Modelling and Analysing Cyclist Road Safety Performance in Scotland: a Safety in Numbers perspective

By

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Abstract

Reported cyclist casualties are disproportionally high relative to their modal share. This is a well-documented problem and yet we currently do not have local or national models that can estimate exposure (i.e. intensity of travel by bike). There is therefore is limited capacity among practitioners and professionals to estimate normalised risk at a disaggregate level and there is little evidence available for network level risk factors associated with cyclists' safety. Simultaneously an increasingly popular vulnerable road user policy development is the safety in numbers effect. The main theory behind safety in numbers is simply that more cyclists, or pedestrian activity, reduces the overall risk of having an accident.

This research investigates whether there is a safety in numbers effect in Scotland; examines if there are wider spatial, demographic and policy differences affecting cyclists; and develops a novel modelling method to estimate cyclist exposure based on open data and open software. A comparison of traditional road safety macro-level global regression models, with local meso-level geographically weighted regression models to investigate safety in numbers was used to explore the nature of the safety in numbers effect in Scotland.

The comparison of the global and local model forms yielded four main results. First, local models' account of spatial dependence provide a better statistical fit than the traditional global models. Second, both the global and the local models confirm that there is a safety in numbers effect in Scotland but that the effect is less than reported in the literature and referenced in Scottish policy documents and guidance. Third, the local models confirm that safety in numbers is not static and that the effect varies spatially, depends on local infrastructure factors and the intensity of cycling activity. Finally, a safety in numbers effect can co-exist with hazard in scarcity, weaker safety in numbers effects were found among women and between injury severity levels.

Edinburgh was identified as an urban area with high potential for a safety in numbers effect within Scotland because, unlike across the most of Scotland, cycling doubled between 2001 and the 2011 census and is likely to double again by 2021 given current trends. The results found that there is a safety in numbers effect in Edinburgh for slight casualties but that there is little to no effect for killed or serious injuries (KSIs). The strength of the effect (i.e. less cycling risk) is associated with higher concentrations of some types of cyclist infrastructure but not others. Unprotected on-road cycle lanes, advanced stop lines and bus lanes were not positively associated with improved cyclist safety, however quiet routes, off-road cycle lanes and segregated facilities were found to be safer. Therefore, despite higher cycling activity, Edinburgh does not yet benefit substantially from a safety in numbers effect. This confirms that cycling numbers alone do not produce safety in numbers; and effective and ineffective cycling infrastructure was also identified.

A further finding and benefit of using spatial modelling is the visualisation of safety in numbers in a local context to identify where it does or does not manifest and this also facilitates evaluation of facilities and other policy interactions or factors. Furthermore, the safety in numbers effect can be used as a Safety Performance Function to assess road safety which is a superior metric than rate-based measures. This has not previously been demonstrated in the literature and therefore this research contributes and adds to the understanding of the safety in numbers effect and demonstrates the need to develop cycling flow models to provide evidence based research.

Keywords: Safety in Numbers, Spatial Model, Exposure, Cyclists, STATS19, Traffic safety.

Declaration

I hereby declare that this thesis was composed by myself and that the work herein is mine unless otherwise stated.

Signed……………… [redacted] ………….

Date: …………………………20/09/2019…………………………………………..

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Publications

Edinburgh Napier University regulations state that any publication resulting from the research undertaken for this thesis must be noted.

The articles published are the following (copy appended at end of thesis):

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List of Abbreviations

AADF	Average Annual Daily Flow
AADT	Average Annual Daily Traffic
AIC	Akaike Information Criterion
APM	Accident Prediction Model
ASL	Advanced stop line
ATC	Automatic Traffic Counter
ATP	Active Travel Plan
CBA	Cost benefit analysis
CAPS	Cycling Action Plan for Scotland
CI	Confidence interval
CEC	City of Edinburgh Council
CMF	Crash modification factor
CRAN	Comprehensive R archive network
CSV	Comma separated value
EC	European Commission
ETSC	European Transport Safety Council
EU	European Union
DfT	Department for Transport
GEE	Generalised estimating equation
GEH	Geoffrey Edward Havers
GLM	Generalised Linear Models
GOF	Goodness of fit
GWR	Geographically weighted regression

HLT	Hosmer-Lemeshow test
ITF	International Transport Forum
IZ	Intermediate data Zone
KSI	Killed and serious injury
LA	Local authority
LL	Log Likelihood
LRT	Likelihood Ratio Test
mph	Miles per hour
mvkm	million vehicle kilometres
NCN	National Cycling Network
NHS	National Health Service
NRA	National Roads Authorities
NSS	National Statistics Scotland
O-D	Origin-Destination
OECD	Organisation for Economic Co-operation and Development
ONS	Official National Statistic
OR	Odds ratio
OSM	Open street map
PCT	Propensity to cycle Tool
PA	Population Averaging
QIC	Quasilikelihood under the independence model criterion
R	R project
RoSPA	Royal Society for the Prevention of Accident
SiN	Safety in Numbers
TfL	Transport for London

TRL	Transport Research Laboratory
TRO	Transport Regulation Order
TS	Transport Scotland
SPF	Safety performance indicator
SPI	Safety performance indicator
STRADA	Swedish Traffic Accident Data Acquisition
STS	Scottish Transport Statistics
SUMP	Sustainable urban mobility plan
VIF	Variance inflation factor
Vkm	Vehicle kilometres
VRU	Vulnerable road user
WHO	World Health Organisation

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CHAPTER 1

Introduction

1.1 Introduction

The numbers of cyclists' road injuries continues to rise despite focus on increased cycling and cycling safety. Within the transport system cyclist casualties are disproportionally high relative to their modal share.

Why examine cyclist safety?; if we ask this question in the context of the overall road safety picture in Scotland one may, possibly argue that cycling is a small part of the transport system and that the resultant numbers involved in road collisions are low compared to motorists and pedestrians. If, however, we step out of the transport context and instead consider cyclist road safety from a public health perspective (Davis and Cavill, 2006, Stradling, Meadows, and Beatty, 2000; Fox, 1999; Curtis and Headicar, 1997), environmental (Robinson, 2006), and social equity (Rock et. al., 2017) perspectives the impact of poor road safety becomes more apparent.

The first is a direct impact, cyclists involved in road traffic collisions presenting at hospitals, public health clinics or general practitioners. The second is indirect, overall public health can be improved with daily activity; active travel serves to reduce emissions, noise and carbon consumption and the bicycle is one very efficient substitute to private car travel in urban areas. Finally social equity is impacted because car based accessibility is only available to those who can afford to own a car or have the ability to drive and if the transport system is less safe for vulnerable road users then those with a lack of choice are exposed to higher risks from traffic, pollution and noise (Gough, 2017). Active travel and sustainability policies encouraged and promoted sustainable transport policies and public health policies, however little road safety focus is directly linked to cyclist road safety performance such that an increase in a promoted activity should not result in negative impacts. Loo and Anderson (2016) point out that the subject of road safety is missing from global summits on poverty reduction, public health, engineering and often transport.

Finally, there is a symbiotic feedback between these two policies, poor road safety deters cycling and the use of unsustainable transport modes because they are safer will result in a largely inactive population which will not improve public health.

1.2 Background and Research motivation

Road deaths are a global problem according to the World Health Organisation (WHO, 2018) who estimate that about 1.3 million people die each year on the world's roads and that 25,300 people lost their lives across the European Union (EU) in 2017. The European Transport Safety Council (ETSC) estimate that cyclists account for nearly 21% of all road deaths in the European Union (ETSC, 2015). This is despite the fact that European roads are among the safest in the world; in 2017, the EU reported 49 road fatalities per one million inhabitants compared to 174 road deaths per million globally.

The UK has one of the best road safety performance records in the world, it has continued to enjoy excellent road safety records with 27 fatalities per million inhabitants in 2017 which is well below the EU average. In the UK, vulnerable road users accounted for almost half of the all road deaths, 21% are pedestrians, 14% are motorcyclists, 8% are cyclists and 3% moped riders. Cycling represents only 4% of the modal share in urban areas and 1% in rural areas (Scottish Household Survey, 2015) therefore, 8% of the total number of people killed annually is disproportionately high.

To address road safety and prevent road injuries and death in Scotland, the Scottish road safety framework aims to achieve "*a steady reduction in the numbers of those killed and those seriously injured, with the ultimate vision of a future where no-one is killed on Scotland's roads, and the injury rate is much reduced*." (Scottish Government, 2009; pg.16). The framework includes targets to reduce slight injuries by 10%, serious injuries by 55% and fatal injuries by 40% benchmarked against the 2010 figures. Cyclists, are at particular risk because they have a higher potential for injury and burden of injury severity (Chong, et al., 2010) and non-motorised road users face a fatality risk almost ten times greater than the risk for car passengers for a given distance travelled in cities (OECD/ITF, 2019; pg.9).

The progress towards this goal among cyclists shows serious injuries have continued to increase at a slow but steady pace and were 18% above the baseline in 2017 (See Table 9.1, Chapter 9); when set against the targets the comparison is stark, slight injuries increased above the target by 18%, serious injuries increased by 162% and actual fatalities were 45% above the fatalities target for cyclists. The overall transport performance however paints a much better road safety picture, the targets have already been achieved and continue to improve, in 2017 the overall injury reductions were 46%, 39% and 50% in excess of the targets set for slight, serious and fatal injuries.

In addition to the lack of road safety performance, there is increasing evidence that suggests that the true impact of road safety in cities goes well beyond the direct suffering caused by injuries alone because road safety determines the success or failure of the sustainable urban mobility transition (OECD/ITF, 2019; pg.11). Increasing cycling and walking goes hand in hand with a range of health benefits that governments seek to achieve through active travel policies, not to mention other social, economic and environmental benefits such as reducing carbon emission from car use.

Road safety and road safety objectives must be viewed, not in isolation, but together with these policies in a meaningful and integrated manner to ensure the successful implementation of wider benefits. Therefore, addressing cyclist road safety to reduce preventable injuries and inadequate road safety performance requires cross departmental and institutional cooperation, from the law, planning, transport, education, public information and health perspectives.

The Safety in Numbers (*SiN*) effect is often cited in policy and advocacy parlance with reference on to a particular piece of research by Jacobsen in 2003. It describes a lower risk of injury or collision due to higher levels of bicycle flow such that the increasing number of cyclists directly influences the hazardous behaviours of car drivers (Jacobsen, 2003; Bhatia and Wier, 2011; Jacobsen, 2015; Scholes et al., 2018). In the UK and Scotland policy makers hope that increasing cycling in low cycling contexts, through encouragement and better facilities (in their opinion), that injury risk will reduce at more than the proportional rate at which cycling increases (Aldred et al., 2017).

In order to measure the *SiN* effect a suitable measure of exposure is needed, however similar to many EU countries, not all cities have the capacity as yet to measure the level of risk experienced by vulnerable road users (VRUs) in urban traffic (Castro et al., 2018). According to the International Transport Forum (2013), most authorities lack the factual basis to assess cyclist safety or the impact of ‘safety improving’ policies. In the UK the lack of appropriate expertise, tools, and models were frequently cited as hindering the capacity of local organisations to provide support for cycling (Aldred et al., 2017). According to Kolgin and Rye (2015) the current lack of theoretical understanding and modelling within the field of planning for cyclists is important and is needed to understand and fully grasp the marginalisation of cycling in transport planning.

Unlike for motorised transport, cyclist exposure is typically difficult to estimate due to lack of data collection and a lack of national or regional transport models that include vulnerable road user modes. Therefore, it is difficult for researchers or local authorities to determine if a change in the number of accidents over time is due to increased accident risk, (users or environment becomes more unsafe) or if the increase in accidents is due to a higher proportion of cyclists using the existing roads and routes and therefore that there are more incidents. Consequently, the availability of data to ascertain a representative level of ‘exposure’ or simply how much cycling there is ‘when and where’ is limited and is one of the prevailing challenges in cycling research, or indeed any vulnerable road user research and is a key issue which this research attempts to address.

This research is motivated by a need to gain a greater understanding into how these aspects play a part in cycling safety performance so that the full benefits of policies that encourage active travel, better cities and environments can be enjoyed equally by all people. To do this safety strategies or systems with specific relevance to cyclists are needed to reduce cyclist injury and improve risk performance so that cycling can begin to flourish for all ages and abilities. Transport needs to implement a safe system whereby cyclists achieve global road safety targets that align with the overall safety goals and aspirations equally.

This research aims to investigate whether there is a safety in numbers (*SiN*) effect in Scotland; to examine if there are wider spatial, demographic and policy differences affecting cyclists; to model cyclist exposure; and to assess the factors associated with cyclist injury severity. It is anticipated that the empirical research will inform a framework for the estimation and monitoring of cyclist risk performance and to elaborate the understanding of the safety in numbers effect at a country and urban city level.

1.3 Thesis Structure

This thesis is comprised of nine chapters, including this, Chapter 1, which serves as a general introduction to the thesis. The following sections briefly describe the contents of the next eight chapters and the main topics covered in each case. The first three chapters cover the literature review, the research focus and the methodology. The next four chapters report and discuss the thesis research and results. The final chapter concludes the thesis with a summary of the main findings and conclusions, a description of how the findings achieved the research objectives and questions, the contributions to knowledge and finally a discussion of research limitations.

Chapter 2 reviews the relevant international, UK and Scottish scientific and academic literature and government publications about cycling road safety planning, design and measurement to provide background and context to the thesis and to identify, research gaps and challenges to the proposed research. **Chapter 3** defines the research objectives and the subsidiary research questions and discusses the research methods. **Chapter 4** reviews the research methodology and describes the regression models and statistical analysis techniques and maps them to each chapter of the thesis.

Chapter 5 examines STATS19 between 2010 and 2012 for Scotland to determine factors associated with killed or severe injury (KSI) cyclist collisions and to understand the risk factors involved in KSI injury accidents compared to slight injury accidents.

Chapter 6 compares three types of generalised linear models to examine cyclist road safety risk at the population (global) level and at the local authority (LA) area level and uses the results to evaluate the *SiN* effect to determine if more cycling reduces cyclist casualties to the same extent across Scotland. The chapter also addresses cyclist exposure measures and their applicability to road safety research at both global and local levels.

Chapter 7 describes the application of a novel methodology for developing a cycling flow model and model validation methods to provide more accurate estimate of total cycling distances including cycling on off-road facilities. A combination of traditional (Census and Automatic Traffic Counts) and novel (OpenStreetMap) data was used to produce flow estimates at both link and meso-spatial area levels. This is illustrated using Edinburgh City as a case study.

Chapter 8 investigates whether there is a localised cyclist *SiN* effect in Edinburgh, due to increased mobility, and examines if the road environment and cycling environment are contributory factors that have an impact on road safety or if SiN effect is due to increased flow alone.

Chapter 9 outlines the conclusions, recommendations and limitations and then proposes further and future research.

CHAPTER 2
Literature Review

"Road safety is a multi-sectorial issue and a public health issue—all sectors, including health, need to be fully engaged in responsibility, activity, and advocacy for road crash injury prevention" World Health Organisation (2004. Pg. 7).

2.1. Introduction

Transport is a constant part of life's mobility, offering accessibility to our needs, whether direct or indirect, from the moment one orders internet goods or decides to travel somewhere for work or recreation. However, mobility comes with an element of inherent injury risk due to conflicting movements and interactions between modes. Furthermore, there is a lack of equity between transport users in terms of their injury risk and availability of choice.

Government policies seek to improve active travel while simultaneously pushing for reduced overall road injury accidents. Global road safety performance has consistently improved in the UK and Scotland but there has been an increase in the number of injury accidents among cyclists, particularly since 2005. While increased cycling mobility may explain this increase, it is still at odds with the improvements observed across motorised transport. Injury accident reduction continues to improve despite a sustained increase in vehicle miles travelled and car ownership, and it is forecast to keep increasing in the future. Cyclists have been encouraged to take to the roads to increase cycling use and modal share, to reduce car use, improve population heath and reduce carbon production. However, unlike motorised transport, that has reduced its accident risk, cyclists experience the opposite effect such that cyclist injuries, particularly serious injuries, are rising more steeply than cycle use in the UK (DfT, 2015).

The following chapter is structured as a two-part literature review; the first section will provide a background to the study that addresses national and international aspects of cyclist road safety and policy and the second section will discuss cyclist safety in the context of safety in numbers (*SiN*). The literature review will then conclude with a discussion of the knowledge gaps identified and the expected contributions to knowledge. This structure is illustrated in Figure 2-1 below.

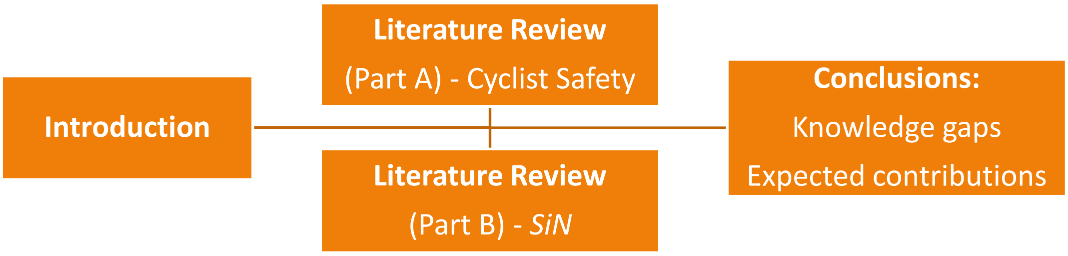


Figure 2-1 Chapter 2 Literature Review outline structure

Part A

2.2. Literature Review (Part A)

This section examines and discusses cyclist safety vertically at European, National and local levels and then horizontally across several different contexts: from policy to infrastructure, measurement to modelling and finally the different theories and safety performance indicators.

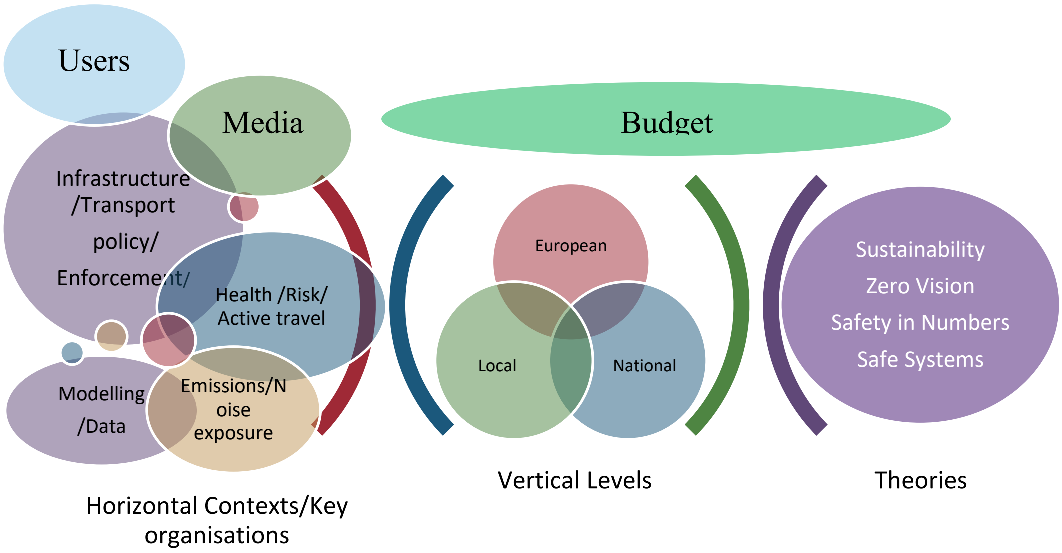


Figure 2-2 Cycling Road Safety Contexts, levels and theories

2.2.1. An EU perspective

The European Transport Safety Council (2015) estimate that pedestrians and cyclists account for nearly 30% of all road deaths, at 21% and 8% respectively. The reduction in the number of pedestrian and cyclist deaths has slowed markedly in the last five years (Figure 2-3). European roads are some of the safest in the world; in 2017, the EU reported 49 road fatalities per one million inhabitants compared to 174 road deaths per million globally. Road deaths are a global problem, the World Health Organisation (WHO, 2018) estimates that about 1.3 million people die each year on the world's roads and that 25,300 people lost their lives across the EU in 2017. According to estimates, 135,000 people were seriously injured on Europe's roads in 2014 (EC, 2016; pg 1). The UK has continued to enjoy excellent road safety records with 27 fatalities per million inhabitants in 2017, a 5% decrease compared to 2016, and it was one of the best states in the EU. In 2017, vulnerable road users (pedestrians, cyclists and motorcyclits) accounted for almost half of the road victims. 21% of all people killed on roads were pedestrians and 25% were two-wheelers (14% motorcyclists, 8% cyclists and 3% mopeds riders). Pedestrian and cyclist fatalities have decreased at a slower rate than other fatalities by 15% and 2%, respectively, from 2010 to 2016, compared to the overall fatality decrease of 20% (EC, 2019). Accidents in urban areas are different, in character, to accidents on rural roads and motorways. Within urban areas, 40% of the fatalities are pedestrians and 12% are cyclists. This means that 56% of the total fatalities in urban areas are vulnerable road users (EC, 2019).

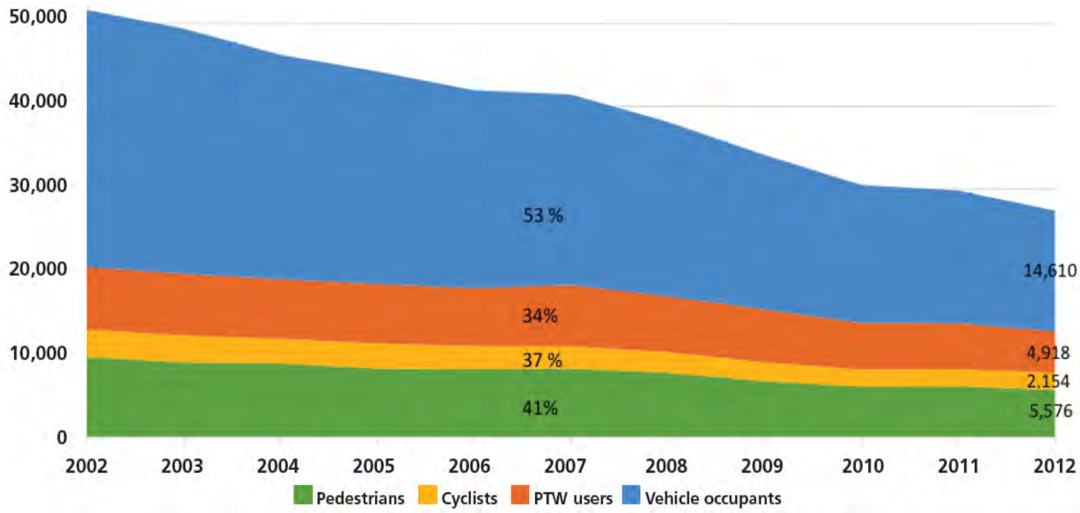


Figure 2-3 Reduction of road deaths since 2002 (Adminaite, D., Allsop, R. and Jost, G. (2015), Figure 1, pg.7) among EU 28 countries.

Unprotected users, i.e. pedestrians and cyclists, are at particular risk because they have a higher potential for injury and burden of injury severity (Chong et al., 2010). Moreover, significant under-reporting of pedestrian and cyclist collisions in the EU is a common issue. According to the OECD/ITF (2013) most authorities lack the factual basis to assess vulnerable road user (VRU) safety or the impact of 'safety improving' policies. The core of their problem is the calculation of accident incidence rates, both fatal and varied levels of severity. As such, safety is the quotient of the number of accidents divided by a measure of exposure. National or local/regional authorities lack either one or both pieces of information. Additionally, under-reporting of personal injury accidents effects analysis (discussed further in Section 2.1.7).

In a wider European context, the International Transport Forum's Working Groups' findings suggest that most European national and regional or municipal authorities lack adequate VRU data on which to base their safety assessments and policies (OECD/ITF, 2013). Many countries measure their safety performance using a 'Safety Index' or crash incidence rate where safety is the quotient of the number of crashes divided by a measure of exposures (trips, kilometres, miles, hours). The problem with this approach is that both the numerator and denominator are inadequately measured or missing entirely. Consequently, authorities do not have an accurate grasp of the true injury rates, particularly non-fatal injuries. Therefore, authorities cannot determine if observed trends are due to safety changes or volume changes. In order to develop polices to improve safety, it is crucial to improve the knowledge gap so that successful and sustained policy is fact based (OECD/ITF, 2013).

This inaccurate and inconsistent method of reporting impacts VRUs to a greater extent because of legal reporting mechanisms (discussed further in Section 2.1.8) and because they are disproportionately vulnerable to injury compared to motorists, and finally because VRUs serious and minor injuries exhibit the most inaccuracies within official figures. These inaccuracies also have financial implications as accident costs vary substantially by severity level (Wang et al., 2011). Therefore, lack of understanding of the true cost of pedestrian and cyclist accidents (the unobserved parts) hinders national and local policy and safety investment.

Cycling is promoted by national governments and lobby groups, while walking can often be neglected in planning and policy development (OECD/ITF, 2012). Given a relatively modest overall improvement in the numbers cycling, falling distances walked, and increased VRU injury risk, urban transport systems will have to undergo a dramatic change to reach the EU's Transport White Paper (EC, 2011) targets. Subsequently, VRU injury risk may deteriorate further in coming years as active travel increases.

One of the highest performing countries, in terms of road safety, in the EU is Sweden where fatalities among "*protected*" road users continues to decline under the "Vision Zero" road safety strategy. However, "*unprotected*" road users (pedestrians, bicyclists, and motorcyclists) do not have the same positive development. The safety problem focus in Sweden is therefore changing from "*protected*" road users outside cities to "*unprotected*" road users in cities (OECD/ITF, 2016). As many EU countries seek to adopt "Vision Zero" it is important to be cognisant of the fact that this approach, like many existing strategies, needs to focus on VRU performance.

The UK's overall casualty rate for cyclists is now similar to motorcyclists, at 5,800 per billion miles travelled, and walking is somewhat lower, at 2,100 per billion. However, pedestrian fatality risk is still higher than cyclists, at 35.8 per billion miles travelled compared to 30.9 per billion (DfT, 2016; pg.6). Moreover, cyclist injuries, particularly serious injuries, are rising more steeply than cycle use in the UK (DfT, 2015) and yet UK and Scottish levels of cycling, as a mode of transport, are considered low by European standards at 2% (DfT, 2011) despite the encouraging recent increases.

Road safety is interlinked with other European policy objectives, for example, cities that want to encourage a modal shift to more sustainable transport modes such as walking and cycling should make sure that these are safe options, so that the modal shift does not compromise safety. Similarly, access restriction zones such as low-speed zones may contribute not only to environmental objectives but also to increased urban road safety (EC, 2013).

2.2.1.1. Scottish Perspective

The most prominent cyclist casualty trend, since the mid-2000s, is the rise in adult cyclist casualties both in terms of hospital admissions and police road accident casualties. Hospital admissions have increased by 34% and police incidents have increased by 25% between the 2003/2007 average to the 2009/2013 average. Edinburgh has more than double the rate of police reported casualties observed in comparison to Scotland's other large cities of Aberdeen, Dundee and Glasgow. Similarly, in terms of hospital admissions there has also been an increase in adult cyclist admissions across Scotland's four largest cities in recent years (Whyte and Waugh, 2015).

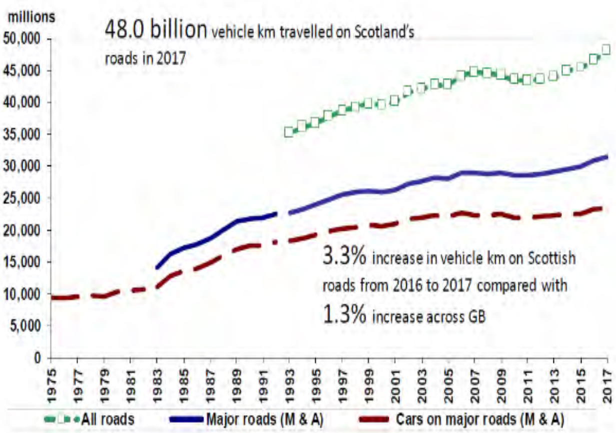
Despite supportive Scottish policies[1], long-term trends for active travel have seen a reduction of 6.5% in the overall levels of cycling in the past decade but an increase in motorised transport, particularly car use, according to the Scottish Transport Statistics (STS) (2019), see Figure 2-4 below.

Approximately 30% of all journeys to work in Scotland were by public or active travel in 2017, the same as 2007 (STS, 2019; pg 17). Cycling retained a low modal share of 3%, except in some cities, such as Edinburgh, where the proportion of residents cycling as their main mode of travel to work has increased from 6% to 9.8% over the last 10 years.

In 2017, commuting accounted for 24.7% of all journey purposes (TS, 2019; pg.183). While the numbers quoted in Figure 2-4 below states that there has been a fall in the distances travelled in Scotland, Transport Scotland (2017) states that there has seen

[1] *The Scottish Government's National Physical Activity Implementation Plan based on the Toronto Charter for Physical Activity; The National Walking Strategy: Let's get Scotland Walking (2014); The Cycling Action Plan (2013) and* A Long Term Vision for Active Travel in Scotland 2030 *(Transport Scotland, 2014)*

an almost doubling in the distance cycled over the past decade with an overall 41% increase in cyclist traffic, kilometres travelled (TS, 2017).



	2012-13	2017-18	Change over 1 year	Change over 5 years
Car Traffic (m/veh km) on all roads	33,777	36,206	2.4%	7.2%
Pedal Cycles (m/veh km) on all roads	310	290	0.7%	-6.5%
ScotRail Passengers (millions)	83.3	97.8	3.8%	17.4%
Bus Passengers (millions)	420	388	-1.5%	-7.6%
Air Passengers (millions)	22.2	28.8	7.1%	29.8%
Ferry Passengers (millions)	9.7	10.3	1.8%	5.7%
Source: STS 2018, Table S1 except Traffic estimates from table 5.3. Note pedal cycle estimates are based on small sample sizes, see chapter 1 for more detail.				

Figure 2-4 Scottish Transport Statistics (TS, 2019) Figure 2 and Table pg. 11.

While the overall cycling modal share of all journeys to work is 3%, the share of the overall distance travelled is still low at 1% of the total million vehicle kilometres (mvkm) travelled (see Figure 2-5 below), with an average distance of 4.5 kilometres cycled compared to 15.2 kilometres driven by car.

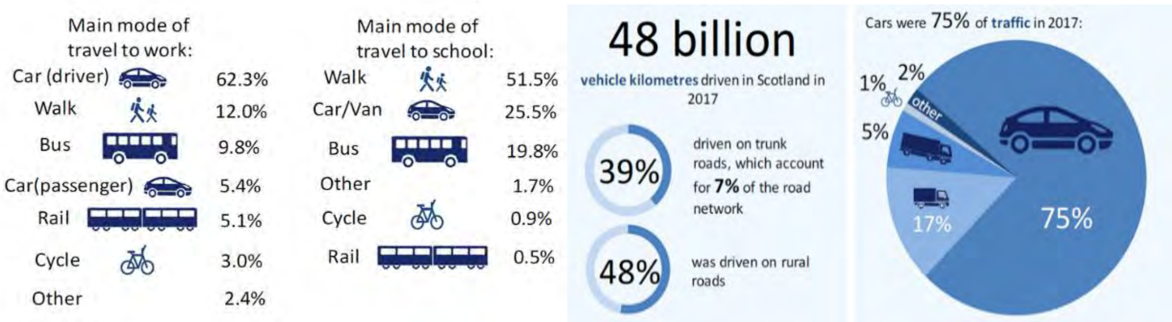


Figure 2-5 Scottish Transport Statistics (2019) Figure 6 and Chart pg. 85.

In terms of road safety trends, road fatalities across all modes continues to fall, some at a faster rate than others. While overall casualties have fallen in some instances, cyclist and pedestrian fatalities have begun to increase and lag behind the overall road safety improvement trend. The long-term trend, between 2007 and 2017, in the number of injury road accidents reported vary between the Police Force divisions across Scotland, ranging from a 20% fall (East Renfrewshire) to a 65% fall (Moray) but the overall trend is downward (TS, 2019).

The overall trend in Scotland has been a steady increase in road traffic and a more than proportional decrease in casualties, Figure 2-6 below. Pedestrians and cyclists account for 15% and 8%, respectively, of road casualties in Scotland (Scottish Transport

Statistics, 2016) while journey to work accounts for 13% and 3%, respectively (National Statistics for Scotland, 2016; TS, 2019).

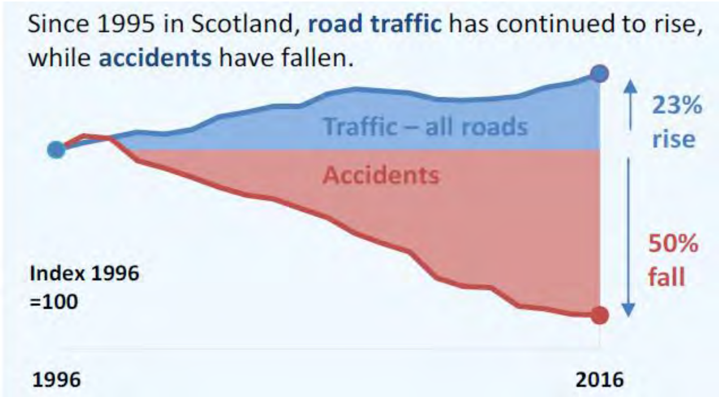


Figure 2-6 The road traffic and collision trends in Scotland over the past two decades *(National Statistics for Scotland, 2017, pg. 10.)*

In the context of the total volume of traffic on the roads in Scotland, the 9,428 total casualties recorded in 2017 represent 19.65 casualties per 100 mvkm. The Road Safety Framework (for Scotland) also monitors the numbers of slight injuries per 100 mvkm (TS, 2019).

The Scottish Road Safety framework target reduction, Figure 2-7 below, sets several reduction targets. Scotland's road safety vision is that there will be: '*A steady reduction in the numbers of those killed and those seriously injured, with the ultimate vision of a future where no-one is killed on Scotland's roads, and the injury rate is much reduced*.' The framework targets aim to achieve an overall 55% reduction in serious injury (from 2010 levels) and 40% reduction in people killed (from 2010 levels) by 2020. The framework specified that the road safety actions for cyclists are developed in a separate document called the Cycling Action Plan for Scotland and its aim is to achieve '*more people cycling more often*' and to '*increase the numbers of children receiving cycle training and therefore promoting road safety*' (Transport Scotland, 2013).

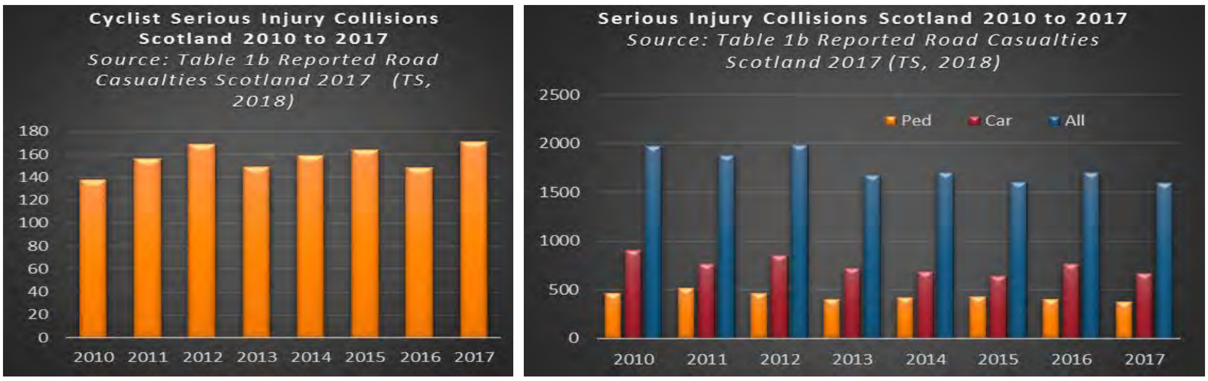


Figure 2-7 (a) Cyclist serious injury trend, (b) Pedestrian, Car and overall serious injury trends 2010-2017. *Source: Reported Road casualties Scotland 2017 (Transport Scotland, 2018).*

If we look at cycling outside of the global figures above the picture is somewhat different to the overall trend, Figure 2-7 (a) and (b) above, cyclist serious injuries have increased between 2010 and 2017 whereas the overall trends for car users and pedestrians have fallen.

The Cycling Action Plan for Scotland (CAPS) vision aims for 10% of everyday cycling trips by 2020 (TS, 2017). One of the best performing cities in Scotland, the City of Edinburgh Council (CEC), has a higher aim of 15% set out in its Active Travel Action Plan because, in 2009, CEC signed the *Charter of Brussels*[2] which also includes the road safety target to reduce the risk of fatal cyclist accidents by 50% by 2020. Furthermore, the core of the Safety Plan for Edinburgh 2020 is '*Vision Zero*', which will be discussed further in Section 2.2.5.1.

2.2.2. Determinants of cycling: Government policies

This section provides an overview of the determinants of cycling, identified in previous research and considered relevant to the current research aims and objectives. This section will consider government policy, the built environment, cycling advocacy and culture. Policy, as a term, has several dimensions and perspectives; mainly the course of action taken individually, by group or groups, institutions, or governments which affects our everyday life (Torjman, 2005).

Important factors that influence transport planning and policies include the historical context (e.g., level of car dominance), the economic history (e.g., growth or decline), and planning traditions and cultures (e.g., whether the city has traditionally been planned for cars or bicycles), and these can affect both the concrete outcome of transport planning and the transport policies that are enacted (Koglin, 2013).

Government policies seek to improve active travel while at the same time push for reduced overall road injury accidents. The global road safety performance for all road transport in the UK has consistently improved, there has also been an increase in the number of injury accidents, particularly among pedestrians and cyclists. This may be attributed to increased active travel, however motorised transport also continues to increase but the numbers of casualties continue to fall, discussed in Section 2.2.1.1.

[2] *The* ***Charter of Brussels****, signed by over 60 cities in Europe, is the primary European Cycling Federation (ECF) policy document. It calls upon policymakers to promote cycling and to set clear, measurable targets for cycling in terms of both modal share (the percentage of trips made by bicycle out of the total). See https://ecf.com/who-we-are/our-mission/charter-brussels for more information.*

Active travel is a determinant of how healthy a population is (Royal Society for the Prevention of Accidents, 2014) but negative perceptions of road safety and higher injury risk limit the potential success of wider active travel policies and directly impacts emergency services. What one does not wish to see is undesirable outcomes due to increase in mobility. Active modes improve population health and reduce the environmental impact of travel, however increased trend in casualties is with associated increase in walking or cycling related injuries or deaths presenting at ever-overburdened hospitals or preventing active travel due to safety concerns in undesirable.

Pucher and Buehler (2008) argue that cycling is highly irresistible given its multiple areas of health, economic and environmental benefits. The UK Department of Health (DH) advise adults between ages 19 to 64 years to undertake either moderate intensity or vigorous intensity physical activity and cycling is considered one such moderate intensity physical activity (DH, 2011). Being active reduces the risks of getting diseases such as coronary heart disease, stroke, and Type 2 diabetes but promotes healthy weight, low risk to obesity, depression and anxiety, improvement in self-esteem, and general well-being (DH, 2011).

The UK government aims, via the Climate Change Act 2008, to reduce greenhouse gas emissions by at least 80% by 2050 and making trips by bike instead of by car reduces emissions of greenhouse gases (GHG), especially CO_2.

Cycling infrastructure is cheap compared to main road upgrades and high-speed rail. However, it is expensive compared to the more traditional British approach of boosting cycling by encouragement, training and promotion (Golbuff and Aldred, 2011). The City of Edinburgh Active Travel Action Plan (2016; pg. 7) states that:

there is evidence of a 'safety in numbers' effect for cycling. More cycling means safer cycling.

Briefly, *SiN* is a recent paradigm in transportation research that has emerged as a causal inference for a non-linear relationship between estimates of the numbers of VRUs in an area and the rate or number of traffic collisions experienced by VRUs. Thus, greater numbers of cyclists modify the behaviour of drivers that create safer streets/roads as illustrated in Figure 2-8 below, and this will be discussed in more detail in Part B of this chapter.

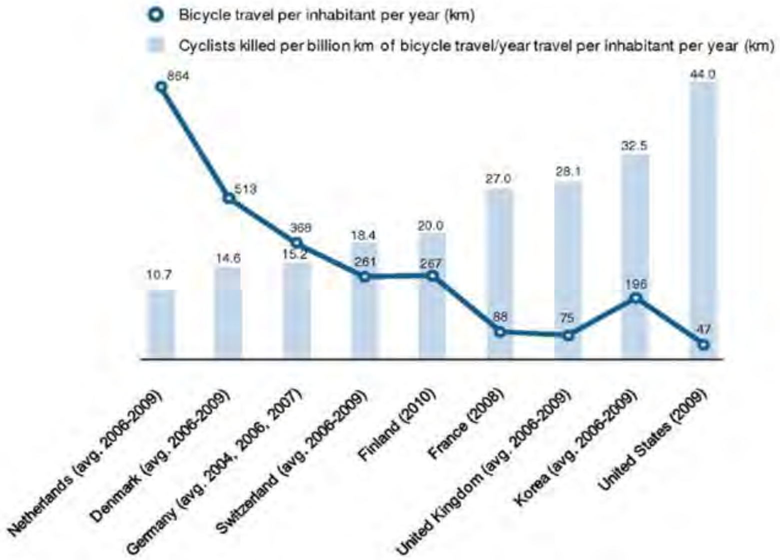


Figure 2-8 Bicycle travel per inhabitant and number of cyclist killed 2006-2009

(Source: OECD/ITF, Cycling, Health and Safety, 2013, Figure 3.12)

Recent research by Sustrans (2016) analysed and mapped areas in Scotland at risk of transport poverty based on income levels, access to important services and car ownership using 2011 Census and the Scottish Index of Multiple Deprivation 2012 data.

The councils with the highest and lowest proportion of data zones at risk, by council area, are illustrated in Figure 2-9 below. The research identified Na h-Eileanan Siar, Dumfries and Galloway, East Ayrshire, Argyll and Bute and the Highlands as high risk, notably the council areas with the lowest proportion were the major cities. The report recommended that a proportion of the high-risk areas could use cycling to bridge the gap and ease transport poverty.

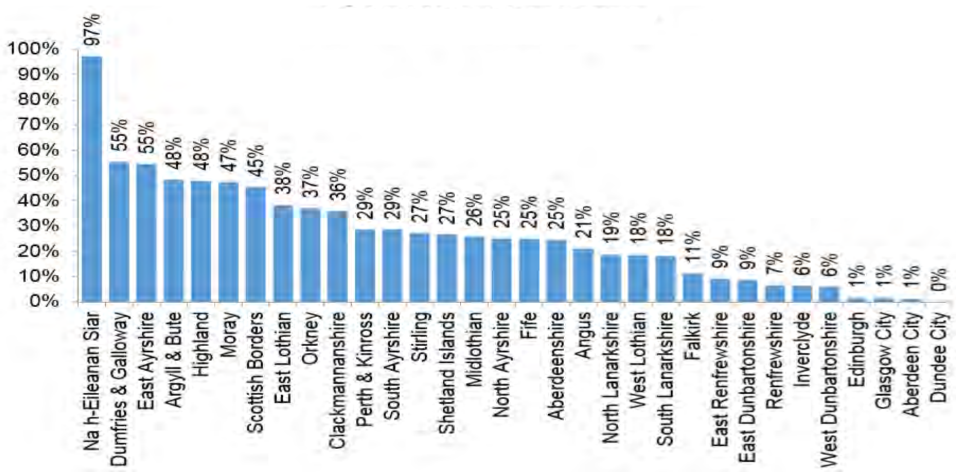


Figure 2-9 Transport poverty risk by council areas in Scotland. *(Source: Sustrans (2016); Figure 2)*

The report does not consider any association between deprivation and road safety (Edwards et al., 2006; Clarke et al., Muir, 2008).

Muir (2008) estimated that the casualty rate in the 10% most deprived areas is7.18 times higher than the least deprived areas. There has been a rise in adult cyclist casualties observed across all deprivation categories and they have been consistently higher in the more affluent quintiles years (Whyte and Waugh, 2015).

Increasing cycling in Scotland touches on several policies, increased cycling to improve overall population health, reduce congestion on roads by cycling instead of taking the car, increase cycling to improve cycling safety, increase cycling to reduce carbon emissions and pollution and finally a means to combat potential transport poverty; hence it is a multi-purpose policy instrument and measure. Therefore, the performance of cycling in terms of road safety *is a multi-sectorial issue and a public health issue—all sectors, including health, need to be fully engaged in responsibility, activity, and advocacy for road crash injury prevention* (WHO, 2004; pg.7).

Some of the barriers to cycling include safety, perceived safety (especially on busy roads), lack of secure cycle parking, hills, weather, cycle theft, lack of information and skills, and finally, culture and attitudes. To address these issues Active Travel Action Plan (ATAP) aims to:

- deliver a citywide 'Quiet Routes' network that people perceive as safe and attractive (cater for less confident cyclists);
- reduce traffic speeds; and
- adopt cycle friendly design principles for all streets.

The ATAP also collect and publish monitoring data to evaluate progress against targets and indicators published in the Edinburgh Bike Life (Sustrans, 2017) report. This report is like the Bicycle Account (such as that produced by the Cycling Embassy in Denmark), which provides detailed monitoring information about cycling from several different sources, together with new research, into one coherent annual report.

2.2.2.1. Road Safety Policy Implementation

The way in which policy is organised and how choices are made about the mechanisms involved in the implementation of measures affects road safety. In her research into road safety in The Netherlands, Bax (2011) found that there was a difference between the culture and rationality of policymakers versus knowledge. This description may be true of the inclusion of *SiN* in a policy document as shown in the previous example above, for example, travel behaviour factors (Schepers et al., 2014) are important to policy.

Road Safety research from countries outside the intended policy area need to take account of the considerable differences between countries in terms of safety conditions and use because outcomes from research in one country should not be generalised (Schepers, et al., 2013: Wegman, 2012).

Schonfelder and Axhausen (2010) discussed how translating policy into practice introduces methodological challenges for understanding issues on the ground. Visualising road safety risk using mapping can help to overcome this as proposed by Jones et al. (2008) who demonstrated that a geographical approach to road traffic accident analysis is useful for the purpose of identifying contextual associations that conventional studies of individual road sections would neglect.

As discussed above, policies are not a catch all for problem solving with respect the VRU, influential policies such as Vision Zero, Sustainable Safety (Wegman and Aarts, 2006), and Safe Systems (WHO, 2011; OECD/ITF 2008) were developed to improve road safety. However, VRUs still lag behind the improvements observed for motorised road users. The success of safety improvement programmes depends upon methods that can produce reliable estimates (El-Basyouny and Sayed, 2006) and an understanding of the factors that affect the likelihood of an accident.

According to Gerike et al. (2019) there is a need for more theoretically well-founded insights on determinants of walking and cycling, including the directions of cause and effect which would help to better understand how interventions and policy measures impact on behaviour and can be designed to purposefully reach policy objectives. Very few evaluation studies have been conducted that capture the broader and complex context within which policies are implemented and collective decision making remains under-studied (Foster et al., 2018; Panter et al., 2017). These are major research gaps that are hard to address but they are important for facilitating evidence-based policy making. Gerike et al. (2019) also stress the need to adopt inter- and trans-disciplinary approaches to successfully bridge the gap between different transport disciplines, urban planning and public health, and for engaging with practitioners. Future developments for active travel face various challenges, such as ageing societies, but also substantial opportunities, for example from changed mind sets or emerging technologies.

However, many empirical studies (e.g. Elvik, 2002; Jacobsen, 2003, Aldred et al., 2018) have not considered the spatial dependence present in the flow data (Fischer and

Griffith, 2008; LeSage and Pace, 2008; Chun et al., 2012; Kerkman et al., 2017) and spatial non-stationarity of flow determinants (Kordi and Fotheringham, 2016; Oshan, 2016), which lead to biased and inefficient modelling results. Most recently there has been increased interest in the use of geostatistical techniques in transport and there have been several studies that have demonstrated the importance of including spatial effects into modelling frameworks.

The current literature lacks empirical study of transport flows, in particular cycling flows on a regional or local scale by considering spatial dependence and non-stationarity into models. Active mobility research has established that individual, social and spatial factors need to be considered to design effective interventions (Götschi et al., 2017).

2.2.3. Infrastructure and Environment

This section will explore the type of infrastructure and urban spaces provided for cyclists, the responsible bodies, evidence regarding the recommended and implemented infrastructure and other transport policies that affect the road environment such as parking, traffic roads orders and bus lanes.

2.2.3.1. Scottish Cycling Network

In Scotland, the network is promoted and developed by Sustrans, in partnership with local and national roads and planning authorities, Transport Scotland, Forestry Commission Scotland, Scottish Canals, Scottish Natural Heritage, National Park Authorities, landowners and other bodies. Sustrans Scotland also runs a Community Links grant programme, which provides grant funding to local authorities, statutory bodies and educational institutions for the creation of cycle network infrastructure for everyday journeys. There are approximately 2,371 miles (3,815 km) of National Cycle Network (NCN) routes in Scotland, including 644 miles of traffic-free routes which use a mix of railway path, canal towpath, forest road, shared-use path, segregated cycle lanes and re-determined rural footways. The remainder of the Network is on road and, where possible, it incorporates only lightly used rural roads or quiet urban streets (Sustrans, 2019).

The NCN caters for both tourists and commuters and forms key parts of local urban route networks and 41% of the Scottish population now lives within a third of a mile of a NCN route (Sustrans, 2019).

For local authorities, cycle campaign charity Spokes prepares an annual survey of cycle funding. In their most recent report, they found that in 2013/14 Scottish local authorities spent £8 million from their own budgets on cycle related capital expenditure, and that total local authority cycling investment, including externally raised funds, was £18.7 million (Spokes, 2014).

2.2.3.2. Types of infrastructure for Cyclists in Scotland

This section describes the main types of cycling infrastructure implemented in Scotland. The Scottish Government/Transport Scotland sets out its best practice guidance on the design of cycling infrastructure in Cycling by Design 2010 (Transport Scotland, 2010), the UK Design Manual for Roads and Bridges (DMRB), Volume 6, Section 3 (Highways Agency, 2012) and Sustrans also provides guidance called *Handbook for cycle-friendly design* (Sustrans, 2014) which makes reference to the aforementioned texts.

Many cities across Europe and the UK were developed with motorised traffic in mind. Consequently, and in retrospect, space for cycling is merged or not provided in a complete user orientated manner. The policies and public desire for healthier transport options has created demand for new spaces within these existing places. While cycling groups lobby local authorities and government for more road space and/or more recently segregated facilities, new spaces are being created from shared spaces more frequently than providing fully separated facilities such as '*cycling superhighways'* within cities and between cities. Examples of fully segregated purpose-built cycling facilities include the Cycle Superhighways in London and the '*Supercykelstier*' (Super Bike Paths) in Greater Copenhagen (European Cyclist Federation, 2015).

2.2.3.2.1 Off-road Cycling Infrastructure

These are traffic-free routes and there are several different forms; the three main forms are described below in Figure 2-10.

(a) (b) (c)

Figure 2-10 Shared cycling infrastructure signage (a) Unsegregated, (b) Segregated and (c) signage placement at the start/end of footway converted to a shared facility[3].

[3] *TfL (2014c); Figure 1.2b, pg.6.*

The handbook states that, “Effective segregation requires sufficient width to be provided for each user group; segregation where insufficient width is provided is largely ineffective” and that, “*Developing the design of a shared use path, including decisions on segregation, should include early consultation with relevant interested parties such as those representing people with disabilities, walkers and cyclists*”. (Sustrans, 2014, pg. 24).

Both facilities described above can be implemented using the reallocation of an existing footway, located adjacent to the road carriageway, by converting them using the signs in Figure 2-10(a) and Figure 2-10(b) above, and a white line in the case of segregation. According to TfL (2014b), shared use reallocation of an existing footway, see Figure 2-10(c) above, does not benefit either user and is therefore not recommended. However, according to Sustrans (2019) their experience suggests that there are significant advantages to implementation and use of unsegregated paths that are shared by all users, particularly on traffic-free routes away from the main road. They recommend that the unsegregated routes maximise the available width and minimise maintenance requirements and the signing and lining clutter.

2.2.3.2.2 On-Road Cycle Facilities

There are several on-road cycle facilities described in the Sustrans guidance which include both physical segregation and reallocation of carriageway space to provide facilities for cyclists. Carriageway reallocation options can be either a mandatory or an advisory cycle lane. While the only physical difference is a solid or dashed white line, the mandatory cycle lane requires a Traffic Regulation Order (TRO) which prohibits motor parking, see Figure 2-11 below. A variant of this type of lane is the shared bus/cycle lane (sometimes also allowing taxis and/or motorcycles). The mandatory lanes provide greater protection for cyclists and should be used where possible and this type of infrastructure offers the following benefits:

- improve cyclists’ safety, perceived safety and comfort and signal that cyclists are valued road users by designating space for cycle users;
- increase motorists’ awareness of potential cycle users;
- create space for cycle users to pass queueing traffic and traffic calming features;
- indicate cycle route continuity and mark the appropriate route for cyclists to follow through a junction;

- reduce traffic speed by narrowing general traffic lanes; and
- be supported by parking, loading and waiting restrictions enforced by civil enforcement officers.

Figure 2-11 (a) Non-mandatory cycle lanes (dashed white line), (b) Mandatory cycle lane (solid white line)[5].

Another option is semi-segregation (Figure 2-12, below) which can be achieved in a variety of ways using physical aids (e.g. flexible bollards, armadillos, concrete kerb buildouts, etc.) to separate the cycle lane from adjacent traffic encroachments.

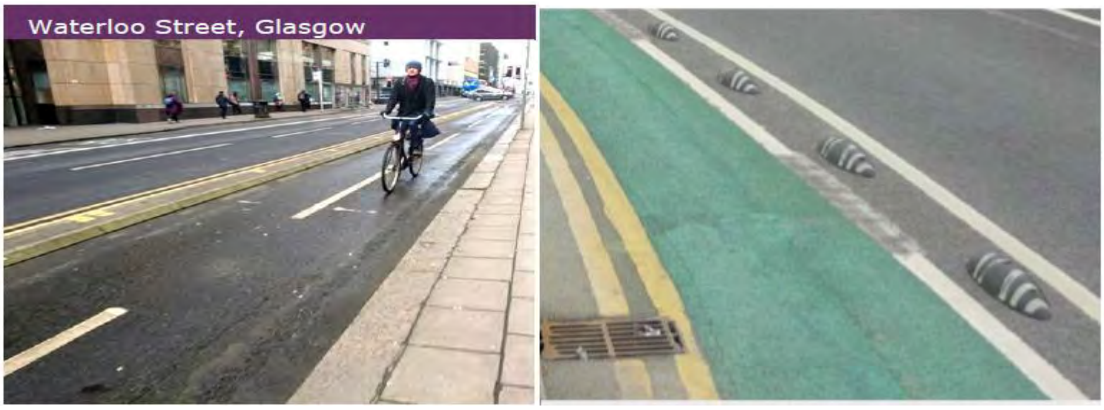


Figure 2-12 (a) Segregated cycle lane[4], (b) Semi-segregation of an on-road cycle lane[5].

