gate-detaljregulering-r20140034/12.--evaluering-av-trafikale-effekter-av-prove)

Rayaprolu, H. S., Llorca, C., & Moeckel, R. (2018). Impact of bicycle highways on commuter mode choice: A scenario analysis. *Environment and Planning B: Urban Analytics and City Science*, 239980831879733. <https://doi.org/10.1177/2399808318797334>

Rietveld, P., & Daniel, V. (2004). Determinants of bicycle use: Do municipal policies matter? *Transportation Research Part A: Policy and Practice*, 38(7), 531–550. <https://doi.org/10.1016/j.tra.2004.05.003>

Rissel, C., Greaves, S., Wen, L. M., Crane, M., & Standen, C. (2015). Use of and short-term impacts of new cycling infrastructure in inner-Sydney, Australia: a quasi-experimental design. *International Journal of Behavioral Nutrition and Physical Activity*, 12(1), 129. <https://doi.org/10.1186/s12966-015-0294-1>

Rowangould, G. M., & Tayarani, M. (2016). Effect of Bicycle Facilities on Travel Mode Choice Decisions. *Journal of Urban Planning and Development*, 1–10. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000341](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000341).

- Ryeng, E. O., Haugen, T., Grønlund, H., & Overå, S. B. (2016). Evaluating Bluetooth and Wi-Fi Sensors as a Tool for Collecting Bicycle Speed at Varying Gradients. *Transportation Research Procedia*, 14, 2289–2296. <https://doi.org/10.1016/j.trpro.2016.05.245>
- Ryus, P., Ferguson, E., Laustsen, K. M., Schneider, R. J., Proulx, F. R., Hull, T., & Miranda-Moreno, L. (2014). *NCHRP Web-Only Document 205: Methods and Technologies for Pedestrian and Bicycle Volume Data Collection* (Vol. D). Washington, D.C.: Transportation Research Board. <https://doi.org/10.17226/23429>
- Salon, D., Conway, M. W., Wang, K., & Roth, N. (2019). Heterogeneity in the relationship between biking and the built environment. *Journal of Transport and Land Use*, 12(1), 1–22. <https://doi.org/10.5198/jtlu.2019.1350>
- Samferdselsdepartementet. (2013a). Belønningsordning for bedre kollektivtransport og mindre bilbruk i byområdene. Retningslinjer [Reward system for better public transport and reduced car use in city areas. Guidelines]. Retrieved from <https://www.regjeringen.no/contentassets/66644bf4b3e642acaf10bea324af42b8/retningslinjer-for-belonningsordningen.pdf>
- Samferdselsdepartementet. (2013b). *Meld. St. 26 (2012–2013) Report to the Storting (white paper) National Transport Plan 2014–2023* (Vol. 26). Retrieved from [https://www.regjeringen.no/contentassets/3fff99ead75f4f5e8bd751161006bffa/pdfs/stm201220130026000en\\_pdfs.pdf](https://www.regjeringen.no/contentassets/3fff99ead75f4f5e8bd751161006bffa/pdfs/stm201220130026000en_pdfs.pdf)
- Samferdselsdepartementet. (2017). *Meld. St. 33 (2016 – 2017) Report to the Storting (white paper) National Transport Plan 2018–2029*. Retrieved from <https://www.regjeringen.no/contentassets/7c52fd2938ca42209e4286fe86bb28bd/en-gb/pdfs/stm201620170033000engpdfs.pdf>
- Samferdselsdepartementet. (2018). Belønningsordningen, bymiljøavtaler og byvekstavtaler [The reward system, City Environment Agreements and City Growth Agreements]. Retrieved September 1, 2018, from <https://www.regjeringen.no/no/tema/transport-og-kommunikasjon/kollektivtransport/belonningsordningen-bymiljoavtaler-og-byvekstavtaler/id2571977/>
- Sardari, R., Hamidi, S., & Pouladi, R. (2018). Effects of Traffic Congestion on Vehicle Miles Traveled. *Transportation Research Record: Journal of the Transportation Research Board*. <https://doi.org/10.1177/0361198118791865>
- Scheepers, C. E., Wendel-Vos, G. C. W., den Broeder, J. M., van Kempen, E. E. M. M., van Wesemael, P. J. V., & Schuit, A. J. (2014). Shifting from car to active transport: A systematic review of the effectiveness of interventions. *Transportation Research Part A: Policy and Practice*, 70, 264–280.

<https://doi.org/10.1016/j.tra.2014.10.015>

- Schepers, P., Fishman, E., Beelen, R., Heinen, E., Wijnen, W., & Parkin, J. (2015). The mortality impact of bicycle paths and lanes related to physical activity, air pollution exposure and road safety. *Journal of Transport & Health*, 1–14. <https://doi.org/10.1016/j.jth.2015.09.004>
- Schneider, R. J., & Stefanich, J. (2015). Neighborhood Characteristics That Support Bicycle Commuting. *Transportation Research Record: Journal of the Transportation Research Board*, 2520(2520), 41–51. <https://doi.org/10.3141/2520-06>
- Schoner, J. E., Cao, J., & Levinson, D. M. (2015). Catalysts and magnets: Built environment and bicycle commuting. *Journal of Transport Geography*, 47, 100–108. <https://doi.org/10.1016/j.jtrangeo.2015.07.007>
- Schuessler, N., & Axhausen, K. W. (2009). Map-matching of GPS traces on high-resolution navigation networks using the Multiple Hypothesis Technique (MHT). *October*, (October), 1–22. Retrieved from <http://www.baug.ethz.ch/ivt/ivt/vpl/publications/reports/ab568.pdf>
- Schwanen, T., Banister, D., & Anable, J. (2012). Rethinking habits and their role in behaviour change: the case of low-carbon mobility. *Journal of Transport Geography*, 24, 522–532. <https://doi.org/10.1016/j.jtrangeo.2012.06.003>
- Schweizer, J., Bernardi, S., & Rupi, F. (2016). Map-matching algorithm applied to bicycle global positioning system traces in Bologna. *IET Intelligent Transport Systems*, 10(4), 244–250. <https://doi.org/10.1049/iet-its.2015.0135>
- Segadilha, A. B. P., & Sanches, S. da P. (2014). Analysis of Bicycle Commuter Routes Using GPSs and GIS. *Procedia - Social and Behavioral Sciences*, 162, 198–207. <https://doi.org/10.1016/j.sbspro.2014.12.200>
- Sener, I. N., Eluru, N., & Bhat, C. R. (2010). Who Are Bicyclists? Why and How Much Are They Bicycling? *Transportation Research Record: Journal of the Transportation Research Board*, 2134(1), 63–72. <https://doi.org/10.3141/2134-08>
- Shakeel, K., Rashidi, T. H., & Waller, T. S. (2016). Choice Set Formation Behavior. *Transportation Research Record: Journal of the Transportation Research Board*, 2563, 96–104. <https://doi.org/10.3141/2563-14>
- Shen, Q., Chen, P., Schmiedeskamp, P., Bassok, A., & Childress, S. (2014). *Bicycle Route Choice: GPS Data Collection and Travel Model Development. Report 2012-S-UW-0019*. Retrieved from <https://ntl.bts.gov/lib/52000/52800/52839/PacTrans-19-625083-Shen-Qing-Small-Project.pdf>
- Shu, S., Quiros, D. C., Wang, R., & Zhu, Y. (2014). Changes of street use and

- on-road air quality before and after complete street retrofit: An exploratory case study in Santa Monica, California. *Transportation Research Part D: Transport and Environment*, 32, 387–396.  
<https://doi.org/10.1016/j.trd.2014.08.024>
- Sim, L. L., Malone-Lee, L. C., & Chin, K. H. L. (2001). Integrating land use and transport planning to reduce work-related travel: a case study of Tampines Regional Centre in Singapore. *Habitat International*, 25(3), 399–414.  
[https://doi.org/10.1016/S0197-3975\(01\)00012-1](https://doi.org/10.1016/S0197-3975(01)00012-1)
- Simpson, P. (2017). A sense of the cycling environment: Felt experiences of infrastructure and atmospheres. *Environment and Planning A*, 49(2), 426–447. <https://doi.org/10.1177/0308518X16669510>
- Smith, M., Hosking, J., Woodward, A., Witten, K., MacMillan, A., Field, A., ... Mackie, H. (2017). Systematic literature review of built environment effects on physical activity and active transport – an update and new findings on health equity. *International Journal of Behavioral Nutrition and Physical Activity*, 14(1), 158. <https://doi.org/10.1186/s12966-017-0613-9>
- Snizek, B., Sick Nielsen, T. A., & Skov-Petersen, H. (2013). Mapping bicyclists' experiences in Copenhagen. *Journal of Transport Geography*, 30, 227–233. <https://doi.org/10.1016/j.jtrangeo.2013.02.001>
- Song, Y., Preston, J., & Ogilvie, D. (2017). New walking and cycling infrastructure and modal shift in the UK: A quasi-experimental panel study. *Transportation Research Part A: Policy and Practice*, 95, 320–333.  
<https://doi.org/10.1016/j.tra.2016.11.017>
- Sørensen, M. W. J. (2013). Regler for syklende [Regulations for cyclists]. Retrieved from <https://www.tiltak.no/b-ende-transportmiddelfordeling/b-3-tilrettelegging-syssel/b-3-5/>
- Sorton, A., & Walsh, T. (1994). Bicycle Stress Level as a Tool To Evaluate Urban and Suburban Bicycle Compatibility. *Transportation Research Record: Journal of the Transportation Research Board*, (1438), 17–24. Retrieved from <http://onlinepubs.trb.org/Onlinepubs/trr/1994/1438/1438-003.pdf>
- Spilsberg, E., Børud, E., Myrberg, G., & Nordgård, G. O. (2008). Sykkelhåndboka - Sammenlignet med utenlandske løsninger [The bicycle handbook - compared with international solutions]. Retrieved from [https://www.vegvesen.no/\\_attachment/106762/binary/182568?fast\\_title=Sykkelhåndboka+-+Sammenlignet+med+utenlandske+løsninger+-+Rambøll](https://www.vegvesen.no/_attachment/106762/binary/182568?fast_title=Sykkelhåndboka+-+Sammenlignet+med+utenlandske+løsninger+-+Rambøll)
- Sprumont, F., Viti, F., Caruso, G., & König, A. (2014). Workplace Relocation and Mobility Changes in a Transnational Metropolitan Area: The Case of the University of Luxembourg. *Transportation Research Procedia*, 4, 286–299. <https://doi.org/10.1016/j.trpro.2014.11.022>

- Statens Vegvesen. (2018). *Byutredninger - Oppsummering av hovedresultater for åtte byområder [City Evaluations - Summary of Main Results for Eight City Areas]*. Retrieved from [https://www.ntp.dep.no/By/Byutredninger/\\_attachment/2145595/binary/1232192?\\_ts=16132856b20](https://www.ntp.dep.no/By/Byutredninger/_attachment/2145595/binary/1232192?_ts=16132856b20)
- Stewart, T. I. (2017). *Integrating GPS, accelerometry and online mapping technologies: exploring built environment correlates of adolescent mobility and domain-specific physical activity* (Doctoral thesis). Auckland University of Technology. Retrieved from <http://hdl.handle.net/10292/10623>
- Stigell, E. (2011). *Assessment of active commuting behaviour: Walking and bicycling in Greater Stockholm* (Doctoral thesis). Örebro University. Retrieved from <http://urn.kb.se/resolve?urn=urn:nbn:se:oru:diva-16372>
- Strømme, K. (2001). *Rett virksomhet på rett sted - om virksomheters transportskapende egenskaper {Right business at the right location – about businesses' traffic generating capacities}* (Doctoral thesis 2001:14). Norwegian University of Science and Technology. Retrieved from <http://hdl.handle.net/11250/229734>
- Sun, Y., Du, Y., Wang, Y., & Zhuang, L. (2017). Examining associations of environmental characteristics with recreational cycling behaviour by street-level strava data. *International Journal of Environmental Research and Public Health*, 14(6). <https://doi.org/10.3390/ijerph14060644>
- Ton, D., Duives, D., Cats, O., & Hoogendoorn, S. (2018). Evaluating a data-driven approach for choice set identification using GPS bicycle route choice data from Amsterdam. *Travel Behaviour and Society*, 13(February), 105–117. <https://doi.org/10.1016/j.tbs.2018.07.001>
- Transportation Research Board. (2016). Chapter 18 Urban Street Segments. In *Highway Capacity Manual: A Guide for Multimodal Mobility Analysis*. Transportation Research Board. <https://doi.org/10.17226/24798>
- Vaage, O. F. (2018). Norwegian Media Barometer 2017. Retrieved August 7, 2018, from [https://www.ssb.no/kultur-og-fritid/artikler-og-publikasjoner/\\_attachment/346186?\\_ts=162d7feae58](https://www.ssb.no/kultur-og-fritid/artikler-og-publikasjoner/_attachment/346186?_ts=162d7feae58)
- Vaismaa, K., Mantynen, J., Metsapuro, P., Luukkonen, T., Rantala, T., & Karhula, K. (2012). Best European practices in promoting cycling and walking. Retrieved from [http://besteuropeanpractices.juvenesprint.fi/en/553/t\\_2247%5Cnhttps://trid.trb.org/view/1255534](http://besteuropeanpractices.juvenesprint.fi/en/553/t_2247%5Cnhttps://trid.trb.org/view/1255534)
- Van Duppen, J., & Spierings, B. (2013). Retracing trajectories: The embodied experience of cycling, urban sensescapes and the commute between “neighbourhood” and “city” in Utrecht, NL. *Journal of Transport Geography*, 30, 234–243. <https://doi.org/10.1016/j.jtrangeo.2013.02.006>

- van Goeverden, K., Nielsen, T. S., Harder, H., & van Nes, R. (2015). Interventions in Bicycle Infrastructure, Lessons from Dutch and Danish Cases. *Transportation Research Procedia*, 10(July), 403–412. <https://doi.org/10.1016/j.trpro.2015.09.090>
- van Schagen, I. N. L. G. (1990). Pedestrians and Pedal Cyclists in a British, Dutch and Swedish Modelling Area. *Institute of Transport Studies, University of Leeds*, 47. Retrieved from <http://eprints.whiterose.ac.uk/2259>
- van Wee, B., & Banister, D. (2016). How to Write a Literature Review Paper? *Transport Reviews*, 36(2), 278–288. <https://doi.org/10.1080/01441647.2015.1065456>
- van Wee, B., & Börjesson, M. (2015). How to make CBA more suitable for evaluating cycling policies. *Transport Policy*, 44, 117–124. <https://doi.org/10.1016/j.tranpol.2015.07.005>
- Vegdirektoratet. (2014). *Sykkelhåndboka {Bicycle Handbook} NPRA Road Directorate Report V122*. Retrieved from [https://www.vegvesen.no/\\_attachment/69912/binary/964012](https://www.vegvesen.no/_attachment/69912/binary/964012)
- Wahlgren, L., & Schantz, P. (2012). Exploring bikeability in a metropolitan setting: stimulating and hindering factors in commuting route environments. *BMC Public Health*, 12(1), 168. <https://doi.org/10.1186/1471-2458-12-168>
- Wang, C. H., Akar, G., & Guldmann, J. M. (2015). Do your neighbors affect your bicycling choice? A spatial probit model for bicycling to The Ohio State University. *Journal of Transport Geography*, 42, 122–130. <https://doi.org/10.1016/j.jtrangeo.2014.12.003>
- Wang, J. Y. T., Mirza, L., Cheung, A. K. L., & Moradi, S. (2012). Transforming Auckland into a bicycle-friendly city: Understanding factors influencing choices of cyclists and potential cyclists. In B. Hughes & I. Petkoff (Eds.), *Australasian Transport Research Forum*. Perth, Australia: Australasian Transport Research Forum Incorporated. Retrieved from <http://trid.trb.org/view.aspx?id=1224151>
- Winters, M, Brauer, M., Teschke, K., & Fuller, D. (2016). Bike Score: Associations between urban bikeability and cycling behavior in 24 cities. *International Journal of Behavioral Nutrition and Physical Activity*, 1–10. <https://doi.org/10.1186/s12966-016-0339-0>
- Winters, Meghan, & Teschke, K. (2010). Route Preferences Among Adults in the Near Market for Bicycling: Findings of the Cycling in Cities Study. *American Journal of Health Promotion*, 25(1), 40–47. <https://doi.org/10.4278/ajhp.081006-QUAN-236>
- Winters, Meghan, Teschke, K., Grant, M., Setton, E., & Brauer, M. (2010). How Far Out of the Way Will We Travel? *Transportation Research Record: Journal of the Transportation Research Board*, 2190(1), 1–10.



<https://doi.org/10.3141/2190-01>

- Yang, L., Sahlqvist, S., McMinn, A., Griffin, S. J., & Ogilvie, D. (2010). Interventions to promote cycling: systematic review. *BMJ*, *341*(oct18 2), c5293–c5293. <https://doi.org/10.1136/bmj.c5293>
- Yen, J. Y. (1971). Finding the K Shortest Loopless Paths in a Network. *Management Science*, *17*(11), 712–716. <https://doi.org/10.1287/mnsc.17.11.712>
- Zhao, C., Nielsen, T. A. S., Olafsson, A. S., Carstensen, T. A., & Meng, X. (2018). Urban form, demographic and socio-economic correlates of walking, cycling, and e-biking: Evidence from eight neighborhoods in Beijing. *Transport Policy*, (January), 1–11. <https://doi.org/10.1016/j.tranpol.2018.01.018>
- Zhu, S., & Levinson, D. (2015). Do People Use the Shortest Path? An Empirical Test of Wardrop's First Principle. *PLOS ONE*, *10*(8), e0134322. <https://doi.org/10.1371/journal.pone.0134322>
- Zimmermann, M., Mai, T., & Frejinger, E. (2017). Bike route choice modeling using GPS data without choice sets of paths. *Transportation Research Part C: Emerging Technologies*, *75*, 183–196. <https://doi.org/10.1016/j.trc.2016.12.009>
- Zolnik, E. J., & Cromley, E. K. (2007). Poisson Multilevel Methodology of Bicycle Levels of Service for Road Networks. *Transportation Research Record*, (2031), 1–8. <https://doi.org/10.3141/2031-01>

## **Appendix: Papers**

### ***Paper I – Adresseavisen office relocation***

Pritchard R, Frøyen Y (2019). *Location, location, relocation: how the relocation of workplaces from suburbs to the inner city impacts commuting on foot and by bike*. European Transport Research Review 11(14):1-20. doi: [10.1186/s12544-019-0348-6](https://doi.org/10.1186/s12544-019-0348-6)

### ***Paper II – Literature review (methods)***

Pritchard R (2018) *Revealed Preference Methods for Studying Bicycle Route Choice—A Systematic Review*. International Journal of Environmental Research and Public Health 15:1–30. doi: [10.3390/ijerph15030470](https://doi.org/10.3390/ijerph15030470)

### ***Paper III – SiT student route choice***

Pritchard R, Frøyen Y, Snizek B (2019). *Bicycle Level of Service for Route Choice—A GIS Evaluation of Four Existing Indicators with Empirical Data*. ISPRS International Journal of Geo-Information, 8:1–20. doi: [10.3390/ijgi8050214](https://doi.org/10.3390/ijgi8050214)

### ***Paper IV – Trondheim intervention***

Vasilev M, Pritchard R, Jonsson T (2018). *Trialing a Road Lane to Bicycle Path Redesign—Changes in Travel Behavior with a Focus on Users' Route and Mode Choice*. Sustainability 10:1-18. doi: [10.3390/su10124768](https://doi.org/10.3390/su10124768)

### ***Paper V – Oslo intervention***

Pritchard R, Bucher D, Frøyen Y (2019). *Does new bicycle infrastructure result in new cyclists? A longitudinal GPS study in Oslo*. Journal of Transport Geography 77:113-125. doi: [10.1016/j.jtrangeo.2019.05.005](https://doi.org/10.1016/j.jtrangeo.2019.05.005)





## Paper I

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ORIGINAL PAPER

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# Location, location, relocation: how the relocation of offices from suburbs to the inner city impacts commuting on foot and by bike

Ray Pritchard\* and Yngve Frøyen

## Abstract

**Purpose:** In recent decades there has been increasing focus on the development of compact and accessible urban environments, in part based on the reasoning that this can help to reduce the transportation requirements of city residents. Travel intensive land uses such as office workplaces are often offered incentives from policy makers to relocate to central locations well served by public transport (transit oriented development). To date, the academic literature on integrated transport and land use planning has largely been focused on the reduction of private car usage and promotion of public transport. This paper adds a complementary dimension, testing the hypothesis that intra-city workplace relocation towards city centres promotes walking and bicycling.

**Methods:** This paper uses a comparative case study method. Employee travel surveys were conducted before and after the 2015 relocation of an office workplace in Trondheim, Norway from urban periphery to city centre. Three similar office relocation cases in Trondheim and Oslo (post-2000) are used for comparison to the case study. Changes in travel distance, time, costs, optimal route and potential for walking and bicycling in the case study are considered alongside actual changes in transport mode.

**Results:** Walking and bicycling levels have a clear inverse relationship with distance to the city centre, due in large part to reduced commuting distances and increased parking costs following relocation. For the case study, the modal share of walking and cycling increased by a factor of 2.5 and 2.8 respectively. Relocation similarly led to a tripling in the number of case study employees who have a commute distance of less than 6 km, the employees' median acceptable cycling distance. Active commuting levels from the former and current workplace locations match closely with the share of active commuting in the Norwegian National Travel Survey data for the corresponding neighbourhoods.

**Conclusion:** Although the function of workplaces and their employees can vary significantly within a city neighbourhood, travel behaviour is to a large extent determined by supply variables like time and cost. Central workplace locations with good public transport accessibility are shown to create significantly improved opportunities for walking, cycling and public transport commuting compared to peripheral workplaces with little competition to workplace accessibility by car.

**Keywords:** Relocation, Office, Commuter mode choice, Bicycle, Pedestrian, Densification, Centralisation

\* Correspondence: [Ray.Pritchard@cantab.net](mailto:Ray.Pritchard@cantab.net)

Department of Architecture and Planning, Faculty of Architecture and Design, NTNU—Norwegian University of Science and Technology, 7491 Trondheim, Norway



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## 1 Introduction

The importance of accessibility on the travel patterns of urban dwellers is well documented through comparisons of cities, city districts and even suburbs [1]. However, there is somewhat less research concerning the travel behaviour changes resulting from the intra-city relocation of transport-attracting land uses such as workplaces. Considering that some studies suggest between 6 and 8% of all companies relocate each year [2], there has been relatively little research concerning the commuting impacts of such relocations, especially in the direction towards the city centre. Previous research has been mostly focussed on the relocation of workplaces in the opposite direction: to suburban areas in line with a decentralisation trend that amongst developed countries was more evident several decades ago. This paper makes contributions to the travel behaviour literature on the relocation of workplaces to city centres, using cases from Norway.

Although the reasons for relocating a workplace are many and varied, one typical benefit of relocating closer to the inner city is an improvement in both active and public transport accessibility, for both employees and visitors alike. For employees, a change from car-based commuting to walking or cycling to work significantly increases the net amount of physical activity they receive in an average week [3–5]. Since inner city real estate prices are typically higher than in the suburbs, the relocation of a workplace from city outskirts to inner city tends to result in reduced access to free car parking. Although the theoretical car accessibility for the labour force may be better or approximately equal in the inner city, congestion effects and reduced free parking work as discouragements for car-based commuting. In this manner, workplace relocation can work as both a carrot and stick initiative for employees to make a switch from commuting by car.

This paper employs a comparative case study method in an attempt to better understand the various phenomena that impact active commuting levels when workplaces relocate towards urban centres. Empirical travel survey data has been collected before and after the 2015 relocation of a newspaper publishing office, Adresseavisen in Trondheim, Norway. A search of academic and grey literature for other cases from Norwegian cities was performed resulting in the addition of three other workplaces that relocated to areas closer to the centres of Trondheim and Oslo since 2000. Commuter travel behaviour for the three additional cases is extracted from existing Norwegian reports. The most recent of these reports concerns an insurance company Gjensidige in Oslo, which relocated its headquarters in 2013 [6]. The municipal administration staff in Trondheim were relocated in 2005 from three clusters to a single cluster in the city centre [7]. In a similar vein, the

Trondheim-based public office Statens Hus for public roads administration workers and county employees in Sør-Trøndelag was relocated in 2000 [8, 9]. Each of the existing reports discusses the changes in employee transport mode to work before and after the respective workplace relocation.

## 2 Background

This study focuses upon relocation towards city centres as a result of a reversal in land use policies that catered for the exact opposite: decentralisation or suburbanisation. Most city regions have grown enormously in land use area since private car ownership became affordable. Mass private motorisation in the 1950s and 1960s contributed to widespread traffic congestion and increased pollution in urban areas across much of North America, Europe and Australia. Planners at the time observed this mismatch in supply and demand of public space and began major road and highway expansions, thus increasing the urban footprint. In time, this allowed for the introduction of employment decentralisation policies under the logic that this would reduce both traffic flows through overloaded city centres and the distance between employers and their workforces [10].

The vast majority of literature concerning company relocation has been focused on movement away from the city centre to the suburbs or more general trends towards suburbanisation. This applies equally for studies performed outside of Norway ([10–19]; Geographic Institute of Utrecht University 1990 in [20]) to those within Norway [21–28]. Common findings across all studies are increased car modal share – typically a result of reduced public transport accessibility and favourable car parking allowances at the suburban location [17, 20, 23, 27]. Interestingly, the increase in car use at the expense of all competing modes was also witnessed for a suburban relocation in which the average distance between the employee residences and place of work decreased [11]. A study which followed up the commuting behaviour of more than 7000 employees across 42 London offices post-relocation showed that car modal split increases slightly in the 7 years following decentralisation to the outskirts of London [14]. This finding is echoed for two Norwegian follow-up surveys in Trondheim [28] and Oslo [29].

A relatively small proportion of the international literature is devoted to companies relocating towards the city centre (City of Copenhagen 1993 in [29]; [2, 30, 31]). These studies are discussed in more detail in section 5. Amongst Norwegian studies of company relocation, a somewhat higher proportion are focussed on moves towards the city centre [6, 7, 9, 26, 29, 32].

Three of the Norwegian relocations [6, 7, 9] are chosen for case-comparison analysis based on their similarity to the Adresseavisen case study introduced in this paper. Criteria for case selection was that the comparative relocations occurred in or after the year 2000 and with a comparable change in distance from suburbs to the city centre.

Although the majority of cities still have a cluster of employment functions in the city centre, many have suburban mixed-use centres that combine residential and workplace functions. To better understand the relationship between central and suburban workplace location, existing research has measured commuting behaviour using outcomes such as trip frequency, trip length, mode choice and Vehicle Kilometres Travelled (VKT) [33]. Commuting distance, or trip length, has additionally been measured in many studies of urban form and travel behaviour. Næss [34] found that central workplaces in Oslo and Copenhagen had shorter commute distances compared to their suburban counterparts whilst equivalent locations in Helsinki had longer. However, Norwegian National Travel Survey (NNTS) data from 2009 comparing regions within Oslo showed that employees working in the city centre have slightly longer commutes than the city average [35]. It should be noted that commute distance is to a large extent affected by the specialisation of the workplace, and so the sample of workplaces is critically important for the outcome of such analyses.

Since commute distance has a number of weaknesses as a metric, comparison-based articles have begun to make use of the composite travel measure Vehicle Kilometres Travelled (VKT - alternatively called VMT when miles are used). VKT reflects changes in both spatial variables, such as average distance, and modal changes like increased non-motorised transport usage ([10]). The extensive meta-analysis from Ewing and Cervero [33] concludes that VKT is most strongly related to destination accessibility relative to other built environment measures, meaning that areas with good active and public transport accessibility such as inner cities produce lower VKT than suburban mixed-use centres.

A review of Nordic literature regarding workplace relocation shows increases in public and active transport use for central workplace location relative to suburban locations across all of the applicable studies [34]. This said, national travel survey data from nine Norwegian cities in 1984–1985 shows the rate of walking and cycling increases in the urban area excluding the city centre (combined modal share of 24%) relative to the city centre (12%) [36]. This, reason Strand et al., was most likely due to structural differences in workplaces whereby more peripherally

located businesses recruit their workers locally to a greater extent than centrally located businesses (as cited in [37] p. 5).

Whilst there are many other studies comparing the travel impacts of different workplace locations, they tend not to control for self-selection influences (whereby businesses in the same manner as residents may choose to locate in a particular area independent of built-environment influences). It is possible to control for this influence by observing short-term changes resulting from workplace relocation – in this case in the less studied direction: towards the city centre. This paper compares four such relocation cases in Norway.

### 2.1 Norwegian planning context

Norway has been early in its adoption of sustainable development policies, something which is reflected by the leadership of former Norwegian prime minister, Gro Harlem Brundtland, in authoring the Our Common Future report [38]. Densification and compact urban development policies are now commonly utilised in metropolitan areas across Norway. Such policies can be considered a response to the practice of decentralisation of compact transport intensive workplaces, both between cities and within cities in Norway up until the early 2000s [23, 24, 28, 29, 37, 39].

Increased focus upon the interactions between land use, urban form and transportation was the trigger for a reversal in urban development policy, beginning formally with the introduction of the first national guidelines for integrated land use and transport in 1993 [40]. Today, the planning guidelines for integrated housing, land use and transport planning are referenced in the Norwegian Planning and Building Act. The Act includes the same key policies from 1993 through the inclusion of a compact city clause: “The development patterns and transport system should promote the development of compact cities and urban areas, reduce transport requirements and facilitate the use of sustainable transport modes” ([41], sec. 3). It goes further to state: “Effective traffic management and good accessibility for business-related transport must be prioritised in the planning process” [Ibid. sec.4.6].

Oslo and Trondheim are the two cities of interest in this paper. The nation’s capital city Oslo is by far Norway’s largest city whilst Trondheim is the fourth largest urban metropolitan region in Norway (after Oslo, Bergen and the Stavanger-Sandnes metropolitan area).

A modernistic urban development plan for Oslo was adopted in 1950 [42]. Zoning regulations separated city

functions such as housing and workplaces whilst dispersion favoured car use. However, it was not until the second revision in 1991 that densification was addressed and 1994 before the local centre hierarchical structures were re-evaluated to address integrated transport accessibility requirements [Marianne Knapskog: Accessibility in Norwegian urban planning - Dutch ABC location policy in Norwegian integrated land use and transport planning (PhD thesis), forthcoming]. Today Oslo is growing faster than the other major cities in Norway, a contributing factor to its higher rate of densification compared to the three next-largest cities of Bergen, Stavanger and Trondheim [43]. Oslo has additionally increased its levels of active and public transport users most of the four cities in the period from 2001 to 2009 [Ibid. p.99].

In Trondheim, the importance of workplace location first came into focus during the regional transport plan development in the 1960s [24]. This is unsurprising given the removal of car import restrictions to Norway in 1960. It was during this period that planners realised that the expected commercial growth and car use would lead to far more car traffic than it was possible to manage through the city centre. This was a key factor contributing to the establishment of a regional centre at Heimdal, approximately nine kilometres south of the city centre of Trondheim ([24], p. 102). Dutch-inspired ABC planning policies have been practised in Trondheim since the late 1990s with a focus on “the right business in the right place” regarding its strategy for business growth and workplace development [28]. With regards to transport, the municipal master plan for Trondheim introduced in 2008 a target to increase the modal share of environmentally friendly transportation from 42% to 50% for all urban journeys by 2018 ([44], p. 70). The plan states that a minimum of 60% of new office workplaces should be built along the primary public transportation arc, a goal that was introduced by city planners in 2008 [ibid., p.62]. The most recent data from the years 2001 to 2010 indicates that 65% of all newly built offices have met this spatial criterion [ibid. p.63].

The return of workplaces from suburban localities to city centres is in part a result of integrated transport and land use policies – both at the national and city level. Depending on the workplace function, there may additionally be many other reasons for relocation, such as business image, agglomeration benefits, floor space costs and changes in employee numbers [45, 46]. Whilst individual differences will always affect the spatial location of a workplace, urban planning policy can have wide-reaching and long-lasting effects on the localisation of employment within cities.

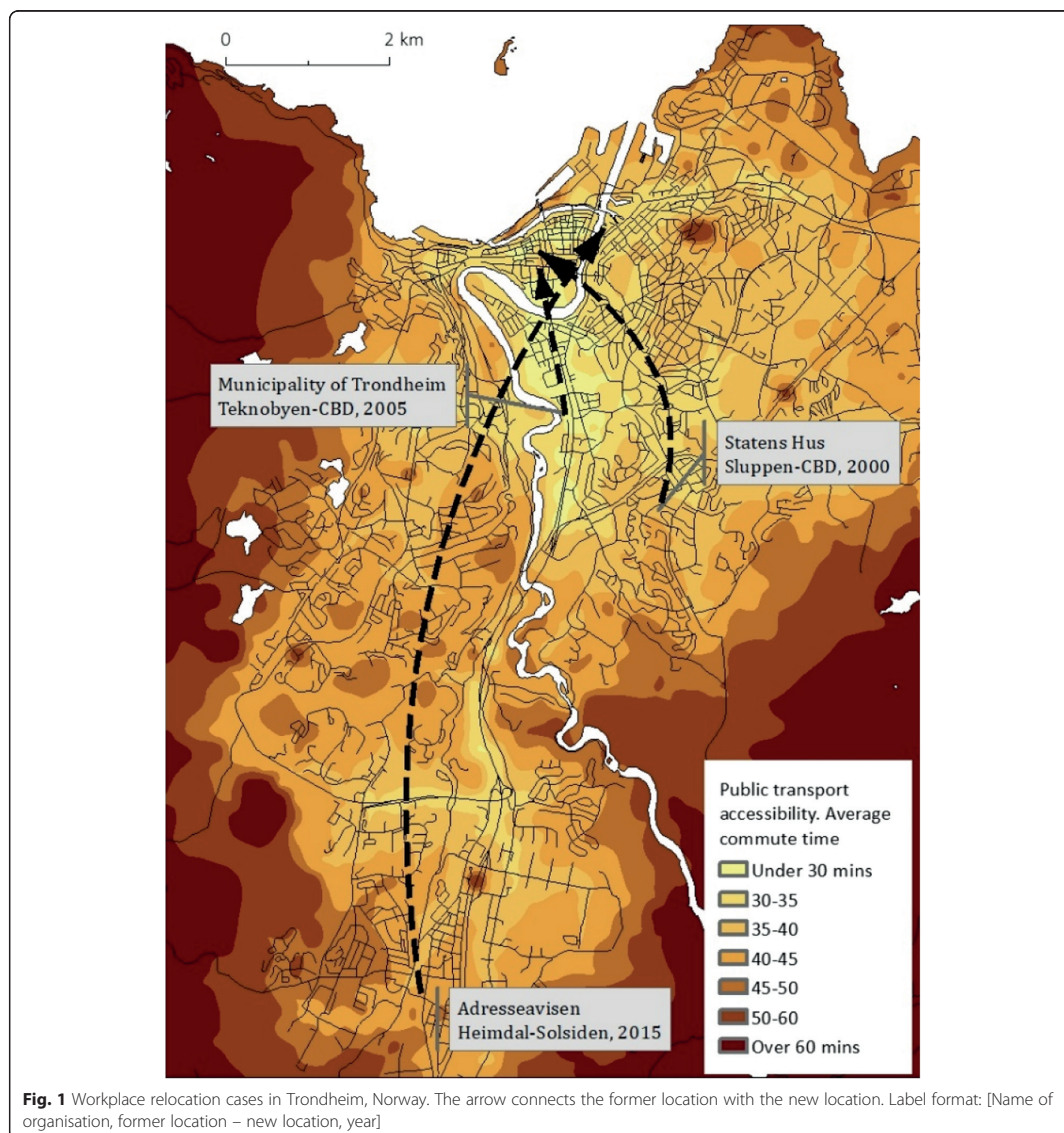
### 3 Methods and introduction to cases

This paper takes inspiration from existing research looking at interactions between land use and transport in the context of workplace location. By accumulating research from Norway on central workplace relocations, it is possible to observe active transport outcomes in relation to changes in accessibility, business structure and economic factors like parking. In addition to reviewing the literature on workplace relocations, this study makes use of a before and after survey in connection with the central relocation of the Trondheim-based newspaper *Adresseavisen*. The newspaper's existing and new office locations are shown in Fig. 1, together with the two other Trondheim relocation cases: Trondheim Municipality and Statens Hus. Fig. 2 meanwhile shows the former and present locations of the Oslo-based headquarters of insurance company *Gjensidige* that similarly relocated their premises from the suburbs to the inner city. Public transport accessibility is displayed in the background of Figs. 1 and 2, in order to provide contextual information for these cities. Public transport accessibility is calculated as the average public transport travel time from any given origin to a raster grid of all potential destinations within a city.

#### 3.1 The case study: *Adresseavisen*

*Adresseavisen*, Norway's oldest newspaper and Trøndelag County's largest, relocated its primary office from Heimdal, 10 km south of the centre of Trondheim, to *Verftsgata* near *Solsiden*, one kilometre east of the city centre in June 2015. In connection with the relocation, an online travel survey was distributed via e-mail to approximately 300 employees in June 2015 and June 2016. The 2015 before-survey was distributed two weeks prior to the office relocation. The repetition of the survey after one year allowed for the settling of travel routines after the relocation. The same approach was used in the three other cases. Resampling at the same time of year ensures seasonal comparability, a factor which can otherwise have significant impacts on Norwegian commuter travel behaviour, especially for pedestrians and cyclists.

The before and after surveys contained questions about commuting behaviour on the day of the survey, as well as most common travel patterns in the summer and winter months. It additionally asked respondents to estimate the travel impacts of the office relocation and to recall their existing behaviour in the before and after surveys respectively. Respondents were also asked to list the location of an intersection near to their home, whilst answering questions concerning demographics, their willingness to bicycle/walk to work and their access to and costs associated with different transport modes.



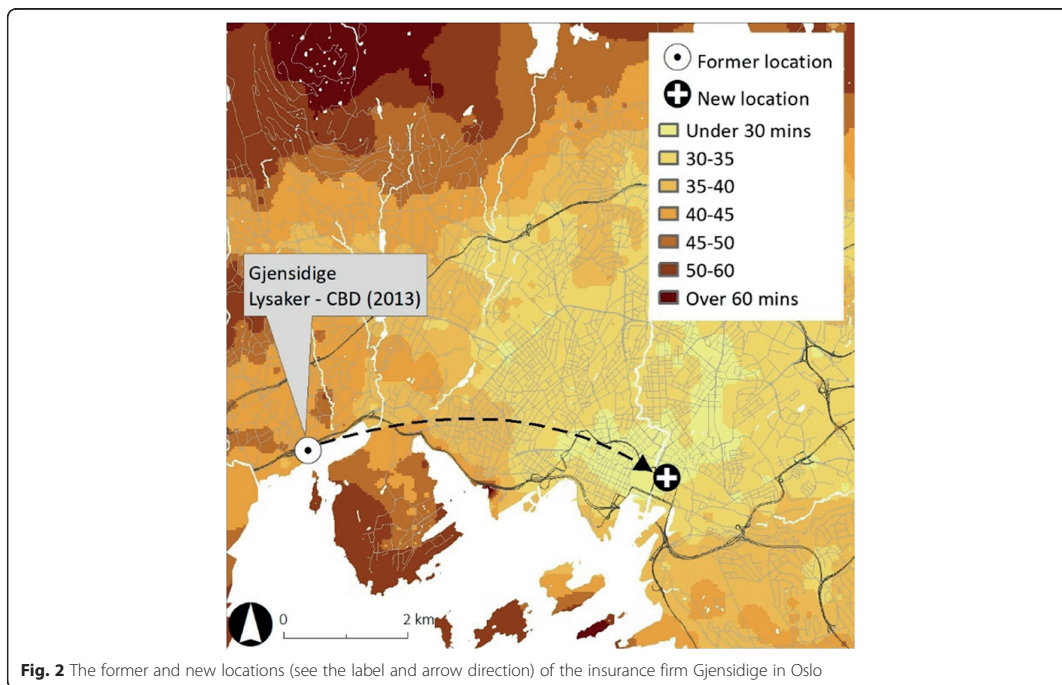
### 3.2 Norwegian comparison cases

The literature concerning Norwegian workplace relocations and commuting behaviour was assessed to find suitable cases for comparison to the Adresseavisen case study used in this article. Three existing before-after studies between 2000 and 2016 were found concerning the travel impacts of relocation toward city centres in Norway. These three cases from the cities of Trondheim and Oslo are described below. In addition, nine other cases were found, mostly using the same before-after

travel survey methodology to assess commuting changes following workplace relocation. Two of these were related to relocation towards the city centre of Oslo but were excluded from the comparative cases due to their age (pre-2000). Changes in active and public transport mode for each of the altogether 12 existing Norwegian relocation studies are summarised in the [Appendix](#).

Statens Hus, a public office in Trondheim co-located their offices to the city centre from three different clusters,





**Fig. 2** The former and new locations (see the label and arrow direction) of the insurance firm Gjensidige in Oslo

two of which were located approximately four kilometres south of the city centre (Sluppen) in 2000 [8]. The approximately 500 public servants were split between two different organisations: the county of Sør-Trøndelag and the Norwegian Public Roads Administration. In addition to employee survey data from 2000 and 2001, follow-up surveys were performed in 2004 and 2012 to observe long-term effects of relocation. Free parking that was previously available to all employees was reduced by half, whilst the remaining employees had the opportunity to pay for public parking themselves at an average cost of 65 kroner (7€) per day.

Trondheim Municipality relocated nearly 1000 administrative employees from 3 building clusters located between one and four kilometres outside of the Trondheim centre to a single cluster immediately adjacent to the relocated Statens Hus in 2005/2006 [7]. A travel survey was performed in September 2004 and 2006. Prior to relocation, there were sufficient car parking spaces for half of all employees, mostly free. This reduced to 35 places, with only a small fraction reserved for political or administrative leaders. The remainder were available for 700 kroner/month (75€) to employees who could demonstrate need (due to temporary mobility impairment, pre-school aged children etc.).

A Norwegian insurance firm Gjensidige, relocated its headquarters with nearly 1000 staff from Sollerud, six kilometres outside of Oslo, to the Oslo city centre in 2013 [6]. After a previous abundance of parking space in the former location, Gjensidige was only able to offer 1.6 parking spaces per 1000m<sup>2</sup> of floor space at the new location in accordance with the local parking norms. These had to be reserved in advance (due to their low availability), otherwise employees who drove were expected to find parking elsewhere. The nearest multi-storey car park charged 240 kroner/day (26€). Meanwhile 7% of the employees who previously drove stated that they had access to free street parking after the relocation, presumably further from the city centre.

Gjensidige is an interesting case as its prior relocation out of the city centre is also well documented. In 1991, Gjensidige co-located 1200 staff from its eight offices spread across the Oslo city centre to the single suburban complex at Sollerud [23]. The peripheral relocation came towards the end of a period where the relocation of companies to the urban periphery was a relatively common occurrence in Norway [24, 28, 29, 37]. Whilst only located 8 min walk from the Lysaker train station, the public transport accessibility decreased considerably compared to the Oslo city centre. Simultaneously, the number of employees with access to free parking increased from 6% to 43%. Active transport usage was unaffected by



the change, however, the use of public transport dropped by 31% compared to the former situation.

In total, 12 Norwegian intra-city workplace relocation studies are summarised in the [Appendix](#) (encompassing relocations both in and out of the inner city).

### 3.3 Commute distance and travel time estimation for Adresseavisen

In the absence of revealed preference route choice information from the two employee surveys conducted amongst Adresseavisen employees, this paper calculated shortest paths as a proxy for the commuting distance and travel time for different transport modes. Origins are the home addresses (provided as the nearest street intersection) of unique employees, whilst the two destinations are the former and new locations of Adresseavisen. Whilst car and pedestrian journeys are modelled by optimising Dijkstra's shortest path algorithm [47], bicycle trips are routed on a traffic stress weighted transport network allowing the prioritisation of routes suitable for cycling (for a given distance trade-off). Public transport journeys are modelled in terms of combined access/egress time, waiting time (defined as half the time between consecutive departures) and travel time.

Bicycle journeys are routed in a Level of Traffic Stress (LTS) weighted transport network in order to allocate increased impedance upon streets poorly suited for cycling [48, 49]. LTS is loosely based on the Dutch CROW Design Manual for Bicycle Traffic [50], whereby road segments are classified in four levels from one to four (LTS 1 has the lowest traffic stress) according to their degree of separation from other road users [49]. Separation is defined in terms of both physical infrastructure, such as the provision of bicycle paths, approximate volumes of traffic and in terms of posted speed limit (affecting the safety and number of overtaking manoeuvres).

The approach used for converting LTS levels into optimised bicycle routes is adapted from existing research [48]. Segments in the transport network with high LTS are least attractive and are therefore allocated a higher impedance factor – equivalent to the maximum detour rate bicyclists are willing to take. For this study an impedance factor of 1.20 was used, indicating routes up to 20% longer in distance are considered as potential options. The detour rate is selected based on a route choice model that found that cyclists are willing to cycle up to 19% longer for a commuting journey if they are able to use a bicycle path [51]. GPS-based research in Oslo, Norway reveals mean bicycle detour rates of 21%, median of approximately 12%, whilst 85th percentile detour rates equated to 30% longer trips [52]. The skewed distribution in such revealed preference data makes it

difficult to pinpoint a reasonable value for acceptable detour rate, especially since the type of infrastructure is not considered, thus the modelled willingness to detour from Broach et al. was used.

For this paper, the impedance factor is multiplied by the bicycle travel times for the segment (one for each direction), as opposed to distance used by Cervero et al. The bicycle travel time takes account of topography, and thus provides a benefit over distance when estimating bicycle route choice, particularly in hilly environments common place in Norway. The impedance factors adopted for each LTS level are as follows: 1 for LTS 1; 1.07 for LTS 2; 1.14 for LTS 3; 1.20 for LTS 4. Thus if a route with LTS 3 is adjacent to an LTS 2 route, the impedance factor will make the weighted travel time on the LTS 3 route appear 7% longer than the LTS 2 route (since  $1.14/1.07=1.07$ ). The routing algorithm seeks the route with shortest weighted travel time, and will therefore select the LTS 2 route, all else being equal. The selected route is used for subsequent calculations of travel distance.

Routing pedestrians and car drivers using the shortest travel time path is a simplification that ignores variation in route choices amongst these users. For pedestrians, however, the simplification is not entirely unrealistic, as existing research suggests that between two-thirds and three-quarters of pedestrians choose routes that they believe to be the quickest [53]. For car drivers, research suggests that the quickest path is only chosen 40% of the time, however, in most cases, drivers seek to minimise their perceived travel time [54].

The literature on public transport route choice acknowledges that travel time and cost are by far the most important variables explaining choices, whilst other variables become more important for longer journeys considering multiple transport modes and comfort [55]. For this study, public transport routes are assumed to optimise travel time.

The Trondheim transport network with bicycle infrastructure attributes was created from a merger of Open Street Map data with the Norwegian National Road Database which is publically available from the Norwegian Public Roads Administration (NPRA).<sup>1</sup>

### 3.4 Analytical tools

Simple statistical methods have been used in this paper to assess the impact of the various different factors on the modal choice of employees, run in the statistical analysis software IBM SPSS Statistics 25. The Geographic Information Systems (GIS) software ArcMAP 10.6 has been used to run various calculations of commute distance and travel time for the four predominant transport modes as discussed in section 3.3. This

has also been used to produce background maps of Trondheim and Oslo showing public transport accessibility (as shown in Figs. 1 and 2).

#### 4 Results

Complete survey responses were received from 112 employees in 2015 and 90 in 2016, giving a response rate of 37% and 30% respectively. A subset of 42 employees responded to both surveys, meaning that there were in total 160 unique employees who responded. The sample was split evenly with respect to gender (49% respondents female), and there was a large spread of ages between 18 and 65 with a median of 43 years. Information on the sample representativeness was not available. The majority of respondents (70%) had higher education, over 90% had access to a car they could use on a daily basis and 75% had access to a bicycle in working condition.

##### 4.1 Mode share and case comparison

In general the Adresseavisen office relocation resulted in large increases in the percentage of employees commuting by bicycle (from 10 to 28%) and on foot (from 6 to 15%), however the changes were much less pronounced for female employees (from 15 to 22% cycling and 7 to 11% walking). The change in use of public transport meanwhile (from 12 to 32%), was approximately equal across genders. The changes in modal split suggest that men are more willing or able to adapt their means of travel, although the results do not explain why this is the case. The changes in transport modal share (walking, cycling, public transport, car/motorcycle) were assessed for independence using a Chi-square test which revealed

a significant difference between the two survey years,  $\chi^2(3) = 36.39, p < .001, \phi = 0.44$ .

Considering the mode choices before and after relocation, 195 valid responses were received (109 from 2015 and 86 from 2016). A multinomial logistic regression model was used to determine which factors were significant in explaining the mode choice of all employees, with the explanatory variables that are significant at the 95% confidence level included in Table 1 below. Due to their low frequencies, walking and cycling were combined into a single mode choice for the final model estimation.

Tested non-significant variables included gender, age, education, number of toll ring crossings, working time, perceptions of bicycle safety, provision of bicycle infrastructure along the shortest path, self-reported mode sensitivity to additional trips, response year, number of public transport changes and travel times with different modes of transport. Many of these variables are known to be relevant predictors of mode choice from other studies but did not appear significant in the current study due most likely to the small sample size. The travel time estimates with different modes of transport were omitted due to collinearity with distance. Collinearity also explains the non-significance of some other variables, especially the provision of bicycle infrastructure along the shortest path. Here there exists a positive association between the infrastructure provision and total commute distance (due potentially to the bicycle facilities commonly found along arterials in Trondheim which are more frequently utilised on commute journeys).