Sustrans advice on effective segregation states that segregation will benefit all users but stresses that their implementation requires significant additional width to provide the same level of service. Similarly, the DfT (2012, para 7.9) recommend that, *segregation need no longer be considered the starting point in the design process* and it encourages *designers to think through their decisions rather than start from a default position of implementing any particular feature.*

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[4] *Edinburgh Street Design Guidance (CEC, 2017), C4-Segregated lanes , pg.2 http://www.edinburgh.gov.uk/downloads/file/10576/c4_-_segregated_cycle_tracks_-_hard_segregation*

[5] *London Cycle Design Guidelines (TfL, 2016), pg.37, http://content.tfl.gov.uk/lcds-chapter4-cyclelanesandtracks.pdf)*

The meta-analysis of cycling injury models conducted by Elvik and Bjørnskau (2017) observed that most research does not control for the quality of cyclist infrastructure.

The literature review by Aldred et al. (2018) found that there is relatively limited literature on the safety of cycle lanes/on-road lanes and the results are conflicting, the studies that have investigated the safety of these facilities lacked cyclist exposure and therefore relative risk is as yet largely unknown.

2.2.3.2.3 Quiet Routes

Quietways, or 'quiet routes', are low-intervention routes with largely unsegregated cycling provision because they are designated on quieter streets with low traffic volumes and low traffic speeds. The main interventions on the vast majority of the network will be wayfinding, surfacing improvements, removing barriers such as chicanes and improving the flow of the route. There may need to be some removal of parking, but this is kept to a minimum (TfL, 2014b).

2.2.3.2.4 At Junction

The main treatment used in Scotland are Advanced Stop Lines (ASL) for cyclists. They offer a visible area to wait, segregated from other traffic. Motorists must stay behind the first stop line and not obstruct the forward areas.

Previous studies have differing conclusions as to the beneficial effect of staggered stop lines/ASL. Buch and Jensen (2012) found that they have a limited effect on the safety when constructed at junctions with separate right-turning lanes. However, Linderholm (1992) and Herrstedt et al. (1994) conclude that ASL improve the safety of cyclists, but the sample size of both studies was relatively small.

In a more recent study by Osmann, Madsen and Lahrmann (2017), the findings were inconclusive regarding whether ASL improve or deteriorate the safety of cyclists but the study did find that layouts with a narrow bicycle lane and a staggered stop line were less safe for cyclists than layouts with bicycle tracks and no staggered stop line.

2.1.3.2.5 Shared Space

A design approach that has evoked much debate in the UK is '*Shared Space'* which is supposed to prioritise pedestrians and cyclists over motorised traffic and hence be safer and more inviting. However, a recent study by Homes (2015), which included Edinburgh, concluded that regardless of their mode of transport, disability status or gender, respondents actively avoid shared space schemes and that there was a pattern of non-reporting of accidents with only 11% of incidents reported to the police, which calls into question the validity of operational safety of a shared space.

There is an overall lack of coherent thought on 'what' and 'how' space should be provided for the safety of cyclists. This fact also creates design and policy conflict, which at times manifests as physical conflict between users.

Despite the variety and volume of documents produced there is still no clear guidance or clear direction given to decision makers or designers about the traffic and cycling or pedestrian volumes or usage that warrants segregation, shared use or when to provide segregated facilities at junctions. The ultimate decision about what infrastructure is implemented and determination of need rests with the local authorities. The following sections describe the typical infrastructure found in Scotland.

A comprehensive review of cyclist collisions for TfL (Talbot et al., 2014) made several recommendations about cycling infrastructure and among them were: to establish criteria for when to separate cycle and motorised traffic; provide guidance that references traffic flows and speed and indicate where complete segregation in space or time is appropriate; establish guidance on carriageway and lane widths that avoid creating pinch points for cyclists; introduce advanced signal phasing or infrastructure for cyclists to give segregation in time or space at junctions; and change the regulations to allow cyclists to cross the first stop line at ASL at any point.

The advice provided to the Scottish Government on walking and cycling by SPICe[6] states that: *Walking and cycling are healthy and environmentally friendly forms of transport; they produce near zero carbon emissions, minimal noise and require little road space.* (Rehfisch. A, 2014; pg. 3).

2.2.4. Relationship between Cyclist Infrastructure and Road Safety

High quality cycling infrastructure can help to create transport systems in which people can cycle without the danger and stress of mixing with motor traffic (TfL, 2014a, Pucher and Buehler, 2008). A recent systematic review (Aldred et al., 2016) found that people under-represented in UK cycling statistics, especially women and elderly people, tend to more strongly prefer cycling on infrastructure that is wholly or largely separated from motor traffic.

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[6] *Scottish Parliament Information Centre (SPICe). They provide factual information about MSPs and Parliamentary Business. They are produced for use by MSPs, parliamentary staff and the general public.*

A significant barrier to mainstream cycling in Scotland is perceived risk (Bill et al., 2015), some research points to the lack of segregation and route continuity (Schepers et al., 2014) while others argue that poor safety behavioural mechanisms are at play (Tin Tin et al., 2011).

Safety concerns are an established deterrent to cycling (Heinen et al., 2010; Willis et al., 2014; Branion-Calles et al., 2019). When cycling infrastructure is provided the users tend to perceive their environment as safer than with traffic environments (Parkin et al., 2007; Winters et al., 2011; Manton et al., 2016). Increasing access to cycling infrastructure is promoted as a potentially effective way of increasing cycling uptake and modal share in cities with low bicycling levels who wish to increase cycling (Buehler and Pucher, 2012). Previous research has demonstrated that perceived safety varies with age, by gender and level of cycling experience, across a range of different cycling environments (Parkin et al., 2007; Lawson et al., 2013; Bill et al., 2015; Manton et al., 2016).

A recent survey of infrastructure implementation stakeholders found that allocating road space to active modes of transport requires a strong and visible commitment from councils. The results showed that some councils pull away from robust measures due to fear of local objections even if the vocal minority does not reflect the views of the wider community. The researchers see this as risk aversion on the part of the council and cited it as a significant inhibitor to local action, even standing in the way of changes that could be popular with residents: “Recommendations to implement segregated cycling facilities were overruled by elected Members, despite public support” (Aldred et al., 2017).

The provision of on-road cycle lanes, particularly when they are located adjacent to parked cars, does not provide an optimal means of providing protection from collisions with vehicles. Furthermore, drivers tend to reduce their passing distance when passing a cyclist in a cycle lane in the presence of a parked vehicle but increased their passing distance when there was neither a parked car nor a cycle lane. The researchers make the point that, according to road traffic law, drivers are required to overtake a cyclist safely on the main carriageway but not when the cyclist is in a cycle lane (Beck, 2019).

Branion-Calles et al. (2019) examined the relationship between the availability of cyclist infrastructure and perceptions of safety amongst cyclists living in large Canadian and US cities. The results, within cities, found that cyclists that had more infrastructure were more likely to perceive cycling as safe. Specifically, a 10-unit increase in Bike Lane

Score was associated with six percent higher odds of a bicyclist perceiving the safety of bicycling as safe compared to neutral. Bicyclists who are male, younger, lower income, have young children, have a high-school education, and bicycle more frequently are predicted to be more likely to perceive bicycling in their city to be safe. These findings suggest that increasing the availability of bicycle facilities by expanding bicycling networks may result in increases in perceptions of bicycling safety for existing bicyclists, but also that individual characteristics play a substantial role in bicycling safety perceptions. This study did not define the quality or type of infrastructure provided.

A basic principle of safe traffic and transport systems is the separation of traffic flows that differ in speeds, direction or mass at moderate speeds (Wegman and Aarts, 2006). Under this context of safety, the separation of cyclists from motor traffic is justified and it seems the principle may also be applicable when it comes to pedestrians and cyclists, according to a study by Chong et al. (2010) - cyclist collisions with pedestrians carry serious injury risk comparable to motor vehicles. Therefore, the decision to provide on-road cycling infrastructure and share infrastructure must consider relative speeds and mass and as such a vehicle-bike and a bike-pedestrian interaction are unequal in terms of both speed and mass.

Marquésa and Hernández-Herrador (2017) carried out a review of different studies that examined the impact of bikeways on cycling safety, Figure 2-13 below. The columns of the table show the authors of the study, the date, the place of the study, the type of analysis (longitudinal, cross-sectional or review). The authors were unable to draw definitive conclusions because of the varied results (positive, negative or neutral) regarding the impact of bikeways on cyclist's safety.

Table 1
Summary of different specific studies about the impact of bikeways on cycling safety. The columns of the table show the authors of the study, the date, the place of the study, the type of analysis (longitudinal, cross-sectional or review) and the main conclusions of the study (positive, negative or neutral) regarding the impact of bikeways on cyclist's safety.

Author(s)	Year	Place of study	Type of analysis	Main conclusion
Welleman and Dijkstra	1988	The Netherlands	Review	Positive between intersections but negative at intersections.
Wegman and Dijkstra	1988	The Netherlands	Review	Positive between intersections but negative at intersections.
Gårder	1994	Sweden	Review	Negative in overall, but positive between intersections.
Pasanen	2001	Helsinki	Cross sectional	Negative.
Jensen	2007	Copenhaguen	Longitudinal	Negative (however, exposure was not controlled).
Agerholm et al.	2008	Western Denmark	Longitudinal	Negative (however, exposure was not controlled).
Reynolds et al.	2009	N/A	Review	Mainly positive.
Lusk et al.	2011	Montreal	Cross sectional	Positive.
Teschke et al.	2012	Toronto and Vancouver	Longitudinal	Positive
Chen et al.	2012	New York	Longitudinal	Neutral (possibly positive after exposure analysis)
Nosal and Miranda-Moreno	2012	Montreal	Cross sectional	Positive
Thomas and DeRobertis	2013	N/A	Review	Positive
Lusk et al.	2013	USA (19 cities)	Cross sectional	Positive
De Rome et al.	2014	Australia Capital Territory	Longitudinal	Positive

Figure 2-13 Table of studies investigating cycling infrastructure safety effects. *(Marquésa and Hernández-Herrador, 2017; Table 1)*

Winters et al. (2012) conducted a study to quantify the injury risk associated with 14 route types, from off-road paths to major streets. They argue that when it comes to injury risk, there may be discourse between empirical evidence and perceptions. Thus, even with the provision of protective infrastructure people may not feel safe enough to cycle. Their research compared observed risk at the injury sites with those at randomly selected control sites along the same route. They found that major streets with shared lanes and no parked cars had the highest perceived risk, followed by major streets without bicycle infrastructure and paved multiuse paths, residential streets, bike paths, and residential streets marked as bike routes with traffic calming were perceived to be most safe. They found discrepancies however; between cycle tracks (perceived as less safe than observed) and multiuse paths (perceived as safer than observed). They concluded that while perceptions usually corresponded with observed safety, the perceptions about certain separated route types did not align.

It is difficult to gain a clear indication of what works, what does not work well and where or how to apply cycling infrastructure for effective improvement in safety perceptions and reduction in observed collision risk. The type and quality of infrastructure research varies greatly and the use of existing footways as new spaces for cyclists does not sufficiently address need. According to Kolgin and Rye (2015) the current lack of theoretical understanding and modelling within the field of planning for cyclists is important and is needed to understand and fully grasp the marginalisation of cycling in transport planning. Practical changes for cycling and mobility planning could be triggered if this gap is filled because the case for these practical changes would be stronger. As discussed above in section 2.1.1.2 there are no transport models for cycling in Scotland or for its major cities.

Recent research comparing Copenhagen and Stockholm found that neither cyclists' perceptions of priority nor the differences in the provision of cycling infrastructure between the two cities could adequately explain the differences in cycling levels. The authors argue that the historical difference between Copenhagen and Stockholm with respect to cycling policies polarise citizens' attitudes and prioritisation of modes in traffic and which modes they prioritise themselves (Haustein et al., 2019).

Many UK cycle tracks are narrow and badly paved, and force users to give way at driveways and side roads (Franklin, 2002). As discussed above, in many cases pavements have simply been re-badged (referred to above as "*re-allocated*") for cyclists to use, without modification. Wardlaw (2014) points out that cycling must enjoy institutional respect and that re-allocation is a shoddy execution of cycling infrastructure provision that probably poses the biggest risk to infrastructure being accepted by existing cyclists, let alone by the wave of newcomers that has been called for.

2.2.5. Road Safety Theories

The following three sections describe prevailing road safety approaches or theories followed to achieve road safety visions and aims, they include '*Vision Zero'*, Sustainable Safety (i.e., a safe system) and finally forgiving roads.

2.2.5.1. Vision Zero

The basis of Swedish road safety work is '*Vision Zero'*, a strategic approach towards a safe system, whereby no one is at risk of being fatally or severely injured while using road transport. There is no safety plan in a traditional sense, but instead a system of management for road safety objectives are set and based on cooperation to develop targets, measures and annual results to discuss and evaluate achievements. The aim is to create long-term and systematic road safety efforts and one of its strengths is the integration of police and health data using a system called STRADA. While this is preferable to using police data alone, it still only provides information on seriously injured people who visited an emergency hospital following a crash.

Sweden, like many EU countries, has experienced an increase in seriously injured cyclists and pedestrians; in 2013 almost one in every two serious road injuries was due to a pedestrian fall. It is worth noting that pedestrians who suffer serious injury after a fall in the road traffic environment are not included in official statistics (STA, 2013). Therefore, the number of people with minor injuries are likely to be under-reported (ITF, 2016) in Sweden even with the STRADA system in place and similarly, serious injuries among cyclists also appears to be troublesome under *Vision Zero*. This is an important point to note because many countries, including the UK, look to adopt *Vision Zero*, but many of the data collection issues for cyclists would still need to be addressed under this system.

In May 2018, the European Commission confirmed the EU's long-term goal of moving close to zero fatalities and serious injuries by 2050, responding to the 2017 Valletta Declaration to reduce the number of road deaths by 50% between 2020 and 2030 as well as to halve the number of serious injuries (EC, 2019).

2.2.5.2. Sustainable Safety

Unlike rail and air transport, road traffic systems are not designed with safety as a starting point (Wegman et al., 2012). A safe system according to Wegman and Aarts (2006) includes five principles: Functionality; Homogeneity; Predictability; Forgivingness; and finally, State awareness of the road user.

One of the main problems surrounding the understanding of cyclists' risk is a lack of suitable data (as discussed in Section 2.1.9), consequently state authorities suffer from a lack of understanding or awareness. According to Wegman (2010, pg. 12) one of the key aspects of the Sustainable Safety approach is ethics such that *We do not want to hand over a traffic system to the next generation with the current fatality and injury levels; these must be considerably fewer*.

2.2.5.3. Forgiving Roads

A forgiving road is defined as, a road that is designed and built in such a way as to interfere with or block the development of driving errors and to avoid or mitigate negative consequences of driving errors, allowing the driver to regain control and either stop or return to the travel lane without injury or damage (Bekiaris and Gaitanidou, 2011).

It is this principle that has led to the use of road restraint systems, inclusion of hard strips and hard shoulders to rural carriageways, the use of kassel kerbs and maintenance of flush grass verges etc. and also the removal or amelioration of carriageway hazards such as poles, parked vehicles and signs. Provision of a forgiving road route or environment for cyclists is not discussed in the literature.

2.2.6. Transport Equity

In 2004, the World Health Organisation report on Road Traffic Injury Prevention stated that: *road crash injury is a social equity issue – equal protection to all road users should be aimed for since non-motor vehicle users bear a disproportionate share of road injury and risk* (WHO, 2004; pg.31) and that transport, suffers from levels of inequality because different road user groups are not served with equal access to safety.

Disadvantaged groups include the elderly, children, young people, those on low incomes, people with mobility issues, pedestrians, cyclists, motorcyclists (WHO, 2004), women, ethnicity in combination with deprivation (Steinbach et al., 2007), and child ethnicity (Steinbach. R, 2014). Disadvantaged groups of road users can be defined as 'vulnerable' in several ways, by the amount of protection in traffic or by the amount of task capability (SWOV, 2012).

Despite an overall and consistent long-term reduction in the number of fatal and injury collisions in Scotland, there is an unequal share of improvements across road user groups as illustrated in Figure 2-14 below, which depicts the percentages of the total casualties against the proportion of modal share for each group.

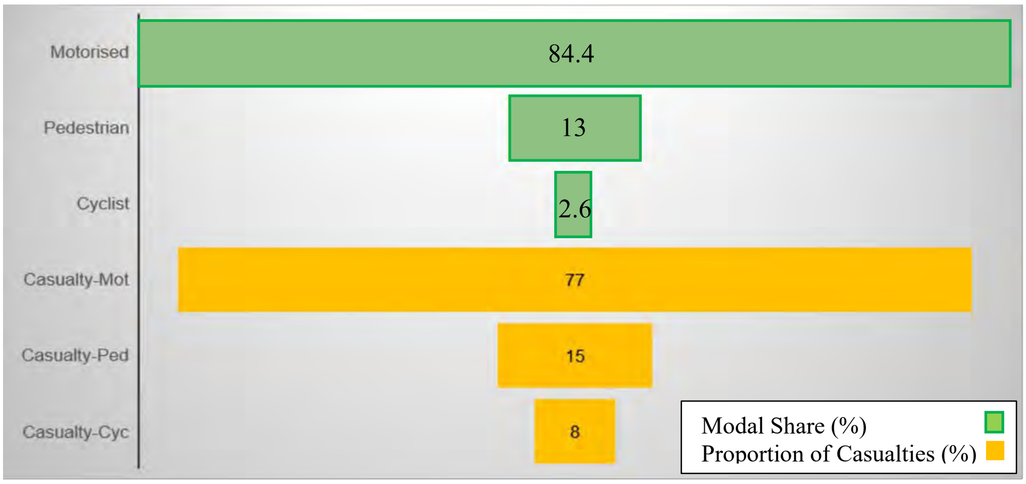


Figure 2-14 Comparison of mode share (NSS, 2015) and proportion of casualties (TS, 2016).

The unequal safety risk is also demonstrated in Figure 2-14 below, it illustrates the relative risk across different road users in different countries (Elvik, 2004). The research highlights that the risk of injury is particularly high for walking and cycling in six different countries, estimated based on injuries recorded in the official accident records and travel behaviour surveys made in the same countries.

Equity concerns fairness and proposes equal treatment of individuals, or groups should receive equal shares of resources, bear equal costs, and in other ways be treated the same. It means that public policies should avoid favouring one individual or group over others (Litman, 2014). Moreover, if road safety theories (see Section 2.1.5) and transport planning were based on equity rather than benefit-cost analysis, our roads could become *'inherently safe'* environments as described by Artas and Wegmen (2008).

Rock et al. (2014) suggests that the lack of coherence when addressing equity in transport may be compounded by the varying types of equity and impact categories, and the cross disciplinary nature of the road safety area and prevalence of the use of costs and benefits of transport.

When Elvik (2009) investigated transport where cost-benefit was the policy focus rather than social equity, he found that implementing measures that adhere to cost-benefits do not reduce the difference in fatality risk (injury risk was not examined) between different groups of road users. This is an important analysis because Norway is one of the northern European countries that has a *Vision Zero* road safety policy and it still has a disproportionate risk of fatality among VRUs.

Treating non-motorised transportation as a single mode is not feasible due to the many differences and it is the unique and different needs of pedestrians and bicyclists that can inform practitioners and policy makers (Schoner and Lindsney, 2015). While cycling is strongly supported by both government agencies and lobby groups, walking is often neglected in planning and policy development (OECD/ITF, 2012). Government strategies also tend to deal with these users separately, for example in Scotland there exists the National Walking Strategy: Let's get Scotland Walking (2014), the Cycling Action Plan (2013) and the Inclusive Mobility Plan and then all other transport is dealt with in the main transport policy documents, including road safety.

Relative risk of injury in different countries. Drivers' risk= 1.00						
Means of travel	**Norway**	**Denmark**	**Sweden**	**The Netherlands**	**Germany**	**Great Britain**
Pedestrian	**4.35**	**6.65**	**4.13**	**6.07**	**3.50**	**7.15**
Cyclist	**3.90**	**7.76**	**5.73**	**5.67**	**9.50**	**14.02**
Moped/mc	**8.30**	**29.94**	**17.87**	**197.60**	**31.25**	**20.26**
Car driver	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Car passenger	**0.75**	**1.94**	**0.87**	**1.13**	**1.50**	**1.25**
Bus	**0.25**	**0.12**	**0.13**	**0.20**	**0.13**	**0.59**
Tram	**0.60**		**0.87**	**0.02**	**0.25**	
Train	**0.05**	**0.04**	**0.13**	**0.02**	**0.05**	**0.22**

Figure 2-15 Relative transport risk across different users. *(Source: Elvik (2013), Table 3.1 Relative risk of injury of different methods of transport in different Countries.)*

Dealing with transport and risk equity is important because one of the major barriers to effective and sustained increase in active transport is the elevated risk of injury and death compared to other modes. Pedestrians are 23 times more likely and cyclists are 12 times more likely to be killed in traffic accidents than a car occupant, according to Pucher and Dijkstra (2003), and other research reports estimate that the rates are higher at 14 times more likely, see Figure 2-15 above.

A better understanding of risk equity is central to this research because cyclists continue to have higher injury risks than motorised users (excluding motorcyclists) and there is little guidance for performing transport equity analysis. When it is considered, it is often *ad hoc* or biased based on the concerns and values of a selection of stakeholders involved whereby potentially significant impacts may be overlooked or undervalued because all stakeholders do not participate (Litman, 2016). Aldred et al. (2017) also found that stakeholders and actors influence decisions concerning cycling infrastructure.

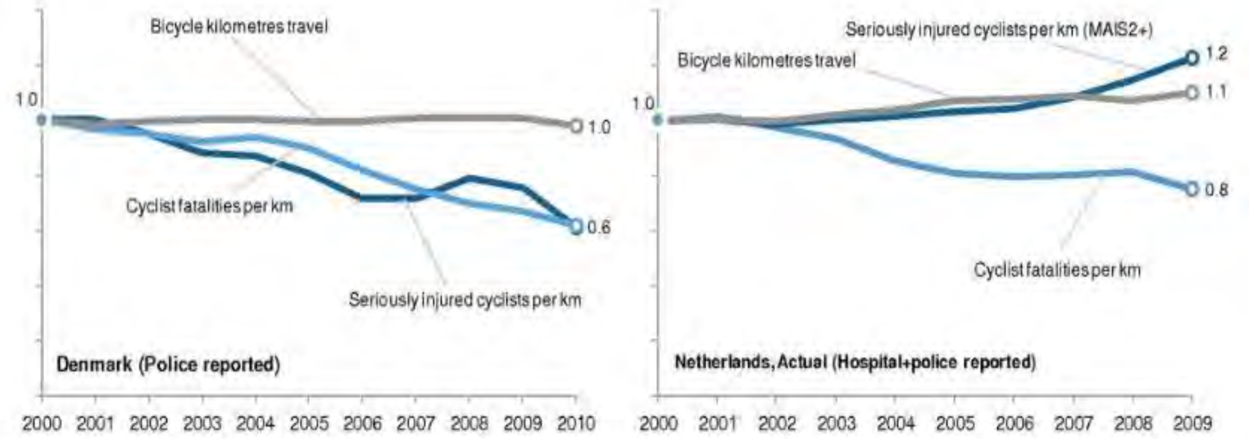
2.2.7. Reporting Road Collisions

In the UK, the main data source is the STATS19 and this can be linked to road traffic data containing traffic volumes, road type, operating speeds, weather conditions and maintenance data. It is also possible to link hospital admissions data with police data, but this is not routinely done. While the STATS19 is consistent and comprehensive in many respects, its function is to capture collisions that occur on public roads that are reported to the police. Collisions that occur on footways or off-road shared or segregated pedestrian and cyclist facilities are not included, even the gold standard STRADA system fails to capture this category of transport collisions robustly. Relatively little is known about the nature of unreported collisions involving VRUs and *research on single-bicycle crashes is still in its infancy* (Schepers et al., 2012). Under-reporting of non-fatal accidents is quite prevalent which stems from lack of coordination between police and hospital records (IRTAD, 2012).

A limitation of the STATS19 data is the '*under-reporting'* of road traffic injuries (Ward, Lyons, and Thoreau, 2006), particularly accidents in which a pedal cyclist is the only participant and discrepancies exist between the numbers of non-collision cycling injuries captured in the STATS19 and Hospital Episode Statistics in England (Benington, 2012). During 2011 and 2012, 69.7% of injuries to cyclists that required admission to hospital resulted from non-collision incidents but only 3% to 4% of all non-collision incidents were recorded in the STATS19 (NHS, 2012).

The SafetyNet project (European Road Safety Observatory, 2006) linked Scottish STATS19 data and the Scottish Hospital In-Patients (SHIPS) data between 1997 and 2005 and found an increasing trend towards police recording serious injuries as slight injuries which has an appreciable effect on the serious injury reported trend in Scotland (Broughton and Keigan, 2010). The report also highlighted that injuries reported out with hospitals or police data based, such as primary care centres, were not included Accident costs vary substantially by severity level (Wang et al., 2011). Therefore, the true cost of pedestrian and cyclist accidents (the unobserved parts) must be included. Furthermore, 37% of adults interviewed in the Scottish Household Survey did not report their incident to the police (Transport Scotland, 2016).

In the previous sections we have discussed two issues, under-reporting and misreporting that have been found to effect cyclists STATS19 records in Scotland. Since under-reporting and misreporting of the casualty severity go under the 'epidemiological radar' (Pike and Christie, 2015) and disproportionally affect cyclists, Handy (2014) suggests that potentially important interactions may be systematically missed leading to potentially erroneous inferences (Mannering and Bhat, 2014). Furthermore, under-reporting complicates the analysis of long-term trends and hides the true safety picture.



Source: City of Copenhagen, SWOV Road Safety database

A conservative estimate of police record under-reporting is that only 50% of cycling injuries are captured in Europe (OECD/ITF, 2013), see Figure 2-16 below.

Figure 2-16 Danish and Belgian casualty rates and kilometres travelled 2001-2011 *(Source: OECD/ITF, Cycling, Health and Safety, 2013, Figure 3.14)*

In summary, road safety data should include more complete information in order to build a clearer and more accurate picture of the problem to inform policy and performance indicators.

2.2.8. The legal position of cyclists when an accident happens.

Generally, anyone cycling on a footway in Scotland is committing an offence under the provisions of Section 129(5) of the Roads (Scotland) Act 1984, however access legislation means that footpath riding is generally an accepted practice. Cyclists have a right to cycle on carriageways. It is not an offence for a cyclist to cycle across a footway or footpath to access a cycle track, driveway or other land where cycling is allowed.

However, the 2003 Act does allow cycling on any path where access has not been restricted by a Traffic Regulation Order or through other legal means. In practice, this allows cyclists to use most paths in urban parks and rural areas and also allows cyclists to use a “core path” under the provisions of the 2003 Act. This means that cyclists may be able to cycle on a footpath, or even a footway, designated as a core path without committing an offence (Rehfisch, 2014).

Cyclists have considerable rights to pedestrian space although the nuances of where, such as ‘core’ routes, may be lost on most VRUs. There is no legal requirement to report an accident that does not involve a vehicle, although a bicycle is technically considered to be a vehicle, in practice it is seldom thought of in this way.

The UK is one of only five European states (Malta, Ireland, Romania, and Cyprus) that has a fault-based system for traffic collisions. Other European countries have a presumed liability system where a driver is automatically assumed at fault if the collision involved a vulnerable user. If the system were changed, in line with other European countries, some argue that it would shift the burden of proof from the VRU onto the motorised user and as a consequence the legal weight results in a behavioural shift where drivers are more careful because walking and cycling has more protection under the law.

In a review by the Law Society for Scotland (2015), they concluded that there does not appear to be robust evidence of a direct causal link between strict liability legislation and levels of cycling and fatalities of injuries when countries like the UK and Ireland are reducing fatalities without strict liability legislation in place. This review only considered fatal cyclist collision, if the review considered serious and slight collisions its conclusions may have been different given the increasing serious injury trends over the past decade in Scotland.

2.2.9. Measuring cycling activity (Exposure)

Traffic demand is based on space and time, therefore the supply of infrastructure and services need to be represented in a formal way in order to model them at a network scale (Willumsen, 2008). Traffic demand models collate as such variation of the types of travel, transport modes available, types and density of populations and how this will all change over time (Bates, 2008).

The traditional ‘Four Stage Model’ (Hensher and Button, 2008) was designed for large scale road construction projects. The four stages are:

1) Trip generation - predict the number of trips likely to enter and leave a zone for different time periods;

2) Trip distribution - reproduce a matrix of person movements from origin to destination for different time periods and the number of trips that are likely to occur;

3) Modal split - predict the proportion of persons using public transport or other modes;
4) Traffic assignment/route choice models – take a matrix of trips and assign them onto the network based on shortest path algorithms.

Different levels of detail can be included in a four-stage model which determines the complexity. However, these models are cumbersome to operate requiring extensive data collection, expertise, model estimation and forecasting exercises that typically take years to collate (McNally, 2008; Kitamura et al., 2000; Dickey, 1983). Collecting large amounts of data and long design periods may not be a barrier for long-term, large scale investments but they are for small scale investments such as cycling infrastructure and the use of such a model may not be economically viable (Bates, 2008). Other issues with the traditional four-stage model include:

- traffic flow estimation is typically limited to classified roads, fully representing local road networks requires high levels of detail and coding;
- walking and cycling have frequently not been included; and
- the network required for pedestrians and cyclists required on-road, off-road and shared routes.

These models can predict the flow of vehicles on a certain road, the number of trips between two cities, or the numbers transported per kilometre. In theory, they can be adjusted to include cycling but they traditionally excluded cyclists even though these theories and models contain knowledge that is considered very important in transport planning but is still underdeveloped for cycling (Kolgin and Rye, 2014). Urban spaces are very different from the perspective of a cyclist and car driver, cyclists have access to a broader range of spaces which need to be mapped in addition to the motor traffic-based road network. There is a distinct lack of evidence-based understanding of cycling activity patterns (Law, Sakr and Martinez, 2014).

Transport Scotland (2014) recognised the complexity of collecting data on cycling and identified a number of high-level indicators that can provide information about cyclists, including the Scottish Household Survey which is considered the most robust source of data on cycling trends in Scotland (Transport Scotland, 2014). These documents only provide national statistics and do not provide guidance for local monitoring specifically.

While it is relatively straightforward to estimate car ownership, based on official data such as car registrations and tax records, no such robust data exists for cyclists. Estimates vary from year to year and between publications.

2.2.9.1. Transport models for cyclists

The strategic transport model for Scotland does not include estimates for VRUs, which include cyclist and motorcyclist modes, and while more detailed models exist for Edinburgh, they cover only partial sections of the city and were not specifically developed for cycling. Such models are rare in the UK, London currently has the only cycling modal specific model, Cynemon (Transport for London, 2017a) which is illustrated in Figure 2-17 below. Another recent development is the Propensity to Cycle Tool (PCT) (Lovelace et al., 2017), a transport planning tool for cycling that provides options to investigate cycling scenarios such as cycling growth or gender balance. The aim of the PCT is not to predict exactly where people are currently cycling but rather to prioritise where to put new infrastructure.

Aldred et al. (2017) surveyed stakeholders and actors in England about cycling infrastructure implementation and found that institutional barriers such as a lack of appropriate expertise, tools, and models were frequently cited as hindering the capacity of local organizations to provide support for cycling.

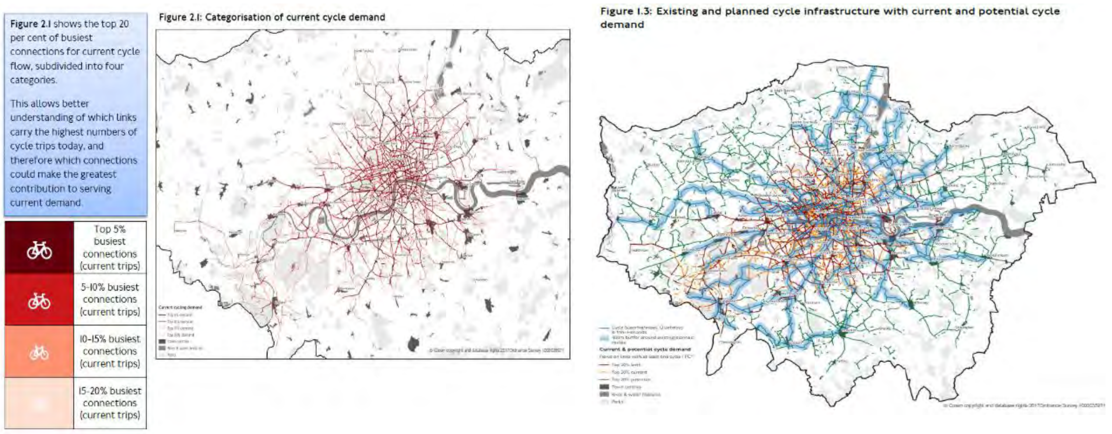


Figure 2-17 Cynemon model illustrating the categorisation of current cycle demand and the existing and planned infrastructure. (*Source: TfL, Strategic Cycling Analysis 2017.)*

Addressing technical limitations, such as availability of models, can help local policy makers by providing detailed evidence for local investment strategies (Lovelace et al., 2017). Developing a clear vision for a local cycle network can help build the case for larger scale change (Aldred et al., 2017) and reduced marginalisation of cycling infrastructure planning (Kolgin and Rye, 2014).

The availability of this information also allows the authority to evaluate road safety impacts and the level of service of the whole network, with respect to cyclists, and develop their strategic cycling network, cycle superhighways and to plan future routes.

Unlike research into motorised transport, cyclist exposure is typically difficult to estimate due to lack of data collection and, as discussed in the previous section, lack of transport models. Therefore, it is difficult for researchers to determine if a change in the number of accidents over time is due to increased accident risk, (users or environment becomes more unsafe) or if the increase in accidents is due to a higher proportion of cyclists using the existing roads and routes and therefore that there are more incidents. Cycling as a mode of transport, for any purpose, in Scotland is a minority transport choice and it is more prevalent in urban areas, 4% versus 1% in rural areas, Scottish Household Survey 2015 (NSS, 2016). Consequently, the availability of data to ascertain a representative level of 'exposure' or simply how much cycling there is 'when and where' is very limited and is one of the prevailing challenges in cycling research, or indeed any VRU research and is a key issue which this research attempts to address.

2.2.9.2. Cycling mobility data

The previous section discussed the availability of transport models that include or were developed specifically for cyclists. This section discusses the importance of having this data and why it is needed.

Data collected on commuting to work for the census is the most robust data available on cycling in the UK, data collection on cycling for other purposes, recreational cycling for example, is limited although some open source data such as STRAVA are available. While census data only captures trips to work or study, it is highly correlated with utility cycling (Goodman, 2013) and therefore can be used as a proxy for all cycling (Parkin, 2004). As discussed in Section 2.2.1.1, commuting accounts for 24.7% of all journeys in Scotland (STS, 2019).

The choice or availability of exposure variables form important analytical choices and should should be explicitly justified when when developing accident prediction models (Hauer, 2015). Unless models are developed in this way, the final model may not be the best possible fit for the available data and the intended use (Elvik, 2016). Transport modelling has a broad swath of modelling and simulation techniques for the evaluation of predominantly motorised transport. Traditionally, transport models are spatially too coarse to provide meaningful information for cycling (Iacono et al., 2009).

While it is usual to include traffic volume, such as average annual daily traffic or peak hour flows, this information is not usually available for cyclist flows at micro or meso level. Quite often a proxy estimation, based on trip production or population, may be the only information available. Indeed, one of the prevailing challenges in cycling research is ascertaining a representative level of 'exposure' or simply how much cycling happened and where despite the fact that traffic exposure is a key determinant of the likelihood of being in a road collision (Loo and Anderson, 2016).

Therefore, it is difficult for researchers and local authorities to determine if changes in observed accident trends over time are due to increased accident risk (users or environment becomes more unsafe), or if they are a function of the higher numbers of cyclists using the existing roads and routes resulting in more incidents, i.e. increased exposure. According to the ITF/OECD (2013), most authorities lack the factual basis to assess cyclist safety or the impact of 'safety improving' policies.

However, Loo and Anderson (2016) argue that local variations in population demographics and social composition are relevant; road safety records such as collisions per population, which are place-based, or road collisions per registered vehicles in a society, they are not true risk rates because a people-based road safety indicator fails to consider mobility (Erdogan, 2009). Instead, mobility-based exposure measures, such as are used for motorised transport modes, are required to evaluate cyclists' collisions and illustrate the space-time element to cyclist flow, where the cyclist population forms a web of paths that flow through a set of space-time locations (Carlstein et al., 1978). The selected exposure variable should be a true predictor of the dependent variable, collisions, rather than an extraneous one (Matkan et al., 2011), where the choice of exposure variables can have an impact on the overall model suitability (Elvik, 2016).

Therefore, analysing the area in which the collision victim lives versus the location of the road collision itself is challenging and requires the combination of different data sets to underpin risk exposure (Loo and Anderson, 2016). At a meso level, this is difficult because the accidents do not necessarily occur within the area the person lives.

2.2.9.3. The role of Accident Models in Transport Policy and Practice

As in most scientific fields, a dichotomy has evolved between what is used in practice and what is used by safety researchers, with methodological sophistication that has moved well beyond what can be practically implemented to guide safety policy (Mannering and Bhat, 2014).

A recent review of the literature on accident prediction modelling and survey question responses from several National Road Administrations (NRAs) in Europe, US and Australia, found that models are usually developed either as a single regressive equation, i.e. Safety Performance Function (SPF) which are valid for specific conditions or as a combination of a base SPF, that were developed for standard road configurations and a set of Crash Modification Factors (CMFs) that accounted for differences between site conditions and the specified base conditions (Yannis et al., 2016). The survey revealed that despite recent advances in the field of accident prediction modelling, 70% of respondents rarely or never use accident prediction modes (APMs, discussed in Chapter 4) systematically for decision making or for the implementation of road safety treatments. Since accident prediction modelling provides a scientifically sound basis for the evaluation and selection of road safety measures and for efficient decision making with limited availability of funds, the study highlights that it is vital to promote the use of APMs by NRAs in Europe, designers and road safety engineers. Additionally, the study pointed out that most NRAs seem to exhibit a preference for the Cost Benefit Analysis (CBA) procedures (Yannis et al., 2016). This has an impact on how cyclists are assessed because much of the data pertaining to their safety is not available and therefore it is difficult to cost safety impacts with certainty.

The high proportion of transport agencies that do not use accident models may be because they have difficulty interpreting the results. Visualisation of model results could be beneficial; Kabacoff (2008; pg 45) states that human beings are remarkably adept at discerning relationships from visual representations.

Accident prediction modelling has been the focus of research for many decades; however, the use of more detailed data holds the key to future advances in accident analysis (Lord and Mannering, 2010) and knowledge development. Feldman and Small (2012) also discuss the importance of moving beyond population average models and the merits of investigating subgroups to better understand how places and people interact.

2.2.10. Safety Performance Indicators

The primary goal of road safety engineering and analysis is to reduce the frequency and severity of collisions on the roadway network (Young and Park, 2013).

Safety Performance Indicators (SPIs) are an instrument for managing and monitoring transport safety (Tingvall et al. 2010). They are essential for determining and strengthening the weaknesses in the system prior to crashes occurring.

The Scottish National Performance Framework Indicator for road safety is the overall reduction in the number of road deaths. The Cycling Action Plan for Scotland (CAPS) (2013) established national indicators to inform the national picture of cycling participation and safety and it has yet to set a safety performance indicator for accidents. Research into the development of SPIs for cycling and pedestrian safety is therefore under-developed.

The CAPS provides annual reports on a suite of national indicators to inform the national picture of cycling participation. It also aims to develop local monitoring, using data from local cycle counts and surveys to develop a coordinated approach to data collection. Local level monitoring of cycling safety is included in the City of Edinburgh Council (CEC) Active Travel Action Plan (ATAP) targets to produce a cycling casualty rate index to monitor road safety based on count data, commencing 2016. This is part of the Charter of Brussels commitment to reduce the casualty rate for cycling (per km travelled) by 50% from 2010 to 2020 as discussed previously.

The International Transport Forum (2019; pg. 9) makes a number of recommendations to address emerging casualty trends and about what should be measured to monitor these emerging trends: that appropriate indicators should be used to measure the safety of vulnerable road user to measure, monitor and benchmark the levels of risks experienced by a specific road user group; the volume of travel by each VRU group should be controlled for rather than use absolute numbers of fatalities; that gender questions and social aspects of road safety should also be examined in more detail and require robust casualty data as well as reliable data on trips to achieve this; and an immediate focus should be placed on the analysis of casualty matrices to reveal number of people in each user group which are killed or seriously injured in crashes.

There are a number of challenges to achieve these, first is the volumes of travel be each group because VRU are not included in the vast majority of transport models and estimate and the second issues is measuring travel volume when the there is gender bias due to levels of uptake, in cycling for example.

2.2.11. Literature Review (Part A) Summary

The literature review presented above identified several research gaps that will be discussed in more detail in the conclusions section. In summary, a review of the literature concerning cyclist modelling and data collection revealed that there is a lack of data available for policy makers, practitioners and monitoring. Transport models either do not include cycling or are too costly to produce for standalone cycling schemes. Further, CBA is favoured for transport assessment and evaluation which means that cycling infrastructure is difficult to evaluate without transport model modelling data that would *otherwise supply a measure of 'exposure'. This lack of data and methods to model cycling flows has marginalised cycling planning within wider transport planning.*

The literature identified that relative risk between cyclists and other roads users is disproportionately high and that transport equity is not considered in transport planning or monitoring. Further, there is a lack of research examining road safety evaluation within sub-groups of users.

There appears to be a disconnection between the need for accident prediction models, with only 70% of European transport agencies using these methods to assess their schemes, and practical application. Making research accessible and delivering an impact can be a challenge especially when sophisticated methods are employed. Thus, there can be a trade-off between scientific quality of the research, producing results that are harder to convey to policymakers, and simpler methods and results which may prove easier to grasp.

While there are many high-level indicators to monitor cycling in Scotland, such as the number of trips, distance travelled and public preferences about cycling infrastructure or perception of safety, there is a lack of useful local level safety performance indicators linked to minor, serious injuries.

Finally, the main types of cyclist infrastructure recommended by guidance documents tends to be shared or re-allocation of space type infrastructure which aligns with risk averse councils who tend to opt for the least controversial options rather than (arguably) the most useful for the user. There is no literature available on how safe these options are compared to alternatives and the literature reviewed did not provide conclusive evidence.

Part B

Because cycling, and walking, is relatively risky the question must be asked: *whether increasing these activities will increase injuries and fatalities if a government successfully increases cycling and walking?* (Wegman et al., 2012).

2.3. Literature Review (Part B)

Many countries, including the UK, aim to increase the number of kilometres cycled, or walked, but reduced risk can only happen if conflicts between users are prevented and safety problems associated with cyclists and pedestrians are addressed.

This section discusses the Safety in Numbers (SiN) effect in the context of road safety. The SiN effect is often cited in policy and advocacy parlance with reference to a particular piece of research by Jacobsen in 2003.

2.3.1.1. Support for SiN

Local governments and advocacy groups in Scotland (CTC, 2016; CEC, 2016) promote the increasingly popular transport paradigm '*Safety in Numbers'* to encourage active travel through more cycling and walking. The research evidence often cited states that doubling the cycling or walking volume is associated with only a 32 % increase in the expected accidents (Jacobsen, 2003), for example:

'*There is good evidence to support the idea that cycling gets safer the more people do it'*, and

'*the more people cycle, the safer it is for each individual cyclist, since places with high levels of cycling are associated with lower risks',* and

'The safest places to cycle are those with high cycle use' and *'More and safer cycling can, and should, go hand in hand'*, -Cycling UK (2016).

'*there is evidence of a 'Safety in Numbers' effect for cycling. More cycling means safer cycling.*' -The City of Edinburgh Active Travel Action Plan (2016)

'Research has found that once walking and cycling levels double in a particular area, the risks associated with the activity fall by around a third. This is attributed partly to drivers having an increased awareness of people on bikes and partly to an area being more likely to have cycling infrastructure' - John Lauder (24th May 2017), Sustrans

Scotland National Director discussing Safety in numbers: Scottish cycling collision hotspots.

'We know better cycle infrastructure increases the feeling of safety and ultimately the number of people on bikes. The more people in a place who cycle, the safer it becomes for everyone' - John Lauder, The Scotsman (20th May 2017),

'*Put quite simply: the more people in a place who cycle, the safer it becomes for everyone'* - John Lauder, Sustrans Scotland National Director.

SiN is a theory that explains a link between crash risk and exposure and is based on the research conducted by Jacobsen (2003). He investigated 115 cities in the US and Denmark, as well as 14 European countries including the UK, at a population level to examine the relationship between the numbers of people walking or bicycling and the frequency of collisions with vehicles. He concluded that, *A motorist is less likely to collide with a person walking or cycling if more people walk or cycle. Policies that increase the numbers of people walking and cycling appear to be an effective route to improve the safety of people walking and cycling* (Jacobsen, 2003; pg. 4)

Examining the original research paper, it does include reference to doubling in cycling resulting in a reduction in risk by approximately a third, but this is an average result for the whole study which included several countries, including the UK, illustrated below in Figure 2-18.

Table 1 Calculated results

Data	Injury measure	Exposure measure	Exponent for growth in injuries	95% Confidence interval
Walking in 68 California cities	Injuries/capita	Portion journey to work trips on foot	0.41	0.27 to 0.54
Bicycling in 68 California cities	Injuries/capita	Portion journey to work trips on bicycle	0.31	0.22 to 0.41
Walking in 47 Danish towns	Injuries/capita	Kilometres walked/capita/day	0.36	−0.10 to 0.82
Bicycling in 47 Danish towns	Injuries/capita	Kilometres bicycled/capita/day	0.44	0.19 to 0.69
Bicycling in 14 European countries	Fatalities/capita	Kilometres bicycled/capita/day	0.58	0.38 to 0.42
Walking in 8 European countries	Fatalities/capita	Trips on foot/capita/day	0.13	−0.71 to 0.98
Bicycling in 8 European countries	Fatalities/capita	Trips on bicycle/capita/day	0.48	0.22 to 0.75
Bicycling in the United Kingdom:	Fatalities	Billion kilometres ridden annually		
1950–73			0.41	0.35 to 0.47
1974–83			0.012	−0.25 to 0.28
1984–99			1.5	1.11 to 1.88
Bicycling in the Netherlands, 1980–98	Fatalities	Billion kilometres ridden annually	−1.9	−2.7 to −1.1

Figure 2-18 Safety in numbers: more walkers and bicyclists, safer walking and bicycling, *(Jacobsen, 2003; Table 1, pg. 206).*

A value of the exponent being at unity implies that there is a proportional change in cyclist injuries with increased cycling, an exponent value at less than unity implies that there is a less than proportional change For example, a doubling of cycling volume is associated with a 33%[7] increase, which is what the *SiN* advocates are referring to above based on an exponent of 0.41 in the Jacobsen (2003) research.

The exponent results varied from 0.41 to 1.5 between 1950-1973 and 1984-1999, respectively. While these results are for fatalities, the interpretation of the overall findings of the report have been interpreted or take as 'a given' subject to increasing cycling volumes. The hypothesis was originally proposed by Smeed (1949), but it is the work by Jacobsen and Elvik that has informed recent research in the area. The *SiN* effect may be due to changes in driver behaviour as suggested by Jacobsen (2003). The following sections examine the literature concerning SiN developed since 2003.

2.3.2. Safety in Numbers (SiN)

This is a relatively recent concept that it is becoming increasingly common in transport policy dialogue and also among cycling proponents, but it has yet to be substantiated (Bhatia and Weir, 2011).

Several studies confirm that the risk of injury to pedestrians and cyclists is highly non-linear (Ekman, 2000; Leden et al.; 2000, Elvik, 2009; Jacobsen 2003; Robinson 2005; and Tin et al. 2011) and cite this relationship as evidence of the *SiN* effect.

A behavioural study conducted in Denmark and Norway by de Goede et al. (2014) explored the possibility of long-term and short-term *SiN* effects using conflict studies at selected intersections. The study found marked behavioural differences between the Danish and Norwegians, the Norwegian cyclists being much more 'risk taking', however cyclists were observed to avoid mingling with traffic where no facilities were provided for them in both countries. The findings suggested that there was evidence of a long-term SiN effect which develops over time, but the results did not support a short-term *SiN* effect.

Jacobson (2003) suggested that motorists adjust their behaviour in the presence of increased numbers of cyclists as a possible mechanism to explain SiN. Elvik (2009) hypothesised that it would be reasonable to assume that the *SiN* effect should combine favourably with the effect of lowering the numbers of motor vehicles. It was found that, in theory, the total number of accidents could decrease if a substantial share of trips by motorised transport is transferred to walking or cycling. This shows that the high injury rate for pedestrians and cyclists in current transport systems does not necessarily imply

[7] Double cycling is $2^{0.41} = 1.328$, a 33% increase.

that encouraging walking or cycling rather than driving will lead to more accidents. Similar research however does not agree with Elvik's results and two studies found that transferring short trips by cars to bicycles does not change the number of fatalities but significantly increases serious injuries (Stipdonk and Reurings, 2012; Schepers and Heinen, 2013). Luukkonen and Vaismaa (2015) examined the connection between cycling safety and volume. Their findings point to multiple factors affecting both the growth of cycling (and walking) and road safety, most notably the quality of infrastructure, land use planning and traffic network planning.

Wegman et al. (2012) argue that, simply adding '*numbers*' to the system without adding quality, may be wrong and there is no evidence that low fatality rates are explained by numbers alone. In contrast, the research by Wegman et al. supports the sustainable safety theory discussed in Section 2.1.5.2.

Another possible explanation or mechanism for *SiN*, offered by Thompson et al. (2015), suggests that it is safety in density rather than volume. They created a virtual transport system to replicate a *SiN* environment by using Agent-Based modelling controlling for two major variables, growth in cycling and density. They investigated increased cycling (from 9% to 35%) over a period of time, while maintaining constant car volumes, but varied the cycling density. The results suggest that low-density travel by cyclists among motor vehicle traffic may expose individuals to per capita risks of collisions that are not countered by the number of cyclists in the remainder of the system. Whereas high-density travel associated with increased cycling volumes decreased per capita collision risk. This may explain why cities whose relative cycling volumes have increased but their collisions have not decreased, as predicted by *SiN*, may be due to cycling under low or medium density conditions. Further, they suggest that activism and the desire to reclaim road territory may be responsible for inadvertently increasing exposure to risk. This theory may be true given the results of a longitudinal analysis of cycling safety in Britain in 1991, 2001 and 2011 across 202 local authorities by Aldred et al. (2017). However, despite finding a *SiN* effect, it did not translate to a global road safety expected improvement over the study period between 1991 and 2011.

The prevalence of single-bicycle accidents was investigated by Schepers (2012) in the Netherlands. Using multiple data sets and negative binomial regression, the analysis found that the relationship between bicycle use and single-bicycle crashes increased at roughly 0.75 power[8] of the number of kilometres travelled by bicycle. This is higher than the *SiN* parameter found by Jacobsen (2003) and Elvik and Bjørnskau (2014), who derived values to be roughly 0.4 power and 0.43 power, respectively, for bicycle-motor vehicle crashes. Schepers (2012) concluded that this demonstrates that proportionally more incidents will occur in the single-bicycle category of crashes than vehicle-bicycle crashes when bicycle kilometres travelled increases. Furthermore, Schepers also found that risk varies across the age groups examined, where elderly drivers are safer inside a car than on a bicycle. From a road safety perspective, the car–bicycle shift is, on balance, advantageous for young drivers and disadvantageous for elderly drivers (Stipdonk and Reurings, 2012; Schepers and Heinen, 2013).

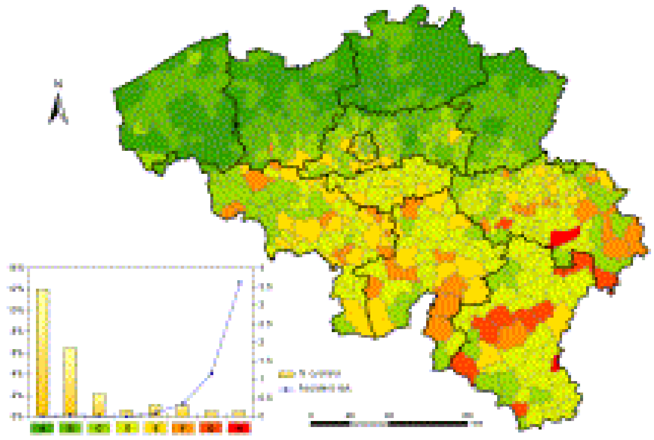


Figure 2-19 Bicycle use and risk of severe/fatal accidents in Belgium. Source: (Vandenbulcke, 2011) Figure 2.8, pg. 56.

Several studies, including the research discussed above, investigated *SiN* at a country or global level. Vandenbulcke, et al. (2009) explored bicycle commuting and injury risk at the spatial scale of communes in Belgium. The relative risk varied spatially, as illustrated in Figure 2-19 above, with green representing lower injury risk which correlated to higher commuter cycling.

In Copenhagen, Kaplan and Prato (2015) demonstrated that spatial correlation both within and between injury categories existed. They found that deprivation may play a part, because the *SiN* effect does not extend to deprived areas despite having relatively

[8] *A power of 0.5 implies that a doubling of traffic volume will be associated with a 33 % increase in the expected number of accidents, since the square root of 2 equals about 1.41*.

higher numbers who walk or cycle in comparison to more affluent neighbourhoods (Christie and Pike, 2015).

However, in a review of public green space across |England by Brown et al (2010) found that the most affluent 20 % of wards have five times more parks or general green space (excluding gardens) per person than the most deprived 10 % of wards. Access to and the option of using these spaces for part of a cycling journey, hence removing exposure to traffic, could be one explanation for the safety difference.

Further, Elvik (2016) points out that it remains to determine causality of the *SiN* effect, hindered by the following:

- Pedestrian and cyclist data are generally based on short-term counts.
- Reported pedestrian and cyclist accidents in official statistics is very low, particularly for cyclists.
- Nearly all *SiN* studies use cross-sectional data, which makes identification of causal relationships difficult, and do not control for confounding variables.
- There are several options available for fitting models.

These points are echoed by Jacobsen et al. (2015), they stress the importance of recognising that *SiN* is a phenomenon and not necessarily a causal relationship. Therefore, efforts should be made to identify the reasons behind *SiN*, which may not be the same in different contexts, for promoting cycling safety, especially in areas of low bicycle usage.

A rare before and after study of cycling infrastructure implementation in Seville was recently conducted following the implementation of extensive segregated cycle tracks in the city between 2000 and 2013 (Marquésa and Hernández-Herrador, 2017). The study found that there was a marked reduction in cyclist collisions following the implementation of the network. The results of multilinear regression found that the segregated network had a substantial effect on cycling safety and that there was *SiN* effect. The researchers concluded that the results qualitatively and quantitatively agreed with the results reported by Jacobsen (2003). Interestingly, the study also found that the segregated network influenced the gender balance during the study period such that more women cycled.