The sign of the parameter estimate  $b$  in Table 1 indicates the direction of the relationship on the dependent variable mode choice. As an example, a commute

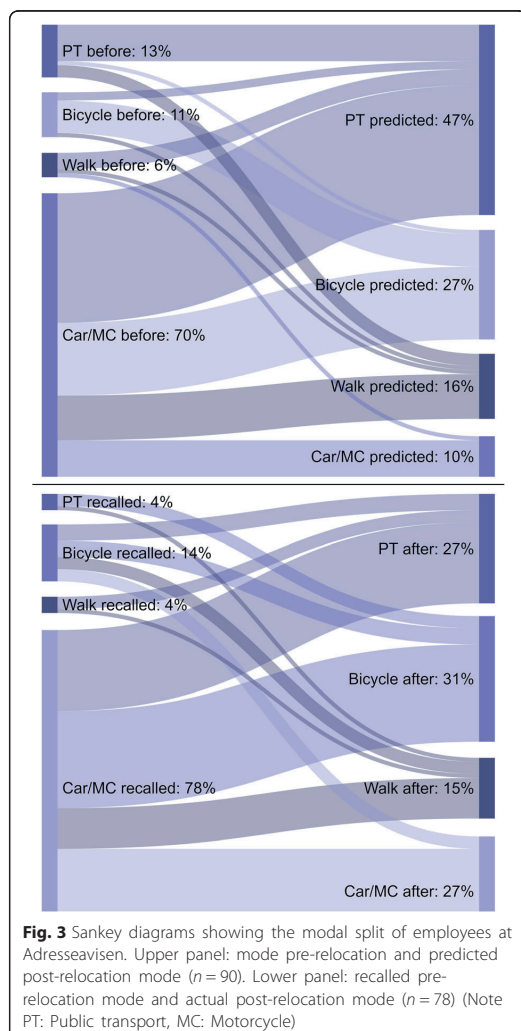
**Table 1** Results of the multinomial regression model for active versus motorised transportation modes

Parameter	Pedestrian/Bicycle: Public transport <sup>a</sup> b (Standard Error - SE)	Pedestrian/Bicycle: Car/motorcycle <sup>b</sup> b (Standard Error - SE)
Intercept	0.067 (0.916)	0.070 (0.877)
Bicycle availability	-1.948 (0.731)**	-2.39 (0.677)***
Car availability	-0.654 (0.657)	2.375 (0.724)**
Child < 10 years	0.381 (0.615)	1.189 (0.530)*
Distance < 2 km	-2.579 (1.169)*	-1.066 (0.636)
Distance > 7.5 km	2.542 (0.652)***	2.337 (0.580)***
Paid Parking	1.435 (0.627)*	-1.879 (0.515)***
McFadden R <sup>2</sup>	0.381	
-2 (Log likelihood)	90.161	
Sample size	195	

<sup>a</sup>Choose public transport over continuing to bicycle or walk to work

<sup>b</sup>Choose car/motorcycle over continuing to bicycle or walk to work

Model  $\chi^2(12) = 148.49, p < .001. *p < .05, **p < .01, ***p < .001$



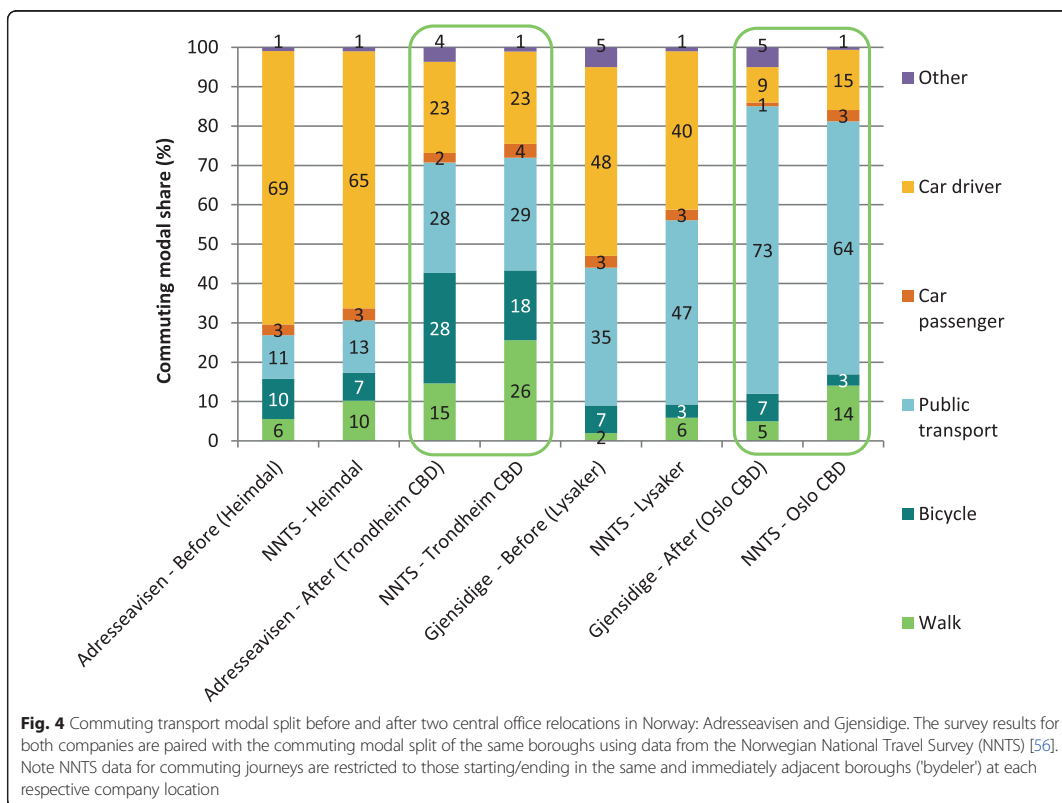
distance of more than 7.5 km increases the likelihood of the selection of either public transport or car/motorcycle over the reference category of walking and cycling, as indicated by the positive values of  $b$ . This can alternatively be interpreted as a decreased likelihood to walk or cycle for longer distances. On the other hand, the availability of a bicycle or the necessity to pay for car parking will decrease the likelihood of car/motorcycle selection relative to cycling and walking, as shown by the negative parameter estimates. The model overall had a pseudo  $R^2$  value (McFadden) of 0.381, suggesting a reasonable degree of explanation is provided by the combination of variables in Table 1.

In the pre-relocation survey, respondents were asked about their expected travel mode (which occurred 1 month later), whilst respondents one year later were asked to recall their most used travel mode prior to relocation. Since the surveys were conducted in the summer the questions about expected and recalled modes were also about the summer. The responses are plotted in a Sankey diagram in Fig. 3 below. The figure illustrates that many more (47% of before sample) expected to travel by public transport (PT) than actually did (27% after). Flows are difficult to compare with high precision since the two survey samples are cross-sectional, however close to half the former car drivers expected to be using public transport (32% of the total before sample) compared to the one quarter that actually swapped to public transport (20% of the total after sample). The actual levels of walking and cycling are approximately equal to those predicted.

The before and after impacts for the Adresseavisen case study are compared with the most recent comparison case, the private insurance company Gjensidige, which relocated only 2 years earlier. This data is presented in Fig. 4 together with the commuting data for the corresponding boroughs extracted from the Norwegian National Travel Survey (NNTS) [56]. Both companies have a relatively high degree of specialisation, although this is arguably greater for Adresseavisen due to its dominance amongst newspaper publishers in the county of Trøndelag.

The commuting patterns at both offices before and after the relocation is very similar to the NNTS commuting behaviour in the respective boroughs (bydeler in Norwegian), although the match is better for the Adresseavisen case. This indicates that although company function can vary significantly within a borough (as it does in the NNTS dataset), the spatial features of the area such as accessibility with various modes and parking availability significantly influence the commuting behaviour. There are however differences in the levels of walking and cycling between the two cases and their boroughs. Considering the combination of bicycling and walking as active transport, the differences diminish.

The tendencies in Fig. 4 are corroborated by results from Gjensidige's earlier relocation out of the city in 1991 which also used borough control groups [23]. The control groups were derived from a 1990 travel survey related to the impact of toll cordons in Oslo. Similarities between the control and actual modal split are clearly evident before relocation (when located in the Oslo inner city), however significant differences ( $p < .05$ ) appear for motorised modes post-relocation (to Lysaker). Combined walking and



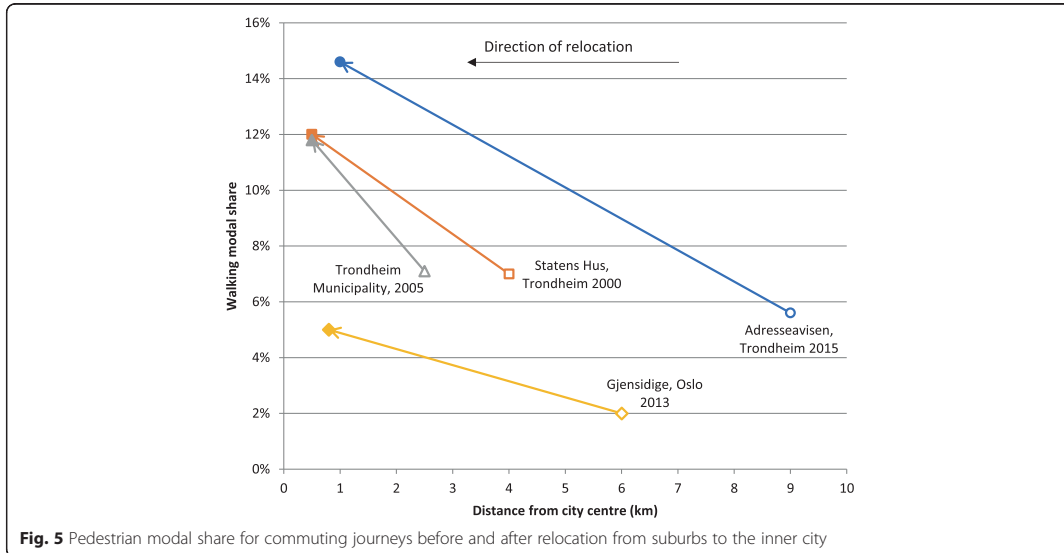
bicycle modal share was however very similar between the Gjensidige locations and their respective controls in 1991 (14% active transport modal share for both of Gjensidige's locations, and 11% for both the controls).

In Figs. 5 and 6, walking and cycling modal split for the case study and three comparison cases is plotted against distance from city centre. Distance was chosen in part due to its simplicity and since it remains constant over time, which is not the case for most other measures of accessibility. The figures show that rates of walking and bicycling increase more prominently in Trondheim than Oslo. The NNTS data from 2014 suggests that walking rates in both cities are similar (Trondheim 28% and Oslo 32%), however, Trondheim has nearly double the bicycle modal share of Oslo (9% vs. 5%) [56]. A potential explanation can relate to the average commute distance to work. Since Oslo is more than three times larger than Trondheim, the urban area and potential spread of employees is also higher, making active travel less likely.

#### 4.2 Travel distance and travel time

An independent samples t-test was performed on stated commute distances and times provided by Adresseavisen employees. Stated distance to work was on average less in the city centre location ( $M = 9.17$  km,  $SE = 1.29$ ) than the former location in the south of Trondheim ( $M = 13.99$  km,  $SE = 1.27$ ). The difference, 4.82 km, 95% CI [1.25, 8.40] was significant  $t(183) = 2.661$ ,  $p = 0.008$ . The stated travel time did not exhibit any changes significant at the 95% confidence level.

The distance to work was also calculated according to the LTS weighted shortest path in GIS from the 160 home locations provided by respondents. This distance was less to the new central location ( $M = 8.44$  km,  $SE = 0.76$ ), compared to the former suburban location ( $M = 10.58$ ,  $SE = 0.62$ ), and the difference, 2.14 km, 95% CI [1.04, 3.23] was significant  $t(159) = 3.847$ ,  $p < .001$ . Interestingly the perceived commuting distance to the suburban workplace location (13.99 km) was substantially longer than the actual (calculated) distance (10.58 km), a



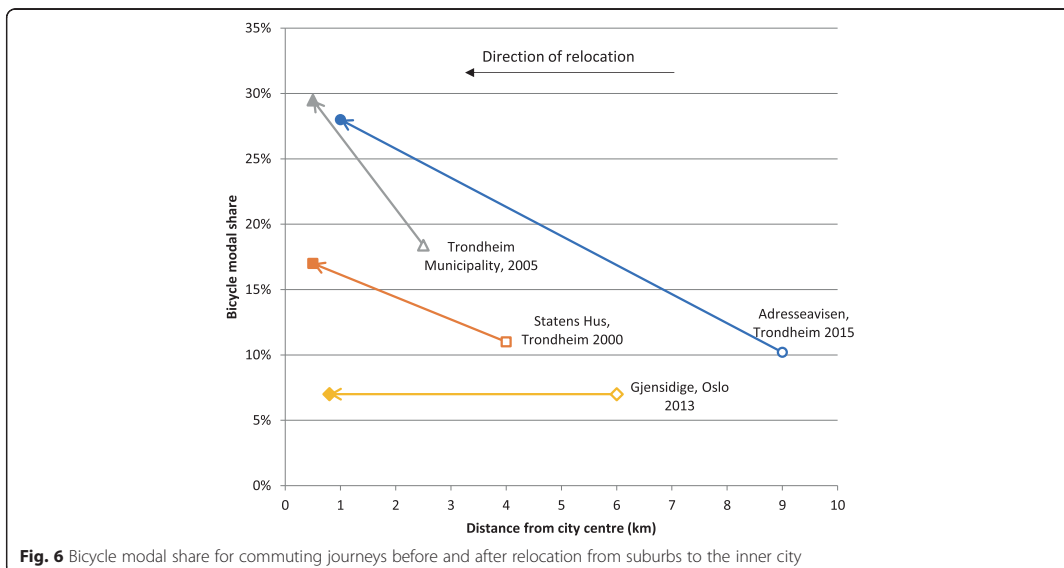
**Fig. 5** Pedestrian modal share for commuting journeys before and after relocation from suburbs to the inner city

difference which diminishes when considering the inner city workplace distances. Calculating commuting distance for the case study is elaborated upon in Section 3.3.

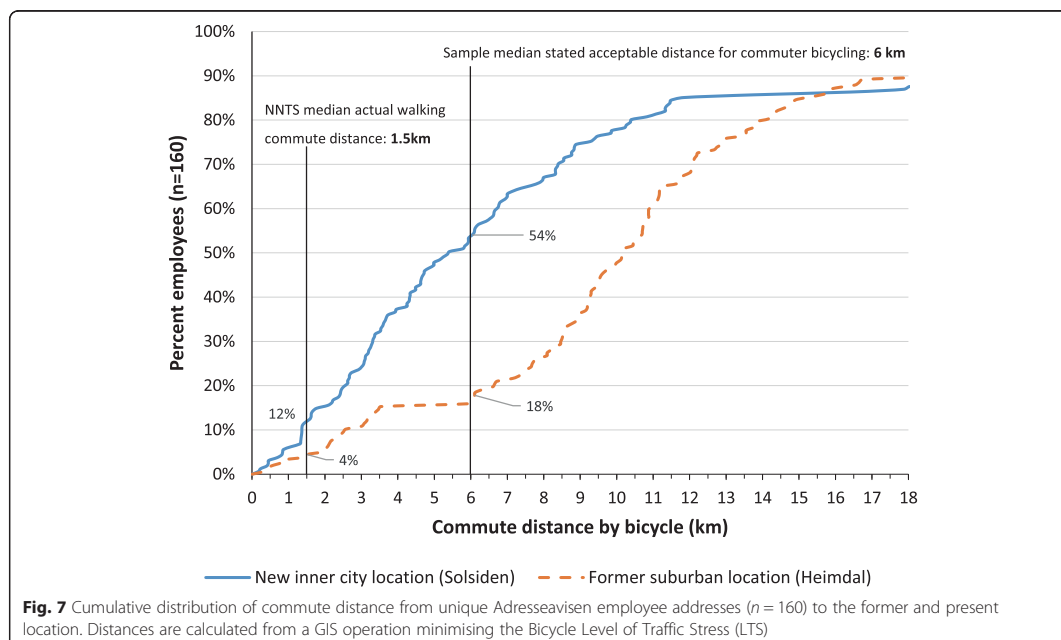
Since the distance and walking times are direct functions of each other (assumed average walking speed of 5 km per hour), the walking time had the

same significant reduction as walking distance ( $p < .001$ ).

The mean LTS adjusted cycling time (see Section 3.3) is reduced from 43.6 min (SE = 2.5) at the former location to 29.6 min (SE = 2.9) in the present central location. The reduction of 14.0 min, 95% CI [10.0, 18.0] was significant  $t(159) = 6.8, p < .001$ .



**Fig. 6** Bicycle modal share for commuting journeys before and after relocation from suburbs to the inner city



A significant reduction [ $t(159) = 8.5, p < .001$ ] was also found in public transport travel time from home to work (in minutes) was observed during the relocation from the suburbs ( $M = 49.8, SE = 3.0$ ) to the city centre ( $M = 38.3, SE = 3.3$ ). The reduction, 11.5 min, 95% CI [8.8, 14.1] includes walking to and from stops, waiting and in-vehicle time. Interestingly, although public transport accessibility is greatly improved at the new location, the number of legs in the fastest possible public transport journey did not change to a significant degree ( $p \geq .05$ ).

The mean calculated driving time after relocation (based on the assumption that cars travel at 90% of posted speed limits) reduces by 20% from 14 to 11 min, however, the difference was not significant ( $p = 0.303$ ). If intersection and congestion delays were also taken into account when calculating driving time, the difference would likely diminish since the inner city is more susceptible to delays of this nature and thus travel time following relocation would increase.

#### 4.3 The potential for cycling and walking following relocation

As discussed in Section 2, travel distance is not a reliable indicator of change between urban

environments on its own. In the Adresseavisen case, distance is shown to significantly decrease after relocation back to the city. This allows us to observe potential for cycling and walking. In Fig. 7, the cumulative distribution curves of commute distance are shown for the former and present workplace locations of Adresseavisen. Distances are calculated as described in Section 3.3.

The median maximum distance survey participants were willing to cycle was 6.0 km ( $n = 126$ ) and a median walking distance of 1.5 km applies for NNTS respondents in Trondheim who walk to work (in lieu of maximum threshold information from the sample). These two tolerance estimates for walking and cycling distance are depicted as two vertical lines in Fig. 7 above. The number of people who are within 'cycling threshold' from the new workplace thus increases from 18% to 54%. Similarly the number of people within the 'walking threshold' triples from 4 to 12% following the relocation. This difference integral between the two cumulative curves also allows one to understand the walking and cycling potential of the new location (assuming that employees' home locations do not change in the short term). In reality, there is no fixed limit on acceptable distance, as this depends



on individual preferences, but the relocation illustrates the impact of shorter distances on walking and cycling potential.

An alternative method to consider the potential is to use the ratio of car travel time against cycling, walking and public transport. To illustrate this, the average ratio between bicycle travel time and driving time reduced from 3.5 to 2.4 when relocating from Heimdal to Solsiden. For public transport (including stop access/egress, waiting and in-vehicle time) the result is 3.6 to 3.1. Reduction in these ratios indicates decreasing competitiveness of car travel. The ratios are influenced by both lower average driving speeds in inner city areas (more intersections, traffic calmed streets and lower speed limits) and reduced travel time by bicycle or public transport. However, this effect is likely underestimated since the routing method used to calculate driving times does not take consideration of delays resulting from intersections or congestion (which are more frequent/likely to impact the inner city location).

#### 4.4 Vehicle Kilometres travelled (VKT)

The car VKT is calculated by summing the distance driven by employees. Using the average car VKT per respondent for both survey periods allows an estimation of the total car VKT for all 300 employees. Driving distance is modelled as for walking distance using the shortest travel time path in GIS, meaning that actual driving distances are likely longer (additional trips and detours are excluded). For the Adresseavisen case study, the 300 employees drove in total 5822 km daily to and from the suburban location in 2015, compared to 1787 km to the inner city location in 2016. This represents a 69% reduction in car VKT, reflecting the mode shift away from cars discussed in section 4.1 and the reduction in commute distance (see section 4.2).

#### 4.5 Additional trip frequency

The total number of additional trips, or trips that are combined with the journey to or from work, increased following the relocation of Adresseavisen employees. The total number of additional trips in the suburban location ( $M = 0.83$ ,  $SE = 0.08$ ) was lower than the inner city location ( $M = 1.27$ ,  $SE = 0.11$ ). The difference,  $-0.44$ , 95% CI  $[-0.71, -0.18]$  was significant  $t(171) = -3.275$ ,  $p = 0.001$ . Respondents were also asked if they felt additional trips generally affected their choice of transport mode, however, this did not change significantly before and after relocation ( $p \geq .05$ ).

#### 4.6 Parking

In the after study for Adresseavisen, respondents were asked about the availability of different parking types at the new workplace, whilst they were previously questioned about their willingness to pay for parking in anticipation of the move. This showed that 31% of employees were willing to pay for parking at the new location. This illustrates the importance of parking cost on transport mode choice given the other 69% were not willing to pay for this service. The after study showed that 24% of employees received or acquired free parking. This is representative of the Trondheim city centre where 26% of all employees in the central 'Midtbyen' district state that they have access to free parking, mostly subsidised by their employer (Trondheim [57]).

Table 1 displays the results of a multinomial logit model in which parking is shown to have significant effects on the choice of transport mode (comparing active to both public and private motorised transport). For the comparison of active transport with car or motorcycle, the relationship is strongly significant ( $p < .001$ ) in the expected direction: paid parking reduces the likelihood of driving to work. Comparing public and active transport modes also yields a significant relationship in which paid parking increases the likelihood of public transport commuting (significant at the 95% confidence level, to be discussed further in Section 5.4).

#### 4.7 Demographic variables

The survey asked participants to respond to some questions not directly connected to travel behaviour but that could be confounding factors if found to have changed during the relocation. These questions concerned the maximum acceptable distance to cycle, the typical number of working hours and perceived safety of bicycling, however, none of these changed significantly following the relocation.

The multinomial logit model presented in Table 1 shows that having a child under the age of 10 years positively influences the decision to drive to work compared to commuting by bicycle or on foot (significant at the 95% confidence level). This is likely connected to the additional trips associated with accompanying young children to and from school/kindeergarten or other activities which is not always practical in combination with the journey to work if this is by an active mode of transportation.

## 5 Discussion

### 5.1 Reduction in distance to work and VKT

Distance between workplace and the city centre can be considered as a proxy for accessibility, and has

been shown, together with the density of population and jobs at the workplace location, to be strongly significant ( $p < .001$ ) in explaining the average commute distance in the Norwegian cities of Oslo, Trondheim and Bergen [58].

The relocation of Adresseavisen resulted in a significant reduction to the commute distance (from 10.6 to 8.4 km) for employees. A travel behaviour survey of 925 employees from 20 companies in Trondheim showed that peripheral and central locations had similar average commute distances (9.6 km and 8.7 km respectively) to Adresseavisen's former and new location [59]. The 2012 relocation of a university institute in Karlsruhe, Germany from a peripheral location to the inner city exhibited a comparable reduction in travel distance to Adresseavisen (from 30 to 27 km), accompanied also by a reduction in travel time [30]. Given the high degree of specialisation of universities, the literature suggests that we can expect the average commuting distance to be greater [34, 60]. For both cases, however, the reduction in the commuting distance appeared conducive to the observed increases in walking, bicycling and public transport usage.

Car VKT for the Gjensidige relocation were reduced by 82% despite no significant change in the distance being commuted by employees [6]. The equivalent calculation for Adresseavisen (see section 4.4) was a 69% reduction in car VKT, combined with the aforementioned reduction in commute distance. Thus commute distance alone cannot explain the changes in car VKT but in combination with restrictive measures for car use and the extent to which alternatives for non-motorised travel are satisfactory for employees. For decentralisation cases, commute distances have been found to increase substantially as a result of relocation from the city centre and this was the largest contributing factor to the overall increase in VKT ([10], p. 1069).

With a reduction in distance and improvement in accessibility on foot and by bike comes an increase in active transport use. In some cases, improved bicycle network connectivity can lead to increased bicycle modal share despite increased average commuting distances, as was the case for the relocation of Ericsson's headquarters towards the inner city of Copenhagen (City of Copenhagen 1993 in [29]). Public transport access was, however, not significantly improved, and no significant changes were therefore witnessed for the public transport modal share.

## 5.2 Travel time

As a key supply variable influencing the transport mode, travel time with various transport modes was

considered in the multinomial logit model, however, due to its strong collinearity with distance, was removed from the final model. Distance was chosen over travel time due to its stability and connection to policies related to land use, although preliminary logit models with more covariates suggest that travel time by car was slightly better at predicting travel mode for the Adresseavisen employees (potentially since this is the dominant transport mode for the full dataset).

The stated travel time did not change significantly for the Adresseavisen employees, which is partly explained by the modal shift from car to slower transport modes for many employees and non-significant change in travel time for those who continue to drive to the new workplace.

Increased levels of active transport can have considerable benefits for the wellbeing of employees. Increased time spent cycling and walking provides health benefits such as improved cardiorespiratory fitness [61] and reduced stress [62]. In a British study, employees were found to have significantly improved overall psychological well-being in connection with switching from car to active travel means [63].

Other research comparing the behaviour of different modes of commuters suggests that bicycle commuters have a higher quality of life than other commuters [64, 65]. Although public transport users do not receive the same health benefits as cyclists or pedestrians from their primary mode of transport, one study found that they spend on average 19 min per day walking to and from stops [3].

## 5.3 Additional trips increase

The Adresseavisen case showed that the central relocation significantly increased the number of additional trips taken on the way to or from work (from 0.8 to 1.3). This additional trip behaviour, also known as trip-chaining, is more probable given the increased diversity of activities in proximity to a central workplace than a peripheral one. This argument is corroborated by findings from an office decentralisation in Melbourne, Australia, which showed a 10% reduction in the number of daily activities per person connected to the work trip after relocating out of the city (from 2.2 to 2.0) [11].

The impact of additional trips connected to the commute is less clear. Reduced car commuting from one member of a household can subsequently free up a car for other household members. The increase in the total number of additional trips associated with "placing shops and services near workplaces and at neighbourhood gateways could induce trip-chaining



and more efficient automobile travel” suggest Cervero and Duncan [46]. In a study of household travel behaviour in the Puget Sound area, USA, Krizek [66] found that a shortened commute was correlated with both lower VKT and higher frequency of trips, suggesting that “households who shorten their commute are more prone to participate in more tours through the course of the day”.

For trip-chaining, independent of modal shift, to have a positive effect, at least two null hypotheses should be upheld. The first is that the number of non-commuting trips remains constant during a relocation. This is not always the case, as additional trips may be performed out of convenience and accessibility at the new central location (increased choice of non-work destinations near to the new workplace). The second null hypothesis, as discussed by Schneider, is that the any trips that get combined with the commute are not independently “walkable” or “bikeable” ([67], p. 70). To illustrate this idea, consider that a journey from home to the shops and back was previously walked, but after being ‘trip-chained’ with the much longer commute, is no longer walkable and is therefore driven. In this example, even if the total number of trips performed is reduced due to trip-chaining, the VKT is not reduced due to the substitution of a walking trip with a vehicle trip.

#### 5.4 Parking

In section 4.6, the reduction in Adresseavisen employees’ car use as a result of paid parking was presented. Whilst the inverse correlation between parking costs and car usage is well supported in the academic literature [68–71], the other finding (significant at the 95% confidence level) that paid parking increases the likelihood of public transport commuting over active commuting is less intuitive. This finding reflects more than simply the relocation itself, as the relocation covariate was tested to be non-significant in the multinomial logistic regression model. Neither public transport users, bicyclists nor pedestrians are required to pay for parking. The unintuitive result may be due to collinearity between paid parking and public transport accessibility in the Adresseavisen case which is stronger than any collinearity between paid parking and walkability/bikeability. The former suburban workplace location had ample free parking and relatively poor public transport, whilst the new inner city location has free car parking for a minority of employees in combination with much improved public transport offering (see section 4.2 regarding public transport travel times).

Thus, paid parking, due to its close correlation with better public transport services, can explain why public transport is more attractive relative to bicycling and walking.

Travel behaviour for the cases discussed in this study is dependent on a mix of factors that influence the cumulative attractiveness to choose one mode of transport over another. When car accessibility is left unchanged, car users may not see any reason to change their mode of transport, despite the increased competitiveness of alternatives. An example of this is the steady car modal share of Ericsson following relocation from Brøndby in Copenhagen’s western suburbs to a more central location at Sydhavnen with unchanged car parking and public transport accessibility (City of Copenhagen 1993 in [29]).

Although there are many benefits of reduced car use in cities, free or highly subsidised parking from municipalities and employers remains a very common phenomenon. In the early 1990s the extent of the parking subsidy in the USA was estimated to lie between 1.2 and 3.7% of the nation’s gross domestic product, a level roughly equal to the nation’s annual defence expenditure ([71], p. 207).

#### 5.5 Policy implications

The former tendencies towards intra-city decentralisation have been largely reversed in Trondheim and Oslo for the case of compact transport-generating urban land-uses like offices. However, for more land-intensive workplaces, such as developments in the Forus area between the Norwegian cities of Stavanger and Sandnes, debate continues regarding the benefits of decentralisation [72]. Economic and political arguments play a greater role in the relocation of such public services relative to commercial offices, given their important societal role and much greater land acquisition costs involved.

To assess the direct impacts of compact urban development policies on workplace travel behaviour is difficult. Norwegian cities are in general densifying in line with national and regional policies for integrated transport and land use. However, the potential is not fully utilised. For example in Trondheim, in the period 2000-2012 the “potential for densification, in terms of population density, was equal to the population increase (19.7%) if no new land was added for urban use; however, the actual outcome was 7.6%” [73].

Density, parking costs, subsidies towards sustainable transport amongst many other policies all contribute to lower traffic volumes from centrally located workplaces [33]. The multinomial logit model for the Adresseavisen commuter mode choice (see Table 1)

reveals the importance of commute distance and parking costs on transport mode, together with access to different means of transport (car and bicycle in particular, but potentially also public transport as discussed in section 5.4). All of these factors are connected to the density of the company location (amongst other land use variables). As Tennøy [35] points out: “[in] European cities, there is a clear and strong covariance between centrality and density, parking access, public transport accessibility, and the number of people living within walking- and bicycling distances.” The disaggregation of factors is complex due to this covariance, but empirical evidence points repeatedly towards the same conclusions: central workplace locations with good public transport accessibility will create far more opportunities for public and active transport than peripheral workplaces with little competition to workplace accessibility by car.

It should be noted that commuting behaviour is affected by the location of both workplace and residence. Whilst workplace locations are determined by such policies as compact urban development, the choice of residential location is affected by different political and economic factors. It is worth considering that if residential relocation is subject to market restrictions, then relocations (including those towards workplaces) are impeded. The reduction of stamp duty is proposed by van Ommeren as a potential policy change that can reduce the economic burden of moving home, thus giving employees an improved opportunity to reduce their commuting distance [60]. Policy initiatives that seek to reduce excessive commuting or private car usage can thus be focussed on multiple areas in terms of relocation or workplaces and homes, together with a suite of policies affecting the costs or travel times of different transport modes.

### 5.6 Limitations

This study has several limitations that could be amended in future studies concerning travel behaviour in connection to land use changes. The ideal circumstance for before and after research studies is to have a panel study design in which the same group of participants responds to both surveys (fixed sample rather than population- or cross-sectional sampling). The panel group for this study was only 42 employees, making it too small to perform regression analyses upon.

A second limitation concerns the mode choice modelling possibilities with the dataset. Since the sample size is relatively small, there are certain combinations of factors that would often be used in

a mode choice model for which there are very few or no individuals. Certain variables known from the literature to influence mode choice appeared as non-significant in the multinomial logistic regression performed in this study, due in large part to the sample size. It may also be of interest to consider how the relocation affects route choice, or alternatively to test the assumption of stability of supply variables such as distance or parking availability before and after relocation. The sample size and data collection approach restricts the opportunities to perform such tests, so future studies may address these limitations with a larger dataset, such as a national travel survey or in connection with a larger workplace relocation.

## 6 Conclusion

This study considers the relocation of Adresseavisen to the inner city of Trondheim in comparison to three similar workplaces in the Norwegian cities of Trondheim and Oslo. The cases demonstrate substantial increases in walking, cycling and public transport commuting, and in the case of Adresseavisen, the numbers of cyclists, pedestrians and public transport users approximately tripled following relocation. Although the function of workplaces can vary significantly within a city neighbourhood or borough, the spatial attributes of the workplace destination are found to be a dominant factor in determining the modal split of employees. Level of Traffic Stress weighted bicycle distance to work was used to demonstrate the potential for cycling and walking before and after relocation. The number of employees living within acceptable cycling and walking commute distance was found to triple after relocation, roughly in line with the actual changes in numbers of bicycle and pedestrian commuters. In addition to commute distance, the multinomial logit model revealed that access to different transport modes (especially car and bicycle) were significantly associated with the choice of mode. Paid car parking also appeared to influence mode choice, increasing the likelihood to walk or bicycle to work significantly, whilst having a child under the age of 10 was associated with a decreased likelihood of making an active transport commute.

## 7 Endnotes

<sup>1</sup>NPRA public dataset for Norwegian road network merged with Open Street Map network: <ftp://vegvesen.hostedftp.com/~StatensVegvesen/vegnett/Sykkeldata/>

## 1 Appendix

**Table 2** Summary of modal share changes (in percent) for existing Norwegian workplace relocation studies

Direction of relocation	Year of relocation	$\Delta$ distance to city centre (km)	Name of workplace	Type of business	City	Walk modal share before	$\Delta$ walk modal share	Bicycle modal share before	$\Delta$ bicycle modal share	Public Transport modal share before	$\Delta$ Public Transport modal share	Method of data collection	Reference
To city centre	2013	-5.2	Gjensidige <sup>β</sup>	Insurance	Oslo	2	3	7	0	35	38	Before - After	[6]
To city centre	2000	-3.5	Statens Hus <sup>β</sup>	Public office	Trondheim	7	5	11	6	12	26	Before - After	[8, 9]
To city centre	1993	-2.5	IDG Norway <sup>a</sup>	Media, data, marketing	Oslo	4	3	4	3	25	18	After only	[29]
To city centre	2005	-2.0	Municipality of Trondheim <sup>β</sup>	Public office	Trondheim	7	5	18	11	15	14	Before - After	[7]
To city centre	1976	-1.5	Institute of Transport Economics	Research institute	Oslo	6	-1	n/a	n/a	33	19	Before - After	[26]
Net distance to city centre unchanged	2006	0	Centre for Interdisciplinary Environmental and Social Research (CIENS)	Research institute	Oslo	6	0	24	5	30	9	Before - After	[32]
To suburbs	2000	3.5	Oslo University Hospital <sup>a</sup>	Hospital	Oslo	14	-4	14	-4	53	-11	Before - After	[25]
To suburbs	1991	5.0	Gjensidige <sup>a</sup>	Insurance	Oslo	7	0	7	0	59	-18	Before - After	[23]
To suburbs	1985	7.6	Fokus Bank	Bank	Trondheim	13	-9	8	-6	30	-21	Similar bank in the same city block in lieu of before	[24]; [28]
To suburbs	1976	11.5	Tanum <sup>a</sup>	Bookstore	Oslo	7	-1	7	-1	79	-51	Before - After	[26]
To suburbs	1977	15.5	Atlas Copco <sup>a</sup>	Industrial sales	Oslo	3	3	3	3	22	-14	Before - After	[26]
To suburbs	1998	29.5	Oslo Airport <sup>ab</sup>	Airport	Oslo	1	-1	1	-1	21	24	Before - After	[22]

Notes<sup>β</sup> Post-2000 studies included for detailed comparison with the company relocation case study of Adresseavisen in Trondheim

<sup>a</sup> Walking and cycling modal shares were presented as a combined value in the original reports, and have been approximated for this table by halving

<sup>b</sup> Oslo airport relocated to an area with a purpose-built train station, which was not present in the before situation, thus explaining the increased public transport patronage despite decentralisation

## 8 Additional file

**Additional file 1:** Case study survey responses (Adresseavisen). (XLSX 79 kb)

### Abbreviations

CI: Confidence Interval; GIS: Geographic Information Systems; LTS: Level of Traffic Stress; NNTS: Norwegian National Travel Survey; NPRA: Norwegian Public Road Administration; SE: Standard Error; VKT: Vehicle Kilometres Travelled

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### Availability of data and materials

The datasets generated and analysed during this study are included in this published article (Additional file 1).

### Authors' contributions

Conceived and designed the study: RP. The collection, analysis and/or interpretation of data: RP, YF. Wrote the manuscript: RP. Edited and revised the manuscript: RP, YF. Both authors read and approved the final manuscript.

### Competing interests

The authors declare that they have no competing interests.

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### References

- Stead, D., & Marshall, S. (2001). The relationships between urban form and travel patterns. An international review and evaluation. *Eur J Transp Infrastruct Res.* 1(2), 113–141 Available at: [http://www.ejtr.tudelft.nl/issues/2001\\_02/pdf/2001\\_02\\_01.pdf](http://www.ejtr.tudelft.nl/issues/2001_02/pdf/2001_02_01.pdf).
- Van Wee, B., Bakker, D., & Van Der Hoorn, T. (1997). *Office suites suit the railways: The effect of office location to public transport nodal points on passenger mobility* (European Transport Forum Annual Meeting) (pp. 269–282) Available at: <https://aetransport.org/public/downloads/uzrA/2219-514ec450e2e42.pdf>.
- Besser, L. M., & Dannenberg, A. L. (2005). Walking to public transit. *Am J Prev Med.* 29(4), 273–280. <https://doi.org/10.1016/j.ajpre.2005.06.010>.
- Sahlqvist, S., Song, Y., & Oglivie, D. (2012). Is active travel associated with greater physical activity? The contribution of commuting and non-commuting active travel to total physical activity in adults. *Prev Med.* 55(3), 206–211. <https://doi.org/10.1016/j.ypmed.2012.06.028>.
- Wener, R. E., & Evans, G. W. (2007). A morning stroll: Levels of physical activity in Car and mass transit commuting. *Environ Behav.* 39(1), 62–74. <https://doi.org/10.1177/0013916506295571>.
- Christiansen, P., & Julsrud, T. E. (2014). *TØI report 1344/2014. Effekter av Gjensidiges omlokalisering fra Lysaker til Bjørvika [Effects of Gjensidiges relocation from Lysaker to Bjørvika]*. Oslo: Institute of Transport Economics Available at: <https://www.toi.no/getfile.php?mmfileid=38240>.
- Paulsen, K. E., Kvidal, M., & Strømmen, K. (2008). *Endringer i reisevaner etter samlokalisering av kommunal administrasjon i Midtbyen [Changes in travel behaviour after relocation of municipal administration to Midtbyen]*. Trondheim: Trondheim Kommune Available at: <https://153.110.202.34/attachment.asp?id=49199>.
- Meland, S. (2002). *SINTEF Report STF22 A013. Flytting til nye Statens hus i Trondheim: effekter på reisevaner [Moving to the new Statens Hus in Trondheim: effects on travel behaviour]*. Trondheim: SINTEF.
- Meland, S. (2012). *SINTEF Report A23625. Arbeidsreisen – reisevaner og utvikling. En undersøkelse knyttet til Statens hus og Teknobyen i Trondheim [The commute - travel behaviour and development. A survey relating to Statens Hus and Teknobyen in Trondheim]*. Trondheim: SINTEF Available at: [https://www.sintef.no/globalassets/upload/teknologi\\_samfunn/6060/rapporter-2012/a23625\\_arbeidsreisen--reisevaner-og-utvikling.pdf](https://www.sintef.no/globalassets/upload/teknologi_samfunn/6060/rapporter-2012/a23625_arbeidsreisen--reisevaner-og-utvikling.pdf).
- Cervero, R., & Wu, K.-L. (1998). Sub-centring and commuting: Evidence from the San Francisco Bay Area, 1980–90. *Urban Stud.* 35(7), 1059–1076. <https://doi.org/10.1080/0042098984484>.
- Bell, D. A. (1991). Office location - city or suburbs? - travel impacts arising from office relocation from city to suburbs. *Transportation*, 18(3), 239–259. <https://doi.org/10.1007/BF00172938>.
- Cervero, R., & Landis, J. (1992). Suburbanization of jobs and the journey to work: A submarket analysis of commuting in the San Francisco bay area. *J Adv Transp.* 26(3), 275–297. <https://doi.org/10.1002/atr.5670260305>.
- Daniels, P. W. (1972). Transport changes generated by decentralized offices. *Reg Stud.* 6(3), 273–289. <https://doi.org/10.1080/09595237200185231>.
- Daniels, P. W. (1981). Transport changes generated by decentralized offices: A second survey. *Reg Stud.* 15(6), 507–520. <https://doi.org/10.1080/09595238100185451>.
- Aguilera, A., Wengleski, S., & Proulhac, L. (2009). Employment suburbanisation, reverse commuting and travel behaviour by residents of the central city in the Paris metropolitan area. *Transp Res A Policy Pract.* 43(7), 685–691. <https://doi.org/10.1016/j.tra.2009.06.004>.
- Burke, M. I., Li, T., & Dodson, J. (2011). What happens when government workers move to the suburbs? Impact on transport of planned decentralization of employment in Brisbane, Australia. *J Transp Res Board.* 2255, 110–116. <https://doi.org/10.3141/2255-12>.
- Sprumont, F., & Viti, F. (2017). *The effect of workplace relocation on individuals' activity travel behavior* (pp. 1–20). Brisbane: World Symposium on Transport and Land Use Research Available at: <http://dx.doi.org/10.5198/jtlu.2018.1123>. et al. WSTLUR.Pdf.
- Vale, D. S. (2013). Does commuting time tolerance impede sustainable urban mobility? Analysing the impacts on commuting behaviour as a result of workplace relocation to a mixed-use Centre in Lisbon. *J Transp Geogr.* 32, 38–48. <https://doi.org/10.1016/j.jtrangeo.2013.08.003>.
- Yang, X., et al. (2017). Commute responses to employment decentralization: Anticipated versus actual mode choice behaviors of new town employees in Kunming, China. *Transp Res Part D: Transp Environ.* 52, 454–470. <https://doi.org/10.1016/j.trd.2016.11.012>.
- van Wee, B., & van Der Hoorn, T. (1996). Employment location as an instrument of transport policy in the Netherlands: Fundamentals, instruments and effectiveness. *Transp Policy.* 3(3), 81–89. [https://doi.org/10.1016/0967-070X\(96\)00018-2](https://doi.org/10.1016/0967-070X(96)00018-2).
- Aarhus, K. (2000). Office location decisions, modal split and the environment: The ineffectiveness of Norwegian land use policy. *J Transp Geogr.* 8(4), 287–294. [https://doi.org/10.1016/S0966-6923\(00\)00009-0](https://doi.org/10.1016/S0966-6923(00)00009-0).
- Burheim, J. et al. (2000) PROSAM Report 70. Endringer i reisevaner til/fra hovedflyplass ved flytting fra Fornebu til Gardermoen [Changes in travel behaviour to/from Oslo airport after moving from Fornebu to Gardermoen]. Available at: <http://www.prosam.org/index.php?page=report&nr=70>.
- Hanssen, J. U. (1995). Transportation impacts of office relocation. A case study from Oslo. *J Transp Geogr.* 3(4), 247–256. [https://doi.org/10.1016/0966-6923\(95\)00024-0](https://doi.org/10.1016/0966-6923(95)00024-0).
- Kollbotn, K., Langmyhr, T., & Lervåg, H. (1993). NIBR report 1993:10. *Arbeidsplassenes betydning for kollektivtrafikken - eksempel fra Trondheim. [workplace impact on public transport - example from Trondheim]*. In *Bystruktur og kollektivtrafikk: ein studie frå Trondheim* (pp. 102–117). Oslo: Norwegian Institute for Urban and Regional Research (NIBR).
- Konst, F. (2003). PROSAM Report 95. *Reisevaneundersøkelsen Rikshospitalet. Før og etter flytting. [Travel behaviour survey Oslo University Hospital. Before and after moving]*. Oslo: PROSAM Available at: <http://www.prosam.org/index.php?page=report&nr=95#>.
- Monsen, G. (1983). *Samlokalisering av bolig og arbeid: Bedriftslytting - endring i arbeidsreise og energiforbruk [co-location of home and work: Company relocation - change in commute and energy consumption]*. Oslo: University of Oslo.
- Naess, P., & Sandberg, S. L. (1996). Workplace location, modal Split and energy use for commuting trips. *Urban Stud.* 33(3), 557–580. <https://doi.org/10.1080/00420989650011915>.

28. Strømmen, K. (1996). *Reisevaner ved bedrifter med ulik lokalisering. En studie av reisevaner ved Fokus Bank og TEAB i Trondheim* (Travel behaviour at differently located workplaces. A study of travel behaviour at Fokus Bank and TEAB in Trondheim). Trondheim: Department of City and Regional Planning, Norwegian University of Science and Technology.
29. Fosli, O. (1995). *TØI note 1021/1995. Lokalisering av virksomheter - konsekvenser for transport og miljø: en litteraturstudie*. (Location of companies - consequences for transport and the environment: a literature study). Oslo: Institute of Transport Economics (TØI-notat (online)) Available at: <https://www.toi.no/getfile.php?mmfileid=14182>.
30. von Behren, S., Puhe, M., & Chlond, B. (2016). *Assessing the impacts of office relocation on travel behavior and the Organization of Activities within households* (Transportation Research Board 96th Annual Meeting) (pp. 1–16).
31. Walker, I., Thomas, G. O., & Verplanken, B. (2015). Old habits die hard: Travel habit formation and decay during an office relocation. *Environ Behav*, 47(10), 1089–1106. <https://doi.org/10.1177/0013916514549619>.
32. Tennøy, A., & Lowry, M. (2008). *TØI report 997/2008. Reisevaner for ansatte i CIENS-bedriftene før og etter samlokalisering i Forskningsparken* (Travel survey among employees in the CIENS-institutes before and after relocation to Forskningsparken). Oslo: Institute of Transport Economics Available at: <https://www.toi.no/getfile.php?mmfileid=10810>.
33. Ewing, R., & Cervero, R. (2010). Travel and the built environment. A meta-analysis. *J Am Plann Assoc*, 76(3), 265–294. <https://doi.org/10.1080/01944361003766766>.
34. Næss, P. (2012). Urban form and travel behavior: Experience from a Nordic context. *J Transp Land Use*, 5, 21–45. <https://doi.org/10.5198/jtlu.v5i2.314>.
35. Tennøy, A., Øksenholt, K. V., & Aarhaug, J. (2014). Transport effects and environmental consequences of central workplace location. *Transportation Research Procedia*, 4, 14–24. <https://doi.org/10.1016/j.trpro.2014.11.002>.
36. Solheim, T. (1988). *TØI report 0858/1988. Bilens rolle i bysamfunnet* (The car's role in urban society). Oslo: Institute of Transport Economics (TØI-notat (trykt utg.)).
37. Næss, P., & Larsen, S. L. (1994). *NIBR report 1994:17. Hvor jobber de som kjører mest? Energibruk og reisebidelfordeling for arbeidsreiser ved seks bedrifter i Stor-Oslo* (Energy use and modal split for journeys to work among employees of six workplaces in Greater Oslo). Oslo: Norwegian Institute for Urban and Regional Research (NIBR-report) Available at: [http://urn.nb.no/URN:NBN:no-nb\\_digibok\\_2009072901148](http://urn.nb.no/URN:NBN:no-nb_digibok_2009072901148).
38. Brundtland, G. H. (1987). *Our common future*. Oxford: Oxford University Press.
39. Sætnen, H. (2016). From controversial policy idea to successful program implementation: the role of the policy entrepreneur, manipulation strategy, program design, institutions and open policy windows in relocating Norwegian central agencies. *Policy Sci*, 49(1), 71–88. <https://doi.org/10.1007/s11077-016-9242-4>.
40. Miljøverndepartementet. (1993). *Statute T-5/93. Rikspolitets retningslinjer for samordnet areal- og transportplanlegging* (National guidelines for integrated land use and transport planning). Norway: Available at: <https://www.regjeringen.no/no/dokumenter/t-593-areal-og-transportplanlegging/id107851/>.
41. Kommunal- og moderniseringsdepartementet (2014) *Statlige planretningslinjer for samordnet bolig-, areal- og transportplanlegging* (Governmental planning requirements for housing, land use and transport planning). Available at: <https://www.regjeringen.no/contentassets/689bae9d728e4e8a633b024dcd6b34c/sprbatp.pdf>.
42. Rolfsen, E., & Reguleringsvesen, O. (1950). *Generalplan for Oslo: et utkast lagt fram som diskusjonsgrunnlag for de kommunale myndigheter og etater og for andre interesserte* (General plan for Oslo: a draft presented for discussion by the municipal authorities and for other interested parties). Oslo: Oslo reguleringsvesen.
43. Hernández-Palacio, F. (2014). On the feasibility of and effectiveness of urban densification in Norway. *Nordic Journal of Architectural Research*, 1–35 Available at: <http://arkitekturforskning.net/na/article/view/496/444>.
44. Hansen, E. A., & Harkjær, A.-M. (2012). *Kommuneplanens arealdel 2012-2024: Planbeskrivelse* (municipal land use plan 2012-2014: Plan description). Trondheim: Available at: [https://www.trondheim.kommune.no/globalassets/10-bilder-og-filer/10-byutvikling/byplankontoret/kommuneplan/kpa-2012-2024/3\\_planbeskrivelse\\_kpa2012-24\\_web.pdf](https://www.trondheim.kommune.no/globalassets/10-bilder-og-filer/10-byutvikling/byplankontoret/kommuneplan/kpa-2012-2024/3_planbeskrivelse_kpa2012-24_web.pdf) (Accessed: 6 Oct 2018).
45. De Bok, M., & Van Oort, F. (2011). Agglomeration economies, accessibility and the spatial choice behavior of relocating firms. *J. Transp. Land Use*, 4(1), 5–24. <https://doi.org/10.5198/jtlu.v4i1.144>.
46. Cervero, R., & Duncan, M. (2006). Which reduces vehicle travel more: Jobs-housing balance or retail-housing mixing? *J Am Plann Assoc*, 72(4), 475–490. <https://doi.org/10.1080/01944360608976767>.
47. Agrawal, A. W., Schlossberg, M., & Irvin, K. (2008). How far, by which route and why? A spatial analysis of pedestrian preference. *Journal of Urban Design*, 13(1), 81–98. <https://doi.org/10.1080/13574800701804074>.
48. Cervero, R., Denman, S., & Jin, Y. (2018). Network design, built and natural environments, and bicycle commuting: Evidence from British cities and towns. *Transp Policy*. <https://doi.org/10.1016/j.tranpol.2018.09.007>.
49. Furth, P. G., & Mekuria, M. C. (2013). *Network connectivity and low-stress bicycling* (Transportation Research Board 92nd Annual Meeting). Washington: Transportation Research Board Available at: <http://docs.trb.org/prp/13-0427.pdf>.
50. CROW. (2016). *Design manual for bicycle traffic*. Ede: Centre for Research and Contract Standardization in Civil and Traffic Engineering C.R.O.W.
51. Broach, J., Dill, J., & Gliebe, J. (2012). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transp Res A Policy Pract*, 46(10), 1730–1740. <https://doi.org/10.1016/j.tra.2012.07.005>.
52. Hulleberg, N., Flügel, S., & Evarsson, G. (2018). *TØI report 1648/2018. Vekter for sykkelinfrastruktur til bruk ved rutevalg i regionale transportmodeller* (Empirical based infrastructure weights for bicycle route choice).
53. Guo, Z., & Loo, B. P. Y. (2013). Pedestrian environment and route choice: Evidence from new York City and Hong Kong. *J Transp Geogr*, 28, 124–136. <https://doi.org/10.1016/j.jtrangeo.2012.11.013>.
54. Zhu, S., & Levinson, D. (2015). Do people use the shortest path? An empirical test of Wardrop's first principle. *PLoS One*, 10(8), e0134322. <https://doi.org/10.1371/journal.pone.0134322>.
55. Grison, E., Burkhardt, J.-M., & Gyselinck, V. (2017). How do users choose their routes in public transport? The effect of individual profile and contextual factors. *Transport Res F: Traffic Psychol Behav*, 51, 24–37. <https://doi.org/10.1016/j.trf.2017.08.011>.
56. Hjorthol, R., Engebretsen, Ø., & Uteng, T. P. (2014). *TØI report 1383/2014. Den nasjonale reisevaneundersøkelsen 2013/2014 - nøkkelrapport* (2013/14 National travel survey - key results). Oslo: Institute of Transport Economics Available at: <https://www.toi.no/getfile.php?mmfileid=39511>.
57. Trondheim Municipality. (2017). *Kommunedelplan: energi og klima 2017–2030* (Municipal plan for energy and climate 2017–2030). Trondheim: Trondheim Municipality Available at: [https://www.trondheim.kommune.no/globalassets/10-bilder-og-filer/10-byutvikling/miljoenheten/klima-og-energi/vedlegg-1-kommunedelplan-energi-og-klima\\_-171116\\_endelig.pdf](https://www.trondheim.kommune.no/globalassets/10-bilder-og-filer/10-byutvikling/miljoenheten/klima-og-energi/vedlegg-1-kommunedelplan-energi-og-klima_-171116_endelig.pdf) (Accessed: 6 Oct 2018).
58. Engebretsen, Ø., Næss, P., Strand, A. (2018). Residential location, workplace location and car driving in four Norwegian cities. *European Planning Studies*, 26(10):2036–2057.
59. Strømmen, K. (2001). *Rett virksomhet på rett sted - om virksomheters transportkappende egenskaper* (right business at the right location - About businesses' traffic generating capacities). Norwegian University of Science and Technology Available at: <http://hdl.handle.net/11250/229734>.
60. van Ommeren, J. (2000). *Commuting and relocation of jobs and residences*. Aldershot: Ashgate.
61. Oja, P., et al. (2011). Health benefits of cycling: A systematic review. *Scand J Med Sci Sports*, 21(4), 496–509. <https://doi.org/10.1111/j.1600-0838.2011.01299.x>.
62. Petrunoff, N., Crane, M., & Rissel, C. (2018). A case study exploring associations of quality of life measures with Car and active transport commute modes in Sydney. In M. Friman, D. Etema, & L. E. Olsson (Eds.), *Quality of Life and Daily Travel* (pp. 183–198). Cham: Springer International Publishing (Applying Quality of Life Research). [https://doi.org/10.1007/978-3-319-76623-2\\_10](https://doi.org/10.1007/978-3-319-76623-2_10).
63. Martin, A., Goryakin, Y., & Suhrcke, M. (2014). Does active commuting improve psychological wellbeing? Longitudinal evidence from eighteen waves of the British household panel survey. *Prev Med*, 69, 296–303. <https://doi.org/10.1016/j.ypmed.2014.08.023>.
64. Páez, A., & Whalen, K. (2010). Enjoyment of commute: A comparison of different transportation modes. *Transp Res A Policy Pract*, 44(7), 537–549. <https://doi.org/10.1016/j.tra.2010.04.003>.
65. Crane, M., et al. (2016). 'Correcting bias in self-rated quality of life: An application of anchoring vignettes and ordinal regression models to better understand QoL differences across commuting modes. *Qual Life Res*, 25(2), 257–266. <https://doi.org/10.1007/s11136-015-1090-8>.
66. Krizek, K. J. (2003). Residential relocation and changes in urban travel: Does neighborhood-scale urban form matter? *J Am Plann Assoc*, 69(3), 265–281. <https://doi.org/10.1080/01944360308978019>.
67. Schneider, R. J. (2011). *Understanding sustainable transportation choices: Shifting routine automobile travel to walking and bicycling*. Berkeley: University of California Berkeley.

68. Hess, D. (2001). Effect of free parking on commuter mode choice: Evidence from travel diary data. *Transp Res Rec*, 1753, 35–42. <https://doi.org/10.3141/1753-05>.
69. Newman, P., & Kenworthy, J. (2015). *The end of automobile dependence. How cities are moving beyond Car-based planning*. Washington: Island Press/Center for Resource Economics. <https://doi.org/10.5822/978-1-61091-613-4>.
70. Pickrell, D. H., & Shoup, D. C. (1980). Employer-subsidized parking and work-trip mode choice. *Transp Res Rec*, 786, 30–39.
71. Shoup, D. C. (2011). *The high cost of free parking*. Chicago: American Planning Association/Planners Press.
72. Naess, P., Cao, X. J., & Strand, A. (2017). Which D's are the important ones? The effects of regional location and density on driving distance in Oslo and Stavanger. *Journal of Transport and Land Use*, 10(1), 945–964. <https://doi.org/10.5198/jtlu.2017.1183>.
73. Hernández-Palacio, F. (2017). A transition to a denser and more sustainable city: Factors and actors in Trondheim, Norway. *Environ Innov Soc Trans*, 22, 50–62. <https://doi.org/10.1016/j.eist.2016.06.002>.

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## Paper II

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Review

# Revealed Preference Methods for Studying Bicycle Route Choice—A Systematic Review

Ray Pritchard 

Department of Architecture and Planning, Faculty of Architecture and Design, NTNU—Norwegian University of Science and Technology, 7491 Trondheim, Norway; raymond.pritchard@ntnu.no

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**Abstract:** One fundamental aspect of promoting utilitarian bicycle use involves making modifications to the built environment to improve the safety, efficiency and enjoyability of cycling. Revealed preference data on bicycle route choice can assist greatly in understanding the actual behaviour of a highly heterogeneous group of users, which in turn assists the prioritisation of infrastructure or other built environment initiatives. This systematic review seeks to compare the relative strengths and weaknesses of the empirical approaches for evaluating whole journey route choices of bicyclists. Two electronic databases were systematically searched for a selection of keywords pertaining to bicycle and route choice. In total seven families of methods are identified: GPS devices, smartphone applications, crowdsourcing, participant-recalled routes, accompanied journeys, egocentric cameras and virtual reality. The study illustrates a trade-off in the quality of data obtainable and the average number of participants. Future additional methods could include dockless bikeshare, multiple camera solutions using computer vision and immersive bicycle simulator environments.

**Keywords:** bicycle; bicycle route choice; revealed preference; naturalistic; built environment; physical activity; route choice model

## 1. Introduction

The promotion of cycling is increasingly seen as an effective and efficient tool for reducing the negative environmental impacts of transport whilst improving quality of life [1]. By enabling a shift from motorised transportation to cycling, cities can reduce both their greenhouse gas contribution and improve regional air quality through reduced motorised transportation [2]. Increasing cycling rates in this manner has been demonstrated to have substantial health benefits, despite the increased exposure to air pollution and traffic [3].

Traditionally transport planners have made use of such techniques as manual traffic volume counts at set points in a traffic network to create traffic demand models (for all modes of transport). Today, count data remains valuable in many respects and a wide variety of automated sensor technologies are available to provide continuous information on traffic flows. This type of data collection is not within the scope of this article, since it does not reveal details about bicyclist trip lengths, infrastructure preferences or network behaviour. However reviews and evaluations of the available technologies for the volume counting of bicycles can be found from the US National Cooperative Highway Research Program (NCHRP) [4,5] and select other sources [6–8].

This research systematically reviews the scientific literature for data collection techniques that allow researchers and planners to understand the route choice behaviour of bicycle users. It builds and expands upon earlier research concerning information technology dependent means for determining the location of physical activity—by considering also more traditional methods that have been used to determine bicycle route choice. Krenn et al. [9] conducted a review of GPS studies in the scientific and grey literature that examine physical activity. Loveday et al. [10] similarly explore the

use of GPS in a comprehensive review of wearable or portable technologies that measure location. Buehler & Dill [11] conduct a review of the literature concerning the evaluation of bicycle networks and other bicycle infrastructure, meaning that a number of less technology dependent methods were uncovered. Lastly, a review by Romanillos et al. [12] considered all big data technologies associated with cycling—covering GPS, crowdsourcing and smartphone related methods together with live point data and origin-destination data. In contrast to other review papers, this paper includes bicycling for all trip purposes, focuses on all methods that can be applied to the empirical determination of whole journey route choice and covers digital publications from all years up until late 2017. Whole journey route choice refers specifically to the route choice along an entire origin-destination journey, turn-by-turn.

Route choice data based on actual cycling behaviour is well suited to context-specific applications such as the evaluation of new infrastructure, safety assessments or pollutant exposure. It should however be noted that tracing the whole journey of cyclists is not an entirely new endeavour. Individual travel surveys often request participants to recall recently traversed routes and the transport mode used. In recent years, GPS technology has become very affordable and increasingly omnipresent, allowing its use in large studies on travel behaviour. The goal of this paper is to compare the traditional and newer techniques that have been applied to the study of bicycle route selection.

## 2. Methods

This paper systematically reviews the revealed preference methods that have been applied to the study of whole-journey bicycle route choice. Empirical data on bicycle route choice can also be collected through aggregate volume measures (like heat maps from the aggregated tracking of multiple users) and through naturalistic studies of point locations such as observations at intersections. Additionally stated preference techniques are often used for hypothetical route choice, where respondents are presented with a series of choices to compare against a trade-off such as time or cost. However, since such techniques do not review the full journey of the individual decision maker, the bicycle user, they are not covered in this review. The process through which the literature has been identified is described in detail below.

To identify sources, searches were made in December 2017 in the Scopus (Elsevier) and Transport Research International Documentation (TRID) databases. The TRID database is a combination of the Transportation Research Board's Transportation Research Information Services database and the Joint Transport Research Centre's International Transport Research Documentation Database maintained by the Organisation for Economic Co-operation and Development. The TRID database importantly contains transport-related theses and grey literature such as reports that are not published in Scopus or many other journal databases. Only English language records were reviewed with no publication date restrictions, using the query "route choice" or "naturalistic" or "revealed preference" in combination with any of the strings bicycl\*, bik\* or cycl\* (where the asterisk indicates all iterations hereafter). Records were required to be available in digital format to be included in this review. The search strategy is summarised in Figure 1 below [13].

In total, 112 empirical studies were uncovered by this search strategy. The principal selection criterion for empirical studies was that the methods had been applied to the study of bicycle route choice, and that the whole journey is captured by the method. The majority of these empirical studies were published in journals or as book chapters (65), followed by conference proceedings (30), reports (14) and theses (3).

The following section presents the results, or introduction to the literature. This is followed by the discussion in which the timeline of publications, geographical distribution of research and the numbers of participants for different method families are displayed.

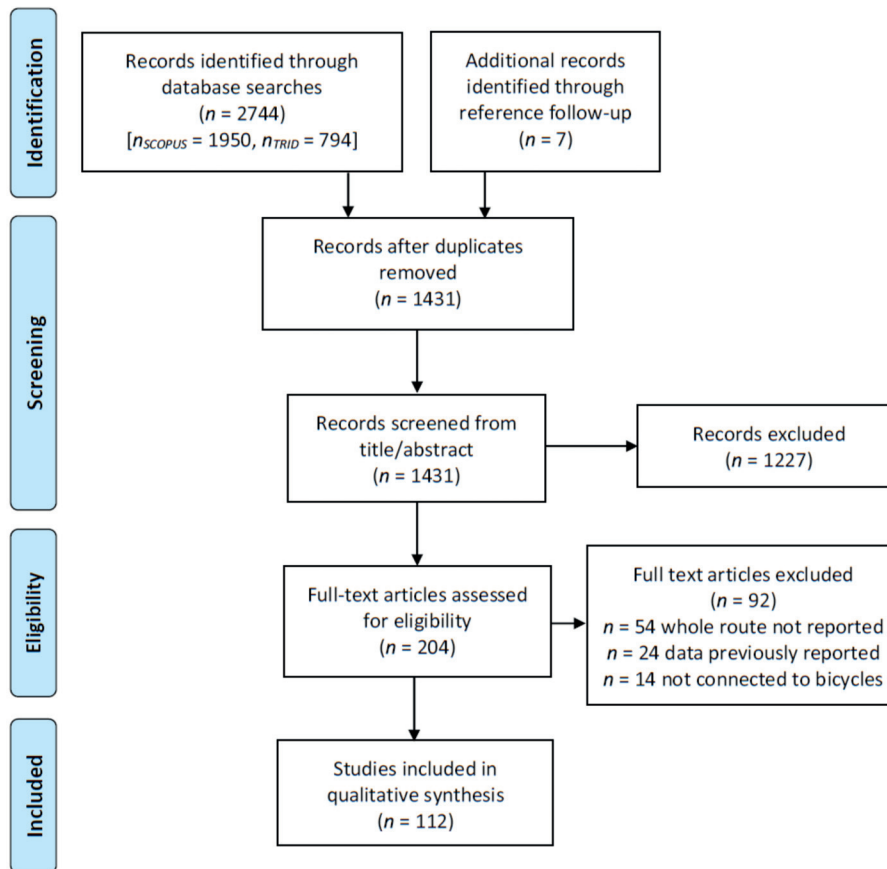


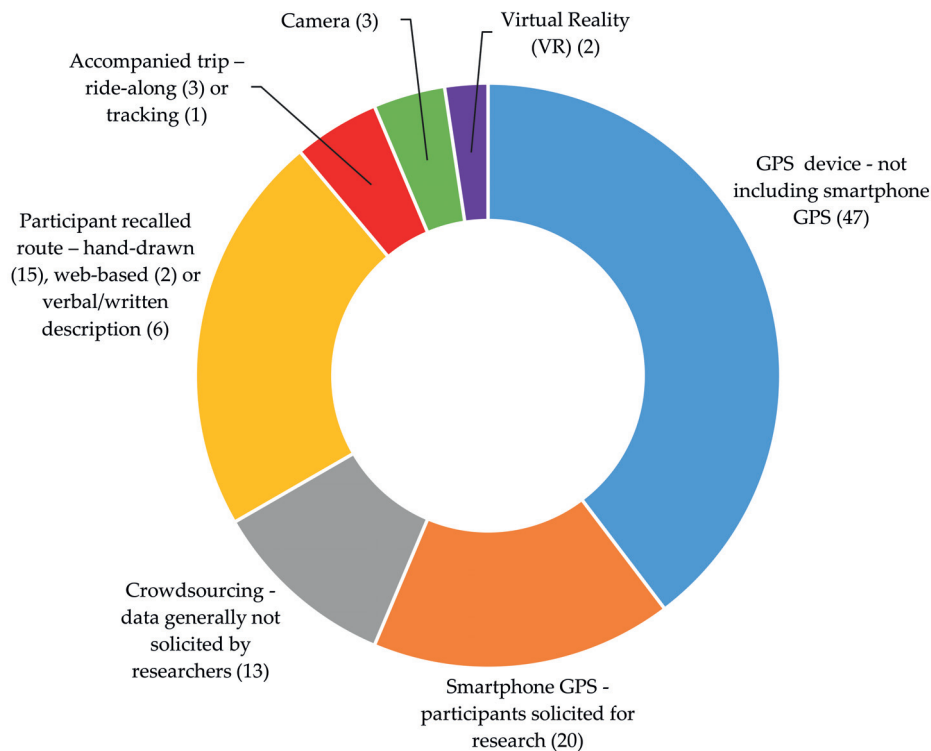
Figure 1. Pathway diagram of included and excluded articles in review.

### 3. Results

The results section of this paper is structured as follows. Firstly, the primary method families for classification purposes is explained. This is graphically illustrated in Figure 2, which displays the numbers of articles categorised in each family. Families are defined according to the primary method used to ascertain location/route choice, although in many studies, multiple methods are used that could provide this information. Detailed findings are subsequently discussed, with the further breakdown of the seven method families into 34 sub-groups. This second level of classification according to research design rather than method is used to ensure that no one sub-group contains more than ten studies, simplifying the summary of findings. A tabularised summary of the literature using this method family and sub-group structure is introduced in Appendix A, Table A1. Because many of the studies utilise multiple methods, the Table A1 includes a column qualitatively indicating the frequency of method combination for each sub-group. The other methods are not restricted to route choice, but may be supplementary data sources such as accelerometer measurements, heart rate monitors or cameras. More checks in the ‘integration with other methods’ column indicates more frequent combination with other methods.

Method families must have a substantially different methodological set-up to other families. Hence, even though the first three families make use of GPS technology, they are split into separate families due to differences in research design (researcher acquisition of GPS device, participant GPS

ownership through smartphone, and collection of crowdsourced GPS data). A summary of the literature in each family is made using the same structure (sub-groups) as in Table A1. In many cases, empirical studies make use of two or more methods for ascertaining route choice, however only the principal method (or the method that is considered most important for determining route choice) is used for classification in Table A1.



**Figure 2.** Seven method families for categorisation of the literature (numbers of articles in parentheses).

### 3.1. GPS Devices

A total of 47 articles were found that discuss unique data collection efforts using Global Positioning System (GPS) devices (excluding smartphone GPS and crowdsourcing studies but inclusive of GPS integrated into other devices such as helmet cameras or sports watches). A study of the accuracy of Smartphone GPS relative to enhanced GPS units demonstrated that whilst GPS devices were significantly more accurate than smartphone GPS, no statistically significant difference was found between smartphone manufacturers [14]. Additionally other data sources are required to be able to determine the street position of cyclists (on bicycle lane, footpath or traffic lane).

The frequency of geo-located point provision and thus geospatial accuracy of GPS devices was reported in 21 of the 47 studies. Frequency values ranged from 0.2 Hz [15] to 10 Hz [16–18], with a median of 1 Hz (or one position located per second). Such frequencies were not experienced to be problematic for recording route choices, although other issues including lack of signal, inaccurate positioning or loss of battery power were significant causes of data loss [9]. The review article from Krenn et al. [9] also reports data loss issues concerning charging of GPS units for eight of 24 included studies.

Missing data was also a problem for a longitudinal study of children’s school journeys in northern England conducted in 2007 where an estimated 39% of journeys were not recorded due to problems

obtaining an initial position fix from satellites [19]. One Portland-based study used a Personal Digital Assistant (PDA) with GPS functionality, meaning that it was simple to set up to ask travel survey questions prior to beginning or finishing a trip segment [20]. The user interface was a contributing element to getting participants to check battery charge, resulting in the relatively low data loss of 8% [20].

Most of the 34 studies that utilise an instrumented bicycle setup (two or more devices attached to either a research-team or participant-owned bicycle) utilised GPS devices rather than smartphones. As might be expected, the use of portable GPS loggers improves satellite fix and accuracy in comparison to smartphone-embedded GPS units [14]. It should be noted however that weatherproofing of GPS devices and other instrumentation (or failure to!) for use in longer terms studies can also create signal issues. Thus, special consideration should be given to this during testing phases of future research projects.

Three of the earliest studies, published between 2007 and 2010 found that data collection was very time intensive for the research teams due to the need to extract data every few days from the units. [19–21]. This became less of an issue in subsequent research that made use of wireless mobile data transmission [22,23], shorter data collection periods such as for test tracks or predetermined routes [17,24–28] or simply had larger memory cards [29].

Since many of the studies published after 2010 use largely similar GPS devices, the remaining studies are discussed according to five sub-groups, as outlined in Table A1. Each sub-group has sufficiently different methodological design to justify a distinction, with the intent to have no more than 10 articles per sub-group. It should be noted that the distinction between what constitutes an “instrumented” set-up as opposed to a standard GPS study was small, however for this paper “instrumented” refers to studies in which two or more separate devices are carried or mounted to a bicycle/vehicle.

#### 3.1.1. Instrumented Research Bicycles/Pedelects

Instrumented research bicycles were generally loaned out to participants to obtain data over relatively short time periods, and are sometimes also referred to as bicycle Data Acquisition Systems [30,31] or Instrumented Probe Bicycle [25]. Instrumented research bicycles were used in studies of both conventionally powered [17,25,26,30,32–36] and pedal-assisted electric bicycles (pedelec) [16,22,24,28,37]. The bicycles are loaned to participants in a configured state (with GPS as the primary means of determining route choice), and the use of a single bicycle type can have benefits when observing such phenomena as steering, overtaking distances or acceleration/vibration [25,26,36,37]. This is because minor differences in suspension and steering between different bicycle models are removed as a confounding factor. Instrumented research bicycles and pedelecs are used most often in the context of specific research designs, usually focussing on a specific area or even fixed route. Thus participants are generally only required to cycle for a limited time—typically one to two trips. An exception was a pedelec study in which participants were loaned an instrumented bicycle for a period of two weeks [16].

#### 3.1.2. Instrumented Participant Bicycles/Pedelects

Other instrumented bicycle studies made use of similar experimental set-ups mounted to participants' conventional bikes [27,31,38–41]. Some of these studies required participants to use their bicycles in an instrumented form for a week or more [39,41], whilst the others were similar to the instrumented research bicycles in their experimental design, requiring users to make only one to two trips. A smaller number of studies instrumented participants' pedelec bicycles, for between 4 and 30 weeks. The four week study investigated the behaviour of both conventional bicyclists ( $n = 31$ ), pedelec users ( $n = 49$ ) and higher-powered s-pedelec users ( $n = 10$ ) in Germany [42]. The longer term 30 weeks study occurred amongst 61 pedelec users in Ghent, Belgium but without any additional user involvement such as through the completion of a travel diary [15]. Long-term measurements were enabled by having automatic activation when the pedelec is in use, and whilst neither study specified charging routines for the instrumentation, it could be expected that the use of the pedelec battery would significantly reduce the effort required of participants.

### 3.1.3. Instrumented Quasi-Bikeshare

A third type of instrumented bicycle study incorporating GPS devices is for quasi bikeshare schemes. Unlike public bikeshare in which any paying member of the public can use a bicycle, quasi bikeshare is available only for a subset of the population. In this review, two studies were uncovered that discuss pilot bikeshare schemes for exclusive use within university environments. One was implemented at the University of Tennessee, USA in which seven pedelecs and six conventional bicycles in the same bikeshare system were configured with GPS devices for the use of around 100 mostly undergraduate student users [43]. The other study discusses a university bikeshare system at UMONS in Belgium but only a detailed description of the proposed sensor configuration to be implemented was included [23]. It should be noted that GPS equipped bikeshare bicycles used in bicycle route choice research are categorised according to research design rather than bicycle type, resulting in two more bikeshare papers being discussed in results Section 3 [44,45].

### 3.1.4. Instrumented Participant (Two or More Devices)

Four studies make use of a collection of instruments, but as wearable devices rather than bicycle-mounted systems. All of these studies required participants to carry instrumentation with them for a minimum of one week. A longitudinal study of children's school route and mode choice in northern England made use of a smartphone with external GPS receiver to allow annotation of journeys as they are made [19]. A pollution focused study in Colorado USA made 45 participants travelling with all modes to wear a modified backpack containing GPS together with air intake tubes connected to air quality instrumentation [46]. Lastly two before and after infrastructure evaluation studies in Portland [47] and Salt Lake City, USA [48] required 341 and 939 participants respectively to wear both a GPS device and accelerometer.

### 3.1.5. Participant-Borne/Wearable GPS Devices

Other wearable GPS devices included helmet cameras with built in GPS functionality [49–51], whilst all but one of the remaining studies used GPS devices that were either wearable [20,52–56], participant-borne [18,29,57–61] or mounted to participants' bicycles/vehicle [62].

GPS device data have been collected much earlier in the context of travel surveys, but these studies tend not to contain the search terms used by this paper [63–65].

## 3.2. Smartphone Applications

There are 20 papers that discuss the use of smartphone applications to capture travel behaviour, of which 16 specifically collect data related to cyclists, two are for all transport modes, and two are for vulnerable road users. Broadly speaking, smartphone applications for route choice studies can be split into two categories of passive or active user registration. Passive smartphone studies require mode identification or be involved in instrumented research bicycle set-ups where mode is no longer a variable. Active studies meanwhile tend to focus solely on cycling, and require the user to manually start and stop GPS logging via the application interface. This section will start by discussing generic issues related to smartphone applications followed by a focus on passive and active smartphone apps.

Frequency of data provision was reported by five of the smartphone-based studies, all of which recorded data at 1 Hz (or one position located per second). It should be noted that four of these studies were in association with active applications [66–69], whilst the remaining study used a smartphone in a long term instrumented pedelec study [70]. The instrumented pedelec research group sought to actively minimise battery drain, despite the connection of the instrumentation to the large pedelec battery. This was achieved by recording the accelerometer and GPS readings for the first four seconds of every minute, and using this information to determine if the bicycle was in motion. When no motion was recorded, the smartphone would return to a low energy sleep mode. Active smartphone applications however require the user to start and stop GPS recording. The total



length of active GPS time is strongly correlated with battery consumption, however because it is mostly inactive, battery use was rarely reported to be a concern. One exception was for an active smartphone study that also included a bicycle courier sub-group, who could be expected to flatten a smartphone battery when recording for a full day of cycling [71]. The solution was to provide this group dedicated GPS devices with larger battery capacity. Thus battery concerns are mostly restricted to the passive smartphone application subset, however only the aforementioned instrumented pedelec study mentioned battery concerns.

Similar to GPS devices, smartphones can experience connectivity issues in obtaining a satellite fix. Such problems can be worse because the devices are not specifically designed to provide optimum location information, but also because the GPS sensor in the mobile is frequently shielded by clothes or items in a bag. The connectivity issues in smartphones can be alleviated through combination with other integrated sensors such as cellular network location [72]. Wearable and bicycle-mounted options minimise shielding, increasing chances of a fast connection to satellites.

### 3.2.1. Passive Smartphone Application

The oldest paper describes the development and pilot testing of a smartphone application called TRAC-IT, which explores the potential to replace traditional travel surveys [72]. It additionally investigates techniques for mode detection and the practicality of a critical points algorithm, intended to reduce data transfer requirements to that which is necessary for reconstructing a route. A similar study specifically for Blackberry phones sought to develop a mode classifier integrated with trip segmentation using 658 verified trips [73]. This was the only smartphone application study not to use either Google Android or Apple's iPhone Operating System (iOS).

A separate passive study focussed on the development of an app called LogYard, for automatic crash notification for vulnerable road users and in particular all-terrain vehicle users [66]. The authors tested the concept in a pilot study on cyclists, which, after the collection of simulated crash and bicycle movement data, demonstrated an algorithm that could detect accidents.

### 3.2.2. Passive Smartphone Application for Instrumented Research Bicycle/Pedelec

An instrumented research bicycle set up similar to those mentioned in results section 1 was used in four studies, three of which were implemented on pedelecs. All of the pedelec studies utilised wireless data transfer, whilst a fourth instrumented bicycle study used a conventional bicycle with four helmet-mounted video cameras, requiring manual data download. The conventional instrumented bicycle was used in a fixed route experiment by researchers in Portland [68]. In addition to the helmet cameras and 1 Hz smartphone GPS location, the experiment also included a galvanic skin response stress sensor and a power meter. In total six subjects rode the instrumented bicycle at different times of day in order to ascertain the impact of variable traffic levels.

A similar fixed route setup was made in Austria, with the instrumentation of two different types of electric bicycles in combination with a test of electrically and conventionally powered mopeds [74]. The e-bike experiment collected data from altogether 145 participants, with a fish-eye camera complementing the smartphone-integrated GPS. A custom-designed app allowed remote operator control of the instrumented bicycle via a Wireless Local Area Network base station at the experiment site.

A larger study in Brighton, UK equipped a fleet of 35 e-bikes with a smartphone and power assistance sensors in a so-called Smart E-bike Monitoring System (SEMS) [67]. SEMS was powered by the e-bike battery and saved energy by running in a low power sleep state for the majority of the time. Every 25 s the phone woke and queried the accelerometer for 1.5 s. The system was kept active if movement was detected, otherwise the phone returned to the sleep state. Ninety-three participants took ownership of the research bicycles for up to eight weeks, and were provided with real-time feedback about their cycling activity via an online portal.

A year-long field trial of 31 smartphone-instrumented electric bicycles was performed at the University of Waterloo in Canada [70]. Unlike most instrumented research designs, the pedelecs were given to users in return for their participation, and were not rotated amongst a larger pool of participants. External sensors were limited to battery usage and performance, whilst discharge of the battery was minimised by keeping the phone in a sleep mode most of the time, only querying location and battery indicators for the first four seconds of every minute.

### 3.2.3. Existing Active Smartphone Applications

Active user smartphone apps are commonly used in the literature, where users are required to manually start and stop GPS recording. One benefit of active user apps is that the frequency of GPS recordings can be relatively high without battery depletion concerns (where passive apps frequently need to optimise energy use through reduced sensitivity). Several of the apps are specifically designed for research and planning purposes, such as CycleTracks, originally developed by the San Francisco County Transportation Authority and used in a five month study of 1083 users in the same city [75]. GPS data is collected and stored locally on the device, with uploads data upon completion of a trip. The same application was also used in studies of three other US cities: Austin, Texas with 317 bicyclists [76], Seattle with 197 bicyclists over a 3.5 years period [77] and Columbus, Ohio with 76 cyclists [78]. The CycleTracks application was developed with specific consideration to minimise battery drain whilst in use, turning off when the phone battery level reaches 10% [76].

The success of the CycleTracks application in multiple studies lead to its replication in a number of other regions, who built their own version of the application based on the original code. Three studies of this nature were found including: ORCycle in Oregon with 381 users [79], CycleAtlanta with 1529 users [69] and CycleLane in Eugene, Oregon with 103 users [80].

One smartphone study made use of the recreational tracking application Map My Tracks to collect the GPS traces of cyclists and bike couriers in Madrid [71]. The study required participants to upload their tracks collected in the tracking application or with GPS devices to either the project website or application, making the required level of involvement from users higher than most other studies in this category. Note that studies that directly obtain data from sports or recreational applications without researcher input, are considered by this study to be crowdsourcing, and are discussed in the next section.

### 3.2.4. Other Customised Active Smartphone Applications

A similar tailor-made app was commercially developed for use by the City of Toronto, confusingly called CycleTrack, which achieved a high level of participation: 4556 users and 33,220 journeys recorded over nine months [81]. Interestingly over half of participants reported that they had not cycled since they were children, a contrast from most other smartphone-based studies, whose participants were mostly experienced riders.

Other customised apps includes the Mon RésoVélo smartphone application created by McGill researchers, who obtained 10,000 trips from nearly 1000 users in Montreal, Canada, during four months of 2013 [82]. BeCity is a customised application built in same manner as the sports monitoring application Endomondo, but provides users with routing feedback due to the lack of other commercial actors performing this for cycling [83]. Other customised smartphone apps for research or planning purposes were implemented in Gothenburg, Sweden, with 15 bicyclists instructed to ride on selected routes [84] and in a route choice model study using data from 774 cyclists for Transport for London [85]. These studies did not provide details concerning the application development or frequency of geo-located positions.

## 3.3. Crowdsourcing

Thirteen papers make use of crowdsourcing as the principal method for obtaining location, amongst which ten utilised smartphone GPS applications and the one remaining study used



a crowdsourcing platform for GPS devices. The ten crowdsourcing smartphone studies are split into sports applications (Strava, Sports Tracker and Endomondo), research/planning-oriented smartphone applications (Fiets Telweek, BikePRINT, RiderLog), a citizen science platform (Amazon Mechanical Turk) and individually donated GPS logs.

### 3.3.1. Recreational/Sports Applications

Three studies included in this paper make use of the bicycle training oriented smartphone application Strava and the associated paid service StravaMetro, however none showed the full routes of individuals. Instead the studies made use of origin-destination data, link/street counts or node counts [86–88]. This is because of StravaMetro's policy of data aggregation whereby it is not possible to see how any individual route looks, most likely due to the privacy interests of users. Despite not meeting the inclusion criteria for this paper, Strava was included nonetheless because of the size of the dataset, the potential for individual route data to become available (it is deliberately reduced in quality) and because individual users can still opt to donate their routes to researchers. One such data donation initiative is the Bike Data Project, started after the 2015 release of Frederick Gertten's Bikes Vs Cars documentary, which easily links to the user accounts of three sports applications Moves, Runkeeper and Strava (<http://bikedataproject.com>). Whilst Strava does not presently provide the individual route traces as a crowdsourcer, it has been used as a supplementary method by researchers for ride-along and ethnographic studies. More information on ride-along as a method is found in results Section 3.5.1. Lastly, it should be noted that Strava also allows for the input of GPS data from bicycle computers and GPS devices other than smartphones.

A similar mobile application called Sports Tracker was used in a separate study focussed on providing automatic popularity-based routing in Helsinki [89]. In this study, the full route trace of individuals was used, with a public dataset of nearly 30,000 routes from 1994 users. An issue witnessed by the researchers was the skewed distribution of routes, where 5% of the users had recorded 50% of the tracks. High variation in participation is however an issue across the crowdsourcing studies, and effects also the studies using GPS devices [58].

Endomondo, the final sports application to be included here, was used in the context of the European Cycling Challenge (ECC) in 2013 [90]. The ECC is an annual initiative in the month of May that seeks to gamify cycling across participating European cities (<http://www.cyclingchallenge.eu>). The Bologna dataset obtained by the researchers contained no information about the numbers of users, but approximately 5900 routes were available in the raw data. Subsequent years of the ECC have used different mobile tracking applications, but in general, the cities participate for a nominal fee on the basis that they subsequently own the data collected by their residents. The ECC website displays heat maps of different cities and a leader board of top cities (per capita and in total) to gamify the experience and motivate use, whilst at the end of May the top cities are presented prizes.

The study that did not use smartphones instead gathered crowdsourced data from GPS devices (such as sports watches and cycling computers) through the recreation-oriented web platform RouteYou, a data sharing platform to enable users to find appropriate routes for recreational travel [91]. In this study, 190,610 bicycle-related records were collected over two years from 6300 unique users living in East Flanders, Belgium.

### 3.3.2. Customised Applications for Nationwide Data Collection

A practice-oriented smartphone application called RiderLog was used by researchers in Sydney to validate an agent-based model and census data for the same region [92]. RiderLog is similar to the ECC in terms of goals, but rather than utilising a commercial application was specifically developed for the Australian Bicycle Network. The application is intended to stimulate cycling as an active transportation mode and provides users with a platform to monitor their progress.

Fiets Telweek, or Bicycle Counting Week, is an initiative from The Netherlands (similarly performed in Flanders) to crowdsource cycling data to better understand the behaviour of Dutch

cyclists. The event has occurred for a single week each September since 2015, and it was this first year of data that was used in one study of Amsterdam cyclists [93]. The Amsterdam dataset available to the researchers included 12,413 trips from around 5000 users, and approximately one quarter of these trips were subsequently used in their creation of a discrete choice model for cyclist behaviour.

Prior to the start of Fiets Telweek in 2015, BikePRINT was developed to make use of smartphone GPS data through a custom-designed app, whilst displaying data in an interactive map that made it more user friendly [94]. The graphical interfaces demonstrated in the article do not reveal individual routes, but neither is it explicitly stated that the data is aggregated like Strava. Unfortunately, little detail is given about the process of data collection, however BikePRINT's commercial successor The Urban Future (a spinoff from the NHTV Breda University of Applied Sciences), is at the time of writing hosting the 2015 to 2017 data for Fiets Telweek (<http://app.cycleprint.eu>).

### 3.3.3. Volunteered (Post-Collection) Data

A small study collected volunteered GPS log files from both smartphones and GPS devices via Korean bicyclist groups [95]. Data collection efforts here demonstrated a greater representation bias than other crowdsourcing studies, as it focused only on enthusiast cyclists, all 54 of whom were male and aged between 19 and 42. Should the aforementioned Bike Data Project or similar platforms supporting volunteered data donation grow to represent many users, these representation problems could disappear.

### 3.3.4. Instrumented Public Bikeshare

Two studies made use of instrumented bicycles in regular bikesharing schemes, whereby the first study retrofitted 130 Capital Bikeshare bicycles in Washington DC with GPS units [44]. The devices were retrieved after four weeks deployment, during which time 36 GPS units were lost, together with their data. The recovered units recorded data for two weeks on average prior to the battery running out, and recorded in total 3596 trips. Loss of trip data was avoided in the second bikeshare study due to the use of real-time location from the GPS-enabled Grid Bikeshare in Phoenix, USA [45]. The frequency of GPS readings was, however, relatively low, varying from one per minute to 25 per minute; a frequency sufficient for bikeshare fleet operators but not always sufficient for bicycle route analysis.

Although no studies in this review made use of dockless bicycles, their increasing presence in cities around the world warrants their brief mention. Public dockless bikeshare systems use GPS-enabled bicycles in distributed fleets without specific docking stations. GPS is a necessity for the system to work since users can locate bicycles in real time via a smartphone application. Like the Grid Bikeshare study, data from dockless bicycles could potentially be obtained via fleet operators, representing a very significant future source of empirical route choice data.

### 3.3.5. Citizen Science Crowdsourcing Platform

Finally, a pilot demonstration of Amazon Mechanical Turk (AMT), a citizen science crowdsourcing platform, was used to gather participants for a smartphone GPS study [96]. Ten participants are reported on in this paper, however the research project aimed to collect data for 200 participants in total. AMT is a platform matching a large pool of workers and employers (called 'requesters') to perform relatively simple tasks such as data categorisation or image labelling. The researchers collected data in this manner for a payment level of \$5, requiring participants to install a smartphone app, use the app for three days, upload the trip data, answer a survey and finally recruit somebody outside of the AMT network to do the same [96]. Although a large number of potential workers is available, they are geographically dispersed, meaning that findings collected from participants may not be representative for a particular city or region. Qualitative research may however find the disperse worker pool to be of an advantage for comparative studies of cycling environments.

### 3.4. Participant Recalled Route—Hand-Drawn, Web-Based or Verbal/Written Description

#### 3.4.1. Hand-Drawn (Paper-Based) Route Collection

The collection of hand-drawn route data requires very few resources, making it highly versatile for implementation in various studies, most commonly in combination with interviews or paper-based surveys, distributed in various manners. Many of the 15 studies in this category use a largely similar research design, thus in the interests of brevity, only the major methods are discussed in this category, whilst the remainder have been summarised in Table A2.

The first study using hand-drawn routes was conducted in Davis, California where the implementation of an on-street bicycle lane was to be evaluated [97]. Interviews were conducted before ( $n = 254$ ) and after ( $n = 110$ ) the bike lane was built, in which cyclists in households north of the implementation area were asked to draw their usual route to downtown or campus (which lay south of the area of interest). A number of other studies make use of similar interview techniques, but generally for intercepted cyclists in a specific study area [98,99].

Two Dutch studies investigate the implementation of a bicycle network scheme in Delft, one focussing on the route choices of cyclists prior to network implementation in 1982 [100], and the other discussing and comparing this with the detailed post-implementation data, collected three years later [101]. The pre-intervention data collection was performed in a single day, with 15 roadside locations where bicycle counts for bicycles were performed, together with interviews during which cyclists were given a mail-back route choice questionnaire [100]. In total, 60% or 2194 cyclists returned the route choice survey, whose main question concerned plotting the entirety of the journey undertaken on the day the interview. The second study, a project summary report, summarises the impacts of the initiatives in Delft. The study reports that “about 58% of the observed changes in bicycle volumes are caused by route shifts” but that “compared to travel time and directness, the type of facility is as such an unimportant route choice factor” [101].

Mail-back surveys were also given to passers-by in a study in Guelph, Canada [102] whilst another study by the same main author performed in Ottawa ( $n = 1603$ ) and Toronto, Canada ( $n = 1360$ ) used mail-back questionnaires attached to the parked bicycles [103]. Response rates in the second study were between 45% and 53% for the two cities, which is noteworthy considering the single contact and lack of follow up of participants. Another study used this approach in combination with manual distribution and collection in Phoenix, USA ( $n = 150$ ) [104].

The third major category of recruitment in this section is for studies that require participants to fill in paper surveys on-site without the same follow up as in interviews. This was done at large events where booths could be established [105,106] or at workplaces or schools [107–110].

Finally, one study utilised a travel diary concept for the recording of routes as part of an ethnographic study of 26 cycling activists in Quito, Ecuador [111]. The participants in the study were asked to maintain a diary of incidents they had whilst cycling that were to be supplemented with freehand drawn mental maps (not assisted with a base map). Such an approach is highly dependent on the participants being very familiar with the area they cycle in and an ability to convey this information accurately in a sketch. Routes drawn in this manner may not have the same resolution as those that are map-assisted.

#### 3.4.2. Web-Based/Digitally Drawn Routes

The first study to use web-based or digitally drawn route choices was implemented amongst 142 staff and students of the University of Auckland [112]. Route choices of both cyclists and potential cyclists were recorded in a web-based GIS tool, although the exact details of the method are not explained.

The same concept was used in a second web-based data collection paper in the city of Copenhagen, for which 398 responses were received [113]. The study required cyclists to identify locations along their most recent route (which they traced turn-for-turn) where they had up to three positive and

three negative experiences, leading to 890 points being located. Such experiences could have been the perception of danger at a blind corner or a positive comment regarding a widened bicycle lane. This data was collected in a Google Maps Application Programming Interface (API), allowing for data to be entered directly by users into a mapping interface with relative simplicity.

#### 3.4.3. Verbal/Written Descriptions

Seven participant recalled route choice studies were located that use principally written or verbal descriptions of routes rather than visual depictions. The oldest study in this systematic literature review uses a described route choice data collection protocol in New York, USA. Two methods were devised, the first of which asked 35 families to list the route (presumably with road names) of their most recent bicycle trip and the second of which involved a verbal description of current route in 155 intercept interviews [114].

Three studies use even more limited descriptions of route choice, that only partially capture the route choice of cyclists—specifically through the inclusion of one to two additional points along a new piece of bicycle infrastructure in addition to origin and destination. The first of these evaluated the impact of a well-established off-road trail in Minneapolis, USA with 3121 cyclists stopped in a human intercept survey [115]. The second study using access and egress points to cycling infrastructure collected data via an online survey of usual bicycle trips in Montreal [116]. The study additionally asked for suggestions for new bicycle infrastructure locations. The high number of responses ( $n = 2917$ ) was achieved through wide publication in conventional media formats, social networking websites and on the street. The third study uses only a single point (in addition to origin and destination) along a newly opened cycleway in Sydney to determine route choice; a point where 783 interviewed cyclists were intercepted as they waited at a traffic light [117]. Although cyclists were asked if they had changed route after the cycleway was opened, it was not required for them to specifically provide details of the existing route.

One approach to avoid poor geographical resolution is to interview cyclists about their route choice, where communication between interviewer and interviewee can ensure an accurate transcription of route choice details. This was done in a Vancouver telephone interview study with 74 participants for all modes, who had previously participated in a survey of cyclists and indicated willingness to be contacted for future research [118]. A benefit of this particular methodological set up was that participants had previously received a cycling map of Vancouver they were prompted to use as a visual aid when discussing typical routes with the interviewer. Route descriptions were also requested of 100 bike share users in Santiago, Chile, who were intercepted at stations by interviewers with paper-based surveys [119].

The poor ability of listing methods to accurately identify origin and destination mean that average trip lengths collected in this manner can be considerably shorter (or longer) than actual routes. Additionally many cyclists may not be sufficiently familiar with their environment to be able to give an accurate description of where they had or usually cycled. Benefits of this method are simplicity of execution, and in the case of interviews, the potential to gather richer open answers regarding variables that may have influenced route choice.

### 3.5. Accompanied Journey—Ride-Along and Tracking Based

#### 3.5.1. Ride-Along Survey

A technique with high potential for qualitative and ethnographic cycling research is the ride-along survey, a form of interview in which the interviewer accompanies the participant for part or their entire journey. Accompanied interviews were used to inform the design of a stated preference study from Transport for London [120]. In this case, ride-along surveys were performed with 16 participants, who were approached by interviewers at traffic lights and bike parks and then accompanied for 10–15 min of the remainder of their journey. A short roadside interview was conducted post-ride in which cyclists

were asked questions about their route choice. Participants chose their routes themselves and were offered a gift voucher in return for their participation. The qualitative results here were used to inform the design of an online stated preference survey, which tested three key attributes: type of cycle lane, type of road and journey time.

The two remaining papers focussed upon more ethnographic research. The first of these incorporated ride-along interviews conducted with 15 inhabitants around Utrecht in The Netherlands, combining GPS tracking, tape-recording and video documentation (from interviewer perspective) [121]. Although GPS provides good location data, the video in this case provided information that was more important for the ethnographic study purpose (interaction with other road users during busy commuting times). This technique allowed researchers to retrace their 'steps' in visual field notes. Participants were recruited through an online discussion group and snowballing from contacts within the research group. Unlike the London study, the conducive environment to 'conversational cycling' in The Netherlands meant that the ride-along interview was indeed conducted mid-ride rather than post-ride, something the authors recognise may not be always be possible in other contexts.

The other ethnographic study also makes use of GPS, although in this case, was intended to examine the use of dedicated ride-logging smartphone applications [122]. Reflective diaries and structured interviews with 20 experienced club cyclists in and around Stoke-on-Trent, UK formed the basis of the research material whilst the author additionally accompanied the same cyclists on a number of group rides.

Benefits of the study design using ride-along surveys are the ability to interpret gestures and body language, together with other shared experiential factors that are not easily captured through the majority of other techniques. A downside can be that the observed behaviour of the cyclist (particularly risk-taking behaviour or the breaking of traffic laws) is influenced because they are conscious of being recorded or observed. This phenomenon can be mitigated if trust is developed between the interviewer and participant through more immersive researcher participation, as was demonstrated in an aforementioned study of cycling activists in Quito, Ecuador [111].

### 3.5.2. Tracking

One study made use of tracking, but was GPS-assisted using devices fitted to trackers' bicycles to allow for simpler data collection [123]. Methodologically the study involved tracking of 119 cyclists from a number of fixed destinations and a number of interception locations. A trip was considered finished after a cyclist dismounted. The route data for intercepted subjects is however incomplete since the initial part of the journey is not recorded. The research ethics of this methodology are not discussed in the article, although future studies should consider this.

### 3.6. Camera

Three studies make use of egocentric cameras as the primary means for determining route choice. Two used helmet-cameras [124,125] whilst one used two bicycle mounted cameras [126]. This naturalistic bicycle data was used to gather first hand cyclist experiences in the context of traffic safety and planning for cycling. The most recent of these used the video footage taken by 24 commuter cyclists in Plymouth, UK to perform video-guided interviews with the participant post-ride. The researcher reviewed the videos prior to the interview in order to develop a customised set of interview questions for each participant. Participants were also able to reflect upon what they saw in the video and volunteer comments. Neither of the other studies included this element, one of which was intended to capture overtaking distances on specific routes by the researcher themselves [126], the other classifying accidents or near-accidents [125].

Route choice was not explicitly a part of any of the studies, however all three studies have a forward-facing camera that shows the route being ridden. The video footage alone could be used to recreate route choices by a reviewer familiar with the area; however, those studies that were interested

in both naturalistic behaviour and location tended to make use of cameras in GPS-instrumented bicycle set-ups as described in results Sections 1 and 2.

### 3.7. Virtual Reality (VR) Simulated Environments

A VR cycling simulator called Cycle SPACES was developed in Breda in The Netherlands and is discussed in a pilot study of a proposed cycle superhighway in the same city [127]. A speed sensor allows users to adapt their speed in the virtual modelled environment (displayed with an Oculus Rift VR headset), whilst other variables such as time of day or the colour of the bicycle highway could be modified with push buttons on the handlebars. The participants were observed to react as expected in the different modelled environments, relaxing considerably in the future scenarios in which greater separation from traffic was displayed. Although route choices were not enabled in this experimental set-up, the addition of steering control together with eye-tracking, artificial intelligence of other road users, dynamic resistance and leaning have all been identified as future additions to the Cycle SPACES project.

A Japanese bicycle simulator experiment with 23 university students tests two scenarios that each provide the rider with visual feedback regarding speed, whilst a control group performs the experiment without visual input [128]. The experimental set up includes an exercise bicycle, speed sensor and large visual display. The first scenario shows a virtual bicycle icon on a Google map, which moves in accordance to pedalling speed, whilst the second scenario shows Google Street View images (taken at 10 m spacing) displayed in relation to pedalling speed. The route was fixed between the university and the nearest train station, without choice of route. Significant differences ( $p < 0.05$ ) were found between the control and street image groups for enjoyment, outdoor-feeling and speed of cycling. Although route choice was not a studied element of the study, this would be a logical future step for virtual reality research.

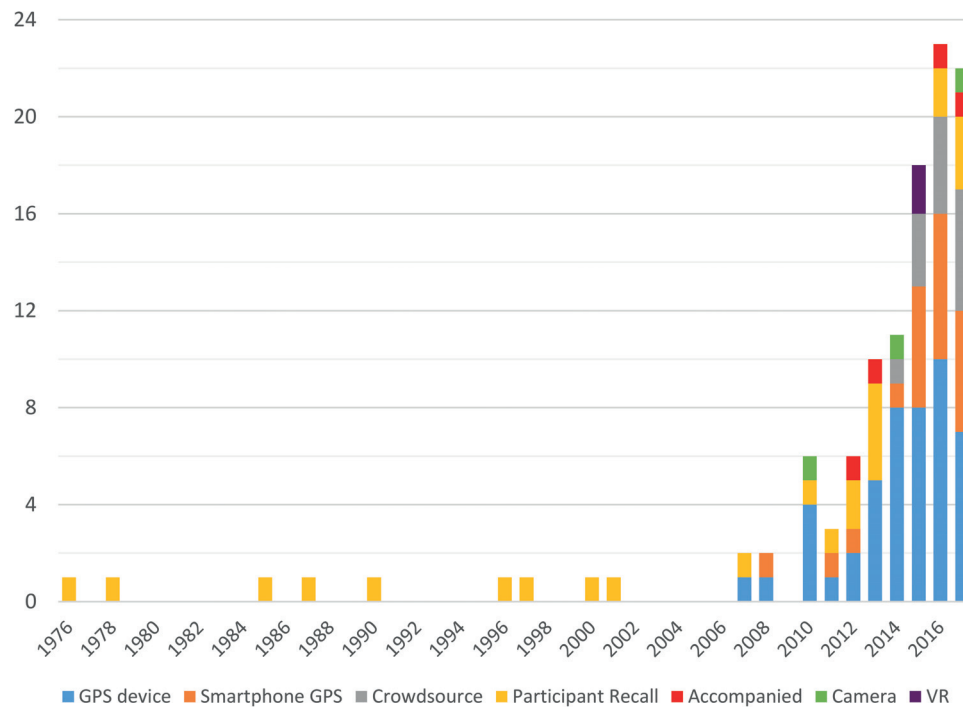
Neither of the simulator-based VR studies study route choice unlike the majority of articles in this review, however as a relatively emergent field, the methods introduced here show promise for scaling up into this realm.

## 4. Discussion

This study presents a systematic review of methods that have been applied to the study of whole journey bicycle movement. The research publications included within this review are mostly quite new, with 99 of the 112 studies published between 2010 and 2017. This is illustrated in Figure 3 below. In addition to the growth of research in general, much of the growth in research production can be attributed to the arrival of affordable GPS technology around the early-mid 2000s. GPS technology is used in over two thirds of the research papers collected through this systematic review, as illustrated in Figure 2 in the methods section. A modest increase in the number of papers utilising more mature methods like participant recalled routes can also be witnessed. Because the review required the digital availability of full-text articles, there is a systematic bias towards newer (especially post-internet) research, as is the case for the majority of review articles.

The numbers of participants is displayed in Figure 3 as a box-and-whisker plot for all 92 articles that reported this figure. Four method families are shown, whilst the remainder are aggregated under 'other' due to the low number of articles in the method families: accompanied trips, camera and virtual reality. The graph shows that the lowest numbers of participants does not vary greatly, but median number of participants can be quite different based on method family.