The specific mechanisms for the observed SiN effects remain unclear (Thompson et al., 2015). Many authors referenced above suggest driver behaviour is better where there are more cyclists. Drivers may be more likely to cycle, to know people who cycle or be more used to seeing cyclists while driving, so they are more attuned to looking for them. The argument is also made for better infrastructure. However, whatever the precise mechanism may be, policymakers hope that low cycling contexts with relatively high risks (such as Scotland) can increase cycling levels and that this increase will lead to a decrease in risk and hence a less than proportional increase in injuries (Aldred et al., 2017).

2.3.3. Spatial SiN effect

There is relatively little attention given to the spatial patterns associated with SiN, where more pedestrians and cyclists leads to less accident risk. The population level, macro, research by Jacobsen (2003) has become increasingly prevalent in transport planning policy and advocacy. The models developed provide global results, where the spatial variations within aggregated zones, municipalities and local authority areas respectively are an average of the whole areal unit.

Furthermore, the exposure variables are often population-based rather than mobility-based. Anselin (2010) points out that there is a need to better understand the fundamental processes behind the spatial and space-time correlation that is incorporated into current models. The complex dynamics that result in the existence of spatial interaction are still poorly reflected in model specifications.

Research at meso level in the Belgium (Vandenbulcke et al., 2011) and more recently in Hong Kong (Yao and Loo, 2016) demonstrate the planning potential for information at this scale. While meso level modelling of cyclists is uncommon, the more usual micro or macro levels have seldom been developed for cyclists (Lovegrove and Wei, 2013) but are commonly developed for vehicular models.

2.3.4. In the absence of SiN

All the research previously discussed only considers what happens if there is a SiN effect, however given the urban concentration of the majority of cycling there is a case for examining the opposite effect, which is likely to affect rural areas for example.

Many empirical studies have shown that risk decreases as exposure increases, more recently however, the co-existence of *SiN* and increased risk, where levels of walking or cycling activity is low, has also been identified. Two studies discuss this phenomenon and describe it as a *Hazard-in Numbers* (Elvik, 2013; pg. 57) and a *Risk-in-Scarcity* (Tin Tin et al., 2011; pg.362).

Tin Tin et al., (2011) found that cyclist's safety deteriorates when fewer people use a bicycle and more used a car. While there may be an aggregate *SiN* effect across a city, Vendenbulcke (2011) found that the effect is weaker or absent in rural areas where the risk of having a serious or fatal accident is high. Regional differences are important to consider, and *SiN* may not be a feasible reality outside cites due to infrequent user volumes or where high-quality infrastructure is absent.

Recent figures from London demonstrate a statistically significant rise in serious injuries and slight injuries among cyclists (TRL, 2014) at rates that cannot be explained by increased bicycle volumes alone. Consequently, an assumption that greater numbers of cyclists will reduce road injury risk under all circumstances may be overly simplistic. Further, a promotion of cycling that relies on *SiN* to increase safety may potentially lead to passivity and thwart efforts to improve.

2.3.5. The Co-existance of SiN and increased cyclist risk

A longitudinal study of *SiN,* conducted by Aldred et al. (2017), found that despite confirming the existence of a *SiN* effect in the UK across 202 council areas, the observed killed and serious injury risk per cyclist grew during the time period investigated (1991 to 2011) and did not decrease in the non-linear rate expected and described by *SiN*. The study instead found that, across the full time period of 1991 and 2011, cycling became relatively riskier compared with both motor vehicle use and walking.

This demonstrates that at a national level, *SiN* can coexist with a decline in cycle safety even alongside a small rise in cycling levels (numbers). This finding is puzzling and as yet unexplained in the research literature, but it does concur with the observed increase in cycling casualties in Scotland.

2.3.6. The SiN Artefact

Jacobsen (2003) use a straightforward approach to analyse three variables, of the general model form:

$$I = aE^b \tag{2.1}$$

Parameters are calculated using (ordinary) least squares analysis, such that I is the injury measure, E is the measure of walking or bicycling, and a and b are the parameters to be calculated. The parameter b indicates the change in the number of injuries in response to a change in walking and bicycling. For an individual pedestrian or cyclist, the relevant risk measure for a unit of walking or cycling can be estimated by dividing both sides of equation (2.1) by the measure of walking and bicycling, E, resulting in equation (2.2):

$$I/E = aE^{(b-1)} \tag{2.2}$$

Equation (2.2) thus results in the non-linear relationship, illustrated in Figure 2-20 below.

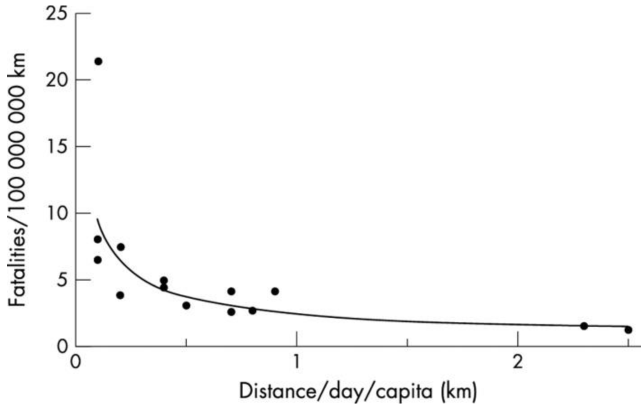


Figure 2-20 Bicycling in 14 European countries in 1998, Figure 3 (Jacobsen, 2003).

El-Basyouny and Sayed (2006) argue that the relationship between accident frequency and exposure being frequently nonlinear indicates that accident rates are not appropriate representations of safety, yet this approach is one often used in research concerning *SiN*.

An examination of how SiN has been calculated, described above, was interrogated by Elvik (2013) and he argues that the accident prediction models of this form maybe a statistical '*artefact'*. He points out that the '*artefact*' or erroneous nature of the calculations manifests due to the fact that risk is measured as the number of injured road users per kilometre travelled and exposure to risk is measured as the number of kilometres travelled by mode per head of population/inhabitant, such that:

$$Risk = A/B,\ \ Exposure = B/C \tag{2.3}$$

By calculating the risk in this way, defining exposure as rate or share, can give rise to an artefactual negative relationship between exposure and risk. Elvik (2013) demonstrated this by using a fictitious set of data, results illustrated in Figure 2-21 below, that yielded a *SiN* relationship. In so doing, Elvik highlights the need to be cautious of the nature of the negative relationship between exposure and risk and that accident prediction models of this form do not reveal the true relationship with respect to *SiN*.

A meta-analysis by Elvik and Bjornskau (2016) to examine studies that investigated *SiN* found that 11 out of a possible 26 studies exhibited a variety of methodological shortcomings that warranted their exclusion from the analysis, studies using the risk relationship discussed above were among those excluded. The 15 studies that were included all investigated confounding factors, to some degree and controlled for exposure in each case, the most comprehensive being the model developed by Prato et al. (2014), discussed above, that controlled for 16 different independent variables.

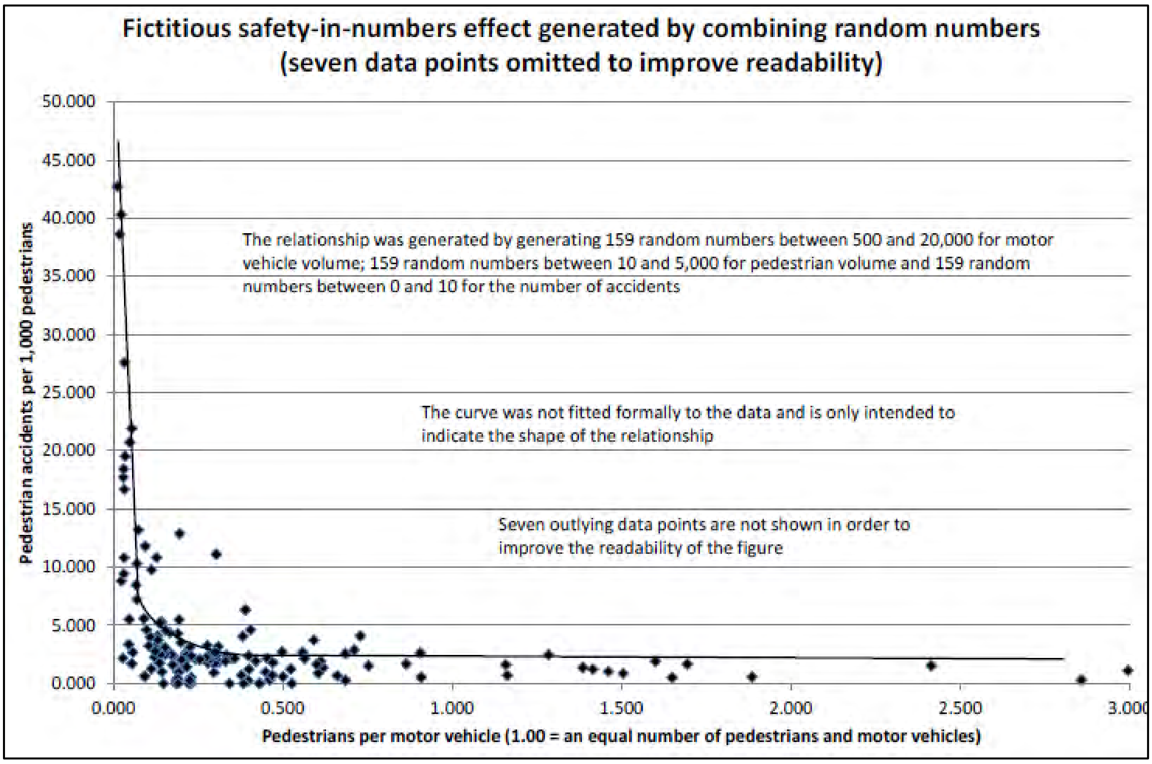


Figure 2-21 Safety-in-Numbers artefact example, Figure 4, Elvik (2013).

Based on the research discussed in this section and the results of the comprehensive review by Elvik (2013, 2014 and 2016), the type of model described by equation (2.3) is not considered for the investigation of *SiN* in this research. The model does not deal with exposure or confounding factors that could explain causal links between accidents and independent variables and finally the calculation produces a mathematical artefact.

2.3.7. Literature Review (Part B) Summary

The literature review presented above identified a number of research gaps concerning the adoption of SiN as a theory or model for transport policy and planning purposes. There are still unanswered questions about the mechanisms of SiN. Additionally, the effect is a global population average.

The SiN effect has been shown to be absent in low-flow or low-density cycling environments, and it may vary spatially as a result but there is no research that demonstrates this. Furthermore, there are two methodological issues to address, the model form and the availability of exposure data, also identified in Part A.

2.4. Conclusion

The following section outlines research gaps identified in the literature above. '*Safety in Numbers'* has become a popular paradigm in transport policy and planning for walking and cycling, for example "*there is evidence of a 'safety in numbers' effect for cycling. More cycling means safer cycling*." (The City of Edinburgh Active Travel Action Plan 2016). Confounding factors of behaviour and infrastructure vary between locations so research may not be applicable everywhere. The strength of the *SiN* effect and visualisation of relative VRU risk in Scotland has received little attention previously. Therefore, there is a need for research to evaluate and investigate if this effect actually works in practice.

There is evidence that '*under-reporting'* and '*misreporting'* of the casualty severity disproportionally affects VRUs in Scotland. As a result, VRU crashes go under the 'epidemiological radar' (Pike and Christie, 2015) and potentially important interactions are missed, leading to erroneous inferences (Mannering and Bhat, 2014). Therefore, the magnitude and burden of injury due to increased walking or cycling may not be understood (Bhatia and Weir, 2011). There is a lack of research into VRU road safety exploring this missing information and in particular single bike crashes and pedestrian-cyclist crashes.

By mapping the injury risk, it will be possible to critically analyse VRUs with respect to location, infrastructure and risk perception as part of this research. Very few studies identified in the literature review investigate road safety spatially in small areas and there is a lack of practical use of APM evidence (Yannis et al., 2016). Combining these two aspects of accident analysis could help advance the use and understanding of accident information more widely to non-expert policy and decision makers than is currently the case.

Yannis et al (2016) identified that 70% of NRAs rarely or never use APMs for decision-making or for the implementation of road safety treatments and Bax (2011) highlighted the difference between the culture and rationality of policymakers versus knowledge in decision making. APM has produced sophisticated results but there appears to be an issue between practical application that suggests either the APMs are not well understood or practical implementation is not possible.

2.4.1. Summary of key gaps in research

2.4.1.1. Cyclist safety trends

The emerging road safety problem across Europe is the difference between "protected" and "unprotected" road users, the latter seeing an increased trend in injury collisions. Therefore, a focused study of VRUs road safety in Scotland is relevant. In Scotland, pedestrian and cyclist casualties account for 23% of all casualties (Scottish Transport Statistics, 2015) while their combined modal share is only 15.6% of journeys to work. Compared to motorised users they have a much higher injury risk and burden for their modal share.

2.4.1.2. Safety in Numbers

To promote more walking and cycling and dispel safety concerns, both transport policymakers and advocacy groups refer to the *SiN* effect. Based on previous research, it is expected that there will be a stronger *SiN* effect observed where there has been growth in walking or cycling and that rural areas will not benefit equally from this effect. Furthermore, rural areas cater for walking and cycling tourism that create a short-term increase in numbers. Therefore, new policies should differentiate between urban and rural VRU injury rate expectations. Very limited studies of SiN have compared neighbouring areas, they typically investigate countries, junctions or road sections and many consider cyclists and pedestrians separately (Elvik, 2009b).

The SiN effect, for either pedestrians or cyclists, has been queried from a number of different perspectives, namely to establish causal links, safe systems and infrastructure perspectives (Wegman et al., 2012; Luukkonen and Vaismaa, 2015), behavioural changes (Bhat and Wire, 2013; de Goede et al., 2014), spatial differences (Vendenbulcke, 2011; Kaplan and Prato, 2015) and demographic variation (Christie and Pike, 2015) all without conclusive agreement on the nature of the effect mechanisms.

Another issue surrounds the potential for missing data to bias results where single –bike injuries may increase due to increased VRU mobility but are not reflected in police records. Furthermore, *SiN* does not deal with the magnitude or the burden of pedestrian injury (Bhatia and Weir, 2011), potential additional single cyclist crashes or pedestrian injuries that may result. There is an important distinction to be made, such that SiN predicts non-linear risk reduction but not the elimination of risk for VRUs.

There is also a need to ask the question 'who is safe in numbers?', because the SiN effect does not extend to deprived areas despite having relatively higher numbers who walk or cycle in comparison to more affluent neighbourhoods (Christie and Pike, 2015). This is another potential 'flaw' in the *SiN* concept (Edwards et al., 2006; Christie et al., 2010), such that it appears to be selective in terms of deprivation level.

Pike and Christie (2015) make the argument that Jacobsen's paper and the popularisation of *SiN* has led to a paradigm shift among planners and engineers approach to pedestrians and cyclists, allowing them to allow for increased numbers without the fear that the increase would result in more traffic collisions and casualties. A significant point to consider is the fact that some of the research, used as policy evidence and promoted by advocacy groups, could be founded on erroneous data (Elvik, 2013; Elvik and Bjornskau, 2016).

Is also worth highlighting that the literature review did not identify any examples where the phenomenon was tested under Scottish conditions. Wegman et al. (2012) make the salient point that adopting and generalising results from other countries should be done with the utmost care, if at all, and make a further point that the results cannot be reasonably transferred from one setting or country to another.

SiN is a very cost-effective concept in policy terms, meaning that simply increasing numbers walking or cycling improves road safety, and as such it does not require, or at least requires very little, infrastructure investment. SiN is referenced in Scottish planning and policy documents to encourage active mobility, therefore confirmation of the effect under Scottish conditions is warranted. In the absence of an observed *SiN* effect, policy should move towards the harder choices that increase VRU infrastructure investment, i.e. implement parking and road space restrictions for motorists in urban centres so that more space is devoted to walking and cycling.

The research outcomes expect to find that *SiN* is not observed equally across ward areas, particularly rural areas, and that policymakers should focus on increased and sustained strategic infrastructure investment to improve VRU safety as the locus of change rather than VRUs themselves. Finally, two studies (Elvik, 2013 and Tin Tin, 2011) suggest that SiN may co-exist with hazard-in-scarcity or hazard-in-numbers, due to low cycling activity, but there is no mechanism available to measure where either effect manifests. Most previous studies have been cross-sectional, and there has been one longitudinal study by Aldred et al., (2017) however the SiN effect has not been explored spatially.

2.4.1.3. Data

The shortcomings in the main data source, recorded collisions in the police STATS19 data affect VRU official figures in the following ways: under-reporting of the injury severity by police, unreported cyclist only injuries, unreported pedestrian only injuries and unreported pedestrian-bicycle crash injuries. Following the re-evaluation of police statistics, the research expects to illustrate that a different injury pattern will emerge. Therefore, this research is significant because it aims to capture a currently unseen part of the transport system with particular focus on VRUs. Moreover, it will contribute to the growing knowledge and provide further justification for the inclusion/effectiveness of wider statistical evidence. Police and hospital systems should be linked: STRADA in Sweden uses a systematic link between police and health data to provide accurate information on the severity and consequences of crashes (OECD/ITF, 2015). Road safety data is a major challenge, for promotion of active travel modes evidence-based transport planning (Castro et al., 2018).

2.4.2. Impact

Accessible research that creates an impact is challenging especially when a research problem uses sophisticated methods and modelling. Few accident investigations have utilised an area-based geographical approach to assist analysis communication.

Accessible research knowledge has a twofold impact benefit, in the first instance information in the public realm will be useful to interest and advocacy groups to influence political decisions, and secondly practitioners and policymakers will be better equipped to understand issues at a local and regional level to make informed evidence-based decisions. APMs are not widely used in practice to make policy decisions or inform safety strategy measures despite their ability to provide empirical evidence-based results.

Visualising the results of APM parameters across local area zones may provide a more accessible platform to communicate information to non-technical practitioners and decision makers which would be a considerable practical improvement and may promote increased use of APMs in policy and decision making by NRAs to improve infrastructure safety management.

2.4.3. Legal

It is a fact that the current STATS19 system does not include all injury accidents and there is no legal requirement to do so unless a vehicle is involved. The research expects to provide evidence to support making legal changes and changes to reporting practices to benefit active travel modes such as cyclists. Potential avenues for better social equity in transport are specifically; who is legally required to report a transport injury, who determined the injury definition in the official record and who bears the burden of proof.

Similarly, increased prevalence of cargo bikes may also create more severe injury risks because of their size and mass. Therefore, the issue of adequate space for overtaking and accommodating larger bike size needs consideration in road safety terms too. New technologies such as autonomous cars may impact VRU safety, using the area-based VRU risk visualisation could be used to monitor change.

2.4.4. Equity

Equity within the transport system for VRUs is essential for those who do not have the choice or access to a private car due to deprivation, age, gender, disability, and location. The current method for gauging performance in the EU is global number of fatalities per population per country and, to a lesser extent, fatalities expressed by kilometres travelled.

It is hoped that this research will develop SPIs based on risk equity rather than aggregate global numbers of fatalities within a population.

2.4.5. Vision Zero

This approach, adopted by Edinburgh in 2016, has been successful in Sweden however VRUs still experience higher injury severity rates relative to drivers there too. The OECD/TTF (2015) reported that cyclist fatalities increased by 10% and serious injuries increased for 8 consecutive years in Sweden.

Therefore, development of VRU SPIs, which target injury severity rather than overall global numbers, would redress the balance between VRUs and the dominance of motorised modes within road safety monitoring.

2.4.6. Monitoring

Monitoring of cycling safety and cycling growth are regularly reported in Scotland. However, the monitoring is at a national or City/Council level only. Recently CAPS has recommended local councils evaluate cycling safety using the metric collisions per mvkm. While this is possible at this scale, more detailed information is not available due to lack of cycling volume data or transport models that include cycling.

Furthermore, SPIs are required to monitor existing cycling infrastructure, such as the prevalence of dooring, safety performance of on-road cycle infrastructure and off-road infrastructure.

The next chapter is Chapter 3, it presents the research focus and provides a discussion on the research objectives and the research design which are based on the knowledge gaps identified in the literature review above. Following Chapter 3, the methodology will be discussed and presented in Chapter 4.

CHAPTER 3

Research Focus

3.1 Introduction

This chapter outlines the study focus, objectives and research questions, based on the literature review and the research gaps discussed in *Chapter2*. The chapter then discusses the conceptual research framework, the methodology design and finally the main data sources.

3.2 Research Focus

The following section describes three levels of questions that frame and focus the study and the structure of the research questions as illustrated in Figure 3-1 below.

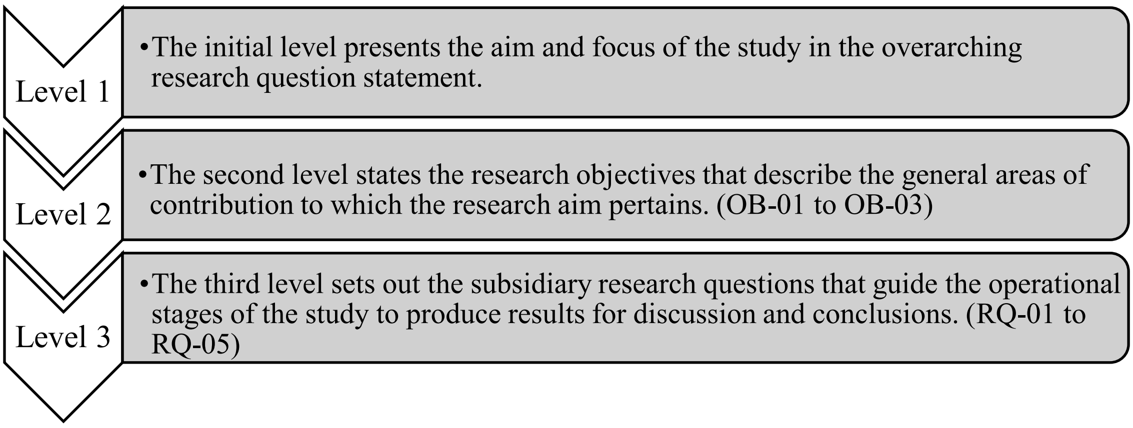


Figure 3-1 Research Question Map

3.2.1 The Research Question (Statement of the Problem)

Cyclist road safety performance lags behind the improvements achieved for motorised users despite having the same road safety targets and a separate dedicated organisational structures in place to promote cycling and improve cyclist safety in Scotland. Scottish health, social and environmental polices seek to increase mobility alongside transport policy commitments to improve road safety which leads one to pose the question: Why has cyclist road safety performance failed to improve in tandem with motorised modes over the past decade in Scotland? When mobility policy is successful, pedestrian and cyclist safety performance should yield the benefit of the *SiN* effect according to most research and the various government and non-government organisations.

However, increased numbers of cyclist deaths and in particular serious injuries do not accord with trends expected. While road safety is the object of this research it feeds into adjacent themes of population health and inequality and as pointed out by Raworth (2012) our societies not only need to provide a ‘safe space’ for humans but also a ‘just space’.

The *aim* of this research is to investigate whether there is a *SiN* effect in Scotland due to increased cycling mobility and to examine if there are wider spatial, demographic and policy differences affecting cyclists.

Gaining a greater understanding into how these aspects play a part in cycling safety performance means that we can develop safety strategies or systems with specific relevance to cyclists and in so doing cyclist injury and risk performance can begin to become more equitable in tandem and within global road safety targets.

3.3 Research Objectives

Based on the knowledge gaps identified in Chapter 2 the research objectives are defined as follows:

OB-01: Examine road safety policy and investigate how this has had an impact on cyclist road safety in Scotland;

OB-02: Critically analyse road safety evidence focusing on cyclists to develop an understanding of the wider factors involved and;

OB-03: Use the understanding gained, from the first and second research objectives, to develop specific performance indicators for cyclists.

3.3.1 Subsidiary Research Questions

The following research questions aim to answer the research objectives and provide results for interpretation and conclusions:

RQ-01: Is there a global *SiN* effect evident among cyclists in Scotland?;

RQ-02: Is there a reduction in cyclist’s injury because of increasing cycling evident at a local population level?;

RQ-03: What are the local level factors that influence the likelihood that a cyclist will be involved in an accident and do they accord with local safety perceptions?;

RQ-04: Are the prevailing national road safety polices a good fit for cyclists, if not why?, and can we provide better cyclist specific accident and safety evidence at a local level?; and

RQ-05: What should Safety Performance Indicators measure to ensure cyclists benefit from road safety investment and the road safety system equitably?

The next section describes the conceptual research framework developed to answer the research questions.

3.4 Research Framework

This section describes the development of the conceptual research framework (CRF), illustrated in Figure 3-2 below. The CRF encompasses the initial research world view, the research approach, the research design and finally the research methods which will be discussed in the following sections.

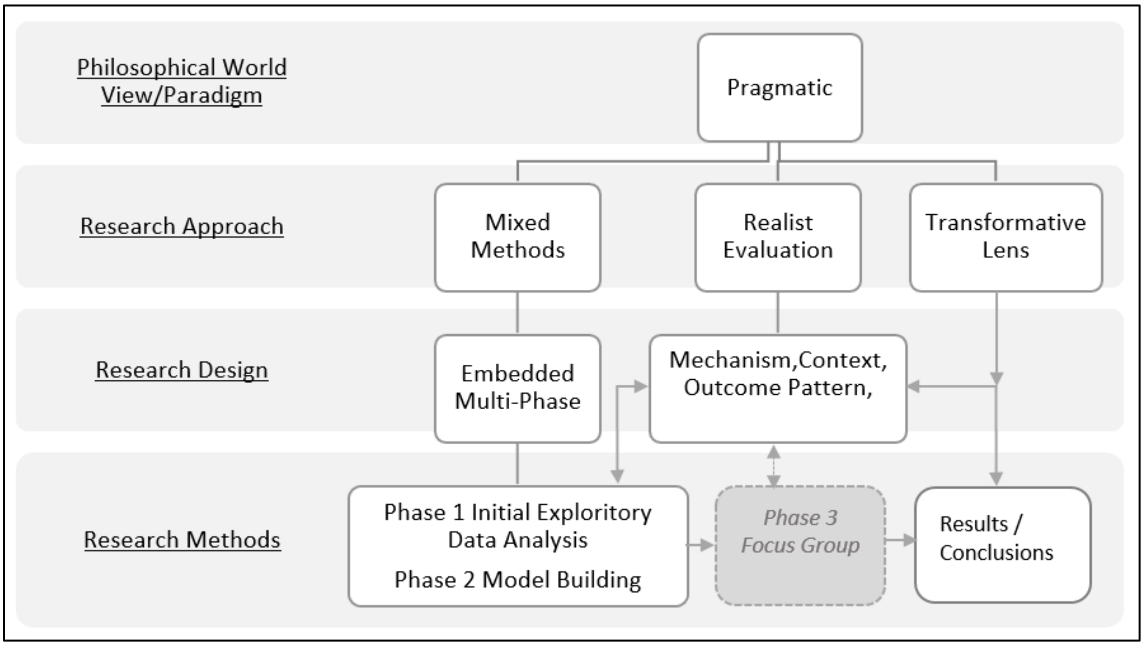


Figure 3-2 Conceptual Research Framework

3.4.1 A Pragmatic Worldview

Pragmatic research seeks to clarify meanings and looks for consequence (Cherryholmes, 1992). pragmatism is a worldview which arises out of actions, situations, and consequences rather than antecedent conditions and instead of focusing on methods, pragmatic researchers use all approaches available to understand the problem (Creswell, 2008). It does not strictly conform to the using of qualitative or quantitative methods because both methods maybe needed to answer the research questions. As such pragmatism opens the door for the use of multiple methods in the same study (Creswell, 2008).

3.4.2 Empirical Research (Empiricism)

Empirical research is based on observations or experience that produce empirical evidence, also called *empiricism*. The collection of empirical data evidence requires a plan and research design (see section 3.5), the research cycle is illustrated in Figure 3-3 below. Empirical research produces empirical observations that are not absolute (Popper, 2005).

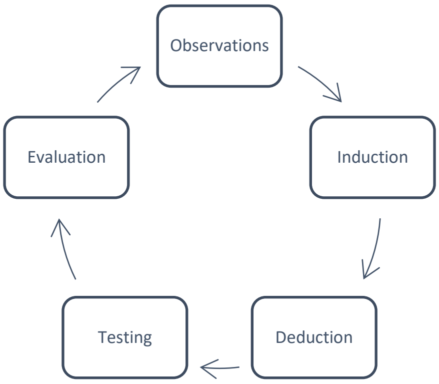


Figure 3-3 The empirical research cycle (Mietus, 1994).

3.4.3 Validity

Positivist empirical research is theory driven whereby general conclusions are drawn from results. As this research sits within a pragmatic paradigm, positivist validity is also applicable to the empirical research here. Easterbrook et al. (2008) describe the following four tests to validity and potential weaknesses in the empirical research:

- *Construct validity* focuses on whether the theoretical constructs are interpreted and measured correctly
- *Internal validity* focuses on the study design, and particularly whether the results really do follow from the data.
- *External validity* focuses on whether claims for the generality of the results are justified.
- *Reliability* focuses on whether the study yields the same results if other researchers replicate it.

3.4.4 Mixed Methods

Mixed method research, also referred to as multi-strategy research (Bryman, 2001), is the application of a number of different research strategies related to the research questions and research design. The research philosophy is a pragmatic one (Sahlqvist et al., 2015). It is chosen for this research for two reasons, firstly it affords a flexible approach to the development of the methodology design, analysis and evaluation by employing both qualitative or quantitative methods and secondly, while quantitative numerical elements of research are important, from a policy impact perspective (Manderscheid, 2016), qualitative methods are useful in exploring the complexities of cyclist road safety in a holistic way (Handy, 2014).

Mixed method research is a powerful inquiry approach, which is challenged with balancing the need for extensive data collection, the time-intensive nature of analysing multiple sources of data, as well as the requirement to be familiar with both quantitative and qualitative forms of research (Shull et al., 2008). Mixed methods will be embedded (Creswell, 2014) within different parts of the methodology design.

The research has two phases, Phase 1 and Phase 2, having mixed-methods embedded and sometimes not. A third Phase 3 is on-going research based on the thesis work and finding (post thesis). Therefore, the research design is better described as a '*multiphase mixed method'* (Creswell, 2014). The research methods employed in *Phase 1* and *Phase 2* are discussed in more detail in the sections to follow.

3.4.5 Realist Evaluation

A mixed-method allows flexibility, which is an advantage, but lack of perspective or focus may hinder the ability to answer the research questions. Therefore, the conceptual research framework (CRF) includes realist evaluation because it suits both the mixed-method and multivariate methodology proposed so that the research doesn't lose sight of '*what works for whom in what circumstances and in what respects and how? (Pawson and Tilley, 2004).*

Realist evaluation seeks to identify the mechanisms, context, outcome patterns in the research (Slater and Kothari, 2014) a particularly apt evaluation perspective when dealing with cyclists. Mixed-methods and realist evaluation are a good fit for this research, particularly the use of focus groups in research to '*think through'* results (Pawson and Tilley, 2004).

3.4.6 Transformative Research

Part of the motivation for this research is the lack of injury equity and stagnant cyclist road safety improvement in Scotland, as such there is a higher risk of injury depending on which mode one chooses to travel or has to travel by to work, education *etc*. Therefore, there is a power play between motorised and non-motorised road users (Kolgin, 2014) which needs to be addressed. Injury risk is not equitably distributed due to vulnerability and deprivation (Bhat et al., 2013). Transportation equity analysis is important and unavoidable; transport planning decisions often have significant equity impacts (Litman, 2016).

A transformative lens incorporates the intent of this research to advocate for improvement in cyclists road safety equity to improve society by addressing the issues of power (Sweetman et al., 2010). The prevailing UK approach to road safety has disproportionally benefited motorised users, who have experienced safety improvements both in terms of fatalities but also serious injuries. Positioning this research within a transformative theoretical lens is necessary because it draws attention to marginalised cyclists within the transport planning system (Kolgin, 2014). Therefore, the CRF includes a transformative lens as part of the research approach that will help the interpretation of results.

3.5 Research Design

The research design is a logic map or plan of the research that sets out how the research was conducted. It maps out the major parts of the research study which together aim to provide empirical evidence to answer the research questions.

3.5.1 Initial Exploratory Data Analysis (Phase 1)

The exploratory data analysis (EDA), Figure 3-4 below, is the preliminary phase of the research methodology and it has the following objectives:

1. Pre-modelling and analysis data cleaning
2. Determine a list of candidate variables for the regression analysis and modelling (Table 3.1 below); and
3. Develop the base ArcGIS model and R project model to enable, visualisation and attribute association across variables and within areas.

According to Hauer (2015). the purpose of conducting an EDA is to convert data into numbers and then to transform numbers into insight.

Methodology Design	
Phase 1: Initial Exploratory Data Analysis (EDA)	Phase 2: Multivariate Model and Analysis *(Phase 3)*

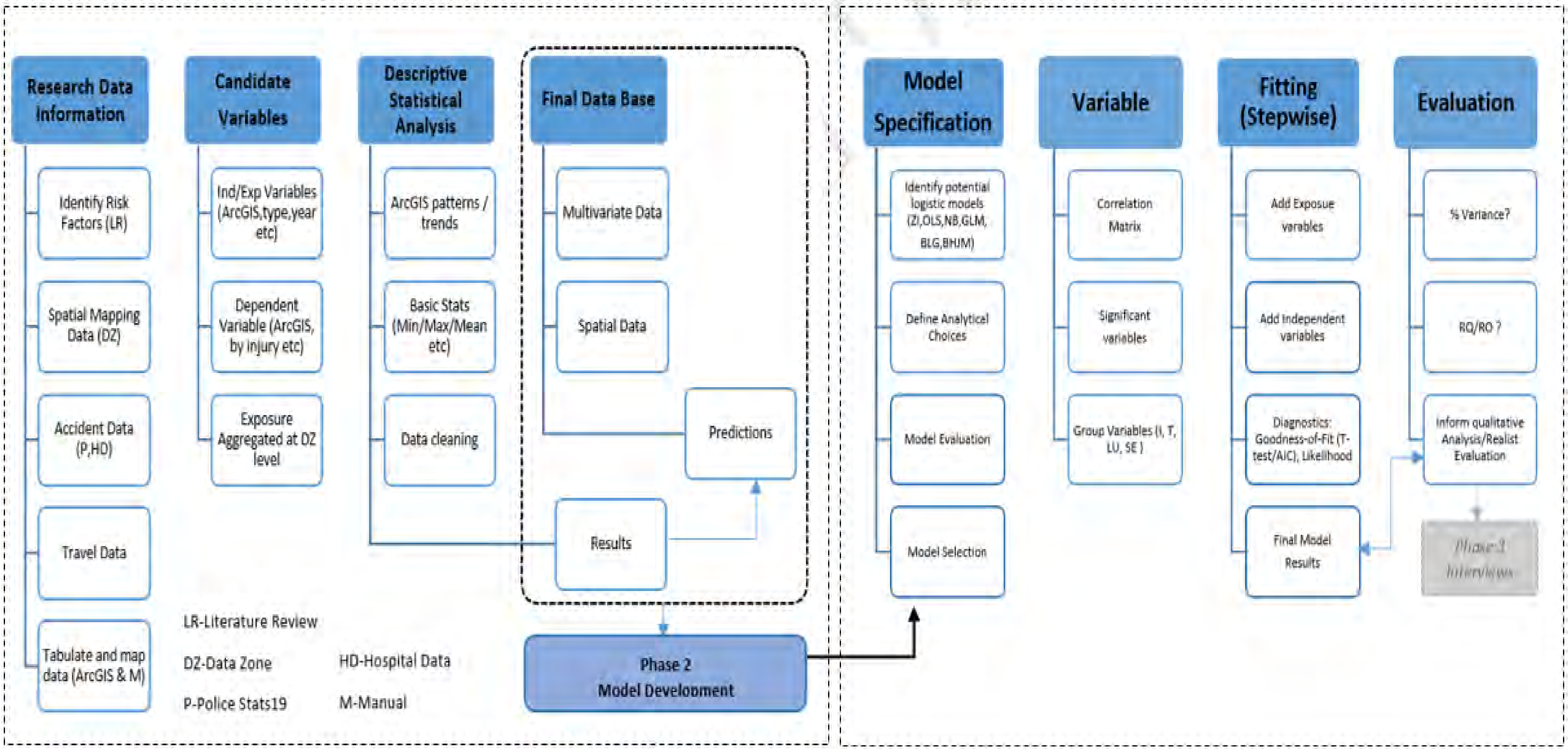


Figure 3-4 Methodology Design Framework

To this end, the EDA will use R Project, Excel and ArcGIS to analyse the accident, travel, demographic, land use and infrastructure data to produce descriptive statistics to describe the data.

The use of spatial analysis in conjunction with traditional analytical tools allows several determinants of injury to be explored in conjunction with physical determinants so that the determinants of risk can be explored to explain why some areas are riskier for cyclists than others. The visualisation of accident and injury information against spatial information serves as a means of analysing neighbourhood influences and unravelling aggregated data. This helps to communicate trends and provide more accurate local trends and variations across multiple small areas within a city or region.

3.5.2 Model Building (Phase 2)

At this point, the model development and fitting and final choice of regression may adversely effect subsequent results (El-Basyouny and Sayed, 2006) or methodological errors (Lord and Mannering, 2010) surrounding the data. The aim of the model fitting process therefore is to find a regression functional form that is a best fit for the available data and intended use which is a critical part of the modelling process (Lord and Mannering, 2010; Hauer, 2015).

There is no general rule that establishes the superiority of one modelling technique over another. Instead, empirical evidence from several studies suggests that the superiority of one method over another could depend heavily on data (Savolainen and Mannering, 2007). The objective of this part of the research methodology is to provide evidence-based responses to the research questions which will be discussed in Chapter 4.

3.6 Data Collection

A variety of primary and secondary data sources were used to inform the research and analysis, see Table 3.1 below. The census data was chosen due to its population-wide coverage of cycling, the level of quality assurance and demographic detail that can be obtained from the results. It also enabled comparison of trends over long periods of time and origin destination flow data files are also available at a number of geographical scales.

While the Census data, STATS19 and many of the DfT and TS files and data sets are available as an open data source the following were only available upon application and request: the Transport Model for Scotland from Transport Scotland; data file for Quiet Routes, Bus Lanes and vector mapping from City of Edinburgh Council and finally the permission the use the Cyclestreets.net routing engine. The following section provide a short overview for each of the data listed in Table 3-1 above.

3.6.1 STATS19

Injury road accidents reported to the police are recorded on a ‘STATS19’ form. These data are submitted to Transport Scotland by the police.

3.6.2 Data zone

Data zones are groupings of 2001 Census output areas with populations of between 500 and 1,000 household residents. There are 6,505 data zones across Scotland, which nest within local authority boundaries.

3.6.3 The Scottish Index of Multiple Deprivation (SIMD)

This deprivation index identifies small area concentrations of multiple deprivation across Scotland in a consistent way. The SIMD 2012 ranks data zones from most deprived to least deprived. The data zones can then be divided into quintile or decile groups using the rankings.

3.6.4 Scottish Government urban/rural classification

This classification provides a consistent way of defining urban and rural areas across Scotland. The classification is based upon two main criteria: (i) population as defined by the National Records of Scotland (NRS), and (ii) accessibility based on drive time analysis to differentiate between accessible and remote areas in Scotland. The classification is available in three forms: a two-fold classification, which distinguishes between urban and rural areas; a six-fold classification, which distinguishes between urban, rural, and remote areas through six categories; and, an eight-fold classification which further distinguishes between remote and very remote regions.

Table 3.1 Summary of the data sets used to inform the research.

Source	**Data Type**	**Use**	**Chapter**
Census 2011	Travel to work or education by mode of travel	Census data to provide distance commuted by each mode.	6, 7
	Car ownership	Regression model variable Chapter 6 and Chapter 8.	6, 8
	Population	Regression model variable.	6
	Origin Destination Flow Data	Used to create cycle flow volumes.	6
OSi	Boundary Data shape files for Scottish council areas 2011 and Intermediate Data Zone Geographies 2011.	ArcGIS models and R project models for analysis and data aggregation and maps.	6, 7 and 8
National Records of Scotland	Scottish Government urban/rural classification	Regression explanatory model variables	5, 6
	Scottish Index of Multiple Deprivation 2012	Regression explanatory model variables	5, 6
DfT	Major roads traffic count data, Average Annual Daily Flow	Used to validate modelled flow against observed floes flows.	7
	Minor roads traffic count data, Average Annual Daily Flow	Used to calibrate and validate cycling flow model	7
	Major roads raw count data	Used to calibrate and validate cycling flow model	7
	Minor roads raw count data	Used to calibrate and validate cycling flow model	7

Source	**Data Type**	**Use**	**Chapter**
	Road lengths in Scotland	Used to provide explanatory variable in Chapter 7.	6
	STATS19 Casualties csv files	Used to provide the dependant and explanatory variable.	5, 6, 7 and 8
	STATS19 Accidents csv files	Used to provide the dependant variable.	5, 6, 7 and 8
	STATS19 Vehicles csv files	Used to provide explanatory variables.	5
Edinburgh City Council	City of Edinburgh cycle counters raw data.	Used to validate modelled flow against observed flows.	7
	ArcGIS geodatabase containing shapefile for the Bus lanes, Quiet Streets, 20mph streets, road network for Edinburgh.	Used to create explanatory variables for regression models in Chapter 8.	8
	Vector mapping tiles for 2011 aerial photography for Edinburgh.	Used to digitise cycling infrastructure in ArcGIS and create a shapefile for on-road, off-road and shared footways. Used to create explanatory infrastructure variable for regression models.	8
Transport Scotland	Transport Model for Scotland (Version TMfS12) for the base year 2012. [Available upon application request to TS from]	Used to provide the traffic exposure explanatory variable.	8
Cyclestreet.net	Application Interface Programme (AIP) key. [Available upon request from Cyclestreet.net only]	Required to use cyclestreets.net routeing engine to model the Census 2011 origin destination flows.	7

Source	**Data Type**	**Use**	**Chapter**
Scottish Government Statistics	2009-2010 Urban Rural Classification associated shapefiles [ZIP, 11728.0 kb: 09 Aug 2010]	Urban Rural Classification associated shapefiles [ZIP, 11728.0 kb: 09 Aug 2010] to associate STATS19 accident georeferenced records.	5

3.7 Discussion

This research will employ a phased approach to understanding the research questions and use a pragmatic realist framework that will surround the mixed method methodology with a transformative lens.

An overview of the CRF, Figure 3-2 above, and research design applied in this study defines four knowledge acquisition phases that sit within the overarching research paradigm. The top two boxes refer to the research paradigm and the overall approach to answer the research questions including the transformative lens, the third box specifies the research design and finally the fourth box outlines the methodology phases.

Knowledge and causality is difficult to uncover when data is unavailable or missing, the realist evaluation is included to aid evidence building within the empirical study and the transformative lens will aid in the final interpretation of the empirical evidence. The CRF evolved to answer the study research questions, is influenced by the original motivation for the study, the transformative lens and methodology.

This section provided a detailed description of the methodology employed in box four for each of the Phases 1and Phase 2 (Phase 3 is included but does not form part of the thesis). This approach seeks to provide an improvement in human interests and society through addressing issues of power and social relationships in transport, specifically cyclists.

The next chapter discussed the research methods and outlines the methods for each of the subsequent chapters.

CHAPTER 4

Methodology

4.1 Introduction

The previous chapter discussed the development of the Conceptual Research Framework (CRF), Methodology Design and elaborated the data collection. This chapter informs the methods that will be used in each of the following chapters.

This chapter has two objectives, the first objective is to introduce each method that will be part of the subject matter of the subsequent chapters and analysis. Each chapter will utilise one of methods at least once; Figure 4-1 provides an overview of the relationships between chapters and the discussion in the previous Chapter 3.

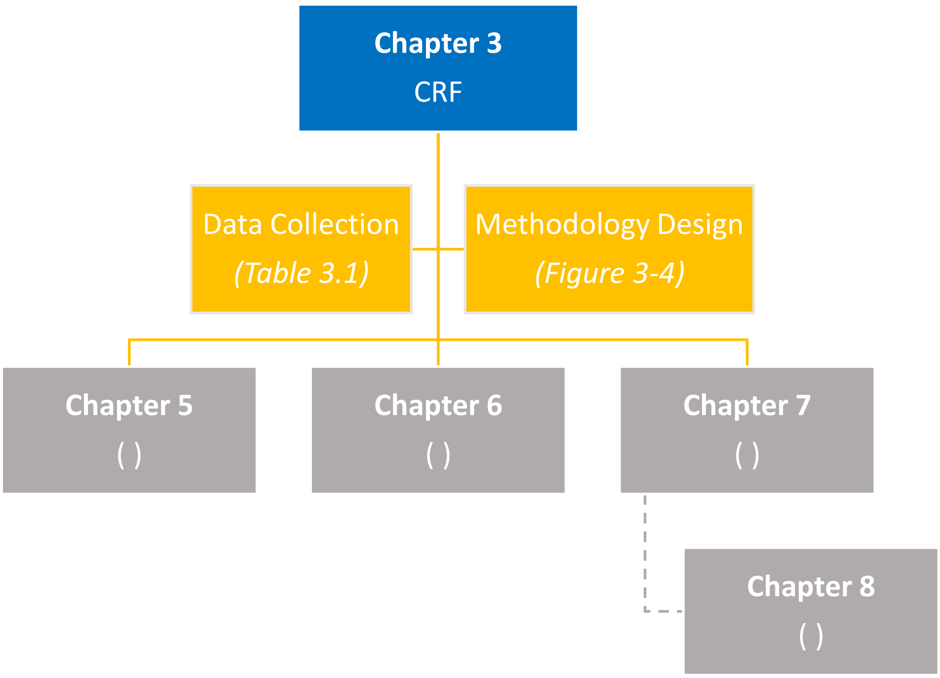


Figure 4-1 Overview of research methods to be assigned to Chapters 5 to 8.

The second objective aims to provide justification for the selection of one method over another through examanation of previous research on collision models. This chapter serves as a methodological toolbox and it aims to assist in the identification of the broader picture behind the complex phenomena that take place and more specifically to result in the understanding of accident risk with specific focus on cyclists.

The chapter is structured as follows: overview of accident models, accident model forms, a review of studies using various models, the general observations from the review, model building, goodness-of-fit and conclusions. After the accident modelling forms have been discussed and the models to be used have been justified, the Figure 4-1 above is repeated and populated with the methods selected from the methodological toolbox that will be applied in the following chapters of this thesis.

4.2 Accident Prediction Models

Generalised linear models (GLM) as accident prediction models (APM), were first introduced to road accident studies by Maycock and Hall (1984). They typically use either a negative binomial (NB) or poisson (P) distribution error structure. APMs, of various functional forms, were developed to analyse accident history for a sample of sites, links or regions, to evaluate the factors, design elements or other variables to explain observed accident frequency or safety performance. Statistical techniques were utilised to investigate the relationship among variables. Their purpose is twofold, to predict the frequency of accidents or attempt to explain the association between different accident types or severities and several independent variables (Lord and Mannering, 2010; Vandenbulcke, 2011).

APM for road safety impact assessment generally take the following form (Eenink et al., 2008):

$$E(\lambda) = \alpha\, Q_{MA}^{\beta}\, Q_{MA}^{\beta}\, e^{\sum y_i x_i} \tag{4.1}$$

Where the estimated expected number of accidents, E(λ), is a function of traffic volume, Q, and a set of variable risk factors, x_i (i = 1, 2, 3, …, n), α is a constant particular to the model location, β represents the elasticity factor to raise the effects of traffic volume and y_i are the co-efficient of the risk factors. The effects of various risk factors that influence the probability of accidents, given exposure, is generally modelled as an exponential function, e (Eenink et al., 2008). These generalised linear models are recognised as the most appropriate for accident prediction models (Maher and Summersgill, 1996).

4.2.1 Poisson-Lognormal Regression Model (PLN)

Recently, some researchers have used the Poisson-lognormal model as an alternative to the negative binomial and poisson-gamma model (Lord and Mannering, 2010) for modelling cyclist crash data (Kim et al., 2002; Prato et al., 2014).

Prato et al. (2014) analysed the factors that contributed to increased cycling risk in the Copenhagen region. The study assessed 269 traffic zones and controlled for both motorist and cyclist traffic exposure. They used a Poisson-Lognormal regression extension, a multivariate accident frequency model to evaluate the effects of 16 different infrastructure and socio-economic characteristics particular to each of the 269 traffic zones. The estimation of Poisson-gamma and Poisson-lognormal models developed used with conditional autoregressive priors within a full hierarchical Bayesian framework. This methodology presents a means to accommodate heterogeneity using conditional autoregressive priors which are estimated as part of the modelling process to even out the heterogeneity and therefore this method is applicable to answer the research question.

4.2.2 Zero-Inflation Poisson Regression (ZIP)

The ZIP extension of the multivariate model was developed to handle data with a significant number of zeros (Lee and Mannering, 2002 and 2010; Lord; Vandenbulcke et al., 2014). ZIP models operate on the principle that the excess zero density cannot be accommodated by a traditional count structure, instead it is accommodated by a splitting regime that models an accident-free versus an accident-prone case of a certain location.

The probability of a location being in a zero or a non-zero state can be determined by using a binary logit or probit model (Lord and Mannering, 2010). The ZIP extension assumes a dual-state process which is responsible for generating collision data by considering one process that generates only zero collision counts and the other process only generates non-zero collision counts from a given Poisson model. The ZIP extension does create another problem, such that locations with zero data will be associated with a long-term mean zero according to Lord et al. (2007) therefore the ZIP extension does not adequately reflect the crash-data generating process where data is missing or unreported which is particularly problematic in cyclists research as discussed in Chapter 2. Therefore, this form will not be considered further.

4.2.3 Case Control Logistic Regression Model (Bayesian Framework)

Vandenbulcke et al. (2011, 2014) used a spatial Bayesian modelling approach in a case-control strategy, inspired by epidemiology and ecology, to model a binary dependant variable (accident, no accident location) to predict cycling accident risk in Brussels. His research differs from previous accident frequency models because he developed an accident prediction model that predicted where an accident is likely to occur where no reported (unreported) cycling accident had previously occurred. The research used data from the SHAPES survey which collected unreported cyclist accidents data using an on-line registration survey conducted between 2007 and 2009.

This method was used in a similar case-controlled study by Aldred et al. (2017) using control sites to represent an expected outcome if injury risk was distributed randomly. The study made use of a cycling flow model previously developed by the London transport authority, which the authors described as– unusually – to have a model of cycling flow across the network.

This method presents a robust way to analyse cyclist safety however a network level cycling model is not available for Scotland, while one will be developed for Edinburgh as part of this research, the method is not comparable to previous research into the SiN effect and a Scottish / Edinburgh comparison would also not be possible for this reason. Therefore, this method will not be incorporated into the research.

4.2.4 Generalised Linear Mixed Models (Mixed Effects Models)

Mixed-effects models are panel models that have a combination of fixed and random effects (Hilbe, 2014). Likelihood-based models using panel-data structures violate the basic assumption that observations are independent. Thus, the effect of an explanatory variable, the parameter estimates, on the frequency of the dependent variable, cyclist collisions, is constrained to be equal for all observations (e.g., million vehicle kilometres travelled is the same across all panels or clusters).

Lord and Mannering (2010) point out that traditional statistical modelling, such as Poisson and NB, do not permit parameter estimates to vary across observations. The unobserved variations (i.e., unobserved heterogeneity) from one location to the next (unobserved heterogeneity) should be reflected in some difference across estimated parameters of some of the explanatory variables. When model parameters do vary across observations, they are fixed, the resulting parameter estimates may be biased and erroneous inferences could be drawn (Lord and Mannering, 2010).

Yiannakoulias et al. (2012) used disease mapping to show commuter cyclist collision risk and a generalised linear mixed model to predict cyclist collisions within Hamilton city census tracts in Canada across three time periods, 1996, 2001 and 2006. Their approach does not consider multivariate independent explanatory variables, but it does offer useful geographical analysis of the spatial distribution of risk and takes account of local risk rather than per capita or count only analysis and in so doing provided a more empirically meaningful and tangible representation of cyclist collision risk and its varies across space.

The mixed-effects models provide a potential method to deal with heterogeneity in the datasets which has a panel structure. Therefore, including the panels as random variables may be beneficial. However, the random-effects results can be difficult to interpret due to the discrete estimates of the random and fixed parts.

4.2.5 Poisson and Negative Binomial

As discussed, the dependent model variables (cyclist collisions), are discrete, however they also include a large number of small or zero values and the longitudinal data structure is ordered into panels or clusters spatially and temporally and also referred to a pooled data. Both of these characteristics violate distributional assumptions as described by Hilbe (2011, Table 3.2 page 35), violation 2. excess zeros in the data and 6. data structured as panel (i.e. clustered and longitudinal data). The Poisson and the negative binomial models can take account of excess zeros in the data, or "overdispersion".

When longitudinal data comes in panel form, such as the data in this study where the data is pooled across Scottish council areas, each council area constitutes a panel. The problem arises because each panel cannot be considered independent which is a central assumption of maximum likelihood theory, where within-panel correlation results in over-dispersed data (Hilbe, 2011; page 37). Therefore, the Poisson and negative binomial models were examined against models developed to accommodate this extra correlation.

The negative binomial (NB) model is one of the most frequently used models in crash-frequency modelling (Lord and Mannering, 2010). NB is also widely used for both pedestrian and cyclist's collision analysis. NB, sometimes referred to as Gamma Hierarchy or Negative Binomial Poisson, deals with the extra Poisson variation of collisions and overcomes possible over dispersion in the data (Lord and Mannering, 2010). In terms of road safety engineering and the development of national level safety performance functions the NB are regarded as the standard method (Young and Park, 2013) typically used to capture the key and basic points in transportation safety analysis.

NB has been used to investigate the *SiN* effect among pedestrians and cyclists (Daniels et al., 2010; Wei, F. and Lovegrove, G., 2011, Elvik, 2016; Schepers, 2012) at a macro and micro-level. Further, Zhang et al., (2014) applied NB at a zonal level.

Due to the number of previous studied that used the NB model the investigate *SiN*, this model will be used because it is well understood in the literature and because several studies have used the model form to investigate *SiN*.

4.2.6 GEE

The generalised estimating equation models are an extension of the generalized linear model GLM where the variance function is adjusted using a correlation matrix (Hilbe, 2014; pg. 239). The GEE method is based on the quasilikelihood theory (Wedderburn 1974), and no assumption is made about the distribution of response observations. In road safety analysis Lord and Persaud (2000) used the GEE to model four-leg intersection collisions in Toronto.

This method accounts for variation as crashes have varied by the temporal change of traffic flow, economy, weather, and crash-reporting practices. The GEE specifies how the average of a response variable of a subject changes with covariates while allowing for the correlation between repeated measurements on the same subject over time (Cui, 2007; pg, 209).

This method estimates regression parameters that have a population average interpretation and a correlation structure is treated as a nuisance parameter (Hardin and Hilbe 2003). Therefore, some of the statistics derived under the likelihood theory cannot be applied to GEE directly. For instance, AIC a widely used method for model selection in GLM, is not applicable to GEE. However, under appropriate modification of the AIC method, Pan (2001) proposed a model-selection method for GEE and is termed the quasilikelihood under the independence model criterion (QIC).

This method will be included for the research methods toolbox because similar to the mixed-effects model it can accommodate the panel structure of the data.

4.2.7 Injury Severity Models

Accident severity is often measured categorically, for instance, the severity level of an accident can be classified as fatal, serious injury, slight injury or no injury (property damage only). Since the accident severity is ordered, typically ranging from slight to serious injury and to a fatality, the use of discrete ordered response models (such as binary logistic, ordered logit and probit models) for analysing accident severity data is a logical application. However, ordered response models have two limitations which are related to the constraint on the variable influence (e.g. a variable would either increase or decrease accident severity) and under-reporting, especially for low severity levels in accident data (Kim et al., 2007).

For studies analysing accident injury severities in cyclist accidents, the binary logistic regression model has also been frequently estimated when the injury severity levels are recorded in binary form (i.e., fatal, serious and slight injury risk comparisons). Examples of studies applying the logistic model to examine accident injury severity in cyclist accidents include the work by Kim et al. (2007), Martínez-Ruiz et al. (2014), Hollingworth et al. (2015) and Wahi et al. (2018). Generally, these researchers were in an attempt to model the probability of fatalities/severe injuries using a variety of variables such as junction control measures, age, gender of the cyclist, helmet wearing, speed and vehicle type.

The multinomial logistic (ML) regression model is an extension of the binomial logistic regression model above. It is used when the dependent variable has more than two nominal (unordered) categories, in road safety research it is used to examine injury severity responses. Bhat and Mannering (2014) conducted a comprehensive review of statistical methodologies, they observed the modelling approaches that consider ordering of injury severities, such as the ordered probit and logit models, have been applied with increasingly sophisticated forms to overcome possible restrictions imposed by traditional ordered-modelling approaches, see Appendix A 4.1. Also, as with count models, accident severity models have been extended to consider unobserved differences in injury severity outcomes across the population using finite-mixture/latent-class approaches.

The focus of this research is to investigate a SiN effect; therefore, the injury severity models will be used to explore the cyclist accident and injury severity factors to provide context or identify trends in the data. Therefore, the more complex forms of injury severity will not be employed, the binary logistic model offers simplicity and it will facilitate comparison with previous research. This model form will be used in Chapter 5 and Chapter 8.

4.2.8 Geographically Weighted Regression Models

The global models mentioned above take no account of spatial heterogeneity into the spatial interaction modelling. The spatial non-stationarity, a form of heterogeneity, which means the varying relationships between dependent and independent variables across the study area, can be explored by the innovative method of geographically weighted regression (GWR) (Brunsdon et al., 1996; Fotheringham, et al., 2002).

One drawback of using GLMs to analyse spatial data is that one model is assumed to fit all locations in a global way, thus area variation is lost in the overall results of the model fit. Geographically Weighted Regression (GWR) is a form of GLM that can vary over spatial areas. The theory behind GWR is to provide a means for modelling data using standard regression methods, as discussed in the previous section, in combination with a way to also describe the spatial variation relationships that can be used to identify localised trends or exceptions to global trends (Fortheringham, Brundson and Charlton, 2002). With specific reference to collision data analysis the following studies have use GWR models Hadayeghi (2010), Li et al. (2013) and Gomes et al. (2017).

GWPR models are sometimes referred to as a '*local*' models whereas the models discussed in the preceding sections above (i.e. GLM, GEE and GLMM) are referred to as '*global*' models. A further benefit of GWPR lies in the ability of the model to produces a local coefficient for each geographic area (or panel) which is an advantage over a *global* model that only provides single coefficient estimates for each independent variable included. The following model form was used by Hadayaghi (2010):

$$\ln{(Y_i)} = \alpha(u_i) + \beta(u_i)X_i \tag{4.2}$$

where, $u_i(= (u_{x_i}, u_{y_i}))$ indicates the coordinates of i^{th} point. One important step in the implementation of GWPR is the spatial kernel function and the bandwidth, which determines the number of observations around each subject point and the distance decay in the weighting function. The estimator from Generalized Weighted least square is

$$\beta\left(u_{x_i}, u_{y_i}\right) = \left(X^t\, W\left(u_{x_i}, u_{y_i}\right)X\right)^{-1} X^t W(u_{x_i}, u_{y_i})\, y \tag{4.3}$$

4.2.8.1 Distance matrix, kernel and bandwidth

A fundamental element of the GWR model is the spatial weighting function (Fotheringham et al. 2002) because it defines the spatial relationship, spatial dependency, between the observed variables such that $W(u_{x_i}, u_{y_i})$ is a n×n diagonal matrix (*n* = the number of observations) that allocates the geographical weighting of each observation point, *i*, for the model calibration point *i* at location (u_{xi},u_{vi}). The weighting matrix is defined by, the type of distance specified (i.e., Euclidian etc.), the kernel function and its bandwidth. In this research, the Euclidean distance was used. Where W is an n x n matrix,

$$W\left(u_{x_i}, u_{y_i}\right) = \begin{matrix} w_{i1} & 0 & 0 & L & 0 \\ 0 & w_{i2} & 0 & 0 & 0 \\ 0 & 0 & w_{i3} & 0 & 0 \\ M & M & M & 0 & M \\ 0 & 0 & 0 & 0 & w_{in} \end{matrix} \tag{4.4}$$

Where W_{in} is the weight of the data at point n on the calibration of the model around point *i*. In the global OLS model every observation has a weight of unity, so *Win* equals to one.

For GWR models however, there are several choices for defining the diagonal elements of the weighting function, including: bi-square nearest neighbour function, the exponential function and the Gaussian Function. Generally, these functions are the distance d_{ij}, Euclidean distance. For example, the weights from the exponential kernel function is calculated as:

$$W_j(s) = exp(-d_{ij}/\gamma) \quad (4.5)$$

Where d_{ij} is the distance from calibration location i to location j and γ is the kernel bandwidth parameter. The key controlling parameter in all kernel function options is the bandwidth, γ. In practice, a fixed bandwidth suits regular sample configurations whilst an adaptive bandwidth suits highly irregular sample configuration. Adaptive bandwidths ensure enough local information for each local calibration of a given GWR model

The GWR models provide a method that can be compared to the GLM models and accommodate spatial dependence within the model. Therefore, it is a suitable model to answer the research questions.

4.2.9 Conventional Spatial Models

The spatial autoregressive (SAR) model and the spatial error model (SEM) are two types of spatial models that control spatial autocorrelation by adjusting the regression using eigenvector spatial filtering to estimate non-normal probability models, such as Poisson, with georeferenced data containing non-zero spatial autocorrelation to account for spatial autocorrelation in random variables by incorporating heterogeneity into parameters in order to model non-homogeneous populations The eigenvectors are spatial proxy variables that require estimation prior to modelling in a similar way to principle component analysis (PCA) but unlike PCA, which utilises scores for each variable, eigenvectors are themselves constitute the variable to be entered into the equation for each spatial unit and have to be estimated; in effect they are a spatial filter (SF) that enables the researcher to implement a GLM while still accounting for positive spatial autocorrelation. (Chun and Griffith, 2013). The SAR model is described by:

$$Yi = \rho WYi + \beta Xi + \varepsilon i \quad (4.6)$$

Where Y is a vector of the cross-sectional dependent variable, WY is a spatially lagged variable with a weight matrix W, ρ is the coefficient for the lagged variable, β is the vector of coefficients, X is the vector of variables and ε is a normally distributed random error term with zero mean and variance σ^2. The SEM model is described as (Anselin, 1988):

$$Y_i = \beta X_i + u_i \quad (4.7)$$

$$u_i = \lambda W u_i + \varepsilon_i \tag{4.8}$$

Where u_i is an error term to account for spatial correlation and λ is the spatial autoregressive coefficient. In order to use these spatial filter techniques to model count data, the count dependent variable must be converted into a continuous variable by dividing it by an exposure variable, creating a rate, and then a SAR or SEM model may be applied.

These models form can deal with spatial dependence and the panel structure of the data, but they are computationally more complicated that the mixed-effect model and require separate estimation of a spatial filter. Similar to the PLM above these methods will not be considered for inclusion in the methods toolbox.

4.2.10 A Question of Scale? Micro, Macro and Meso

Based on the literature review the scale at which road safety is modelled impacts results and interpretation. While there has been considerable research into road safety at a country or city level (macro) and individual link or junction level (micro), very little research has focused on the differences within a city or region at a meso scale.

Road safety research and accident prediction modelling has tended to be either at a micro level, individual junctions or crossings, or at a macro level, region or country level. Micro or macro level accident prediction models (APM) are seldom developed for cyclists (Lovegrove and Wie, 2013) and focus mainly on vehicular problems.

There is growing recognition among road safety researchers that a meso level safety analysis can be more beneficial than municipal or national level (Young and Park, 2013; Bax, 2011 and Vandenbulcke, 2011). Nationally aggregated road safety figures may not reflect local level scenarios because they don't represent local variation and similarly, micro level is too fine a measure. While micro level is useful to design engineers at a link or junction level it is too specific to be used by planners or policy makers who need a policy tool rather than design tool at a local level. Bhat et al. (2013) emphasises the importance of considering spatial dependency when adopting meso spatial units of analysis which this research will consider.

4.2.11 Methodology Summary Conclusions

In order to investigate the *SiN* effect, and provide comparable empirical evidence, it will be necessary to develop a multivariate APM. None of the extensions and forms reviewed above offer a perfect fit for the data and research questions so one of the first tasks will be to determine which regression model approaches provide the best fit for the data and research design.

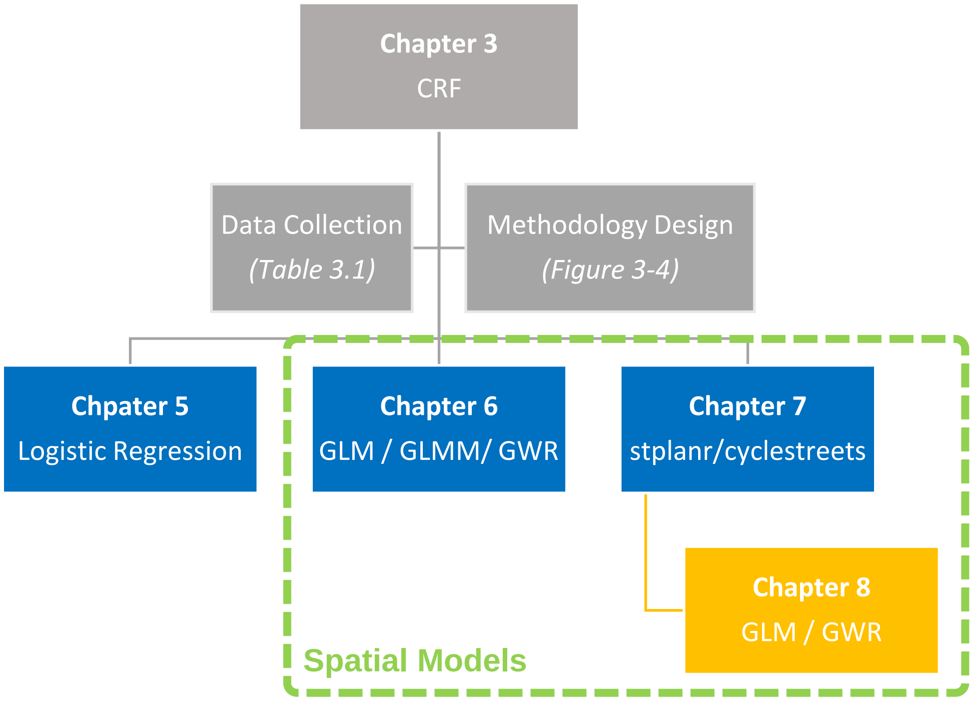


Figure 4-2 Research methods toolbox for analysis in Chapter 5 to 8.

It is clear that the models should be multivariate or bivariate because cyclist causal factors associated with *SiN* are under researched, the model should also account for spatial dependence because the literature review identified a research gap concerning possible spatial aspects of *SiN* and models should include exposure variables, i.e. traffic and cyclist volumes, because the literature review found that this is often missing from previous research and pedestrians and under reporting will have to be taken into consideration. Based on the review of the methods in this Chapter the models that will be utilised to address the research gaps and research questions are discussed below.

In Chapter 5 multivariate logistic regression models will be used to evaluate the STATS19 data to identify important variables associated with cyclist injuries. In Chapter 6 four types of generalised linear models (GLM) will be used, the first are the GLM with poisson or negative binomial extensions (i.e. to deal with overdispersion) because they are the recommended models for accident analysis for motorised transport, the next GLM used are generalised linear mixed models (GLMM) because unlike the GLM they have an additional element that can account for random variation (i.e. the mean count of accidents is not independent across the data) which may be a factor in *SiN* if the assumptions of independence are not true under the GLM forms , another model that deals variation of the mean is the generalised estimation equations (GEE) which will also be examined because the data sets are pooled samples that this type of model was developed for; although they are not generally used in transport modelling, finally geographically weighted poisson regression (GWPR) models will be used because they can model spatial dependence which has not been research previously to examine *SiN* and if there is spatial dependence among the variables this model may perform better than a GLM, GLMM or GEE. In Chapter 8 the models that preform the best, between the GLMM, GEE and GWPR, will be used to examine SiN in Edinburgh and to establish if a GLM or the preferred model from Chapter 6 preforms better for multivariate datasets. The modelling strategy described is illustrated in Figure 4-2 above.

The next section discusses the analytical issues and model fitting processes that will be used in the following chapters.

4.3 Analytical Issues

The comparison of spatial data and non-spatial data give rise to two effects: spatial autocorrelation (dependence) and spatial heterogeneity (Vandenbulcke, 2011; Chun and Griffith, 2013). Lord and Mannering (2010) list several issues that also need consideration, over dispersion, under dispersion, time variable explanatory variables, temporal correlation, low mean or sample size, injury severity and crash type correlation, under reporting and omitted variable bias.

4.3.1 Spatial Autocorrelation

Spatial heterogeneity is a special case of observed or unobserved heterogeneity, a familiar problem in standard econometrics. In contrast to spatial dependence, tackling this issue does not always require a separate set of methods. The only spatial aspect of the heterogeneity is the additional information that may be provided by spatial structure. For example, this may inform models for heteroscedasticity, spatially varying coefficients, random coefficients and spatial structural change

In conventional GLMs, the relationship between the dependent and independent covariates is assumed to be consistent across the geography of the study area when estimating parameters. This assumption may be violated, however, because the collision rate is likely to be affected by many spatial factors, e.g. demographic and land use characteristics. Local indicators of spatial association (LISA) introduced by Anselin in 1995 identify the spatial association and pattern of spatial association and spatial heterogeneity or difference in spatial patterns or dissimilar patterns. Local Moran I or

Local Spatial Autocorrelation technique or spatial autocorrelation has been used to identify statistically high clustering locations and outliers.

One of the most widely used indices of spatial autocorrelation was developed by Moran (1948) and Geary (1954) called the Moran Coefficient (MC) I (Chun and Griffith, 2013). The Moran's I test for the residuals obtained from OLS estimation can be used to detect the presence of spatial correlation:

$$MC = \frac{n}{\Sigma_i \Sigma_j c_{ij}} \quad \frac{\Sigma_i \Sigma_j c_{ij} \ (y_i - \bar{y})(y_j - \bar{y})}{\Sigma_i (y_i - \bar{y})^{2}} \tag{4.9}$$

Where n is the number of spatial units indexed by i and j; y is the dependent or independent variable we are interested in; $\bar{y}$ is the mean of y, and c_{ij} is a matrix of spatial weights. The value of Moran's I rests between -1 and +1; a Moran's I value of 0 denotes a random spatial pattern, i.e. no spatial autocorrelation, clustering, between spatial units i and j. This calculation identifies negative associations, -1, and positive associations, +1.

4.3.2 Multicollinearity

If one or more correlation coefficients are close to 1 or -1, the variables are highly correlated and a severe multicollinearity problem may exist; remove one of the correlated independent variables in the model (Hoang Diem Ngo, 2012).

Prior to fitting the models a correlation matrix for all the explanatory variables was produced to examine the presence of multi-collinearity. Where correlation between explanatory variables, i.e., correlation values above +/- 0.5, included in the models that showed symptoms of multi-collinearity (e.g., sign change of coefficients when an additional variable are included/removed or unexpected coefficient values) were removed. In addition, the variance inflation factor (VIF) of the explanatory variables were examined post-hoc to the fitting process. The VIF is considered high if it exceeds a value of ten (10) (Zuur, Hilbe and Ieno, 2013) however other texts recommend that the threshold should be lower less than or equal to five (5) (Heiberger and Holland, 2015). Therefore, a VIF less than eight (8) was considered suitable and compromise between recommended thresholds.

Where symptoms of multi-collinearity were observed, during stepwise regression model fitting, they were mitigated by removing the highly correlated explanatory variables, identified in the correlation analysis or they were removing after the fitting process post-hoc by examining the VIF of each included variable. This process was iterative, but it ensured that optimum models, for the data, were produced and only included significant model variables.

4.4 Model Building

This research examines and compares the prevailing modelling approach used to examine collision counts, negative binomial, with mixed models and geographically weighted regression. According to Hoang Diem Ngo (2012) model building involves five steps, variable screening, model adequacy or goodness-of-fit, testing the modelling assumptions, dealing with model problems and finally validity testing.

The next sections describe the methods used to assess model goodness-of-fit for each of the model types and how they are similar for cross comparison purposes.

4.4.1 Stepwise Selection and All-possible-regressions selection

Stepwise regression is a combination of the forward and backward selection techniques. In this method, after each step in which a variable was added, all candidate variables in the model are checked to determine if their significance has been reduced below the specified level. If a non-significant variable is found, it is removed from the model. Stepwise regression requires two significance levels: one for adding variables and one for removing variables. Stepwise Regression determines the independent variable(s) added to the model at each step (Hoang Diem Ngo, 2012).

All possible regressions selection procedure gives all possible models at each step with the suggested independent variable(s) that are associated with the following criteria. Based on these criteria, the analyst subjectively decides the potential independent variables to be included in the model. (Hoang Diem Ngo, 2012).

4.4.2 Generalised Linear Model Goodness-of-Fit Assessment

All model variables were collated using Microsoft Excel comma-separated value

[9] (CSV) and then imported into R for the modelling and graphing work. These variables were selected for testing as they were shown to be important in previous studies or considered to have an association with cyclist casualties.

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[9] *A .csv file contains the values in a table as a series of ASCII text lines organized such that each column value is separated by a comma from the next column's value and each row starts a new line. R loads the .csv file and converts it into a data frame.*

The model fitting process was applied manually, first each explanatory variable was tested for significance, then evidence of multi-collinearity was addressed if present and finally the selection of the preferred model was aided by also using stepwise regression analysis. The significance of the explanatory variables was determined using the Wald χ^2 (chi-square) test and if the significance values (P-values) were below 0.05, such that a p-value < 0.05 is indicative of 95% likelihood that the explanatory variable should remain in the model. All significant variables remained in the models and those that were not significant were removed.

Within R stepwise analysis can be processed in a number of ways, 'forward', 'backward' or 'both', but regardless of which option selected it involves dropping variables into or from the model in small steps to test their significance in terms of explained variability in the dependent variable (Punch, 1998). Model comparison and goodness-of-fit (GOF) was interpreted using the following three values:

1. Log Likelihood (LL)
2. Akaike Information Criterion (AIC)
3. *Pseudo* R-Squared.

The pseudo R-Squared value is used to provide an indicative measure of model goodness-of-fit because it is difficult to provide an accurate estimate for GLM forms in the same was as linear models, for example GLMs, such as Negatives binomial models, are fitted according to one scaled deviance, but measured according to another (sum of squares), so the process of fitting minimises the scaled deviance but not the sum of squares. A maximum score of 1 indicates that the model explains 100% of the variability in the dependent variables is explained by the variables modelled, and a score of 0.5 would indicate that 50% of the variability is explained.

For this research, no single measure of goodness-of-fit is relied upon but rather a combination of the AIC, pseudo R-Squared, model behavior during fitting and finally the fitted residual. It is therefore inaccurate to portray the fitting process of GLM and its extensions as mechanistic as a degree of subjectivity is used throughout the study's modelling such that another model fitter may arrive at different results. This conscious subjectivity is informed by the previous literature and is shaped by the research the questions. The GLM models were analysed using stepwise selection.

4.4.3 Geographically weighted regression Model Goodness-of-Fit

Collinearity is dealt with in a similar way to global models, discussed above, the correlation coefficients are examined and the VIF value along with addition of procedures to address local collinearity. Gollini et al. (2015) point out that collinearity is more problematic in GWR models because:

- multi-collinearity effects can become pronounced with the smaller spatial samples used in each local estimation and
- if the data are spatially heterogeneous in terms of its correlation structure, some localities may exhibit collinearity while others may not.

The following diagnostic approach recommended by Gollini et al. (2015) was used to investigate the nature of local collinearity:

- local correlations amongst pairs of predictors (> 0.8);
- local variance inflation factors (VIFs) for each predictor (>10);
- local variance decomposition proportions (VDPs) (>0.5); and
- local design (or cross-product) matrix condition numbers (>30).

The later diagnostic is the optimal diagnostic, local condition numbers, considered superior to local correlations and local VIFs for investigating collinearity according to Wheeler (2007).

- The GWR models use a similar stepwise 'forward' selection technique or pseudo stepwise procedure that follow the following four steps (Harris et al/, 2015):
- Select all possible bivariate GW regressions by sequentially regressing a single independent variable against the dependent variable;
- Find the best performing model, using the minimum AIC_c, and permanently include the corresponding independent variable in subsequent models;
- Sequentially introduce a variable from the remaining group of independent variables to construct new models with the permanently included independent variables, and determine the next permanently included variable from the best fitting model that has the minimum AIC_c;
- Repeat step 3 until all independent variables are permanently included in the model.

4.5 Conclusions

The methodology literature review identified a number of approaches to investigating the *SiN* effect and several multivariate accident prediction modelling techniques. The work carried out by Elvik (2013, 2016) highlighted the mathematical issues with previous research in to *SiN* and Bhat and Mannering (2014) demonstrated the need to consider modelling in terms of injury severity rather than using a single response variable due to the variation between minor, serious and fatal injury.

In terms of the applicability of the model scale, a meso scale emerged as the most promising level at which to assess VRU safety particularly because the research will utilise geospatial ArcGIS mapping and analysis.

While recent research has highlighted the merits of meso level road safety evaluation (Vandenbulcke, 2011, Schepers, 2012) the current literature review has not found studies applicable to countries with low levels of cycling and walking, in particular the UK and Scotland where excessive zeros maybe problematic and the analysis will also have to consider heteroscedasticity and multicollinearity issues.

As discussed in Section 4.8.2.1 above, the use of the term '*local*' refers to a regression model that investigates variables within each geographical unit added to the model, the use of the term '*global*' refers to a regression model that considers all geographical units without taking account of their local placement to each other. The use of '*local*' and '*global*' has this meaning which is not to be confused with spatial geography. Similarly, the use of '*meso*' means a medium sized aerial unit, '*micro*' level refers to junction level analysis, '*macro*' refers to country level and meso in this research refers to the Scottish intermediate data zone unit.

The next four chapters use the methods, fitting processes and analysis described in this chapter.

CHAPTER 5

Exploring STATS19 in Scotland

5.1 Introduction

This Chapter examines STATS19 data to determine factors associated with killed or severe injury (KSI) cyclist collisions that may reveal reasons or trends for the continued increase. Based on the literature review, this chapter focuses on examining the impact of posted speed limits and cyclist infrastructure as they are two main policy measures or interventions promoted to achieve improved cyclist safety.

The aim of this chapter is to critically analyse road safety evidence using the STATS19 cyclist injury data to develop an understanding of the risk factors involved in KSI injury accidents compared to slight injury accidents. The research will also aim to focus on infrastructure, particularly cyclist infrastructure, because the literature review (Chapter 2) identified a lack of consensus about the safety benefits of cycling infrastructure. Furthermore, there has been a lack of research into STATS19 factors that may indicate wider policy or enforcement trends or to identify suitable metrics needed to monitor risk factors or gender specific risk factors. As discussed in Chapter 2, the literature review showed that women's participation in cycling is 30% or less (Pucher and Buchler, 2008) than their male counterparts in the UK.

The analysis in this chapter uses road casualties recorded by the police in Scotland from 2010 to 2012. This timeframe was used to facilitate the comparison of any findings with analysis in subsequent chapters. The following chapters will examine and use cycling flow data exposure metrics, based on the Census 2011, to investigate *SiN* and thus this research has examined three years of STATS19 data centred on the year 2011.

This chapter is structured in the following way: Section 5.2 examines accident and casualty STATS19 dataset characteristics and the methodology; Section 5.3 discusses the results, concentrating on the significant findings; Section 5.4 presents a discussion of the results and their relevance to cycling safety in Scotland and safety performance indicators and; the final Section 5.5 presents the summary, conclusions and main findings.

5.2 Methodology

This research aims to determine the important influential variables or factors associated with an increased risk of cyclists being involved in a KSI accident compared to a slight injury using binary logistic regression models. The STATS19 databases provided the data which comprised three separate datasets for casualties, accidents and vehicles. They were joined and filtered to extract cyclist collisions and severity types; Table 5.1 below provides the descriptive statistics for the categorical variables. In Scotland, twice as many men as women cycle once or twice a week for transport (TS, 2016; Table 25b), therefore a separate female subset of the data was extracted and examined from that overall dataset.

The binary logistic regression provides a method for modelling a binary response variable, which takes values 1 (success) and 0 (failures), described in the methodology in Chapter 4. The aim of binary logistic regression is to find the best fit model to describe the relationship between the dichotomous dependent variable and the set of explanatory variables for cyclist injury severity outcomes. The explanatory variables were first analysed in a univariate model and then a multivariate model that was mutually adjusted for all included variables. The included explanatory variables were selected by examining the correlations between the variables using a correlation matrix and by adding or removing variables from the model iteratively. Any variable displaying signs of multicollinearity, for example an unexpected negative or positive model estimate or signs changing after adding or removing a variable, was excluded from the model. The models were estimated by the maximum likelihood method, the Akaike Information Criterion (AIC) and the *pseudo* R^2 were used to assess the model goodness of fit, as discussed in Chapter 4.

This research follows the approach by Akgün et al. (2018) and Rash-ha Wahi et al. (2018) and it serves as background development for the research in subsequent chapters and builds on previous research such as Daniels et al. (2008) that used multi variate binary logistic regression to investigate the injury severity of cyclists risk factors. In addition to binary logistic regression, the Chi-square (χ^2) test[10] was used, when appropriate, to examine differences in proportions between groups or categories. Multivariate binary logistic regression is used to compute the odds ratio (OR) with accompanying 97.5% confidence intervals (CI) for the risk of injury related to cycling KSI accidents, where 2.5% is the lower CI and 97.5% is the upper CI. The analyses were conducted using R Project (CRAN, 2019). The parameter estimates are used to calculate the OR that describes the influence of an explanatory variable on the KSI outcome, it is the exponent of the parameter β, as follows:

$$\mathrm{OR(odds\ ratio)} \;=\; \exp(\beta) \tag{5.1}$$

In the following sections, the magnitudes and particularly the signs of the estimated parameters are discussed in terms of the OR described above in Equation (5.1). When reading the results the values have the following meaning, a positive parameter estimate β indicates that the probability of a KSI increases, conversely a negative β indicates that the probability decreases and is more likely to be a slight injury collision. In other words, the estimated parameters that are greater than zero imply that increases in the corresponding variables tend to exacerbate the injury risk propensity, if the estimated parameter is less than zero and increase in the corresponding variables will tend to diminish or reduce the risk. The intensity of the effect is ranked using the OR to rank the influence of each variable on the average injury risk, where one (OR=1) represents no difference in odds. The full results are presented in Appendix 5.1 and the odds ratio plots for the significant explanatory variable are provided in Figure 5-1 below. The main characteristics of the descriptive statistics presented in Table 5.1 are discussed in the next section, before the results section, to highlight pertinent data trends or differences between the data sets.

5.2.1 The dataset characteristics

Before progressing to the modelling, it is useful to examine the characteristics of the data presented in Table 5.1 below. The dependent variable in the proposed models is injury

[10] *Pearson's chi-squared test (χ^2) is a statistical test applied to sets of categorical data to evaluate how likely the observed difference between sets was chance. If the test statistic exceeds the critical value of χ^2, the null hypothesis (H_0) can be rejected, and the alternative hypothesis (H_1) can be accepted. If the test statistic falls below the threshold χ^2 value, then no clear conclusion can be reached, and the null hypothesis is sustained, but not necessarily accepted.*

outcome, which is dichotomous to which the response of interest is a KSI and the contrasting response is a slight injury.

There was a total of n=2504 cyclist injury records eligible for inclusion in the study (missing and null (na) records were excluded and factors with more than 50% ‘other’ or ‘unknown’ in records were also excluded). The proportion of slight injuries is 80.7% (n = 2020) and KSI make up the remaining 19.3% (n=484). The proportions observed in the female only subset was similar, 79.9% (n=367) slight injuries and 20.1 (n=97) KSIs. The female only subset represents 18.7% of the complete dataset, therefore the proportion of female KSIs are slightly higher at 20.9% (female) compared to 19.3% (male and female). This is worth noting here because the ratio of men to women cyclists is 2:1, therefore proportionally one would expect an equivalent proportion of the injuries, about one third. To gain a sense of other differences between the two datasets the proportions for each variable were compared, see Table 5.1 under the delta heading. The day of the week was the only explanatory variable that differed by a notable amount, women have more injury accidents over the weekend and less mid-week (Tuesday and Wednesday) than the overall dataset. The road conditions were also different, injuries were higher in dry road conditions and lower in wet conditions, slightly more on single carriageways and roads posted with a 30 mph speed limit but slightly lower on 40 mph roads, lower away from pedestrian crossings but more at pedestrian controlled facilities, more in large urban areas but less in other urban towns and accessible rural areas. This illustrates how the overall data set is biased towards the majority of male injury collisions, which is arguably “good news” for women cyclists, but any differing trends may be masked or obscured due to sample bias, therefore separate analysis is justified. This bias towards male cyclists exits in the STATS19 and hospital admissions data (Millar, 2005).

Other notable trends in the main data were that junctions account for most injury locations (69.4%), most cyclist collisions occur during daylight (80.8%) and fine conditions at 30 mph posted speed limit roads (81.2%).

The dataset includes an urban or rural binary variable in the STATS19 data, to provide more explanation of the type of urban or rural area involved; because of the high KSI risk associated with rural roads, the Scottish six-fold urban rural classification variable was added. The classification was assigned to each record by using R Project mapping and GIS tools based

Table 5.1 Descriptive Statistics for Scottish STATS19 data from 2010 to 2012

Model Variable Code	**Model Variable Code**			**ALL (N= 2504)**		**Female (N=467)**		
N= 2504		*Level*	*Description (STATS19 Code[1])*	*Freq*	*%*	*Freq*	*%*	*delta*
KSI (Dependant)	**0**	*(Reference level)*	Not a Killed or Serious Injury	2020	80.70	367	79.10	-1.60
	1		Killed or Serious Injury	484	19.34	97	20.90	1.56
Carriageway_Hazards	0	*(Reference level)*	None	2459	98.24	450	97.00	-1.24
	1		Vehicle load on road	3	0.12	0	0.00	-0.12
	2		Other object on road	30	1.20	10	2.20	1.00
	3		Previous accident	2	0.08	0	0.00	-0.08
	6		Pedestrian in carriageway - not injured	6	0.24	3	0.60	0.36
	7		Any animal in carriageway (except ridden horse)	4	0.16	1	0.20	0.04
Day_of_Week	1	*(Reference level)*	Sunday	248	9.91	87	18.80	**8.89**
	2		Monday	418	16.70	78	16.80	0.10
	3		Tuesday	395	15.78	35	7.50	**-8.28**
	4		Wednesday	415	16.58	50	10.80	**-5.78**
	5		Thursday	397	15.86	77	16.60	0.74
	6		Friday	377	15.06	73	15.70	0.64
	7		Saturday	254	10.15	64	13.80	**3.65**
Police_Attend_Scene_of_Accident	1	*(Reference level)*	Yes	1691	67.56	302	65.10	**-2.46**
	2		No	813	32.48	162	34.90	**2.42**
Junction_Detail	0	*(Reference level)*	Not at junction or within 20 metres	765	30.56	138	29.70	-0.86
	1		Roundabout	322	12.86	52	11.20	-1.66
	2		Mini-roundabout	50	2.00	7	1.50	-0.50
	3		T or staggered junction	802	32.04	146	31.50	-0.54
	5		Slip road	24	0.96	5	1.10	0.14
	6		Crossroads	235	9.39	54	11.60	**2.21**
	7		More than 4 arms (not roundabout)	65	2.60	22	4.70	**2.10**
	8		Private drive or entrance	49	1.96	6	1.30	-0.66
	9		Other junction	192	7.67	34	7.30	-0.37

Table 5.1 Descriptive Statistics for Scottish STATS19 data from 2010 to 2012 *(Continued)*

Model Variable Code	Model Variable Code			ALL (N= 2504)		Female (N=467)		
N= 2504	*Level*		*Description (STATS19 Code[1])*	*Freq*	*%*	*Freq*	*%*	*delta*
Light_Conditions	*1*	*(Reference level)*	Daylight	2022	80.78	380	81.90	1.12
	4		Darkness - lights lit	399	15.94	70	15.10	-0.84
	5		Darkness - lights unlit	35	1.40	8	1.70	0.30
	6		Darkness - no lighting	39	1.56	4	0.90	-0.66
	7		Darkness - lighting unknown	9	0.36	2	0.40	0.04
Road_Surface_Conditions	1	*(Reference level)*	Dry	1823	72.83	358	77.20	**4.37**
	2		Wet or damp	636	25.41	98	21.10	**-4.31**
	3		Snow	6	0.24	2	0.40	0.16
	4		Frost or ice	34	1.36	6	1.30	-0.06
	5		Flood over 3cm. deep	5	0.20	0	0.00	-0.20
Road_Type	1		Roundabout	285	11.39	44	9.50	-1.89
	2	*(Reference level)*	One way street	50	2.00	7	1.50	-0.50
	3		Dual carriageway	199	7.95	35	7.50	-0.45
	6		Single carriageway	1940	77.51	372	80.20	**2.69**
	7		Slip road	8	0.32	1	0.20	-0.12
	9		Unknown	22	0.88	5	1.10	0.22
Special_Conditions_at_Site	0	*(Reference level)*	None	2461	98.32	460	99.10	0.78
	1		Auto traffic signal - out	6	0.24	1	0.20	-0.04
	3		Auto signal part defective	1	0.04	0	0.00	-0.04
	4		Roadworks	17	0.68	1	0.20	-0.48
	5		Road surface defective	15	0.60	1	0.20	-0.40
	6		Oil or diesel	4	0.16	1	0.20	0.04
Speed_limit	20	*(Reference level)*	20 mph Posted Speed Limit	61	2.44	14	3.00	0.56
	30		30 mph Posted Speed Limit	2028	81.02	388	83.60	**2.58**
	40		40 mph Posted Speed Limit	119	4.75	12	2.60	**-2.15**
	50		50 mph Posted Speed Limit	25	1.00	5	1.10	0.10
	60		60 mph Posted Speed Limit	253	10.11	44	9.50	-0.61
	70		70 mph Posted Speed Limit	18	0.72	1	0.20	-0.52

Table 5.1 Descriptive Statistics for Scottish STATS19 data from 2010 to 2012 *(Continued)*

Model Variable Code	**Model Variable Code**			**ALL (N= 2504)**		**Female (N=467)**		
N= 2504		*Level*	*Description (STATS19 Code[1])*	*Freq*	*%*	*Freq*	*%*	*delta*
Weather_Conditions	1	*(Reference level)*	Fine no high winds	2027	80.98	373	80.40	-0.58
	2		Raining no high winds	281	11.23	55	11.80	0.57
	3		Snowing no high winds	6	0.24	2	0.40	0.16
	4		Fine + high winds	31	1.24	5	1.10	-0.14
	5		Raining + high winds	38	1.52	4	0.90	-0.62
	6		Snowing + high winds	1	0.04	0	0.00	-0.04
	7		Fog or mist	9	0.36	1	0.20	-0.16
	8		Other	45	1.80	8	1.70	-0.10
	9		Unknown	65	2.60	15	3.20	0.60
Pedestrian Controlled Crossing	0	*(Reference level)*	None	1924	76.80	345	74.40	**-2.40**
	1		Zebra	46	1.80	9	1.90	0.10
	4		Pelican, puffin, toucan crossing	205	8.20	41	8.80	0.60
	5		Pedestrian phase at traffic signal	278	11.10	59	12.70	1.60
	7		Footbridge or subway	1	0.00	0	0.00	0.00
	8		Central refuge	50	2.00	10	2.20	0.20
Scottish Urban Rural 6 Fold Classification	1	*(Reference level)*	Large Urban > 125,000 people	1427	57.00	277	59.80	**2.80**
	2		Other Urban 10,000-124,000	54	21.60	88	19.00	**-2.60**
	3		Accessible Small Town 3,000-9,999	73	2.90	15	3.20	0.30
	4		Remote Small Town 3,000-9,999	47	2.00	11	2.40	0.40
	5		Accessible Rural <3,000	311	12.40	45	9.70	**-2.70**
	6		Remote Rural<3,000	102	4.10	27	5.80	1.70
Age of cyclists- (16 - 0 years)	0	*(Reference level)*	17 Years and over	2073	82.80	391	84.30	1.50
	1		16 years and under	431	17.20	73	15.70	-1.50
Age of cyclists- (60 years +)	0	*(Reference level)*	59 years and under	2372	94.70	447	96.30	1.60
	1		60 Years and over	132	5.30	17	3.70	-1.60

[1] Road Accident Safety Data Guide: Look-Up Tables from DfT [Source:https://data.gov.uk/dataset/cb7ae6f0-4be6-4935-9277-47e5ce24a11f/road-safety-data]

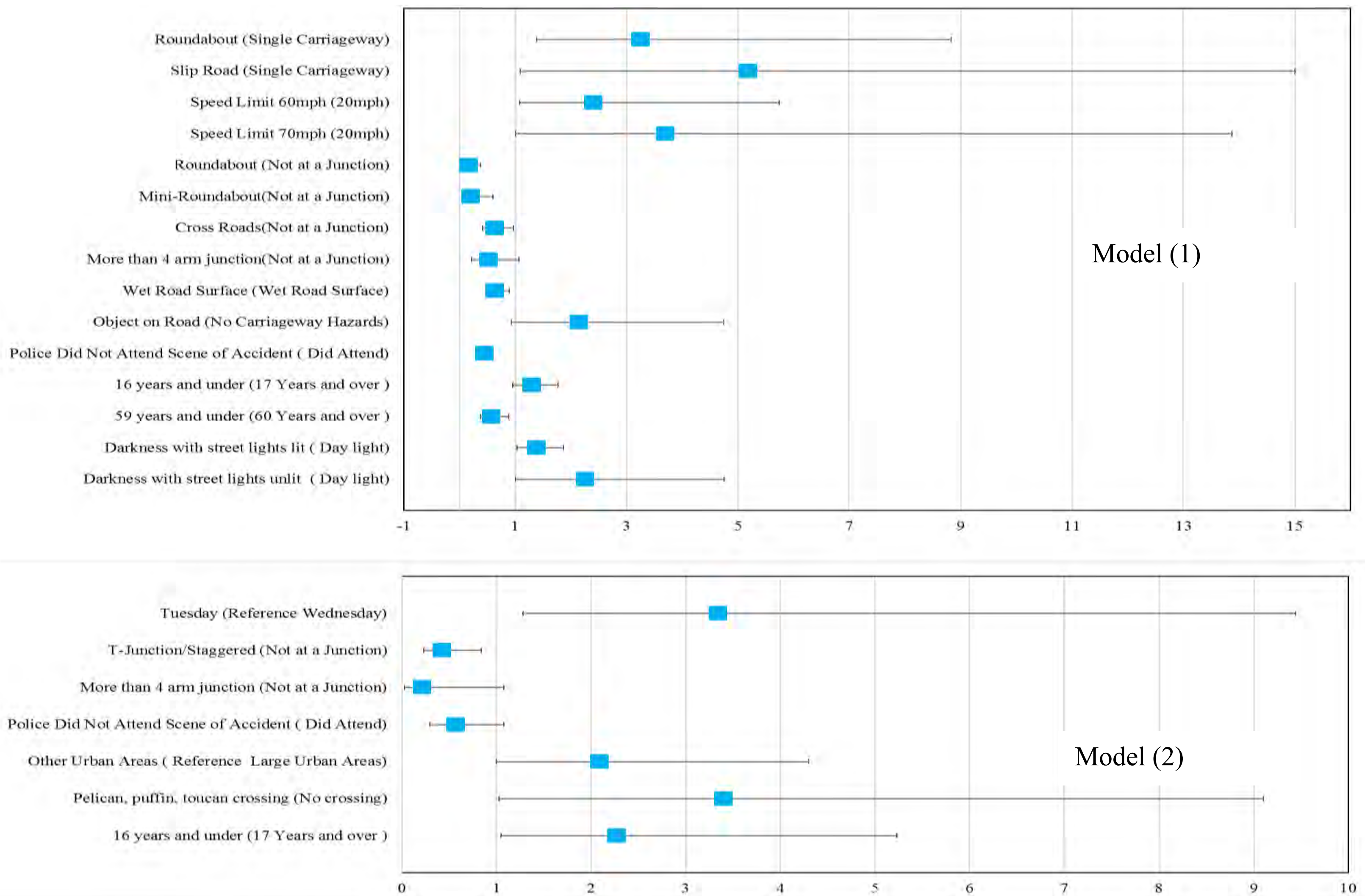

Figure 5-1 Cyclist injury KSI risk in Scotland: odds ratios (97.5% CI), overall model (n=2504), female only model (n=467). The reference level is shown in brackets. (Coefficients that were not significant at the 90% level were restricted to zero and omitted from the table. Possible or no injury is the base case with coefficients restricted at zero, see Appendix 5.1 for full results tables Table A 5.1 and Table A 5.2)

on the STATS19 georeferenced data and shapefiles from the Scottish Data Records. Two multivariate binary logistic regressions were fitted, the first modelled all the injuries recorded in the data set (n=2504), Model (1), and the second model fitted a sub-set containing only female cyclist injury records (n=467), Model (2). The next section moves on to a discussion of the results of these two multivariate binary logistic regression models.

5.3 Results of the binary logistic regression

The first model, Model (1), examined what predicted a cyclist injury being a KSI (n=484) versus a slight injury (n=1934). The second model, Model (2), examined what predicted a female cyclist injury being a KSI (n=367) versus a slight injury (n=97). There were 14 explanatory variables included, with sub-levels or categories within them, giving 52 different categories in total. In Model (1) there were 15 significant explanatory variables, in Model (2) there were only 7 and they were not the same, as illustrated in Figure 5-1 above in terms of the odds ratio and the CI. The complete set of results are provided in Appendix 5.1.

An anova chi-square (χ^2) test was carried out to assess the model fit; the overall model χ^2 =168 with 43 degrees of freedom and an associated p-value of less than 0.001 (p-value = $1.3e^{-16}$), therefore the overall model fits significantly better than an empty, null, model. The *pseudo* R^2 was 0.122 and 0.1 respectively for Models (1) and (2). While these were relatively low, these models do not include either cyclist or motorised exposure variables, because STATS19 does not include this data, and as these provide the main explanatory variables in collisions statistics the diagnostic fit is considered acceptable here.

The results were interpreted as the odds of a cyclist being involved in a KSI collision (KSI=1) over the odds of having a slight collision (KSI = 0) by holding all variables at a fixed value and taking the exponent of the estimated parameter using Equation (5.1) above.

The following factors in Model (1) led to a significantly higher probability of a KSI: roundabouts, slip roads, presence of an object in the road carriageway, being an adult and darkness both in lit and unlit street conditions. In Model (2), the following factors led to a significantly higher probability of a KSI: day of the week being a Tuesday, urban areas, pedestrian controlled crossing (pelican, puffin or toucan) and being an adult.

Using the odds ratio, illustrated in Figure 5-1 above, to rank the magnitude of risk, Model (1) shows that slip roads have the highest odds ratio (odds ratio = 5.2, $p<0.05$) but the confidence interval (CI 97.5%) range is wide. This is most likely due to the small number in the sample because only 1% (Table 5.1) of cyclist injuries take place at slip roads. Roundabouts were the next highest location (odds ratio = 3.2, $p<0.05$) were cyclists were significantly more likely to have a KSI when the STATS19 coded the junction by road type. However, the junction detail category showed that all junctions had a significantly lower KSI risk at a junction compared to locations not at, or within 20 meters from, a junction. This result would seem to contradict the previous finding, but it is in fact consistent with previous research findings. Previous research found that intersection-related crashes were associated with a lower probability of severe injuries and higher probabilities of minor and no-visible injuries (Behnood and Mannering, 2017).

Similarly, the findings agree with Boufous et al. (2012) who found that while 58% of cyclist crashes happen at intersections, intersections did not increase the risk of severe injury in cyclists involved in traffic crashes. They suggest that this may be explained by the fact that both cyclists and other vehicles tend to slow down while approaching intersections resulting in less severe injuries.

And finally, Moore et al. (2011) found that crashes occurring at non-intersection locations during June, July, or August were 25.9% more likely to result in severe bicyclist injury. In this research, Staggered junctions and T-junctions were not significantly associated with higher KSI risk compared to non-junction sections; 31% of injury accidents were on the road away from a junction which is nearly the same as T-junctions/Staggered junctions (32%). This result is consistent with the literature and it is an important distinction to make that while more cyclist casualties happen at junctions less of them result in a KSI compared to the road link away from a junction.

Taking 20 mph speed limits as the reference level, there is a higher odds ratio (3.7, $p<0.05$) of a KSI on 70 mph speed limit roads, but the number of records represents a low overall proportion of cyclist injuries which is reflected in the confidence intervals (CI 97.5%: 1.00, 13.87). The 60 mph speed limits also have high odds ratio of a KSI (odds ratio = 2.4, $p<0.05$) but represent a higher proportion of cyclist's injury accidents (CI 97.5%: 1.08, 5.74).

This finding is in line with previous research in the literature, for example Kim et al. (2007) found that the largest effect on cyclist injury severity is caused when estimated vehicle speed prior to impact is greater than 80.5 km/h (50 mph).

A cyclist is twice (odds ratio = 2.15, $p<0.10$) as likely to have a KSI when there is an object in the road carriageway, the range of the confidence interval and the significance level both indicate that this result is not strongly significant. One of the carriageway objects that can be recorded is a ‘carriageway defect’, Figure 5-2 below shows that carriageway defects are one of the ‘other carriageway object’ categories that could be in the carriageway. However, 98% of this category was coded ‘none’ and a road ‘defect’ is the next most frequently recorded category. Road surface defects were recorded as a contributory factor in 1% of all cyclist collisions. There were no significant carriageway hazard variables identified in the female model.

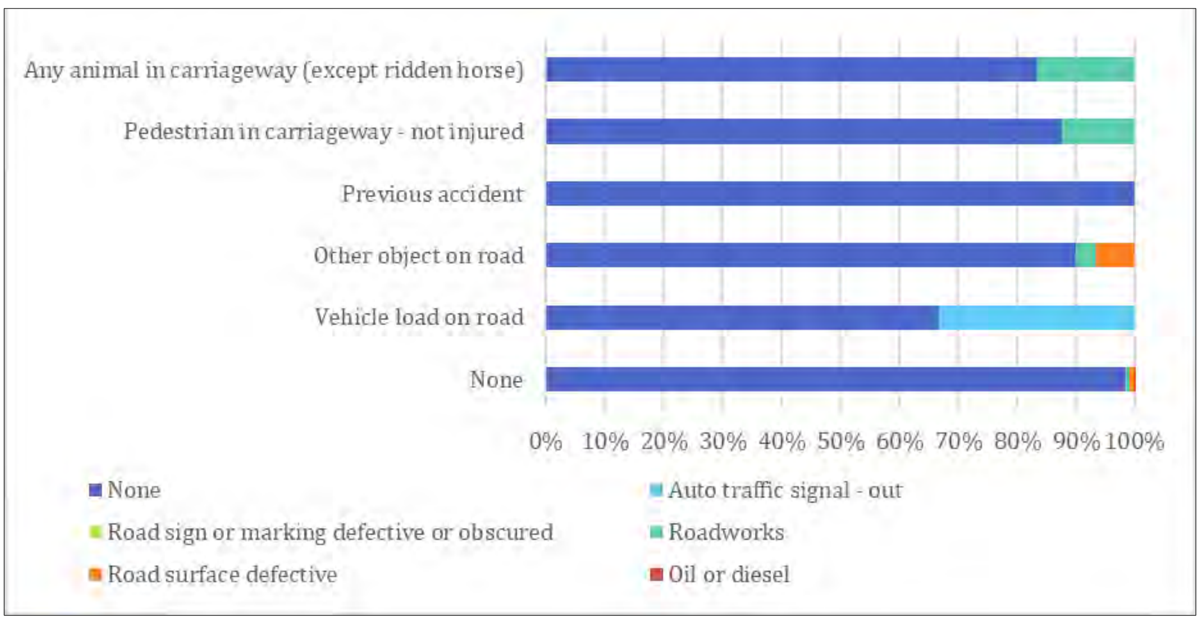

Figure 5-2 Comparison of cyclist collisions by Carriageway Hazard and Special Condition at Site.

When the road carriageway was reported wet or damp, the analysis reveals that a cyclist is less likely (odds ratio = 0.50, $p<0.01$) to have a KSI than in dry conditions. The range of the confidence intervals is small, it is significant at the 99% confidence level and the sample represents 25% of the total sample which all indicate that this result is significant. This result agrees with the literature, for example, Knowles et al. (2009) found that 80% of cyclist injury collisions took place in fine conditions on dry roads and Akgün et al. (2018) found no significant impact on cyclist casualty severity at roundabouts due to weather and road surface conditions. However, Kim et al. (2007) found that inclement weather increases the probability of fatal injury. The binary variable is was KSI which was also the case in the research by Akgün et al. (2018) but not in Kim et al. (2007) which looked at fatal (killed) cyclist collisions separately, which may explain the difference.

In Model (2), female cyclists were more than three times more likely to have a KSI than a slight injury collision at pelican, puffin or toucan crossing facility (odds ratio = 3.4; 97.5% CI, 1.03 – 9.10; p=0.01), this finding is consistent with Aldred and Crosweller (2015) who concluded that higher risk among female cyclists was die to female cyclist having shorter and slower trips than men which were associated with higher incident rates. The confidence intervals are large and the sample size was small so it cannot be said with certainty that this result is significant, however it suggests that female cyclists have a higher KSI likelihood than male cyclists at these locations.

Cyclist injury associated by age in the overall Model (1) shows that cyclists of both genders had a lower risk of a KSI (odds ratio = 0.58; 97.5% CI, 0.38 – 0.88) than adults 60 years of age or over. This result aligns with other studies that found that older adults are more likely to suffer fatal injuries in bicycle accidents (Behnood and Mannering, 2017; Martínez-Ruiz et al., 2014; Kim et al., 2007; Broughton, 2003). However, Akgün et al. (2018) did not find statistical significance for either age or gender in their cyclist casualty severity analysis.

Cyclist injury associated by age in the overall Model (2) shows that younger female cyclists (16 years and under) have a higher risk of a KSI (odds ratio = 2.26; 97.5% CI, 1.05 - 5.23) than older females over 16 years of age. This result fits with previous studies (Behnood and Mannering, 2017; Martínez-Ruiz et al., 2013; Kim et al., 2007) that considered age as a cyclist injury factor.

Cyclist gender is not presented in the final model estimations because it was not found to be significantly related to the injury severity, a chi square (χ^2 = 0.79 < 2.71) confirmed this finding. There was however a statistically significant higher likelihood of a KSI in rural areas compared to urban areas, this association was lower among female cyclists the chi square (χ^2 = 3.31 < 3.84, significant at the 10% CI) and higher among male cyclists (χ^2 = 23.06 < 10.38, significant at the 1% CI). Model (2) also showed that a female cyclist was twice as likely to have a KSI in other urban areas (the six-fold urban rural classification for Other Urban areas with a population between 10,000 and 124,000) compared to large urban areas with a population over 125,000.

A review by Embree et al. (2016) of fourteen cyclist injury studies concluded that gender was not associated with bicycling injury risk, however Tin Tin et al. (2010) showed higher rates of traffic injuries in male pedal cyclists. Therefore, when location is not accounted for there is no difference between genders, however the KSI risk differs between urban and rural areas.

The day of the week was not significant in Model (1), but in Model (2) female cyclists were three times more likely to have a KSI collision on a Tuesday than a slight injury (odds ratio = 3.34; 97.5% CI, 1.28 – 9.44; p=0.05), this highlights the difference in mobility patterns between male and female cyclists, illustrated in Figure 5-3 below..

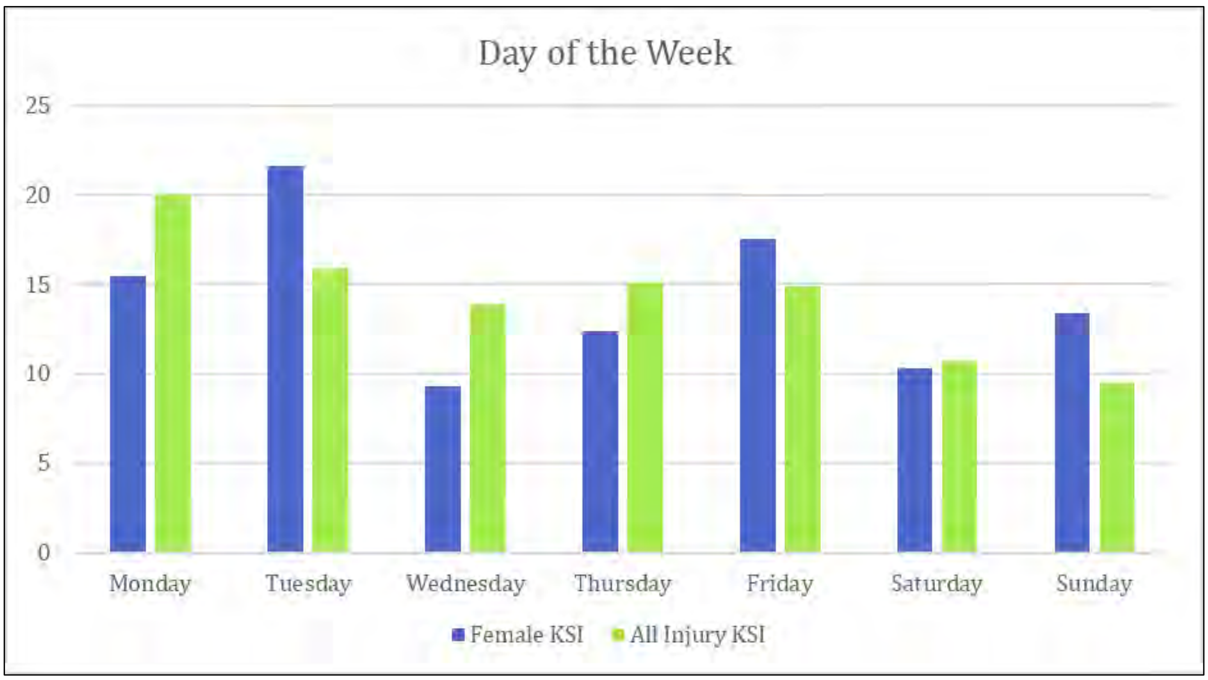

Figure 5-3 Comparison of the overall KSI frequency and female KSI.