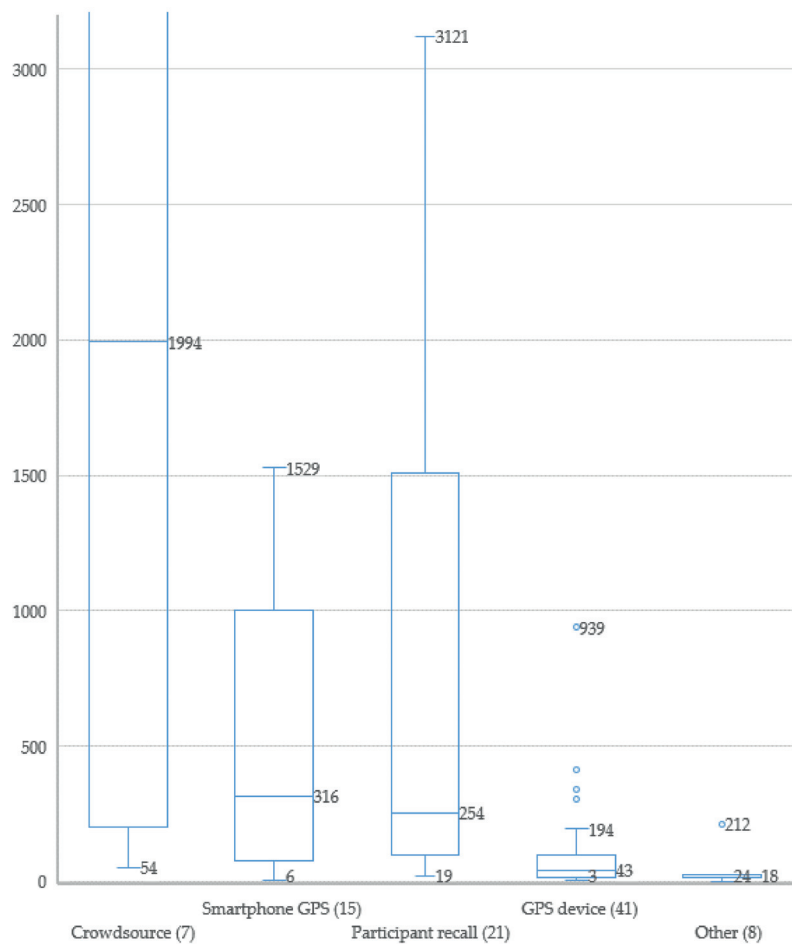


**Figure 3.** Revealed preference bicycle route choice publications for whole journeys (112) sorted by method family.

Crowdsourcing studies have understandably the highest median number of participants (1994), although it should be noted that many of the studies reported findings from Strava, which do not presently provide individual route journeys. The high participant numbers in Strava are also the reason for not displaying the plot for crowdsourcing in its entirety (13,684 unique users are captured in the largest study covered by this review [86]). Smartphone GPS studies (316) and participant recalled route choice studies (254) follow next in median sample size, due most likely to the relative low-cost and simplicity of collecting data respectively. GPS devices, although utilising the same technology from crowdsourcing and smartphone studies, have a relatively lower median number of participants of 43, whilst the three remaining method families have a collective median of 18. This can be partly explained by each of the method families. Accompanied journey studies generally involved more qualitative methods (with generally lower sample sizes) making use of such techniques as interviews with participants. One notable exception involved tracking, unbeknown to 212 subjects [123]. Camera based studies are generally focussed on traffic safety, and whilst the data collection is not so time consuming as for interviews, requires prohibitively large amounts of time for manual data processing in order to establish route choices of more than a small number of participants. Machine learning and other image recognition technologies may assist in reducing the time required for this method in future work. The final method categorised under “other” in Figure 4 is virtual reality, which comprised only two studies, both at the demonstration stage. For such simulator studies, considerable amounts of time is required in creating the virtual environment to test, however after a model is created, it should be reasonably possible to sample much larger numbers of participants.

The geographical spread of research according to city of data collection is shown in Figure 5. The USA is the most prolific producer of articles included in this review at 31 papers, followed by the UK and Canada with 12 and 11 respectively. Of the 112 empirical articles that form the basis of this

review, 109 were performed in developed countries, defined here as those countries with a very high Human Development Index (HDI) in the 2016 Human Development Report (<http://hdr.undp.org/en/countries>). This means in practice that only 3% of the empirical data collected on whole-journey bicycle routes is in developing country contexts (China, Ecuador and South Africa). To put this in perspective, just over 20% of all research is produced by countries that do not have a very high HDI (based on submission institution of the ~33 million citable English language documents in Scopus from 1996 to 2016 <http://www.scimagojr.com/countryrank.php>). Hence, whilst over-representation of developed countries is present across all fields of research, it is considerably higher for bicycle route research. This is surprising given the relatively low costs of collecting route choice data (especially for surveys and smartphone apps) compared to research as a whole. However, this observation could indicate that funding is far from the sole determinant of research production. Indeed the low amount of cycling research may be due to a different focus in the research performed in developing countries, where the promotion of bicycles for transportation may be less prioritised.



**Figure 4.** Reported number of participants by method family (number of included studies in parentheses). The category other includes accompanied trips, camera and VR.



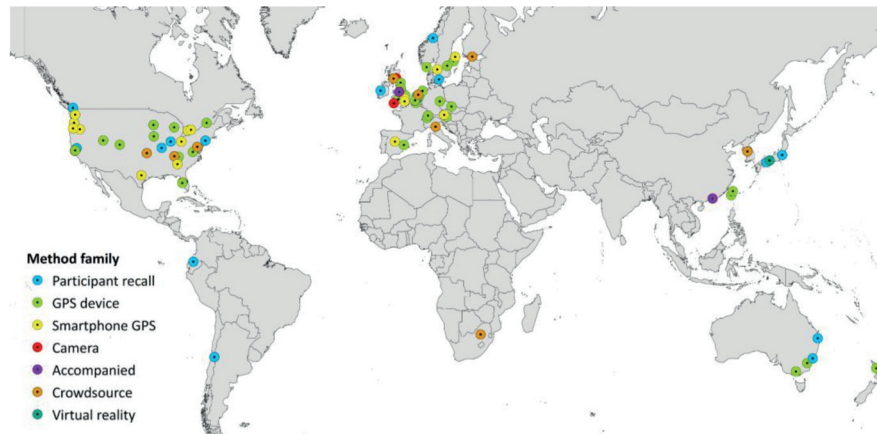


Figure 5. Geographical spread of the empirical research (112) by location of data collection.

#### 4.1. Reasons for Route Choice

GPS is utilised in two thirds of all the research collected, providing a relatively high level of resolution for route choice behaviour between different streets and paths. However, with the exception of some smartphone studies and others with a user interface, the decision-making process behind the route choice is not typically revealed through this method. This is a common limitation of revealed preference studies, where the primary contribution is in showing the preference made rather than demonstrating why.

To understand more about the decisions being made by bicyclists, the other methods can be used. Follow-up interviews or surveys as part of GPS based studies has been demonstrated to provide attitudinal parameters [18,61,85]. Crowdsourcing as a method does not generally allow the study designer to ask questions of participants as the data is usually collected for a different purpose (sports applications for example), potentially some time ago. Participant recalled routes and accompanied journeys are typically performed as part of intercept surveys or organised interviews, which lend themselves well to establishing reasons for participants' route choice. Cameras can be used to inform reasons for bicycle route choice, however in a limited manner since only visually identifiable reasons such as traffic or road surface condition in the immediate vicinity of the cyclist can be observed. The ideal situation is not only to accompany cyclists, but to record this on camera whilst interviewing cyclists, as was done in a qualitative study in Utrecht in the Netherlands [121]. The final method family of virtual reality allows testing of past, current or future scenarios, limited only by the time needed to create these virtual environments. Users can be interviewed whilst participating in the simulator environment, or can provide real time feedback through handlebar mounted buttons as discussed in Section 3.7 above. VR technologies are thus highly promising for participatory planning and user consultation of bicycle infrastructure, and it can be expected that this subset of the research will grow in coming years.

Revealed preference data alone does not however lack usefulness simply because it does not establish reasons for route choice. To the contrary, revealed preference data allows for large amounts of quantitative material to be collected, which combined with good sample representativeness, provides a holistic snapshot of a region's cycling preferences. GPS based studies can sample many hundreds or even thousands of users, however combination with other methods such as cameras or follow-up interviews are necessary to begin to establish reasons for a particular route being chosen. Egocentric cameras alone can provide some of the context behind route choice, however data processing times for establishing a single route trace make this a more suitable supporting method to complement accompanied journeys or instrumented bicycle research designs. Surveys or interviews in which

participants recall their routes can be highly informative across large samples, however generally only one to two routes can be recalled with reasonable accuracy. Short or infrequent trips, trip chains and trips taken some time ago are poorly represented in participant recalled route choice studies. Comprehensive travel diary studies that ask for route choice of all trips (together with the usual trip purpose and mode) are uncommon, potentially because of the effort of the recall is too great or the risk of incorrect routes being drawn too high. Such considerations should be made in the context of the target sample and research purpose. If the sample is young children, GPS based tracking may prove to be difficult because of increased privacy concerns from parents and research ethics committees. Likewise, if the purpose of the study were to quantitatively determine the surface riding quality, the use of accelerometers would be more useful than interviews.

#### 4.2. Representation

An issue that was witnessed repeatedly across different methods is the statistical representation of the participants. One study summarises the typical representation problems that occur in revealed preference bicycle studies: “the GPS participants were slightly older, were more likely to have a college degree, had higher incomes, and were more likely to have full-time jobs than other regular cyclists” [20]. Similar results were found by other studies, despite large numbers of participants [93].

In many cases the research aims target particular groups of participants, such as through the specific targeting of elderly bike users [37,42]. The intention here is evidently not to assume representativeness by choosing one demographic, however other studies also chose specific users to the detriment of representation. The best example of this is the adult commuter cyclist target group, who are frequently chosen because they are simplest to recruit, although not necessarily most numerous or representative of the general population [15,18,21,39,46,58,62,99,102,103,119,123,124,128,129]. Unless the sample is targeted with the specific aim to improve representativeness, we risk producing results that poorly demonstrate how bicyclists behave, let alone the target cycling population (those who do not presently use a bicycle regularly).

A number of studies specifically avoided targeting a particular transport mode during recruitment in order to get a better picture of normal road user behaviour [61,72,73,96]. It should be noted however that the lack of representation amongst cyclists targeted for GPS studies is not necessarily improved when considering all transport modes. One combined GPS and travel diary study reported participants were better educated, wealthier and older than the those captured by census data; similar attributes for the samples in much of the bicycle research [61].

Adult men are highly overrepresented in many sports and recreation-focussed smartphone apps. In some low cycling areas, this may indeed be representative of the cycling population, however the consideration should also be made for the main target group of bicycle promotion initiatives: infrequent and non-cyclists. This is in contrast to most GPS data studies, which seek to achieve better gender and age balance during participant recruitment [12].

Removing technology-based data collection methods from the discussion gives a different perspective. A large study of cyclists conducted in Groningen, The Netherlands ( $n = 1012$ ) and Växjö, Sweden ( $n = 1003$ ) stopped participants mid-journey to answer questions concerning trip purpose, origin-destination, actual route choice and route choice motive [98]. The random sampling process meant that both gender and age were well represented, although the authors explain that the sampling sites were selected based on high vulnerable road user flows, and were thus not reflective of each city's general population.

The sampling methodology, as much as the actual data collection method can determine the representativeness of the sample. In the example above, random sampling was used together with a survey requiring little participant involvement—resulting in excellent representation for the area sampled. If the sampling methodology involves searching for potential participants on bicycle forums, it should be considered that the forums are not representative of the general cycling public, but rather a special-interest subgroup of cyclists. Similarly, the use of sports applications as a data collection method predetermines the sample to be biased towards middle-aged men. Good representation is not

simple to achieve, but the targeting of everyday cyclists is best achieved through random sampling in the area of interest. This can mean more time is required to achieve the desired sample size, but can also be performed using randomised telephone directory lists or mail-out surveys.

#### 4.3. Future Research

Aerial drone and computer vision software (that automatically identifies mode, position and velocity of multiple road users) is being increasingly used in combination to record traffic behaviour. Presently this has been applied mostly to intersection or individual segments of interest, due to a limited scope in a single camera.

Although elements of route choice can be easily observed in this manner, the capture of entire route choices of cyclists is unlikely to be possible unless either the drone tracks individuals or multiple elevated cameras are used to identify and subsequently re-identify the same users. This is prohibitively difficult in a manual video analysis study; however, advanced computer vision technology could allow the identification and subsequent re-identification at multiple points in a network of fixed elevated cameras. Surveillance and privacy related issues may however make both of these methods unworkable from a research ethics standpoint, and must be seriously considered prior to implementation.

### 5. Conclusions

This literature review provides an overview of the techniques that are available to track whole-journey cyclist movements in the bicycle network and by doing so can allow for insights concerning the preferences of bicycle users. Sample selection must however be taken into consideration concerning the transferability of such insights. Samples should ideally be broadly representative of the general public or preferably the target audience (for example young children if the aim is to promote cycling to school). The prioritisation of infrastructure spending in accordance with what is demonstrated to have the greatest impact for a representative sample will most efficiently allow for an increase in cycling modal share.

The literature review revealed some key findings regarding the collection of cyclist data. GPS-related data sources were used in two thirds of the empirical studies covered by this review. Experimental research designs using GPS-instrumented bicycle setups were common in the literature, however there appears to be more growth potential in the use of smartphone GPS and crowdsourcing. For these data sources, automatic mode-classification algorithms are often required. Less technology-oriented approaches involving participant recall of routes are demonstrated to be able to achieve similar levels of participation to smartphone-based approaches, although usually restricted to a single route. GPS alone does not provide the resolution necessary to determine the choice of infrastructure located on a single segment (such as footpath or bicycle lane), and in these cases camera technology, interviews or accompanied journeys is necessary.

Data privacy was at times observed to hinder the participant recruitment process, especially when considering passive smartphone recorded data. The availability of location data from smartphones can reveal a significant amount of personal information including work, home, leisure activities and behaviour. It is thus essential that any proposed data collection approach ensures participant anonymity and is approved by a local research ethics committee prior to implementation. This includes not only personal details but also the obscuration of precise origins and destinations if these could be used to identify participants. Participants in travel surveys of this nature must also be well informed of the process by which the research is conducted.

Finally crowdsourcing-based studies, together with virtual reality simulators and advanced computer vision processing of video data can be expected to develop significantly in the coming years, providing new and rich future data sources for the study of bicycle route choice.

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Appendix A

Table A1. Classification of the 112 empirical studies based on principal route choice methods used into family and primary method group.

Family	Sub-Group	Main Benefits	Main Drawbacks	Integration with Other Methods	Sources
GPS device—not including smartphone GPS (47)	Instrumented research bicycle	Pre-configured for data collection Flexible experimental set up Consistent data (same bicycle for all users)	Participants must charge instrumentation for longer term studies	✓✓✓	[17,25,26,30,32–36]
	Instrumented research pedal-assisted electric bicycle (pedelec)	Same as for instrumented research bicycle Pedelec power source allows longer term data collection Simple activation of GPS on start up	Initial purchase cost of bicycle Unfamiliarity of users with pedelecs can result in abnormal cycling behaviour	✓✓✓	[16,22,24,28,37]
	Instrumented participant bicycle	Familiarity with own bicycle gives good naturalistic data	Difficulty of comparing secondary data sources such as vibration because of bicycle variety	✓✓	[27,31,38–41]
	Instrumented participant pedelec	Pedelec power source allows longer term data collection Simple activation of GPS on start up	Difficulty in recruiting participants (if low numbers of pedelecs used)	✓✓✓	[15,42]
	Instrumented quasi-bikeshare (university pilot scheme)	Comparison of many users possible with autonomous data retrieval	Maintenance and purchase cost of pilot scheme	✓✓	[23,43]
	Instrumented participant (two or more devices borne by participant)	Intermodal Pre-configured for data collection User interface (if present) can assist engagement with user (for travel survey or to remember charging)	Mode identification necessary Can be troublesome for users to carry all instrumentation (depending on size)	✓✓	[14,19,46–48]
	GPS integrated in other device (excl. smartphone and accelerometer)	Intermodal User interface (if present) can assist engagement with user (for travel survey or to remember charging) Compact device, easy to carry in pocket or bag	Mode identification necessary	✓	[20,49–51]
	Wearable GPS device	Intermodal Low participant burden	Mode identification necessary Participants can forget to charge battery	✓	[52–56]
	Participant-borne GPS device (no mention of wearability)	Intermodal Compact device, easy to carry in pocket or bag	Mode identification necessary Participants can forget to take GPS on all journeys or to charge battery	✓	[18,21,29,57–61]
	Handlebar-mounted GPS participant bicycle (without additional instrumentation)	No need to perform mode identification Participant does not need to remember to take GPS on bicycle journeys	Participants can easily forget to charge battery if taking infrequent bicycle trips	✓	[62]
Smartphone GPS—participants solicited for research (20)	Passive user registration—no input required from user, trips detected automatically	Intermodal Can be combined with travel diary (participants can confirm mode/trip purpose)	Mode identification necessary Recruitment more difficult than for active user apps, where participant has more control over the data they record	✓✓	[66,72,73]

Table A1. Cont.

Family	Sub-Group	Main Benefits	Main Drawbacks	Integration with Other Methods	Sources
	Passive user registration—smartphone based instrumented research bicycle (and pedelec)	Same as for GPS-instrumented research bicycle/pedelec Simpler configuration of instrumentation with smartphone (if only basic sensors used)	Same as for GPS-instrumented research bicycle/pedelec Energy saving required, which reduces data quality	✓✓✓	[67,68,70,74]
	Active user registration (user activates GPS through app)—using or developed from the app “CycleTracks”	Few battery problems Proven method—readily obtainable for other studies User control over data provision (can opt to not record specific journeys)	User must engage with trip to begin, pause and stop recording	✓✓	[69,75–80]
	Active user registration—other customised app specifically designed to provide data for planners/researchers	Backend system allows simple access to necessary user data User control over data provision	User must engage with trip to begin, pause and stop recording App must be developed	✓✓	[81–85]
	Active user registration—via recreation-oriented apps	Collating of data can be automated via access tokens No need to develop app User control over data provision	User must engage with trip to begin, pause and stop recording User must upload data in some experimental designs	✓	[71]
	Recreational/sports application (smartphone)—data collection not solicited by researchers	Data obtained en masse via some application owners Longitudinal data Detailed data can be volunteered	Sports app users are not representative of general public Data privacy often restricts full access to individual trips	✓	[86–91]
	Customised smartphone application for nationwide data collection (intended for data sharing)	Large dataset Whole country data for comparison	Data privacy often restricts full access to individual trips	✓✓	[92–94]
	Volunteered data from previously collected routes (access to existing data solicited by researchers)	Same as for sports applications, but only for volunteered routes User control over data provision	Representativeness Recruitment of GPS users can be difficult	✓	[95]
	Instrumented public bikeshare bicycles	Representativeness Large dataset Longitudinal access can be obtained via operators of GPS-enabled bikeshare fleet	Generally limited to GPS only User data may be retained for data privacy reasons	✓✓	[44,45]
	Citizen science crowdsourcing platform (Amazon Mechanical Turk)—for smartphone study	Affordable means of obtaining responses with low researcher burden Can sample from global network of users Cannot meet with participants readily	Difficult to be geographically specific (platform users are spread globally)	✓✓	[96]
	Participant recalled route—hand-drawn (15), web-based (2) or verbal/written description (6)	Interviewer can ask for clarification (including use of different parts of street) as route is drawn Large numbers of respondents possible Interception not always practical or legal (some jurisdictions classify cyclists in a similar manner to motorised vehicle users)	Accuracy—lack of familiarity with area Limited application beyond usual journey or most recent Relies on map familiarity Limited application beyond usual journey or most recent	✓✓	[97–99]
	Hand drawn from mail-back surveys after interception of passers-by			✓	[100–103]

Table A1. Cont.

Family	Sub-Group	Main Benefits	Main Drawbacks	Integration with Other Methods	Sources
	Hand drawn from paper surveys completed on-site (at destination)	Interviewers can assist as required Ease of recruiting large numbers of participants Can tailor map according to destination environment (such as workplace)	Relies on map familiarity Limited application beyond usual journey or most recent	✓	[105–110]
	Hand drawn from printable survey distributed online/advertisements	Large survey distribution possible (through forums, newspapers, noticeboards, bicycle shops etc.)	Relies on map familiarity Limited application beyond usual journey or most recent High participant burden to print survey Map detail vs. size trade-off (whole city is difficult to appropriately represent in map)	✓	[104]
	Hand drawn from mental mapping journal (specific target audience)	Longitudinal time frame (multiple journeys, not just most recent or usual) Participant reflection in journal	No map guidance Uncertainty in matching participant-recalled routes to reality	✓	[111]
	Mapping Application Programming Interface (API) for online route tracing	Low participant burden—large quantitative datasets possible Routing algorithms can be used to suggest routes for origin–destination Can be integrated with Public Participation Geographic Information System (PPGIS) for obtaining geo-located user feedback	Only limited numbers of routes generally recalled Relies on map familiarity	✓✓	[112,113]
	Description using list of road names used along route (verbal or online)	Quick methodology, readily applicable to intercept interviews	Accuracy—recall error/lack of familiarity with road names	✓	[114]
	Description using points/landmarks along route (verbal or online)	Quick methodology, readily applicable to intercept interviews Can be map-assisted	Imprecise—often only two points along route	✓	[115–117]
	Description from detailed interview	Interviewer can ask for clarification	Accuracy—lack of familiarity with area	✓✓	[118,119]
Accompanied trip—ride-along (3) or tracking (1)	Ride-along	Experiential ‘sensescapes’ can be captured and discussed real-time Best captures the context of the bicycle user Suitable in environments where conversational cycling not practical	Transcribing can be difficult (reduced clarity from participants when cycling in addition to noise)	✓✓✓	[121,122]
	Post ride-along interview	Reasons for choices can be explained	Lack of real-time participant reflection compared to ride-along	✓✓✓	[120]
	Unobtrusive tracking from distance	Recruitment not necessary	Lack of ‘participant’ consent Time intensive Difficult to capture journeys originating from homes	✓	[123]
Camera (3)	Egocentric camera on rider/bicycle (commonly used as a supplementary method)	Naturalistic behaviour and interactions can be captured including traffic violations and interactions with other road users	Time intensive for route choice Requires researcher familiarity with area	✓✓	[124–126]
Virtual Reality (VR) (2)	Immersion in virtual/photographed street environment	Proposed changes to built environment can be evaluated in detail Non-cyclists’ revealed preference behaviour can be tested in a safe environment	Modelling time requirement for virtual environment Some participants experience dizziness in VR simulators	✓✓	[127,128]

Table A2. Hand-drawn route recall studies.

Reference	Main Field of Application	Respondents (Valid)	Type of Route Drawn	Recruitment Methods
Lott et al., 1978 [97]	Transport planning—before and after evaluation	364 cyclists in Davis, USA	Usual route to downtown or campus (located on the other side of infrastructure)	Interviews of cyclists at their homes before and after the infrastructure development.
Van Maarseveen et al., 1985 [100]	Transport planning—before evaluation	2194 cyclists in Delft, The Netherlands	Current journey when intercepted	Distributed mail-back survey to intercepted cyclists (60% return rate)
Wilmink & Hartman, 1987 [101]	Transport planning—before and after network evaluation	Cyclists in Delft, The Netherlands	Current journey when intercepted	Distributed mail-back survey to intercepted cyclists (return rate not stated)
Van Schagen, 1990 [98]	Data collection to guide creation of a route choice model	Cyclists in Groningen, The Netherlands (1012) and Växjö, Sweden (1003)	Current journey when intercepted	Intercept interview in areas with high cyclist numbers
Aultman-Hall, 1996 [103]	Safety—bicycle routes and accident locations	Bicycle commuters in Ottawa (1603) and Toronto, Canada (1360)	Current regular bicycle commute	Mail-back questionnaires attached to the cross-bars of parked bicycles (49% returned)
Aultman-Hall et al., 1997 [102]	Transport planning—GIS demonstration	338 cyclists in Guelph, Canada	Commonly used bicycle journeys	Mail out survey (10% return), distributed mail-back survey to intercepted cyclists and through placement in bicycle shops
Hyodo et al., 2000 [108]	Route choice model—railway station accessibility	Cyclists in Utsunomiya (502) and Kurume, Japan (252)	Usual bike routes to school or work	Distributed surveys at high schools, bicycle parking facilities and railway stations
Howard & Burns, 2001 [104]	Transport planning—level of stress	150 experienced commuter cyclists in Phoenix, USA	Last journey to work, not map-assisted	Printable survey distributed digitally through webpages, email, cycling list server, and advertised/physically distributed at bike shops/community meetings
Suzuki et al., 2012 [109]	Transport planning—traffic volume and bicycle network issues	1419 cyclists in Takamatsu, Japan	Written detailed route on map	Paper survey sent to offices and high schools, interviews in downtown areas
Manum & Nordström, 2013 [107]	Transport planning—bikeability	Commuter cyclists in Trondheim, Norway	Route between home and workplace	Paper survey distributed at three employer hubs in city centre
Kang & Fricker, 2013 [99]	Transport planning—on-street vs. off-street facility use	178 cyclists in West Lafayette, USA	Route to university indicated visually on map (to interviewer)	Intercept interviews at bicycle racks at destination
Yang & Mesbah, 2013 [110]	Stated vs. revealed preference for factors influencing cycling	19 cyclists in Brisbane, Australia	Last cycling trip ending at home	Pilot study amongst university students and staff
Manton et al., 2016 [106]	Safety—cycling risk (also using stated preference)	104 cyclists in Galway, Ireland	Regularly used cycling routes, colour-coded according to perceived risk	Paper based surveys completed at large university events
Boettge et al., 2017 [105]	Transport planning—cycling risk assessment for siting facilities	89 cyclists in St. Louis, USA	Recently used bicycle route, colour-coded according to perceived risk	Booths at cycling events allowing participants to complete survey on site
Gamble, Suizek, & Nielsen, 2017 [111]	Ethnography, understanding cycling activism	26 cyclists in Quito, Ecuador	Freehand mental map of noteworthy recent journeys in journal (not map assisted)	Specific target audience of cycling activists—who received a disposable camera and journal with prompts



## References

- Buehler, R.; Pucher, J. Sustainable Transport in Freiburg: Lessons from Germany's Environmental Capital. *Int. J. Sustain. Transp.* **2011**, *5*, 43–70. [[CrossRef](#)]
- Macmillan, A.; Connor, J.; Witten, K.; Kearns, R.; Rees, D.; Woodward, A. The Societal Costs and Benefits of Commuter Bicycling: Simulating the Effects of Specific Policies Using System Dynamics Modeling. *Environ. Health Perspect.* **2014**, *122*, 1–26. [[CrossRef](#)] [[PubMed](#)]
- De Hartog, J.J.; Boogaard, H.; Nijland, H.; Hoek, G. Do the health benefits of cycling outweigh the risks? *Environ. Health Perspect.* **2010**, *118*, 1109–1116. [[CrossRef](#)] [[PubMed](#)]
- Ryus, P.; Ferguson, E.; Laustsen, K.M.; Schneider, R.J.; Proulx, F.R.; Hull, T.; Miranda-Moreno, L. *NCHRP Web-Only Document 205: Methods and Technologies for Pedestrian and Bicycle Volume Data Collection*; Transportation Research Board: Washington, DC, USA, 2014; Volume D, ISBN 978-0-309-37517-7.
- Ryus, P.; Butsick, A.; Proulx, F.R.; Schneider, R.J.; Hull, T. *NCHRP Web-Only Document 229: Methods and Technologies for Pedestrian and Bicycle Volume Data Collection: Phase 2*; Transportation Research Board: Washington, DC, USA, 2017; ISBN 978-0-309-45737-8.
- Nordback, K.L. Estimating Annual Average Daily Bicyclists and Analyzing Cyclist Safety at Urban Intersections, Ph.D. Thesis, University of Colorado, Denver, CO, USA, 2012.
- Minge, E.; Falero, C.; Lindsey, G.; Petesch, M.; Vorvick, T. *Bicycle and Pedestrian Data Collection Manual. Report MN/RC 2017-03*; Minnesota Department of Transportation: St. Paul, MN, USA, 2017.
- Kothuri, S.; Nordback, K.; Schroppe, A.; Phillips, T.; Figliozzi, M. Bicycle and Pedestrian Counts at Signalized Intersections Using Existing Infrastructure. *Transp. Res. Rec. J. Transp. Res. Board* **2017**, *2644*, 11–18. [[CrossRef](#)]
- Krenn, P.J.; Titze, S.; Oja, P.; Jones, A.; Ogilvie, D. Use of global positioning systems to study physical activity and the environment: A systematic review. *Am. J. Prev. Med.* **2011**, *41*, 508–515. [[CrossRef](#)] [[PubMed](#)]
- Loveday, A.; Sherar, L.B.; Sanders, J.P.; Sanderson, P.W.; Esliger, D.W. Technologies that assess the location of physical activity and sedentary behavior: A systematic review. *J. Med. Internet Res.* **2015**, *17*. [[CrossRef](#)] [[PubMed](#)]
- Buehler, R.; Dill, J. Bikeway Networks: A Review of Effects on Cycling. *Transp. Rev.* **2015**, *1647*, 1–19. [[CrossRef](#)]
- Romanillos, G.; Zaltz Austwick, M.; Ettema, D.; De Kruijff, J. Big Data and Cycling. *Transp. Rev.* **2016**, *36*, 114–133. [[CrossRef](#)]
- Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G.; Altman, D.; Antes, G.; Atkins, D.; Barbour, V.; Barrowman, N.; Berlin, J.A.; et al. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Med.* **2009**, *6*, e1000097. [[CrossRef](#)] [[PubMed](#)]
- Lindsey, G.; Hankey, S.; Wang, X.; Chen, J.; Gorjestani, A. *Feasibility of Using GPS to Track Bicycle Lane Positioning. Report CTS 13-16*; Intelligent Transportation Systems Institute, University of Minnesota: Minneapolis, MN, USA, 2013.
- Lopez, A.J.; Astegiano, P.; Gautama, S.; Ochoa, D.; Tampère, C.; Beckx, C. Unveiling E-Bike Potential for Commuting Trips from GPS Traces. *ISPRS Int. J. Geo-Inf.* **2017**, *6*, 190. [[CrossRef](#)]
- Dozza, M.; Bianchi Piccinini, G.F.; Werneke, J. Using naturalistic data to assess e-cyclist behavior. *Transp. Res. Part F Traffic Psychol. Behav.* **2016**, *41*, 217–226. [[CrossRef](#)]
- Garcia, A.; Gomez, F.A.; Llorca, C.; Angel-Domenech, A. Effect of width and boundary conditions on meeting maneuvers on two-way separated cycle tracks. *Accid. Anal. Prev.* **2015**, *78*, 127–137. [[CrossRef](#)] [[PubMed](#)]
- Plazier, P.A.; Weitkamp, G.; Berg, A.E. Van Den “Cycling was never so easy!” An analysis of e-bike commuters' motives, travel behaviour and experiences using GPS-tracking and interviews. *J. Transp. Geogr.* **2017**, *65*, 25–34. [[CrossRef](#)]
- Pooley, C.; Whyatt, D.; Walker, M.; Davies, G.; Coulton, P.; Bamford, W. Understanding the school journey: Integrating data on travel and environment. *Environ. Plan. A* **2010**, *42*, 948–965. [[CrossRef](#)]
- Dill, J.; Gliebe, J. *Understanding and Measuring Bicycling Behavior: A Focus on Travel Time and Route Choice. Report OTREC-RR-08-03*; Oregon Transportation Research and Education Consortium: Portland, OR, USA, 2008.
- Harvey, F.; Krizek, K. *Commuter Bicyclist Behavior and Facility Disruption. Report MN/RC-2007-15*; Minnesota Department of Transportation: St. Paul, MN, USA, 2007.



22. Paefgen, J.; Michahelles, F. Inferring usage characteristics of electric bicycles from position information. In Proceedings of the 3rd International Workshop on Location and the Web—LocWeb '10; Boll, S., Schöning, J., Eds.; ACM Press: Tokyo, Japan, 2010; pp. 1–4.
23. Ioakimidis, C.S.; Rycerski, P.; Koutra, S.; Genikomsakis, K.N. A university e-bike sharing system used as a real-time monitoring emissions tool under a smart city concept. In *EVS29 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium*; Electric Drive Transportation Association: Montréal, QC, Canada, 2016; pp. 1647–1657.
24. Allemann, D.; Raubal, M. Usage Differences between Bikes and E-Bikes. In *AGILE 2015, Geographic Information Science as an Enabler of Smarter Cities and Communities*; Bacao, F., Santos, M.Y., Painho, M., Eds.; Lecture Notes in Geoinformation and Cartography; Springer International Publishing Switzerland AG: Cham, Switzerland, 2015; Volume 217, pp. 201–217. ISBN 978-3-319-16786-2.
25. Oh, J.; Kwigizile, V.; Ro, K.; Feizi, A.; Kostich, W.; Abdullah, R.; Hasan, H.; Mousa, F.A. *Effect of Cycling Skills on Bicycle Safety and Comfort Associated with Bicycle Infrastructure and Environment*; Report TRCLC15-01; Transportation Research Center for Livable Communities: Kalamazoo, MI, USA, 2017.
26. Lai, C.H.; Doong, J.L.; Chuang, K.H.; Hsu, C.C. The Likelihoods of Bicyclist Steering Patterns in Response to Being Passed by Motorists. *Procedia Manuf.* **2015**, *3*, 3339–3344. [[CrossRef](#)]
27. Kircher, K.; Ahlstrom, C.; Palmqvist, L.; Adell, E. Bicyclists' speed adaptation strategies when conducting self-paced vs. system-paced smartphone tasks in traffic. *Transp. Res. Part F Traffic Psychol. Behav.* **2015**, *28*, 55–64. [[CrossRef](#)]
28. Berntsen, S.; Malnes, L.; Langåker, A.; Bere, E. Physical activity when riding an electric assisted bicycle. *Int. J. Behav. Nutr. Phys. Act.* **2017**, *14*, 7. [[CrossRef](#)] [[PubMed](#)]
29. Shin, D.K. Explanation of Factors Influencing Cyclists' Route Choice Using Actual Route Data from Cyclists. Ph.D. Thesis, The University of Leeds, Leeds, UK, 2016.
30. Jahangiri, A.; Elhenawy, M.; Rakha, H.; Dingus, T.A. Investigating cyclist violations at signal-controlled intersections using naturalistic cycling data. In Proceedings of the 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), Rio de Janeiro, Brazil, 1–4 November 2016; IEEE: Rio de Janeiro, Brazil, 2016; pp. 2619–2624.
31. Lin, P.-S.; Kourtellis, A.; Katkooi, S.; Chen, C.; Cruse, L. *Naturalistic Bicycling Behavior Pilot Study. Report BDV25-977-13*; Florida Department of Transportation: Tallahassee, FL, USA, 2017.
32. Chuang, K.H.; Hsu, C.C.; Lai, C.H.; Doong, J.L.; Jeng, M.C. The use of a quasi-naturalistic riding method to investigate bicyclists' behaviors when motorists pass. *Accid. Anal. Prev.* **2013**, *56*, 32–41. [[CrossRef](#)] [[PubMed](#)]
33. Jarjour, S.; Jerrett, M.; Westerdahl, D.; de Nazelle, A.; Hanning, C.; Daly, L.; Lipsitt, J.; Balmes, J. Cyclist route choice, traffic-related air pollution, and lung function: A scripted exposure study. *Environ. Health* **2013**, *12*, 14. [[CrossRef](#)] [[PubMed](#)]
34. Dozza, M.; Fernandez, A. Understanding bicycle dynamics and cyclist behavior from naturalistic field data (November 2012). *IEEE Trans. Intell. Transp. Syst.* **2014**, *15*, 376–384. [[CrossRef](#)]
35. Bigazzi, A.Y.; Figliozzi, M.A. Roadway determinants of bicyclist exposure to volatile organic compounds and carbon monoxide. *Transp. Res. Part D Transp. Environ.* **2015**, *41*, 13–23. [[CrossRef](#)]
36. Etemad, H.; Costello, S.B.; Wilson, D.J. Using an instrumented bicycle to help understand cyclists' perception of risk. In *IPENZ Transport Group Conference*; Engineering New Zealand: Auckland, New Zealand, 2016; pp. 1–8.
37. Kovácsová, N.; de Winter, J.C.F.; Schwab, A.L.; Christoph, M.; Twisk, D.A.M.; Hagenzieker, M.P. Riding performance on a conventional bicycle and a pedelec in low speed exercises: Objective and subjective evaluation of middle-aged and older persons. *Transp. Res. Part F Traffic Psychol. Behav.* **2016**, *42*, 28–43. [[CrossRef](#)]
38. Cole-Hunter, T.A. Effects of Air Pollution Exposure on Adult Bicycle Commuters: An Investigation of Respiratory Health, Motorised Traffic Proximity and the Utility of Commute Re-Routing. Ph.D. Thesis, Queensland University of Technology, Brisbane, Australia, 2012.
39. Gustafsson, L.; Archer, J. A naturalistic study of commuter cyclists in the greater Stockholm area. *Accid. Anal. Prev.* **2013**, *58*, 286–298. [[CrossRef](#)] [[PubMed](#)]
40. Bíl, M.; Andrášik, R.; Kubeček, J. How comfortable are your cycling tracks? A new method for objective bicycle vibration measurement. *Transp. Res. Part C Emerg. Technol.* **2015**, *56*, 415–425. [[CrossRef](#)]

41. Parkin, J.; Rotheram, J. Design speeds and acceleration characteristics of bicycle traffic for use in planning, design and appraisal. *Transp. Policy* **2010**, *17*, 335–341. [[CrossRef](#)]
42. Gelhert, T. *Traffic Safety of Electric Bicycles*; German Insurance Association, Insurers Accident Research (Unfallforschung der Versicherer): Berlin, Germany, 2014.
43. Langford, B.C.; Chen, J.; Cherry, C.R. Risky riding: Naturalistic methods comparing safety behavior from conventional bicycle riders and electric bike riders. *Accid. Anal. Prev.* **2015**, *82*, 220–226. [[CrossRef](#)] [[PubMed](#)]
44. Wergin, J.; Buehler, R. Where Do Bikeshare Bikes Actually Go? *Transp. Res. Rec. J. Transp. Res. Board* **2017**, *2662*, 12–21. [[CrossRef](#)]
45. Khatri, R.; Cherry, C.R.; Nambisan, S.S.; Han, L.D. Modeling Route Choice of Utilitarian Bikeshare Users with GPS Data. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2587*, 141–149. [[CrossRef](#)]
46. Good, N.; Mölter, A.; Ackerson, C.; Bachand, A.; Carpenter, T.; Clark, M.L.; Fedak, K.M.; Kayne, A.; Koehler, K.; Moore, B.; et al. The Fort Collins Commuter Study: Impact of route type and transport mode on personal exposure to multiple air pollutants. *J. Expo. Sci. Environ. Epidemiol.* **2016**, *26*, 397–404. [[CrossRef](#)] [[PubMed](#)]
47. Dill, J.; McNeil, N.; Broach, J.; Ma, L. Bicycle boulevards and changes in physical activity and active transportation: Findings from a natural experiment. *Prev. Med.* **2014**, *69*, S74–S78. [[CrossRef](#)] [[PubMed](#)]
48. Brown, B.B.; Tharp, D.; Tribby, C.P.; Smith, K.R.; Miller, H.J.; Werner, C.M. Changes in bicycling over time associated with a new bike lane: Relations with kilocalories energy expenditure and body mass index. *J. Transp. Health* **2016**, *3*, 357–365. [[CrossRef](#)] [[PubMed](#)]
49. Johnson, M.; Chong, D.; Carroll, J.; Katz, R.; Oxley, J.; Charlton, J. *Naturalistic Cycling Study: Identifying Risk Factors for Cyclists in the Australian Capital Territory. Report 322*; Monash University Accident Research Centre: Melbourne, Australia, 2014; ISBN 0732623928.
50. Hamann, C.J.; Pooley, M.; McGehee, D.; Peek-Asa, C. A naturalistic study of child and adult bicycling behaviours and risk exposure. In Proceedings of the International Cycling Safety Conference; Gothenburg, Sweden, 18–19 November 2014; pp. 1–15.
51. Hatfield, J.; Dozza, M.; Patton, D.A.; Maharaj, P.; Boufous, S.; Eveston, T. On the use of naturalistic methods to examine safety-relevant behaviours amongst children and evaluate a cycling education program. *Accid. Anal. Prev.* **2017**, *108*, 91–99. [[CrossRef](#)] [[PubMed](#)]
52. Casello, J.M.; Rewa, K.C.; Nour, A. An Analysis of Empirical Evidence of Cyclists' Route Choice and Its Implications for Planning. In Proceedings of the Transportation Research Board 91st Annual Meeting, Washington, DC, USA, 22–26 January 2012; p. 14.
53. Casello, J.M.; Nour, A.; Rewa, K.C.; Hill, J. Analysis of Stated-Preference and GPS Data for Bicycle Travel Forecasting. In Proceedings of the Transportation Research Board 90th Annual Meeting, Washington, DC, USA, 22–26 January 2011; pp. 1–18.
54. Wati, K.; Burke, M.; Sipe, N.; Dodson, J. Children's cycling trends, accessibility to and utilisation of urban facilities in selected Australian urban environments. In *Australasian Transport Research Forum*; Griffith University: Brisbane, Australia, 2013; pp. 1–19.
55. Krenn, P.J.; Oja, P.; Titze, S. Route choices of transport bicyclists: A comparison of actually used and shortest routes. *Int. J. Behav. Nutr. Phys. Act.* **2014**, *11*, 7. [[CrossRef](#)] [[PubMed](#)]
56. Dessing, D.; de Vries, S.I.; Hegeman, G.; Verhagen, E.; van Mechelen, W.; Pierik, F.H. Children's route choice during active transportation to school: difference between shortest and actual route. *Int. J. Behav. Nutr. Phys. Act.* **2016**, *13*, 11. [[CrossRef](#)] [[PubMed](#)]
57. Menghini, G.; Carrasco, N.; Schüssler, N.; Axhausen, K.W. Route choice of cyclists in Zurich. *Transp. Res. Part A Policy Pract.* **2010**, *44*, 754–765. [[CrossRef](#)]
58. Dalton, A.M.; Jones, A.P.; Panter, J.; Ogilvie, D. Are GIS-modelled routes a useful proxy for the actual routes followed by commuters? *J. Transp. Health* **2014**, *2*, 219–229. [[CrossRef](#)] [[PubMed](#)]
59. Yeboah, G.; Alvanides, S. Route Choice Analysis of Urban Cycling Behaviors Using OpenStreetMap: Evidence from a British Urban Environment. In *OpenStreetMap in GIScience*; Jokar Arsanjani, J., Zipf, A., Mooney, P., Helbich, M., Eds.; Lecture Notes in Geoinformation and Cartography; Springer International Publishing Switzerland AG: Cham, Switzerland, 2015; pp. 189–210. ISBN 978-3-319-14279-1.
60. Apparicio, P.; Carrier, M.; Gelb, J.; Séguin, A.M.; Kingham, S. Cyclists' exposure to air pollution and road traffic noise in central city neighbourhoods of Montreal. *J. Transp. Geogr.* **2016**, *57*, 63–69. [[CrossRef](#)]

61. Montini, L.; Antoniou, C.; Axhausen, K.W. Route and Mode Choice Models Using GPS Data. In Proceedings of the Transportation Research Board 96th Annual Meeting, Washington, DC, USA, 8–12 January 2017; pp. 1–14.
62. Luo, D.; Ma, X. Analysis of Cyclist Behavior Using Naturalistic Data: Data Processing for Model Development. In Proceedings of the 3rd International Cycling Safety Conference, Gothenburg, Sweden, 18–19 November 2014; pp. 1–17.
63. Wolf, J.; Guensler, R.; Bachman, W. Elimination of the Travel Diary: Experiment to Derive Trip Purpose from Global Positioning System Travel Data. *Transp. Res. Rec. J. Transp. Res. Board* **2001**, *1768*, 125–134. [[CrossRef](#)]
64. Wolf, J. Application of New Technologies in Travel Surveys. In Proceedings of the International Conference on Transport Survey Quality and Innovation, San Jose, Costa Rica, 16–21 November 2004.
65. Doherty, S.T.; Noël, N.; Gosselin, M.-L.; Sirois, C.; Ueno, M. Moving Beyond Observed Outcomes: Integrating Global Positioning Systems and Interactive Computer-Based Travel Behavior Surveys. In *TRB Transportation Research Circular—Personal Travel. The Long and Short of It*; Murakami, E., Pisarski, A.E., Eds.; Transportation Research Board: Washington, DC, USA, 1999; pp. 449–466.
66. Sandsjö, L.; Sjöqvist, B.A.; Candefjord, S. A Concept for Naturalistic Data Collection for Vulnerable Road Users Using a Smartphone-Based Platform. In Proceedings of the International Technical Conference on the Enhanced Safety of Vehicles (ESV), Gothenburg, Sweden, 8–11 June 2015; p. 6.
67. Kiefer, C.; Behrendt, F. Smart e-bike monitoring system: real-time open source and open hardware GPS assistance and sensor data for electrically-assisted bicycles. *IET Intell. Transp. Syst.* **2016**, *10*, 79–88. [[CrossRef](#)]
68. Liu, F.; Figliozzi, M.; Caviedes, A.; Le, H.; Mai, L. *Utilizing Egocentric Video and Sensors to Conduct Naturalistic Bicycling Studies. Report NITC-RR-805*; National Institute for Transportation and Communities: Portland, OR, USA, 2016.
69. Watkins, K.E.; LeDantec, C. *Using Crowdsourcing to Prioritize Bicycle Route Network Improvements. Report FHWA-GA-16-1439*; Georgia Department of Transportation: Forest Park, GA, USA, 2016.
70. Rios, I.; Golab, L.; Keshav, S. Analyzing the usage patterns of electric bicycles. In *Proceedings of the Workshop on Electric Vehicle Systems, Data, and Applications—EV-SYS '16*; ACM Press: New York, NY, USA, 2016; pp. 1–6.
71. Romanillos, G.; Zaltz Austwick, M. Madrid cycle track: Visualizing the cyclable city. *J. Maps* **2016**, *12*, 1218–1226. [[CrossRef](#)]
72. Gonzalez, P.A.; Weinstein, J.S.; Barbeau, S.J.; Labrador, M.A.; Winters, P.L.; Georggi, N.L.; Perez, R.A. Automating Mode Detection Using Neural Networks and Assisted GPS Data Collected Using GPS-Enabled Mobile Phones. In Proceedings of the 15th World Congress on Intelligent Transport Systems, New York, NY, USA, 16–20 November 2008; pp. 1265–1276.
73. Nour, A.; Casello, J.M.; Hellinga, B. Developing and Optimizing a Transportation Mode Inference Model Utilizing Data from GPS Embedded Smartphones. In Proceedings of the Transportation Research Board 94th Annual Meeting, Washington, DC, USA, 11–15 January 2015; p. 16.
74. Saleh, P. *E-bicycles—Bicycles or mopeds? Overview about the project “SEEKING—SAFE E-BIKING.” In International Conference on ESAR “Expert Symposium on Accident Research”*; Otte, D., Krettek, C., Eds.; Fachverlag NW in der Carl Schuenemann Verlag GmbH: Hannover, Germany, 2014.
75. Charlton, B.; Sall, E.; Schwartz, M.; Hood, J. Bicycle Route Choice Data Collection using GPS-Enabled Smartphones. In *Proceedings of The Transportation Research Board 90th Annual Meeting*; Washington, DC, USA, 23–27 January 2011; pp. 1–10.
76. Hudson, J.G.; Duthie, J.C.; Rathod, Y.K.; Larsen, K.A.; Meyer, J.L. *Using Smartphones to Collect Bicycle Travel Data in Texas. DOT Grant No. DTRT06-G-0044*; Texas Transportation Institute: College Station, TX, USA, 2012.
77. Chen, P.; Shen, Q.; Childress, S. A GPS data-based analysis of built environment influences on bicyclist route preferences. *Int. J. Sustain. Transp.* **2017**, 1–14. [[CrossRef](#)]
78. Akar, G.; Park, Y. *Tracking Bicyclists’ Route Choices, Case Study: The Ohio State University. NEXTRANS Project No. 171OSUY2.2*; Ohio State University: Columbus, OH, USA, 2017.
79. Figliozzi, M.A.; Blanc, B.P. *Evaluating the Use of Crowdsourcing as a Data Collection Method for Bicycle Performance Measures and Identification of Facility Improvement Needs. Report SPR 768*; Portland State University: Portland, OR, USA, 2015.
80. Zimmermann, M.; Mai, T.; Frejinger, E. Bike route choice modeling using GPS data without choice sets of paths. *Transp. Res. Part C Emerg. Technol.* **2017**, *75*, 183–196. [[CrossRef](#)]

81. Li, S.; Muresan, M.; Fu, L. Cycling in Toronto: Route Choice Behaviour and Implications to Infrastructure Planning. In Proceedings of the Transportation Research Board 96th Annual Meeting, Washington, DC, USA, 8–12 January 2017.
82. Strauss, J.; Miranda-Moreno, L.F. Speed, travel time and delay for intersections and road segments in the Montreal network using cyclist Smartphone GPS data. *Transp. Res. Part D Transp. Environ.* **2017**, *57*, 155–171. [[CrossRef](#)]
83. Torres, S.; Lalanne, F.; del Canto, G.; Morales, F.; Bustos-Jimenez, J.; Reyes, P. BeCity: Sensing and sensibility on urban cycling for smarter cities. In Proceedings of the 34th International Conference of the Chilean Computer Science Society (SCCC), Santiago, Chile, 9–13 November 2015; Institute of Electrical and Electronics Engineers: Santiago, Chile, 2015; pp. 1–4.
84. Manum, B.; Nordström, T.; Gil, J.; Nilsson, L.; Marcus, L. Modelling bikeability; Space syntax based measures applied in examining speeds and flows of bicycling in Gothenburg. In Proceedings of the 11th International Space Syntax Symposium; Lisbon, Portugal, 3–7 July 2017; pp. 1379–1394.
85. Crockett, J.; O'Hare, S.; Barritt, A.; Gordon, A.; Inayathusein, A.; Forrest, R. In the Peleton or in the Break—Factors Affecting Cyclists Route Choice in London. In *European Transport Conference*; Association for European Transport: Barcelona, Spain, 2016; pp. 1–26.
86. Sun, Y.; Mobasheri, A. Utilizing Crowdsourced Data for Studies of Cycling and Air Pollution Exposure: A Case Study Using Strava Data. *Int. J. Environ. Res. Public Health* **2017**, *14*, 274. [[CrossRef](#)] [[PubMed](#)]
87. Norman, G.; Kesha, N. Using smartphones for cycle planning. In *Institution of Professional Engineers New Zealand (IPENZ) Transportation Conference*; Engineering New Zealand: Christchurch, New Zealand, 2015; p. 10.
88. Musakwa, W.; Selala, K.M. Mapping cycling patterns and trends using Strava Metro data in the city of Johannesburg, South Africa. *Data Br.* **2016**, *9*, 898–905. [[CrossRef](#)] [[PubMed](#)]
89. Bergman, C.; Oksanen, J. Conflation of OpenStreetMap and Mobile Sports Tracking Data for Automatic Bicycle Routing. *Trans. GIS* **2016**. [[CrossRef](#)]
90. Schweizer, J.; Bernardi, S.; Rupi, F. Map-matching algorithm applied to bicycle global positioning system traces in Bologna. *IET Intell. Transp. Syst.* **2016**, *10*, 244–250. [[CrossRef](#)]
91. Baker, K.; Ooms, K.; Verstockt, S.; Brackman, P.; De Maeyer, P.; Van de Walle, R. Crowdsourcing a cyclist perspective on suggested recreational paths in real-world networks. *Cartogr. Geogr. Inf. Sci.* **2017**, *44*, 422–435. [[CrossRef](#)]
92. Leao, S.Z.; Pettit, C. Agent Based Modelling of Urban Systems. In *Lecture Notes in Computer Science*; Namazi-Rad, M.-R., Padgham, L., Perez, P., Nagel, K., Bazzan, A., Eds.; Springer International Publishing AG: Cham, Switzerland, 2017; Volume 10051, ISBN 978-3-319-51956-2.
93. Ton, D.; Cats, O.; Duives, D.; Hoogendoorn, S. How Do People Cycle in Amsterdam? Estimating cyclists' route choice determinants using GPS data from an urban area. *Transp. Res. Rec. J. Transp. Res. Board* **2017**, *2662*, 75–82. [[CrossRef](#)]
94. Bussche, D.; Van de Coevering, P. BikePRINT—In Depth Analysis of Cyclist Behaviour and Cycle Network Performance Using Extensive Gps-Track Data. In *European Transport Conference*; Association for European Transport: Frankfurt, Germany, 2015; pp. 1–17.
95. Lee, D.; Park, S.; Hahn, M. A study on bicycle crash risk based on GPS trajectories collected from bidirectional traffic. In Proceedings of the 2014 IEEE Asia Pacific Conference on Circuits and Systems (APCCAS), Ishigaki, Japan, 17–20 November 2014; IEEE: Ishigaki, Japan, 2014; pp. 383–386.
96. Assemi, B.; Schlagwein, D.; Safi, H.; Mesbah, M. Crowdsourcing as a Method for the Collection of Revealed Preferences Data. In *2015 IEEE Symposium on Service-Oriented System Engineering*; Wirtz, G., Townend, P., Eds.; IEEE: San Francisco Bay, CA, USA, 2015; Volume 30, pp. 378–382.
97. Lott, D.F.; Tardiff, T.; Lott, D.Y. Evaluation by experienced riders of a new bicycle lane in an Established Bikeway System. *Transp. Res. Rec. J. Transp. Res. Board* **1978**, *683*, 40–46.
98. Van Schagen, I.N.L.G. *Pedestrians and Pedal Cyclists in a British, Dutch and Swedish Modelling Area*; Institute of Transport Studies, University of Leeds: Leeds, UK, 1990.
99. Kang, L.; Fricker, J.D. Bicyclist commuters' choice of on-street versus off-street route segments. *Transportation* **2013**, *40*, 887–902. [[CrossRef](#)]
100. Van Maarseveen, M.; Jansen, G.R.M.; Bovy, P.H.L. Estimating OD Tables Using Empirical Route-Choice Information with Application to Bicycle Traffic. *Transp. Res. Rec. J. Transp. Res. Board* **1985**, *1045*, 15–23.

101. Wilmink, A.; Hartman, J.B. *Evaluation of the Delft Bicycle Network Plan. Final Summary Report*; Ministry of Transport and Public Works, Transportation and Traffic Engineering Division: The Hague, The Netherlands, 1987.
102. Aultman-Hall, L.; Hall, F.L.; Baetz, B. Analysis of bicycle commuter routes using geographic information systems: implications for bicycle planning. *Transp. Res. Rec. J. Transp. Res. Board* **1997**, *1578*, 102–110. [[CrossRef](#)]
103. Aultman-Hall, L. *Commuter Bicycle Route Choice: Analysis of Major Determinants and Safety Implications*, Ph.D. Thesis, McMaster University, Hamilton, ON, Canada, 1996.
104. Howard, C.; Burns, E. Cycling to Work in Phoenix: Route Choice, Travel Behavior, and Commuter Characteristics. *Transp. Res. Rec. J. Transp. Res. Board* **2001**, *1773*, 39–46. [[CrossRef](#)]
105. Boettge, B.; Hall, D.; Crawford, T. Assessing the Bicycle Network in St. Louis: A PlaceBased User-Centered Approach. *Sustainability* **2017**, *9*, 241. [[CrossRef](#)]
106. Manton, R.; Rau, H.; Fahy, F.; Sheahan, J.; Clifford, E. Using mental mapping to unpack perceived cycling risk. *Accid. Anal. Prev.* **2016**, *88*, 138–149. [[CrossRef](#)] [[PubMed](#)]
107. Manum, B.; Nordström, T. Integrating Bicycle Network Analysis in Urban Design: Improving bikeability in Trondheim by combining space syntax and GIS-methods using the place syntax tool. In *International Space Syntax Symposium*; Kim, Y.O., Park, H.T., Eds.; Sejong University: Seoul, Korea, 2013; p. 14.
108. Hyodo, T.; Suzuki, N.; Takahashi, K. Modeling of Bicycle Route and Destination Choice Behavior for Bicycle Road Network Plan. *Transp. Res. Rec. J. Transp. Res. Board* **2000**, *1705*, 70–76. [[CrossRef](#)]
109. Suzuki, K.; Kanda, Y.; Doi, K.; Tsuchizaki, N. Proposal and Application of a New Method for Bicycle Network Planning. *Procedia Soc. Behav. Sci.* **2012**, *43*, 558–570. [[CrossRef](#)]
110. Yang, C.; Mesbah, M. Route Choice Behaviour of Cyclists by Stated Preference and Revealed Preference. In *Australasian Transport Research Forum*; Bunker, J.M., Burke, M., Eds.; Australasian Transport Research Forum Incorporated: Brisbane, Australia, 2013; pp. 1–17.
111. Gamble, J.; Snizek, B.; Nielsen, T.S. From people to cycling indicators: Documenting and understanding the urban context of cyclists' experiences in Quito, Ecuador. *J. Transp. Geogr.* **2017**, *60*, 167–177. [[CrossRef](#)]
112. Wang, J.Y.T.; Mirza, L.; Cheung, A.K.L.; Moradi, S. Transforming Auckland into a bicycle-friendly city: Understanding factors influencing choices of cyclists and potential cyclists. In *Australasian Transport Research Forum*; Hughes, B., Petkoff, L., Eds.; Australasian Transport Research Forum Incorporated: Perth, Australia, 2012.
113. Snizek, B.; Sick Nielsen, T.A.; Skov-Petersen, H. Mapping bicyclists' experiences in Copenhagen. *J. Transp. Geogr.* **2013**, *30*, 227–233. [[CrossRef](#)]
114. Kobas, G.V.; Drury, C.G. The Bicyclist's Exposure to Risk. *Hum. Factors Ergon. Soc. Annu. Meet.* **1976**, *20*, 484–487. [[CrossRef](#)]
115. Krizek, K.J.; El-Geneidy, A.; Thompson, K. A detailed analysis of how an urban trail system affects cyclists' travel. *Transportation* **2007**, *34*, 611–624. [[CrossRef](#)]
116. Larsen, J.; El-Geneidy, A. A travel behavior analysis of urban cycling facilities in Montréal, Canada. *Transp. Res. Part D Transp. Environ.* **2011**, *16*, 172–177. [[CrossRef](#)]
117. Standen, C.; Crane, M.; Collins, A.; Greaves, S.; Rissel, C. Determinants of mode and route change following the opening of a new cycleway in Sydney, Australia. *J. Transp. Health* **2017**, *4*, 255–266. [[CrossRef](#)]
118. Winters, M.; Teschke, K.; Grant, M.; Setton, E.; Brauer, M. How Far Out of the Way Will We Travel? *Transp. Res. Rec. J. Transp. Res. Board* **2010**, *2190*, 1–10. [[CrossRef](#)]
119. González, F.; Melo-Riquelme, C.; de Grange, L. A combined destination and route choice model for a bicycle sharing system. *Transportation* **2016**, *43*, 407–423. [[CrossRef](#)]
120. Salmon, R.; Chinnock, C.; Duckenfield, T. *Cycle Route Choice. Final Survey and Model Report*; Steer Davies Gleave: London, UK, 2012.
121. Van Duppen, J.; Spierings, B. Retracing trajectories: The embodied experience of cycling, urban sensescapes and the commute between “neighbourhood” and “city” in Utrecht, NL. *J. Transp. Geogr.* **2013**, *30*, 234–243. [[CrossRef](#)]
122. Barratt, P. Healthy competition: A qualitative study investigating persuasive technologies and the gamification of cycling. *Health Place* **2017**, *46*, 328–336. [[CrossRef](#)] [[PubMed](#)]
123. Zacharias, J.; Zhang, R. Revealed Bicyclist Route Preferences and Street Conditions. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2587*, 17–22. [[CrossRef](#)]
124. Simpson, P. A sense of the cycling environment: Felt experiences of infrastructure and atmospheres. *Environ. Plan. A* **2017**, *49*, 426–447. [[CrossRef](#)]

125. Johnson, M.; Charlton, J.; Oxley, J.; Newstead, S. Naturalistic cycling study: Identifying risk factors for on-road commuter cyclists. *Ann. Adv. Automot. Med.* **2010**, *54*, 275–283. [[PubMed](#)]
126. Stewart, K.; McHale, A. Cycle lanes: their effect on driver passing distances in urban areas. *Transport* **2014**, *29*, 307–316. [[CrossRef](#)]
127. De Leeuw, G.; de Kruijf, J. The Act of (Future) Cycling: Testing Urban Designs and Conducting Research in Virtual Reality. In *European Transport Conference*; Association for European Transport: Frankfurt, Germany, 2015; pp. 1–15.
128. Hirose, S.; Kitamura, Y. Preliminary evaluation of virtual cycling system using google street view. *Persuas. Technol.* **2015**, *9072*, 65–70. [[CrossRef](#)]
129. Heinen, E.; van Wee, B.; Maat, K. Commuting by Bicycle: An Overview of the Literature. *Transp. Rev.* **2010**, *30*, 59–96. [[CrossRef](#)]



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## Paper III

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Article

# Bicycle Level of Service for Route Choice—A GIS Evaluation of Four Existing Indicators with Empirical Data

Ray Pritchard <sup>1,\*</sup>, Yngve Frøyen <sup>1</sup> and Bernhard Snizek <sup>2</sup>

<sup>1</sup> Department of Architecture and Planning, Faculty of Architecture and Design, NTNU—Norwegian University of Science and Technology, 7491 Trondheim, Norway; yngve.froyen@ntnu.no

<sup>2</sup> Metascapes, 1752 Copenhagen, Denmark; bs@metascapes.org

\* Correspondence: ray.pritchard@cantab.net

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**Abstract:** Bicycle Level of Service (BLOS) indicators are used to provide objective ratings of the bicycle suitability (or quality) of links or intersections in transport networks. This article uses empirical bicycle route choice data from 467 university students in Trondheim, Norway to test the applicability of BLOS rating schemes for the estimation of whole-journey route choice. The methods evaluated share a common trait of being applicable for mixed traffic urban environments: Bicycle Compatibility Index (BCI), Bicycle Stress Level (BSL), Sixth Edition Highway Capacity Manual (HCM6), and Level of Traffic Stress (LTS). Routes are generated based on BLOS-weighted networks and the suitability of these routes is determined by finding the percentage overlap with empirical route choices. The results show that BCI provides the best match with empirical route data in all five origin–destination pairs, followed by HCM6. BSL and LTS which are not empirically founded have a lower match rate, although the differences between the four methods are relatively small. By iterating the detour rate that cyclists are assumed to be willing to make, it is found that the best match with modelled BLOS routes is achieved between 15 and 21% additional length. This falls within the range suggested by existing empirical research on willingness to deviate from the shortest path, however, it is uncertain whether the method will deliver the comparable findings in other cycling environments.

**Keywords:** bicycle suitability; route choice; detour rate; level of service; infrastructure evaluation; bikeability; Geographic Information System

## 1. Introduction

The promotion of bicycling is increasingly seen as an approach through which towns and cities can become healthier, more equitable, and attractive to live in [1,2]. Whilst many factors are thought to positively influence the levels of bicycling in urban areas, high quality, well-connected bicycle infrastructure is widely considered to be a precondition [3–6]. Since most cities do not meet this criterion, the network of streets and paths available to bicycle users typically varies widely in quality.

In order to improve our understanding of how incomplete bicycle networks are used and valued, many metrics have been developed to assess the bicycle suitability of urban areas. Such metrics typically take account of built environment factors as infrastructure quality, traffic volumes, perceived/actual safety, directness, and attractiveness [7]. A subset of these metrics known as Bicycle Level of Service (BLOS) has been developed along broadly similar principles to the more widely used vehicular Level of Service methods that are commonly used in traffic planning [8].

This research aims to test four existing BLOS methods that consider the bicycle friendliness of mixed traffic urban environments using empirical data from Trondheim, Norway. The empirical data

consists of bicycle route preferences of 467 university students to or from their student accommodation to Trondheim Torv, the city square of Trondheim. Five origin–destination pairs are created from the dataset based on geographical midpoints of the students’ residence clusters. The objective BLOS methods that are tested are developed based on bicyclists’ stated or observed route preferences in the US context. This paper seeks to establish how well BLOS methods, which are used to provide letter-grade or numeric ratings for all streets in the city network, can be used to estimate actual bicycle route preferences in Norway. This is done by generating an optimal route based on a combination of travel time (traditionally the main cost element in route assignment models) and quality of the cycling experience as defined by BLOS. To the authors’ knowledge, ‘reverse engineering’ of BLOS indicators in this manner has not previously been published in the academic literature using the type of empirical data collected (with many unique respondents on a restricted number of origin–destination pairs).

## 2. Background

Bicycle Level of Service is of interest for many transport planners for evaluating the quality of bicycle networks, however, no consensus on the most suitable method has been reached due to a wide variety of contextual and methodological differences. The term Cycling or Bicycle Level of Service can be used to refer to audit-based categorical metrics (e.g., [9]) and methods relying principally on continuous variables such as speed or traffic volume (e.g., [10]). In this paper, BLOS is used to refer specifically to the latter category, which is primarily related to the quality of the infrastructure and comfort for bicycling and often based on the opinions of many users (cyclists or cycling planners). Although sometimes also referred to as BLOS methods, bikeability indicators, which include destination or area-based variables are excluded from the scope of this paper [11–14].

Many researchers have reviewed existing BLOS methods; however, few if any of these have sought to test BLOS suitability for prediction of route choices. Moudon & Lee evaluated the data requirements of a broad range of assessment tools including 15 instruments referred to by the authors as route quality assessment tools for walking and bicycling [15]. Asadi-Shekeri et al. performed a review of pedestrian and bicycle level of service methods and their associated challenges [16]. Callister & Lowry [7] created a toolbox for ArcGIS users containing three BLOS methods, two of which were used in this research (BSL and HCM6). Parks et al. [17] make a comparison of three BLOS methods for evaluating the changes resulting from bicycle facility installation.

These reviews form the starting point for Table 1, which lists a selection of BLOS methods and the effects of the included component variables. The only criterion for inclusion in the table is that the BLOS method is designed for application to urban mixed-traffic street links or segments (sections of streets between intersections). Supplementary methods to the initial list were found through snowballing of references and searches in the Scopus database. The criterion results in the exclusion of such methods as those that are focused solely on intersections [18], separated bicycle or shared paths [19–21], rural areas [22,23], urban arterials [24], or bicycle lanes [25,26]. Audit-based metrics are also excluded from Table 1, including those in Australia and the UK that use the term “Cycling Level of Service” [9,27,28] and select others that use the term bicycle level of service but are either ‘scorecard’ based or lack an empirical foundation for the combination of variables [29,30].

Due to different notations for the different forms of BLOS, a higher BLOS is in this paper used to refer to better suitability for cycling (corresponding with A for BCI and HCM6 or 1 for BSL and LTS respectively). With few exceptions, the BLOS indicators are influenced by the component variables in the same manner (e.g., the positive effect of bicycle facility’s presence or negative impact of vehicular traffic). There are however two exceptions apparent in Table 1. An increase in the number of traffic lanes for a given Annual Average Daily Traffic (AADT) will normally reduce the number of vehicles in the lane closest to bicycle traffic. This will decrease the number of interactions between vehicles and bicyclists, thereby increasing the BLOS. Level of Traffic Stress, in contrast, is negatively influenced (reduction in LOS) by the number of traffic lanes, presumably because this is connected to higher overall vehicular volumes (or that the nearest lane volume is not considered) [31]. The second exception



Bicycle Level of Service methods are typically developed with the intention to rate the bicycle quality of individual road/path links. In this research, the same rating approach is applied at the network scale to consider how well link ratings are reflected in the choice of entire routes. This involves using the BLOS methods to create potential routes for comparison with empirical choices.

Route choice set creation for travel behaviour research is most typically scrutinised on the basis of creating choices that are realistic and representative for any given road user [42]. A method known as labelling is used for route choice creation to optimise a single attribute assumed or known to affect route choice within certain bounds [43]. This study uses a similar approach, however rather than optimising the utility of a single attribute (for example energy expenditure), the authors' take the approach of optimising route choice using the multi-attribute BLOS indicators in combination with travel time. Changing the relative importance of travel time and the 'label' based on BLOS can therefore result in different optimal routes being created.

From Table 1, four methods were selected for evaluation with the empirical data in Trondheim. The selected BLOS methods are chosen based on a balance between their commonality of use and the relative ease with which they can be applied. A key criterion for the selection of indices to be tested is that the score weighting is primarily related to the quality of the infrastructure and comfort for bicycling as opposed to destination accessibility. It was a specific aim to choose methods where most of the GIS data sources necessary could be expected to be found or acquired without additional field data collection. Unfortunately, non-American BLOS methods were not able to be tested due to model complexity of the Danish BLOS method [38] and very different context to the Norwegian test data for two other BLOS methods developed in India [32,41]. The final selection was comprised of (in descending order of complexity):

1. Sixth Edition Highway Capacity Manual BLOS (HCM6) [8,44]
2. Bicycle Compatibility Index (BCI) [37]
3. Level of Traffic Stress (LTS) [40,45]
4. Bicycle Stress Level (BSL) [34]

Each of the four methods is briefly described below.

#### 2.1. Sixth Edition Highway Capacity Manual BLOS (HCM6)

Chapter 18 in the Sixth Edition of the Transportation Research Board's Highway Capacity Manual (hereafter called HCM6) presents a methodology for calculating Bicycle LOS for urban street segments that finds its roots in the Real-Time Bicycle LOS (RTBLOS) method from Landis et al., 1997 [10]. The HCM6 method is unchanged from the 2010 Highway Capacity Manual and was first published in a more detailed report commissioned by the US National Cooperative Highway Research Program in 2008 [8,39]. Whilst the Highway Capacity Manual describes the bicycle LOS in relation to both intersections and links (i.e., linear sections of road between intersections), only the link methodology is used in this paper for comparability with the three other methods described below.

As can be seen in Table 1, there are many similarities in terms of included variables between the RTBLOS method and the HCM6 method. Commercial land use intensity has been excluded from the HCM6 approach, whilst the presence of a street kerb is added to the HCM6 method to adjust the effective lane or bicycle facility width. Parameters have additionally been adjusted in HCM6 which is widely used by transportation practitioners in the USA, where the Highway Capacity Manual was developed. Callister and Lowry [7] developed an ArcMAP toolbox which combines the many equations detailed in the 2010 HCM and HCM6 into the final BLOS link output (a letter grade between A and F), and it is this toolbox that is used to develop a map for the case study area in this paper. The main difference between HCM6 link and HCM6 segment calculations are the consideration of intersections and driveway access points at the segment level which is not accounted for at the link level. Intersections are, however, taken account of using a separate approach that is applied to all four BLOS methods, detailed in Section 3.5. As a result, the link approach of HCM6 is used for this study.

## 2.2. Bicycle Compatibility Index (BCI)

The BCI methodology was developed by Harkey et al. in 1998 for urban and suburban roadway segments (in this case, the same as links), making it suitable for comparison with the HCM6 bicycle approach and for application to the mixed traffic environment of the case study area [37]. The methodology has a much simpler form than the HCM6 approach, being a single linear equation comprised of nine variables as displayed in Equation (1) below. In the same manner as the link BLOS used for HCM6, intersections are not treated directly by the BCI method but are performed independently as discussed in Methods.

$$\begin{aligned} \text{BCI} = & 3.67 - 0.966\text{BL} - 0.410\text{BLW} - 0.498\text{CLW} + 0.002\text{CLV} \\ & + 0.0004\text{OLV} + 0.022\text{SPD} + 0.506\text{PKG} - 0.264\text{AREA} \end{aligned} \quad (1)$$

where:

BL = presence of a bicycle lane or paved shoulder > 3.0 ft no = 0 yes = 1

BLW = bicycle lane width in feet (to the nearest tenth)

CLW = curb lane width in feet (to the nearest tenth)

CLV = curb lane vehicles per hour in the travel direction

OLV = other lane(s) volume in travel direction

SPD = 85th percentile vehicle speeds miles/h

PKG = presence of a parking lane with more than 30 percent occupancy; no = 0, yes = 1

AREA = type of roadside development; residential = 1 other type = 0

AF = adjustment factor for truck volumes, parking turnover and right-turn volumes

To ensure compatibility with the HCM6 and its previous editions, the numeric BCI value (where a lower number corresponds to a higher bicycle standard) is converted to an A to F letter grading system using percentile scores. The percentile boundaries are as follows: A/B—5th, B/C—25th, C/D—50th, D/E—75th and E/F—95th.

## 2.3. Level of Traffic Stress (LTS)

Level of Traffic Stress (LTS) is a four-level BLOS method loosely based on the Dutch CROW Design Manual for Bicycle Traffic [46]. The original methodology was developed in connection with a report from Mekuria et al. in 2012 for the California Department of Transportation and received minor modifications in 2018 [31,40]. Criteria for allocation to each category is made according to the posted speed limit, number of lanes, AADT, and the provision of separate infrastructure, such as bicycle lanes and paths. The four levels of traffic stress are linked to a classification of cyclists into four categories from Geller in 2006: “interested but concerned”—split into two groups representing suitability for children (LTS 1) and adults (LTS 2), “enthused and confident” (LTS 3), and “strong and fearless” (LTS 4) whilst the final group “No Way No How” is not classified into any of the LTS levels [47,48].

LTS levels 1 and 2 are intended to represent the lowest stress and good cycling conditions, with separation from traffic in the form of bicycle-specific infrastructure or only occasional interactions with vehicular traffic at low speeds. Network links graded as LTS 1 or 2 are considered by the methodology developers to be acceptable for the majority of adults [31]. The original methodology stresses the importance of connectivity for any pair of points, defined as “the ability to get between the two points without exceeding a specified stress threshold and without exceeding the specified level of detour” [Ibid., p. 8]. The level of detour, referred to in this paper as the detour rate (the percentage additional distance of a route compared to the shortest path between origin and destination) is applied for route choice optimisation discussed in Section 3.6.

#### 2.4. Bicycle Stress Level (BSL)

The Bicycle Stress Level method was developed by Sorton and Walsh in 1994 to quantify the intensity of the traffic in terms of speed and hourly vehicular volumes which, in combination with outside lane width, are presented as the main sources of traffic stress to cyclists [34]. The BSL method uses a 5-point scale scoring system for each of the three aforementioned criteria which are then averaged to give a stress level between 1—very low and 5—very high. The hourly traffic volume is proposed to be superior to AADT but is not generally collected in connection with evaluations of bicycle suitability at the network level. As a result, a standard estimation for hourly traffic volume is made based on the 10 percent of the AADT as recommended by Sorton and Walsh in cases where hourly volumes have not been measured or estimated [34]. With only three explanatory variables, the method omits many other environmental and psychological factors that are proposed to influence BLOS (see Table 1). It is included in this study to assess whether simple indicators like this are sufficient for the purpose of route choice estimation in the same way as more complex BLOS methods. Although the three parameters necessary to produce the BSL rating can be easily aggregated via attribute tables in GIS, the ArcMAP toolbox used earlier for HCM6 also contained a tool for BSL calculation, and this was therefore employed for this paper [7].

### 3. Methods

#### 3.1. Survey and Mapping API

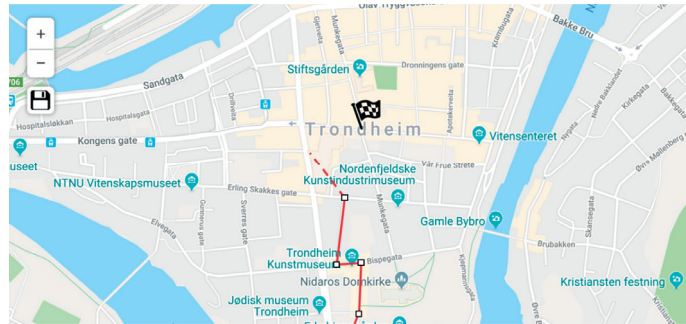
The primary empirical data source used in this paper was obtained through a web-based mapping survey where university students were asked to draw their preferred route by bicycle between their student residence complex and the Trondheim City Square. By choosing the centre of Trondheim, the presumption is that students would be familiar with the location and several potential routes to get there given it is near to many common destinations and is frequently used as a meeting place. In November 2015, approximately 3000 students across four university-managed residence complexes were emailed an invitation to the study by the Student Welfare Organisation in Trondheim. The largest student complex Moholt houses approximately 2000 students and was therefore considered as two separate origins due to its larger geographical footprint. This meant that route choices were mapped along five origin–destination pairs based on geographical midpoints of the students' residence clusters and the Trondheim city square.

Although the focus was on bicycle travel behaviour, the survey invitation was titled “student travel behaviour study” in order to receive responses from non-cyclists and cyclists alike. This was done to avoid response bias towards those who already cycle [49,50]. This assist to ensure that the sample is generally representative of the overall (student) population, an important consideration compared to most bicycle travel behaviour studies that are focused primarily on existing cyclists (whose potential to cycle more is limited) [51]. As a motivation for completing the survey, participants were given the chance to win a gift card worth €50. The online survey contained 20 general questions concerning participants' socio-demographic characteristics and personal travel behaviour both at the beginning of the 2015 autumn semester and at the time of answering the survey (early winter with some snow).

Upon completion of the survey form made in Jotform.com, participants were redirected to a second webpage that contained a Google Maps mapping Application Programming Interface (API), built upon the same principles detailed in Snizek et al., 2013 [52]. The survey generated a unique identifier for each participant which was sent to the second webpage via the Hypertext Transfer Protocol (HTTP) POST request method. The POST request method requires the receiving web server to accept data contained within the request message (in this case a user ID number) and is often used in connection with file uploads or a customised “thank you” message following survey submission. The redirect URL for this paper had the form [http://trondheim.routr.dk/?user\\_id=\protect{T1}\textbraceleftID\protect{T1}\textbraceright](http://trondheim.routr.dk/?user_id=\protect{T1}\textbraceleftID\protect{T1}\textbraceright) in which trondheim.routr.dk was the web host whilst {ID} was received directly from Jotform upon survey completion. This allowed the matching of survey responses and the mapping API



webpage. The mapping API webpage was specifically created for the study and contained a Google Maps background map centred on Trondheim, a polyline drawing tool and instructions to draw a single preferred bicycle route between their student residence and the city square, illustrated below in Figure 1.



**Figure 1.** Google Maps based mapping API used to collect participant responses on bicycle route choice. The end point, Trondheim City Square, is indicated to users with a flag.

Early in the data collection process, it was discovered that the route data received via the mapping API was highly variable in quality and that this was likely due to the poor functionality of the mapping website on smartphone browsers. In particular, the drawing, navigation, and zoom functions were found to respond poorly to touch screen input. The respondents that this applied to were asked to repeat the mapping task using a personal computer. In total, 677 routes were gathered by the mapping API and stored for further data processing, as described below.

Despite the commonality of web-based mapping applications, this data-collection method is seldom applied to studies of bicycle route choice [51]. It does, however, offer insights from a large respondent population without the need for more time and cost-intensive Global Positioning System (GPS) methods, whilst avoiding the need for digitisation of hand-drawn or verbally described routes. It should be noted that web-based mapping applications are subject to the same limitations as other mapping tools, particularly with respect to imperfect user knowledge (both of maps generally and of their local environment)—making data collection in this manner less reliable than methods which track movements such as GPS or ride-along interviews.

### 3.2. Network Information

In addition to the data gathered from the mapping API described above, there were several other data sources that needed to be utilised in order to develop a complete bicycle network upon which the analysis of the data could be performed. These are detailed below in Table 2.

### 3.3. Data Preparation

The first stage of empirical data processing involved removal of duplicate route responses, which may have been the result of participants refreshing the mapping API webpage. From a total of 677 routes drawn, 611 remained after duplicate responses were removed, giving a response rate of 20%. For the purpose of determining route choice, the data received in the mapping API had to be both complete and relatively detailed. In the cases where route choice was not possible to determine from the raw data, the routes were removed from further analysis, leading to a dataset with 518 responses. Map-matching was performed on the routes using ArcMAP 10.6. The process involved the creation of a 50-metre buffer around each route which was found to provide the optimum level of matching (incrementing buffer size by 10 metres each time) without excessive false positive matches to neighbouring streets. The maximum buffer width is a function of the urban structure

of the city—particularly the length of city blocks or distance between parallel streets. Thereafter, two further datasets were created containing the origins and destinations for the corresponding route. A shortest path search (based on non-modified link lengths) from origin to destination on the transport network contained within the 50-m buffer was performed. 467 routes were able to be matched using this procedure.

**Table 2.** Data sources for the GIS transport network.

Data Source	Input Data Set	Data Type
Norwegian Mapping Authority & Norwegian Public Roads Administration	Street network including paths and topography (Norwegian “elveg” database)	Geodatabase—centrelines of roads
Norwegian National Road Database	AADT traffic volumes, speed limit and lane width data	ArcMAP API toolbox
Authors, kart.finn.no aerial photography	Missing links for pedestrians and bicycle users. Supplementary information for the network (parking, bicycle lanes, kerb presence)	Geodatabase (manual editing)
Survey respondents	Mapped bicycle route choice (mapping API)	Geographic JavaScript Object Notation (GeoJSON)

#### 3.4. Network Impedance Based on BLOS

Bicycle Level of Service methods are used to generate potential route choices using a modification of the approach from Cervero et al., 2019 in which a Level of Traffic Stress (LTS)-classified transport network is used to allocate additional impedance (together with travel time) for streets and intersections poorly suited for cycling [53]. The approach involves the distribution of impedance (as an additional length) based on BLOS score.

Links in the transport network with poorer standard as defined by the various BLOS methods are the least attractive and are therefore allocated a higher impedance (up to the maximum detour rate bicyclists are considered willing to take). Impedance is allocated in two stages: as a multiplicative impedance factor for link length, and as an additional penalty length added to the links as they enter intersections.

The first stage of allocating impedance to link lengths applies Cervero et al.’s method for LTS to all four BLOS methods. This method applies the maximum level of impedance to the links with LTS4, and zero impedance to the links with LTS1. Cervero et al. allocate a maximum impedance factor (to be multiplied by link length) of 1.15, which stems from the assumption that a 15% detour rate is considered to be acceptable for cyclists. Since LTS2 and LTS3 street links are of a standard in between links classified as LTS1 and LTS4, they are allocated impedance factors of 1.05 and 1.10 respectively. This method, limited to link impedance, has previously been applied to generate bicycle routes using an impedance factor of 1.20 (or 20% detour rate) on a network classified according to LTS [54].

The second stage of Cervero et al.’s impedance allocation occurs at intersections. This approach creates buffers of varying sizes around intersections in order to transfer the LTS attributes of the poorest standard link in an intersection to the buffer length of other links in the intersection [53]. The rationale behind this is to transfer some of the traffic stress involved in crossing an intersection onto the links in the intersection with lower traffic stress. The largest buffer of 25 m corresponds to links with the highest traffic stress, LTS4. Thus, if a quiet bicycle path (LTS1) intersects an LTS4 road, 25 m of its length nearest the intersection is replaced by an LTS4 standard link, thereby receiving an increased impedance when the link impedance factor is applied as described earlier. Whilst Cervero et al. use unevenly distributed buffer sizes of 0, 10, 15, and 25 m for the LTS categories 1 to 4 respectively, this paper uses evenly distributed buffer sizes of 0, 8.33, 16.67, and 25 m (for the same LTS categories). The even distribution of buffer sizes (between 0 and a maximum of 25 m) extends the principle used in the link allocation stage and ensures that all four BLOS methods receive the appropriate share of intersection impedance.



In this paper, the multiple buffers are converted into an additional ‘penalty length’ measured in metres to be added to all links that cross a higher level of traffic stress link. The maximum penalty length is the additional length added to a link of the highest standard which crosses one of the lowest standards (such as LTS1 with LTS4) and is described by Equation (2) below. Using a length rather than multiple concentric buffers simplifies the GIS requirements of intersection impedance allocation (especially since BSL has five rather than four levels whilst BCI and HCM6 have six levels each). The penalty length is allocated to links at intersections using 10-centimetre radius buffers. Such small buffers are used to avoid issues with closely spaced intersections, including intersections of bicycle paths with roads [54].

$$\text{Penalty length}_{max} = (\text{Impedance factor}) \cdot (\text{virtual buffer length}) - (\text{virtual buffer length}) \quad (2)$$

Table 3 below displays impedance factors (for link length multiplication) in column 2 and maximum penalty length (for links entering intersections) in column 4 for the LTS method based on a sample maximum detour rate of 15%. The same principle applies for the three other BLOS methods. The maximum penalty length applies only to LTS1 links (since they have no impedance from the link impedance allocation). For other links which cross a link of higher LTS, the penalty length applied is reduced. For example, at the intersection of an LTS2 and LTS3 link, the penalty length applied to the LTS2 link would be equal to the difference in maximum penalty lengths, i.e.,  $1.67 - 0.42 = 1.25$  m (using the sample numbers from Table 3). The LTS3 link in this example is the link with the highest level of traffic stress and will therefore receive no additional penalty length, in the same manner as the original method from Cervero et al. [53].

**Table 3.** Lookup table for maximum additional ‘penalty length’ at intersections in the bicycle network with different Levels of Traffic Stress. The impedance factor in the second column is multiplied with link lengths in addition to give a ‘perceived link length’. Similar tables can be made for the BCI, BSL and HCM6 methods.

LTS Level	Impedance Factor for Links (for Max Detour Rate of 15%)	Virtual Buffer Length (in Metres)	Maximum Penalty Length (in Metres)
1 (best)	1	0	0
2	1.05	8.33	0.42
3	1.10	16.67	1.67
4 (worst)	1.15	25	3.75

The only difference in replicating Table 3 above for the other BLOS methods is the number of rows (equal to the number of classification categories in the method). Both the impedance factor and the virtual buffer length are evenly distributed into (up the max impedance factor defined by the max detour rate and to 25 m for virtual buffer lengths).

The additional lengths or travel distances generated by this approach means that a shortest path search on the network will be less likely to make use of links with poor quality (such as those with LTS4). This paper replicates the approach outlined above for all four BLOS methods in order to generate route choices that take account of bicycle infrastructure quality, described in greater detail below.

### 3.5. Detour Rate

Empirical data on detour rates does exist however and is reported and calculated in many ways. A route choice model from Portland, USA that found that cyclists perceived distance to be 16% shorter on bicycle paths compared to regular routes, all else being equal [55]. This is equivalent to a willingness to cycle 19% longer for a commuting journey if they are able to use a bicycle path for the whole journey:  $1/(1 - 0.16) = 1.19$ . Other literature from Ohio uncovered a mean detour rate of 13.5% [56]. A small sample of 50 cyclists in Indiana was found to have a similar detour rate of 13% [57]. A Brazilian study of the same size found that cyclists travelled on average 14.6% longer than the

shortest path [58]. One smartphone application used in Bologna found a mean detour rate of 14% from 4272 bicycle commuting journeys, which the authors claim are generally more direct than other journeys made by bike [59]. Aultman-Hall performed a study using recalled hand-drawn route choices from 397 participants in Ontario, Canada and found that individuals were willing to divert 0.4 km from the shortest path for trips that averaged 3.7 km (i.e., 10.8% detour) [60].

Although many of these values for detour rates are similar, arriving at a maximum acceptable detour rate is troublesome due to heterogeneity of users, contexts and approaches, as indicated by the wide range of means starting from 6% [61] and up to as much as 67% [62].

Norwegian cyclist route behaviour is very appropriate for the consideration of detour rates due to the hilly topography and urban form common to many Norwegian cities. Hulleberg et al. found that for 721 GPS users in Oslo, a mean detour rate of 21% was observed whilst the median was approximately 12% longer than the shortest path [63]. This study demonstrates how skewed the distribution of detours from the shortest path can be. Since most literature suggests that cyclists are not willing to cycle more than 50% longer than the shortest path, this was used as an upper limit for the iteration of the detour rate. This corresponds with impedance factor intervals of 0.05, this meant that 11 iterations were performed between 1.00 and 1.50. The intention of this procedure was to create multiple optimal routes which can subsequently be checked for association with the empirical route choice data.

The maximum impedance factor of 1.15 used in Table 3 is not empirically founded, and is used to demonstrate the procedure for calculating penalty length [53]. The impedance factor to be multiplied with link length is shown for Level of Traffic Stress in Table 4 below as a function of the 11 detour rates. For links intersecting other links with lower BLOS standard, a second table is required to summarise the additional ‘penalty length’ (in metres) for each detour rate iteration. An example for application to LTS is shown in Table 5, which extends on the principles explained in Table 3 and Section 3.4. All possible combinations of links with a higher standard intersecting those with a lower standard are shown in this table, whilst the original figures from Table 3 and the 15% detour rate are marked with asterisks. Tables 3–5 are used for illustration purposes for LTS, but they have also been created for BCI, BSL, and HCM6 in order to produce the results presented in this paper.

**Table 4.** Level of Traffic Stress link impedance factors (to multiply with length) to create the ‘perceived link length’.

LTS level	Detour Rate (Percentage Additional Length)										
	0	5	10	15	20	25	30	35	40	45	50
1 (best)	1	1	1	1	1	1	1	1	1	1	1
2	1	1.02	1.03	1.05	1.07	1.08	1.10	1.12	1.13	1.15	1.17
3	1	1.03	1.07	1.10	1.13	1.17	1.20	1.23	1.27	1.30	1.33
4 (worst)	1	1.05	1.10	1.15	1.20	1.25	1.30	1.35	1.40	1.45	1.50

**Table 5.** Level of Traffic Stress penalty length (in metres) for all links at intersections (applies to all network links with LTS lower than the maximum LTS in the intersection). The asterisks indicate the connection with the final column in Table 3.

LTS <sub>link</sub> to LTS <sub>max</sub>	Detour Rate (Percentage Additional Length)										
	0	5	10	15 *	20	25	30	35	40	45	50
1 to 2	0	0.14	0.28	0.42 *	0.56	0.69	0.83	0.97	1.11	1.25	1.39
1 to 3	0	0.56	1.11	1.67 *	2.22	2.78	3.33	3.89	4.44	5.00	5.56
1 to 4	0	1.25	2.50	3.75 *	5.00	6.25	7.50	8.75	10.00	11.25	12.50
2 to 3	0	0.42	0.83	1.25	1.67	2.08	2.50	2.92	3.33	3.75	4.17
2 to 4	0	1.11	2.22	3.33	4.44	5.56	6.67	7.78	8.89	10.00	11.11
3 to 4	0	0.69	1.39	2.08	2.78	3.47	4.17	4.86	5.56	6.25	6.94

### 3.6. Route Choice Generation and Evaluation with Empirical Data

The procedure detailed below was used to generate routes using the four BLOS methods described in Section 2 and subsequently assess their association with empirical map-matched route choices.

1. Collect necessary transport and land use GIS parameters in the area of interest from existing data sources (see Table 2) or field data.
2. Combine the necessary parameters to produce the BLOS index value for each link in the transport network area using GIS attribute tables.
3. Create a range of plausible detour rates and corresponding impedance factors (for different BLOS levels) from the shortest path (e.g., 0 to 50% in this paper). See example in Table 4 for LTS.
4. Create a new parameter for each link ‘perceived link length’ by multiplying the link length with the impedance factors from step 3.
5. Create a new parameter ‘perceived intersection length’ for intersections with three or more links and variability in BLOS amongst links (see lookup example in Table 5 for LTS).
6. Combine the two components for each link to produce a new parameter ‘perceived length’. This is the sum of ‘perceived link length’ and the relevant ‘perceived intersection length’ lookup value for cases in which the link intersects another link with a lower (poorer standard) BLOS.
7. Calculate a new parameter ‘perceived travel time’ using ‘perceived length’ and the underlying topography (in this study, performed using Network Analyst in ArcGIS). For this paper, travel time is dependent on cycling speed which is a direct function of link gradient the Norwegian Area and Transport Planning (ATP) model. The ATP model is an ArcGIS extension which performs a variety of functions and includes a simple speed model for different gradients. On slopes with a gradient of  $-10\%$  or more (downhill), a maximum speed of 40 kph is used. Similarly, above 8% gradient (uphill), a constant speed of 3 kph is used. On level ground, cyclists are assumed to cycle at 16 kph. Speed is linearly decreased as the gradient increases from 0 to 8% and is linearly increased when the (downhill) gradient approaches  $-10\%$  (from 0% gradient). Note that the original link gradient is assumed to apply to the ‘perceived length’.
8. Now, for each OD pair and detour combination, find the optimal route which minimises the perceived travel time (these are hereafter called generated routes). Since there are 11 different detour rates iterated in this example, each OD pair will have 11 (not necessarily unique) generated routes.
9. For each OD pair, find the degree of overlap between the empirical map-matched routes and the generated routes. Since there are very few empirical routes that use the entirety of the generated route, we can measure instead the number of cyclists on each link of the shortest path to give a ‘length-weighted’ number of cyclists on a generated route according to the numbers of cyclists found to use its component links. This is described using the notation in step 10.
10. Say that there are  $n$  unique generated routes of interest  $R_1, \dots, R_n$ . For each  $j \in \{1, \dots, n\}$  we have  $m_j$  links, and the lengths of these links are denoted by  $L_{1,j}, L_{2,j}, \dots, L_{m_j,j}$ . The total length of the  $j$ th route would then be  $L_{tot,j} = \sum_{i=1}^{m_j} L_{i,j}$ . Now let  $C_i$  be the number of cyclists recorded on link  $i$ . Then the number of ‘weighted cyclists’ (denoted by  $W_i$ ) on link  $i$  within route  $j$  is therefore  $W_{i,j} = C_{i,j} \frac{L_{i,j}}{L_{tot,j}}$ . The percentage of cyclists on a specific generated route is then the sum of weighted cyclists along that route’s component links divided by the total number of participant-drawn routes (which we know from Section 3.3 to be 467) as given by Equation (3)

$$\text{Percentage cyclists using generated route } R_j = \frac{\sum_{i=1}^{m_j} \left( C_{i,j} \frac{L_{i,j}}{L_{tot,j}} \right)}{467} \quad (3)$$

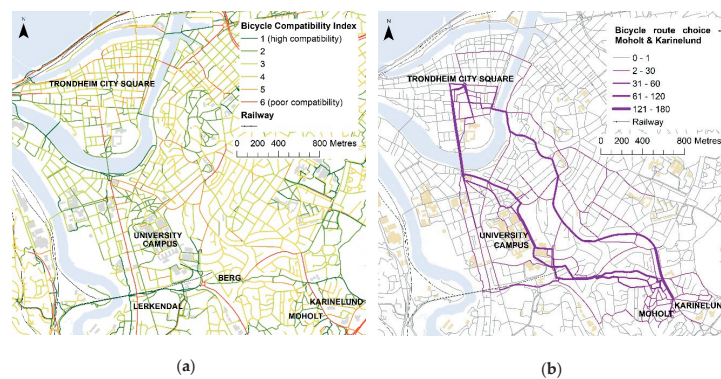
11. Plot the percentage cyclists on each generated route  $R_j$  against the iterated detour rates (on the x-axis. The optimal value (highest percentage match on the y-axis) provides an empirical indicator

of willingness to deviate from the shortest path to use high-quality infrastructure (in terms of bicycle suitability in relation to surrounding options).

## 4. Results

### 4.1. BLOS Map Creation and Empirical Route Choices

The intention of the study was to assess the suitability of BLOS methods for the creation of realistic bicycle route choices. Following the procedure outlined in steps 1 and 2 of Section 3.6, four BLOS maps were produced for each of the different methods: BCI, BSL, HCM6, and LTS. In Figure 2a below, the map of the Bicycle Compatibility Index in the study area is shown, and similar maps were created for the three other BLOS methods. In Figure 2b, the empirical routes for the two student residences Moholt and Karinelund are shown, which represent three of the five OD pairs since the largest student village was subsequently split into Moholt North and Moholt South. The paper then attempts to uncover whether there is an association between each BLOS method and the empirical route choices by following the steps 3 to 10 from Section 3.6.

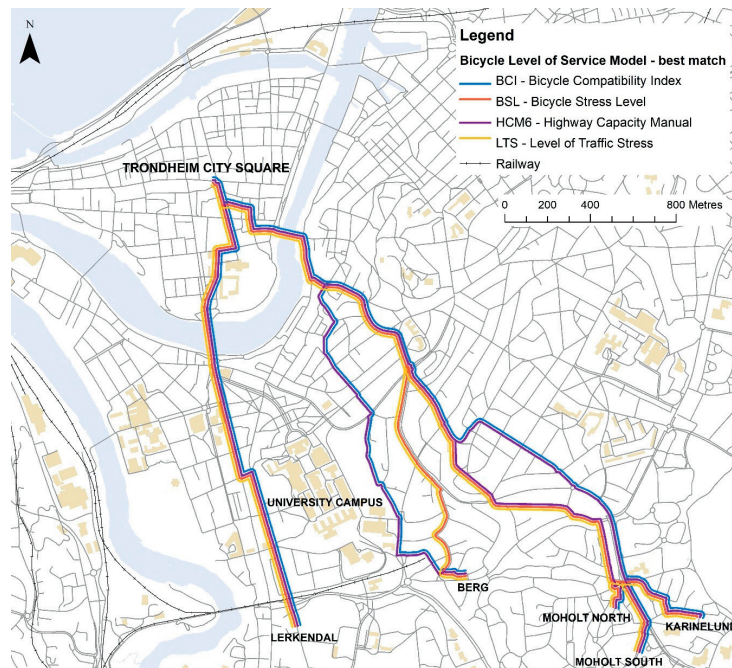


**Figure 2.** (a) Bicycle Compatibility Index for Trondheim. (b) Heat map of the student route preferences from the student villages Moholt ( $n_{north} = 140$ ,  $n_{south} = 100$ ) and Karinelund ( $n = 57$ ).

### 4.2. Route Generation

By subsequently iterating the level of impedance allocated to links based on their BLOS, it was possible to generate a variety of ‘shortest path’ routes. With 4 BLOS methods, 5 OD pairs, and 11 iterations of detour rate, this meant that 220 routes were generated in total. Despite the relatively large range of detour rates trialled (0–50%), the variation in routes generated was relatively small. With only 23 unique generated routes from 220 iteration runs, the effect of the iteration steps was lower than expected. Each OD pair had between 2 and 6 unique routes generated by the alternative approaches. The maximum percentage difference in length between any generated routes on a single OD pair was 4.3% (for Moholt North).

The quality of the route generation approach was determined by taking the average percentage overlap between empirical routes and the generated route. For each combination of four BLOS methods and five OD pairs, the route with the highest overlap with empirical routes is selected, giving a total of 20 best-generated routes. These are displayed in Figure 3 below. Immediately apparent is the high degree of coincident routes generated. For example, from the westernmost student residence Lerkendal, all of the routes generated have the same ‘best’ route. For this example, the generated route overlaps with on average 52% of the empirical routes (see step 9, Section 3.6). For the four other OD pairs, a larger variety of empirical route choices is observed, and the percentage overlap is therefore also lower (Berg: 16%, Moholt North: 20%, Moholt South: 28% and Karinelund: 24%).



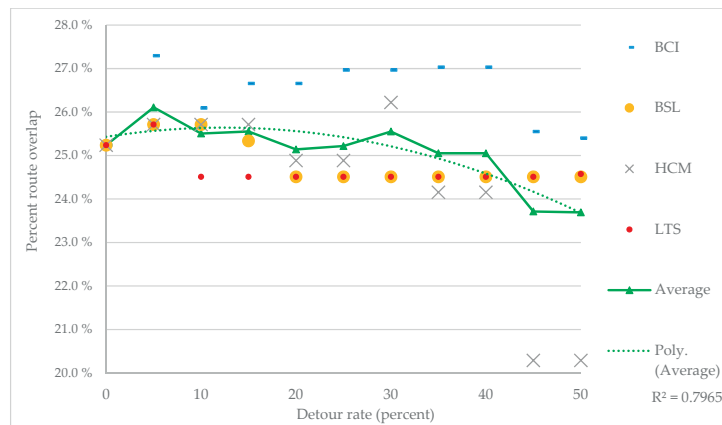
**Figure 3.** Best routes generated (across all iterations of detour rate) along five OD pairs using four BLOS methods.

#### 4.3. BLOS Model Comparison

The four BLOS models' performance is compared by percentage route overlap with the empirical route choice data in Figure 4 below. The plotted data is the average percentage overlap from each of the five origin–destination pairs (which each have a minimum of 50 route preference responses). The figure shows relatively similar performance between the methods, despite the different BLOS method inputs, with route overlap for the alternative approaches ranging between 20 and 27% across the full range of detour rates. This suggests that the importance of the shortest travel time may be more dominant than the effect of the different levels of service, which is supported by the low degree of generated route variety in Figure 3. Alternatively, this may be the result of a significant degree of overlap between simple methods such as BSL with more complex methods like HCM6. The two methods with fewest parameters, BSL and LTS, have identical best route geometry with three and four parameters respectively. The similarity is also reflected by the similarity of the percentage route overlap in Figure 4. BCI and HCM6 each produce 16 route suggestions for the group of 5 OD pairs, whilst LTS and BSL produce only 8 route suggestions.

The method that performs best across all iterations of detour rate is BCI, with eight explanatory parameters. Trends in relation to detour rate are not immediately obvious, and therefore the average of the four methods is depicted in green together with a line of best fit. The line of best fit shows a local maximum for detour rate of approximately 15%. The tendency for a global maximum to form around this value is expected given empirical research on detour rates (see Section 3.5), but this trend is not as clearly evident in the individual BLOS methods, lending some uncertainty as to whether this finding is significant.





**Figure 4.** Percentage route overlap between empirical and generated routes for four BLOS models. The line of best fit is indicated by the dashed line.

An alternative means by which the detour rates can be compared is considering the mean level of detour needed for each method and OD pair combination to achieve the best match with empirical data. For Moholt North, the best match is achieved by BCI, for Moholt South, Berg, and Karinelund, both BCI and HCM6 produce the same best match result, whilst for Lerkendal, all methods produce the same best match route. The average detour rate of these 11 best match results across the 5 OD pairs is 21% (additional length). This figure is also within the range expected by the existing empirical research on detour rates.

## 5. Discussion

This paper seeks to establish how well BLOS methods, which are used to provide letter-grade or numeric ratings for all streets in the city network, can reflect actual route preferences. To the authors' knowledge, this is the first 'reverse engineering' of BLOS indicators in the academic literature using OD route choice data. BCI performs the best of the four methods across all iterations of detour rate, achieving the highest percentage overlap with empirical routes. HCM6 performs equally as well for four of the five OD pairs, and together with BCI has the most explanatory factors. Both HCM6 and BCI have factor coefficients that are empirically determined. The two remaining methods, BSL and LTS, have only three and four explanatory factors respectively and equation coefficients that are not based on the empirical evidence potentially explaining the lower percentage match with the empirical route preferences.