According to Hollingworth et al. (2015), weekly cycling distance demonstrates a dose–response relationship with risk of cycling accident-related injury, such that the longer people cycle, in terms of distance and time, the more associated they may be with increased risk for accident-related injury. This may be the case here because more women are employed in part-time work then men (EU, 2014) so their cycling patterns will differ throughout the week due to part-time working hours and family commitments (Miaffi, Malgieri and Di Bartolo, 2014). Further investigation of women's working patterns and a measure of exposure for female cyclists would be required to fully explain this result.

Cyclist accidents during the hours of darkness (even with street lighting) were associated with higher likelihood of a KSI compared to daylight. However, the light condition variables were not significant in the Model (2), one reason for this may be that male cyclists take more risks at night. According to Dutch research (Cobey et al., 2013), male cyclists are less likely to have lights fitted to their bikes and it may also be partly because women may often avoid nighttime cycling for personal safety reasons.

The results presented here discuss the data in Table 5.1. This table contained information from the accident and the casualty records from STATS19 data, now the third part of the record, vehicles, is used in conjunction with the above to develop further results using binary logistic regression.

5.3.1 Further Analysis

5.3.1.1 Police attendance at the scene of a cyclist injury accident.

STATS19 contains a record of police attendance which was examined for completeness but surprisingly yielded some interesting results; cyclist accidents are less likely to be attended if they have a KSI rather than a slight injury accident (odds ratio = 0.45; 97.5% CI, 0.33 - 0.59; p=0.01) and the result was similar in Model (2), so there is no gender difference in attendance rates. It was hypothesised that the result may have an association between urban and rural areas where rural areas may be more difficult to attend due to distances or resources. However, the interaction term for police attendance with urban or rural locations was not significant.

To determine if the likelihood of not attending a KSI was typical, the cyclist KSI and slight injury data was compared with car KSI and slight injuries data. The chi square (χ^2 = 185.33 < 10.84, CI 0.01) confirmed that police attendance at cyclist KSI collisions compared to car KSI collisions revealed that there is a significant difference between police attendance rates for these modes. Cycle KSIs are not attended in 24.4% of cases, compared to only 3.7% non-attendance of cars, Table 5.2. There was a similar significant disparity for slight injury collisions, 55% of cyclists are not attended compared to 15% of cars, Table 5.3 below. The trend over time for police attending a collision, between 2005 and 2014, is shown in Figure 5-

4 below, and it may be seen that the difference in the gap between cyclists and cars attended by the police has not changed over time.

Table 5.2 2x2 contingency table to compare Cyclist and Car driver police KSI attendance rates

KSI 2x2 (Df= 1)	Cyclists	Car	Total	χ^2
Did Not Attend	95 (24.4%)	99 (3.73%)	194	185.33
Attended	389	2658	3047	
Total	484	2757	3241	

Table 5.3 2x2 contingency table to compare Cyclist and Car driver Slight injury police attendance rates

Slight 2x2 (Df= 1)	Cyclists	Car	Total	χ^2
Did Not Attend	718 (55.15%)	2672 (14.7%)	3390	753.22
Attended	1302	18199	19501	
Total	2020	20871	22891	

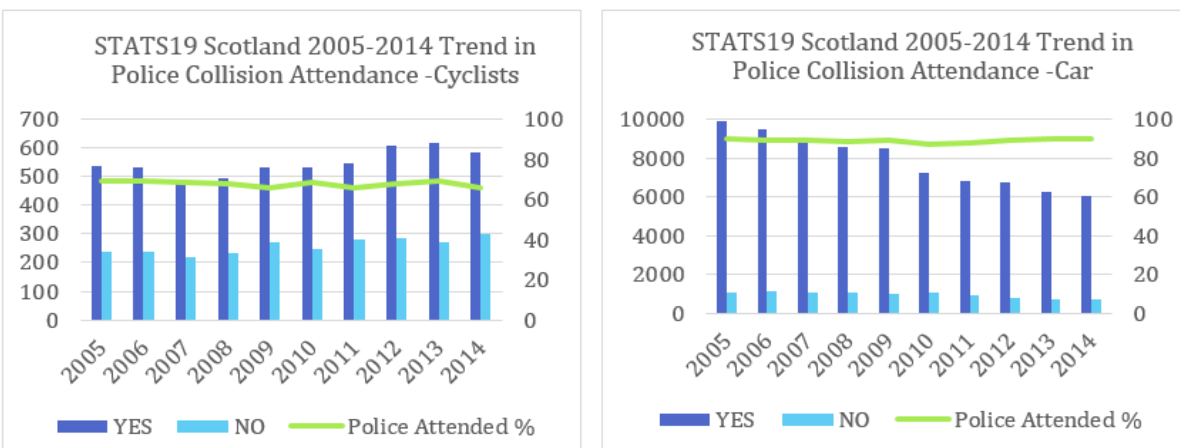

Figure 5-4 Comparison of the long term trend for police collision attendance rates between cyclists and car drivers in Scotland 2005-2014.

5.3.1.2 Cyclist Infrastructure

The comparison of urban and rural locations shows that collisions associated with cycling infrastructure occur mainly in urban areas, Figure 5-5 below and Table 5.1 above.

The categories allocated in the STATS19 index code , '*Vehicle_Location.Restricted_Lane'* are shown below; KSI and slight injuries feature as frequently when cyclist infrastructure is present as with the main carriageway without any infrastructure and the "*Cycleway or shared use footway (not part of main carriageway)*" and "*Footway (pavement)*" have the highest proportion of cyclist only injuries with 21.4% and 7.5%, respectively.

Table 5.4 2x2 contingency table to compare cyclist KSI and Slight injury collision rates when cycle infrastructure is present or not present.

2x2 (Df= 1)	KSI	Slight	Total	χ^2
Present	33	154	187	0.4
Not present	468	1891	2359	
Total	501	2045	2546	

The chi squared (χ^2 = 0.40 < 2.71) confirmed that there is no difference in the KSI likelihood if the cyclist injury occurs on the main carriageway or where cycle infrastructure is present, Table 5.4, it may be conclude that there is no difference in KSI risk when "*Cycle lane (on main carriageway)*" is present.

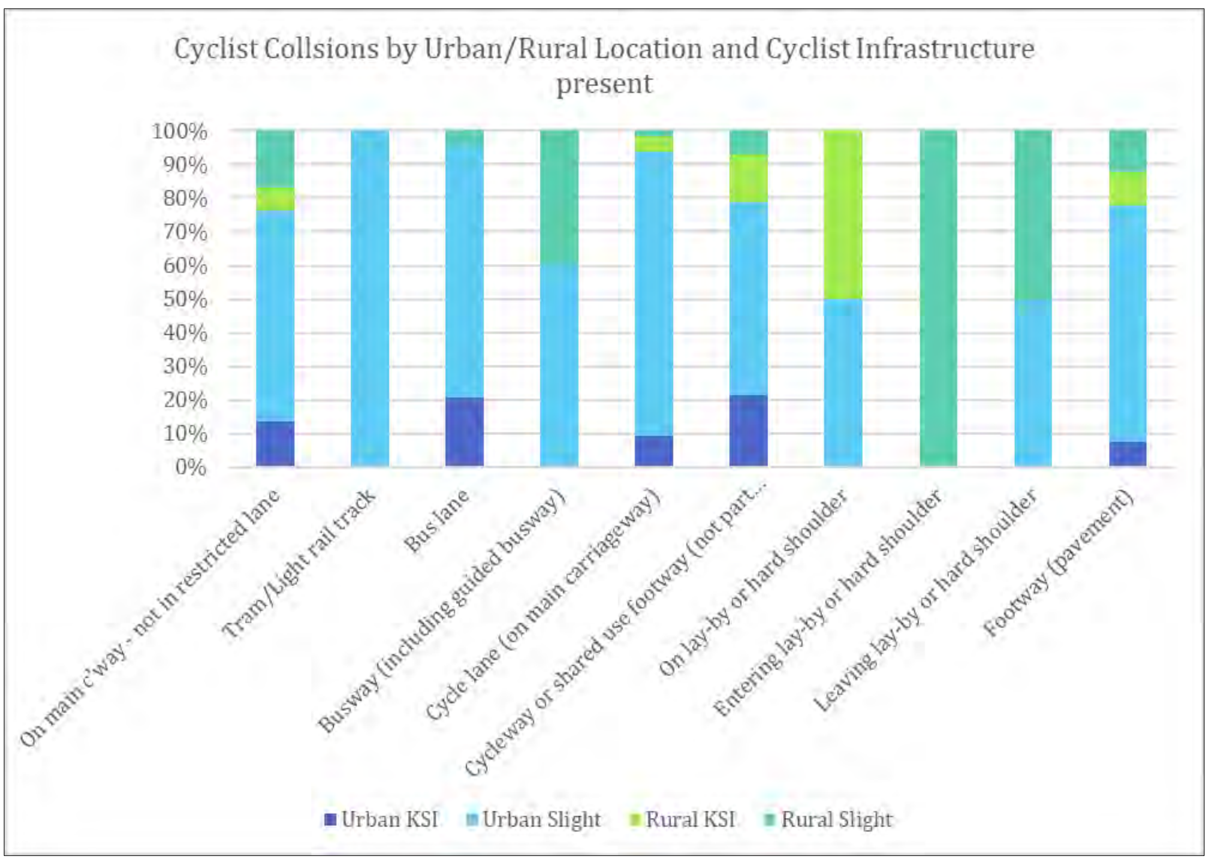

Figure 5-5 Comparison of the urban/rural locations by cyclist infrastructure.

The same test was repeated for Bus lanes and the Cycleway or shared use footway or Footway (pavement) and similar results were found. There are very few segregated cycle lanes in Scotland and quiet streets are not a recorded category/type of road in the STATS19.

5.3.1.3 Cyclist collisions with an object in the carriageway

The results above show that an object in the road carriageway is a hazard that increases the odds of a cyclist having a KSI. The vehicles dataset of the STATS19 has a more detailed variable, it has 13 possible variable codes as follows: None (no object), Previous accident, Road works, Parked vehicle, Bridge (roof), Bridge (side), Bollard or refuge, Open door of vehicle, Central island of roundabout, Kerb, Other object, Any animal (except ridden horse).
Given the high number of cyclist-only injuries and the results above that demonstrate that cyclist infrastructure provided and the main carriageway do not significantly alter the odds of having a cyclist KSI, we now look to find evidence of what may have caused the collision or injury within the cycling infrastructure, see Figure 5-5 above. The variable index codes for hitting the following objects did not feature in the data: bridge structure, bollards, refuge or the central island of a roundabout. Most cyclist collisions do not involve an object in the carriageway, however a notable proportion are present in cycle lanes and bus lanes when the variable '*none*' is removed, Figure 5-6 below.

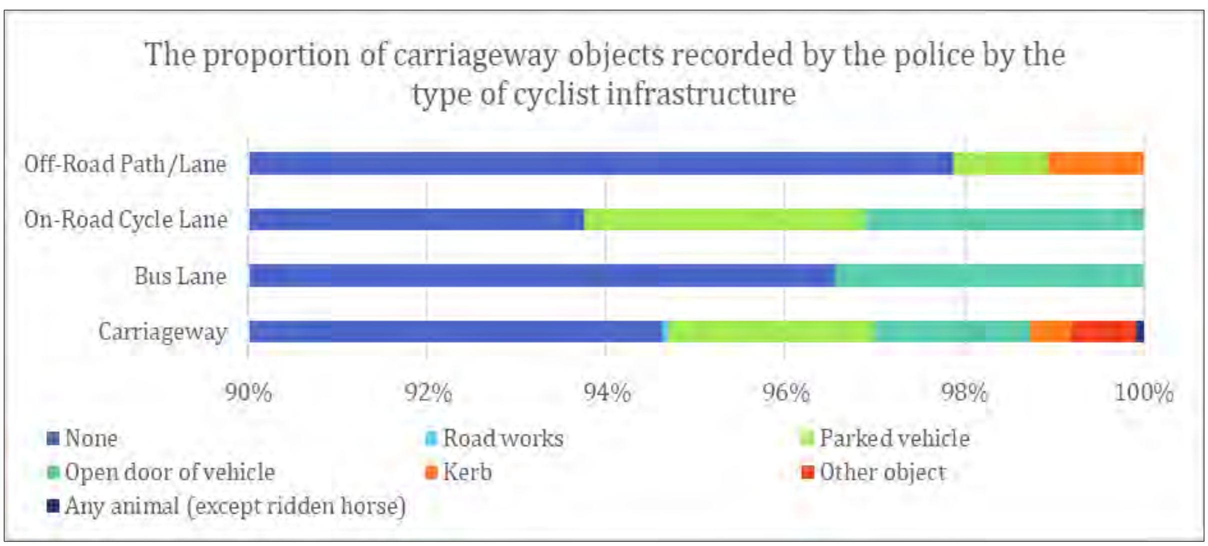

Figure 5-6 Proportion of carriageway objects hit within cyclist infrastructure types.

Figure 5-6 shows that the safety of both bus lanes and on-road cycle lanes are affected by parked vehicles and the open door of a vehicle. Bus lanes, on-road cycle lanes and the main carriageway feature cyclist injuries involving the open door of a vehicle. The off-road cycle facilities (that may be legally shared with pedestrians if a sign is posted) feature cyclist injuries involving parked vehicles and the pavement kerb but not the open door of a vehicle. Also notable is the absence of cyclist collisions involving parked vehicles in bus lanes, this is likely due to stronger parking enforcement in bus lanes.

Finally, Figure 5-7 below illustrates the types of manoeuvre across the different types of cyclist infrastructure, on-road cycle lanes and the main carriageway feature cyclist '*going ahead other'* most frequently.

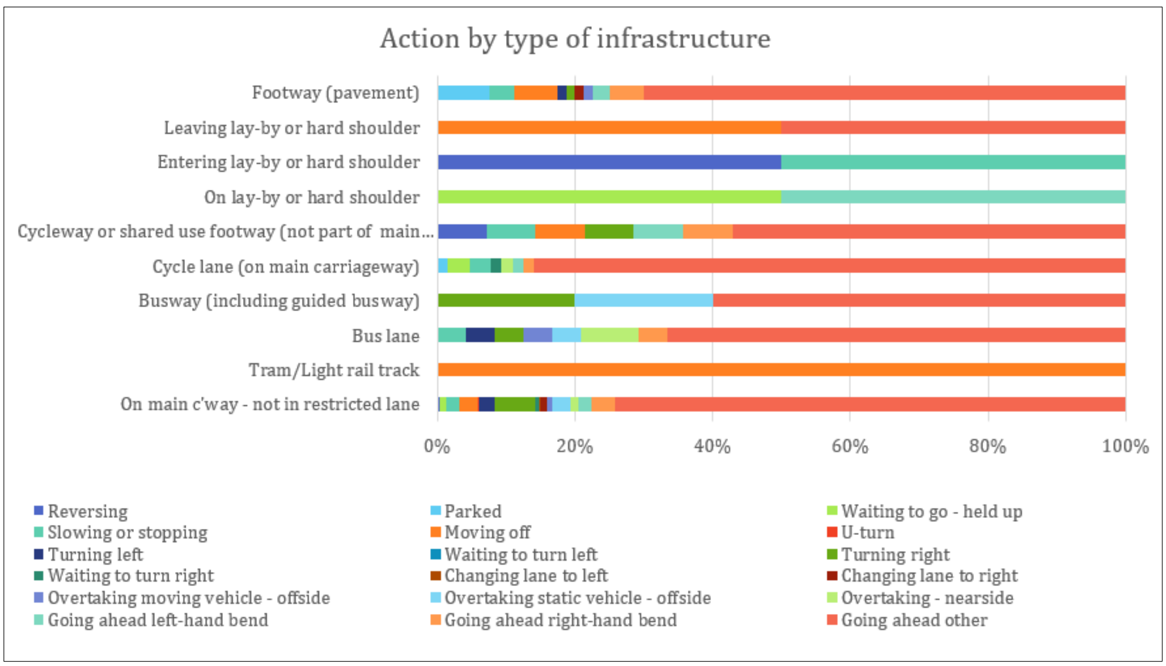

Figure 5-7 Cyclist manoeuvre by types of infrastructure.

5.4 Discussion

In this section we will discuss the results of cyclist-vehicle related collision factors presented in the previous section.

5.4.1 Male/female

More males than females are injured in cycling accidents and this trend is reported widely (Millar, 2005; Transport Scotland, 2019). The results presented in this chapter revealed several significant cyclists KSI collision factors in the overall model, however the female model results differed. Light conditions, speed limit, road type, carriageway hazards and cyclists over 60 were not significant. This difference is important because cycling for leisure or commuting by bike is approximately two times higher amongst men. Therefore, risk factors that affect only women may be omitted if only the majority is investigated, furthermore there is a risk of missing pertinent issues that may persist as barriers to more women cycling.

One of the variables that was only significant in the female model was collisions at pelican, puffin, toucan or other non-junction pedestrian crossing facilities. This points to three issues: lack of crossing facilities for cyclists or ambiguity among drivers regarding shared facilities; shared paths are often only signed with a circular sign (Diagram 956 from the traffic signs manual, see Figure 2-10, Chapter 2 for an illustration) at the start and end of the facility, apart from this sign the path looks like exactly the same as a pedestrian only footway.

As with lighting conditions women may be using these crossing points because they perceive them as safer in the absence of an alternative. The results also found that the KSI risk for women is higher on a Tuesday. This may indicate that women's cycling patterns, that differ from men's due to their work habits, higher proportion of part-time working, and childcare responsibilities, may be reflected in the results where more or less cycling takes place on particular days. It may also point to women using cycling infrastructure at off-peak times when parking is not restricted and therefore their routes are riskier due to the time of day that they travel.

Motherwell (2018) recommends that gender balanced research should identify how to improve the consistent collection and analysis of gender-disaggregated data. Our results show that datasets need to be reviewed in a disaggregated way to get the whole picture and the extent of infrastructural problems for two reasons: a) to capture the risks that are hidden due to bias in the number of male cyclists and; b) as gender balance develops over time, which is supported by current policy, the infrastructure investments should be suitable for all cyclists.

5.4.2 Carriageway Hazard

The results were inconclusive, however road environment contributory factors account for 3%[11] of all cyclist collisions (DfT, 2014). A large proportion of Scottish roads suffer from poor maintenance, according to the Auditor General for Scotland and the Accounts Commission (Audit Scotland, 2011), the levels of poor road maintenance increases as the road importance decreases. Cyclists are not legally permitted to cycle on motorways or dual carriageways (i.e. the best-maintained roads) and are encouraged to cycle on quieter roads, such as Quiet Routes; as Figure 5-8 shows, C Roads and unclassified are among the worst maintained roads and this is the road category that cyclists use most frequently.

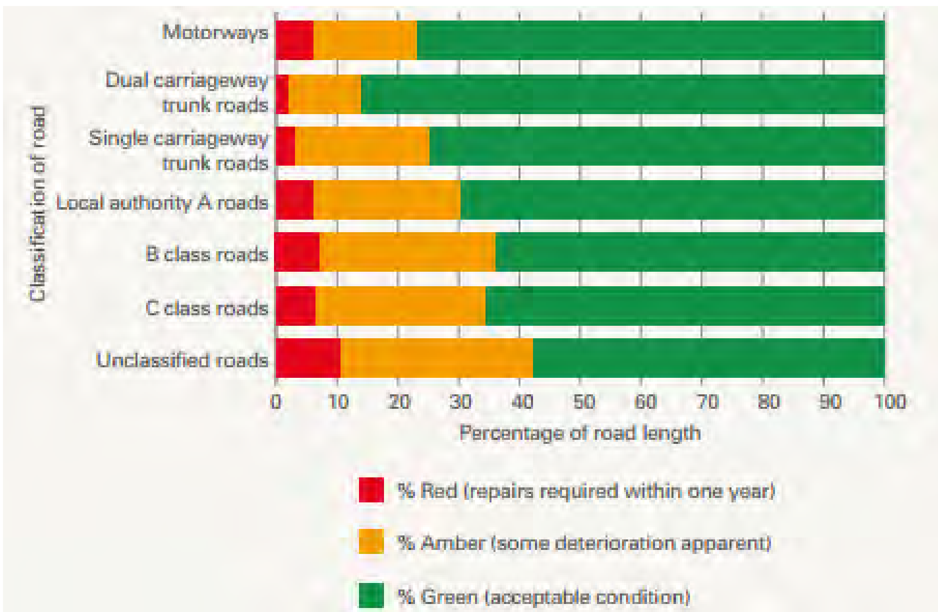

Figure 5-8 The condition of Scottish Roads 2010 by road type.

(reproduced from Audit Scotland, Maintaining Scotland's Roads: A follow up report (2011, pg.8) https://www.audit-scotland.gov.uk/docs/central/2010/nr_110216_road_maintenance.pdf)

Furthermore, research by Taylor (2018), using an instrumented bike, demonstrates that cyclists may be exposed to excessive hand-arm vibration whilst cycling on defective asphalt surfaces, leading to discomfort and potential harm due to significant hand-arm vibration exposure. Poorly maintained and defective pavements increased collision risk and long-term

[11] *Department for Transport, Reported Road Casualties Great Britain Annual Report 2013. Table RAS50005 Vehicles in reported accidents by contributory factor and vehicle type. https://www.gov.uk/government/publications/reported-road-casualties-great-britain-annual-report-2013.*

cyclist health, therefore cyclist routes should be monitored to assess their condition using cyclist specific methods, such as those proposed by Taylor (2018), to improve safety and comfort.

5.4.3 Speed limit

In the overall model, risk of a KSI cyclist collision on a road with a posted speed limit of 20 mph is 2.4 times lower compared to roads with a posted speed limit of 60 mph and 3.7 times lower than roads with a posted speed limit of 70 mph. Both results are consistent with previous research (Akgün et al., 2018; Daniels et al., 2008). However, the results did not show a significant difference between 30 mph and 20 mph which differs from the results found by Aldred et al. (2018); they found that residential or 20 mph streets have lower injury odds than other street types.

The number of collisions found on 20 mph roads in this research was low, n=61, and within the research timeframe of 2010-2012 there were very few 20 mph roads. Most cyclist injury accidents, over 80%, occur on 30 mph speed limit roads but there was no significant injury severity difference (found in this research) compared to 20 mph speed limit roads, which represent nearly 3% of the overall sample. This result is consistent with results comparing the effectiveness of 20 mph speed zones recently conducted by Atkins and Maher (2018), but additional research should be conducted to further monitor and evaluate the impact of 20 mph zones which have been implemented in recent years. This is further discussed within the Edinburgh case study in Chapters 8.

5.4.4 Bus lanes, on-road cycle lanes and shared footways

The results showed that there was no injury risk benefit to cyclists using bus lanes, this result is consistent with Aldred et al. (2018) who found that bus lanes had no impact on cycling injury odds in London. Similarly, the presence of cyclist facilities such as on-road cycle lanes and off-road cycle paths, discussed and illustrated in Chapter 2, did not have a significantly lower proportion of KSIs than cyclist collisions that took place in the road carriageway and did not reduce KSI odds in this study.

This result is disappointing but not unexpected, several previous studies found that on-road cycle lanes, the unprotected kind, were unsafe to use (Schoon and van Minnen, 1994, Daniels et al., 2009, Vandenbulcke et al., 2014, Jensen, 2016 and Beck et al., 2019). Therefore, on-road infrastructure located adjacent to parked cars do not provide an optimal means of providing protection from collisions with vehicles. Furthermore, Beck et al. (2019) found that drivers reduced their passing distance, providing less clear space, when passing a cyclist in a cycle lane in the presence of a parked vehicle but increased their passing distance when there was neither a parked car nor a cycle lane. Stewart and McHale (2014) identified that the presence of nearside parking affects driver at cycle lanes. This research highlights several hindrances that contribute to collisions within the allocated spaces for cycling:

- Parked cars on off-road and on-road cycle lanes and paths
- Opening doors onto bus lanes, main carriageways and on-road cycle lanes
- Cycle lanes located on the main carriageway and adjacent to on-street linear parking are at risk of dooring; and
- Kerbs on the main carriageway and off-road cycle lanes/paths.

If we consider these inherent risks as a sustainable or safe system problem, then it is clear that these facilities are not 'forgiving'. According to Bekiaris and Gaitanidou (2011) a forgiving road is a road designed and built with a driver error mitigation objective to avoid or mitigate negative consequences of driving errorsVandenbulcke et al. (2014) describe this type of infrastructure as 'semi-measures' and recommend that they be avoided. While there has been much research into this concept in relation to motorised transport, there is a dearth of research into this concept for cyclists, the idea of a '*forgiving*' road.

Transitioning into a transport system that contains high quality and prolific cycle facilities will take time and funding, however there are other means to address the risks that do not require new infrastructure.

This research also found that objects in the road, such as a parked vehicle, significantly affect cyclist risk of being involved in a KSI collision. Parking affects cyclists in three ways, dooring, obstructing the lane or pathway, and when a vehicle pulls out from a parking space. The location of cycle lanes in Scotland means that they are prone to parking violations, in part due to poor driver behaviour but also because many on-road cycles lanes are discontinuous and also serve as loading bays. An examination of road DfT contributory factors[12] shows that in 3% of cyclist collisions, cyclists were considered to have had their vision affected by stationary or parked vehicles, see Appendix 5.2.

Furthermore, where the cycle facility is not the primary function of the space, consideration should be given to parking removal if dooring cannot be mitigated by providing a door buffer zone. Wardlaw (2014) provides an analysis of Cycle Law cases and the DfT (Knowles et al., 2009) and found that vehicles pulling out from a side road or parking space occurs in 35% of cyclist collisions.

Parking enforcements should be used to mitigate vehicles occupying the space given over to cyclists. In Scotland, parking was decriminalised in 20 of the 32 local authorities such that the local authority has responsibility for enforcement and not Police Scotland. In 2014, Police Scotland withdrew their police wardens across the remaining areas (Rehfisch, 2018). Double parking and pavement parking will be addressed under the Transport (Scotland) Bill: Pavements Parking and Double Parking, if this is passed then the SPIs identified here should be monitored by the local authorities to ensure that cyclist benefit and safety is improved because parking enforcement impacts cyclist safety. The prevalence of dooring should be monitored as a SPI where cycle facilities also serve as a bus lane, loading bay or where they are located directly adjacent to parked vehicles.

5.4.5 Police attendance

Between 2010 and 2012 there were 95 KSI cyclist collisions that were not attended by the police, of which only 8 were single-cyclist-only collisions. Excluding these collisions, 18% of cyclist KSIs between 2010 and 2012 involving another vehicle were not attended as recommended. It is interesting to note that vehicle collision rates have continuously dropped between 2005 and 2014, by approximately 40%, and yet police attendance rates remained low for cyclists despite fewer incidents across the network. This is also somewhat surprising because on average, since 2010, cars and taxis have been involved in 85.3% of collisions involving a cyclist (Cycling Scotland, 2018). Cycling UK recommend that the police should

[12] *Department for Transport, Reported Road Casualties Great Britain Annual Report 2013. Table RAS50005 Vehicles in reported accidents by contributory factor and vehicle type. https://www.gov.uk/government/publications/reported-road-casualties-great-britain-annual-report-2013.*

investigate all road collisions thoroughly and systematically and pass all charging decisions to the prosecution services where there has been an injury; without this data it is impossible to tell if the system as a whole is failing cyclists. The guidance for road policing for the investigation of fatal and serious injury road collisions, provided by the College of Police (2013), states that officers should attend a scene of a collision to secure any available material for evidence to maximise investigation opportunities later, to identify witnesses to secure their initial accounts (because people leave the scene after emergency services arrive), to provide accounts of people's driving prior to the collision and to record the scene location.

Considering the points discussed above, that elaborate the importance of attendance at the scene of a serious or fatal collision, and then considering the results in this chapter, that there is a statistically significant lower attendance at the scene of a collision of a cyclist compared to a car, the opportunity and ability to successfully prosecute dangerous or careless driving are considerably lower post-collision. Potentially, the lack of police attendance may reduce the safety benefit that police visibility and presence brings. If drivers perceive that there is less risk of police presence; they may have less than optimal road safety behavior which effects vulnerable road users due to speeding, lack of due consideration and close passing among other things.

According to the ETSC (2011) law enforcement guidelines, the fear of being sanctioned is the central mechanism for avoiding certain behaviours where drivers are more willing to comply with the rules if they feel that they are likely to be caught and punished. According to the Transport Research Laboratory report by Elliot and Broughton (2005), enforcement is effective in reducing accidents and speeds, sustained enforcement has a lasting 'halo' effect of up to eight weeks and a distance effect ranging between 1.5 to 5 miles, furthermore random enforcement was also found to be highly effective, illustrated in Figure 5-9 below.

Police visibility is a key component of road safety which should be delivered equitably across all modes of transport, particularly vulnerable road users. Lack of safety is cited by cyclists as both a concern and a deterrent. The DfT report by Thornton et al. (2010) stated that nearly three quarters of women and almost half of men surveyed agreed with the statement "*it's too dangerous for me to cycle*".

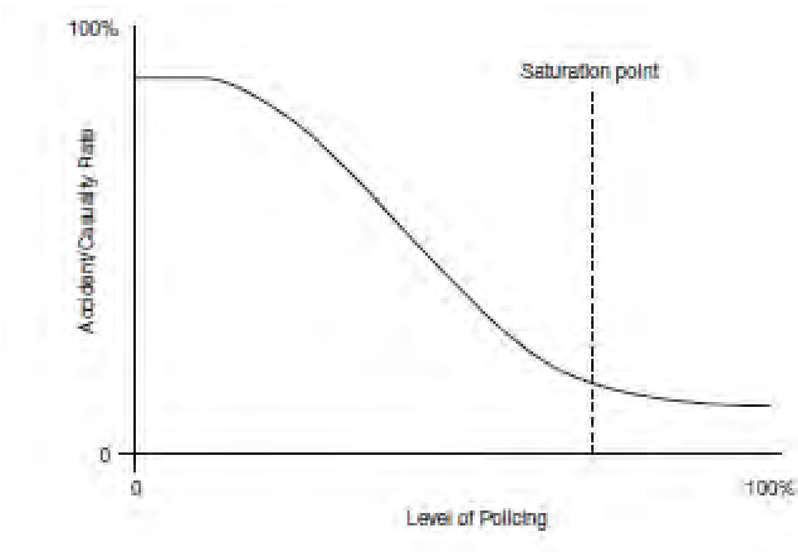

Figure 5-9 Theoretical relationship between levels of policing and accident or casualty rates *(reproduced from Elliot and Broughton (2005), Figure 6.1)*

Similar findings are also reported by Sustrans (2012) and TfL (2014) found that 56% of adults surveyed felt that urban roads were unsafe to cycle on and that 59% of non-cyclists rate safety as a reason for not cycling. However, police do not have a duty to record all injuries reported to them, as pointed out by Allsop (ONS, 2006; pg.5) in his review of Road Accident Statistics. The quality and coverage of collision data depends on motivating the police officer to complete the record compared to competing demands on their time.

Research by Davis (2019), commissioned to explore police enforcement of 20 mph zones in Scotland to provide evidence on the Restricted Roads (20 mph speed limit) (Scotland) Bill, found that:

- most police resources are focused on detecting speeding on the open road because that's where the vast majority of the KSIs occur, according to the police. As a result, police focus enforcement on higher speed limit roads (above 40 mph) and so this is where traffic policing is largely focused;
- police view 30 mph and 20 mph as largely 'self-enforcing';
- Police Scotland do not provide any additional road policing resource to adequately enforce 20 mph speed limits. However, that may change if the Restricted Roads (20 mph speed limit) (Scotland) Bill became law; and

- there is almost no recognition of the deterrent effect of 30 mph speed limit violations on travel mode selection and the deterrent effect to walking and cycling.

According to Davis (2009), serious questions must be asked based on the views expressed by Police Scotland in the interviews. Firstly, focusing enforcement on higher speed roads is erroneous because the majority of reported serious injuries occur on built-up roads with a speed limit of less than 40 mph, which is due an embedded ethos in Police Scotland regarding roads policing. Secondly, most of the Scottish population live in urban areas where lower speeds dominate the road networks, therefore current policing practices may leave most citizens vulnerable due to a lack of speed compliance coupled with low levels of traffic policing.

REPORTED CASUALTIES BY SPEED LIMIT [2012 TO 2016 AVERAGE] [13]

	20 mph	30 mph	40 mph	50 mph	60 mph	70 mph	Total
Killed	0	2	1	1	4	0	9
Seriously Injured	5	110	10	3	27	2	158
Minor	27	561	31	5	62	4	688
All Severities	32	673	42	9	93	6	855

Figure 5-10 The Scottish Annual Cycling Monitoring Report – reported cyclist casualties by speed linit. [on-line] *(Source: Transport Scotland, 2018; pg 10)*

The lack of enforcement focus on 30 mph and 20 mph roads may explain the disparity found in this research between police attendance at cyclist collisions compared to car collisions and the odds ratio was calculated to test this hypothesis, Figure 5-10 above shows the number of casualties by speed limit. The odds ratio of police attending a cyclist KSI at higher speed roads (i.e., 40 mph, 60 mph and 70 mph) was twice as likely (OR = 2.05; χ^2 = 5.69 < 3.84; CI 95%) compared to lower speed roads (i.e., 20 mph and 30 mph) and the result was significant. This result combined with the previous results raised three issues, first that police understanding of road collision statistics may need to be improved, second that the lack of a visible police presence may contribute to the cyclists feeling unsafe or drivers lack of compliance with the legal limits, and third that policing policies, active travel policies, and transport policies are not fully integrated or aligned in a meaningful and effective way that may hinder active travel and road safety targets.

This highlights a potential opportunity to fundamentally change how active travel and road safety can be improved at an institutional level. Therefore, police attendance should be monitored for improvement and speed enforcement should divert resources to enforce lower speed roads and used as a SPI to evaluate road safety enforcement for cyclists. Furthermore, Mäkinen et al. (2003), in their review of traffic enforcement and policing in the EU, indicated that the enforcement policies in the EU need to be critically reviewed periodically to see whether it reflects the original criteria. These findings agree with the findings in this research which has highlighted a need to align policing policy with active travel policies so health, social equity, equality and environmental policies can achieve their aims.

5.4.6 Dooring

There were n=41 cyclist collisions that involved a door opening onto a carriageway, this is known as "dooring" and it is a criminal offence[13], there were 8 KSI doorings and 36 Slight doorings reported to police between 2010 and 2012.

This figure is higher than the "*Vehicle door opened or closed negligently*" recorded as a contributory factor (DfT, 2012) [14], see Appendix A 5.2, but the figures presented here figures are similar to the dooring prevalence found in Edinburgh (CEC, 2012) and by Wardlaw (2014). The number of KSI from dooring is a potentially avoidable safety issue that could be mitigated.

In monitory terms the annual dooring KSI count represents a total injury cost of approximately £1.1million[15] (*Hit object in the carriageway: open door of vehicle*) and £1.8million (*Vehicle door opened or closed negligently)* per annum and is potentially much higher if we also consider under-reporting. To put that figure into context, the total transport budget for cycling was £20.2M[16] in 2011, therefore the potential saving is high and warrants the introduction of driver training policies in Scotland such as the "Dutch Reach" that changes driver behavior. In Holland, the "Dutch Reach" is considered commonplace and doorings are now a rarity (Dutch Reach Project, 2019).

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[13] *Regulation 105 of the Road Vehicles (Construction and Use) Regulations 1986 http://www.legislation.gov.uk/uksi/1986/1078/regulation/105/made and Section 42 Road Traffic Act 1988 http://www.cyclistsdefencefund.org.uk/the-law-for-cyclists-hit-by-vehicl)*

[14] *Reported Casualties in Scotland 2011, Table R and Table Shttps://www.transport.gov.scot/media/29699/j245189.pdf*

[15] *Transport Scotland, Table 10 (2016) Serious Injury cost £275,247, Slight injury cost £27,708.*

[16] SPOKES, 2012: Bulletin 113

5.5 Limitations

At junctions, it is recommended and is common practice to provide cycle stop areas (ASLs), however it was not possible to examine this type of on-road infrastructure because it is not included in the STATS19 data. The impact of the presence of ASLs will be further considered and discussed in the Edinburgh case study in Chapters 8.

The results presented in this chapter only represent the injuries reported and recorded by the police, according to Millar (2005) only one-third of all cycling casualties resulted from 'on road' incidents.

The research in this chapter does not consider exposure and it is therefore explorative. However, exposure will be considered and explored further to analyse cyclist risk in Chapter 6, Chapter 7 and Chapter 8.

5.6 Conclusions

The following conclusions can be drawn from the results and discussion and will be presented in the context of each of the research, associated with the second research objective and research questions that this chapter sought to answer.

OB-02: Critically analyse road safety evidence, focusing on cyclists, to develop an understanding of the wider factors involved.

This research focused on cyclist infrastructure to examine how the road environment affects cyclist safety and confirmed that cyclist infrastructure does not improve the odds of having a KSI compared to utilising the main carriageway. Differences between risk factors among male and female cyclists have a different KSI pattern between the overall Model (1), and the female only Model (2) highlights the difference between genders in terms of mobility pattern which is reflected in the STATS19 results in this chapter. According Miaffi, Malgieri and Di Bartolo (2014, pg. 7) *there is a lack of gender-differentiated statistics.*

The results illustrate that there are institutional barriers within Police Scotland in relation to speed enforcement of lower speed roads which are predominantly in urban areas where most cycling takes place. The analysis shows that police attendance at a cyclists KSI is twice as likely to be attended if the collision occurs on a higher speed road. This infers that their policy to focus enforcement resources in these higher speed areas exposes cyclists to increased risk due to a lack of speed compliance coupled with low levels of traffic policing.

RQ-4: Can we say that existing road safety policy and subsequent implementation processes have been a good fit for cyclists and if not, why, can we model better?

The results presented here highlight areas of policy and implementation that would improve cycling safety. Current police policy for road collision attendance is not applied equitably between transport modes, police attend 67% of cyclist and 96% of motorist collisions. As discussed above, visibility of enforcement is a key component of road safety enforcement strategy. The current policy permits the design and implementation of cycling infrastructure that is not 'forgiving' and due to other factors concerning parking enforcement and driver behaviour, the sum of the total is unsafe. Therefore, the system as a whole needs to be improved, across enforcement, education and engineering.

More recent policies, such as 20 mph zones, should be encouraged and supported/enforced to ensure their effectiveness. The introduction of the 20 mph limit and 'Safe Pass' demonstrate the significant impact police enforcement and police visibility can make to improve cyclist safety. West-Midlands police report a 20% reduction in cyclist injury collisions since the introduction of their innovative approach to address close passing of cyclists.

Overall, the picture is one of transport and wider policy marginalisation and the adherence to traditional transport planning norms and while the transport planning intention is aimed at sustainability, the reality often marginalises walking and cycling (Koglin and Rye, 2014). Further, when motorised transport dominates, the symbolism has an effect on peoples' behaviour and while urban planning might have sustainability as its foundation, it can lead to materialities that produce unsustainable mobilities (Koglin, 2017). The transport related literature reveals a lack of coherence when addressing equity concerns which is possibly compounded by the different types of equity and by the cross disciplinary nature of transport (Rock et al., 2013).

RQ-05: What should Safety Performance Indicators measure to ensure cyclists benefit from Road Safety investment equitably?

Our understanding of what metrics we need to monitor concerning cyclist safety is at an early stage in the UK; according to the Highways England Cycling Strategy (HE, 2016), further work is needed to develop new metrics that more accurately monitor progress. Therefore, research presented here contributes to the understanding and application of various metrics to monitor progress.

The results highlight two main findings, police enforcement does not benefit cyclists equitably; that several SPI metrics within the STATS19 should be used for monitoring attendance; and parking enforcement should focus on cycle lanes and shared footways to ensure parked vehicles and dooring are mitigated and finally to ensure cycle facilities are free from avoidable hazards and objects that are causing harm, see Figure 5-10 below.

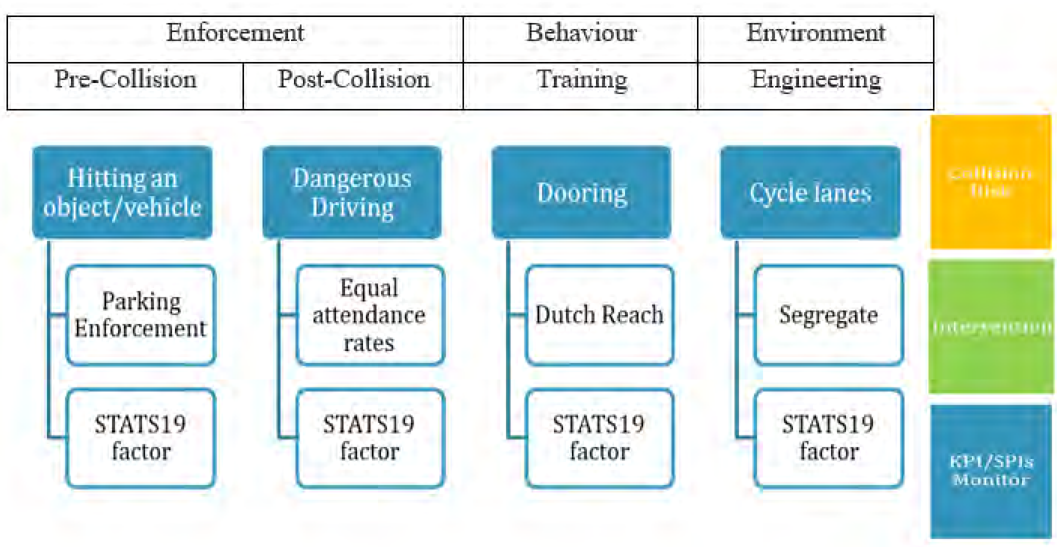

Figure 5-11 A systems KPI cyclist matrix

The main findings in this chapter were that: 20 mph speed limits have not been found to lower the risk of a KSI cyclist collision; that road links rather than junctions have the highest risk of a KSI for cyclists (which should be distinguished from the fact that junctions result in most casualties); cyclists involved in a KSI or slight injury are attended less often than casualties involved in a car accident; that the research findings agree with previous research on age and gender; that there is an urban rural KSI risk between male and female cyclists; that the KSI risks associated with female cyclists differ from those pertaining to male cyclists; that existing cyclist infrastructure does not reduce the KSI risk amongst cyclists; and that the

STATS19 data can be used to monitor cyclist related performance areas and used to monitor the effectiveness of current infrastructure policy.

Few studies have analysed the risk of cycling crashes after adjustment for exposure (Martínez-Ruiz et al., 2014), therefore the next three chapters will examine and explore the risk of cycling crashes adjusting for exposure. Based on the differences found in this chapter between the overall Model (1) and Model (2), the following chapters will also seek to examine trends amongst women where available data permits. Since the current cycling encouragement efforts have failed to increase representation of women in cycling transport, this research (in agreement with Aldred et al., 2016; McDonald, 2012; and Prati, 2018) argues that gender equality needs to be considered.

CHAPTER 6

Safety in Numbers (*SiN*) in Scotland

6.1 Introduction

The overall aim of this chapter is to investigate whether there is a cyclist safety in numbers (*SiN*) effect in Scotland, if it is due to increased mobility, and to examine spatial, demographic and policy differences affecting cyclists (see OB-02, Chapter 3). The previous chapter examined factors that exacerbated or diminished the likelihood of a cyclist being involved in a killed or serious injury (KSI) collision versus a slight injury collision in Scotland but it did not control for the levels of cycling or 'exposure' from place to place. This chapter examine the road safety risk at population level and at local council area level (LA) and evaluates the *SiN* effect to determine if more cycling reduces cyclist casualties to the same extent across Scotland.

This chapter has three objectives: first, to further examine the STATS19 data sets and to assess a number of candidate explanatory variables from a variety of data sources, see Table 3.1, using generalised linear regression models; second, to compare the application of global models to local models to account for spatial dependence using geographically weighted regression (GWR); and third, objectively examines if there is a local *SiN* effect and if the magnitude of the effect varies locally.

The GWR approach has been used in previous research to evaluate the impact of health, geographical and ecological studies but has, to the best of the author's knowledge, remained largely unused for transport related research and hence it is compared with the prevailing road safety research approaches.

Chapter 4 contains the details of the regression models that will be used in this chapter, the negative binomial generalised linear model (GLM-NB), the generalised estimating equation models (GEE), the generalized linear mixed model (GLMM) and finally Geographically Weighted Poisson Regression (GWPR), see Table 4.2, Chapter 4.

This chapter is organised in the following way: Section 6.2 provides a short description of the data and data analysis; Section 6.3 compares *SiN* in Scotland using the traditional GLM with the spatial GWR models and also compares the effect of using exposure measurements; Section 6.4 examines the *SiN* effect using GLM models between disaggregate cyclists sub-groupings, for example male and female *SiN* effects; and finally Section 6.5 discusses the chapter conclusions and main results.

6.2 Description of the Data and Variables

This section describes each of the variables used in the models discussed in the following sections of this Chapter. The descriptive summary statistics for the dependent and explanatory variables are listed in Table 6.1 below. A description of how the values for each variable was created is discussed here, along with a brief justification for inclusion of each variable which is based on the literature review findings discussed in Chapter 2.

6.2.1 Data Preparation and Pre-Modelling Analysis

This section provides an overview of the analysis and data preparation conducted prior to fitting various models. The objective of this section is to understand the structure of the data and to inform the model fitting in the next section; specifically to identify if the data sets display temporal dependence, spatial dependence or collinearity that may need to be considered or controlled for in the fitting process.

The STATS19 data is a georeferenced database, it provides both easting and northing and longitude and latitude coordinates for each collision, within Scotland, and the code corresponding to each of the 32 Scottish Council Areas.

Several R Project packages were employed to convert the STATS19 database files into spatial datasets to merge the collision data with shape files containing the Scottish boundary data and aggregated to the Scottish Council Area. The estimation of the GLM-NB, GLMM-NB and the GWR was conducted in R using the 'MASS', 'pscl' and 'COUNT' package for the GLM-NB, the 'lmr4' package was used for the GLMM-NB and the 'GWmodel' package was used for the GWR from R Project (CRAN, 2019). At the time of writing, the 'GWmodel' does not support the calibration of the GWR with the Negative Binomial structure. Therefore, the Poisson structure of the GWR was deemed suitable and thus, a geographically weighted Poisson regression (GWPR) was implemented in the following sections.

Table 6.1 Descriptive Statistics

Statistic		N	Mean	St. Dev.	Min	Max
		Dependent variable - Cyclists				
	Abv.					
All casualties	*(ALL)*	2504	78.20	129.00	2	691
KSI casualties	*(KSI)*	484	15.10	20.20	1	108
Slight casualties	*(SL)*	2020	63.10	109.00	1	583
All Female casualties	*(f_ALL)*	464	14.50	28.10	1	155
Female KSI casualties	*(KSIf)*	97	3.03	5.10	0	28
Male KSI casualties	*(KSIm)*	387	12.10	15.40	0	80
KSI in an Urban Area	*(KSIu)*	354	11.10	19.70	0	101
KSI in a Rural Area	*(KSIr)*	130	4.06	4.09	0	15
KSI Under 16yrs of age	*(KSI16)*	53	13.50	11.30	1	50
KSI Over 60yrs of age	*(KSI60)*	132	4.12	5.44	0	31
Speed limit over 30mph	*(Speed30)*	2089	65.30	125.00	2	653
			Explanatory variables			
Commuters (Cyclists)	*ln NCyc_*	*No.*	1,381	2,309	70	12,526
Annual distance cycled	*lnNCyc_mvkm*	*mvkm*	24	40.20	1	218
Annual distance driven	*ln mvkm_v*	*mvkm*	3,467	2,284	405	8,148
Total Road length	*Ln RL*	*km*	1,853	1,726	311	8,109
2011 Population	*ln Pop*	*No.*	74,149	60,705	9,725	285,693
No car Households	*ln NO_Car*	*%*	26.60	8.18	14	51
A-Road length	*lnRL A*	*km*	326	438	38	2,352
B-Road length	*lnRL B*	*km*	234	247	8.30	979
C-Road length	*lnRL C*	*km*	334	387	26.90	1,539
UN-Road length	*lnRL U*	*km*	836	622	176	2,948
SMID (15% National)	*SMID_N_15*	*%*	0.47	0.81	0.00	4.44
Urban area	*Urban*	*%*	58.10	32.40	0.00	99.80

6.2.1.1 Multicollinearity

The association between pairs of explanatory variables was examined using a correlation matrix. The degree of correlation betwwen pairs is measured between one and zero (1 - 0), where zero indicates no association and 1 identifies perfect correlation between the pairs. The correlation matrix decribes multicollinearity in the dataset which was examined prior to fitting the multivariate models. The collinearity between variables and significance is illustrated in Figure 6-1 below which shows the coefficient correlation matrix where significant coefficients (p>0.05) are coloured either blue or red, blue represents positive correlation and red represents negative correlation relationships.

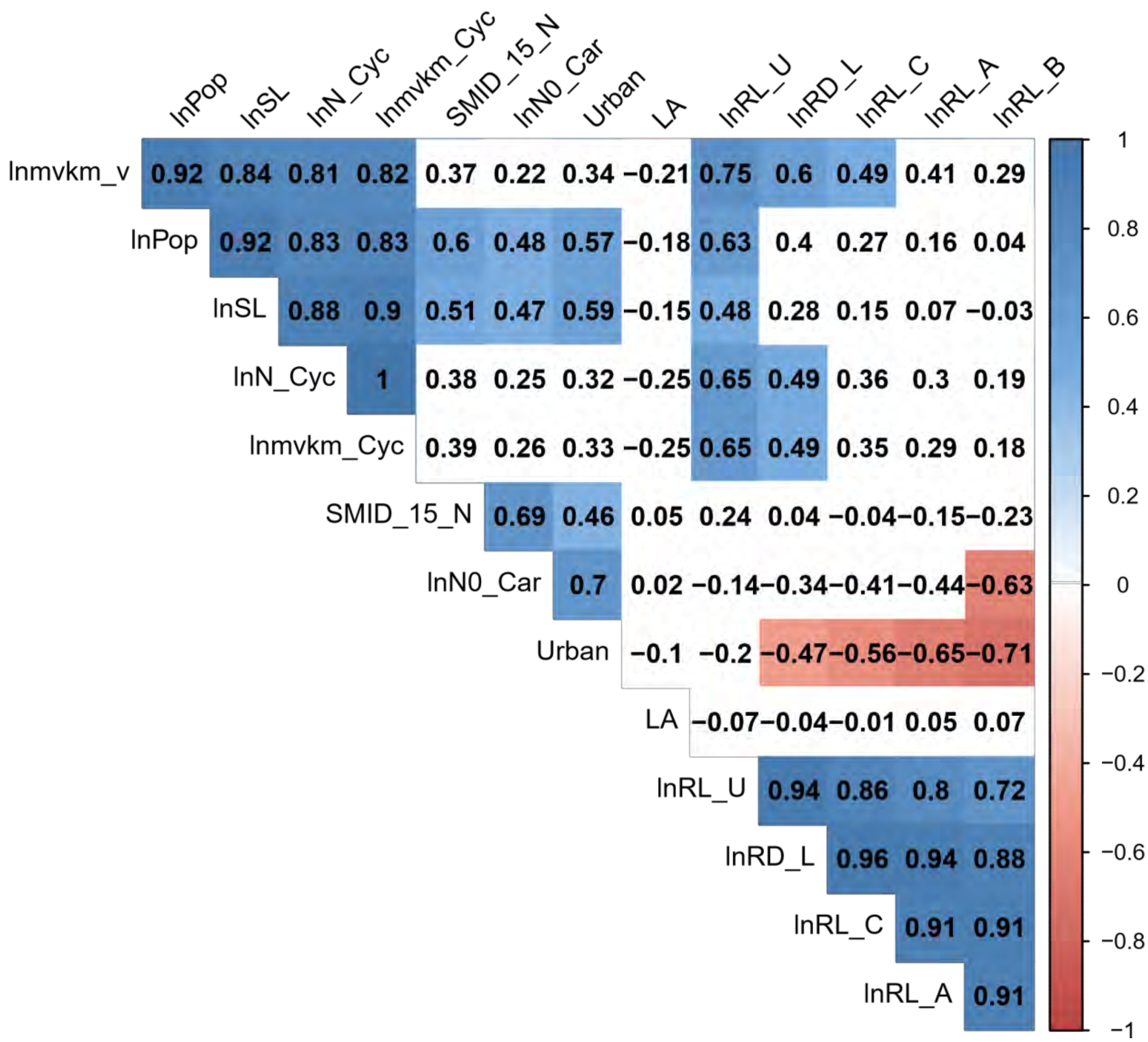

Figure 6-1 Exposure and Dependent variable correlation matrix and significant values (Blue and Red cells are significant correlation coefficients).

Given the considerably high, and significant (p>0.05) correlation values found between the potential exposure variables, motorist million vehicle kilometers (mvkm_v) and cyclist million vehicle kilometers (mvkm_Cyc) were 0.82 and mvkm_v and the count of cyclists (N_Cyc) was 0.81, the most appropriate metric for use must be determined. There is a lack of consensus on the most appropriate metric for research into cyclist collisions and hence these three variables were tested separately using the GLM-NB model and the GWPR model, discussed in Section 6.4.

In each set, the Variance Inflation Factor (VIF) was applied to assess multicollinearity and all the variables that had a value greater than, or equal to, five, which indicates a moderate multicollinearity (Heiberger and Holland, 2015), were eliminated.

6.2.1.2 Spatial dependence

Prior to model fitting, the presence of spatial autocorrelation and spatial non-stationarity (i.e. heterogeneity) was examined to check for potential effects. As discussed in Chapter 2, and Chapter 4 previously, much of the research into collision analysis does not consider the effects of spatial variance whereas other research areas (i.e. health, agriculture and ecology etc.) incorporate the spatial nature of the data to provide further understanding of the fitted models.

In time series analysis of repeated observations, the within time interval has a sample size of 1 with sequentially correlated measures. Therefore, the correlation is within a single observation and given the prefix "auto" such that it can be differentiated from the meaning of "correlation". Spatial correlation analysis was initially introduced by Morgan (1948) and Geary (1954). Chun and Griffith (2013) describe spatial correlation as a conceptual extension of simple linear time series into a topographical or geographical structure which is why 'spatial' is added to the word autocorrelation. Therefore, spatial autocorrelation, such that 'spatial' means a map or geographical area, has a sample size of 1 with repeated adjacent correlated measures or neighbours.

As a first step, a cursory visual inspection of the dependent variables for cyclist KSI collisions and all injury collisions produced Figure 6-2 below which clearly illustrates that the dependent variable, all injuries and KSIs, vary across the Scottish Council Areas (n=32 panels). According to Hilbe (2011; page 447-448), there are two methods to adjust the GLM model to account for extra correlation associated panels:

- Generalised estimating equations (GEE), or population averaging (PA), and
- Random-effects model

To examine if the differences are significant and should be accounted for in the model fitting process, GLM (fixed effects), GLMM (random-effects) and GEE models were fitted with a KSI dependent variable and number of cyclist commuters (lnN_Cyc). The spatial units were assessed differently in each model, the GLM-NB models included the LA as factor variables, the GLMM-NB included LA as a random variable and the GEE takes account of the variation across the panel structure, which was again the LA defined by an ID variable within the model, see Appendix 6.1.

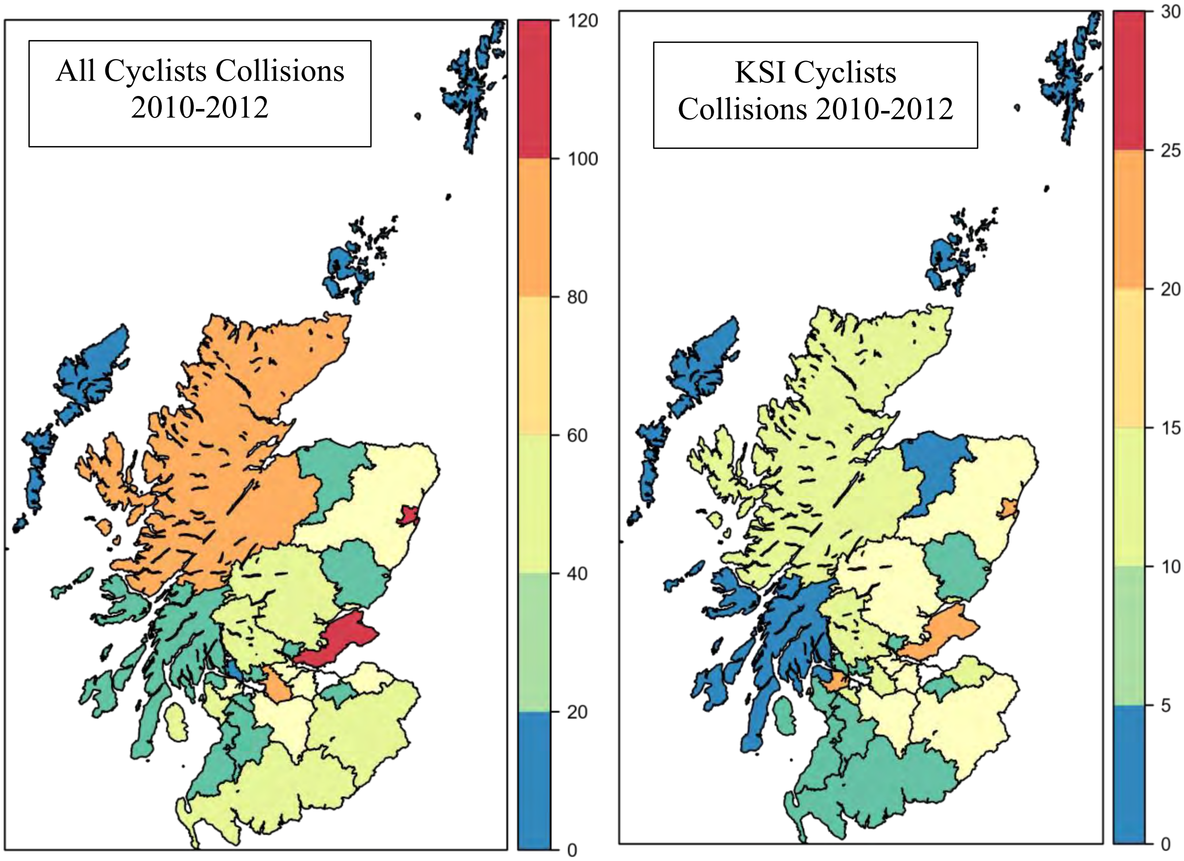

Figure 6-2 All injury collisions and KSI collisions in each Scottish Council Area LA 2010-2012 (n=32).

Both the GLM-NB and GLMM-NB results showed that there was significant effect across the LA, the GLMM-NB provided a better fit with significantly lower Akaike's information criterion (AIC) values. In the GLM, 8 of the 32 LAs were significant (Perth and Kinross (934), the Highlands (927), Moray (930), East Renfrewshire (922), the Scottish Boarders (914), Renfrewshire (935), South Lanarkshire (938) and West Lothian (940)). The frequency of KSIs in each LA is illustrated in Figure 6-3 below, Edinburgh (code reference

923 in Figure 6-3) and Glasgow City (code reference 926 in Figure 6-3) stand out because they are the LAs with the highest number of KSIs.

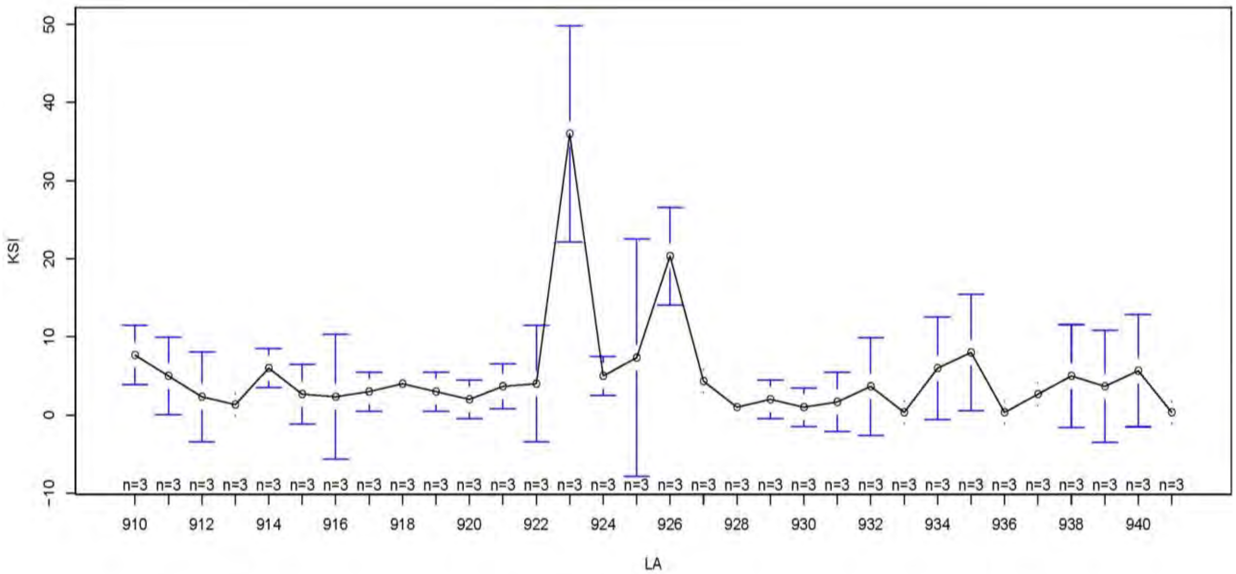

Figure 6-3 Cyclists KSI mean and range across Scottish Council Areas (n=32) between 2010-2012 (n=3).

The data structure is arranged in panels and the GEE has been recommended as a way to account for lack of independence across the panel. Therefore, before conducting the main analysis using GLM-NB, GLMM and the GWR models, GEE models were fitted and compared to assess model appropriateness and goodness-of-fit for this research, see Appendix 6.1 for the model comparison in Table A6.1. It was found that the GEE did appear to account for lack of independence better than the GLM-NB and the GLMM, however it was not possible to directly compare them using the AIC, a widely used method for model selection in GLM, as it is not applicable to GEE directly (Cui, 2007, pg. 209). Therefore, it would not be possible to also compare these models directly with the GWPR which also use AIC in addition the AICc, which is corrected to adjust for small sample size because the GWPR estimates local GLMs within each zone/area.

The GEE uses a quasi-form of the AIC maximum-likelihood estimation using quasi-likelihood under the independence model criterion (QIC). The *SiN* effect was marginally lower, 0.76 compared with 0.7 in the GLM-NB and GLMM models, and this is because the GEE model has not ignored dependence in the data between the LAs. As Figure 6-3 illustrates, the variance is not uniform and therefore violated the independence assumption of the GLM s, see Appendix 6.1 for full model results. The GEE is not directly comparable, they are not typically applied in transport research despite their ability to manage spatial variance and therefore they will not be considered further.

The results confirm that there is both auto correlation and variance across the panels; therefore, a GLM should consider this. Another approach is GWPR that creates local GLMs for each panel or spatial area. Each of these approaches will be discussed in the following sections and later applied to the data and the merits or limitations of each will be assessed. The next section will also compare the three exposure variables available.

6.3 Measuring the Safety in Numbers effect in Scotland

This section examines the global *SiN* effect in Scotland using the GLM-NB models, then it examines the local effect of *SiN* using GWPR at the LA level to examine the influence of spatial variation by comparing the spatial GWPR against the traditional GLM-NB model. As part of the comparison this section also compares the model results using three different exposure metrics: the number of commuter cyclists in each LA taken from the 2011 Census; the measure of the annual distance cycled taken from the DfT transport and travel statistics; and finally the total annual traffic volume in each LA. This is particularly pertinent to cyclist safety research as the availability of exposure metrics is often limited, and this may affect research findings.

Further, it is hoped that this analysis will provide direction for future research to inform researchers or professionals of the most appropriate exposure metric for research into cyclist collision analysis and to provide justification to municipalities and national agencies for the inclusion of cyclists into transport models.

To compare the GLM-NB, GLMM-NB and the GWPR, nine models were fitted to examine the relative importance and significance of using different exposure variables to estimate *SiN*. The dependent variable was cyclist KSIs and three exposure variables were tested: the number of commuter cyclists (ln N_Cyc); the annual cyclist traffic volume (ln mvkm_Cyc) and the motorised traffic volumes (ln mvkm_Veh) for each LA, Table 6.1 above. Three different model forms were applied, GLM-NB, GLMM-NB, Table 6.2 below, and the GWPR, Table 6.3 below.

Table 6.2 Comparison of the Exposure Variables using GLM-NB and GLMM-NB Mixed Effects Models.

"KSI"	**GLM NB**		**GLMM NB**		**GLM NB**		**GLMM NB**		**GLM NB**		**GLMM NB**	
Predictors	*IRR (β)*	*std. Error*	*IRR (β)*	*std. Error*	*IRR (β)*	*std. Error*	*IRR (β)*	*std. Error*	*IRR (β)*	*std. Error*	*IRR (β)*	*std. Error*
(Intercept)	-2.25 *** (-3.42 – -1.08)	0.60	-2.32 *** (-3.52 – -1.13)	0.61	0.60 * (0.09 – 1.10)	0.26	0.52 * (0.00 – 1.04)	0.26	-6.89 *** (-9.64 – -4.13)	1.41	-6.15 *** (-8.91 – -3.38)	1.41
ln N Cyc	0.70 *** (0.53 – 0.87)	0.09	0.70 *** (0.53 – 0.87)	0.09								
lnmvkm Cyc					0.70 *** (0.54 – 0.87)	0.09	0.70 *** (0.53 – 0.88)	0.09				
lnmvkm v									1.17 *** (0.83 – 1.51)	0.17	1.06 *** (0.72 – 1.40)	0.17
Random Effects (LA – Scottish Council Area**)**												
σ^2			0.10				0.10				0.10	
τ_{00}			0.17 $_{LA}$				0.17 $_{LA}$				0.29 $_{LA}$	
ICC			0.63 $_{LA}$				0.63 $_{LA}$				0.75 $_{LA}$	
PseudoR^2	0.738		0.676		0.738		0.676		0.644		0.588	
Deviance	32.144		197.532		32.188		197.465		29.691		204.907	
AIC	202.457		205.532		202.395		205.465		212.746		212.907	

(PseudoR^2 *uses Cox & Snell estimate. Confidence intervals in parenthesis)*   * $p<0.05$ ** $p<0.01$ *** $p<0.001$

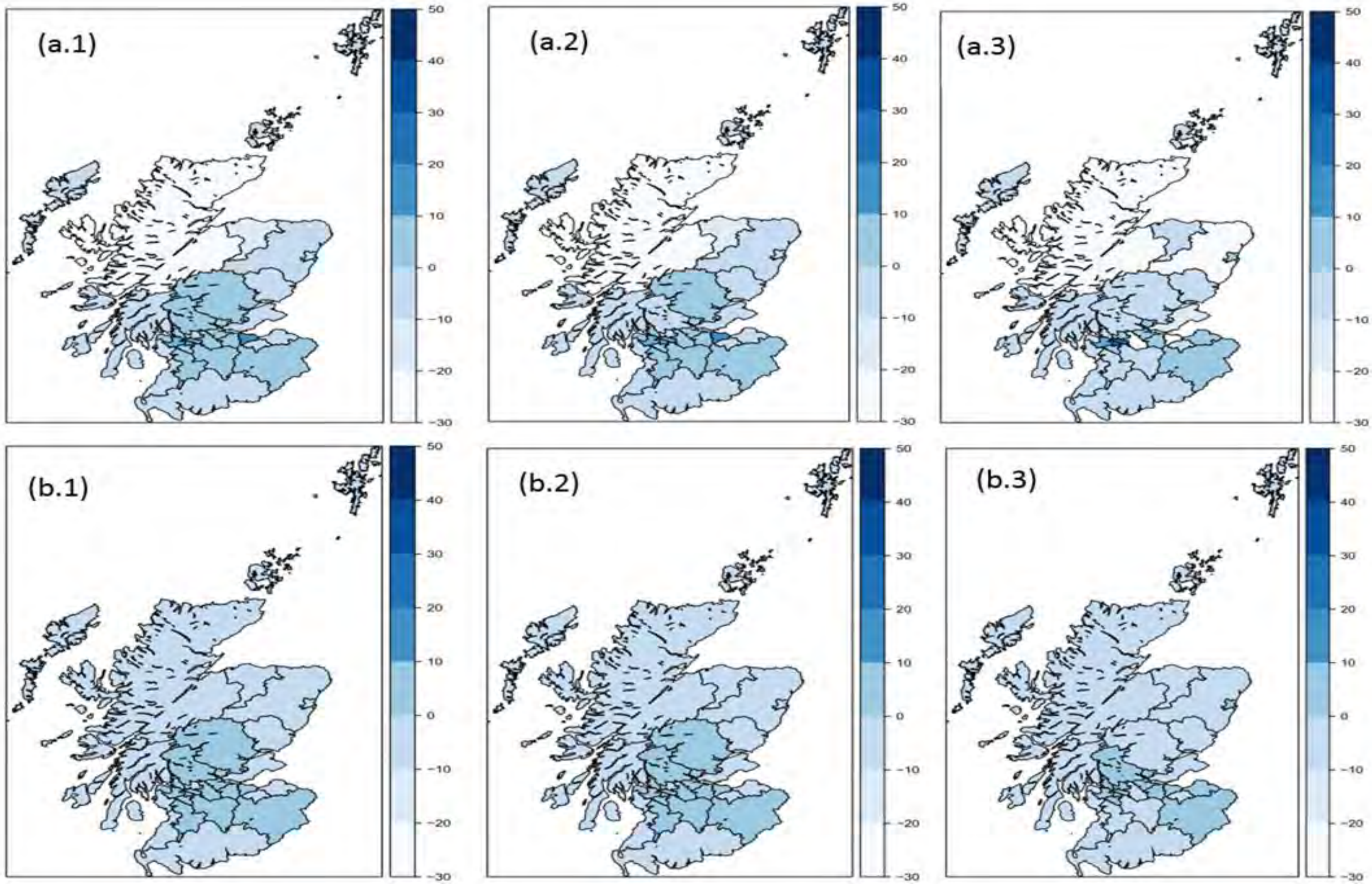

Figure 6-4 NB response residuals for number of cyclists (a.1), distance cycled (a.2), and distance driven (a.3) comparison with NB Mixed model for response residuals for (b.1), distance cycled (b.2), and distance driven (b.3)**.**

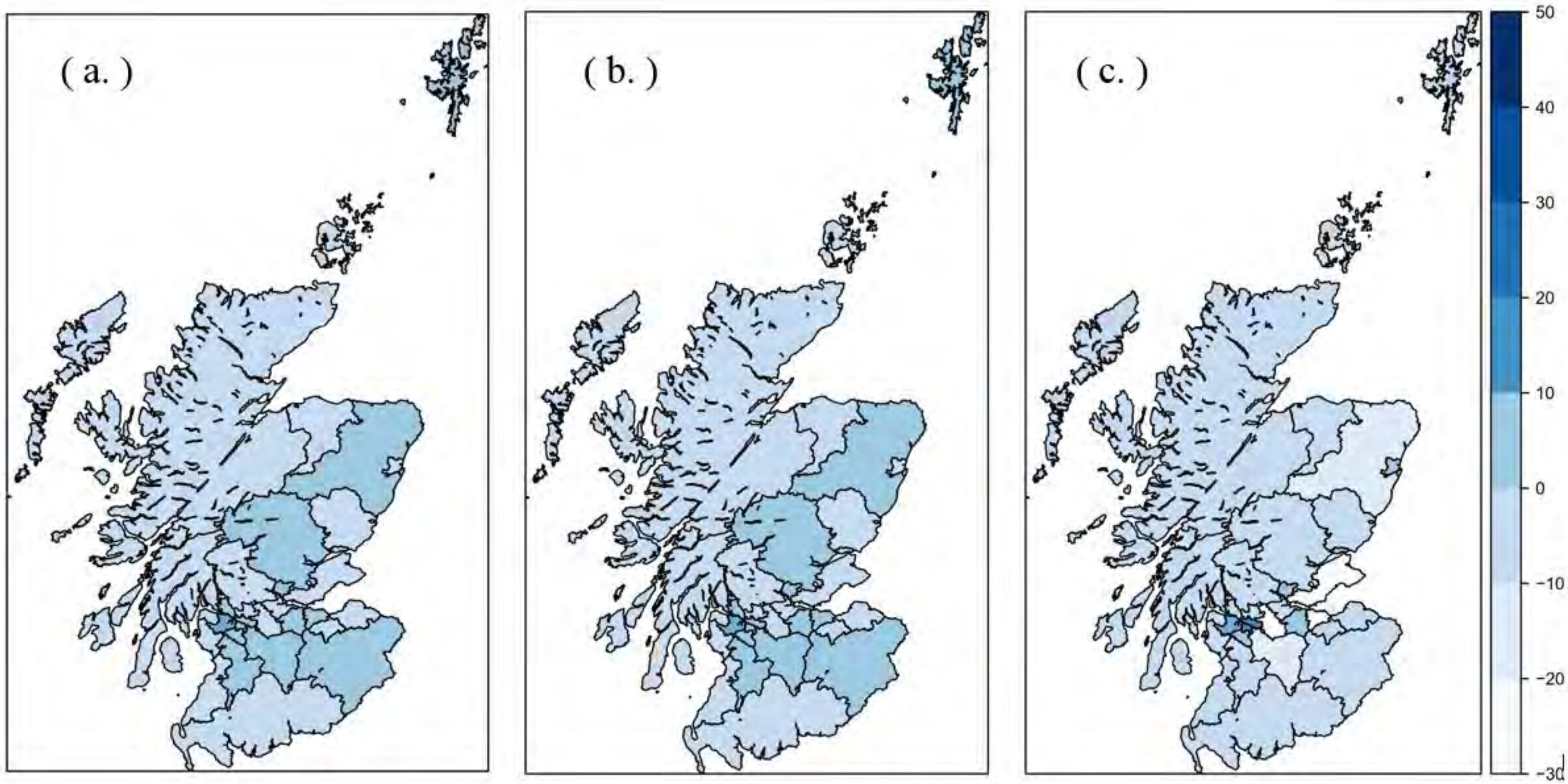

Figure 6-5 The GWPR response residuals for model of KSI fitted with a) Number of cyclists, b) Cycling traffic volumes and c) Motorised traffic volumes.

Table 6.3 Comparison of the Exposure Variables using the GWPR Model.

"KSI"			**GWPR (*Local*)**			**GLM (*Global*)**	
Predictors	*Minimum*	*1st Q*	*Median*	*3rd Q*	*Maximum*	*IRR (β)*	*std. Error*
(Intercept)	-3.34	-2.53	-2.34	-2.19	-0.34	-2.68 ***	0.29
ln N Cyc	0.38	0.73	0.74	0.76	0.84	0.76***	0.04
Pseudo R^2			0.887			0.790	
Deviance			55.8			99.97	
AICc			72.2			104	

* *p<0.05* ** *p<0.01* *** *p<0.001*

"KSI"			**GWPR (*Local*)**			**GLM (*Global*)**	
Predictors	*Minimum*	*1st Q*	*Median*	*3rd Q*	*Maximum*	*IRR (β)*	*std. Error*
(Intercept)	-0.185	0.454	0.665	0.727	1.18	0.41 ***	0.14
ln mvkm_Cyc	0.385	0.729	0.742	0.753	0.84	0.77***	0.04
Pseudo R^2			0.887			0.790	
Deviance			55.7			99.46	
AICc			72.5			103.5	

* *p<0.05* ** *p<0.01* *** *p<0.001*

"KSI"			**GWPR (*Local*)**			**GLM (*Global*)**	
Predictors	*Minimum*	*1st Q*	*Median*	*3rd Q*	*Maximum*	*IRR (β)*	*std. Error*
(Intercept)	-9.54	-7.89	-7.33	-6.03	-3.75	-6.78***	0.676
ln mvkm_v	0.74	1.07	1.25	1.31	1.52	1.16***	0.08
Pseudo R^2			0.643			0.512	
Deviance			176			240.23	
AICc			194			245	

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 6.4 Evaluation of the Fixed Effects, Mixed Effects Models and the GWPR model residues for spatial dependency/autocorrelation.

"KSI" *Model*	*Moran's I*	*p-value*	*H0 (reject p>0.05)*
GLM (lnN_Cyc)	0.217	0.02*	H1
GLMM (lnN_Cyc)	0.243	0.01*	H1
GLM (lnmvkm_Cyc)	0.217	0.02*	H1
GLMM (lnmvkm_Cyc)	0.24	0.01*	H1
GLM (lnmvkm_v)	0.018	0.1	H0 (reject p>0.05)
GLMM (lnmvkm_v)	0.144	0.08	H0 (reject p>0.05)
GWPR (lnN_Cyc)	-0.065	0.6	H0 (reject p>0.05)
GWPR (lnmvkm_Cyc)	-0.068	0.6	H0 (reject p>0.05)
GWPR (lnmvkm_v)	-0.002	0.4	H0 (reject p>0.05)

* $p<0.05$

The model residuals were used to test for the presence of spatial dependence using the Moran's I test statistic (see Chapter 4 for details), presented in Table 6.4 below. The difference between the GLM-NB and GLMM-NB residuals are plotted in Figure 6-4, and the GWPR residuals are plotted in Figure 6-5 above. The next section discusses the results from the analysis described above.

6.3.1 Comparison of Exposure Metrics for *SiN* in Scotland

A comparison the GLM-NB and the GLMM-NB results show that there is a *SiN* effect, but that it is weaker than the reported figures in the literature, 0.7 compared to 0.41 (Jacobsen, 2003). However, it is less than 1 for both of the cycling exposure measurements, the number of cyclist that commute (ln N Cyc) and the DfT estimated cycling volume (lnmvkm Cyc) in LA, representing the typical *SiN* "non-linear" effect, albeit with a smaller effect than might have been anticipated. The AIC difference is not significant, 202 and 205 for the GLM=NB and GLMM-NB respectively, and the pseudo R^2 was 0.74, which is a good fit considering that it is a univariate model. The traffic exposure variable was positively associated with cyclist KSI collisions, but it explained the lowest dependent variable variation compared to the two cycling exposure variables and the model goodness-of-fit was not as good because it had a significantly higher AIC (213) and a lower pseudo R^2 of 0.68.

The likelihood ratio test (LRT) was used to test the worth of the fitted models, a key test for assessing the worth of a model (Hilbe, 2014), and all six GLM-NB and GLMM-NB were significant and therefore significantly better than the null model. Next, the Hosmer-Lemeshow test (HLT) was used to assess if the model estimates were significantly different from the observed frequencies of KSIs in each LA, all models were not significantly different. Based on the AIC, R^2 and the LRT and HLT, the models present a good fit. Next, the spatial dependence was examined using the model residuals, the GLM-NB residuals varied more than the GLMM-NB, illustrated in Figure 6-6 below, and all the GLM-NB model residuals display more variation than the GLMM-NB models for all three exposure variables. This indicates that the GLMM-NB has adjusted for some of the variation between the LAs.

The Moran's I statistic was used to test if spatial variation was present in the residuals from each model including the GWPR models. The Moran's I vary between −1 and 1, where 0 (zero) indicates a lack of correlation (random and disperse) and 1 represents correlation or similarity between the neighbours. Negative values −1 represents a lack of association. The results confirm that the GLM-NB and GLMM-NB models did not remove spatial dependence, see Table 6.4, and that the spatial dependence is significant and positive. Spatial dependence was not found to be significant among the residuals for the traffic volume (lnmvkm v) GLM-NB and GLMM-NB models. The GLMM-NB models treated the variation as a random effect which reduced the residual variation, but the GLM-NB was statistically a better fit. Therefore, the GLM-NB was compared to the GWPR.

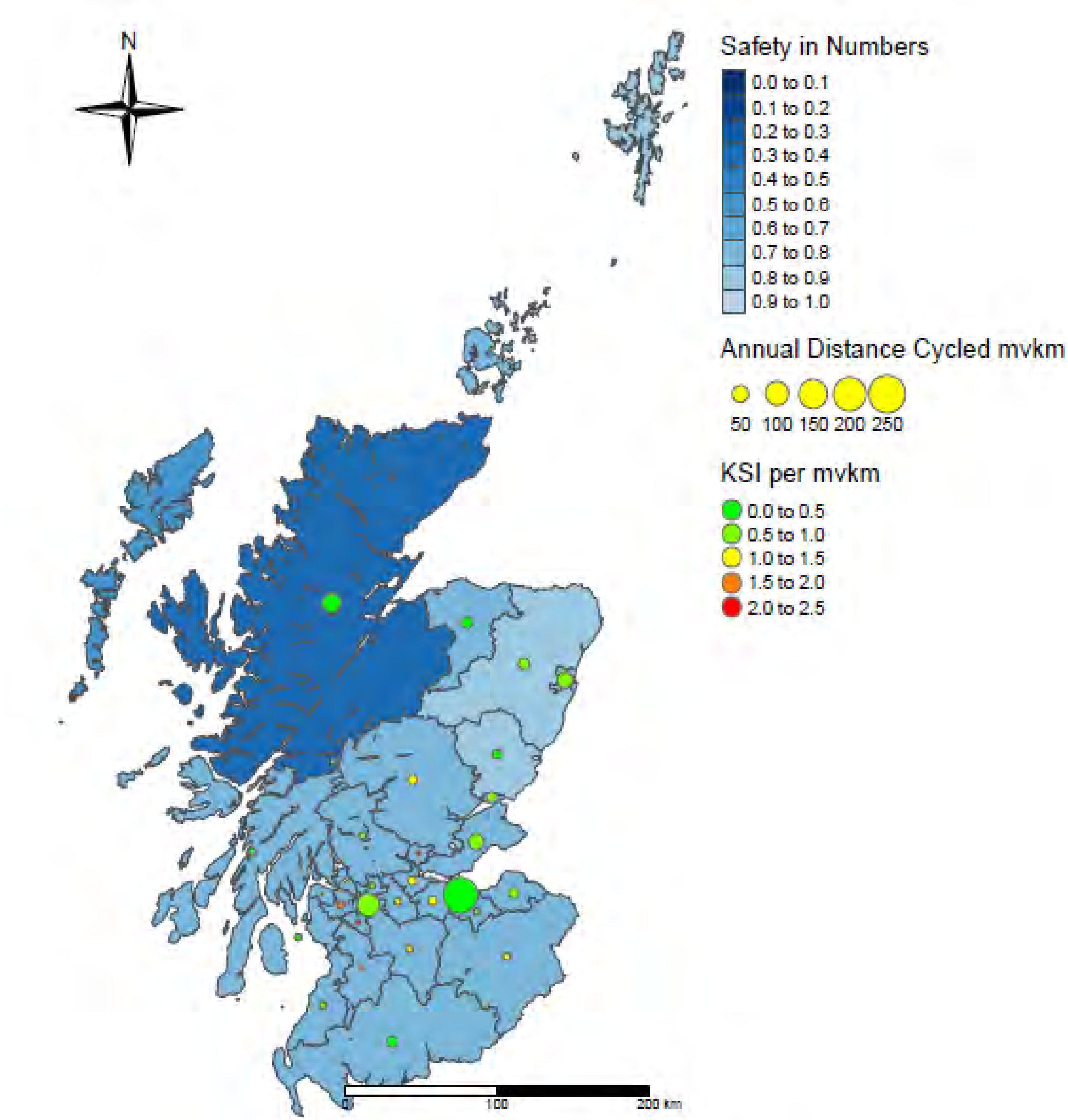

Figure 6-6 Model results illustrating *SiN* (Blue) in Scotland across local council areas, the level of cycling (million vehicle kilometers) and the KSI (STATS19) risk (KSI divided by million vehicle kilometers).

The results of the GWPR models are presented in Table 6.3 which includes results of an equivalent GLM-NB model for comparison. The GWPR model shows that the *SiN* effect varies across the LAs from 0.38, which implies a very high *SiN* effect, to 0.84 which implies a much weaker *SiN* effect. Both the cyclist exposure variables performed similarly, and the model fit is significantly better than the GLM-NB model; AIC of 72 compared to 104; pseudo R^2 of 0.88 compared to 0.79; and the GWPR model deviance was also lower.

Similar to the results in the previous section, that compared the GLM-NB and GLMM-NB, both cyclist exposure variables explain more of the model variance than the traffic volumes. The presence of spatial dependence in the GWPR model residuals was tested, described above, but the Moran's I test was not significant, see Table 6.4. This illustrates the GWPR model's ability to deal with the spatial dependence to provide a better fit and explanation of the *SiN* effect.

The GWPR estimates local model parameters for each LA, the local co-efficient or *SiN* values are illustrated in Figure 6-6 above and the strongest *SiN* effect was found in the Highlands which confirmed that higher levels of cycling are associated with *SiN*, illustrated in Figure 6-7 below.

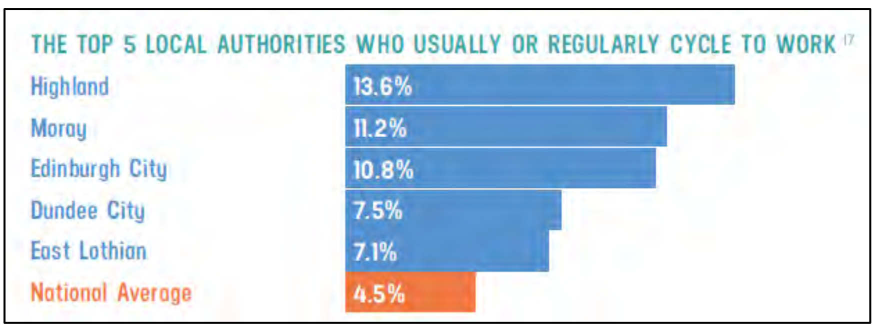

Figure 6-7 The Scottish Annual Cycling Monitoring Report - top five local council areas by percentage of cycling to work. [on-line] *(Source: Transport Scotland, 2018; pg 14)*

The annual distance cycled in each LA is also shown in Figure 6-6 above, and the number of KSIs per mvkm cycled is shown for comparison. Regionally, the Highlands and Moray had the highest proportions of cycling to work followed by Edinburgh (Cycling Scotland, 2018). The 2011 Census shows that these three had the highest proportions of the LA population that cycled to work or education, 3.6% (Highlands), 3.5% (Moray) and 5.7% (Edinburgh). The GWPR model, Figure 6-7 above, shows that the Highlands and Moray have the best SiN effect 0.38 and 0.58 respectively, see Appendix A6.4 for the full table of results. Edinburgh, interestingly, only achieved a relatively weak *SiN* effect of 0.75 and the four worst LAs were Dundee City, Shetland Islands, Aberdeenshire, Angus, and Aberdeen City with SiN effects over 0.80. While the four worst LAs follow a trend of low cycling levels compared to Edinburgh, they also have average KSI and slight injury rates per population, but Edinburgh has much higher rates than any other LA in Scotland.

Therefore, despite having higher levels of cycling it only has an average (0.7) SiN effect within Scotland which suggests that there are other factors influencing *SiN* that are not explained by this model.

Furthermore, the Highlands have been identified as one of the regions at risk of transport poverty (see Chapter 2 – Part A for detail) due to high levels of deprivation, according to the Scottish Index of Multiple Deprivation, see Appendix A6.3. The report (Sustrans, 2016) recommended cycling as a means of travel to access services and avoid transport poverty due to car ownership costs. The SiN results in the Highlands are better than most of Scotland so encouraging those at risk of transport poverty to cycle is less likely to exposure them to higher road safety risk, the same however cannot be said for less safe regions. Therefore, this research demonstrates how measuring SiN and mapping the outcome can aid the evaluation of other policies.

The information illustrated in Figure 6-6 above highlights three very important issues in road safety, the first is that the KSI rate calculated by dividing the 'exposure' denominator into the KSI numerator takes no account of external factors, the factors discussed in Chapter 5. Second, the 2004 to 2008 average risk was 0.56 KSI per mvkm cycled and 0.03 KSI per mvkm driven (excluding motorcycles) from Transport Scotland (2019) additional road safety tables17. The median KSI rate is 0.67 KSI per mvkm cycled in Figure 6-7 above, full results provided in Appendix A 6.3, which illustrates that the KSI rate ranges from 0.13 to a maximum of 2 and that the KSI per mvkm does not seem to follow a SiN effect pattern. Third, the relationship between the number of accidents and exposure, called the 'safety performance function'(SPF), is not accounted for by a rate measurement of risk, an SPF it is seldom linear (Hauer, 1995)., hence the *SiN* effect is the SPF not an effect as such.

According to Hauer (1995) the division of accident frequency by exposure serves two main purposes: to equalise for differences in intensity of use (i.e. more cycling or distance

[17] *Transport Scotland, extra-road-casualty-and-accident-tables.xls, Table 1, 2 and 3 [Source: https://www.transport.gov.scot/publication/reported-road-casualties-scotland-2018-datasets/]*

cycled; and to compare differences between the characteristic rates in order to find causal factors. Hauer recommends that, as the use of accident rates do not provide an indication of one place being safer than the other, they should not be used for this purpose, however the *SiN* effect can.

6.3.2 Summary Conclusions (Comparison of Exposure Metrics for *SiN*)

This section demonstrates that spatial dependence is a significant effect that is not captured in the traditional GLM-NB models recommended for the analysis of road collisions or the GLMM-NB models. The comparison of the residuals for the GLM-NB and GLMM-NB models with the GWPR illustrated that the GWPR accounted for spatial dependence. The GLMM-NB model accounted for heterogeneity between the LAs but the model did not perform statistically better than the GLM-NB so it will not be used in further sections. The next section develops multivariate GLM-NB models for several different dependent variables.

Finally, there was very little statistical difference between the univariate model fitted with number of cyclists (lnCyc_N) and the distance cycled (lnmvkm_Cyc) exposure variables. The number of cyclists is often used as a proxy for the overall distance travelled by cyclists for all trip purposes (Goodman, 2013) and the data source is the 2011 Census which captures the whole of the Scottish population. However, the distances cycled are estimates calculated from small sample sizes and should therefore be used with caution (TS, 2018). Also, these estimates report activity of cyclists on public highways and not on cycle paths and footpaths adjacent to them. Cycle activity elsewhere (for example on canal towpaths, byways or bridleways) is not included in road traffic statistics. Furthermore, the published estimates are derived from small sample sizes and therefore their accuracy is limited. Consequently, the subsequent models in this Chapter will use the number of cyclists taken from the 2011 Census as the exposure metric.

6.4 Multivariate GLM-NB using disaggregate cyclist variables

The results discussed in Chapter 5 demonstrated that the risk of a cyclist KSI collision varies by age, gender and location. This section describes the results of nine GLM-NB models developed from the data set described in Table 6.1 above disaggregated by gender, location, injury severity, age and posted speed limit. The results of the best fit models, following stepwise regression analysis (see Chapter 3), are presented in Table 6.5 and Table 6.6 below.

The *SiN* effect across the nine models clearly demonstrates that cyclist collision risk and the *SiN* effect varies within the cyclist group. The estimates range from 0.26 to 0.91, the *SiN* effect is widely cited as having a coefficient of 0.41 (Jacobsen, 2003). A coefficient of 1 or more represents no *SiN* effect and a coefficient less than 1 represents a *SiN* effect and is stronger as the estimate approaches zero. The full model result is presented in Appendix A6.2. The significant results are discussed in the next section.

6.4.1 Results: Disaggregated *SiN*

Eleven models were examined using different dependent variables for comparison: All casualties; KSI casualties; Slight casualties; All Female casualties; Female KSI casualties; Male KSI casualties; KSI in an Urban Area; KSI in a Rural Area; KSI Under 16 years of age; KSI Over 60 years of age; and Speed limit over 30mph as shown in Table 6.1 above.

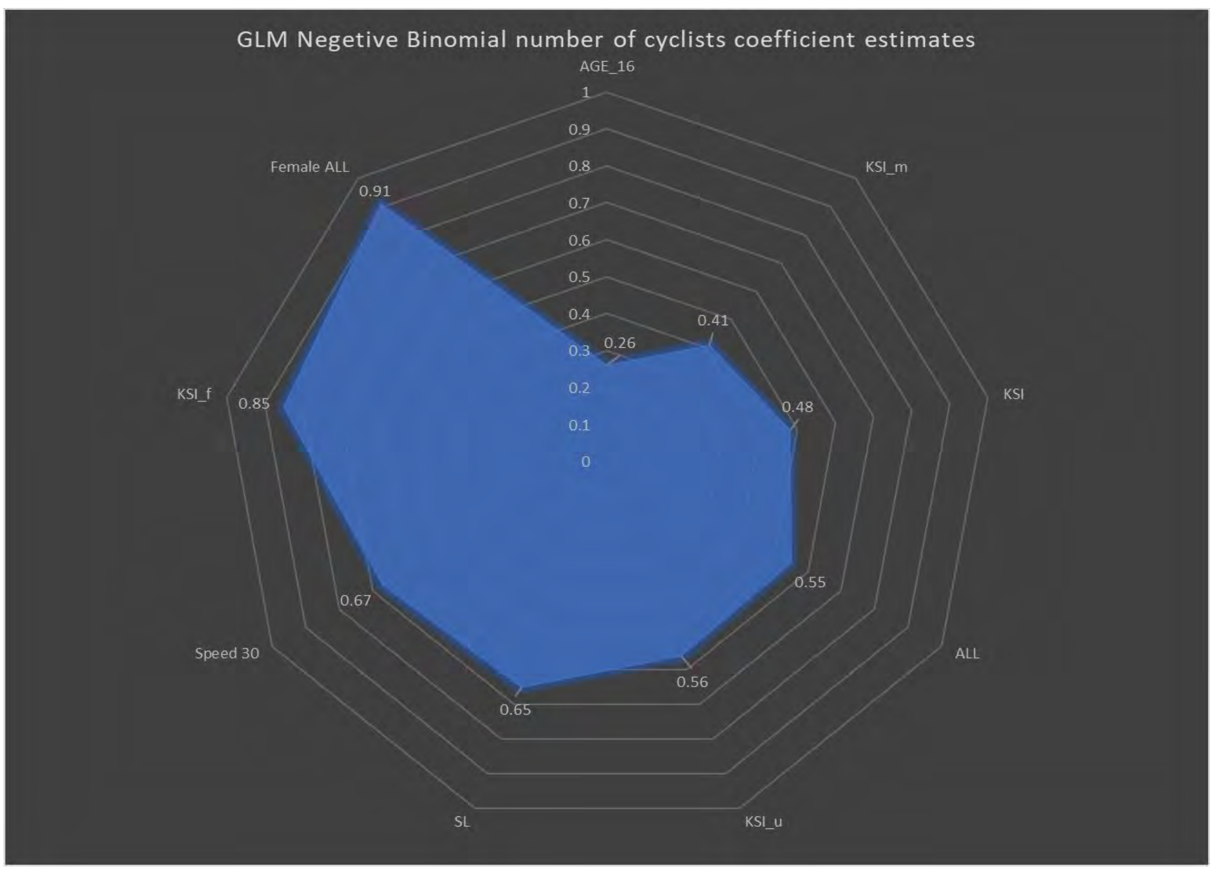

Figure 6-8 Model results illustrating the number of cyclist coefficient estimates from Table 6.5 and Table 6.6.

Three of the dependent variables selected resulted in low numbers of Female KSI casualties; KSI Under 16 years of age; and KSI Over 60 years of age so these results were considered potentially unreliable due to small numbers and over-fitted using multivariate explanatory variables. However, the stepwise regression analyses reduced the number of explanatory variables which reduced the likelihood of overfitting.

The estimates for male KSI (0.41) and the overall KSI (0.48) are very close to the *SiN* estimate of 0.41 (Jacobsen, 2003). However, the female KSI (0.91) is considerably weaker by comparison. This result echoes the findings in Chapter 5 where gender differences were found to effect model results. A *SiN* effect was found in all the models fitted to the Scottish dataset. The variation between the different model estimates for the number of cyclist exposure variables are illustrated in Figure 6-8 above, which is the *SiN* effect estimate.

The *SiN* effect from the all casualties model was 0.55, from the KSI casualties model it was 0.48 and from the slight casualties model it was 0.65. This indicates that slight injury collisions have a lower *SiN* effect compared to KSIs, but across all severities there is a positive *SiN* effect. The literature reviewed either examines fatal casualties or combined killed or serious cyclist collisions and rarely includes or examines slight injuries for a *SiN* effect. Furthermore, research that examined police recording in the STATS19 data of cyclist injury severity shows that there is evidence that cyclist's serious injuries are recorded incorrectly as a slight injury collision (Broughton and Keigan, 2010). Additionally, 37% of cyclists do not report their collision to the police (TS, 2016) so these injuries do not appear in the STATS19 records. The results presented here agree with previous research, however the KSI coefficient estimate of 0.48 is likely to be higher (i.e. tend towards 1, meaning less SiN effect) due to under-reporting and misreporting in Scotland.

The models for female KSI collisions and all female injury cyclist collisions showed the least SiN effect, the coefficient estimates were 0.85 and 0.91 respectively. In contrast, the model for male KSIs had a coefficient estimate of 0.41, less than half that of the female estimates. This result fits with previous research that argue that road safety concerns and risk of injury disproportionally impacts women (Aldred, 2015). The evidence is based on 'near misses' research that found that women reported twice as many 'frightening near misses' on the road than men, this aligns with our findings above.

Table 6.5 GLM-NB model results for all injuries, KSI, Slight injuries, All Female injuries and Male KSIs.(KSI_m)

	ALL		KSI		SL		Female ALL		KSI m	
Predictors	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*
(Intercept)	-4.69 *** (-5.77 – -3.60)	0.55	-5.79 *** (-7.59 – -3.98)	0.92	-5.81 *** (-7.80 – -3.82)	1.02	-4.32 *** (-5.57 – -3.08)	0.63	-6.63 *** (-8.63 – -4.64)	1.02
ln N Cyc	**0.55** *** (0.45 – 0.65)	0.05	**0.48** *** (0.31 – 0.64)	0.08	**0.65** *** (0.55 – 0.76)	0.05	**0.91** *** (0.75 – 1.06)	0.08	**0.41** *** (0.24 – 0.58)	0.09
lnmvkm v	**0.57** *** (0.32 – 0.82)	0.13	**0.74** *** (0.40 – 1.09)	0.18	**0.68** *** (0.37 – 0.98)	0.16			**0.94** *** (0.56 – 1.32)	0.19
ln RD L					**-0.67** *** (-1.06 – -0.28)	0.2	**-0.71** * (-1.26 – -0.17)	0.28		
ln N 0 Car					0.5 (-0.01 – 1.02)	0.26				
ln RL A			**-0.38** *** (-0.53 – -0.24)	0.07					**-0.48** *** (-0.64 – -0.32)	0.08
ln RL B					**0.29** * (0.06 – 0.52)	0.12				
ln RL C	**-0.20** * (-0.37 – -0.03)	0.09								
ln RL U							0.68 (-0.08 – 1.45)	0.39		
SMID 15 N	**0.11** ** (0.03 – 0.19)	0.04			0.07 (-0.03 – 0.17)	0.05				
Urban	0 (-0.00 – 0.01)	0			0.01 (-0.00 – 0.01)	0				
Observations	96		96		96		96		96	
R^2	1.000 / 1.000		0.945 / 0.963		1.000 / 1.000		0.998 / 0.998		0.918 / 0.946	
AIC	598.062		413.756		554.298		382.694		380.536	

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 6.6 GLM-NBmodel results for Female KSI (KSI_f), Urban KSI (KSI_u), Rural KSI (KSI_r), Children under 16 KSI (AGE16), Adults over 60 KSI(AGE60) and KSI at location with posted speed limit over 30 mph(Speed30).

	KSI f		KSI u		KSI r		AGE 16		AGE 60		Speed 30	
Predictors	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*	*Log-Mean*	*std. Error*
(Intercept)	-6.06 *** (-7.34 – -4.77)	0.66	-6.71 *** (-8.99 – -4.43)	1.16	-8.47 *** (-11.45 – -5.49)	1.52	0.6 (-2.41 – 3.61)	1.54	-17.27 *** (-21.95 – -12.59)	2.39	-7.53 *** (-9.07 – -5.98)	0.79
ln N Cyc	**0.85** *** (0.69 – 1.02)	0.08	**0.56** *** (0.39 – 0.74)	0.09			**0.26** ** (0.09 – 0.42)	0.08			**0.67** *** (0.56 – 0.79)	0.06
lnmvkm v			**0.63** * (0.07 – 1.20)	0.29	**1.74** *** (1.01 – 2.47)	0.37	**0.74** *** (0.37 – 1.10)	0.19	**1.42** *** (1.05 – 1.79)	0.19	**0.84** *** (0.57 – 1.11)	0.14
ln RD L							-4.10 *** (-6.15 – -2.05)	1.05			**-0.54** * (-1.03 – -0.06)	0.25
ln N 0 Car									**1.96** *** (1.06 – 2.85)	0.46	**0.96** *** (0.55 – 1.38)	0.21
ln RL A			-0.43 (-0.88 – 0.02)	0.23			**0.90** ** (0.33 – 1.48)	0.29			**-0.44** ** (-0.72 – -0.16)	0.14
ln RL B					**0.51** ** (0.16 – 0.87)	0.18	**0.40** * (0.07 – 0.74)	0.17			**0.39** ** (0.15 – 0.63)	0.12
ln RL C							0.53 (-0.03 – 1.09)	0.29				
ln RL U					**-1.16** ** (-1.98 – -0.33)	0.42	**2.00** ** (0.75 – 3.25)	0.64				
SMID 15 N					**-0.82** ** (-1.42 – -0.21)	0.31	**0.23** *** (0.12 – 0.34)	0.06	**-0.86** *** (-1.34 – -0.38)	0.25		
Urban			**0.01** * (0.00 – 0.03)	0.01								
Observations	96		96		96		96		96		96	
R^2	0.642 / 0.734		0.989 / 0.992		0.548 / 0.658		0.883 / 0.923		0.578 / 0.675		1.000 / 1.000	
AIC	222.948		346.009		261.855		403.709		268.495		555.946	

* *p<0.05* ** *p<0.01* *** *p<0.001*

In addition, Motherwell et al. (2018) reported that women and men's journey patterns are different, and women are more likely to be travelling with children, taking non-direct routes and trip chaining, all of which will slow you down. Furthermore, women cycle less as commuters and for leisure compared to men, so interestingly this does concur with the *SiN* effect. However, it does not account for the fact that overall cycling has increased although it may if women cycle outside the peak activity times (off-peak) thus, as Hauer (1995) pointed out, risk depends on intensity.

The previous section discussed the model results with respect to *SiN*, the next sections turn to the other explanatory variables presented in Table 6.5 and Table 6.6.

6.4.2 Results: Multivariate estimates

The overall KSI model (KSI) and the male model KSI (KSI_m) had low estimated coefficients for the number of cyclists (SiN effect), Table 6.5 above. Interestingly, the A Trunk Road explanatory variable (RL_A) was negatively associated with KSI collisions (i.e. safer) in both models. This is unexpected but not an unprecedented result. Aldred et al. (2017) found that urban trunk roads in London were safer despite higher speeds, higher traffic volumes and absence of cycling facilities. They reasoned that cyclists were most likely using the footways adjacent to the carriageway to avoid mixing with traffic and this is also likely to be the case here. In the first instance, rural A Trunk Roads have 2.5-meter hard shoulders and in urban areas cyclists may utilise the footway. While the use of the footway is not permitted in the main, local authorities are increasingly re-allocating and converting existing footways into shared paths for cyclists and pedestrians (see Chapter 2 for details). As such, the practice may be informally replicated in other areas by cyclists to avoid mixing with traffic. Another informal, but riskier, practice was highlighted in Chapter 5; pedestrian pelican, toucan or zebra crossing facilities were significantly associated with female cyclist collisions. Both results suggest that cyclists may be attempting to seek urban space that they perceive to be safer to avoid mixing with traffic.

Further, the model for cyclist collisions on roads with a posted speed limit of 30 mph or less (Speed_30), Table 6.6 above, showed that there was a negative association with A Trunk Roads but a positive association with B Trunk Roads. In this case, the available space away from traffic may not be available because B Trunk Roads typically have a hard strip (0.5 meters wide) rather than the wider hard shoulder or the availability of a footway wide enough to use. The rural KSI model stepwise regression excluded the cyclist exposure variable and the traffic volume variable coefficient estimate was 1.74, much higher than the other models, and there is no apparent SiN effect. As discussed in the previous chapter, most cycling takes place within urban areas and that rural areas have a higher risk of a cyclist having KSI collisions.

6.4.3 Summary Conclusions (Disaggregated *SiN*)

Disaggregating the different subgroups demonstrates that there are different risk patterns and levels and associated factors among cyclists. This confirms the need to generate gender-disaggregated statistics, identified by Motherwell et al. (2018), to carry out analysis that focuses on women to understand the impact of policy and to monitor the effects of infrastructure place-making on gender equality. This research identified that *SiN* does not materialise for women despite the global increase in the number of people cycling. Further research is needed to understand why the risk and *SiN* effect is not equal within the same system.

The model for cyclist collisions among children under 16 years of age (Age_16) had a very strong *SiN* effect which is unexpected, however the estimated coefficient for unclassified roads is 2. This suggests that children collision risk is very high on these types of roads which are typically residential type streets. The numbers of child fatalities have steadily declined since 2011; the importance of addressing these collisions is reflected in the child fatality and injury targets set out in the Scottish Roads Safety Framework (see Chapter 2 for more details). This is one area of road safety that has seen a great improvement over the past decade; the number of child casualties has halved[18] between 2011/2012 and 2016/2017 in line with targets and this is a plausible reason why the *SiN* effect was high, however the results may be questionable due to the small sample size.

Section 6.3 demonstrated that GWPR provides a better model fit for the data set examined compared to the traditional GLM-NB models, it demonstrated that spatial dependence was significant and that GWPR successfully accounted for the effect.

[18] *Scottish long-term road casualty trends, Table 8 of View Extra road accident and casualty tables.xls [on-line]. (Source: https://www.transport.gov.scot/publication/reported-road-casualties-scotland-2017/)*

Univariate models were developed in this chapter to compare the GWPR and the GLM-NB, further analyses from a multivariate GWPR would have yielded a more in-depth comparison to the GLM-NB results. However, the data disaggregation required to develop this is beyond the scope of the data used in this chapter. Multivariate GWPR will be examined with a larger dataset in Chapter 8.

Many of the LAs had a high *SiN* coefficient estimate for the number of cyclists (lnN_Cyc) (i.e. are less safe) and this suggests that, while there is an overall SiN effect (global average), some LAs may be experiencing a hazard-in-scarcity effect (Tin Tin et al., 2011). As discussed in Chapter 2 - Part B, this is where less people cycle for longer distance which increases their relative exposure to risk.

The C Road variable (RL_C) was negatively associated with the number of cyclists collisions (i.e. safer) in the GLM-NB model, Table 6.5 above, which accords with the *SiN* effect but it is also likely to be due to lower speeds and traffic volumes than A or B roads. This indicates that cycling on these roads may have a *SiN* effect because most of the distances cycled in Scotland are on minor roads[19] (B and C roads, and unclassified roads) accounting for 81% of roads in Scotland (TS, 2014).

As discussed above, most cycling activity is concentrated in urban areas and the results for the urban KSI model is 0.56 which aligns with previous research describing the *SiN* effect. Therefore, *SiN* is likely to present a realistic expectation and should be fostered. Also, urban and rural areas should be developed differently to address road safety.

6.5 Conclusions

The conclusions discussed in this final section includes the summary conclusions from Section 6.3 and 6.4 above. While the existence of a global *SiN* effect is evident in the results, several results within the same data set suggest that the *SiN* effect varies between the type of cyclists and from place to place.

Rapid urbanisation and shorter journeys made in cities provide an opportunity to shift from car use to other, more sustainable modes of transport. This shift has been the major focus

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[19] *Minor roads (C and B Roads) account for 2.5 of the total 3.1 billion miles travelled in the UK in 2011. Source: Table TRA0402: Pedal cycle traffic (vehicle miles) by road class in Great Britain, annual from 1993. https://www.gov.uk/government/statistical-data-sets/road-traffic-statistics-tra).*

of the Scottish Government's Cycling Action Plan, which sets out a vision of 10% of everyday journeys to be made by bike, by 2020. Within the action plan, cities in particular have been identified as major sites for transport behaviour change (Scottish Government, 2017). Therefore, *SiN* is likely to present a realistic expectation and should be fostered but rural areas should be developed differently to address road safety in a different way.

The comparison of the local and global methods in this chapter, the GWPR and GLM-NB, demonstrated that the GWPR provides a better statistical fit and provides more insight into the location and variation of significant effects than the traditional GLM-NB models used in road safety analysis. The outputs from a GLM-NB model provides a set of fixed global parameters. However, the impacts of parameter estimates could not be stationary over geographic space, given the variability in population, road density and traffic, etc. Therefore, it is possible that some variables will have a greater impact in certain counties/regions but will have smaller impacts in others. Thus, the accuracy of a global model to describe country level cyclist risk and indeed the *SiN* effect is not well founded.