The comparison of generated routes with empirical routes gave a considerably different percentage overlap for the Lerkendal student residence compared to the three other student residences. Variation between different OD pairs in terms of percentage overlap is a natural function of variability in actual route choices (assuming the methods work equally well in different network configurations). It is also shown that the two best-performing BLOS methods, BCI and HCM6, also produce double as many routes compared to BSL and LTS. The greater number of routes generated increases the chances of achieving a higher match. It should be noted however that route choice generation algorithms should ideally create the fewest false positives possible whilst also covering the breadth of empirically chosen route options [42].

Two different approaches were used to compare the BLOS methods in relation to detour rate. The first approach considers the average performance of all four models for the five OD pairs, with a line of best fit revealing a local maximum for iterated detour rate of between 10 and 15%. The second approach takes the average iterated detour rate of the 11 equally best matches for each of the five OD pairs is 21% (additional length). These figures show the optimum detour rate used in achieving

the best match with empirical data. Whilst empirical research on detour rates suggests that cyclists are willing to travel approximately 15% longer compared to the shortest path, the route generation process does not create routes with this level of detour. Indeed, the maximum difference in length for generated routes on any OD pair was 4.3%. This small difference is surprising given that the maximum detour rate of 50% was used for all BLOS models.

There are several factors that could explain this discrepancy. The perceived travel time of any given link is increased by the value of the detour rate only if it has the lowest level of service for the corresponding BLOS model. If the link has anything greater than the lowest level of service, the detour rate applied is reduced, as detailed in Table 4. Since the network has few links with the lowest BLOS, the effective maximum change in detour rate of 50% is only applied to these select links. Another explanatory factor relates to the way impedance values are added at intersections; by affecting only links crossing those with a lower level of service. This is a simplification of the reality since interactions with crossing traffic will occur even if travelling on the link least suited for cycling or when entering an intersection where all links have the same BLOS value. Future research may seek to explore the penalty lengths that should be applied to links in intersections with equal or lower BLOS than other incoming links. Finally, if the shortest path has a relatively high BLOS (high quality), then alternatives are less likely to be created since this paper finds the optimum cycling route, based on BLOS weighted travel time.

Given that a 50% detour rate in the link penalty approach does not give a 50% longer route compared to the shortest path, future research should modify to the approach used through the consideration of the factors above. Alternatively, much higher detour rates than 50% could be trialled for generation of additional routes provided it is understood that this detour rate does not reflect the typical additional detour length of routes generated.

The low route variation in the modelling process adopted is not uncommon in reviews of the route generation literature [64,65]. In order to generate a route choice set which better reflects the typical range of bicycle route choices, there are a number of alternative approaches that can be used such as labelling, stochastic methods, link elimination, and link penalty as summarised by Ton et al. [42]. This study's route choice generation is a form of link penalty, in which multiple attributes are combined through the adoption of existing BLOS methods and used to allocate link impedance or cost. The assumption is that BLOS methods combine attributes considered important to users and that this therefore should reflect the likelihood of selection. The assumption is supported by empirical data which suggests that cyclists tend to choose routes that optimise the combination of distance, time, and safety but not any one objective singularly [66].

The objective BLOS methods tested are based upon bicyclists' route preferences in the US context. Whether or not contextual differences are important is difficult to assess since no non-US BLOS methods were tested. Future research may seek to use other methods for the purposes of contextual comparison such as the Danish model of BLOS from Jensen, which represents a considerably different cycling environment [38].

## 6. Conclusions

The methodology adopted in this paper demonstrates that BLOS methods are able to assist in the generate of bicycle route choices, but that the number of unique routes generated is low. The iterated impedance factor demonstrates a tendency to develop optimal routes at between 15 and 21%, however the overall match rate is lower than expected (<30% match when averaging across the five OD pairs). This is partly because the iteration of the multiplicative impedance factor (between 1.0 and 1.5) used in this paper does not lead to an equivalent variation in the length of generated routes. Given that the maximum difference in length between any two routes on a single OD pair was less than 5%, the maximum impedance factor should be increased if the intention is to generate routes that are up to 50% longer than the shortest path. In addition to modifications of the detour approach, future research may seek to use alternative BLOS methods, or make comparisons with alternative route generation

approaches including commonly used internet mapping applications. Wayfinding literature, in which route choices tend to be preferred if they reduce navigational complexity, may also be considered by future research [67].

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## References

1. Macmillan, A.; Connor, J.; Witten, K.; Kearns, R.; Rees, D.; Woodward, A. The Societal Costs and Benefits of Commuter Bicycling: Simulating the Effects of Specific Policies Using System Dynamics Modeling. *Environ. Heal. Perspect.* **2014**, *122*, 335–344. [CrossRef] [PubMed]
2. Harms, L.; Bertolini, L.; Brömmelstroet, M.T. Spatial and social variations in cycling patterns in a mature cycling country exploring differences and trends. *J. Transp. Heal.* **2014**, *1*, 232–242. [CrossRef]
3. Ewing, R.; Cervero, R. Travel and the Built Environment. A Meta-Analysis. *J. Am. Plan. Assoc.* **2010**, *76*, 265–294. [CrossRef]
4. Piatkowski, D.P.; Marshall, W.E.; Krizek, K.J. Carrots versus Sticks: Assessing Intervention Effectiveness and Implementation Challenges for Active Transport. *J. Plan. Educ. Res.* **2019**, *39*, 50–64. [CrossRef]
5. Næss, P.; Andersen, J.; Nicolaisen, M.S.; Strand, A. Transport modeling in the context of the 'predict and provide' paradigm. *Eur. J. Transp. Infrastruct. Res.* **2014**, *14*, 102–121.
6. Madsen, T. Transport cycling behavior: Associations between the built environment and transport cycling in Denmark. Ph.D. Thesis, University of Southern Denmark, Odense, Denmark, 2013. Available online: [https://findresearcher.sdu.dk:8443/ws/files/88330090/PhD\\_thesis\\_tryk\\_Thomas\\_Madsen\\_final.pdf](https://findresearcher.sdu.dk:8443/ws/files/88330090/PhD_thesis_tryk_Thomas_Madsen_final.pdf) (accessed on 20 May 2019).
7. Callister, D.; Lowry, M. Tools and Strategies for Wide-Scale Bicycle Level-of-Service Analysis. *J. Urban Plan. Dev.* **2013**, *139*, 250–257. [CrossRef]
8. Dowling, R.; Reinke, D.; Flannery, A.; Ryus, P.; Vandehey, M.; Petritsch, T.; Landis, B.; Roupail, N.; Bonneson, J. *Multimodal Level of Service for Urban Streets*; NCHRP Report 616; Transportation Research Board: Washington, DC, USA, 2008.
9. Main Roads Western Australia Guidelines for Assessing Cycling Level of Service. Perth, Australia, 2006. Available online: [https://www.mainroads.wa.gov.au/Documents/los\\_guidelines\\_cycling.RCN-D06%5E2347971.PDF](https://www.mainroads.wa.gov.au/Documents/los_guidelines_cycling.RCN-D06%5E2347971.PDF) (accessed on 20 May 2019).
10. Landis, B.W.; Vattikuti, V.R.; Brannick, M.T. Real-Time Human Perceptions: Toward a Bicycle Level of Service. *Transp. Res. Rec. J. Transp. Res. Board* **1997**, *1578*, 119–126. [CrossRef]
11. Nielsen, T.A.S.; Skov-Petersen, H. Bikeability—Urban structures supporting cycling. Effects of local, urban and regional scale urban form factors on cycling from home and workplace locations in Denmark. *J. Transp. Geogr.* **2018**, *69*, 36–44. [CrossRef]
12. Winters, M.; Brauer, M.; Setton, E.M.; Teschke, K. Mapping bikeability: A spatial tool to support sustainable travel. *Environ. Plan. B Plan. Des.* **2013**, *40*, 865–883. [CrossRef]
13. Krenn, P.J.; Oja, P.; Titze, S. Development of a Bikeability Index to Assess the Bicycle-Friendliness of Urban Environments. *Open J. Civ. Eng.* **2015**, *5*, 451–459. [CrossRef]
14. Lowry, M.B.; Callister, D.; Gresham, M.; Moore, B. Assessment of Communitywide Bikeability with Bicycle Level of Service. *Transp. Res. Rec. J. Transp. Res. Board* **2012**, *2314*, 41–48. [CrossRef]
15. Moudon, A.V.; Lee, C. Walking and Bicycling: An Evaluation of Environmental Audit Instruments. *Am. J. Heal. Promot.* **2003**, *18*, 21–37. [CrossRef]
16. Asadi-Shekari, Z.; Moeinaddini, M.; Shah, M.Z. Non-motorised Level of Service: Addressing Challenges in Pedestrian and Bicycle Level of Service. *Transp. Rev.* **2013**, *33*, 166–194. [CrossRef]



17. Parks, J.; Tanaka, A.; Ryus, P.; Monsere, C.M.; McNeil, N.; Goodno, M. Assessment of Three Alternative Bicycle Infrastructure Quality-of-Service Metrics. *Transp. Res. Rec. J. Transp. Res. Board* **2013**, *2387*, 56–65. [[CrossRef](#)]
18. Jensen, S.U. Pedestrian and Bicycle Level of Service at Intersections, Roundabouts, and Other Crossings. In Proceedings of the 92nd Annual Meeting of the Transportation Research Board, Washington, DC, USA, 13–17 January 2013; pp. 1–19.
19. Botma, H. Method to Determine Level of Service for Bicycle Paths and Pedestrian-Bicycle Paths. *Transp. Res. Rec. J. Transp. Res. Board* **1995**.
20. Kang, K.; Lee, K. Development of a bicycle level of service model from the user's perspective. *KSCE J. Civ. Eng.* **2012**, *16*, 1032–1039. [[CrossRef](#)]
21. Petritsch, T.A.; Ozkul, S.; McLeod, P.; Landis, B.; McLeod, D. Quantifying Bicyclists' Perceptions of Shared-Use Paths Adjacent to the Roadway. *Transp. Res. Rec. J. Transp. Res. Board* **2010**, *2198*, 124–132. [[CrossRef](#)]
22. Jones, E.G.; Carlson, T.D. Development of Bicycle Compatibility Index for Rural Roads in Nebraska. *Transp. Res. Rec. J. Transp. Res. Board* **2003**, *1828*, 124–132. [[CrossRef](#)]
23. Noël, N.; Leclerc, C.; Lee-Gosselin, M. CRC index: Compatibility of Roads for Cyclists in Rural and Urban Fringe Areas. In Proceedings of the 82nd Annual Meeting of the Transportation Research Board, Washington, DC, USA, 12–16 January 2003; pp. 1–20.
24. Petritsch, T.A.; Landis, B.W.; Huang, H.F.; McLeod, P.S.; Lamb, D.; Farah, W.; Guttenplan, M. Bicycle Level of Service for Arterials. *Transp. Res. Rec. J. Transp. Res. Board* **2007**, *2031*, 34–42. [[CrossRef](#)]
25. Foster, N.; Monsere, C.M.; Dill, J.; Clifton, K. Level-of-Service Model for Protected Bike Lanes. *Transp. Res. Rec. J. Transp. Res. Board* **2015**, *2520*, 90–99. [[CrossRef](#)]
26. Bai, L.; Liu, P.; Chan, C.-Y.; Li, Z. Estimating level of service of mid-block bicycle lanes considering mixed traffic flow. *Transp. Res. Part A Policy Pract.* **2017**, *101*, 203–217. [[CrossRef](#)]
27. Beynon, R.; Golding-Williams, K.; Jones, P.; Mayo, A.; Russell, T.; Peck, C.; Thomas, C. Design Guidance: Active Travel (Wales) Act 2013. 2014. Available online: <https://gov.wales/sites/default/files/publications/2017-09/active-travel-design-guidance.pdf> (accessed on 20 May 2019).
28. Transport for London. London Cycling Design Standards Consultation Draft—Tools and Techniques. 2014. Available online: [https://consultations.tfl.gov.uk/cycling/draft-london-cycling-design-standards/user\\_uploads/draft-lcdds---all-chapters.pdf](https://consultations.tfl.gov.uk/cycling/draft-london-cycling-design-standards/user_uploads/draft-lcdds---all-chapters.pdf) (accessed on 20 May 2019).
29. Dixon, L. Bicycle and Pedestrian Level-of-Service Performance Measures and Standards for Congestion Management Systems. *Transp. Res. Rec. J. Transp. Res. Board* **1996**, *1538*, 1–9. [[CrossRef](#)]
30. Zhang, Y.; Brussel, M.; van den Bosch, F.; Grigolon, A.; Van Maarseveen, M. A GIS based Bicycle Level of Service route model. In Proceedings of the 13th International Conference on Design & Decision Support Systems in Architecture and Urban Planning, Eindhoven, The Netherlands, 27–28 June 2016.
31. Mekuria, M.; Furth, P.; Nixon, H. MTI Report 11-19. Low-Stress Bicycling and Network Connectivity. Mineta Transportation Institute 2012. Available online: <http://transweb.sjsu.edu/sites/default/files/1005-low-stress-bicycling-network-connectivity.pdf> (accessed on 20 May 2019).
32. Majumdar, B.B.; Mitra, S. Development of Level of Service Criteria for Evaluation of Bicycle Suitability. *J. Urban Plan. Dev.* **2018**, *144*, 04018012. [[CrossRef](#)]
33. Epperson, B. Evaluating Suitability of Roadways for Bicycle Use: Toward a Cycling Level-of-Service Standard. *Transp. Res. Rec. J. Transp. Res. Board* **1994**, *1438*, 9–16.
34. Sorton, A.; Walsh, T. Bicycle Stress Level As a Tool To Evaluate Urban and Suburban Bicycle Compatibility. *Transp. Res. Rec. J. Transp. Res. Board* **1994**, *1438*, 17–24.
35. Landis, B.W. Bicycle Interaction Hazard Score: a Theoretical Model. *Transp. Res. Rec. J. Transp. Res. Board* **1994**, *1438*, 3–8.
36. Turner, S.M.; Shafer, C.S.; Stewart, W.P. Bicycle suitability criteria for state roadways in Texas. Research report TX-97/3988-S; 1997. Available online: [http://rosap.ntl.bts.gov/view/dot/33867/dot\\_33867\\_DS1.pdf](http://rosap.ntl.bts.gov/view/dot/33867/dot_33867_DS1.pdf) (accessed on 20 May 2019).
37. Harkey, D.L.; Reinfurt, D.W.; Knuiman, M. Development of the Bicycle Compatibility Index. *Transp. Res. Rec. J. Transp. Res. Board* **1998**, *1636*, 13–20. [[CrossRef](#)]
38. Jensen, S.U. Pedestrian and Bicyclist Level of Service on Roadway Segments. *Transp. Res. Rec. J. Transp. Res. Board* **2007**, *2031*, 43–51. [[CrossRef](#)]

39. Transportation Research Board Chapter 18 Urban Street Segments. In *Highway Capacity Manual: A Guide for Multimodal Mobility Analysis*; Transportation Research Board of the National Academies: Washington, DC, USA, 2016; ISBN 978-0-309-44148-3.
40. Furth, P.G.; Putta, T.V.; Moser, P. Measuring low-stress connectivity in terms of bike-accessible jobs and potential bike-to-work trips: A case study evaluating alternative bike route alignments in northern Delaware. *J. Transp. Land Use* **2018**, *11*, 815–831. [[CrossRef](#)]
41. Beura, S.K.; Manusha, V.L.; Chellapilla, H.; Bhuyan, P.K. Defining Bicycle Levels of Service Criteria Using Levenberg–Marquardt and Self-organizing Map Algorithms. *Transp. Dev. Econ.* **2018**, *4*, 11. [[CrossRef](#)]
42. Ton, D.; Duives, D.; Cats, O.; Hoogendoorn, S. Evaluating a data-driven approach for choice set identification using GPS bicycle route choice data from Amsterdam. *Travel Behav. Soc.* **2018**, *13*, 105–117. [[CrossRef](#)]
43. Broach, J.; Gliebe, J.; Dill, J. Calibrated Labeling Method for Generating Bicyclist Route Choice Sets Incorporating Unbiased Attribute Variation. *Transp. Res. Rec. J. Transp. Res. Board* **2010**, *2197*, 89–97. [[CrossRef](#)]
44. Transportation Research Board Chapter 17 Urban Street Segments. In *Highway Capacity Manual 2010*; Transportation Research Board of the National Academies: Washington, DC, USA, 2010; ISBN 978-0-309-16077-3.
45. Furth, P.G.; Mekuria, M.C.; Nixon, H. Network Connectivity and Low-Stress Bicycling. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2587*, 41–49. [[CrossRef](#)]
46. *CROW Design Manual for Bicycle Traffic*; Centre for Research and Contract Standardization in Civil and Traffic Engineering C.R.O.W: Ede, The Netherlands, 2016; ISBN 978 90 6628 494 4.
47. Dill, J.; McNeil, N. Four Types of Cyclists? *Transp. Res. Rec. J. Transp. Res. Board* **2013**, *2387*, 129–138. [[CrossRef](#)]
48. Geller, R. *Four Types of Cyclists*; Portland Office of Transportation: Portland, OR, USA, 2009.
49. Envall, P. Accessibility Planning: a chimera? Ph.D. Thesis, University of Leeds, Leeds, UK, 2007. Available online: <http://etheses.whiterose.ac.uk/id/eprint/11279> (accessed on 20 May 2019).
50. Stigell, E. Assessment of active commuting behavior: Walking and bicycling in Greater Stockholm. Ph.D. Thesis, Örebro University, Örebro, Sweden, 2011. Available online: <http://urn.kb.se/resolve?urn=urn:nbn:se:oru:diva-16372> (accessed on 20 May 2019).
51. Pritchard, R. Revealed Preference Methods for Studying Bicycle Route Choice—A Systematic Review. *Int. J. Environ. Res. Public Health* **2018**, *15*, 470. [[CrossRef](#)]
52. Snizek, B.; Nielsen, T.A.S.; Skov-Petersen, H. Mapping bicyclists' experiences in Copenhagen. *J. Transp. Geogr.* **2013**, *30*, 227–233. [[CrossRef](#)]
53. Cervero, R.; Denman, S.; Jin, Y. Network design, built and natural environments, and bicycle commuting: Evidence from British cities and towns. *Transport Policy* **2019**, *74*, 153–164. [[CrossRef](#)]
54. Pritchard, R.; Frøyen, Y. Location, location, relocation: How the relocation of offices from suburbs to the inner city impacts commuting on foot and by bike. *Eur. Transp. Res. Rev.* **2019**, *11*, 14. [[CrossRef](#)]
55. Broach, J.; Dill, J.; Gliebe, J. Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transp. Res. Part A Policy Pract.* **2012**, *46*, 1730–1740. [[CrossRef](#)]
56. Park, Y.; Akar, G. Why do bicyclists take detours? A multilevel regression model using smartphone GPS data. *J. Transp. Geogr.* **2019**, *74*, 191–200. [[CrossRef](#)]
57. Kang, L.; Fricker, J.D. Bicycle-Route Choice Model Incorporating Distance and Perceived Risk. *J. Urban Plan. Dev.* **2018**, *144*, 04018041. [[CrossRef](#)]
58. Segadilha, A.B.P.; da Penha Sanches, S. Analysis of Bicycle Commuter Routes Using GPSs and GIS. *Procedia Soc. Behav. Sci.* **2014**, *162*, 198–207. [[CrossRef](#)]
59. Rupi, F.; Schweizer, J. Evaluating cyclist patterns using GPS data from smartphones. *IET Intell. Transp. Syst.* **2018**, *12*, 279–285. [[CrossRef](#)]
60. Aultman-Hall, L.; Hall, F.L.; Baetz, B.B. Analysis of Bicycle Commuter Routes Using Geographic Information Systems: Implications for Bicycle Planning. *Transp. Res. Rec. J. Transp. Res. Board* **1997**, *1578*, 102–110. [[CrossRef](#)]
61. Hyodo, T.; Suzuki, N.; Takahashi, K. Modeling of Bicycle Route and Destination Choice Behavior for Bicycle Road Network Plan. *Transp. Res. Rec. J. Transp. Res. Board* **2000**, *1705*, 70–76. [[CrossRef](#)]
62. Krizek, K.J.; El-Geneidy, A.; Thompson, K. A detailed analysis of how an urban trail system affects cyclists' travel. *Transportation* **2007**, *34*, 611–624. [[CrossRef](#)]

63. Hulleberg, N.; Flügel, S.; Ævarsson, G. *TØI Report 1648/2018. Vekter for Sykkelinfrastruktur til bruk ved Rutevalg i Regionale Transportmodeller [Empirical Based Infrastructure Weights for Bicycle Route Choice]*; Institute of Transport Economics: Oslo, Norway, 2018; ISBN 9788248021650.
64. Prato, C.G. Route choice modeling: past, present and future research directions. *J. Choice Model.* **2009**, *2*, 65–100. [[CrossRef](#)]
65. Bovy, P.H.L. On Modelling Route Choice Sets in Transportation Networks: A Synthesis. *Transp. Rev.* **2009**, *29*, 43–68. [[CrossRef](#)]
66. Howard, C.; Burns, E.K.; Information, R. Cycling to Work in Phoenix: Route Choice, Travel Behavior, and Commuter Characteristics. *Transp. Res. Rec. J. Transp. Res. Board* **2001**, *1773*, 39–46. [[CrossRef](#)]
67. Dijkstra, J.; De Vries, B.; Jessurun, J. Wayfinding Search Strategies and Matching Familiarity in the Built Environment through Virtual Navigation. *Transp. Res. Procedia* **2014**, *2*, 141–148. [[CrossRef](#)]



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## Paper IV

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Article

# Trialing a Road Lane to Bicycle Path Redesign—Changes in Travel Behavior with a Focus on Users' Route and Mode Choice

Miroslav Vasilev <sup>1,\*</sup>, Ray Pritchard <sup>2</sup> and Thomas Jonsson <sup>1</sup>

<sup>1</sup> Department of Civil and Environmental Engineering, Faculty of Engineering, NTNU—Norwegian University of Science and Technology, 7491 Trondheim, Norway; thomas.jonsson@ntnu.no

<sup>2</sup> Department of Architecture and Planning, Faculty of Architecture and Design, NTNU—Norwegian University of Science and Technology, 7491 Trondheim, Norway; raymond.pritchard@ntnu.no

\* Correspondence: miroslav.vasilev@ntnu.no

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**Abstract:** Redistribution of space from private motorized vehicles to sustainable modes of transport is gaining popularity as an approach to alleviate transport problems in many cities around the world. This article investigates the impact of a trial Complete Streets project, in which road space is reallocated to bicyclists and pedestrians in Trondheim, Norway. The paper focuses on changes in the travel behavior of users of the street, with a focus on route and mode choice. In total, 719 people responded to a web-based travel survey, which also encompassed an integrated mapping Application Programming Interface (API). Amongst the findings of the survey is that the average length of the trial project that was utilized by cyclists on their most common journey through the neighborhood nearly doubled from 550 m to 929 m ( $p < 0.0005$ ), suggesting that the intervention was highly attractive to bicyclists. Respondents were also asked whether they believe the trial project was positive for the local community, with the majority (87%) being positive or highly positive to the change. The intervention had a considerable impact on users' travel behavior in terms of both frequency and choice of active transportation modes, together with leading to a change in route preferences.

**Keywords:** bicycle; infrastructure; trial project; complete streets; mode choice; route choice; tactical urbanism

## 1. Introduction

With limitations in the space available for transport systems in growing cities, policy makers are increasingly seeking ways to encourage city residents to shift away from private motorized vehicles to more space-efficient public and active transport modes. One approach to facilitate this shift has been the redesign of streets in which space is reallocated from motorized vehicles to other users, an approach frequently referred to as Complete Streets, road diets, or lane reductions. Typically, motorized traffic lanes are substituted by a combination of facilities dedicated to public transport, bicycle users, pedestrians, or green space. Koorey and Lieswyn [1] provide an overview of alternative approaches for providing space to different modes of transport within a street cross-section.

Lane reduction projects are generally accepted as beneficial for traffic safety [2–5], and have few adverse impacts on automobile traffic flow [4,6–9]. On one street in San Francisco, the reduction in the number of traffic lanes from four to two and replacement with marked bicycle lanes was found to reduce car volumes by 10%, with the difference redistributed to parallel arterials [8]. Multiple studies have found that cycling volumes have increased in connection with road diets, which could be expected given the typical increase in space available for dedicated bicycle facilities [8–12]. Complete Streets, unlike road diets and lane reductions, do not necessarily imply that vehicle lanes must be

removed, but that the streetscape is altered for the benefit of all road users, which could include lane narrowing, landscaping, resurfacing, or the substitution of verge space with facilities for active transport [13].

Many studies refer to the effects of protected bicycle lanes or separate bicycle paths, which in urban contexts, often involve a road diet or street redesign, as discussed above. Monsere et al. [14] evaluated on-street protected bicycle lanes in five US cities and found that 10% of the cyclists intercepted on these facilities reported that they had previously used a different mode and 24% had changed their route to use the infrastructure. A similar study from Sydney, Australia, found that 40% of respondents surveyed on a newly implemented bicycle path had switched their transport mode to bicycle because of the facility [15]. The cyclists were found to have made a diversion from the shortest path of 351 m on average to take the bicycle path in use. Public response, not limited to cyclists, towards the redistribution of space from motorized vehicles to bicycles has been found to be generally positive [8,9,11].

In general, the majority of the academic literature reveals that bicyclists are willing to cycle longer on separated bicycle facilities in order to avoid major streets [16–20]. However, some studies find the opposite: one study of commuter cyclists in Guelph, Canada, showed a preference for main streets rather than direct off-road paths [21]. However, this was potentially affected by the presence of stairs on some off-road paths, suggesting that not all paths were designed with bicycles in mind.

In the Norwegian context, an early form of Complete Streets solution involving lane narrowing and streetscape alteration first began to be used in the 1970s to reduce traffic speed on major roads passing through small towns [22]. This involved the reconfiguration of a section of major road into a local street better suited to the local town environment, giving birth to the concept of “environmental streets” (*miljøgater* in Norwegian). However, the term was later adopted for road to street reconfigurations where a bypass road was provided nearby, thereby redistributing most of the through traffic. Environmental street projects are intended to have a site-appropriate design with the aim to: reduce traffic speed/volume, improve conditions for bicyclists and pedestrians, and develop attractive street environments that encourage social interaction [22].

Transport infrastructure interventions that require a change in the prioritization from motorized to mixed traffic often cause controversy amongst different stakeholders. As a result, environmental streets have frequently been implemented as trial projects in Norway since the 1990s. The usage of temporary street reconfigurations makes it possible to test the outcome before a political agreement has been reached concerning permanent reconstruction. In a report from the Norwegian Public Roads Administration (NPRA) where 16 trial environmental streets were evaluated, it was concluded that traffic speeds were reduced, improvements were observed in conditions for vulnerable road users, and the streets had become more pleasant and better suited to their location [23].

This paper focusses on changes in mode and route choice following a street redesign that took place in July 2017 in Trondheim, Norway, in which a separated bi-directional bicycle path replaced two lanes of car traffic. It was hypothesized that the reallocation of space to bicyclists and pedestrians would result in an increase in the number of these users along the trial project due to both modal shift and route substitution of existing trips to use the newly implemented facility.

Section 2 below introduces the case study and the methodology that was applied to collect and analyze data. The results are presented in Section 3, followed by the discussion in Section 4, which looks into the following aspects: mode choice, route choice, policy implications, and limitations. The concluding Section 5 outlines the main findings of the study and places them in a broader context.

## 2. Methodology

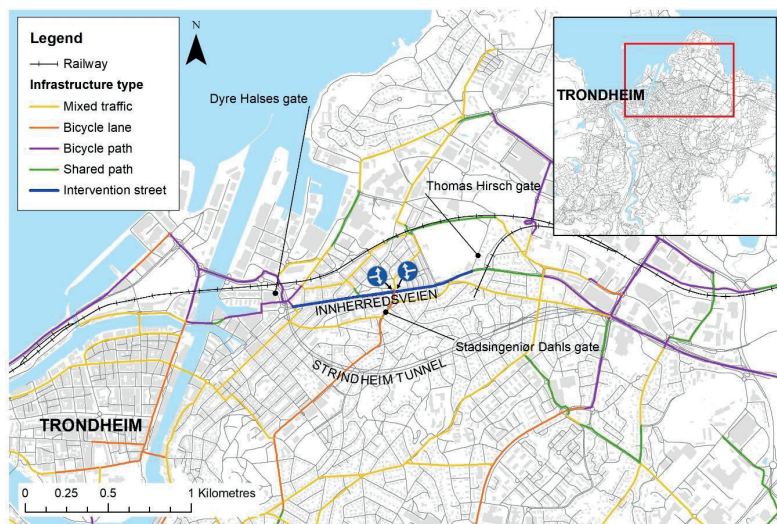
### 2.1. Case Description

The case study location is Trondheim in Norway, the fourth largest metropolitan area in Norway, with a population of 190,000 people [24]. The 2013/2014 National Travel Survey (NTS) shows that



private motorized vehicles are used for 50% of all journeys (8% as passenger), whilst 12% of trips are made by public transport [25]. With a cycling modal share of 9%, Trondheim has one of the highest rates of cycling among the largest Norwegian cities. However, rates vary considerably between summer (12%) and winter (4%) [25]. Relative to other Norwegian cities, the situation for cycling is characterized by reasonable separate infrastructure in a low-density grid outside the city center; however, with a discontinuous inner-city bicycle network [26]. Trips made on foot represent 28% of all journeys in Trondheim, whilst 1% are made by other forms of transport. Although the winters are mild in comparison to other cities at the same latitude (63°N), icy street conditions can typically be expected from late October to mid-April.

A trial Complete Streets project was implemented by the NPRA on a section of Innherredsveien (in blue in Figure 1) in July 2017. Planners intended for the street to continue to be a key corridor for local buses to the east of Trondheim, while at the same time providing a safe and attractive street environment for walking, cycling, street life, and local businesses. The importance of Innherredsveien as the major eastern arterial from the city center to the European E6 highway bypassing Trondheim (connecting the city with the airport) was diminished after the opening of the Strindheim Tunnel (labelled in Figure 1) in 2014. Thus, like some of the earlier environmental streets adopted in Norway in the 1990s, Innherredsveien has a bypass alternative.



**Figure 1.** Location of the trial Complete Streets intervention, bypass tunnel, and existing official bicycle infrastructure network. As part of the intervention, it is forbidden to drive through the marked intersection in the middle of the intervention street.

Pre-intervention, there was no bicycle infrastructure on the section of the street where the trial project was implemented. The physical changes included a reduction in the number of traffic lanes from four to two and the implementation of a 1.8 km bidirectional bicycle path using the freed up road space, starting near to the crossing with Thomas Hirsch gate through to the roundabout with Dyre Halses gate. The project also involved the installation of signage midway along Innherredsveien at the intersection with Stadsingeniør Dahls gate (indicated in Figure 1), prohibiting the use of Innherredsveien for through-traffic. The speed limit was reduced from 50 to 40 km/h along the intervention section.

Two forms of physical separation were used: the installation of temporary concrete traffic barriers (along 35% of the section length) and the painting of wide diagonal stripes (65%) for lateral separation of bicycle and motorized traffic (Figure 2). Pedestrians and cyclists were the major beneficiaries for this reallocated space, but the waiting area for public transport users was also increased greatly on the

northern side of the road (since the two removed lanes were on this side of the road). There are three signalized intersections and one unsignalized intersection along the intervention stretch. On one of the intersections, the first traffic lights in Trondheim dedicated specifically to cyclists were installed.



**Figure 2.** The Complete Streets trial project used two forms of separation: painted horizontal lane markings and concrete barriers [27].

Different street configurations have been debated for Innherredsveien since the bypass tunnel construction commenced and three years following the tunnel's completion, the chosen reconfiguration option was implemented temporarily in order to ensure that it could be reversed. This was due to political disagreement about the project's potential to negatively impact bus travel times and increase car traffic on side streets.

## 2.2. Data Collection

The principal data collection method used in this study is a web-based travel survey encompassing both a questionnaire regarding demographics and transport behavior, together with an integrated mapping Application Programming Interface (API). The survey was built in and hosted by the website EmotionalMaps.eu. Technical information on the API and data collection approach can be found in a separate study [28]. It was a specific requirement for this paper that the geographic data collected through the API could be connected to the individuals' responses via a unique user ID.

The mapping part of the survey allowed the respondents to draw routes that they most commonly traversed and mark points of interest/concern before and after July 2017 when the infrastructural intervention occurred. This allowed the participants to reflect upon their experiences prior to the change, around one year earlier, with their stabilized post-intervention transport behavior. The questionnaire part of the survey included questions on users' demographics, most common travel behavior, use of the street, perceived safety concerns, opinion of the trial project, and feedback on alternative permanent solutions for the street.

To the authors' knowledge, a participant-recalled route choice approach using web-based/digitally drawn routes has not previously been applied to before-and-after evaluations of bicycle infrastructure interventions. In a review [29], Pritchard explored the available revealed preference methods for studying bicycle route choice, and found only two studies where a web-based mapping approach was used to study bicycle route selection [30,31]. However, neither study applied this methodology for the evaluation of bicycle infrastructure interventions.

The survey was intended for people who had used the street both before and after the changes were made. Recruitment was targeted towards residents in the neighborhood surrounding the intervention street through the distribution of 5000 flyers containing a link to the online survey in June



2018. Approximately 2000 of these flyers were distributed manually to easily accessible mailboxes, cyclists, and pedestrians in the intervention area, businesses, parked cars at a nearby shopping center, and a school. The remaining 3000 were delivered by the Norwegian postal and delivery company Bring to addresses with less accessible mailboxes (particularly apartments).

Alternative forms of recruitment included distribution via various social media websites connected to the area of interest, together with the intranet of the nearby university college.

The initiative's impacts on traffic were evaluated on behalf of the NPRA who commissioned the project, through the collection of information on motorized traffic volumes, average running speeds for public transport on the street, manual observations, and video footage of cyclist and pedestrian activity. A report of the findings was prepared by the consultancy Rambøll [32], without the involvement of the authors of the current study.

### 2.3. Analysis

#### 2.3.1. Geographic Information Systems (GIS)

A type of revealed preference methodology called participant-recalled route choice was employed, where participants of the survey were instructed to draw the route through the neighborhood that they used most often both before and after Innherredsveien was reconfigured [29]. These routes were subsequently filtered such that only one route per user per time period (before and after) was included. In cases where participants drew multiple routes, the route closest to the intervention was retained for analysis. Routes with a poor spatial quality that could not be reliably matched to the street network were filtered out. This procedure meant that 606 routes drawn by 385 respondents remained for map-matching. Map-matching was performed in ArcMAP 10.6 by creating a 50 m buffer around the selected original routes and executing a shortest path search from origin to destination on the transport network contained within the buffer. The transport network available was dependent on the mode of transport (such that cyclists could not be routed along the road tunnel for instance).

The route choice changes were only considered for a subset of participants who drew a satisfactory route in both time periods (211 panel respondents). The total length traversed by every route along the 1.8 km intervention section of Innherredsveien was then calculated. This allows an approximation of the change in route choice due to the trial project by comparing the intervention length utilized in the two periods.

#### 2.3.2. Statistical Tests

A binary logistic regression model was run to ascertain the effects of users' characteristics on whether they increased their frequency of cycling. It included gender, occupation, mode before, purpose before, and time of day as predictor variables.

Paired-samples t-tests were run to consider whether the distance travelled on Innherredsveien by the bicyclists during their most usual trip significantly increased after the trial project was implemented. A cumulative odds ordinal logistic regression with proportional odds was run to determine the effect of respondents' occupation and transport mode used before the intervention on their agreement with the statement that the project has been positive for the neighborhood (from "Strongly disagree" to "Strongly agree" in a Likert scale style manner). However, the assumption of proportional odds was violated, as assessed by a full likelihood ratio test comparing the fit of the proportional odds model to a model with varying location parameters  $\chi^2(20) = 44.541$ ,  $p = 0.001$ . Therefore, the responses to this question were rearranged in two alternatives ("Agree" and "Disagree") so that a binary logistic regression model could be applied instead.

Chi-square tests were used to test whether there is a difference in the distribution of the explanatory variables used in the logistic regression models. The same test was also applied to find out whether the change in the distribution of the mode of the most usual trip was statistically significantly different.

The statistical models were run using IBM SPSS Statistics version 25 [33].

### 3. Results

#### 3.1. Overview

In total, 719 people who have used Innherredsveien after the trial project was implemented responded to the electronic survey during the period it was available online—from the 11th of June to the 15th of August, 2018. The descriptive statistics for the sample are shown in Table 1. It can be seen that more than half of the respondents are male and the majority of them are employed (76.8%). It should be mentioned that the survey sample is not representative of the population of Trondheim. For instance, whilst over 40% of the sample stated that their most usual journeys pre-intervention were made by bicycle, trip-level National Travel Survey (NTS) data from 2014 suggests that only 11.1% of the trips that either started or ended in the basic statistical unit areas adjacent to the intervention were made by bicycle ( $n = 396$  trips) [25]. This percentage is only indicative, however, as the trips reported in the NTS concern all trip purposes, while the current study asked respondents about their most usual trip in the vicinity of the trial project. The age variable was categorized in this way in order to achieve statistically significant differences between the sub-groups of cyclists who increased their frequency of cycling in the after period and the sample population of respondents. More about these categories and the increase in cycling can be found in Table 2.

**Table 1.** Descriptive statistics for the survey sample.

Variable	Category	Frequency	%
Gender	Male	415	57.7
	Female	304	42.3
	Total	719	100
Age	≤29	243	33
	30–34	123	17
	35–54	274	39
	≥55	79	11
	Total	719	100
Occupation	Employed	552	76.8
	Student	116	16.1
	Non-employed	50	7
	Total	718	100
Mode of most usual trip “before”	Walking	144	20.9
	Cycling	287	41.6
	Public transport	147	21.3
	Car/Motorcycle/Moped	112	16.2
	Total	690	100
Mode of most usual trip “after”	Walking	155	22.5
	Cycling	369	53.5
	Public transport	96	13.9
	Car/Motorcycle/Moped	70	10.1
	Total	690	100
Purpose of most usual trip “before”	Work	300	43.5
	School	64	9.3
	Personal	326	47.2
	Total	690	100
Purpose of most usual trip “after”	Work	341	49.4
	School	44	6.4
	Personal	305	44.2
	Total	690	100

### 3.2. Mode Choice

Data for the mode choice of the most usual trip on the trial project both before and after the intervention was available for 690 (96%) of the 719 respondents, as the remaining respondents had not used the street prior to the intervention. Survey respondents were asked to report on the mode they used for their most usual trips in the vicinity of Innherredsveien before and after the implementation of the trial project. Cycling was found to be the most common mode pre-implementation (41.6%), followed by public transport users (21.3%) and pedestrians (20.9%), whilst motorists (including a very small number of motorcycle users) represented 16.2% of the sample (Figure 3). In the after period, the dominance of cycling increased to 53.5%, whilst the use of motorized modes of transport decreased to 10.1%. The distribution of the modes used for the most usual trip before the implementation was found to be significantly different from the distribution post-intervention using a chi-square test ( $p = 0.0014$ ).

Figure 3 visualizes the modal shifts (again for the most common trip made in the neighborhood) for the sample population ( $n = 690$ ). The four largest modal changes (each over four percent of the sample population) are public transport to bicycle (6.7%), motorized modes to bicycle (4.5%), public transport to walking (4.3%), and walking to bicycle (4.2%). Figure 3 also visualizes the mode loyalty, or the retention rate of the different modes of transport users, with cyclists' being highest (92% of existing cyclists continued cycling post-intervention), followed by pedestrians (66%), car/motorcycle users (51%), and public transport users (44%). It should be noted that the numbers are only indicative of mode share changes of the street.

Amongst the 690 respondents for whom mode information was available, 15.4% (106) reported that they had changed the mode of their most usual trip to cycling. Of these 106 users, 29.2% (31) had previously used a motorized vehicle, 43.3% (46) had used transit, and 27.4% (29) walked for their most usual trip.

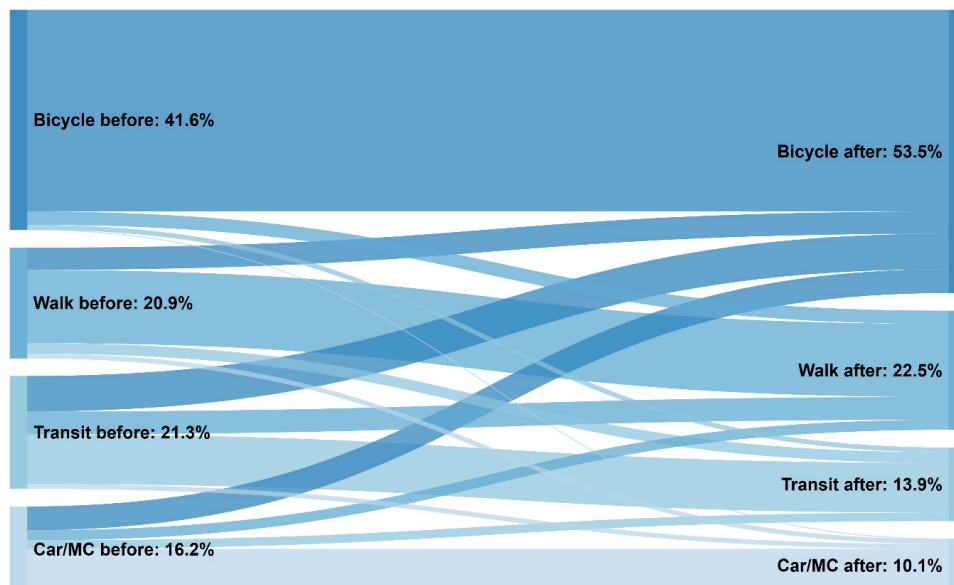


Figure 3. Sankey diagram showing the modal share of survey participants before and after the Complete Streets reconfiguration of Innherredsveien ( $n = 690$ ).

It is worth mentioning that before the intervention took place, there was no bicycle infrastructure on the section of the street where the trial project was implemented, and amongst the 231 cyclists who used Innherredsveien, 65% (151) used the sidewalk, whilst 35% (80) had been cycling on the street.

Amongst all 719 respondents, 577 (80.3%) stated that they use either a normal or a pedal-electric bicycle at least once a month during the warmer half of the year. These respondents were asked about the extent to which their frequency of cycling has been influenced by the implementation of the trial infrastructure project. A total of 272 respondents or 37.8% of the sample increased their frequency of cycling, whilst those who reported a decrease in their frequency of cycling made up only 1.4% of the sample (10). Ten out of the 272 respondents who have increased their frequency of cycling (or 1.4% of all survey respondents) stated that they began to use a bicycle as a direct result of the trial project.

The changes observed amongst survey respondents were also reflected in increases in recorded bicycle traffic volume collected in connection with the NPRA evaluation report. In the report, camera-recorded traffic counts revealed that the number of bicycles had increased at all three observed intersections. From east to west, each intersection's peak hour bicycle volumes (averaged from two hours traffic counting in both the morning and afternoon on two successive days) increased by 95% (592 to 1154), 103% (584 to 1184), and 122% (390 to 866), respectively, from June to September 2017 [32].

A logistic regression model was run, with the intent to estimate the effects of users' characteristics on their frequency of cycling. The model fitted the data poorly and could not explain the variation of the dependent variable (cycling frequency) using the chosen independent variables. No improvement in the overall percentage of predicted cases was found in the classification tables generated with and without the use of the dependent variables by SPSS.

Table 2 presents the proportion of road users who have increased their cycling frequency, split according to demographic attributes, so that more can be understood about the predictive power of these variables.

**Table 2.** Share of road users who have increased their cycling frequency according to demographic characteristics.

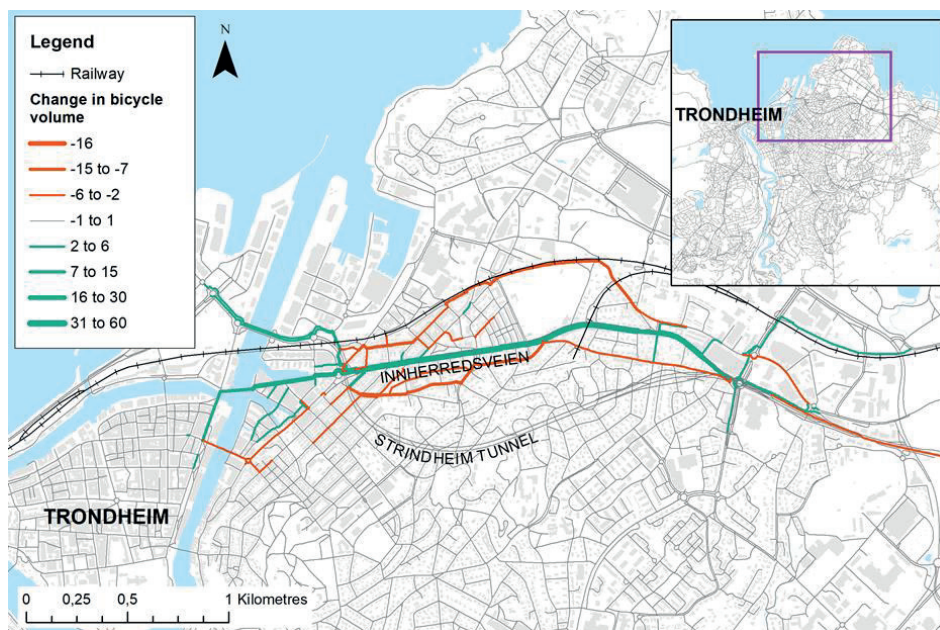
Occupation	Increased	%	Total
Employed	210	39.2%	536
Student	43	41.3%	104
Non-employed	10	20.0%	50
Age	Increased	%	Total
≤29	94	41.6%	226
30–34	55	46.2%	119
35–54	97	36.2%	268
≥55	17	21.8%	78
Gender	Increased	%	Total
Men	146	36.4%	401
Women	117	40.3%	290
Purpose before	Increased	%	Total
Work	105	34.9%	301
School	30	46.9%	64
Personal	128	39.3%	326
Mode	Increased	%	Total
Walking	47	32.6%	144
Cycling	120	41.8%	287
Public	57	38.8%	147
Motorized	39	34.8%	112

Chi-square tests were used to determine whether the proportions of people in different strata who have increased their frequency of cycling are significantly different from the sample population of respondents. A statistically significant difference in the proportions was only found for the variable “Age” ( $p = 0.037$ ).

### 3.3. Route Choice

Of the 211 panel participants who drew (at least) two acceptable routes, 88 used a bicycle in both time periods. There were no outliers in the differences between the intervention length utilized, as assessed by the inspection of a boxplot for values greater than 1.5 box-lengths from the edge of the box. The difference scores were not normally distributed, as assessed by Shapiro-Wilk’s test ( $p = 0.000$ ). However, according to the Central Limit Theorem [34], the mean is normally distributed considering the size of the sample ( $n = 88$  bicycle users) and therefore a paired-samples t-test could be applied. It was found that bicyclists utilized significantly more of the trial project section of Innherredsveien in the after period (mean = 929 m; standard deviation = 470 m) compared to the before period (mean = 550; standard deviation = 555 m). The change in the mean length of intervention utilized was 379 m (95% CI, 242 to 517 m), which was statistically significant,  $t(87) = 5.489$ ,  $p < 0.0005$ ,  $d = 0.59$ .

In Figure 4 below, all of the bicycle journeys (a subset of the aforementioned 211 participants’ routes) drawn in both time periods are displayed as the change in the number of trips per street segment before and after the intervention. An increase following the intervention is depicted in green, whilst a decrease is shown in red. Thus, the map illustrates both the modal change to cycling and route substitution from nearby streets (the reduction in the use of parallel alternative routes to Innherredsveien). This map was only prepared for bicycle users due to the small sample size of other user groups (from the subset of 211 ‘panel’ participants who drew two usable routes).



**Figure 4.** Map showing the change in numbers of bicycle trips on each street segment made by the route choice panel respondents ( $n = 211$ ).

For walking journeys, 32 participants drew valid routes for their most usual trip on or in the vicinity to the trial project in both periods. The average pedestrian utilization of the intervention

section was 441 m, while the corresponding average distance during the after period was 550 m. However, due to the non-normality of the data and the small sample size, the difference between them cannot be assessed for statistical significance.

In the evaluation report, it was concluded that 16% (1500 vehicles/day) of the pre-intervention motorized traffic flow (9500 vehicles/day) has shifted from Innherredsveien to the Strindheim tunnel, while 500 vehicles/day have transferred to other routes. However, it has been found that 800 vehicles/day do not conform to the signage midway along the intervention banning through-traffic, illustrated in Figure 1 [32].

#### 3.4. Attitude

Respondents were asked whether they agree that the trial project has been positive for the neighborhood in terms of noise, safety, air quality, and attractiveness of the urban space. It was found that 87% (627) of the respondents agreed with this statement.

A binary logistic regression model was run, using data for the collected variables to try to explain how the variables affected the participants' attitude towards the project. The binary logistic regression model fitted the data poorly and the explanatory variables could not explain the variation in the users' attitude towards the success of the trial project.

To explore reasons for the poor fit of the model, a further comparison was made between the group of respondents who were positive towards the project, and the total group. Table 3 presents the results of this comparison.

**Table 3.** The share of road users who reacted positively to the intervention.

<b>Occupation</b>	<b>Agree</b>	<b>%</b>	<b>Total</b>
Employed	472	88.1%	536
Student	93	89.4%	104
Non-employed	39	78.0%	50
<b>Age</b>	<b>Agree</b>	<b>%</b>	<b>Total</b>
≤29	198	87.6%	226
30–34	114	95.8%	119
35–54	234	87.3%	268
≥55	58	74.4%	78
<b>Gender</b>	<b>Agree</b>	<b>%</b>	<b>Total</b>
Men	347	86.5%	401
Women	257	88.6%	290
<b>Purpose before</b>	<b>Agree</b>	<b>%</b>	<b>Total</b>
Work	267	88.7%	301
School	57	89.1%	64
Personal	280	85.9%	326
<b>Mode</b>	<b>Agree</b>	<b>%</b>	<b>Total</b>
Walking	135	93.8%	144
Cycling	260	90.6%	287
Public	126	85.7%	147
Motorized	83	74.1%	112

Chi-square tests were used to determine whether the proportions of respondents in different strata who agree that the trial project has been positive for the neighborhood are significantly different from the population as a whole. A statistically significant difference in the proportions was not found within the categories of any of the variables, which explains why the model did not explain the variation. Those respondents with a positive attitude towards the project do not seem to differ much demographically from the respondents in general.



#### 4. Discussion

The main goal of this study was to investigate the changes in travel behavior following the implementation of a trial project, involving the reallocation of street space to vulnerable road users on an arterial street in Trondheim, Norway. The principal data collection method used in this study was a web-based survey, soliciting responses from users of the street and residents living in the area of the infrastructural intervention. The results indicated an increase in the frequency of cycling and a route choice shift to the intervention section. However, limited relationships were established between the user characteristics and the change in their travel behavior.

##### 4.1. Mode Choice

It was hypothesized that the reallocation of space to bicyclists would result in an increase in the number of cyclists along the trial project. In the evaluation report commissioned by the Norwegian Public Roads Administration, it was found that the number of cyclists had increased by between 95 and 120% [32]. However, it should be noted that the pre-intervention counts were performed in June, during the university students' summer vacation, which could have negatively impacted cycling volumes given that roughly 20% of Trondheim's population consists of students.

The survey conducted by the authors was launched around a year after the changes took place, a time period that allowed people to adapt to the new infrastructure so that they could be asked about possible mode and route choice changes. Having this information allowed us to get more in-depth insights into the reasons for the increase in bicycle usage. However, it should be noted that long-term impacts can continue to change even after one year. In the British iConnect study, which evaluated the impacts of new active transport infrastructure, living in proximity of the intervention had been related to changes in activity levels only after the second year, but not at the one-year follow-up [35]. Future research could consider reasons for changes in the long-term use patterns.

One of the possible explanations for the observed increase in bicycle volumes is that some of the users of the street changed their transport mode to bicycling. The respondents were asked for the mode they had used for their most usual trip on or in the vicinity of Innherredsveien. It was found that 106 respondents or 29% of the 369 who used a bicycle in the after period had been previously using a different mode. This corroborates the findings from Standen et al. [15] from Sydney, Australia, where 40% of the cyclists riding on the path had been previously using a different transport mode.

Nearly half (43.4% (46)) of those respondents who switched to cycling had previously been using public transport, which is again similar to the results from Standen et al. [15], where 59% of the intercepted cyclists reported that they had used public transport prior to the intervention. However positive the increase in cycling is, the shift from transit to bicycle use is not the primary intention of the intervention, as it does not contribute to limiting car use, a principal goal for cities in the Norwegian National Transport Plan [36].

In addition to the public transport to bicycle modal shift, Section 3.2 reveals three other modal shifts comprising over 4% of the sample population: private cars to bicycle (4.5%), public transport to walking (4.3%), and walking to bicycle (4.2%). A clear indication of the intervention's success in terms of cycling is that it has attracted substantial numbers of users from all other modes; however, the intervention can also be seen to improve walking conditions, since there are also substantial numbers of users switching from public transport to walking. This could be explained by the freeing up of space on the relatively narrow footpath on the north side of Innherredsveien after cyclists received their own bicycle path. Public transport is the mode that contributes most to the growth of both walking and cycling. Transport mode loyalty or mode retention rate is the percentage of a transport mode's users who continue to use the same mode following the intervention. This is visualized in Figure 3, in which cyclists are observed to have the highest retention rate before and after intervention (92%), followed by pedestrians (66%), car/motorcycle users (51%), and public transport users (44%).

An insight into these findings was provided by Börjesson and Eliasson [16] in a study related to the cost-benefit analysis of cycling investments. The cross-elasticity between car and bicycle use in Sweden was estimated to be low in an indirect way. A stated preference experiment was conducted where the respondents had to choose between bicycle and their second-best mode. It was found that public transport was the alternative for 87% of the respondents, whilst car was the preferred second option for the remaining 13%. Börjesson and Eliasson [16] concluded that amongst transport users who may shift their mode to cycling as a result of bicycle infrastructure improvements, only 10–15% of them would have previously used a car. However, it was noted that their conclusions are context specific, as Stockholm, where the study was performed, has a well-functioning public transport system.

Evidence of the low cross-elasticity between car and bicycle use was also provided by Song et al. [37], who investigated the modal shift resulting from bicycle infrastructure implementation in three cities in the UK using a quasi-experiment panel study. They found that about 20% of the respondents had switched from driving to active transport modes, but also that a similar percentage had done the inverse shift.

Van Goeverden [38] reviewed studies that had assessed bicycle infrastructural interventions in the Netherlands and Denmark. One of the aspects that was considered was mode choice, for which seven studies that had used travel behavior surveys were found and summarized. The results indicated that the shifts from driving to cycling had been minimal. Van Goeverden et al. [38] noted that in some of the referenced studies from Denmark, the changes from public transport were significantly larger than the shift from car-use. These findings collaborate the results about mode shift from the current study.

It has also been of interest to find out whether the improved cycling conditions may have had an impact on users' overall frequency of cycling. Only ten respondents or 1.4% of the sample reported to have decreased their cycling frequency, whilst 37.8% (272) reported an increase, 41% (295) had not changed frequency, and the remainder used a bicycle less than once per month in the after period and were therefore not asked this question. The large number of respondents that reported an increase in their overall cycling frequency (47% of those who had received the question) corroborates findings from a similar study in the USA. The US study evaluated eight newly implemented protected bicycle lanes, with nearly half (49%) of the respondents reporting an increase in personal cycling frequency along the protected bicycle lanes, whilst nearly a quarter (24%) reported an increase in their overall frequency of cycling as a result of the protected lanes [14].

The survey also reveals that 10 respondents amongst those 272 who reported an increase in cycling frequency (or 1.4% of the total sample) had begun using a bicycle as a direct result of the trial project. This finding is significantly lower than the aforementioned protected bicycle lane study, in which the proportion of users who began cycling after the interventions ranged from 6 to 21% across the eight examined locations in the USA (10% on average) [14]. Different contextual conditions for cycling in Norway and the USA could explain some of this variation, as cycling rates in Norway are generally higher (8% versus 1% of all trips nationally) and the provision of bicycle infrastructure is more commonplace [25,39].

The fact that the model using the demographic variables given in Table 2 could not predict the increase in the frequency of cycling of the respondents can be explained by the lack of a significant difference between the sample's demographic subsets compared to the population as a whole. As mentioned in Section 3.2, the only significant difference found was for the variable "age" ( $p = 0.037$ ). This suggests that young people (less than 34 years of age) exhibit a significantly higher propensity to increase their frequency of cycling in response to the street redesign than the older respondents.

The high reported increase in cycling and low variation in change of cycling frequency across the sample's different demographic groups can be indicative of a trial project that appeals equally to all users. In other words, women and men exhibit approximately equal propensity to increase their frequency of cycling after an implementation of this kind of infrastructure. This result differs from what was reported by Standen et al. [15] for Sydney, Australia, where commuters who had changed mode to cycling in response to the opening of a separated bicycle path were more likely to be female.



Similar conclusions were made in a study that used survey data from the evaluation of protected bicycle lanes in five cities in the USA [40]. Dill et al. [40] concluded that female cyclists have a greater propensity to increase their overall cycling frequency because of protected bicycle infrastructure. The discrepancy between the findings of the current study and those from the USA and Australia may again be explained by contextual differences between Norway and those countries. Utility cycling is more male-dominated in the USA (75% male) and Australia (79%), whilst in Scandinavian countries, it is nearly equal, with males making 56% of cycling journeys in Norway [25,39].

#### 4.2. Route Choice

A possible reason for the observed increase in bicycle volumes on Innherredsveien is that existing cyclists decided to change their route so that they could use the trial section. To test this hypothesis, survey respondents were asked to draw the route they had used for their most usual trip on or near Innherredsveien both before and after the street intervention. The length of the trial project section of Innherredsveien that was utilized by the participants before and after the changes were implemented was one means to approximately quantify the route choice changes. Participants who increased their utilization of the street post-intervention can be thought of as being attracted to the intervention. This was expected of cyclists who previously rode on alternative streets or without bicycle infrastructure in Innherredsveien and had now received a separated bicycle path. The opposite applies for those who decreased their utilization of the intervention (which could be expected for car users who now are forbidden from driving the full length of the street).

The significant increase in mean distance that bicyclists were riding on the trial section (379 m; 95% CI, 242 to 517 m) is indicative of an attraction to the Complete Streets initiative amongst cyclists. This supports findings from existing literature, in which between 24 to 48% of bicyclists have been found to change their routes to use the newly implemented bicycle infrastructure [14,15].

The change in bicycle route choice is illustrated in Figure 4, in which it is apparent that the intervention street Innherredsveien greatly increases in popularity amongst cyclists at the expense of neighbouring parallel streets. The parallel streets are mostly part of the existing bicycle network shown in Figure 1 and witness a decrease in usage (depicted in red). This change in route choice preference, also called route substitution, is a major contributing factor to the increase in volumes in the trial project. Figure 4 illustrates all bicycle journeys from the two time periods made by the panel respondents. Therefore, those cyclists who used a different mode earlier have only one route depicted in the figure. Thus, the overall increase in cycling is also illustrated to some degree in Figure 4 through the larger number of bicycle trips made post-implementation, which is represented by generally thicker lines in green than red (although this is not the primary intention). Given the clear impact the intervention has had on the route choice of existing bicycle users, it is recommended that intervention section traffic counts alone are not used to assess the impacts on bicycle mode choice (as was done in NPRA's evaluation report). Should a traffic counting approach be used, parallel streets should always be considered at a minimum to gauge the extent to which route substitution is present [20,41–43]. It is therefore recommended that traffic counts on an intervention street should not be used to assess the impacts on mode choice, given route choice is clearly shown to be affected as well.

The provision of high quality infrastructure on major arterials to the city center is important as it offers cyclists a more direct and faster route, while at the same time improving their perceived feeling of safety. Interventions like this project that deliver improved connectivity are likely to be of more value to users than projects which only improve isolated road segments. By offering a holistic bicycle network with minimal discontinuities, users with a lower tolerance for traffic interaction are empowered to switch to cycling.

Regarding the route choice of motorized vehicles, the evaluation report concludes that 16% of the former motorized traffic (9500 vehicles/day in total) has shifted from Innherredsveien to the Strindheim tunnel, which is a desired consequence of the project [32]. This substitution of route assists in the minimization of congestion, something that is especially important for buses, for which the street

is a key corridor. The tunnel was built in 2014 specifically to relieve the intervention street of traffic issues, and the change could therefore have been made upon the tunnel's opening. The availability of bypass alternatives is an important prerequisite for the implementation of road restrictions in central urban areas, such as the Complete Streets solution investigated in this study. However, the report also notes that 500 vehicles/day or 5% of the former traffic volume (9500 vehicles/day) have transferred to streets other than the bypass tunnel, potentially due to having a destination not well connected by the tunnel following the through-traffic closure. In San Francisco, the replacement of two out of four traffic lanes with marked bicycle lanes was found to reduce car volumes by 10%, with the difference redistributed to parallel arterials [8]. Sallaberry did not, however, investigate whether a mode shift had occurred [8].

Despite the total decrease in motorized volume, it has been found that 800 vehicles/day did not conform to the prohibition [32], something which could be regulated by the authorities in order to reduce traffic volumes to the extent intended.

Considering that participants could only draw one route and one mode for each time period, the mapped data in Figure 4 only reflects the primary mode and route for transport through the neighborhood. Shorter or less frequent journeys made by participants are thus not well represented by the collected data, and the low numbers of routes drawn with sufficient quality for mapping (from 211 of 719 participants) in both time periods limited the analysis scope.

#### 4.3. Policy Implications

The policy implications of the study are related to the outcomes of planning process issues, the detected mode shift changes, and the public approval of the project.

Concerns have been expressed by various stakeholders during the political planning process. For instance, the public transportation authority was concerned that the reduction in the number of traffic lanes in Innherredsveien would result in a reduced capacity and therefore unnecessary delays for public transport. There have also been disagreements between city and county politicians concerning the role of the street. Therefore, after over four years of debate, the project was implemented temporarily so that it could be reversed in case it did not deliver the expectations.

The evaluation report revealed that the concerns were not realized as the average travel time for buses had decreased and the motorized traffic on the intervention street had reduced [32]. Motorized traffic was to a large extent shifted to the bypass tunnel as originally intended. At the same time, the trial project provided a considerable improvement in the conditions for vulnerable road users and a resultant significant increase in their numbers.

The survey sample's four largest modal shifts all involved a change in mode to cycling or walking. This mode shift, however, was not ideal from a sustainability perspective as the main contributor to the increase in the bicycle share was shifts from public transport rather than private car users. This suggests that initiatives such as the one presented in this study are not sufficient alone to achieve the sustainability goal of reduced car use. Such a shift away from cars is desirable, however, from an urban planning perspective due to improved public health outcomes, and reduced congestion and local air pollution. At the global scale, a modal shift away from cars contributes to decarbonizing the transportation sector, which is critical given the ever-mounting pressure to act on climate change. Other policy tools are likely needed to achieve a modal shift away from cars, such as the removal of parking places, higher parking fees, road pricing, higher fuel taxes, etc. The challenge remains, however, to achieve a combination of policy measures that are politically acceptable.

As the initial intention of the trial Complete Streets project was to create improved transport conditions and a more attractive street environment for the residents and other users of the street, it was expected that the general public would be generally satisfied with the changes that have taken place. The public response towards similar redistributions of space from motorized vehicles to bicyclists has been found to be generally positive in the US [8,9,11]. The high approval rate of the project amongst survey participants (87%) and positive contribution towards sustainability goals can have

policy implications, such as permanently redesigning the street in favor of vulnerable road users or encouraging other cities to consider similar initiatives.

The temporality of trial projects can be advantageous when political disagreement stops the initiative from being implemented, and has in this case demonstrated for stakeholders that the project did not result in unacceptable disadvantages for any transport modes. This does, however, require the trial project to be sufficiently well planned to ensure that the temporality itself does not adversely affect the traffic outcome and thus poorly represent a future permanent solution. It is, however, an additional cost in terms of time and materials to rebuild a road twice, even if the temporary solution has less impact than the permanent solution (presuming it is built).

#### 4.4. Limitations

It was assumed that the increase in the utilized length of the trial project section of Innherredsveien has been due to cyclists changing their route or mode because of the improved conditions of the street. However, there may have been other reasons for some of the respondents' decision to change their route, such as a change of the most common trip origin or destination.

Another aspect of the current study that can have impacts on the results is that only the most common trips on Innherredsveien were analyzed, while the rest of their journeys were not studied. Future intervention investigations of route and mode choice can look into all the trips that users make in connection with changes in transport infrastructure. Heinen et al. [44] investigated the modal shifts resulting from new bicycle infrastructure in Cambridge (UK) using a four-year quasi-experimental cohort study and found that partial modal shifts were more common than full modal shifts. It is reasonable to assume that people use different modes for their different trips and hence studying only the most usual one does not give complete information about the changes in users' behavior. It should be noted that this study is based on the post-implementation evaluation of a single (and temporarily deployed) Complete Streets project, with its associated contextual factors, and is therefore only indicative of the impacts of this type of trial project. Further evaluations of trial projects are recommended so that a more complete picture of the effects of such projects can be acquired.

It should also be noted that cyclists were overrepresented in the sample, with 65% (468) of the respondents reporting that they use a bicycle at least once a week during the warmer half of the year. Having in mind that the cyclists are one of the major beneficiaries of the street reconfiguration, self-selection bias may have influenced the results of the study. The overrepresentation of cyclists was in part due to the nature of the recruitment process for the survey. Besides the delivery of flyers to households in the area around implementation and the other alternatives mentioned in Section 2.2, the recruitment also included advertisement via a social media interest group for cycling in Trondheim and the manual distribution of flyers to bicyclists using the cycling path.

Respondents were asked to recall details from their travel behavior from a year earlier, before the implementation, which is associated with a poorer accuracy compared to journeys conducted more recently [29]. Had it been known some time in advance of the intervention commencement, a before-and-after cohort or cross-sectional design could have been applied to achieve more accurate responses.

## 5. Conclusions

Using several data sources, it was found that the trial Complete Streets project has resulted in significant changes in users' mode and route choice behavior.

Nearly half of the cyclists increased their frequency of cycling due to the trial project implementation. This corroborates existing research on improvements in the conditions for active transport modes by showing that these types of changes can stimulate people to cycle and walk more. With respect to the findings on the modal shifts to cycling and walking, it can be concluded the observed change is positive, but that more can be achieved in terms of sustainability if the increase in cycling is primarily the result of a decrease in private car trips.

The project's closure to through-traffic was found to have the desired effect on motorized users as part of the pre-intervention traffic flow shifted to the bypass tunnel. The availability of a bypass has contributed to the success of the project by helping to avoid congestion problems and to maintain the bus service in order.

The length of the trial project utilized by cyclists in the after period has increased significantly, suggesting that the redesign of the street was highly attractive to this group of users. This paper demonstrates significant route choice changes by cyclists who substituted their use of other lower standard bicycle network routes nearby with the intervention street's separated bicycle path.

The high approval rate amongst respondents suggests that the project has been successful in satisfying the needs of residents and users. This demonstrated to the various stakeholders that the solution is well-accepted by the public and hence its permanent implementation is justified.

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## References

- Koorey, G.; Lieswyn, J. Making space: Innovative ways to fit multiple modes within narrow cross sections. *Road Transp. Res.* **2016**, *25*, 44–61.
- Mooney, S.J.; Magee, C.; Dang, K.; Leonard, J.C.; Yang, J.; Rivara, F.P.; Ebel, B.E.; Rowhani-Rahbar, A.; Quistberg, D.A. "Complete Streets" and Adult Bicyclist Fatalities: Applying G-Computation to Evaluate an Intervention That Affects the Size of a Population at Risk. *Am. J. Epidemiol.* **2018**, *187*, 2038–2045. [[CrossRef](#)] [[PubMed](#)]
- Thomas, L. White Paper Series Road Diet Conversions: A Synthesis of Safety Research. *Pedestr. Bicycl. Inf. Cent.* **2013**, 1–17.
- Huang, H.; Stewart, J.; Zegeer, C. Evaluation of Lane Reduction "Road Diet" Measures on Crashes and Injuries. *Transp. Res. Rec. J. Transp. Res. Board* **2002**, *1784*, 80–90. [[CrossRef](#)]
- Pawlovich, M.; Li, W.; Carriquiry, A.; Welch, T. Iowa's Experience with Road Diet Measures: Use of Bayesian Approach to Assess Impacts on Crash Frequencies and Crash Rates. *Transp. Res. Rec.* **2006**, *1953*, 163–171. [[CrossRef](#)]
- Elias, A. Automobile-Oriented or Complete Street? *Transp. Res. Rec. J. Transp. Res. Board* **2011**, *2257*, 80–86. [[CrossRef](#)]
- Shu, S.; Quiros, D.C.; Wang, R.; Zhu, Y. Changes of street use and on-road air quality before and after complete street retrofit: An exploratory case study in Santa Monica, California. *Transp. Res. Part D Transp. Environ.* **2014**, *32*, 387–396. [[CrossRef](#)]
- Sallaberry, M. *Valencia Street Bicycle Lanes: A One Year Evaluation*; City of San Francisco Department of Parking and Traffic: San Francisco, CA, USA, 2000.
- Provence, D. 25th Avenue Road Diet Project. A One Year Evaluation. In *Transportation Fund for Clean Air Project 05r07*; San Francisco Municipal Transportation Agency: San Francisco, CA, USA, 2009.
- Gudz, E.M.; Fang, K.; Handy, S.L. When a Diet Prompts a Gain. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2587*, 61–67. [[CrossRef](#)]
- Monsere, C.; McNeil, N.; Dill, J. Evaluation of Innovative Bicycle Facilities: SW Broadway Cycle Track and SW Stark/Oak Street Buffered Bike Lanes. In *Urban Studies and Planning Faculty Publications and Presentations*; Portland State University Library: Portland, OR, USA, 2011.
- City of Seattle Department of Transportation. *Stone Way Rechannelization: Before and After Study*; City of Seattle Department of Transportation: Seattle, WA, USA, 2010.

13. Laplante, J.; McCann, B. Complete streets: We can get there from here. *ITE J. (Inst. Transp. Eng.)* **2008**, *78*, 24–28.
14. Monsere, C.; Dill, J.; McNeil, N.; Clifton, K.; Foster, N.; Goddard, T.; Berkow, M.; Gilpin, J.; Voros, K.; van Hengel, D.; et al. Lessons from the Green Lanes: Evaluating Protected Bike Lanes in the U.S. *Natl. Inst. Transp. Communities* **2014**, NITC-RR-583, 1–179.
15. Standen, C.; Crane, M.; Collins, A.; Greaves, S.; Rissel, C. Determinants of mode and route change following the opening of a new cycleway in Sydney, Australia. *J. Transp. Heal.* **2017**, *4*, 255–266. [[CrossRef](#)]
16. Börjesson, M.; Eliasson, J. The value of time and external benefits in bicycle appraisal. *Transp. Res. Part A Policy Pract.* **2012**, *46*, 673–683. [[CrossRef](#)]
17. Tilahun, N.Y.; Levinson, D.M.; Krizek, K.J. Trails, lanes, or traffic: Valuing bicycle facilities with an adaptive stated preference survey. *Transp. Res. Part A Policy Pract.* **2007**, *41*, 287–301. [[CrossRef](#)]
18. Krenn, P.J.; Oja, P.; Titze, S. Route choices of transport bicyclists: A comparison of actually used and shortest routes. *Int. J. Behav. Nutr. Phys. Act.* **2014**, *11*, 1–7. [[CrossRef](#)] [[PubMed](#)]
19. Dill, J. Bicycling for Transportation and Health: The Role of Infrastructure. *J. Public Health Policy* **2009**, *30* (Suppl. 1), S95–S110. [[CrossRef](#)] [[PubMed](#)]
20. Heesch, K.C.; James, B.; Washington, T.L.; Zuniga, K.; Burke, M. Evaluation of the Veloway 1: A natural experiment of new bicycle infrastructure in Brisbane, Australia. *J. Transp. Health* **2016**, *3*, 366–376. [[CrossRef](#)]
21. Aultman-Hall, L.; Hall, F.; Baetz, B. Analysis of Bicycle Commuter Routes Using Geographic Information Systems: Implications for Bicycle Planning. *Transp. Res. Rec. J. Transp. Res. Board* **1997**, *1578*, 102–110. [[CrossRef](#)]
22. Bølviken, T. Miljøgate 2014—En statusrapport [Environmental street 2014—A status report]. In *Statens Vegvesens Rapporter Nr.346 [Norwegian Public Roads Administration Reports]*; Norwegian Public Roads Administration: Oslo, Norway, 2014.
23. Statens Vegvesen [Norwegian Public Roads Administration]. *Fra Riksveg til Gate—erfaringer fra 16 Miljøgater [From National Highway to Street—Experiences from 16 Environmental Streets]*; Norwegian Public Roads Administration: Oslo, Norway, 2003; ISBN 8272075431.
24. Statistics Norway. Population. Available online: <https://www.ssb.no/en/befolkning/statistikker/folkemengde/aar-berekna> (accessed on 22 November 2018).
25. Hjorthol, R.; Engebretsen, Ø.; Uteng, T.P. *TØI Report 1383/2014. Den Nasjonale Reisevaneundersøkelsen 2013/2014—Nøkkelrapport [2013/14 National Travel Survey—Key Results]*; Institute of Transport Economics: Oslo, Norway, 2014; ISBN 9788248011316.
26. Pokorny, P.; Pritchard, R.; Pitera, K. Conflicts between bikes and trucks in urban areas—A survey of Norwegian cyclists. *Case Stud. Transp. Policy* **2018**, *6*, 147–155. [[CrossRef](#)]
27. Mapillary. Available online: [https://www.mapillary.com/app/?lat=63.4369257441324&lng=10.433829831494483&z=17&focus=photo&menu=false&dateFrom=2017-07-31&pKey=Ho0mq2xFH73byGRs-Gct-g&fbclid=IwAR1RFCUV24\\_oi79xo-qzOGPuZ1blqjpv32k5azZbOfafyvcri8kNW-MQe-o](https://www.mapillary.com/app/?lat=63.4369257441324&lng=10.433829831494483&z=17&focus=photo&menu=false&dateFrom=2017-07-31&pKey=Ho0mq2xFH73byGRs-Gct-g&fbclid=IwAR1RFCUV24_oi79xo-qzOGPuZ1blqjpv32k5azZbOfafyvcri8kNW-MQe-o) (accessed on 22 November 2018).
28. Pánek, J.; Benediktsson, K. Emotional mapping and its participatory potential: Opinions about cycling conditions in Reykjavík, Iceland. *Cities* **2017**, *61*, 65–73. [[CrossRef](#)]
29. Pritchard, R. Revealed Preference Methods for Studying Bicycle Route Choice—A Systematic Review. *Int. J. Environ. Res. Public Health* **2018**, *15*, 470. [[CrossRef](#)]
30. Wang, J.Y.T.; Mirza, L.; Cheung, A.K.L.; Moradi, S. Transforming Auckland into a bicycle-friendly city: Understanding factors influencing choices of cyclists. In *Australasian Transport Research Forum*; Hughes, B., Petkoff, I., Eds.; Australasian Transport Research Forum Incorporated: Perth, Australia, 2012.
31. Snizek, B.; Sick Nielsen, T.A.; Skov-Petersen, H. Mapping bicyclists' experiences in Copenhagen. *J. Transp. Geogr.* **2013**, *30*, 227–233. [[CrossRef](#)]
32. Rambøll AS. *Evaluering av Trafikale Effekter av Prøveprosjektet i Innherredsveien [Evaluation of Traffic Effects of Innherredsveien Trial Project]*; Rambøll AS: Copenhagen, Denmark, 2018.
33. IBM Corp. *IBM SPSS Statistics Version 25 for Windows, Computer Software*; IBM Corp: New York, NY, USA, 2017.
34. Feller, W. The Fundamental Limit Theorems in Probability. *Bull. Am. Math. Soc.* **1945**, *51*, 800–832. [[CrossRef](#)]
35. Goodman, A.; Sahlqvist, S.; Ogilvie, D. New walking and cycling routes and increased physical activity: One- and 2-year findings from the UK iConnect study. *Am. J. Public Health* **2014**, *104*, 38–46. [[CrossRef](#)] [[PubMed](#)]

36. Ministry of Transport and Communications. *White Paper No. 33 (2016–2017) National Plan of Transport 2018–2029 (In Norwegian: Meld. St. 33 (2016–2017) Nasjonal Transportplan 2018–2029)*; Ministry of Transport and Communications: Vilnius, Lithuania, 2017.
37. Song, Y.; Preston, J.; Ogilvie, D. New walking and cycling infrastructure and modal shift in the UK: A quasi-experimental panel study. *Transp. Res. Part A Policy Pract.* **2017**, *95*, 320–333. [[CrossRef](#)] [[PubMed](#)]
38. Van Goeverden, K.; Nielsen, T.S.; Harder, H.; Van Nes, R. Interventions in bicycle infrastructure, lessons from Dutch and Danish cases. *Transp. Res. Procedia* **2015**, *10*, 403–412. [[CrossRef](#)]
39. Pucher, J.; Garrard, J.; Greaves, S. Cycling down under: A comparative analysis of bicycling trends and policies in Sydney and Melbourne. *J. Transp. Geogr.* **2011**, *19*, 332–345. [[CrossRef](#)]
40. Dill, J.; Goddard, T.; Monsere, M.C.; McNeil, N. Can Protected Bike Lanes Help Close the Gender Gap in Cycling? Lessons from Five Cities. *94th Annu. Meet. Transp. Res. Board* **2015**. [[CrossRef](#)]
41. Parker, K.M.; Rice, J.; Gustat, J.; Ruley, J.; Spriggs, A.; Johnson, C. Effect of Bike Lane Infrastructure Improvements on Ridership in One New Orleans Neighborhood. *Ann. Behav. Med.* **2013**, *45*, 101–107. [[CrossRef](#)]
42. Van Goeverden, K.; Godefrooij, T. *The Dutch Reference Study. Cases of Interventions in Bicycle Infrastructure Reviewed in the Framework of Bikeability*; Delft University of Technology: Delft, The Netherlands, 2011.
43. Lott, D.F.; Tardiff, T.; Lott, D.Y. Evaluation by experienced riders of a new bicycle lane in an Established Bikeway System. *Transp. Res. Rec. J. Transp. Res. Board.* **1978**, *683*, 40–46.
44. Heinen, E.; Harshfield, A.; Panter, J.; Mackett, R.; Ogilvie, D. Does exposure to new transport infrastructure result in modal shifts? Patterns of change in commute mode choices in a four-year quasi-experimental cohort study. *J. Transp. Health* **2017**, *6*, 396–410. [[CrossRef](#)]



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## Paper V

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## Does new bicycle infrastructure result in new or rerouted bicyclists? A longitudinal GPS study in Oslo

Ray Pritchard<sup>a,\*</sup>, Dominik Bucher<sup>b</sup>, Yngve Frøyen<sup>a</sup><sup>a</sup> Department of Architecture and Planning, Faculty of Architecture and Design, NTNU—Norwegian University of Science and Technology, 7491 Trondheim, Norway<sup>b</sup> Institute of Cartography and Geoinformation, Department of Civil, Environmental and Geomatic Engineering, ETH Zürich, 8093 Zürich, Switzerland

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 Mode choice  
 GPS tracking

## ABSTRACT

Well-connected bicycle infrastructure networks are widely accepted to be an important factor for increasing the level of bicycling in urban environments where motorised and active transport modes must co-exist. However, little is known about the extent to which new bicycle infrastructure results in changes of route amongst existing bicyclists as opposed to changes in the mode of transport. This article addresses the route-mode research gap through a panel study in which participant travel behaviour ( $n = 113$ ) is recorded with a smartphone Global Positioning System (GPS) application. The study observes short-term changes to route and mode choice of participants before and after the establishment of a contraflow bicycle lane in Oslo, Norway. Video and radar-based traffic counting are used as supplementary methods to affirm bicycle volume changes in the broader population.

The bicycle lane intervention resulted in a shift in the preferred route in the neighbourhood. The intervention street saw increased numbers of bicycle trips taken whilst the two nearest parallel routes in the same neighbourhood witnessed a decrease. For bicycle trips taken on the intervention street, the mean deviation from the shortest path increased (from 171 to 221 m,  $p < .05$ ). Bicycle counts based on video observations also support the route shift finding. Bicycle modal share did not significantly increase when comparing the panel sub-group exposed to the intervention ( $n = 39$ ) with a quasi-control group ( $n = 47$ ) who were not exposed but had made at least one trip in the near vicinity of the intervention in both time periods.

This natural experiment study provides evidence to suggest that route substitution from nearby streets and paths can explain more of the change in bicycling levels than modal shifts to bicycling in the short term following the opening of the bike lane.

### 1. Introduction

High quality and separate bicycle infrastructure has been frequently established as a precondition for achieving high levels of utility bicycle use (Dill, 2009; Hull and O'Holleran, 2014; Wahlgren and Schantz, 2014). Many studies of environmental correlates have established a link between cycling rates and infrastructure (Mertens et al., 2017; Nielsen et al., 2013; Saelens et al., 2003; Schneider and Stefanich, 2015), however, the empirical data is somewhat limited with respect to single project infrastructural impacts within bicycle networks (Handy et al., 2014; Yang et al., 2010).

This panel study analyses the route and mode choice effects of a contraflow bicycle lane built in August 2017 in Oslo, Norway. GPS-based tracking is used to identify changes before and after the intervention for a group of participants who were recruited specifically for

this study. Video observations and radar traffic counts provide volume changes as a supplementary data source to the GPS panel.

This paper is structured as follows: the background introduces existing research connected to bicycle interventions, the methods section describes the data collection approach, including a description of the intervention area. The timeline of the data collection and intervention is also described here. This is followed by the results section, which reports the changes observed within the GPS panel and comparisons with bicycle count data. Finally, the discussion and conclusion of this paper summarise the main findings, limitations of the study together with recommendations for future research.

### 2. Background

This paper's study design makes use of GPS for data collection, a

\* Corresponding author.

E-mail address: [Ray.Pritchard@cantab.net](mailto:Ray.Pritchard@cantab.net) (R. Pritchard).<https://doi.org/10.1016/j.jtrangeo.2019.05.005>

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longitudinal natural experiment for bicycling and a focus on both route and mode choice behaviour. To the authors' knowledge, the combination of all these three methodological elements in a single study has not been previously published. Existing research has, however, addressed these component elements individually and this is summarised below. Firstly, a number of review studies connected to GPS and bicycle research are reported on, followed by summaries of the relevant results from three systematic reviews on bicycle infrastructure interventions. Subsequently five descriptive studies are introduced with focus on route changes resulting from bicycle infrastructure interventions, whilst the final section of the background summarises two studies that use the same type of contraflow bicycle lane as this case study.

The use of GPS in bicycle research is becoming increasingly common and is now utilised in approximately two-thirds of all studies connected to bicycle route choice (Pritchard, 2018). The use of GPS within active transportation and bicycling has been the subject of two comprehensive reviews (Patricia J. Krenn et al., 2011; Loveday et al., 2015), whilst GPS in combination with other methods have been reviewed by several other researchers, covering more recent combinations of GPS in studies using crowdsourcing, 'big app' data aggregators, instrumented bicycle setups and bike sharing operator data (Buehler and Dill, 2015; Pritchard, 2018; Romanillos et al., 2016).

In a 2017 systematic review of built environment effects on physical activity and active transport, 11 of 28 reviewed articles had levels of cycling as a specific outcome (Smith et al., 2017). The reviewed articles used natural experiments or prospective, retrospective, experimental or longitudinal study designs and all but one demonstrated either a positive or non-significant relationship between infrastructure provision and levels of cycling. Infrastructure types found to have a positive effect on cycling include: combined pedestrian and bicycle access bridges and boardwalks (Goodman et al., 2014), urban trails (Fitzhugh et al., 2010), traffic calming (Morrison, 2004) and bicycle lanes (Lott et al., 1978; Parker et al., 2013). In Portland, USA, the effect of bicycle boulevards was evaluated, however, the length and frequency of bicycle trips performed decreased following the intervention (Dill et al., 2014).

A second systematic review concerning the physical activity impact of built environment infrastructural changes reviewed eight articles that reported on changes in levels of bicycling (Stappers et al., 2018). Positive effects were found for separate bicycle paths which are sometimes also referred to as bikeways (Heesch et al., 2016; Rissel et al., 2015).

Three cross-sectional bicycle infrastructure intervention studies from the grey literature are discussed in a systematic review of 25 cycling interventions studies, with all three found to result in increased cycling frequency (Yang et al., 2010). Evidence regarding net effects on cycling modal share was also reported in two of the three studies. The first, based in Delft in The Netherlands revealed a 3% increase in bicycle modal share in the intervention area compared to a 1% increase elsewhere in the city (Wilmink & Hartman, 1987). The second study from Odense, Denmark revealed a 3.4% increase in cycling modal share from a combination of initiatives including infrastructure improvements but did not have a control group (Troelsen et al., 2004).

Early evaluations of Dutch bicycle planning policies in Tilburg and The Hague in the 1970s and 1980s contributed in part to the widespread development of bicycle infrastructure across much of the Netherlands (van Goeverden et al., 2015). Both cities experienced greatly increased cycling volumes along the routes which received bicycle infrastructure (140% in Tilburg and 76% in The Hague) whilst only a 10–20% increase was observed in the corridor bicycle volumes for both cities. Comparable although less significant changes were observed from a before-after study in Davis, California, where a bicycle volume increase of 87% was observed on the intervention bicycle lane versus 57% for the corridor (Lott et al., 1978). Furthermore, up to 45% of the interviewed bicyclists that took alternative routes prior to the intervention modified their route post-completion to use the new lane. A traffic count study performed in New Orleans demonstrated increase

bicycle volumes on a new bicycle lane and a simultaneous reduction in bicycle volumes in the streets parallel to the intervention (Parker et al., 2013). With a large increase in corridor bicycle volumes, this study's findings suggest that a significant mode and route change occurred as a result of the bicycle lane.

Concerning route change effects, a cross-sectional Global Positioning System (GPS) study from San Francisco found evidence of route substitution through significantly increased bicycle volumes on four intervention streets whilst a decline was observed in neighbouring streets (Fitch et al., 2016). A separate bicycle route choice model using GPS data from the same city quantified the preference for bicycle infrastructure using the Marginal Rate of Substitution (MRS) (Hood et al., 2011). The model estimated an MRS of 0.49, meaning that the average cyclist would rather cycle on 100 m along bicycle lanes to avoid cycling on 49 m of ordinary roads. In addition, the model estimated an MRS of 4.02 for cycling the wrong way down a one-way street, meaning that cyclists will only ride against the traffic flow if it saves them more than four times the distance of a conventional street. This is assumed to apply to streets for which contraflow cycling is not permitted.

Two studies specifically on the effects of contraflow bicycle lanes were uncovered, the first of which demonstrated significant increases in the use of contraflow bicycle lanes and simultaneous reduction in footpath cycling in Oslo, Norway (Bjørnskau et al., 2012). The second study involved an intercept survey of bicyclists in Washington, D.C. which revealed that participants' weekly usage of the bidirectional contraflow bicycle lane street increased from 15% pre-intervention to 80% post-intervention (Goodno et al., 2013).

This paper contributes both to the knowledge regarding this specific type of initiative and more importantly, to the empirical knowledge regarding intervention studies and bicycle route choice. The literature reveals that whilst there are several studies that demonstrate a generally positive association between bicycle infrastructure provision and bicycle modal share, the state of knowledge regarding changes in route choice is less mature. This applies particularly for longitudinal intervention studies, since most of the research presented up to this point uses forms for cross-sectional study design such as traffic counting. Several reviews of research on bicycle travel behaviour have noted the rarity of longitudinal studies using control groups (Handy et al., 2014; Smith et al., 2017; Yang et al., 2010). This paper has made an effort to capture the intervention effects separate from population changes through the use of a quasi-control respondent group.

### 3. Methods

#### 3.1. Study area

A contraflow bicycle lane (i.e. in the opposite direction to one-way vehicular traffic) in Markveien in Oslo, Norway, was opened for cyclists at the end of August 2017. Markveien extends north-south through the district of Grünerløkka and is one of several parallel streets connecting the suburb of Torshov with Oslo city centre. The contraflow bicycle lane is a part of the City of Oslo's City Route 1 bicycle infrastructure project which commenced in 2016. City Route 1 is one of eight City Route bicycle infrastructure projects in Oslo covering 55 km of streets within Oslo's outermost ring road: Ring 3. The planned completion of the City Routes is 2020 and is seen by the City of Oslo as its most important bicycle promotion initiative. The changes are pictured in Fig. 1 whilst the map in Fig. 2 illustrates the bicycle lane together with the existing bicycle infrastructure in Grünerløkka and Torshov.

The 'intervention' (or natural experiment) is a 400 m long section of Markveien, between Grüners gate and Øvrefoss (59°55'32.2"N, 10°45'25.6"E), in which a 2.4 m wide red asphalt bicycle lane substituted parallel car parking on the eastern side of the street. Parallel car parking on the western side of the street remained unchanged. Bicyclists have been permitted to ride contraflow in this street since 2015. There are no bicycle lanes in the same direction as traffic,



Fig. 1. Before and after changes in Markveien (top and bottom images respectively), completed in August 2017 (view to the north from the intersection with Seilduksgata). Source: the City of Oslo Agency for Urban Environment.

meaning cyclists must ride on the road lane. The intervention extends the total length of contraflow bicycle lanes on Markveien from 447 m to 847 m, as shown in Fig. 2. Following the intervention, only 100 m of the Oslo's City Route 1 section of Markveien lacks contraflow bicycle lanes.

Two other streets in the same neighbourhood received bicycle infrastructure modifications during the analysis period (thus making the isolation of the intervention effects harder since they also affect bicycle behaviour). The first was a 245 m segment of Sandakerveien, a one-way street 1 km to the north of Markveien, which received the same treatment as the intervention site in late September 2017 (contraflow bicycle lane in lieu of parallel car parking). Sandakerveien is also part of Oslo's City Route 1 project. The second infrastructure upgrade involved the recolouring (from black to red) and widening of 745 m of bicycle lanes along both sides of Toftes gate in June 2017, a parallel street two blocks to the east of Markveien. Both Toftes gate and Sandakerveien are illustrated together with Markveien in Fig. 2.

### 3.2. Participants

This study tracked the mobility behaviour of a panel of residents from the northern suburbs of Oslo who would be most exposed to a new bicycle lane constructed in Markveien, Grünerløkka. Participants were recruited to the study using multiple approaches. 3000 personalised invitational letters were mailed to addresses < 400 m from the northern section of City Route 1. The mailing area was entirely north of the intersection between Markveien and Grüners gate, where the intervention begins. This was done since it was assumed that the dominant destination for cyclists in the neighbourhood would be central Oslo, south of the intervention.

The study was also distributed through a local newspaper advertisement, flyers, posters and social media connected with the area of interest. Except for social media targeting specific interest groups, the recruitment process was randomised. In total 113 Oslo residents participated in both data collection rounds, 51 of whom were recruited via the letters and unknown numbers recruited via other means.



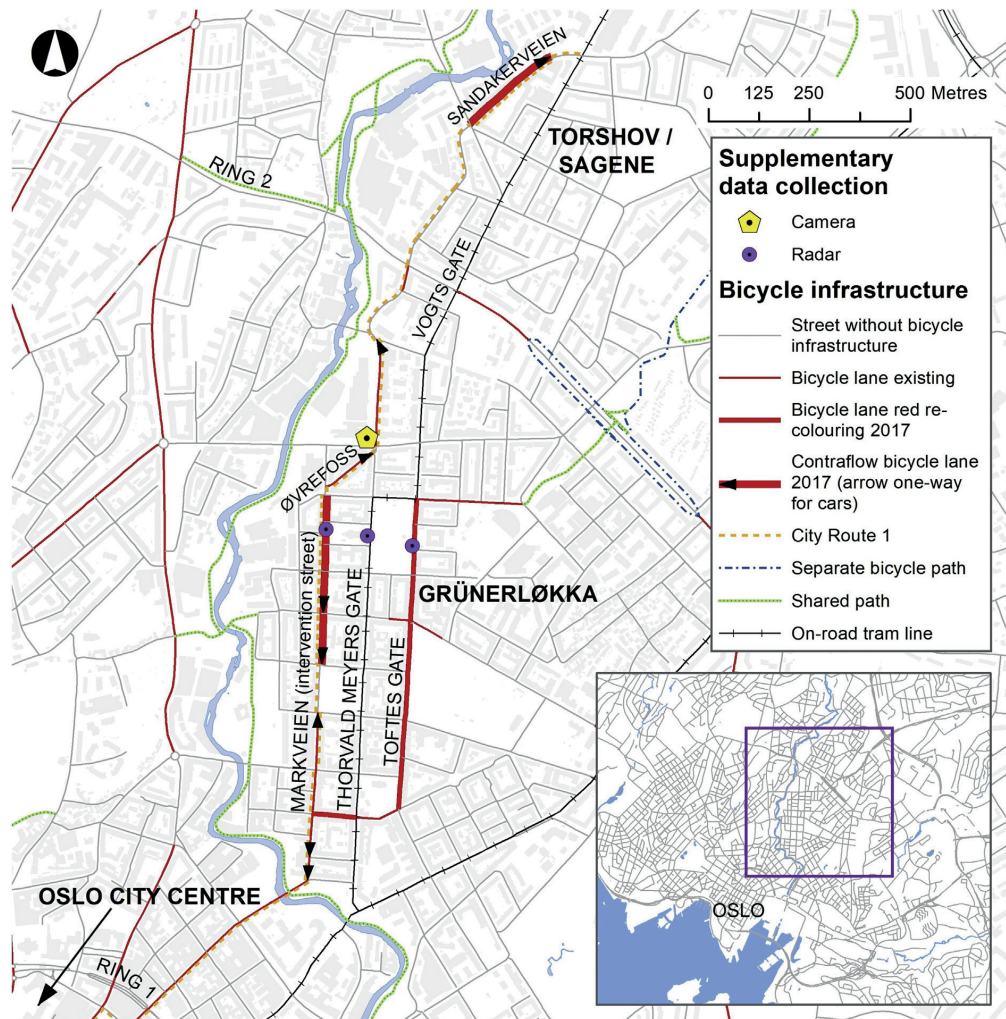


Fig. 2. The intervention street Markveien in Oslo together with existing bicycle infrastructure in Oslo's inner northern suburbs of Grünerløkka and Torshov. Arrows indicate the one-way direction for cars since bicycles are permitted in both directions on all streets.

The bicycle lane intervention was constructed between the 14th and 31st August 2017. The bicycle lane and the study's focus on bicycle travel behaviour were deliberately not referenced in the invitational material in the interest of reducing response bias (Envall, 2007, p. 164). The study purpose was instead described as being related to longitudinal travel behaviour changes in the local environment. Participant travel behaviour was recorded in two four-week periods pre-intervention between 13th May and 9th June and post-intervention from 12th September to 9th October 2017.

### 3.3. Instrumentation: GPS-enabled smartphone application (app)

Participants' own smartphones with integrated Global Positioning System (GPS) were used for gathering panel mobility data from the participant panel. 91% of the Norwegian population had access to a smartphone in 2017 and thus selection bias through this choice of method was considered minimal (Vaage, 2018).

Whilst a number of travel survey-specific commercial apps exist

(Berger and Platzer, 2015; Flügel et al., 2017), a more affordable solution was found that built upon a passive physical activity monitoring app called Moves<sup>®</sup> (shut down in July 2018). A second app, *GoEco! Tracker*,<sup>1</sup> was required to extract information from Moves<sup>®</sup> and re-classify the mode of transport used for motorised journeys, which are classified in Moves<sup>®</sup> as 'transport'. GPS data is recorded first in Moves<sup>®</sup>, and via an application programming interface (API), is automatically collated to a secure server by the *GoEco! Tracker* app (Bucher et al., 2016). This required participants to download both apps and authorise the transfer of data from Moves<sup>®</sup> to *GoEco! Tracker*. More detailed information on the data collection protocol (approved for this study by the Norwegian Centre for Research Data) can be found in the methodological paper from the *GoEco!* project team (Bucher et al., 2016).

<sup>1</sup> [www.goeco-project.ch](http://www.goeco-project.ch)

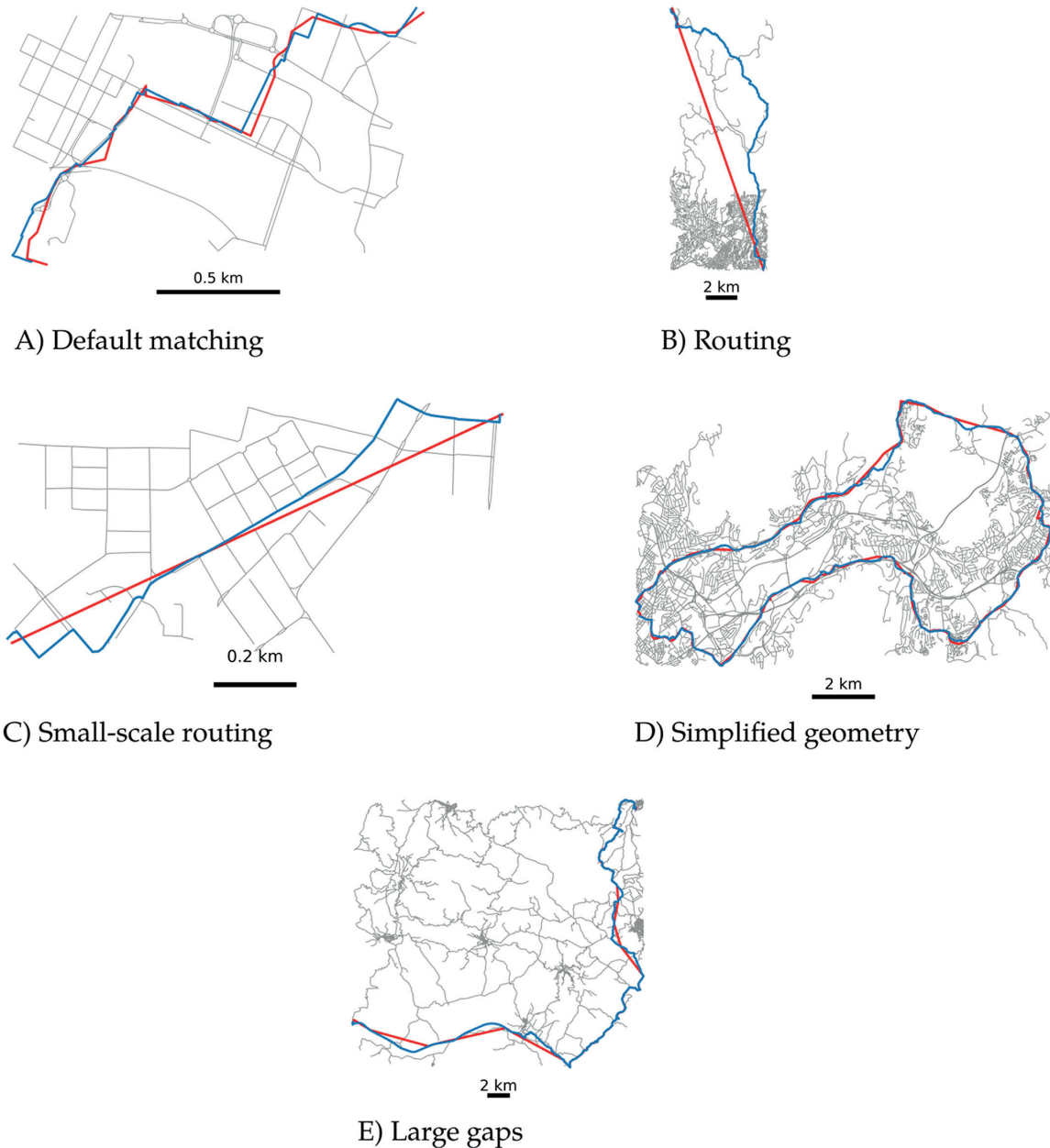


Fig. 3. Examples of the different matching approaches used to handle the varying route data quality. Red lines indicate raw data and blue are matched to the street network. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

#### 3.4. Pre-processing GPS data

Map-matching is a necessary procedure in the preparation of GPS data for subsequent analysis, to determine the distance travelled and to be able to count the number of trips along a specific street or path. Hidden Markov Model-based map-matching was performed on the raw data (after mode validation in GoEco! Tracker) using the Open Source Routing Machine (OSRM) matching profiles for car and walking trips

(Project OSRM, 2018). Additional matching profiles were created for trains, trams and buses, and the profiles for bicycle journeys were adapted by the GoEco! Tracker developers to allow matching to both bicycle-specific and generic routes within OpenStreetMap.

To handle the variable raw data quality (due to different tracking resolution from dissimilar recording devices), several map-matching strategies were used to pre-process the GPS trajectories, as illustrated in Fig. 3 below. By default, OSRM applies a matching algorithm similar to

the one described by Newson and Krumm (2009) (Panel A in Fig. 3). The matching process first locates network nodes in the proximity of each raw GPS point by searching within a radius determined by the tracking device's reported accuracy (for example 20 m). The map-matched route must pass through at least one of the nearby nodes from each GPS point. OSRM maps all possible combinations of nodes between consecutive GPS points and repeats this procedure for the full GPS trajectory. From the many combinations created, an optimum route is determined based primarily on the time difference between consecutive GPS points and the typical speeds of the transport mode.

In case there are too few GPS points along a recorded route, OSRM simply "routes" journeys on the shortest path between the start and end points (see panels B and C in Fig. 3 with two different scales) (Huber and Rust, 2016). In some cases, the opposite situation occurs in which there are very large numbers of GPS points (due to high resolution and/or long journey distance). This results in problems for the computation of a map-matched route in OSRM – potentially due to limitations in the memory for storing all node combinations for routes with large numbers of GPS points. For these journeys, as illustrated in panel D, the number of GPS points is repeatedly simplified using a Douglas-Peucker algorithm (Douglas and Peucker, 1973). This procedure removes the least critical GPS points (based on proximity to consecutive points), yielding a smaller number of possible node-to-node combinations until the matching algorithm delivers a route. Despite the reduced data resolution, this procedure was found to provide satisfactory results. Finally, for recorded journeys in which there are large gaps between consecutive GPS points (more than three kilometres, E), the gaps are individually routed while the parts without large gaps are matched (i.e. a combination of A and B is applied).