OB-02: *Critically analyse road safety evidence, focusing on cyclists, to develop an understanding of the wider factors involved.*

The GWPR demonstrates that the explanatory factors involved in cyclist's road safety are not uniformly applicable to all areas and that the effect magnitude varies. The disaggregate GLM-NB models demonstrated that the *SiN* effect is much weaker among female cyclists.

RQ-01: *At a global level, is there a SiN effect evident among cyclists in Scotland?*

The research discussed in the previous section answers this question in two ways, firstly the results of the nine multivariate GLM-NB models disaggregated by injury severity, gender, location and age showed that male cyclists and urban cyclists gain the most from increasing the number of cyclists whereas rural and female cyclists benefit least. Secondly, there is an overall *SiN* effect in Scotland and the GWPR shows how the effect varies from one LA to another, the overall average magnitude of which is close to the *SiN* effect from the GLM-NB.

RQ-02: *Is there a reduction in cyclist injuries because of increasing cycling evident at a local population level?*

The GLM-NB global models examined the relationship between the number of cyclists and cyclist collisions at population level, in Scotland, and found that for all injury severities and sub-groups examined (male, female, under 16 years of age, over 60 years of age, urban and rural areas) there was a *SiN* effect but that the effect varied, in particular female cyclists had a marginal *SiN* effect with a coefficient estimate of 0.91.

The GWPR, showed that the *SiN* effect varies due to local conditions, illustrated in Figure 6-6 above, however the levels of cycling or numbers of cyclists alone do not fully explain all the results found in the GWPR model. Particularly, the City of Edinburgh has a high level of cycling (relative to Scotland as a whole) but it did not have a stronger *SiN* effect compared to most other LAs. Therefore, it cannot be concluded that increased cycling at a local level population level alone reduces injuries and that other factors must be involved.

RQ-04: *Are the prevailing national road safety policies a good fit for cyclists, if not, why? And can we provide better cyclists specific accident and safety evidence at a local level?*

The results discussed in this section have a number of data limitations, the first two are misreporting and under-reporting (see Chapter 2 for more details) such that the number of cyclist collisions recorded by the police in the STATS19 is lower than the actual number. The second is the data available to represent the number of cyclists or distance travelled by bicycle. Ideally, the distance travelled would be preferable (Elvik, 2009; Hauer, 2015) but the available data is unreliable because DfT estimates are based on small sample sizes.

Therefore, a better way to estimate cycling, to include off-road and canal path cycling etc., is required to improve our understanding and this will be explored in Chapter 7. The spatial GWPR model demonstrates that we can develop models that take account of spatial dependence to reveal local level estimates that can be mapped to provide better cyclist specific accident and safety evidence at a local level. Furthermore, women's cycling and transport needs should be factored into policies because they are currently under-represented in levels of cycling activity and according to this research do not benefit from *SiN* and have higher collision and KSI risk than men.

This research demonstrates how modeling the *SiN* effect and the risk rates at a LA level and mapping them facilitates cross referencing with other policy areas. The example discussed above concerning transport poverty highlights how this can be applied in a very easy to understand and non-technical way so that areas of higher risk for cyclists may not be suitable for such a policy intervention. Gough (2017) points out that people in deprived areas suffer double injustice because they do not contribute to consumption and climate change but are most likely to be impacted, therefore higher KSI risk and low *SiN* would unduly impact people whose only means of transport is their bicycle.

RQ-05: *What should Safety Performance Indicators measure to ensure cyclists benefit from road safety investment and the road safety system equitably?*

The GWPR model mapping in Figure 6-7 shows that such modeling can be used to reveal local level significance of *SiN* and potentially determine other explanatory factors effecting cyclist road safety. Furthermore, this technique is a valuable way to assess road safety against other policy areas and policy measures such as transport poverty and local health indices. As such it has applications to allow easy, non-technical, cross-disciplinary discussion and evaluation.

Disaggregating the different subgroups demonstrates that there are different risk patterns, levels and associated factors among cyclists. This confirms the need to generate gender-disaggregated statistics, identified by Motherwell et al. (2018), to carry out analysis that focuses on women to understand the impact of policy and to monitor the effects of infrastructure place-making on gender equality. This research has identified that *SiN* has not materialised commensurately for women even though increases in overall cycling numbers should be equal. Further research is needed to understand why this is occurring.

This chapter demonstrated that there is a spatial dimension to the *SiN* effect and that the magnitude of the effect varies from place to place. This suggests that a single *SiN* metric is not appropriate for use at country level and that specifically the supposition that "doubling cycling halves risk" should not be applied without local evidence.

The spatial GWPR model was used to estimate local model parameters for each LA which showed that the strongest *SiN* effect was found in the Highlands which was unexpected because Edinburgh has the highest model share of cyclists in Scotland. This suggests that other confounding factors may be affecting the *SiN* value in addition to just the number of cyclists. Andersen and Solbraa (2018) found that the decline in injuries in Denmark could not be attributed to increased numbers of cycling alone, instead they suggest that infrastructure improvements and availability were the factors which had, in reality, an impact on safety for cyclists.

This chapter discussed several limitations and while adjusting for under-reporting and misreporting are beyond the scope of this thesis, the question of appropriate exposure measures will be further explored. The next chapter will elaborate upon a novel traffic method to provide more accurate estimates of all cycling distances travelled including the off-road facilities which the current DfT estimates do not include and Chapter 8 will examine *SiN* more closely to evaluate what factors influence *SiN* and cyclist safety because increased cycling alone does not explain the results found in this chapter.

CHAPTER 7

Development of a Cyclist Flow Model[20]

7.1 Introduction

This Chapter describes the application of a novel methodology for developing a cycling flow model and model validation methods. A combination of traditional (Census and Automatic Traffic Counts) and novel (Open Street Map) data was used to produce flow estimates at both link and meso-spatial area levels. The application of the method is illustrated using Edinburgh City as a case study. The model was developed for the city of Edinburgh because of the availability of observed cyclist flow data, from City of Edinburgh Council, and because Edinburgh has experienced relatively high cycling growth compared to the rest of Scotland, and is therefore the most likely to exhibit a Safety in Numbers (*SiN*) effect that will be the subject of Chapter 8.

The Cycling Action Plan for Scotland (CAPS) vision aims for 10% of everyday cycling trips by 2020 (TS, 2017), the City of Edinburgh Council (CEC) through its Active Travel Action Plan has a higher aim of 15% because in 2009 CEC signed the Charter of Brussels which also includes the road safety target to reduce the risk of a fatal cyclist accidents by 50% by 2020.

Scotland has seen an almost doubling in the distance cycled over the past decade with an overall 41% increase in cyclist traffic, kilometers travelled (TS, 2017). In Scotland, Edinburgh stands out as a city that has increased its modal share and some areas of the city, such as the Meadows and Morningside, the national target in 2011 has already been reached with 10% of trips to work cycled. Further, this growth trend has continued to increase throughout the city.

CAPS provide annual reports on a suite of national indicators to inform the national picture of cycling participation. It also sets out to develop local monitoring tools, using data

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[20] *This Chapter is adapted from the following paper: Meade, S. and Stewart, K., (2018). Modelling Cycling Flow for the Estimation of Cycling Risk at a Meso Urban Spatial Level, Transportation Research Procedia, 34, pg. 59-66. https://doi.org/10.1016/j.trpro.2018.11.014.*

from local cycle counts and surveys to develop a coordinated approach to data collection. Local level monitoring of cycling safety is also included the City of Edinburgh Council (CEC) Active Travel Action Plan (ATAP) targets to produce a cycling casualty rate index to monitor road safety based on count data commencing 2016. Edinburgh has a relatively large number of counters that record cyclist volumes across the city but there is currently no model for cyclist flows either as part of an overall transport model or as a stand-alone cyclist flow model such as the Transport for London Cynemon[21] strategic model.

A review by the International Transport Forum (ITF) of the ability of cities in the EU to plan for vulnerable road users (VRU) concluded that many cities do not have the capacity to measure the level of risk experienced by VRU in urban traffic (ITF, 2019) and Castro et al. (2018) found that this extended to country level. The IFT (2019) state that the challenge lies with the need estimate the total amount of travel for each transport mode within a city and that the responsibility for this type of mobility data traditionally rests with authorities outside the remit of local government road safety teams, and they are *fundamental* to the elaboration of sustainable mobility plans.

Many national authorities seek to increase rates of cycling while at the same time improve road safety, however many authorities lack reliable ‘exposure’ metrics to calculate collision and injury rates (OECD/ITF, 2013). Detailed traffic data has the greatest potential to improve safety analyses (Lord and Mannering, 2010) however one of the prevailing challenges in cycling research is ascertaining a representative level of ‘exposure’ or simply “how much cycling happened and where”, also traffic exposure is a key determinant of the likelihood of being in a road collision (Loo and Anderson, 2016).

The choice or availability of ‘exposure’ variables influence analytical choices when developing accident prediction models (Hauer, 2015), the results presented in Chapter 5 demonstrate the difference between results using three possible ‘exposure’ variables. Quite often proxy estimation, based on trip production or population, may be the only information available. However, Loo and Anderson (2016) argue that population-based exposure or those based on registered vehicles in a society, are not true risk rates.

[21] *Cynemon - Cycling Network Model for London is a new innovative strategic cycling model which estimates the number of cyclists and their routes and journey times across London (TfL, pg. 11. http://content.tfl.gov.uk/londons-strategic-transport-models.pdf*

The research presented in this addresses the following research objective and research questions discussed in Chapter 3:

OB-02: *Critically analyse road safety evidence focusing on cyclists to develop an understanding of the wider factors involved*;

RQ-04: *Can we say that existing road safety policy, subsequent implementation processes have been a good fit for cyclists, and if not why, can we model better?; and*

RQ-05: *What should Safety Performance Indicators measure to ensure cyclists benefit from Road Safety investment equitably?*

The aim of this chapter is to develop a cycling flow model that can estimate cycling traffic volumes, both on-and off-road flows, within a city to address the current challenges faced by road safety and planning professionals responsible for delivering roads safety and sustainability in their cities.

The chapter is organised as follows, the first section, Section 7.2, provides a background and comparison of the changes between the 2001 and 2011 cyclist model shares in Scotland, in Section 7.3 a description of the study is presented, Section 7.4 discusses the methodology and data collection and the validation process, in Section 7.5 the validated model flows are compared to population based estimates to examine the implication of using either method for modeling and risk estimation purposes, Section 7.6 provides an overall discussion of the main findings and finally Section 7.7 provides the overall conclusions discussed with reference to the research objectives and questions.

7.2 Comparison of 2001 and 2011 Census Cyclist Mode Share Data

The change in the percentage of commuter cycling in Scotland between the 2001 and 2011 Census results illustrated in Figure 7.1 below. As a measure of cycling generally, the mode share has not changed substantially between 2001 and 2011. The council area with the highest mode share change is ‘City of Edinburgh’ it increased from approximately 2% to 4.8% in ten years, shown in green below in Figure 7.1.

Between 2001 and 2011 the risk per cyclist at a Scottish Council Area level appears to have deteriorated, Figure 7.2 below, except for the 'City of Edinburgh' that appears to have remained static despite the increased modal share.

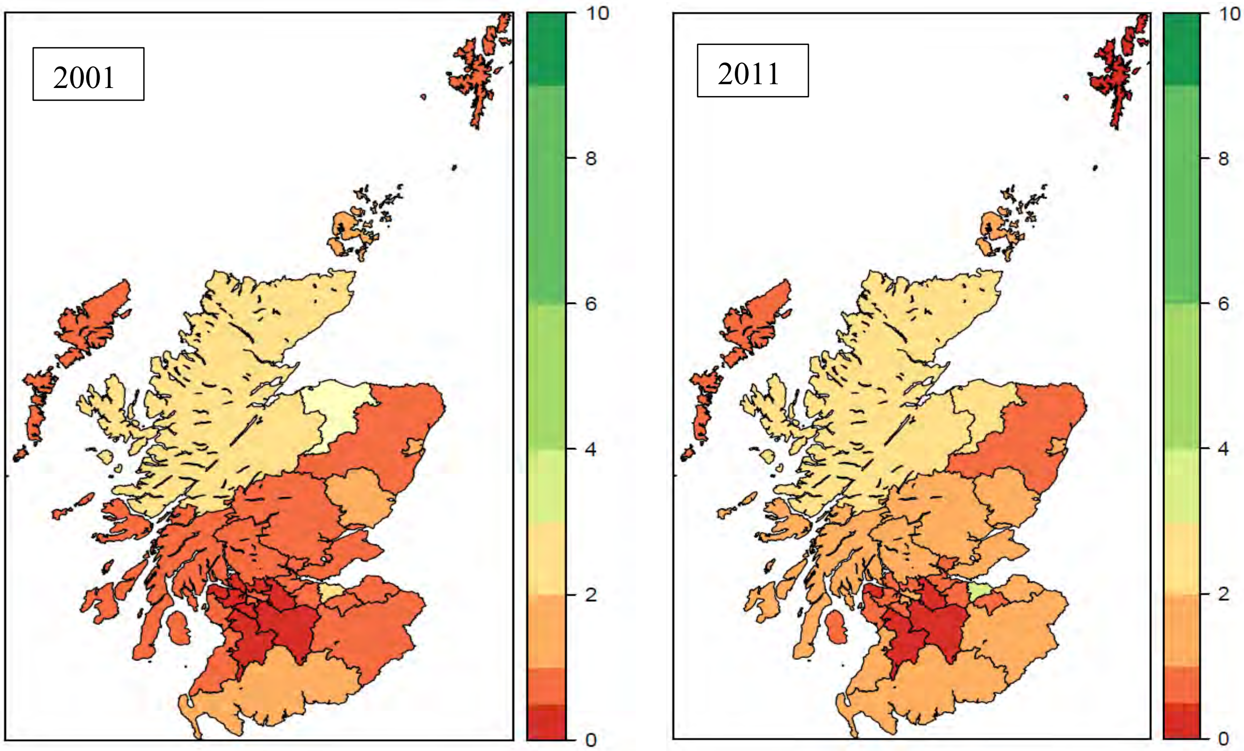

Figure 7-1 2001 and 2011 Census cyclist mode share by Scottish Council Area.

If we examine the change in collision risk, using mode share as the 'exposure', derived for the number of killed or serious injuries in each Scottish Council Area divided by the number of people who said they commuted to work or education by bike, illustrated in Figure 7.2 below, we see that there was a general increase among Scottish Council Area in the levels of cyclist collisions compared to how many people were cycling in the south-west of Scotland. In more detail, Figure 7.3 and Figure 7.4 below, compare the number of residents commuting by bike (on the left axis, from the Census 2001 and 2011) and the cycling mode share, proportion of commuter cycling of all bike trips shown for each Scottish Council Area (on the right axis).

The results presented in Chapter 6 found no significant difference between the models developed using the population count of the numbers of commuter cyclists in each local council area and the DfT estimates of the annual million vehicle kilometers distances travelled. According to Goodman (2013) cycle commuting by residents as a proxy for volumes provides a good representation of cyclists overall travel because commuter cycling is a reasonably good area-level proxy for all cycling (Goodman, 2013). At Scottish Council Area level, cyclist journey distance is very likely to stay within the council area due to its large geographic area.

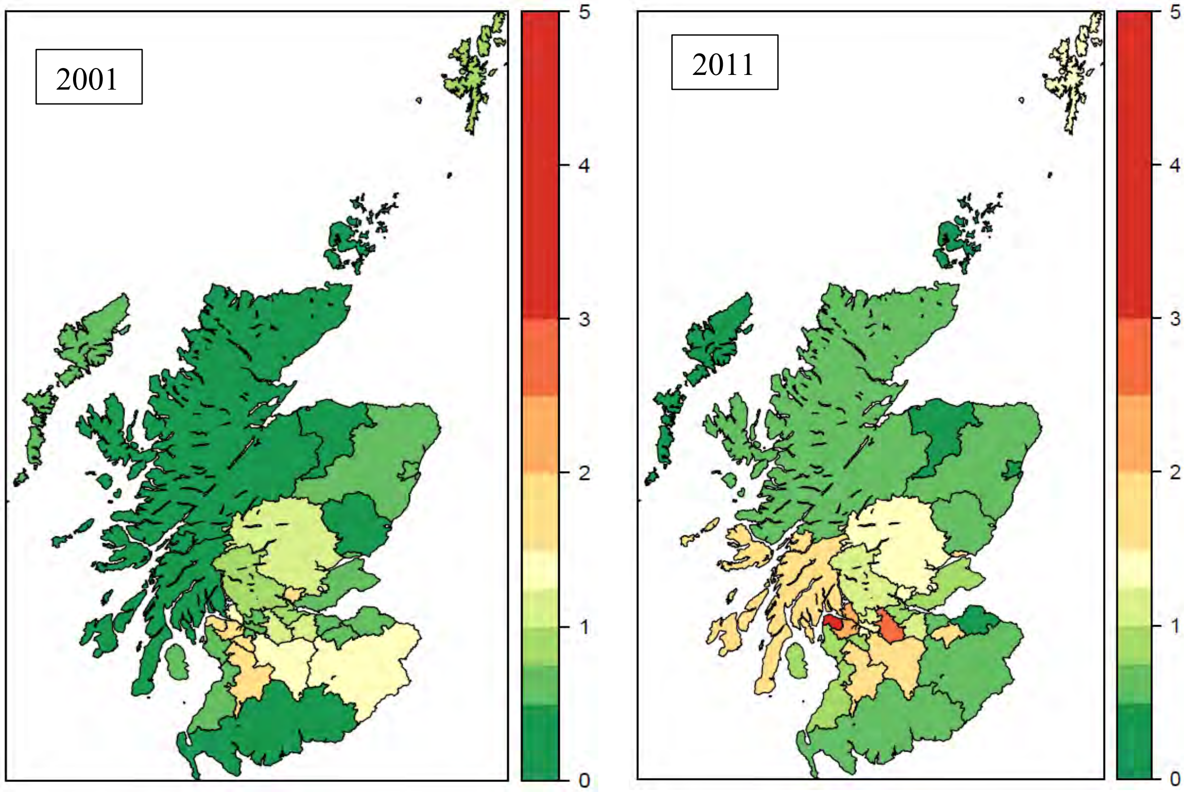

Figure 7-2 Relative change in cyclist risk between 2001 and 2011 by Scottish Council Area.

However, at a smaller scale, the use council area level resident trip rates as a proxy for overall cycling volume is not representative because it will most likely under estimate inter zonal travel through zones.

Moreover, cycle commuter volumes within a small area zone, which include changes within the zone among the zone resident’s cycle commuting rates and residents from other zones that commute from different zones, may include a substantial number of commuters whose origin did not show a change in modal share. Furthermore, if we take cycle commuting percentages per zonal area as a proxy for cycling volume *in a ward or zone* when looking at injury rates, there will be systematic bias in the level of risk derived. The higher count of reported cyclist injury accidents may be due to more cyclist activity or higher injury risk at low levels of cycling.

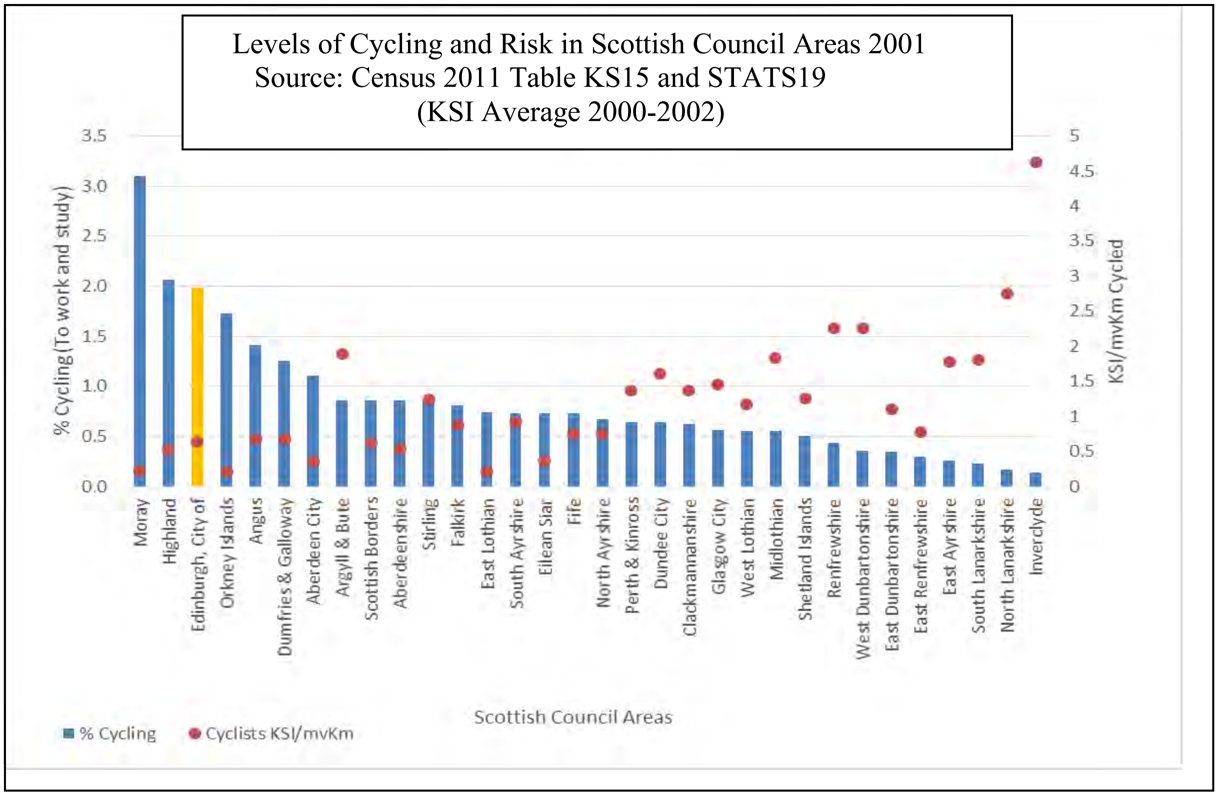

Figure 7-3 Levels of Cycling and Risk by Scottish Council Area 2001 (NRS, 2001)

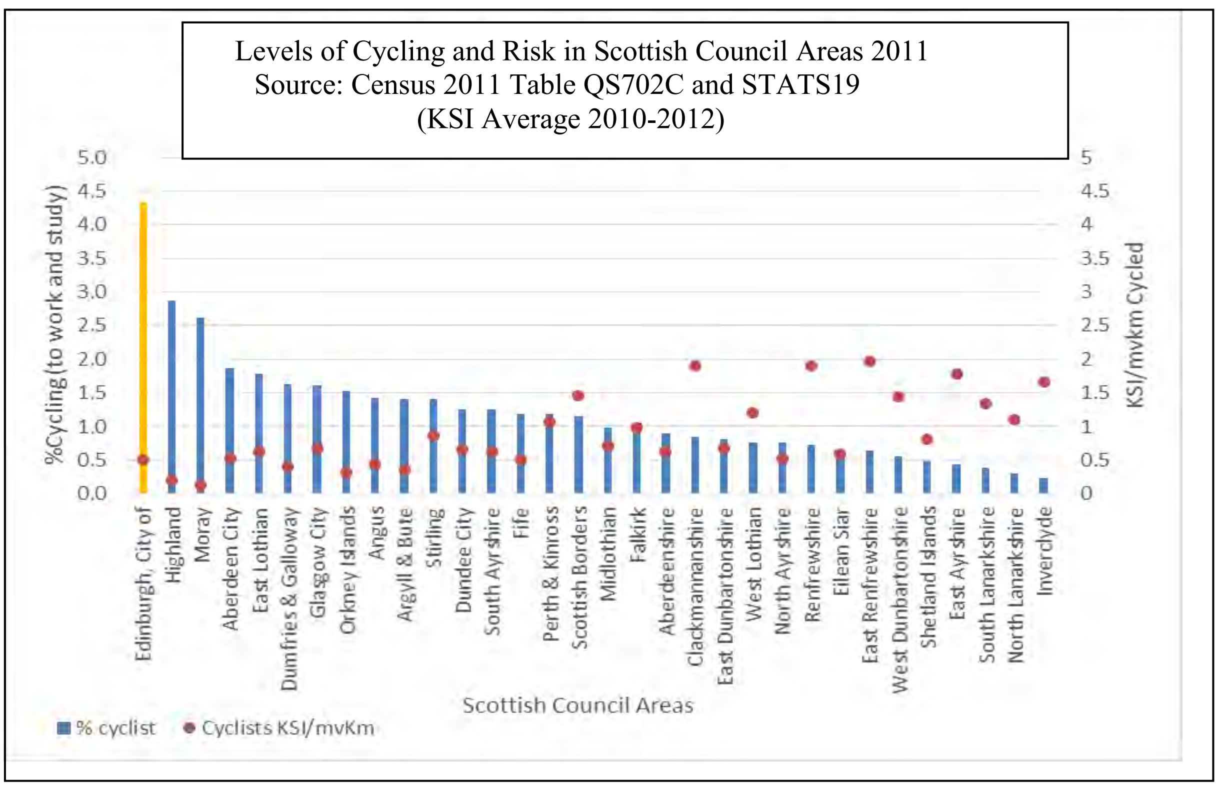

Figure 7-4 Levels of Cycling and Risk by Scottish Council Area 2001(NRS, 2011)

The next section will examine how to measure cyclist activity level (i.e. intensity of use or 'exposure') and compare the results with the proxy measurement discussed above (i.e. population level count of cyclists). To do this we used the City of Edinburgh as a case study for two reasons, cycling is well established and growing which presents an opportunity to examine *SiN* in the next Chapter and because the City of Edinburgh council (CEC) routinely collects cycle flow data at numerous counters across the city which is a vital piece of information required to validate our findings.

7.3 Description of the Study Area

Edinburgh is the capital city of Scotland with a population of about half a million inhabitants. It has a compact form where 55% of the city's population live within 4 km of the center (CEC, 2014). Edinburgh has experienced a doubling of cycling activity between the years 2001 and 2011, see Figure 7-1 above, from 2% to 4.8% a trend well ahead of the national average.

Within the city however the mode share varies from 10% to 2.5%. Edinburgh comprises 18 wards and 111 Intermediate Data Zone Geographies (IZ), Figure 7-5 below, built up from data zones that nest within the local authorities boundaries. They contain between 2,500 and 6,000 household residents.

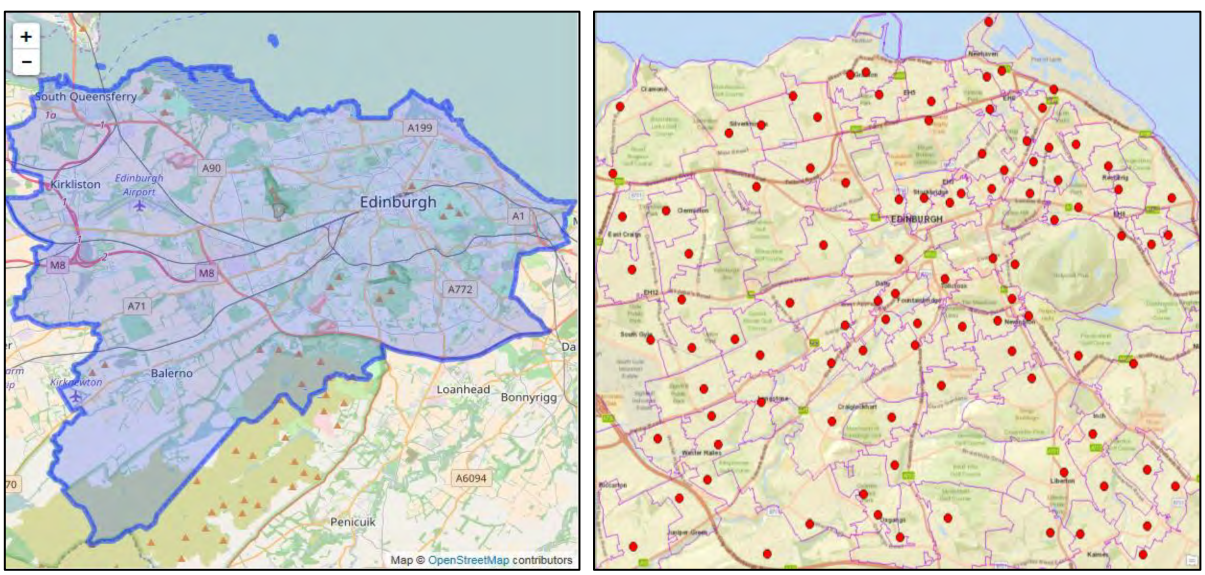

Figure 7-5 Edinburgh city boundary extents and centroid points of the 111 Intermediate Data Zone Geographies (IZ).

The Cycling Action Plan for Scotland (CAPS) vision aims for 10% of everyday cycling trips by 2020 (TS, 2017), the City of Edinburgh Council (CEC) through its Active Travel Action Plan has a higher aim of 15% because in 2009 CEC signed the Charter of Brussels which also includes the road safety target to reduce the risk of a fatal cyclist accidents by 50% by 2020. At the core of the Safety Plan for Edinburgh 2020 is Vision Zero. The ultimate goal is that all users are safe from the risk of being killed or seriously injured, however, unlike London; the city does not have a strategic cycling model.

7.4 Methodology and Data to Estimate levels of cycling

This section describes how the mobility-based 'exposure' model was developed using several data sources, Department for Transport (DfT) for major and minor roads, City of Edinburgh Council (CEC) automatic counters (AC) at on-road and off-road cycle routes and the 2011 census provided the origin destination (O-D) flow data sets (ONS, 2014) for the O-D matrix, see Figure 7-6 below. The 'exposure' data developed in this chapter will be used in Chapter 8. This section also describes how the population-based 'exposure' was estimated for comparison to the Cyclestreets.net has three built-in cycling route options, Fast, Balanced and Quiet to replicate the route choices favored by fast and experienced utility cyclists to cyclists who may wish to avoid traffic and who are willing to choose less direct routes.

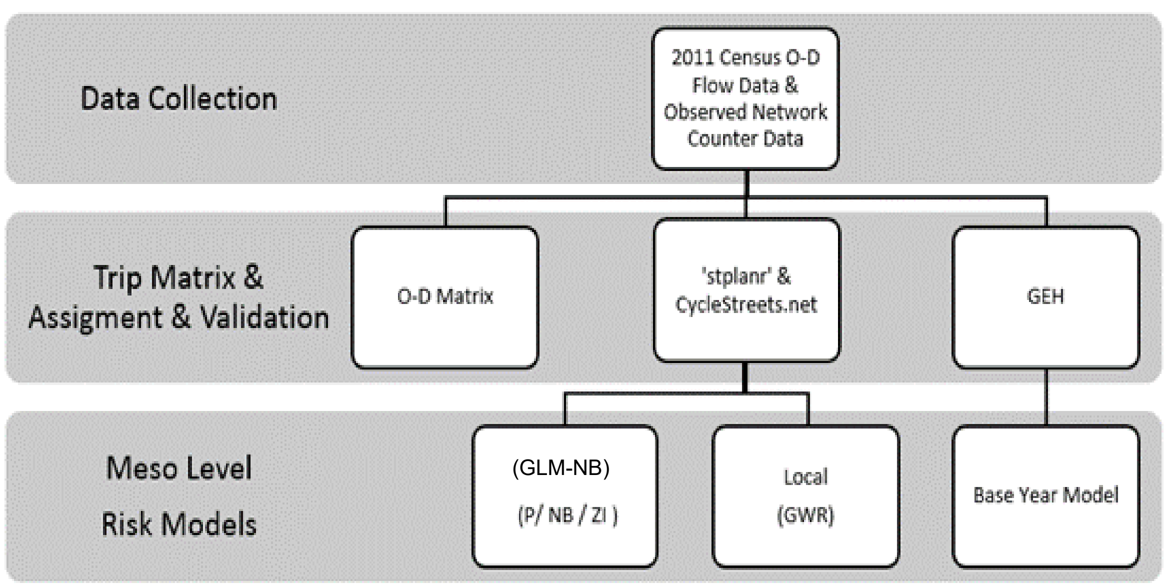

Figure 7-6 Study procedure.

All three options were validated against observed cyclist flow volume data, from the n=96 counter locations in Edinburgh. The three models (Fast, balanced and Quiet) modelled flows were compared to the observed link flows using a GEH (Geoffrey Edward Havers) method. The GEH statistic is a modified Chi² statistic used to calculate a value for the difference between observed and modelled flows, it is a widely used criterion (Giuffre et al., 2017) used by UK Highways Agency and Transport for London (TfL) among others (7.1).

$$GEH_j = \sqrt{\frac{2(O_j - M_j)^2}{O_j + M_j}} \tag{7.1}$$

Where M is the modelled flow and O_j is the average observed flow. A GEH less than 5.0, for 85% of the model, is acceptable. GEHs between 5.0 and 10.0 may warrant investigation. The data information formats differed, therefore a long-term hourly average flow was used. The GEH has limitations; it does not take account of the variability of the count data and typically uses peak hourly flows to determine 'goodness of fit' (Feldman, 2012). For robustness, and to reflect the fact that the GEH is intended for peak hourly motorised traffic flows, the Pearson's correlation coefficient and linear regression were also examined. The best fitting model will provide the 'exposure' explanatory variable for the models developed in Chapter 8.

7.4.1 Population based

To estimate population-based cycling exposure (Lovelace et al., 2016) in each IZ formula (7.2) was used. Where D_{Prod} is the total annual average distance cycled in each IZ, *n* is the number of people who cycled to work (estimated from Census 2011), *f* is the frequency of trips (assuming 400 one-way trips per capita each year[22] (Hall et al., 2011)), *d* is the average trip distance (estimated from TS (2015)) and *p* is the proportion of bicycle commuter trips (assuming the proportion of commuter trips is one third of all cycling trip purposes (Goodman, 2013; Sustrans, 2017)).

$$D_{Prod} = n \times f \times d \times p \tag{7.2}$$

As in previous research (Lovelace et al, 2016) it is assumed that cycling trips to work can be used as a proxy for all cycling trips because they are highly correlated to cycling modal share for all trips (Goodman, 2013). There were n=9478 trips to work by bicycle,

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[22] *This assumption was used because it is used in previous research (Lovelace et al., 2016) and the Propensity to Cycle Tool (Lovelace et al., 2017) and there was no alternative available at the time of writing).*

n=9143 trips started and ended within Edinburgh boundaries and n=335 (3.5%) of trips started and ended in the same IZ, Table 7.1 above.

Table 7.1 Edinburgh Scottish Intermediate Data Zone - Cyclist trips (ONS, 2014).

Origin-Destination Trips Census 2011	No. trips	(%)	Total	*(IZ)*
Inter Zonal (Within Edinburgh)	8808	93	N= 9478	N = 111
Inter Zonal (All trips)	9143	96.5		
Intra Zonal	335	3.5		
Total	9478	100		

The small percentage of trips that started and ended within the same zone (3.5%) means that all the other 96.7% of trips passed into or through at least one other zone to reach their destination. A population-based ‘exposure’ measurement cannot capture this aspect of flow intensity or activity.

7.4.2 Mobility-based Flow Model for cycling

The main dataset used is a table of the origin-destination (OD) pairs from the 2011 Census open access file WU03BSC_IZ2011_Scotland.xls, provided by the UK Data Service of commissioned tables. The OD data was assigned to the transport network using the R package ‘stplanr’[23] (Lovelace et al., 2016), see model process schematic in Figure 7-7 below.

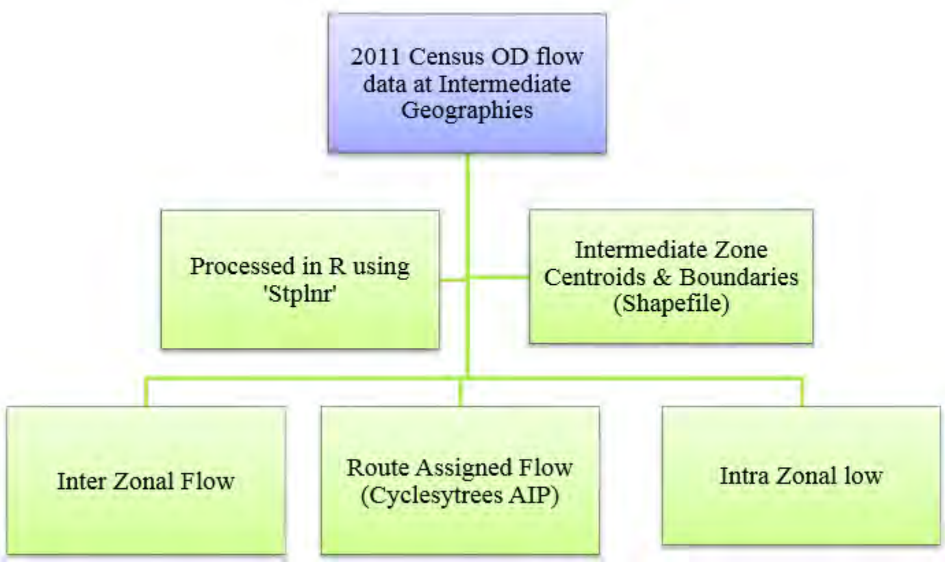

Figure 7-7 Model building schematic

[23] *Since writing the ‘stplanr’ R package has evolved into two separate packages ‘stats19’ and ‘cyclestreets’ stats19 was published on the Comprehensive R Archive Network (CRAN) in January 2019 (Lovelace et al. 2019).*

The routing engine and route assignment are dealt with differently in 'stplanr'. An external routing engine, CycleStreets.net, is employed via an application interface program (AIP) developed specifically for cycling based on an Open Street Map (OSM) that replicates the decisions a knowledgeable cyclist would make to find a route to their from their origin to their (Nuttall and Lucas-Smith, 2006).

The route flow assignment is estimated using stplanr::overline, a function that aggregates overlapping lines (Rowlingson, 2015). First the O-D flows are aggregated in each IZ, then the O-D data is converted into Euclidian flows between O-D pairs (via matrix estimation using doubly constrained gravity model), the flow lines are then allocated to the network using CycleStreets.net and finally the overlapping routes aggregated to produce modelled link flows, Figure 7-9 illustrates the process.

Figure 7-8 Comparison a) IZ with Population Weighted Centroids; b) Euclidean lines between O-D pairs; c) Route allocated flows from stplanr and Cyclestreets.net.

7.4.2.1 'Stplanr' in more detail

Although the Census flow data describes movement over geographical space using geocodes for the O-D it does not contain geographical information (i.e. it is a matrix or data frame). The 'Stplanr' facilitates linking the O-D data to the spatial data. The geographical data is a set of points representing the centroids of the O-D pairs, saved as a Spatial Points Data Frame which provided '*as the crow flies'* lines between IZ population weighted centroids. Linking the data produces an new data file, Spatial Lines Data Frame, which contains the lines between O-D pairs as shown in Figure 7-9 and Figure 7-10 below, each line is associated with the IZ geocode reference for the start and end point, the number of people from the origin zone who took that route and the distance of the route.

While this method evaluates the between-zone ('interzonal') O-D data it does not estimate those commuting within a specific zone (within-zone or 'intrazonal' travel), or those with no fixed workplace. The ‘intrazonal’ flow is estimated separately and added back to their respective zones in the final calculation. For example, Figure 7-11 and Figure 7-12 illustrates how the straight line routes crisscross an IZ.

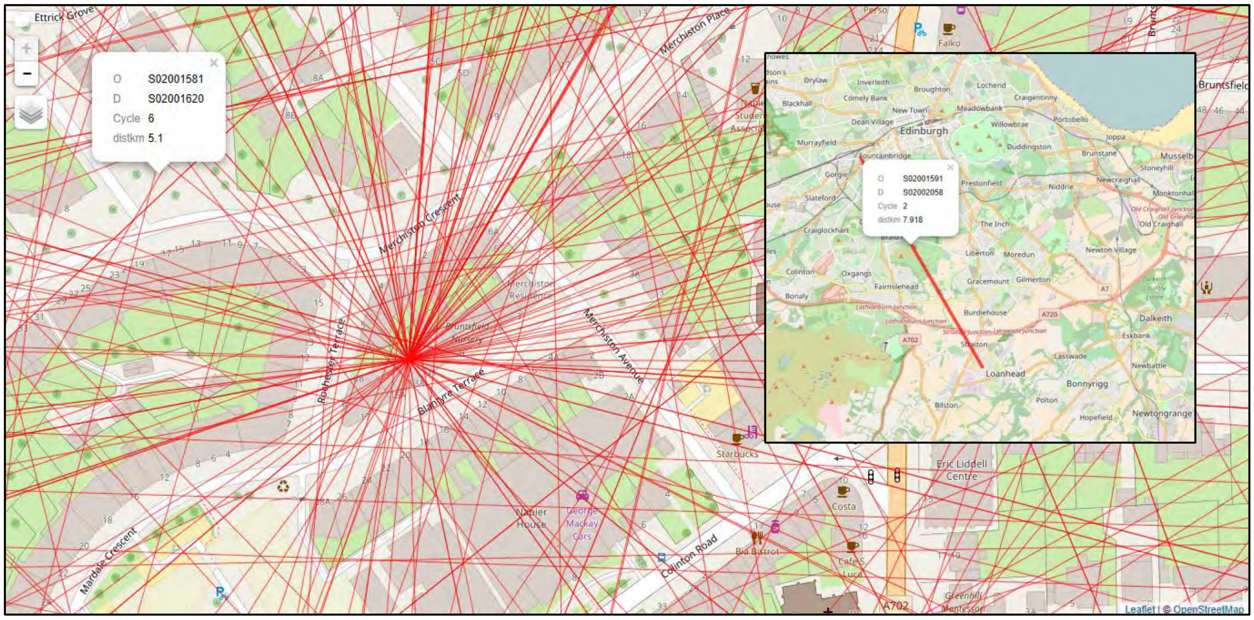

Figure 7-9 O-D pairs straight lines between pairs.

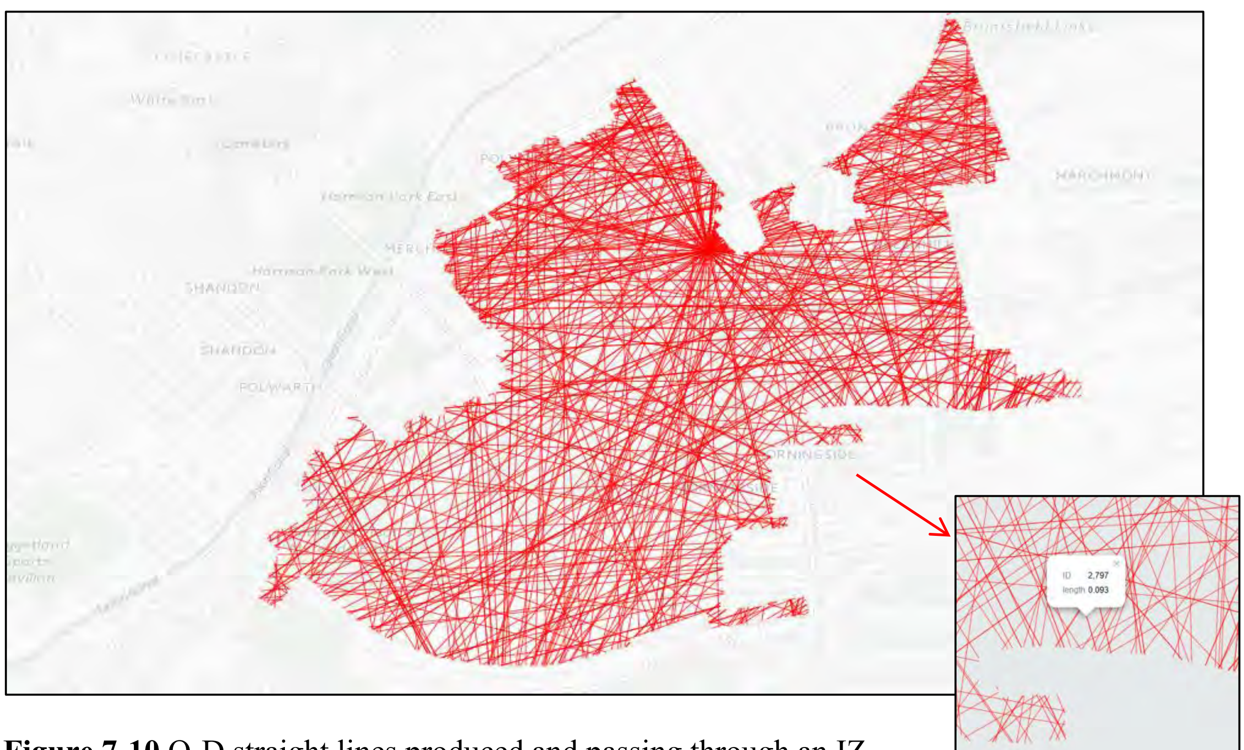

Figure 7-10 O-D straight lines produced and passing through an IZ.

The O-D lines are cut at each IZ boundary and a new data frame is formed which contains the length of each O-D line segment belonging to the individual zone, the zone its associated with and its name, the original O-D and the complete trip distance. It is now possible to measure the intra and inter zonal (i.e. passing through) flows associated with each zone across a network are accounted for.

Cyclestreets.net has three built-in cycling route options, '*Fast*', '*Balanced*' and '*Quie*t' to replicate route choices favoured by fast and experienced utility cyclists to cyclists who may wish to avoid traffic and who are willing to choose less direct routes. All three models were developed because there is no information available to benchmark against. The next section compares the options and discusses the validation against observed (O) cyclist flow volume data.

7.4.3 Flow Model Results Comparisons

The summary statistics of the *Fast*', '*Balanced*' and '*Quie*t' flow models are presented in Table 7.2 below and illustrated in Figure 7-11 to Figure 7-13 below. The thickness of the lines indicate higher volumes, as expected higher volumes in the city center areas were observed. The trip lengths, measured by network distance, show similar tends, however the '*fast*' model mean trip length is shortest. The '*fast'* model vkm totals are smaller than the '*quiet*' model total vkm, which reflects the slightly longer and less direct 'quiet' routes. The 'fast' model covers the largest proportion of the available network, flows tend to be higher on busy main roads, which provide directness and have less flows on quieter routes or off-road routes when compared to the '*quiet*' model.

Table 7.2 Comparison of the CycleStreet.net routing engine options analysis in stplanr.

CycleStreets.net Route Estimation Method	Segments	Network *(km)*	*vkm*	Annual *mvkm*	Trip Length *(Km)* *(mean, median, SD)*		
Fast	N=3481	693	47,688	57.2	5.4	4.5	5.7
Balanced	N=3163	675	48,958	58.7	5.6	4.5	6.3
Quiet	N=3207	645	49,348	59.2	5.7	4.6	6.6

Figure 7-11 Cyclist flow “Fast” (white) option results mapped against quiet roads in green.

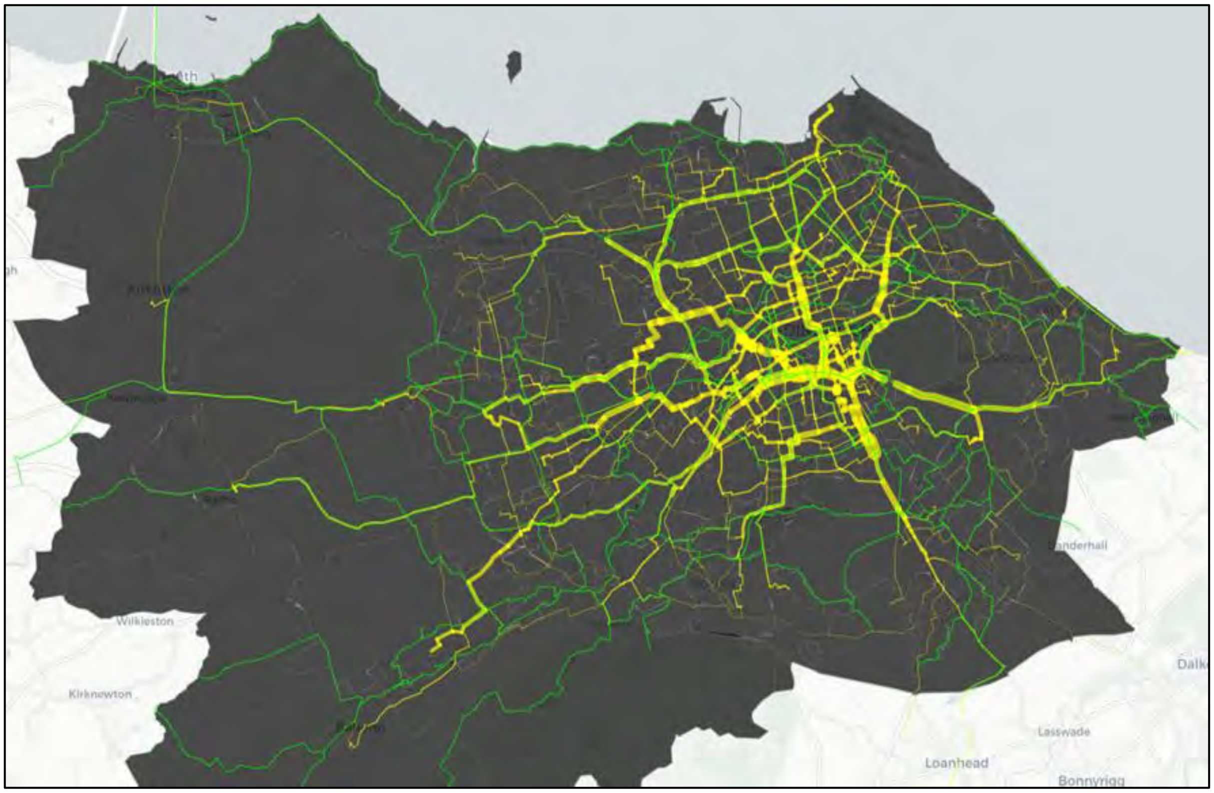

Figure 7-12 Cyclist flow “flow “Balanced” (yellow) option results mapped against quiet roads in green.

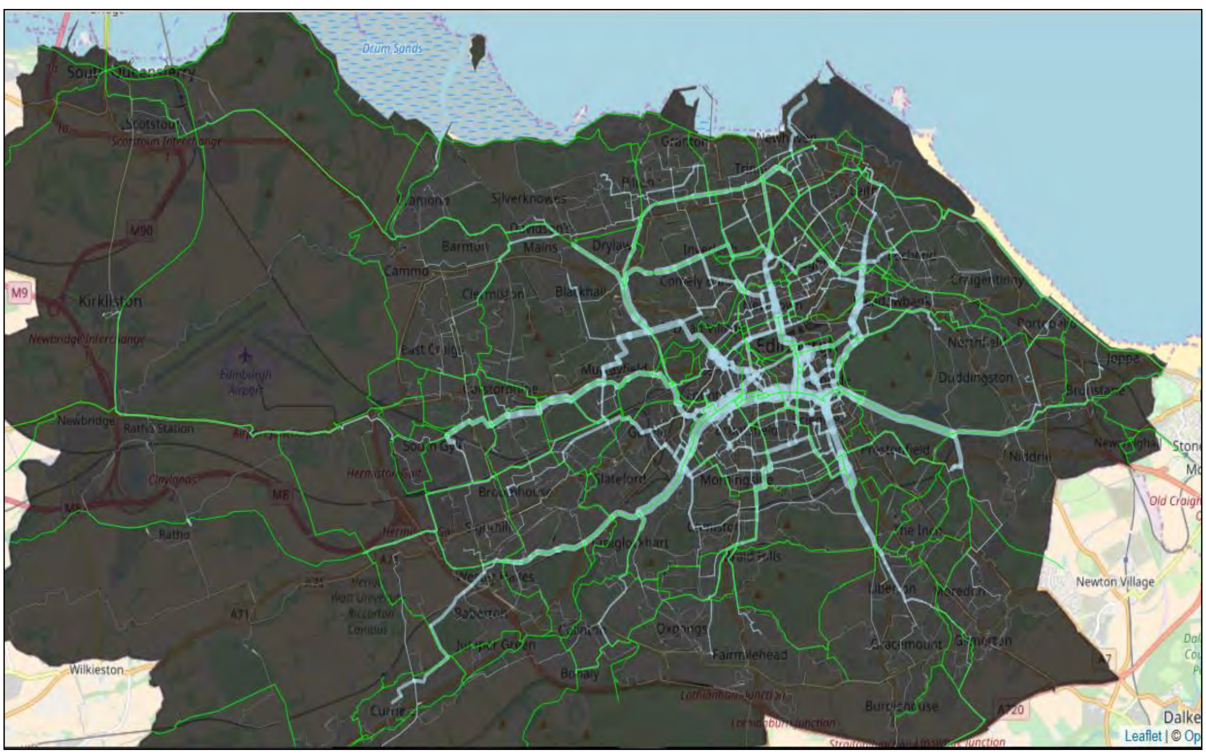

Figure 7-13 Cyclist flow “Quiet” (blue) option results mapped against quiet roads in green.

The ‘green’ lines shown in Figure 7-11 to Figure 7-13 highlight the CEC designated ‘Quiet Routes’, as shown Figure 7-13 overlaps with more of the ‘green’ lines than Figure 7-11.

7.4.4 Model Validation

The three models (Fast, Balanced and Quiet) modelled flows were compared to the observed flows using a GEH (Geoffrey Edward Havers) method, the following section describes the validation process.

The model produced in R allows for easy data comparison using r package Leaflet and Open Street Maps, as shown Figure 7-15 below.

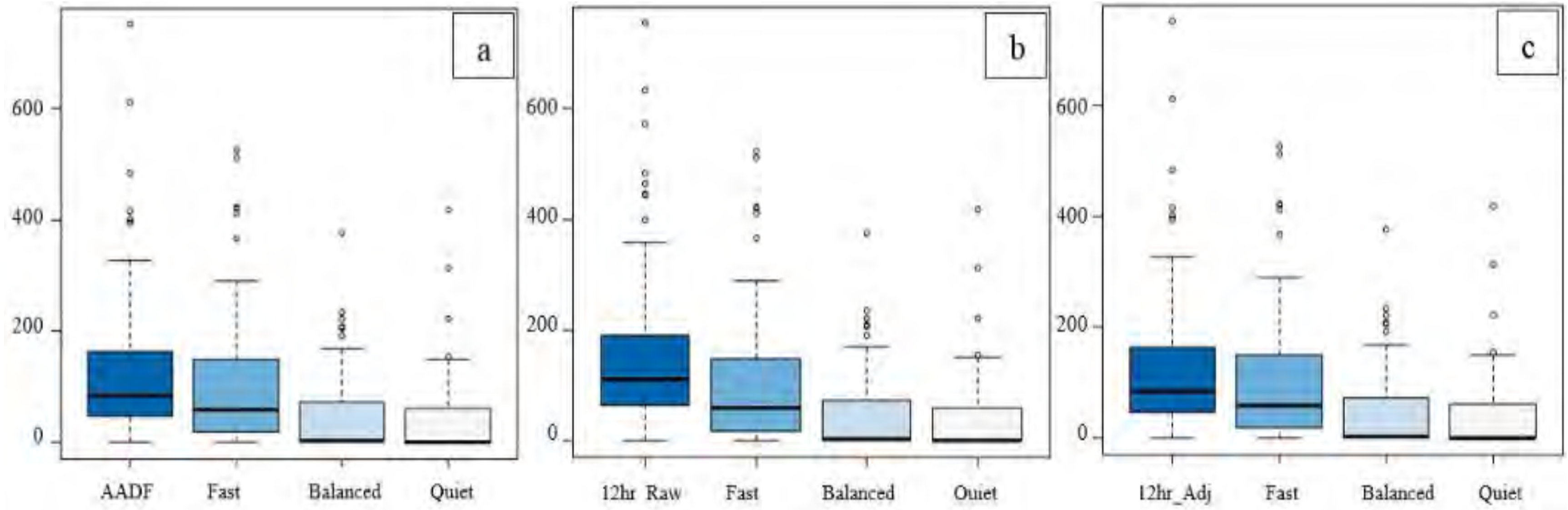

Figure 7-14 Box Plots modelled flows versus a) AADF; b) 12hr; c) 12hr adjusted counts.