The panel produced 36,153 trips (across all modes) during the two months of data collection, 2.7% of which were taken outside of Norway and were not considered for matching. The approach described above allowed the direct matching (A) of 87.3% of all trips, routing (B and C) of 6.0%, simplification and matching (D) of 1.6%, 'large gap' routing of 0.3% (E) whilst the remaining 2.1% had missing mode information or failed. The data collection approach was found to correctly identify the travel mode in approximately 80% of cases in a test of Swiss GoEco! Tracker travel data in which participants were requested to confirm travel mode (Bucher et al., 2016).

### 3.5. Supplementary data collection: video observations and automated traffic counting

In addition to GPS data collection, two further before and after methods were used: bicycle counts extracted from video observations and automated traffic counting of bicycles and motorised vehicles with Doppler radar traffic counters.

In the interest of capturing route choice changes, an elevated Miovision Scout camera (720 × 480 pixels, 30 fps) was temporarily installed above a forked intersection near to the intervention street (see Fig. 2). The forked intersection was chosen as it forms a natural decision point where bicycle users can select one of two alternative routes when cycling towards the city centre (one of which is the intervention street). Similarly, bicycle movements along the same two alternative routes coming from the city centre merge at this point when continuing further north. Cyclist movements in the video recordings were extracted by Miovision through their automated traffic data processing tool. With the configuration shown in Fig. 4, Miovision guarantees ≥ 85% intersection count accuracy (an accurate count correctly registers a cyclist's movement between any two of the three coloured zones). Video data was uploaded to the Miovision Traffic Data Online server and bicycle counts were received in 15-minute intervals going into and out of the two streets of interest.

Radar-based traffic counting was also deployed in three locations including the intervention street Markveien and two nearest parallel alternative streets Thorvald Meyers gate and Toftes gate (see Fig. 2).

The ViaCountII mobile traffic counters use integrated Doppler radar devices (24,165 GHz/100 mW EIRP) to determine the speed, length, vehicle class (including bicycle) and direction of travel (Via Traffic Controlling GmbH, 2016). The accuracy of the counters is not stated in the technical product specifications, but are regularly used by the City of Oslo for traffic counting.

### 3.6. Analytical approach

Data from the three sources were recorded before and after the intervention completion during the time periods illustrated in Table 1. Pre-processed GPS data (after conversion to .shp format) were processed using a combination of software including a Geographic Information System (GIS) program, statistical software and spreadsheets. The automated traffic counts from the video footage (recorded from 6 am to 9 pm excluding start and end days) and radar traffic data (24 h per day) were analysed in spreadsheets.

In order to observe changes in route choice, all bicycle trips (as classified by the GoEco! Tracker app) taken by the panel participants were accumulated for each link in the transport network in the before and after time periods. For any given link, this resulted in two counts for the number of bicycle trips that passed the link during the before and after periods respectively. Thereafter the number of link bicycle trips (*num*) in each period was normalised by dividing by the sum of all link volumes from the corresponding period for the map extent indicated in Fig. 2. The change in bicycle volumes is calculated in GIS using the expression below for each link in the transport network where the before period is 1 and the after period is 2. This mitigates for potential confounding factors such as weather variability or other seasonal variation between the two data collection periods.

$$\Delta \text{Adjusted bicycle volume}_{\text{link } x} = \frac{(\text{num}_{x2}/\Sigma \text{num}_{N2} - \text{num}_{x1}/\Sigma \text{num}_{N1})}{\Sigma \text{num}_{N1}} \quad (1)$$

The scale of the intervention and limited time to adjust behaviour is such that short term modal changes cannot be expected for all journeys taken by the panel. To account for potential modal changes, it was, therefore, necessary to remove journeys that are not in the immediate vicinity of the intervention (defined as being the area bounded by the four nearest parallel streets, two on each side of Markveien). This was done by creating a modal analysis zone (a polygon) in ArcMAP covering this immediate vicinity and selecting only those GPS journeys which intersect with this zone. This zone is shown in Fig. 7 with the red shaded polygon. In this manner, only the subset of journeys that are taken in proximity to the intervention is considered. This is an important consideration given the dataset covers trips taken by the participants across the whole of Oslo and beyond.

Checking for mode substitution was performed by firstly selecting panel participants who had taken at least one journey in the modal analysis zone in both periods ( $n = 86$ ). From this group, a subset of respondents ( $n = 39$ ) was exposed to the intervention, whilst the remainder are considered as a quasi-control group ( $n = 47$ ). Exposure was defined as having used at least one segment of the 400 m intervention section of Markveien in the after period with any mode (excluding trips that cross Markveien since the bicycle lane does not extend through intersections). In other words, the criterion for exposure requires intervention link utilisation (to travel on or alongside the contraflow bicycle lane). This approach was adopted since it is not guaranteed that users crossing Markveien will register changes in side-street appearance if they are more occupied with traffic hazards (and given the dark red bicycle lane has low conspicuity in wet weather and at night).

Existing approaches for exposure typically rely upon area or proximity based measures, often categorised using distance from the intervention (Stappers et al., 2018). Alternative approaches attempt to demonstrate the diminishing influence of the intervention with





Fig. 4. Video camera perspective with bicycle counting zones for automated counting of bicycle movements between the three zones.

Table 1  
Data sources recording periods.

Source	Before	After	Data processing
GPS	28 days 13th May – 9th Jun	28 days 12th Sep – 9th Oct	ESRI ArcMap 10.6, Microsoft Excel, IBM SPSS Statistics 25
Video observation	39 h 12th, 13th, 15th, 16th May	86 h 21st Sep – 26th Sep	Microsoft Excel
Radar traffic counting	7 days 8th May – 14th May	7 days 18th – 24th Sep	Microsoft Excel

proximity through the use of the negative square root of distance (Heinen et al., 2017). The strict link-utilisation definition used in this paper was chosen in favour of the broader definitions above due to a) the short time frame of post-intervention travel behaviour measurement, b) smaller scale of the intervention compared to the examples reviewed by Stappers et al. (2018) above and c) the ability to be able to select participants based on their actual use of a road (due to the GPS data).

The journeys that intersected the modal analysis zone were summarised into a modal share for each user in this sub-group for the before and after periods. Paired samples *t*-tests were then used to compare the change in bicycle modal share for the exposure group and the non-exposure group (a quasi-control group) between the before and after periods.

### 3.7. Difference in differences

Since both the quasi-control and exposure group experience increases in bicycle modal share, the difference in differences approach is used to quantify the changes. This involves considering the difference between the trends (such that when the two groups of interest increase, it is the differences in the increase that are measured).

Since the intention of this paper is to measure the significance of the changes, the classic regression approach is used to calculate the difference in differences for the dependent variable bicycle modal share given by  $y_{it}$  in equation 1 below (Donald and Lang, 2007).

$$y_{it} = \alpha + \beta_1 \cdot Exposure_i + \beta_2 \cdot Post_t + \beta_3 \cdot (Exposure \cdot Post)_{it} + \epsilon \quad (2)$$

$Exposure_i$  and  $Post_t$  are dummy variables introduced to distinguish group membership in which  $Exposure_i$  equals one for the participants in the exposure group ( $n = 39$ ) and is zero for the quasi-control group, and  $Post_t$  equals one for the post-intervention time period and is zero for the pre-intervention period. Running this as linear regression in SPSS provides an estimate for the difference in differences given by the parameter  $\beta_3$  together with the necessary outputs to report statistical significance.

## 4. Results

### 4.1. Characteristics of study participants

The numbers of men and women participating in the panel ( $n = 113$ ) were approximately equal, although men were generally older as can be seen in Fig. 5. The education level of the sample was considerably higher than that of the local population. Eighty five percent of the panel had some form of higher education, compared with census records for Sagene and Grünerløkka that show 60% of the intervention area population had higher education (Holseter, 2018). Before the intervention, 86 members of the GPS panel had conducted 4 or more trips by bicycle during the first month of data collection (or an average of

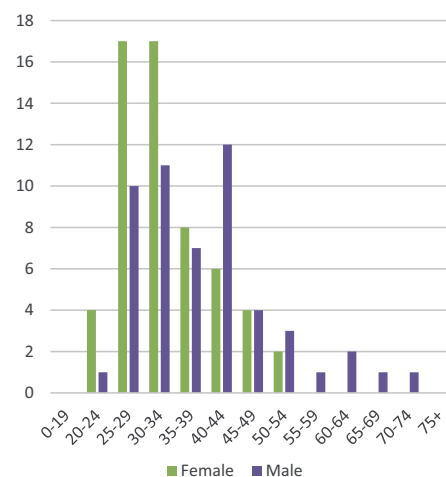


Fig. 5. Age distribution of GPS panel.

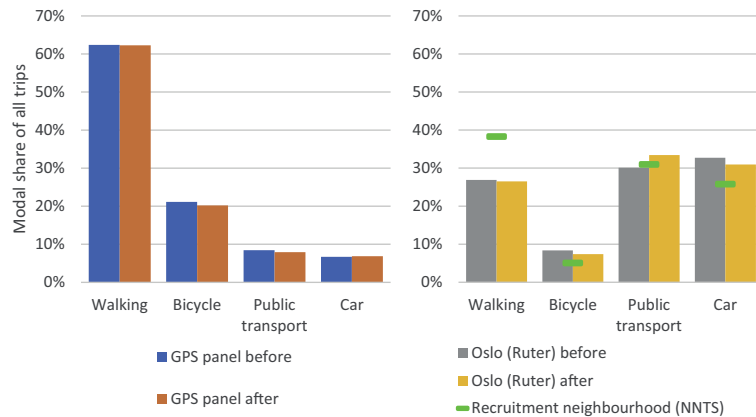


Fig. 6. Transport modal share for the GPS panel (left) relative to the general Oslo population (right) for the before and after data collection intervals. NNTS data is additionally shown to the right for the recruitment neighbourhood in Oslo.

one or more trips per week). There were 83 panel members who took 4 or more bicycle journeys following the intervention (also over a period of one month). As a proportion (76% and 73% respectively) this is significantly higher than the weekly cycling levels for the Grünerløkka (52%) and Sagene (49%) city districts where most participants live (Bayer, 2018).

Seasonal variation in Scandinavia as with many other countries with snowy winters results in variability in the levels of bicycling. The GPS panel modal share data for each month was compared with travel survey data from Ruter, the public transportation authority in Oslo. Ruter's market information system, a type of continuous travel survey has a sample size of approximately 3400 Oslo residents spread throughout the year. The comparison of the GPS data with the population sample from Ruter is shown in Fig. 6 below. Minimal seasonal variation is observed during the before and after data collection periods, however cyclists and pedestrians are greatly overrepresented whilst car drivers and public transport users are underrepresented.

In addition, Fig. 6 displays the modal split for the recruitment neighbourhood (defined as the zone in which invitation letters were distributed). This data is taken from the 2013/2014 Norwegian National Travel Survey (NNTS) (Hjorthol et al., 2014). This reveals that the (average annual) neighbourhood modal shares of public transport (31%) and cycling (5%) are approximately equal to that of Ruter's sample in Oslo. However, walking is more common in the neighbourhood (38%) than the Ruter sample (27%), whilst car journeys are less common (26% versus 32%).

#### 4.2. Route substitution

Positive values for changes in normalised bicycle volume, depicted in light turquoise in Fig. 7, indicate the approximate increase in bicycle trips made by the panel after the intervention compared to before. Negative values, drawn in dark orange, show the corresponding reductions in panel bicycle volumes. The intervention street Markveien has clearly increased in popularity amongst the panel, whilst neighbouring streets Thorvald Meyers gate and the riverside shared path experienced a reduction. Although infrastructural changes were made in Sandakerveien and Toftes gate (as depicted in Fig. 2) during approximately the same time interval as Markveien, mixed results are observed in these streets with a smaller change in travel behaviour. Monthly volumes are used preferentially to daily volumes since the data comes from two one-month-long periods, first in May/June 2017 and afterwards in September/October 2017.

#### 4.3. Deviation rate

A form of quantification for the change in bicycle route choice can be made by considering the deviation distance from the shortest path (calculated in ArcMAP) (Krenn et al., 2014). An independent samples *t*-test was performed using all the bicycle trips taken on Markveien before and after the intervention. The deviation from the shortest path (in metres) after the intervention was built in Markveien was greater (mean = 221, SE = 18), than before (mean = 171, SE = 15), and the difference,  $-50$ , 95% CI  $[-96, -4]$  was significant  $t(289) = -2.16$ ,  $p = .032$ . In other words, the upgraded Markveien was able to induce a 221 m deviation from the shortest path (compared to 171 m before). This demonstrates that the average bicycle user of Markveien had a significantly increased detour from the shortest path in order to use the contraflow bicycle lane configuration than the same street pre-intervention. Existing users presumably continued to use Markveien, so the increase in the mean suggests that the new cyclists who began to use Markveien took greater detours than 221m to use the intervention infrastructure.

#### 4.4. Video comparison

More than 100 h of video footage was processed by Miovision to count the number of bicycles taking Øvrefoss, which leads directly to the intervention street Markveien, and the alternative street Thorvald Meyers gate. Since only bicycles were counted in the footage, the video data cannot be used to determine any changes in modal share – but allows observation of any changes to bicycle route choice. In Table 2 below the percentages of cyclists choosing each of these two streets is shown and compared with the GPS panel counts on the same two streets. It should be noted that not all traffic through the intervention goes through this intersection, and therefore it is only indicative of changes that occur in the intervention. Immediately apparent in Table 2 however is that the scale of the change for the video observations is much less than the GPS panel.

#### 4.5. Directional changes

The contraflow bicycle lane undoubtedly improved the bicycling conditions for northbound cyclists using the intervention, since the replacement of a parking lane with a bicycle lane provided much greater separation from the flow of one-way southbound traffic. The directional flows are displayed in Table 3 below for those routes passing through the directional analysis zone indicated in yellow in Fig. 7. The



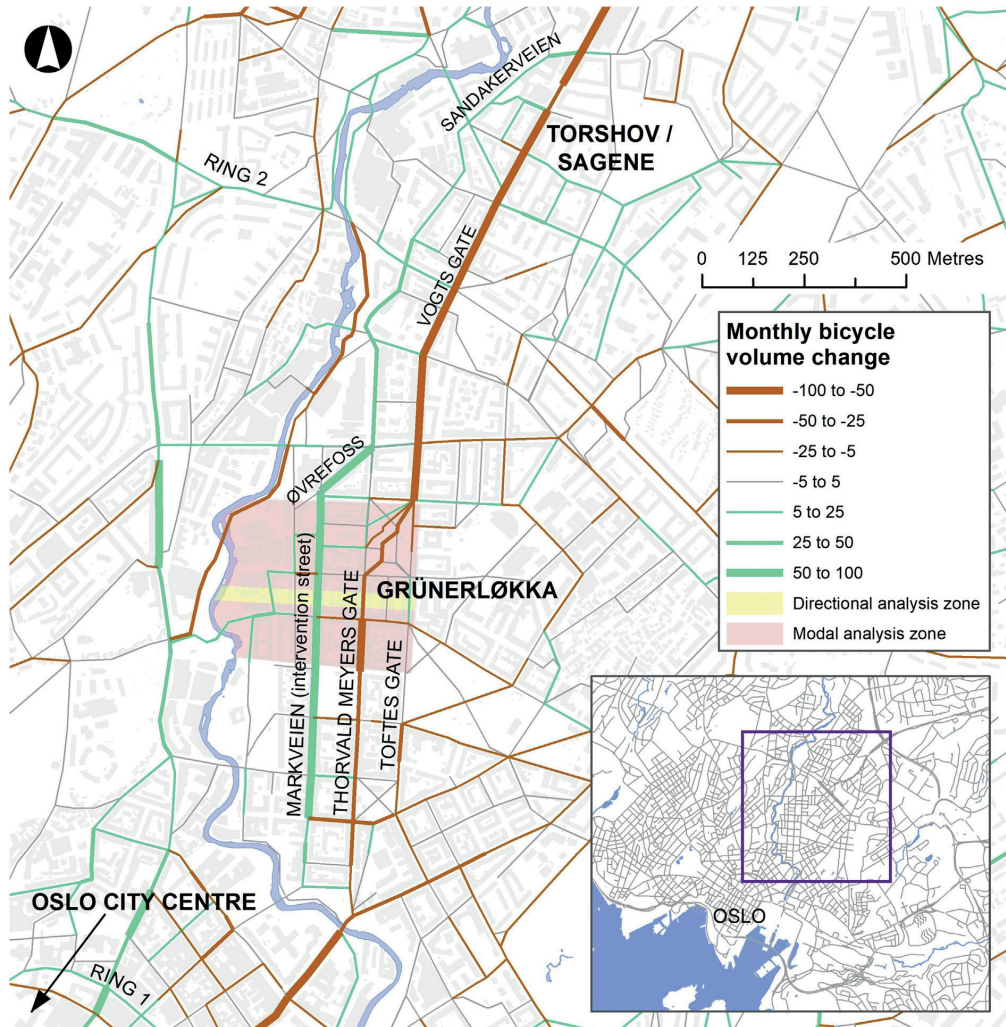


Fig. 7. Change in the number of monthly recorded bicycle trips taken before and after intervention adjusted for seasonal variation. The intervention stretch of Markveien is shown by the dashed violet line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 2**  
Average daily number of observed trips taken by bicycle (in both directions) at the intersection of Øvrefoss and Thorvald Meyers gate (see video camera location in Fig. 2).

Time period	GPS panel (n = 113)		Video observation (population)	
	Intervention 'tributary' (Øvrefoss)	Thorvald Meyers gate	Intervention 'tributary' (Øvrefoss)	Thorvald Meyers gate
Pre-intervention	4.19 (43%)	5.60 (57%)	374 (46%)	439 (57%)
Post-intervention	5.69 (70%)	2.41 (30%)	563 (50%)	566 (50%)

directional analysis zone is a single cross-section of streets surrounding Markveien and all trips that intersect it were counted and sorted by street and direction. This included two parallel streets to the west of

**Table 3**  
Percentage of bicycle journeys on Markveien relative to the total number of trips that cross the directional analysis zone.

Time period	Northbound	Southbound
Pre-intervention	16.0% of 318	16.4% of 372
Post-intervention	29.2% of 226	31.1% of 302

Markveien: Fossveien and Steenstrups gate and three to the east: Thorvald Meyers gate, Bjerkelundgata and Toftes gate.

Markveien is found to become a more popular choice amongst the six streets in both the northbound and southbound direction, with a near-doubling in the percentage of trips taken on this street. No evidence is found in the GPS data to suggest that northbound cycling increased any more than southbound cycling. Video data also supports this finding in which the proportion of northbound cyclists entering the

intersection Øvrefoss increases from 48% to 52% (compared only with Thorvald Meyers gate rather than the 5 other streets). Southbound cycling from the intersection into Øvrefoss also increases from 45% to 48% following the intervention. The difference in proportions between the GPS data and the video data is a limitation of the method in which the video observations can only record directional preferences against one other street. More importantly, however, is the similar increase in cycling independent of direction within each method.

The small difference in north and southbound cycling in both data sources is contrary to expectations, given that the conditions for cycling southbound were largely unchanged. However, the lack of change in directional utilisation of Markveien can potentially be explained by the change in contraflow bicycle direction on the sections of City Route 1 both north and south of the intervention (see Fig. 2). The contraflow bicycle lane alternates between the west and east sides of the road (given the shift in one-way direction for cars). This means that cyclists who are unwilling to share a street with cars are unlikely to utilise City Route 1 since there is no bicycle infrastructure in the car travel direction. The low degree of directional difference may also be the result of the improved perceived safety and comfort of Markveien also when travelling southbound with cars due to the removal of parked cars on the east side of the street (see Fig. 1).

#### 4.6. Mode substitution to bicycle

For the exposure group ( $n = 39$ ), the modal share is calculated based on the 2032 trips they made in the modal analysis zone in both periods. The exposure group had a higher bicycle modal share in the after period (mean = 0.499, SE = 0.056), than the before period (mean = 0.422, SE = 0.053), however the difference,  $-0.077$ , 95% CI  $[-0.166, 0.012]$  was only weakly significant  $t(38) = -1.743$ ,  $p = .089$ . The modal shares above are presented as decimal values but indicate the percentage of all trips taken by bicycle: 42.2% before and 49.9% after for the exposure group.

The quasi-control group ( $n = 4$ ) for the modal analysis is the subset of the panel that was not exposed to the intervention but still performed at least one trip in the modal analysis zone in the before and after period. For the quasi-control, the modal share is calculated based on the 1193 trips they made in the modal analysis zone in both periods. They had a higher bicycle modal share in the after period (mean = 0.342, SE = 0.058) than the before period (mean = 0.312, SE = 0.053). The difference,  $-0.030$ , 95% CI  $[-0.11, 0.05]$  was not significant  $t(46) = -0.728$ ,  $p = .471$ .

Since both the exposure and quasi-control groups experience an increase in bicycle modal share, the difference in differences approach can be used to reveal the effect of the intervention. Linear regression in SPSS provided the difference in differences coefficient  $\beta_3 = 0.047$ , or a treatment effect of 4.7% change in bicycle modal share. The difference (95% CI  $[-0.065, 0.159]$ ) was not significant  $t(171) = 0.419$ ,  $p = .676$ . The 4.7% difference in differences was confirmed through the manual calculation of the means from each combination of the dummy variables (Lechner, 2010).

To make a comparison with volume data in which modal information is available the radar data can be used. The radar counting device registered traffic volumes in each of the three parallel streets for one week at a time in two time intervals as detailed in Table 1. The data is not directly comparable as only three north-south streets are compared instead of all trips in the modal analysis zone, but it approximates the same conditions. The corridor bicycle volumes across the three streets increase from 13.7% to 16.8%. Markveien meanwhile observed a decrease in the bicycle modal share amongst the three streets from 31.5% to 27.8%. The finding does not corroborate either the video evidence or GPS data. Inconsistencies in the radar data are further discussed in the following section.

## 5. Discussion

### 5.1. New infrastructure: rerouted or new bicyclists?

Study designs for longitudinal bicycle infrastructure evaluation studies such as this vary widely; however, few studies register changes of bicycle route choice as well as mode choice. This paper provides evidence for route substitution both through the GIS-plotted changes in Fig. 7, bicycle counts from the video observations and through a significant increase in deviation from the shortest path (by 50 m) on the intervention street. However, the increase in the rates of cycling following the intervention was not found to be significant for the group exposed to the intervention using the difference in differences approach (4.7% increase in modal share,  $p = .676$ ). This is despite reducing the number of trips under consideration to those in the immediate vicinity of the intervention and taking into consideration only the panel subgroup directly exposed to the change.

The lack of significant modal increase may be a result of the small sample size in the exposure group ( $n = 39$ ). Alternatively, it may simply be a function of the relatively minor scale of the intervention – 400 m of bicycle lanes on one side of a street, or the short period of time (one month) residents had to adapt to the intervention changes in the after period. It could be that alternative study designs (including a longer follow-up period) would be able to demonstrate a significant modal shift.

Although route substitution of bicyclists has not been thoroughly researched, existing literature suggests that it can vary greatly depending on the type of intervention and context (Fitch et al., 2016; Lott et al., 1978; Parker et al., 2013; van Goeverden et al., 2015). The aforementioned studies principally use volume or cross-sectional methods to assess changes across two time periods rather than longitudinal study designs, making a generalised assessment of route substitution difficult. The phenomenon is of key importance for regional and national transport models, which until now have rarely considered other effects than minimisation of travel time when routing cyclists (van Wee and Börjesson, 2015). For this study, the intervention did not provide a new network connection but improved the quality of an existing route. Travel time benefits are therefore marginal, however, benefits in terms of traffic safety and thereby attractiveness to existing cyclists are worth considering in future research seeking to model the route substitution effect.

From a theoretical perspective, the observation of changes in route but no (significant) changes in bicycle modal share can be partly explained by the concept of utility maximisation (or optimisation). Utility maximisation is a central concept in microeconomic theory in which actors always make optimal decisions. The assumption is that people make rational decisions which offer a level of utility (or satisfaction) that is greater than or equal to any other option open to them. The theory therefore implies that new bicycle infrastructure will only result in changes to route or mode if it provides a more attractive transport option compared to existing alternatives. Thus should bicycle infrastructure be developed near to competing routes, the marginal utility can be expected to be reduced according to this approach (Broach, 2016). Although information about the intervention was unlikely to be known by all study participants, it was able to provide a degree of utility sufficient to cause route change. Since cyclists have many similar options available to them in this gridded street suburb of Oslo, small changes on the intervention street can make this a superior alternative. The similarity between modes meanwhile is less pronounced for most travellers - thereby requiring a greater change in utility to result in significant change. That route change was clearly witnessed whilst mode change did not significantly change is in line with utility maximisation theory and the relative differences within route and mode choice sets.

A similar study to this paper in the Norwegian context required users to draw their typical routes rather than have their travel

behaviour tracked by GPS. It demonstrated significant changes to both route and mode choice, however the initiative was for bi-directional cycling and was longer (1.8 km versus 400 m), objectively safer (physically separated bicycle path versus contraflow bicycle lane) and included greater restrictions to car usage (two of four road lanes replaced and no-through driving restriction versus substitution of parking lane) (Vasilev et al., 2018). Considering these substantial contextual differences, a much larger change in utility can be expected compared to this paper's intervention – thereby possibly accounting for significant ( $p = .0014$ ) changes also in travel mode. The drawn routes study does have weaknesses in terms of sample representativity, a post-intervention only evaluation (with routes recalled from pre-intervention phase) and lack of complete travel mode information (such as a travel diary). Combining the approaches from this paper and Vasilev et al. (2018) over multiple post-intervention follow-ups would make for a more rigorous bicycle infrastructure intervention study design that can state travel behaviour effects with greater certainty.

The remainder of the discussion section highlights the considerations in selecting this study design, limitations and makes recommendations for future studies.

### 5.2. Strengths and weaknesses of selected methods

A passive smartphone app was selected for this study as it runs in the phone background, reducing participant burden relative to active start-stop apps and more easily enabling the capture of all travel behaviour (Pritchard, 2018). Such apps have the advantage of counting all traffic movements rather than only bicycle journeys, thus providing an indication of modal effects in addition to route changes. The disadvantage with Moves® and many other passive apps is high battery use and a low GPS sampling rate, with GPS points recorded on average once every 76 s for bicycle journeys. The frequency was higher for journeys associated with physical activity (walking GPS points every 45 s) – than motorised travel (105 s between consecutive car GPS points). This is perhaps unsurprising given the measurement of physical activity is the principal aim of Moves®. Since cycling journeys have an average origin-destination speed of 13.1 kph, the mean spacing between consecutive GPS points is 277 m. Given typical distance between parallel streets in the gridded study area are around 100 m, nearly three city blocks can be traversed in the time between GPS points.

A literature review of bicycle route choice data collection methods (Pritchard, 2018) revealed three papers which use passive smartphone GPS, however only one of these stated the GPS sampling rate: one point per second (Sandsjö et al., 2015). For this study, Moves® did not state the GPS point frequency but early trials revealed that the GPS sampling rate to be considerably lower than 1 Hz. The trials suggested that bicycle route choice would remain clear despite the lower sampling rate, however the 76-second period between GPS points was greater than expected (corresponding with an average frequency of 0.013 Hz), potentially due to wide variability between smartphone models.

Although the point frequency from the GPS method used in this paper is low, the process for mode and route matching is automated, thus providing a consistent means of analysing the data across the two time periods. The point frequency did not appear to be highly problematic for mode identification, however walking trips were found to be correctly matched at a higher rate than other trips (most likely due to the combination of characteristic accelerometer movements and low speeds) (Bucher et al., 2016). For map-matching, slightly > 6% of GPS routes required the routing engine in OSRM as described in methods Section 3.4. This uses a shortest path search on the OpenStreetMap network, thereby providing a consistent approach for routing (Huber and Rust, 2016). Comparison of GPS data collected before and after the bicycle lane intervention in Fig. 7 should therefore effectively cancel the impact of potential routing errors that result from low GPS point frequency.

Despite the challenges this created for map-matching and route

quality at higher speeds, the adopted method had many benefits (Moves was shut down in July 2018): compatibility with both Android and iPhone smartphones, automatic trip segmentation, partial mode classification, a freely available API and no need for technical support. The smartphone GPS methodology is, however, challenging in terms of recruitment as data privacy concerns made response rates very low (152 responses from 3000 mailed invitation letters – 51 of whom provided sufficient data for inclusion in the panel).

Portable GPS units have also been used in bicycle route choice research. A review of 21 bicycle route choice studies employing such units found the median rate of geo-location to be one point per second, however concurrent data collection would require the acquisition of many GPS devices, thereby being very costly for a study with similar numbers of participants (Pritchard, 2018).

The average number of daily trips recorded for each panel participant was 6.00 pre-intervention and 5.46 post-intervention. By comparison, 3.40 daily trips were made per person amongst inner Oslo residents in the Norwegian National Travel Survey (NNTS) from 2013 to 2014 (Ellis et al., 2015). The discrepancy is likely the result of two factors: over-segmentation of trips from the app and under-reporting of (especially short) trips in telephone-based travel surveys like the NNTS.

The video recordings provided a means with which the route choice changes of the GPS panel could be compared with population route choice in an intersection. The volumes of bicycles counted on Øvrefoss increased but not to the same degree as the GPS panel, as shown in Table 2. This is likely a result of a combination of factors, including the small sample size, different time periods for recording and a lower trip rate in the GPS panel after the intervention was completed. The video data is reliable, however, only one location is available for any recording, limiting the comparison opportunities with GPS data.

The radar traffic counts on the other hand were problematic from a data consistency perspective. The post-intervention data collection in Markveien revealed an 83% decrease in volumes of northbound cyclists despite the contraflow bicycle lane specifically providing for this group. Directional data, whilst not obviously inconsistent in the two parallel streets could not be used as a result. When considering overall volumes, the intervention street Markveien experienced a reduction as discussed in the results section whilst neighbouring streets experienced an increase in cycling levels. Such a finding conflicts with the GPS and video data and is likely a result of improper radar installation. The manufacturers of the ViaCountII device do not recommend the use of their product where parked cars or other objects may cause reflection of the radar beam from the opposite side of the road. In this highly urban area, video, manual or pneumatic tube counts may have been more appropriate options to understand volume changes in parallel streets.

### 5.3. Potential other causes of variability

Before and after travel behaviour studies must be considerate of several other confounding factors. The intervention was selected as a natural experiment due to the absence of nearby planned bicycle infrastructure projects in early 2017. However as previously mentioned, two other streets received bicycle infrastructure modifications as illustrated in Fig. 2. Sandakerveien was completed in late September and was thus still under construction during the second phase of GPS data collection, which may have led to the modest increases in bicycle volumes here (see Fig. 7). The existing bicycle lane in Toftes gate was widened and marked red, however, this did not lead to travel behaviour changes as substantial as the primary intervention.

Variable weather can strongly impact the modal share of bicycles with cycling rates typically three to four times lower in the winter months compared to the summer in Norway (Hjorthol et al., 2014). For this study, it was a specific aim to avoid data collection during the winter months. The public transport operator Ruter's Market Information Survey shows that the bicycle modal share was not greatly different between the before (8.4%) and after (7.4%) periods in Oslo as



illustrated in Fig. 6. The slight difference can, however, partly explain the reduction in corridor volumes of bicyclists observed in Table 2.

Long term effects are typically larger than short term ones, as collective improvements begin to improve connectivity in the neighbourhood and the level of exposure to infrastructure changes increases. Cross-sectional travel behaviour surveys commissioned by the City of Oslo in 2013 and 2017 show that the two city districts of Sagene and Grünerløkka had statistically significant increases in the numbers of residents who cycled at least once per week. For Sagene, north of the intervention area, this corresponded to an increase from 39 to 49%, whilst for Grünerløkka, the city district containing the intervention, the proportion of residents who used a bicycle once or more per week increased from 40 to 52% (Bayer, 2018). Approximately 0.5% of the adult population of these city districts were sampled (in 2017 this corresponded to 240 of 48,158 residents in Grünerløkka and 168 of 35,377 residents in Sagene). Although a significant change in the number of residents who regularly cycle is observed over the four-year time interval – it is not possible to determine which factors had the most influence on the change using this approach.

Within the infrastructure intervention literature, follow-up periods of up to two years are not uncommon (Smith et al., 2017). A paper which reviewed 17 natural experiments and their impact on physical activity revealed that studies with positive results generally had follow-up times of > 6 months (Mayne et al., 2015). Only one of the 17 studies reviewed had a comparable timeframe to this paper. It evaluated a 23-mile-long multi-use trail (converted from an unused railway) in North Carolina two months after opening and found no statistically significant changes in the levels of physical activity or walking for transportation amongst residents located within 2 miles of the intervention. In addition, 11% of the survey sample was not aware of the trail's presence whilst 23% had made use of it (Evenson et al., 2005). Although the study did not assess travel behaviour in the same manner as this paper (using mode or route choice), it highlights that even relatively large infrastructural changes are not noticed by the entire population. This is supported by feedback provided at the conclusion of the study (in October 2017) from a small selection of the participants ( $n = 14$ ) in which 8 participants reported that they had noticed the contraflow bicycle lane installation in Markveien when prompted: 'Did you observe any changes in your neighbourhood between the two data collection periods? If so, please describe.'

The importance of differences in context, intervention types and follow-up timings makes it difficult to precisely determine the importance of post-intervention follow-up time (Smith et al., 2017). One study which performed two follow-ups of travel behaviour is the UK iConnect study. The iConnect project found that residents located within one kilometre of three selected bicycle infrastructure intervention sites had increased their average weekly physical activity by 45 min after two years, a finding which was not reflected in the one-year post-completion survey (Goodman et al., 2014). Future research should consider adopting this approach with multiple follow-ups in order to provide insights into short-term versus long-term effects of bicycle infrastructure.

## 6. Conclusion

The aim of the study was to observe bicycle route and mode choices in a panel of residents. A natural experiment study design was used in which residents were recruited specifically in connection with the construction of a contraflow bicycle lane in Oslo. The study's principal finding is the demonstration of the route substitution effect. The study additionally shows that the observed increase in the modal share of bicycles was not statistically significant. Route substitution of existing bicyclists is critically important when estimating the network impacts of new bicycle infrastructure (change of route has a very different meaning for the transport network than change of mode). Failing to account for route substitution can lead to an overestimation of the

benefits of bicycle infrastructure development (since more cyclists are estimated than are present).

The paper outlines a smartphone GPS approach to collecting in-depth travel behaviour data from a respondent panel, however achieving satisfactory numbers of responses was troublesome, detrimentally impacting the ability to assess the significance of the intervention. With a panel participation rate of only 2% from the mailed invitations, alternative means of recruitment may be necessary when using similar approaches going forward. Natural experiments are receiving increased attention in the literature, furthering our knowledge about the effects of specific types of bicycle infrastructure provision. Future research efforts should attempt to compare such initiatives and control for contextual differences where possible.

To date, existing research on the impact of bicycle infrastructure has been mostly focussed on either mode or route change. This study contributes to a small but growing body of research that maintains a holistic perspective considering both mode and route factors in the evaluation of bicycle infrastructure over time. Future studies of this nature will assist in bettering our understanding of how bicycle infrastructure is utilised, assisting planners, policymakers and engineers in their efforts to create safe and attractive people-focussed (rather than car-centric) urban areas.

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## Declaration of interest

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## References

- Bayer, S.B., 2018. IRIS Report 2018/252. Reisevaneundersøkelse for Oslo 2017 (Travel Behaviour Survey for Oslo 2017). International Research Institute of Stavanger, Stavanger (Retrieved from). [https://www.oslo.kommune.no/getfile.php/13314342/Innhold/Gate%2C%20transport og parkering/Sykkel/Sykkelstrategier og dokumenter/Undersokelser og rapporter/Reisevaneundersokelse hsten 2017.pdf](https://www.oslo.kommune.no/getfile.php/13314342/Innhold/Gate%2C%20transport%20og%20parkering/Sykkel/Sykkelstrategier%20og%20dokumenter/Undersokelser%20og%20rapporter/Reisevaneundersokelse%20hsten%202017.pdf).
- Berger, M., Platzler, M., 2015. Field evaluation of the smartphone-based travel behaviour data collection app "smartMo". *Transp. Res. Procedia* 11, 263–279. <https://doi.org/10.1016/j.trpro.2015.12.023>.
- Bjørnskau, T., Fyhri, A., & Sørensen, M. W. J. (2012). TØI report 1237/2012. Sykling mot enveiskjøring. Effekter av å tillate toveis sykling i enveisregulerte gater i Oslo. (Contraflow Cycling. Effects of Allowing Two-Way Cycling in One-Way Streets in Oslo). (Retrieved September 1, 2018, from [https://www.toi.no/getfile.php/1325062/Publikasjoner/TØI rapporter/2012/1237-2012/1237-2012-elektronisk.pdf](https://www.toi.no/getfile.php/1325062/Publikasjoner/TØI%20rapporter/2012/1237-2012/1237-2012-elektronisk.pdf)
- Broach, J., 2016. Travel Mode Choice Framework Incorporating Realistic Bike and Walk Routes (Doctoral thesis). Portland State University <https://doi.org/10.15760/etd.2698>.
- Bucher, D., Cellina, F., Mangili, F., Raubal, M., Rudel, R., Rizzoli, A.E., Elabed, O., 2016. Exploiting fitness apps for sustainable mobility – challenges deploying the GoEco! app. In: 4th International Conference on ICT for Sustainability (ICT4S 2016). Atlantis Press (Retrieved from). <https://pdfs.semanticscholar.org/16c7/ba4702ec81529d2410ac30468ecce61cfb8e.pdf>.
- Buehler, R., Dill, J., 2015. Bikeway networks: a review of effects on cycling. *Transp. Rev.* (August 2015), 1–19. <https://doi.org/10.1080/01441647.2015.1069908>.
- Dill, J., 2009. Bicycling for transportation and health: the role of infrastructure. *J. Public*

- Health Policy 30 (Suppl. 1), S95–S110. <https://doi.org/10.1057/jphp.2008.56>.
- Dill, J., McNeil, N., Broach, J., Ma, L., 2014. Bicycle boulevards and changes in physical activity and active transportation: findings from a natural experiment. *Prev. Med.* 69 (S), S74–S78. <https://doi.org/10.1016/j.ypmed.2014.10.006>.
- Donald, S.G., Lang, K., 2007. Inference with difference-in-differences and other panel data. *Rev. Econ. Stat.* 89 (2), 221–233. <https://doi.org/10.1162/rest.89.2.221>.
- Douglas, D.H., Peucker, T.K., 1973. Algorithms for the reduction of the number of points required to represent a digitized line or its caricature. *Cartographica Int. J. Geogr. Inf. Geovisualization* 10 (2), 112–122. <https://doi.org/10.3138/FM57-6770-U75U-7727>.
- Ellis, I.O., Søgnev Haugsbø, M., Johansson, M., Berglund, G., Haug, T.W., 2015. PROSAM report 218. Reisevaner i Osloområdet. En analyse av den nasjonale reisevanerundersøkelsen 2013/14. (Travel Behaviour in the Oslo Region. An Analysis of the National Travel Survey 2013/2014) (Retrieved September 1, 2018, from). <http://www.prosam.org/index.php?page=report&nr=218#>.
- Envall, P., 2007. Accessibility Planning: A Chimera? (Doctoral Thesis). University of Leeds (Retrieved from). <http://etheses.whiterose.ac.uk/id/eprint/11279>.
- Evenson, K.R., Herring, A.H., Huston, S.L., 2005. Evaluating change in physical activity with the building of a multi-use trail. *Am. J. Prev. Med.* 28 (2), 177–185. <https://doi.org/10.1016/j.amepre.2004.10.020>.
- Fitch, D., Thigpen, C., Cruz, A., Handy, S.L., 2016. Bicyclist Behavior in San Francisco: A Before-and-After Study of the Impact of Infrastructure Investments (Retrieved September 1, 2018, from). <http://ncst.ucdavis.edu/project/ucd-ct-to-012>.
- Fitzhugh, E.C., Bassett, D.R., Evans, M.F., 2010. Urban trails and physical activity: a natural experiment. *Am. J. Prev. Med.* 39 (3), 259–262. <https://doi.org/10.1016/j.amepre.2010.05.010>.
- Flügel, S., Hulleberg, N., Fyhr, A., Weber, C., Ævarsson, G., 2017. Empirical speed models for cycling in the Oslo road network. *Transportation* (1), 1–25. <https://doi.org/10.1007/s11116-017-9841-8>.
- Goodman, A., Sahlgvist, S., Ogilvie, D., 2014. New walking and cycling routes and increased physical activity: one- and 2-year findings from the UK iConnect study. *Am. J. Public Health* 104 (9), e38–e46. <https://doi.org/10.2105/AJPH.2014.302059>.
- Goodno, M., McNeil, N., Parks, J., Dock, S., 2013. Evaluation of innovative bicycle facilities in Washington, D.C. *Transp. Res. Rec. J. Transp. Res. Board* 2387, 139–148. <https://doi.org/10.3141/2387-16>.
- Handy, S., van Wee, B., Kroesen, M., 2014. Promoting cycling for transport: research needs and challenges. *Transp. Res.* 34 (1), 4–24. <https://doi.org/10.1080/01441647.2013.860204>.
- Heesch, K.C., James, B., Washington, T.L., Zuniga, K., Burke, M., 2016. Evaluation of the Veloway 1: a natural experiment of new bicycle infrastructure in Brisbane, Australia. *J. Transp. Health* 1–11. <https://doi.org/10.1016/j.jth.2016.06.006>.
- Heinen, E., Harshfield, A., Panter, J., Mackett, R., Ogilvie, D., 2017. Does exposure to new transport infrastructure result in modal shifts? Patterns of change in commute mode choices in a four-year quasi-experimental cohort study. *J. Transp. Health* 6 (July), 396–410. <https://doi.org/10.1016/j.jth.2017.07.009>.
- Hjorthol, R., Engebretsen, Ø., Uteng, T.P., 2014. TØI report 1383/2014. Den nasjonale reisevanerundersøkelsen 2013/2014 – nøkkelrapport (2013/14 National Travel Survey – Key Results). Institute of Transport Economics, Oslo (Retrieved from). <https://www.toi.no/getfile.php?mmfileid=39511>.
- Holster, A.M.R., 2018. Educational Attainment of the Population (Retrieved September 1, 2018, from). <https://www.ssb.no/en/statbank/table/09434>.
- Hood, J., Sall, E., Charlton, B., 2011. A GPS-based bicycle route choice model for San Francisco, California. *Transp. Lett.* 3 (1), 63–75. <https://doi.org/10.3328/TL.2011.03.01.63-75>.
- Huber, S., Rust, C., 2016. Calculate travel time and distance with openstreetmap data using the open source routing machine (OSRM). *Stata J.* 16 (2), 416–423. <https://doi.org/10.1177/1536867X1601600209>.
- Hull, A., O'Holleran, C., 2014. Bicycle infrastructure: can good design encourage cycling? *Urban Plan. Transp. Res.* 2 (1), 369–406. <https://doi.org/10.1080/21650020.2014.955210>.
- Krenn, P.J., Titze, S., Oja, P., Jones, A., Ogilvie, D., 2011. Use of global positioning systems to study physical activity and the environment: a systematic review. *Am. J. Prev. Med.* 41 (5), 508–515. <https://doi.org/10.1016/j.amepre.2011.06.046>.
- Krenn, P.J., Oja, P., Titze, S., 2014. Route choices of transport bicyclists: a comparison of actually used and shortest routes. *Int. J. Behav. Nutr. Phys. Act.* 11 (1), 7. <https://doi.org/10.1186/1479-5868-11-31>.
- Lechner, M., 2010. The estimation of causal effects by difference-in-difference methods. *Found. Trends Econ* 4 (3), 165–224. <https://doi.org/10.1561/08000000014>.
- Lott, D.F., Tardiff, T., Lott, D.Y., 1978. Evaluation by experienced riders of a new bicycle lane in an established bikeway system. *Transp. Res. Rec. J. Transp. Res. Board* 683, 40–46. (Retrieved from). [http://www.john-s-allen.com/research/davis\\_studies/Lott\\_Tardiff\\_and\\_Lott.pdf](http://www.john-s-allen.com/research/davis_studies/Lott_Tardiff_and_Lott.pdf).
- Loveday, A., Sherar, L.B., Sanders, J.P., Sanderson, P.W., Eslinger, D.W., 2015. Technologies that assess the location of physical activity and sedentary behavior: a systematic review. *J. Med. Internet Res.* 17 (8). <https://doi.org/10.2196/jmir.4761>.
- Mayne, S.L., Auchincloss, A.H., Michael, Y.L., 2015. Impact of policy and built environment changes on obesity-related outcomes: a systematic review of naturally occurring experiments. *Obes. Rev.* 16 (5), 362–375. <https://doi.org/10.1111/obr.12269>.
- Mertens, L., Compennolle, S., Deforche, B., Mackenbach, J.D., Lakerveld, J., Brug, J., ... Van Dyck, D., 2017. Built environmental correlates of cycling for transport across Europe. *Health Place* 44, 35–42. <https://doi.org/10.1016/j.healthplace.2017.01.007>.
- Morrison, D.S., 2004. Evaluation of the health effects of a neighbourhood traffic calming scheme. *J. Epidemiol. Community Health* 58 (10), 837–840. <https://doi.org/10.1136/jech.2003.017509>.
- Newson, P., Krumm, J., 2009. Hidden Markov map matching through noise and sparseness. In: Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems – GIS '09, pp. 336–343. <https://doi.org/10.1145/1653771.1653818>.
- Nielsen, T.A.S., Olafsson, A.S., Carstensen, T.A., Skov-Petersen, H., 2013. Environmental correlates of cycling: evaluating urban form and location effects based on Danish micro-data. *Transp. Res. Part D: Transp. Environ.* 22, 4044. <https://doi.org/10.1016/j.trd.2013.02.017>.
- Parker, K.M., Rice, J., Gustat, J., Ruley, J., Spriggs, A., Johnson, C., 2013. Effect of bike lane infrastructure improvements on ridership in one New Orleans neighborhood. *Ann. Behav. Med.* 45 (S1), 101–107. <https://doi.org/10.1007/s12160-012-9440-z>.
- Pritchard, R., 2018. Revealed preference methods for studying bicycle route choice—A systematic review. *Int. J. Environ. Res. Public Health* 15 (3), 1–30. <https://doi.org/10.3390/ijerph15030470>.
- Project OSRM, 2018. Open Source Routing Machine Application Programming Interface Documentation v5.15.2 (Retrieved September 1, 2018, from). <http://project-osrm.org/docs/v5.15.2/api/#match-service>.
- Rissel, C., Greaves, S., Wen, L.M., Crane, M., Standen, C., 2015. Use of and short-term impacts of new cycling infrastructure in inner-Sydney, Australia: a quasi-experimental design. *Int. J. Behav. Nutr. Phys. Act.* 12 (1), 129. <https://doi.org/10.1186/s12966-015-0294-1>.
- Romanillos, G., Zaltz Austwick, M., Ettema, D., De Kruijff, J., 2016. Big data and cycling. *Transp. Res.* 36 (1), 114–133. <https://doi.org/10.1080/01441647.2015.1084067>.
- Saelens, B.E., Sallis, J.F., Frank, L.D., 2003. Environmental correlates of walking and cycling: findings from the transportation, urban design, and planning literatures. *Ann. Behav. Med.* 25 (2), 80–91. [https://doi.org/10.1207/S15324796ABM2502\\_03](https://doi.org/10.1207/S15324796ABM2502_03).
- Sandsjö, L., Sjöqvist, B.A., Candefjord, S., 2015. A concept for naturalistic data collection for vulnerable road users using a smartphone-based platform. In: International Technical Conference on the Enhanced Safety of Vehicles (ESV). Gothenburg, Sweden, pp. 6. (Retrieved from). <http://www-esv.nhtsa.dot.gov/Proceedings/24/ismv/main.htm#0A>.
- Schneider, R.J., Stefanich, J., 2015. Neighborhood characteristics that support bicycle commuting. *Transp. Res. Rec. J. Transp. Res. Board* 2520 (2520), 41–51. <https://doi.org/10.3141/2520-06>.
- Smith, M., Hosking, J., Woodward, A., Witten, K., MacMillan, A., Field, A., ... Mackie, H., 2017. Systematic literature review of built environment effects on physical activity and active transport – an update and new findings on health equity. *Int. J. Behav. Nutr. Phys. Act.* 14 (1), 158. <https://doi.org/10.1186/s12966-017-0613-9>.
- Stappers, N.E.H., Van Kann, D.H.H., Ettema, D., De Vries, N.K., Kremers, S.P.J., 2018. The effect of infrastructural changes in the built environment on physical activity, active transportation and sedentary behavior – a systematic review. *Health Place* 53 (July), 135–149. <https://doi.org/10.1016/j.healthplace.2018.08.002>.
- Troelsen, J., Jensen, S.U., Andersen, T., 2004. Evaluering af Odense – Danmarks Nationale Cykelby (Evaluation of Odense – Denmark's National Cycle City). Odense Kommune (Retrieved from). [http://arkiv.cykelviden.dk/filer/cykel\\_inet.pdf](http://arkiv.cykelviden.dk/filer/cykel_inet.pdf).
- Vaage, O.F., 2018. Norwegian Media Barometer 2017 (Retrieved September 1, 2018, from). [https://www.ssb.no/kultur-og-fritid/artikler-og-publikasjoner/\\_attachment/346186?\\_ts=162d7feae58](https://www.ssb.no/kultur-og-fritid/artikler-og-publikasjoner/_attachment/346186?_ts=162d7feae58).
- van Goeverden, K., Nielsen, T.S., Harder, H., van Nes, R., 2015. Interventions in bicycle infrastructure, lessons from Dutch and Danish cases. *Transp. Res. Procedia* 10 (July), 403–412. <https://doi.org/10.1016/j.trpro.2015.09.090>.
- van Wee, B., Börjesson, M., 2015. How to make CBA more suitable for evaluating cycling policies. *Transp. Policy* 44, 117–124. <https://doi.org/10.1016/j.tranpol.2015.07.005>.
- Vasilev, M., Pritchard, R., Jonsson, T., 2018. Trialing a road lane to bicycle path redesign—Changes in travel behavior with a focus on users' route and mode choice. *Sustainability* 10 (12), 1–18. <https://doi.org/10.3390/su10124768>.
- Via Traffic Controlling GMBH, 2016. ViaCount II Specifications (Retrieved September 1, 2018, from). [https://www.viatraffic.de/fileadmin/viatraffic-content/downloads/katalog2016/en/viatraffic\\_2016\\_GB\\_viacountII.pdf](https://www.viatraffic.de/fileadmin/viatraffic-content/downloads/katalog2016/en/viatraffic_2016_GB_viacountII.pdf).
- Wahlgren, L., Schantz, P., 2014. Exploring bikeability in a suburban metropolitan area using the active commuting route environment scale (ACRES). *Int. J. Environ. Res. Public Health* 11 (12), 8276–8300. <https://doi.org/10.3390/ijerph110808276>.
- Wilmink, A., Hartman, J.B., 1987. Evaluation of the Delft bicycle network plan. Final summary report. In: Ministry of Transport and Public Works. Transportation and Traffic Engineering Division, The Hague, Netherlands.
- Yang, L., Sahlgvist, S., McMinn, A., Griffin, S.J., Ogilvie, D., 2010. Interventions to promote cycling: systematic review. *BMJ* 341 (oct18 2), 1–10. <https://doi.org/10.1136/bmj.c5293>.