Figure 7-15 Counter locations and modelled flows in R model created using ’**stpanr’**

7.4.4.1 Observer cyclist counter data

As mentioned in the previous section, CEC has a relatively large number of cycle counters throughout the city which allowed validation of the off-road modelled flows that could not be validated if the DfT counters were the only data available. In total the study used observed data from n=96 count locations, Figure 7-16 below, to validate modelled link flows, n=54 major roads, n=24 minor roads and n=18 on-road and off-road cycle routes.

The cyclist data varied in metric and completeness, for example; the DfT data provides average annual daily flow (AADF) estimates and weekday 12-hour manual counts, the CEC data provided 24hr raw counts.

On the other hand the O-D flow data from the census only captures trips to work on an average day. Further, the census data was collected in March therefore a 12hour adjusted estimate was derived to take account of seasonality and to provide a common metric from which to use and compare the data sets and the following assumptions were made: work trips covered a 12-hour period between 7am and 7pm and AADF represents 16 hours.

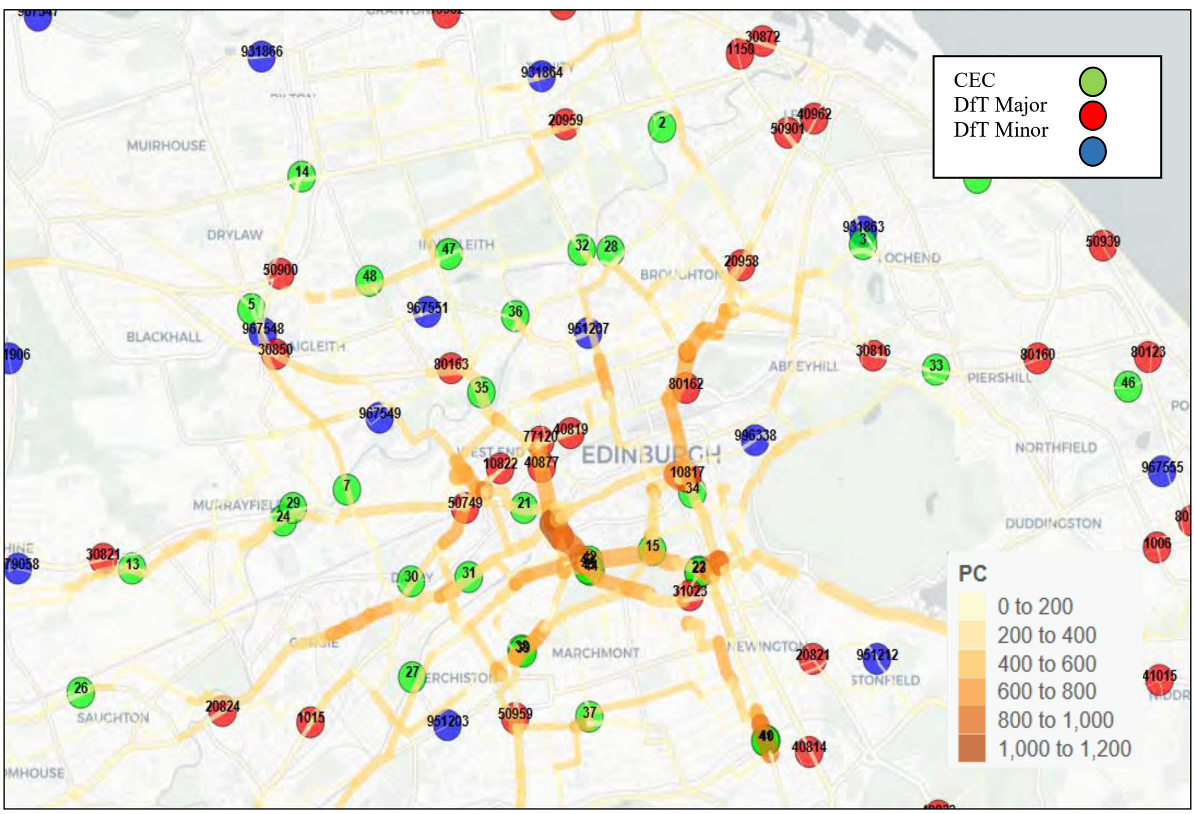

Figure 7-16 Location of (n=96) CEC and DfT traffic/cyclist counters in Edinburgh. Used to validate the flow model.

Exploratory examination of the three flow models options (i.e. fast, balanced and quiet) were compared to three different observed count metrics: AADF, 12hr raw count data and a 12hr seasonally adjusted count, illustrated in Figure 7-14 above.

The comparison indicates that the 'balanced' and 'quiet' modelled flows are quite poor predictors compared to the observer data across all three observed data (i.e. AADF, the 12hr Raw count data and the 12hr adjusted count data). The 'fast' modelled flows however appear to be more consistent with the AADF and the 12hr adjusted observed data. The next section uses the GEH to determine which flow model option provided the best statistical fit.

7.4.4.2 GEH Results

A GEH less than 5.0, for 85% of the model, is deemed acceptable whereas GEHs between 5.0 and 10.0 may warrant investigation. The GEH has limitations; it does not take account of the variability of the count data and typically uses peak hourly flows to determine 'goodness of fit' (Feldman, 2012). For robustness, and to reflect the fact that the GEH is intended for peak hourly motorised traffic flows, the Pearson's correlation coefficient and linear regression were also examined.

The GEH statistic was calculated using the long-term average cyclist per hour unit, O_j in equation (7.1), and the comparison of validation results are shown in Table 7.3 below.

Table 7.3 Cyclist flow model validation results

Validation Statistic	'Fast'	'Balanced'	'Quiet'
GEH(AADF)	97.9%	91.7%	91.7%
GEH(12hr)	90.6%	84.4%	81.3%
GEH(12hr) Adjusted	91.7%	87.5%	85.4%
Pearson's Correlation coefficient (AADF)	0.745	0.616	0.577
Pearson's Correlation coefficient (12hr)	**0.815**	0.5	0.437
Pearson's Correlation coefficient (12hr) Adjusted	0.694	0.699	0.685
R^2(AADF)	0.551	0.373	0.326
R^2 (12hr)	0.661	0.242	0.183
R^2(12hr) Adjusted	0.476	0.484	0.464

The GEH statistic indicates that the 'fast' and 'balanced' models have the best fit between the observed and the modelled data. The AADF in combination with the 'fast' model has the highest GEH score. The 'quiet' model comparison to the 12hr and 12hr adjusted do not meet the GEH thresholds. The GEH was not conclusive; this may be due to use of the long-term average O_j instead of a peak hour flow.

The Pearson's and R^2 however reveal a clear distinction; the 'fast' option in combination with the 12hr count data has the highest correlation coefficient of 0.815. The levels of correlation are high, while the use of a long-term hourly average may have hindered the GEH, the correlation result is conclusive and hence the validation of the model is acceptable and confirms that the novel methodology has estimated on-road and off-road cyclists flows consistent with observed counts and it has been validated against the criteria set out in the guidelines for the validation of conventional transport models.

7.4.4.3 Comparison of the flow model and population estimates

This section compares the results obtained above with the official levels of cycling estimates and cycling flows derived using the population-based cycling exposure proxy described in Section 7.4.1 above. The '*fast*', '*balanced*' and '*quiet*' flow models are summarised in Table 7.3 below, the total network lengths, vkm, the annual million vehicle kilometers (mvkm) and the average trip lengths are given for each model along with the population-based estimate for comparison.

The vkm totals are smaller for the '*fas*t' model and higher for the '*quiet*' model, which reflects the slightly longer and less direct '*quiet*' routes. The '*fast*' model covers the largest proportion of the network, which includes some 'quiet routes' but less off-road routes compared to the 'quiet' model. A recent study suggests that the total mvkm cycled annually in Edinburgh is 57.9 mvkm (Sustran, 2017) which is comparable to the estimate in Table 7.4 below, however the population-based estimate is much lower at 53 mvkm.

As discussed in Chapter 6, 'exposure' provides information about intensity of use or level of activity. Here, the population-based exposure measurement would under estimate the level of cycling taking place. Furthermore, the population-based estimate is an average and cannot be used to normalise risk at a junction or link level and therefore is limited in terms of facilitating analyses of characteristics that differ between places associated with increased or decreased safety. Therefore, the population based estimate would provide a global accident risk rate and potentially overestimate the level of risk because the 'exposure' is under estimated which will be discussed below.

Table 7.4 Comparison of the CycleStreet.net routing engine options analysis in stplanr.

CycleStreets.net Route Estimation Method	Segments	Network *(km)*	*vkm*	Annual *mvkm*	Trip Length *(Km)* *(mean, median, SD)*		
Fast	N=3481	693	47,688	57.2	5.4	4.5	5.7
Balanced	N=3163	675	48,958	58.7	5.6	4.5	6.3
Quiet	N=3207	645	49,348	59.2	5.7	4.6	6.6
Sustrans (2017)				57.9			
D_{Prod}*	-	-	-	53	4.4**	2.1**	-

*Estimated using equation (1) using Census 2011 Table QS701SC (NRS, 2011) data.** TS(2014) Table TD5a, straight line distances.

At a global level, the lower estimate, 53 mvkm for the city of Edinburgh, would over estimate cyclist risk and under estimate actual cycling levels in the city. The population-based estimates at ward for example are likely to misrepresent activity, to illustrate this further the results from the flow model were aggregated at the city ward level and compared against the number of cyclist in each ward, Table 7.5 below. The comparison at Inverleith and the City Centre wards illustrate the differences that can occur, both wards have roughly twice the cyclist volumes (from the modelled flows) compared to the modal share (population-based).

While a global collision rate will be substantially the same, estimating local collision rates at IZ or ward level, using equation (7.2) above, provides two very different results as shown in Table 7.5 below. Therefore, collision rates that use population data hold true if the population under review travelled only within the subject area. If we consider trip data, presented in this study and summarised in Table 7.5 below, of the total 9478 trips, only 3.5% (N=335 trips) occur within its origin IZ zone.

Table 7.5 Descriptive Statistics of the variables used to calculate cyclist collisions risk rates.

Category	Variable	Description	N	Avg	Min	Max	SD
Spatial	IZ	Scottish Intermediate Date Zone	111	-	-	-	-
Collisions	PC	Cyclist Injury (Slight, Serious, Fatal)	240	2	0	25	3
Exposure	Prod	Trip Production in each IZ	9593	86	13	259	56
	vkm	Cyclist Kilometres Travelled per IZ	47688	430	26	1967	392

This illustrates the importance of firstly using vkm as an exposure measure and secondly the need to account for spatial variation. The spatial distributions of the two measures of ‘exposure’ (population v’s distance) differ considerably, highlighted in bold text in Table7.6 below.

Table 7.6 Comparison of the Census data and flow model data as a % of overall cyclist activity at ward level in Edinburgh.

Ward Name	veh_km	% persons aged 16 to 74 who cycle to work (2011 Census)	% of mvkm in each ward 'fast'.
Colinton/Fairmilehead Ward	1199.849	4.6	2.5
Portobello/Craigmillar Ward	1937.139	4.6	4.1
Sighthill/Gorgie Ward	3570.222	3.0	**7.5**
Pentland Hills Ward	2322.498	3.4	4.9
Liberton/Gilmerton Ward	1230.482	2.5	2.6
Fountainbridge/Craiglockhart Ward	2353.732	**6.9**	4.9
Meadows/Morningside Ward	5070.379	**9.9**	**10.6**
Inverleith Ward	4484.553	4.5	**9.4**
Forth Ward	2351.24	4.5	4.9
City Centre Ward	5564.933	4.4	**11.7**
Craigentinny/Duddingston Ward	2029.61	4.4	4.3
Drum Brae/Gyle Ward	1264.593	2.9	2.7
Corstorphine/Murrayfield Ward	3001.181	4.5	6.3
Southside/Newington Ward	5102.885	**9.3**	**10.7**
Leith Walk Ward	2258.176	4.6	4.7
Leith Ward	1313.268	4.8	2.8
Almond Ward	2609.887	3.1	5.5

The spatial distributions of the two measures of cycling exposure (population v's distance), are illustrated in Figure 7-17 below, and they differ considerably. Figure 7-17 (a) and (c) illustrate the 'fast' model flows aggregated at IZ level and the corresponding collision rate and Figure 7-17 (b) and (d) illustrates the modal share and the corresponding collision rate.

The analysis discussed above demonstrates that it is possible to build and validate a cycling flow model and that use of population-based cycling activity as an exposure measure.

Therefore, the analysis in the following chapter will use the cycling flow model developed in this chapter. The next section uses the flow model result again to explore cyclist collision rates at IZ level to compare the difference between the overall average risk rate for KSI and all injury collisions.

7.5 Cyclist Collision Risk Using Flow Model Data

To frame cyclist risk within the context of overall road risk it is worth comparing the KSI and all injury risk rates. The average casualty risk in Edinburgh for any severity or mode was 0.47 per mvkm in 2011 and improved slightly to 0.44 per mvkm in 2016 (TS, 2017). The KSI average casualty risk was 0.06 per mvkm over the same period for all modes.

The collision risk rates for cyclists were calculated using the *'fast'* flow model volumes, discussed above using cyclist collisions for 2011 from the STATS19 database to provide the accident frequency. The average cyclist collision rates calculated were 4.2 per mvkm for all injuries and 0.63 per mvkm for KSI in 2011. Therefore, cyclists risk was roughly a ten times higher than the risk rate for all modes of transport in Edinburgh in 2011 and this agrees with previous research discussed in Chapter 2 (Pucher and Dijkstra, 2003; Elvik, 2004)

The cyclist collision rates, aggregated at each IZ level, for KSI and all injury collisions respectively, are illustrated in Figure 7-18 below, and ranked in relation to the average collisions risk calculated for KSI and slight injuries. Firstly, this illustrates the spatial pattern and secondly that both the KSI and all injury collision rates can be several times higher than the average in some IZ's. If the analysis used population-based cyclist activity estimates the areas with higher collision risk rates will be incorrectly identified for the reasons discussed above in Section 7.4.4.3.

7.6 Discussion

This chapter presented a methodology to estimate cyclist flow patterns by utilising recently developed open source analysis tools (Lovelace et al, 2017) and cycling routing engine applications (www.Cyclestreet.net) that were developed specifically for cyclists. The method application was illustrated by using Edinburgh City as a case study. A combination of traditional (Census and Automatic Traffic Counts), novel (OpenStreetMap) data and prevailing transport model validation methods were used to produce a model containing flow estimates at both link and meso-spatial area levels.

Therefore, the analysis in the following chapter will use the cycling flow model developed in this chapter. The next section uses the flow model result again to explore cyclist collision rates at IZ level to compare the difference between the overall average risk rate for KSI and all injury collisions.

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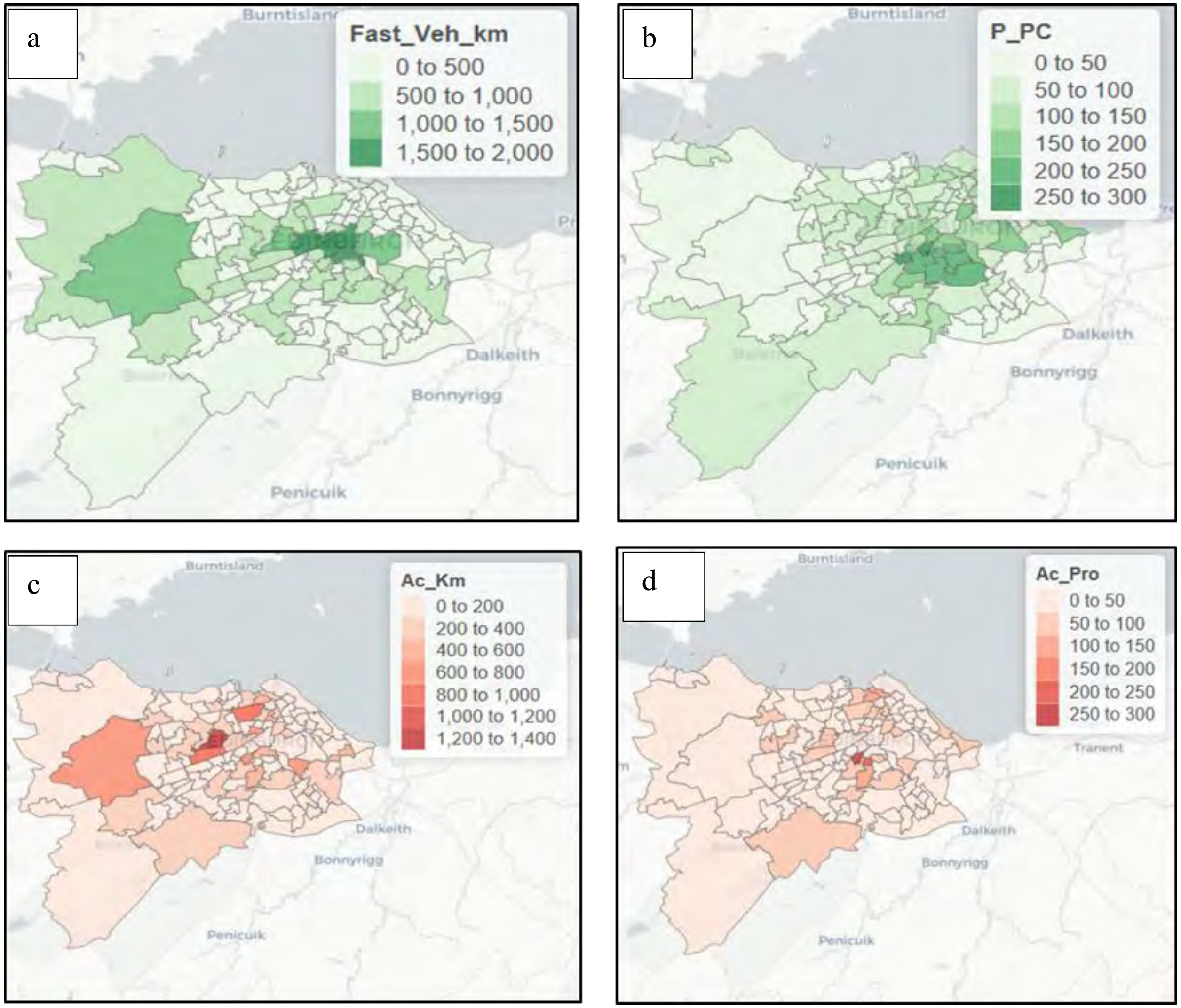

Figure 7-17 (a) Spatial distribution of vkm, (Fast_Veh_Km); (b) Spatial distribution of modal share (P_PC); (c) Spatial distribution of cyclist collision/ aggregate vkm; (d) Spatial distribution of cyclist collision/modal share.

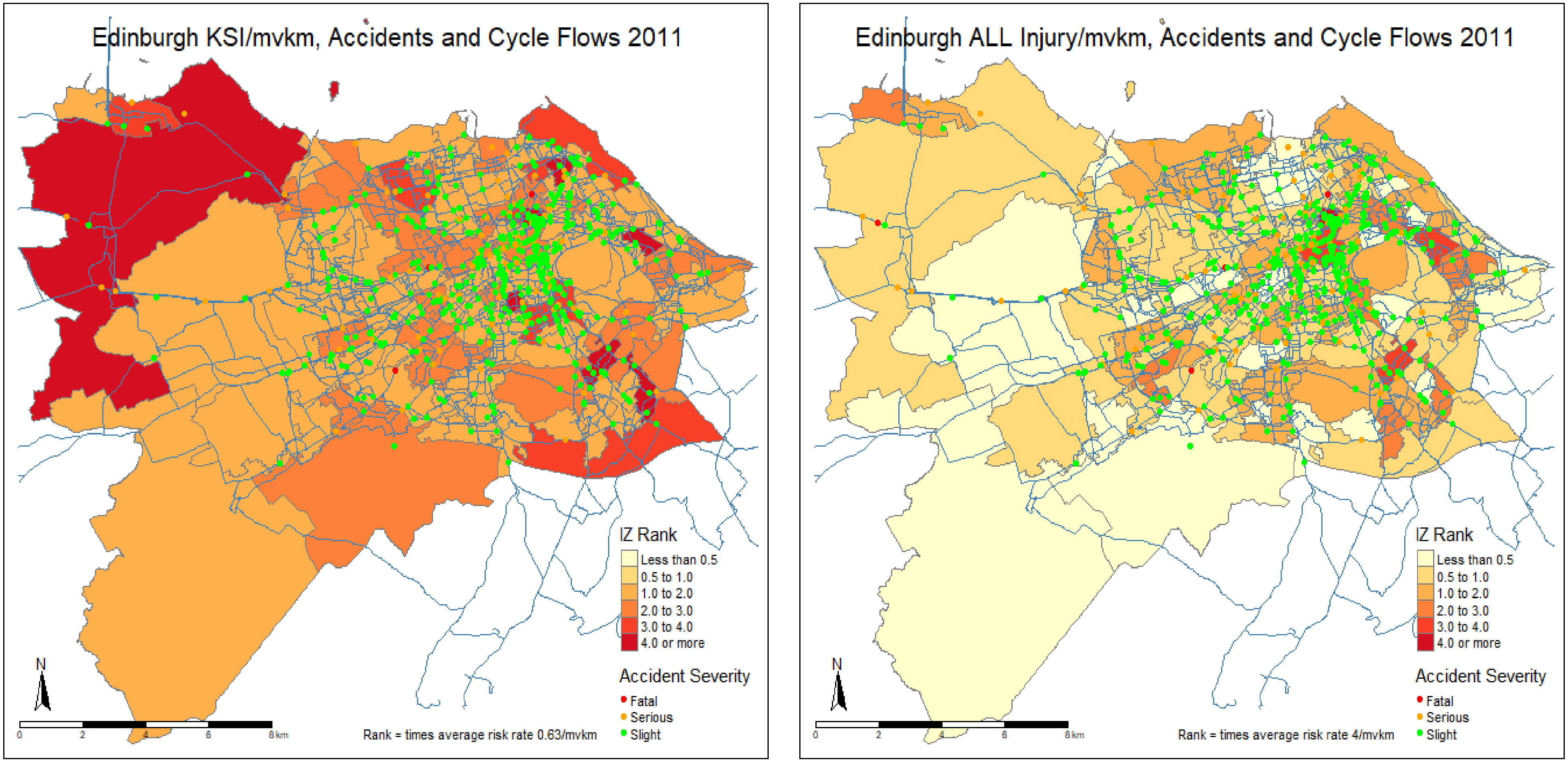

Figure 7-18 Cyclist risk, collisions (Fatal, Serious and Slight injury) per mvkm.

Cyclists appear to favour more direct routes according to the results from the cycling flow model developed, this may suggest that measures such as 'quiet streets or quiet routes' may not successfully attract and encourage people in Edinburgh to cycle. The results also show that 'quiet' routes are slightly longer on average than the '*fast'* option, Table 7.4 above. As discussed, this result may be bias due to the dataset used, however the model validation (see Section 7.4.4) confirms that the census data is a valid proxy for all trips and confirms previous research (Goodman, 2013; Sustrans, 2017).

Based on the knowledge that main reason Scottish people cite for not cycling to work is "*too far to cycle*" (TS, 2017), rather than the busy roads or too much traffic, the argument put forward by Loo and Anderson (2016), that expecting vulnerable road users to avoid travelling on certain routes can be contradictory to promoting their mobility and maintaining equity, suggests that cyclists who value directness over safety would likely fall into this category and therefore use the shorter '*fast'* routes. However, that is not to say that these route are not valuable assets yet to be fully realised, because as discussed above the cycling population is not gender or age balanced.

A key focus of Edinburgh's cycling investment over the next few years will be the "Quiet Routes" network (Sustrans, 2017) which aims to provide facilities for less confident cyclist and hopefully more unaccompanied 12 year olds so that in time the cycling population may grow and become more age and gender balanced. The development of the flow model here provides data on cyclist flows that can be used to either inform or monitor policies and measures.

However, given the existing gender imbalance and the results presented in this chapter suggests that measures or policies aimed to improve cycling safety should focus on links or areas with higher volumes rather than simply aiming to offset routes elsewhere that are assumed less dangerous and therefore attractive. Furthermore, the findings in Chapter 5 suggest that speed enforcement of 20mph and 30mph roads may not benefit from the deterrence factor that police presence may offer because Police Scotland focus their speed enforcement on higher speed roads.

CAPS provide annual reports on a suite of national indicators to inform the national picture of cycling participation. It also sets out to develop local monitoring tools, using data from local cycle counts and surveys to develop a coordinated approach to data collection. The City of Edinburgh Council (CEC) Active Travel Action Plan (ATAP) includes targets to produce a cycling casualty rate index to monitor road safety based on count data commencing 2016. This target is part of the Charter of Brussels commitment to reduce the casualty rate for cycling (per km travelled) by 50% from 2010 to 2020 as discussed previously.

The ATPT also collect and publish monitoring data to evaluate progress against targets and indicators published in the Edinburgh Bike Life (Sustrans, 2017) report. This report is similar to the Bike Account, produced by the Cycling Embassy in Denmark, which provides detailed monitoring information about cycling from several different sources together with new research into one coherent annual report. Therefore, it is difficult for researchers and local authorities to determine if changes in observed accident trends over time are due to increased accident risk, (users or environment becomes more unsafe) or if they are a function of the higher numbers of cyclists using the existing roads and routes resulting in more incidents, i.e. increased exposure.

According to the ITF/OECD (2013) most authorities lack the factual basis to assess cyclist safety or the impact of 'safety improving' policies. It is not currently possible to produce a cycling casualty rate index to monitor road safety across the road network in Edinburgh; however, the research presented in this chapter will make this possible. This research provides transport planners and policy makers with quantitative cycling flow information and a means to visually interrogate cycling flows at link or area level, including on-road and off-road facilities, to better understand road safety, cyclist flow patterns, policy applications and risk within the city of Edinburgh.

The comparison of the population-based exposure measure with the mobility-based vkm demonstrated that global estimates effect measurement of collision risk at a local level. While cycling exposure derived from trip productions may be appropriate at larger spatial units, such local council areas, discussed in the previous chapter, where the majority of cyclist trips will be intra zonal, at smaller spatial aggregations within urban areas such as those presented in this chapter, require cognisance of spatial auto correlation effects in addition to over dispersion. Central to this is the availability of mobility-based exposure such as the cyclist flows modelled using stplanr and CycleStreets.net. The spatial aspect of collision risk and modelling will be discussed further in the following Chapter 8.

Cycling, while beneficial in terms of population health and reducing carbon production, has much higher collision risks, per kilometer travelled, than for car occupants and despite many countries setting road safety reduction targets, cyclist road safety has lagged behind improvements observed among motorised road users. For example, the UK average risk per billion kilometers travelled, between 2006 and 2015 cyclist killed or serious injury collision risk was almost 10 times higher than for car occupants and cyclist risk has increased by almost 20% while motorised transport risk has improved (DFT, 2017). While it may be argued that drivers travel on average a greater distance per trip, it is worth noting that the average cyclist trip is 4.6 km and driver trip is 10.5 km (TS, 2017) so roughly half, showing that the risk gap is still considerable considering the levels of risk illustrated in Figure 7-18.

Where an individual's main mode of transport is their bike or for those who don't have access to a car or public transport this is a considerable transport risk imbalance and it highlights the importance of quantifying this risk when cycling as a mode of transport is recommended to improve health, the environment and, as discussed in the previous chapter recommended as a means to address transport poverty in Scotland.

Finally, during the study period the Edinburgh tram was under construction, while the construction site effected a limited number of streets this would have had an impact on cyclist route choice at the time which the cycelstreets.net routing engine does not account for therefore, the results discussed in this research and used in future work should take this into account

7.7 Conclusions

The research presented in this chapter and discussed above provide new knowledge and answers to the research objectives and questions outlined in the introduction above. The following sections discuss each one and their respective contributions.

OB-02: *Critically analyse road safety evidence focusing on cyclists to develop an understanding of the wider factors involved.*

At present the national and regional transport models do not include cycling, walking or motorcycling, the vulnerable road users group, they only provided estimates for motorised transport. Similarly, the city of Edinburgh does not have a transport model that provides cyclist flow estimates.

Information about exposure means information about traffic participation. The more someone takes part in traffic, the greater their exposure to risk and the bigger the chance of a crash. Crash risks (crash/exposure) information is about risk factors in traffic, such as driving while intoxicated, which is known to be a factor that increases risk. According to Wegman (2016) good data are also required to be able to design a policy to reduce the consequences of crashes.

Therefore, policy planning, monitoring and evaluation against targets is very limited. Bespoke micro-simulation type network models are typically required to provide a mobility-based measure of 'exposure'. **This research developed a model using census data, open source software stplanr and CycleStreet.net and combined several existing observed cycling data sources.** This combined approach offers policy makers and planners empirical information, simply "*how much cycling happened and where*", to monitor cycling numbers and safety more effectively using normalised risk based on 'exposure' rather than frequency of cyclist collisions.

The software used is open source unlike commercial products such as 'VISSIM' that can be cost prohibitive. Authorities should use new emerging research to aid policy monitoring and evaluation and in particular 'open' research because it is low cost and does not require procurement of services from external consultants and is therefore highly cost effective. Therefore, the use of stplanr and OpenStreet.net provide a viable method for estimating route flows to provide mobility-based exposure estimates, subject to sufficient count data availability.

As transport planning and funding moves towards greater prevalence and support of cycling as a transport mode, the analysis and results from the model validations suggests that the current transport model validation methods may need to be updated to include cyclist specific validation methods such as the Pearson's and R^2 validation method used in this research.

RQ-04: *Can we say that existing road safety policy, subsequent implementation processes have been a good fit for cyclists, and if not why, can we model better?*

CEC current policy to promote cycling and provide cycling infrastructure and improve safety follows a parallel approach, in the first instance the CEC are promoting and extending the ‘Quiet Routes’ network to cater for less confident cyclists and secondly move towards a Cycle Friendly City through reduced traffic and traffic speeds.

The results show that cyclists appear to favour more direct routes and this suggests that measures such as ‘quiet streets or quiet routes’ may not successfully attract cyclists in Edinburgh. Furthermore, the main reason Scottish people cite for not cycling to work is “too far to cycle” (TS, 2017) rather than the perceived quietness of the route, as discussed above both the ‘quiet’ and ‘balanced’ route options involved longer distances.

Therefore, the current policy may not change the current situation, however the model developed here can be used to monitor ‘where’ cycling is increasing or decreasing and provides a measure to monitor and target policies with more certainty. As with all transport models this model is valid for the time period it was based upon, therefore the results need to be updated to reflect future trends and data.

RQ-05: What should Safety Performance Indicators measure to ensure cyclists benefit from Road Safety investment equitably?

Many national authorities seek to increase rates of cycling while at the same time improve road safety, however many authorities lack reliable ‘exposure’ metrics to calculate collision and injury rates (OECD/ITF, 2013). Detailed traffic data has the greatest potential to improve safety analyses (Lord and Mannering, 2010). Flow data, ‘exposure’, is required when one wishes to interrogate risk variation or change across particular types of infrastructure, an on-road cycle track, a bus lane or an advanced cycle stop facility at signal controlled junctions, and if the numbers of cyclists or type of cyclist who may choose a particular section of the network differs.

Exposure information is vital for management of our transport infrastructure. In the absence of such information, conclusions about the level of risk associated with parts of a network cannot be ascertained and therefore recommending routes for cyclists that would encourage increased cycling flow, but lead to more collisions may actually be less safe than a less used route with a lower number of injuries per cyclist. It is difficult to determine if the increased use or risk resulted in more injuries. The ability to manage this risk is the cornerstone of road safety analysis for motorised traffic that has led to the ability to systematically augment the transport road network into a safe and efficient network.

The problem with determining this metric is that it must be estimated because transport authorities do not routinely collect enough cycling flow data and cycling is not included in the national or regional transport models developed for Scotland. Therefore, comprehensive estimates across the road network and the National Cycle Network is not available, the data that is collected represents only a small proportion of the routes where cycling takes place. Therefore, while one area may appear to have a high count, or density, of injury across a network in comparison to another area or route segment, the level of cyclist flow would determine the actual risk. This lack of appropriate ‘exposure’ data is a particular problem when making comparisons between areas.

Getting this measure right is not straight forward given our current level of information availability. The metric reported is million vehicle kilometers travelled by the Department for Transport. The estimated is derived from the permanent automatic traffic counters located across the Scottish road network. While this estimate provides an overall estimate is it of little use at a network level. The modelling approach described in this study will be of use to policy makers and planners who may develop and monitor cycling safety more effectively based on empirical information.

Models that use population-based ‘exposure’, where data availability may have restricted analytical choices, should be cognisant of spatial variation and the exposure variable specified when drawing inference about “safety in numbers”. The results presented here suggest that the “safety in numbers” effect may be overestimated if a population-based exposure measure is used which is consistent with the absolute increase in casualties recorded in hospital admissions and police records. Given the current prevalence of “safety in numbers” in cycling policy and advocacy, overestimating the effect may be counterproductive particularly where absolute risk remains high or where cycling ‘exposure’, levels are low. Visualising the model results across local area zones provides a more accessible platform to communicate information to non-technical practitioners and decision makers.

Hauer (1995) makes the point that the number of accidents per unit of time depends on the intensity of use (i.e. exposure) and the relationship between the number of accidents and exposure is seldom linear and is termed the "Safety Performance Function" in transportation systems. When the relationship is non-linear the same frequency of accidents will have different accident rates at difference exposure levels, without this exposure information the safety of an entity or intervention cannot be measured. Therefore, the research carried out in this chapter in necessary to estimate the safety performance function of a given area or road. Furthermore, the non-linear relationship described by Hauer (1995) also describes how to normalise risk between entities, therefor it is a key component of the information needed to investigate *SiN* and the factors that may be associated with it.

This model will be used in Chapter 8 to provide better estimated cycling flows volumes to help provide a better understanding of the mechanisms involved in the *SiN* effect.

CHAPTER 8

Edinburgh

"As a city, Edinburgh has a strong record of transforming its urban environment to encourage people to walk and cycle……… one of the most livable cities in the UK."

- Councillor Adam McVey, Leader of City of Edinburgh Council.

8.1 Introduction

Edinburgh is the cycling success story in Scotland, it has already achieved the Scottish National target of 10% modal share of cycling in parts of the city (see Table 7.6). The *Bike Life*

[24] report prepared for Edinburgh reports year on year cycling growth, reporting that Edinburgh has over 204 miles of cycle infrastructure; 126 miles of this is traffic free and 45% of the population live within 125m of a cycle route (Sustrans, 2017; pg.4). The City of Edinburgh Council has several infrastructural improvement projects planned and has a clearly defined strategy to improve cycling safety and encourage more cycling, set out in the Active Travel Action Plan 2016. The aim is to increase cycling to 15% modal share by 2020, with a 10% by bike target for all trips.

The city has a very active cycling advocacy culture, organisations such as SPOKES[25], who take an active role to promote cycling at national and local government levels; they are one of the partners responsible for the delivery of the Cycling Action Plan for Scotland 2017-2020. Between the 2001 and 2011 Census, the numbers of commuters living in Edinburgh that travelled to work by bike doubled from c.2% to c.4%, the current figure stands at 7.5% of commuters travelling to work by bike (Sustrans, 2017; pg. 5). Therefore, as we approach

[24] *Bike Life was inspired by the Copenhagen bike reports, the reports for seven UK cities began in 2015, the Edinburgh report is prepared by Sustrans Scotland who are the responsible partner in the Cycling Action Plan for Scotland 2017-2020 for CAPs Action 19. (https://www.transport.gov.scot/media/10311/transport-scotland-policy-cycling-action-plan-for-scotland-january-2017.pdf)*

[25] *SPOKES is a cycling advocacy organisation based in Edinburgh established in 1967.*

another Census in 2021 it seems likely that the commuter cycling mode share will double again. As discussed previously, in Chapters 2 and 3, doubling the number of cyclists should create a safety in numbers effect, it is for this reason that Edinburgh will be examined in this chapter.

The objectives of this chapter are two fold, firstly to collect and model information in ArcGIS/ArcMap to provide explanatory variables to describe the existing infrastructure for cyclists that is missing from the STATS19 results discussed in Chapter 5. Secondly, to use the cycle flow model volumes, developed and calibrated in Chapter 7, to provide a cycling exposure variable to compare the traditional (global) GLM-NB with the spatial GWPR model to explore local level factors associated with cyclist injury collisions.

The overall aim of this chapter is to investigate whether there is a localised cyclist *SiN* effect in Edinburgh due to increased mobility and to examine if the road environment and cycling environment are contributory factors (see OB-02, Chapter 3). Additionally, it will look at road safety policy, with respect to cyclist infrastructure, to examine if it has had an impact on cyclist road safety (see OB-01, Chapter 3).

Chapter 4 contains the details of the regression models that will be used in this chapter, the GLM-NB, GLM logistic models and the GWPR model, see Table 4.2.

This chapter is organised in the following way: Section 8.2 provides a short description of the data and data analysis; Section 8.3 examines *SiN* in Edinburgh using the GWPR model; Section 8.4 discusses the results of a binary logistic regression fitted to KSI collisions; and finally Section 8.5 discusses the chapter conclusions and main results.

8.2 Description of the Data and Variables used in this chapter

This section describes how the data was developed for the City of Edinburgh. The cyclist traffic volumes are taken from the novel cycle flow model described in Chapter 7. The flows were imported to ArcGIS to build a strategic model that was used to identify the cycle flow volume for each STATS19 accident record and digitise the cyclist infrastructure from 2010 background aerial photography provided by City of Edinburgh Council (CEC), see Figure 8-1 below. The traffic volumes were also imported into the ArcGIS model from the TMfS12[26]

[26] *Transport Model for Scotland (2012), TMfS12- supplied by Systra.*

supplied by Transport Scotland. The cycle flow model has flows for the on-road and off-road cycle infrastructure, Figure 8-1 illustrates high flows on the off-road routes, such as the Meadows and the Innocent path, and on-road at Lothian Road and The Mound (heat map).

Table 8.1 Descriptive Statistics – Summary of the data aggregated at the intermediate data zone level in Edinburgh (n=111).

Description	*Model Name*	*Mean*	*St. Dev.*	*Min*	*Max*	*Total*	*Units.*
Dependent Variable							
Serious Injury	Serious	0.94	1.35	0	7	104	*No.*
Slight Injury	Slight	5.24	7.95	0	71	582	*No.*
Killed/Serious Injury	KSI	0.98	1.39	0	7	109	*No.*
All Injuries	ALL	6.23	8.95	0	78	691	*No.*
Explanatory Variable							
Cyclist Volume	C_Veh_Km	429.62	391.89	25.93	1,967.30	47.69	*Km*
(Flow Model- Chapter 7)							
Cyclist Volume	C_Veh_Km	429.62	391.89	25.93	1,967.30	47.69	*Km*
Deprivation	SMID_2011	0.45	1.06	0	4	50	*No.*
On-Road Cycle Lane	Cy_Road	446.84	571.53	0	2,614.24	49.60	*Km*
Shared Footway	Share_Ped_on	437.68	1,301.38	0	9,843.91	48.58	*Km*
Shared Path off-road	Off_share	1,443.84	2,099.30	0	18,275.27	158.82	*Km*
Segregated Cycle Lane	Seg_Cy_Lane	104.39	359.37	0	2,298.58	11.48	*Km*
Advanced Cycle Lanes	ALS	5.42	5.88	0	28	602	*No.*
Quiet Routes	Quiet_Route	518.3	976.64	0	6,395	57.53	*Km*
Bus Lanes	Bus_Lane	585.75	882.6	0	5,573.68	64.43	*Km*
Road Length	Road Length	13,849.37	11,814.35	2,377.48	99,064.75	1537.28	*Km*
AADF Car	CAR_vkm	52,390.73	113,211.00	1,859.14	818,839.00	5815.37	*Km*
AADF HGV	HGV_vkm	2,732.83	5,436.12	291.6	39,687.05	303.34	*Km*
AADF LGV	LGV_vkm	5,787.73	8,746.02	385.36	64,563.97	642.44	*Km*
AADF Total Volume	Tot_vkm	60,911.29	127,196.70	2,580.71	920,659.60	6761.15	*Km*
(TMfS_12)							

The City of Edinburgh Council (CEC) also provided records of the National Cycle Network, the Quiet Streets and the Bus Lanes. However, the location of the advanced stop lines at signal controlled junctions, segregated cycle lanes, shared unsegregated footways, shared off-road paths and on-road cycle lanes were not available or were incomplete. Therefore, the ArcGIS model background mapping, shown in Figure 8-2 below, was used to record and inform the gaps in the existing data. The descriptive summary statistics for the dependent and explanatory variables are listed in Table 8.1 above.

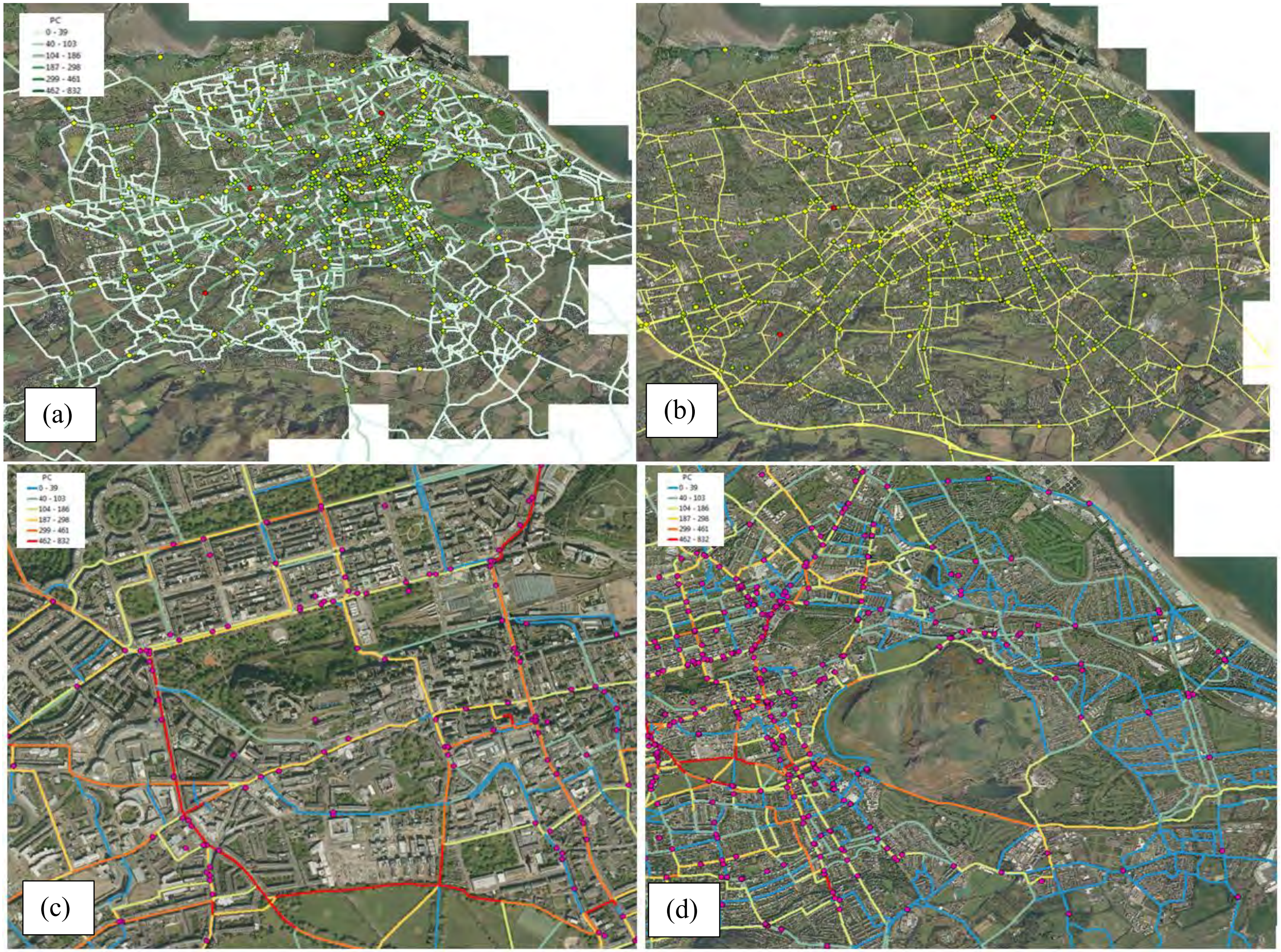

Figure 8-1 ArcGIS model illustrating (a) the cycle flows from Chapter 7, (b) the Transport Model for Scotland 2012 (TMfS12), (c) a heat map of cycle flows in central Edinburgh and (d) a heat map of cycle flows to illustrate off-road flows.

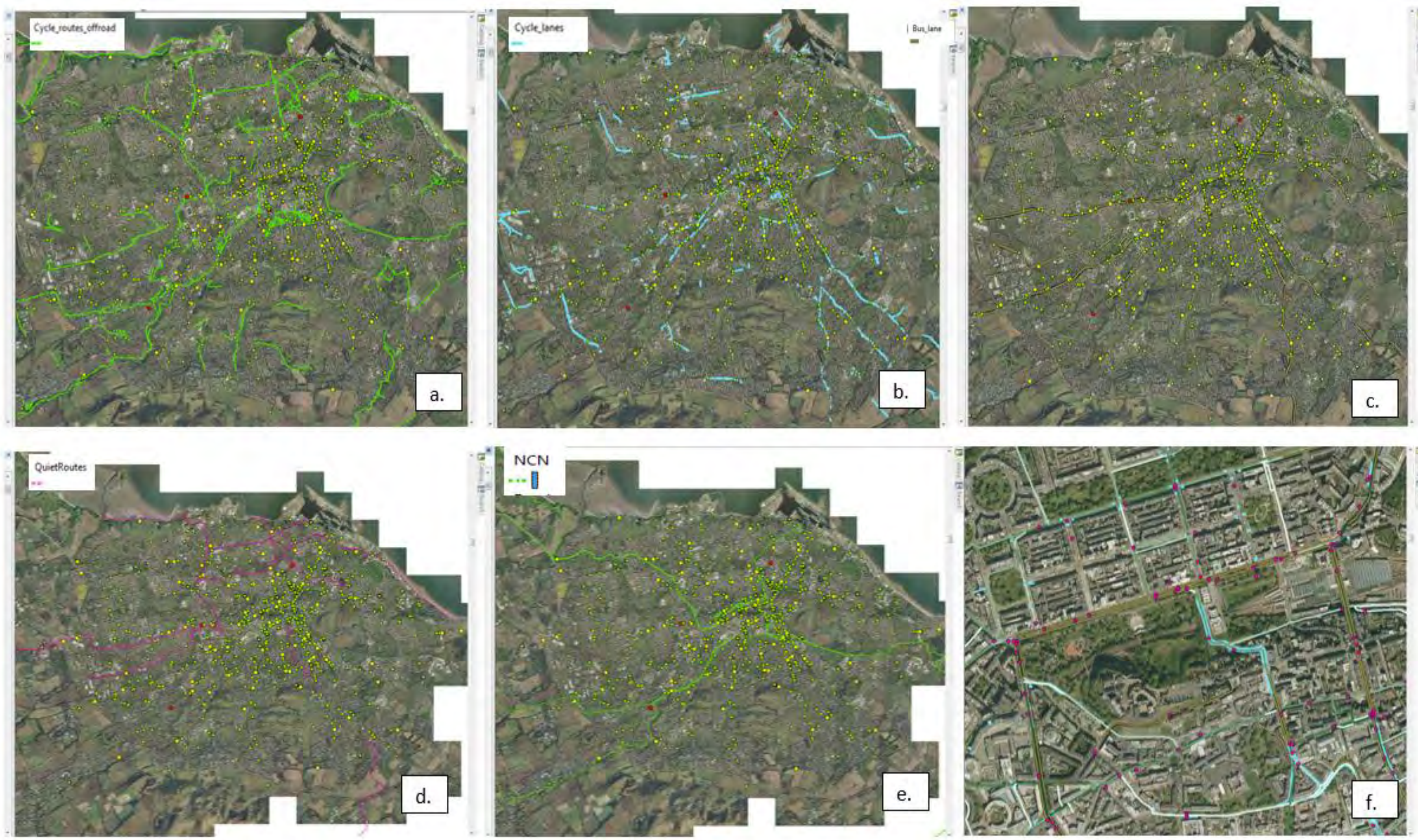

Figure 8-2 ArcGIS model illustrating (a) off-road paths, (b) on-road cycle lanes and ASL, (c) Bus lanes, (d) Quiet Routes (circa.2010/12), (e) the National Cycle Network's Routes and (f) an illustration showing all cycle facilities and collision locations in central Edinburgh.

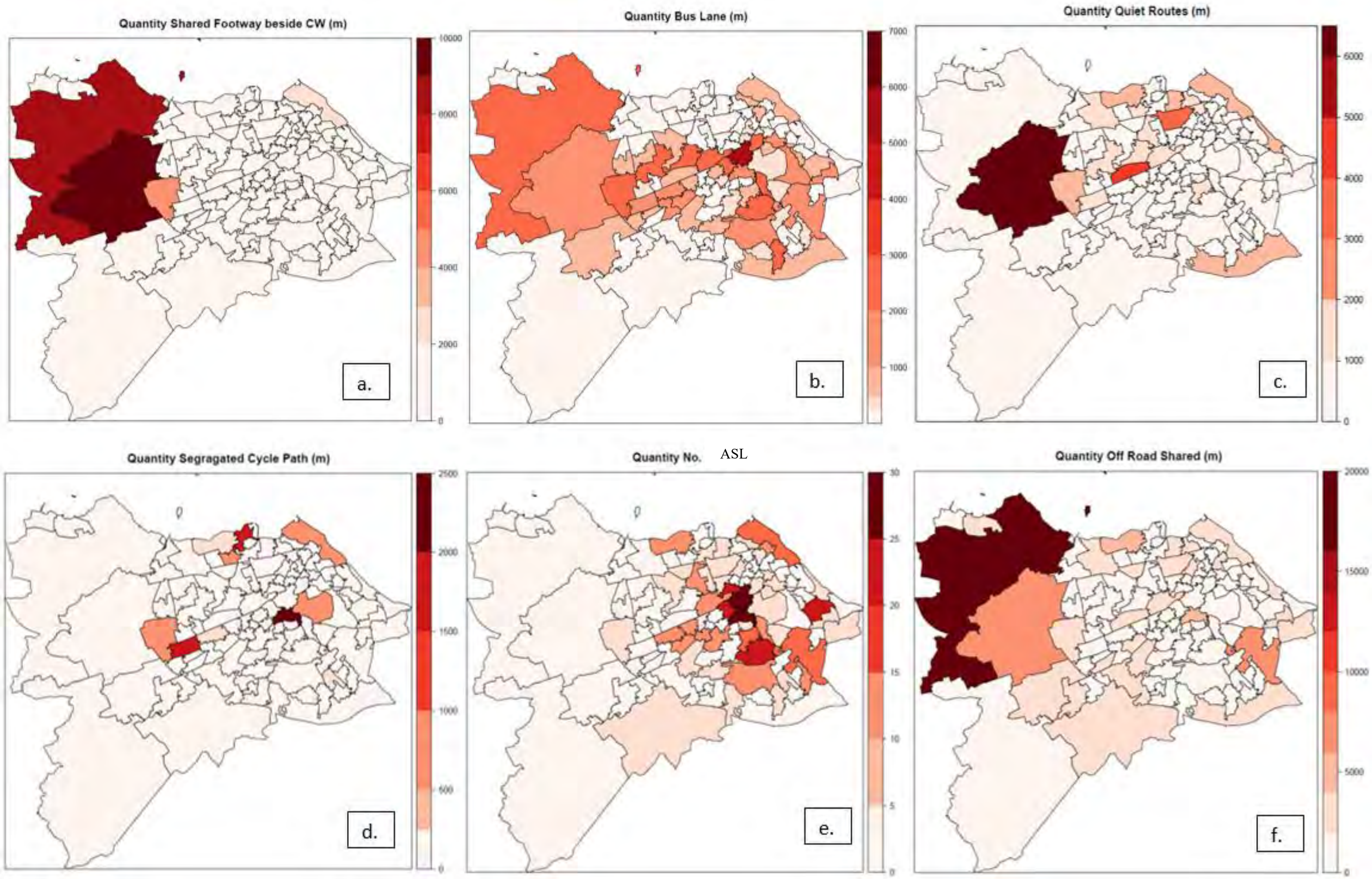

Figure 8-3 Quantities aggregated at the Intermediate data zone level (N=111), (a) shared footways adjacent to road carriageway, (b) Bus lanes, (c) Quiet Routes (circa.2011/12), (d) Segregated cycle lanes (e) the number advanced stop lines for cyclists at controlled junctions, and (f) Unsegregated Off-road shared paths (e.g. The Innocent Railway Route).

The quantities were aggregated at the Scottish Intermediated Data Zone level, Figure 8-3 above, and a sample of the STATS19 collisions (N=198) was cross referenced with the ArcGIS data at each collision record to determine the respective flows and infrastructure details for the KSI binary logistic injury severity model discussed in Section 8.4 below. The next section discusses the diagnostics carried out prior to fitting the models.

8.2.1 Data Preparation and Pre-Modelling Analysis

This section provides an overview of the analysis and data preparation conducted prior to fitting various models.

8.2.1.1 Multi collinearity

Variance Inflation Factor[27] (VIF) was applied to assess multicollinearity and all the variables which had a value lower than, or equal to, five, which indicates a moderate multicollinearity (Heiberger and Holland, 2015), were eliminated.

Multicollinearity was examined prior to fitting the multivariate models. The collinearity between variables are illustrated in Figure 8-4 below which shows the coefficient correlation matrix, where significant coefficients ($p > 0.05$) are coloured either blue or red, blue representing positive correlation and red representing negative correlation relationships.

Given the considerably high, and significant ($p > 0.05$), correlation values found between the potential exposure traffic variables, car volumes (CAR_vkm), heavy goods vehicles (HGV_vkm), light goods vehicles (LGV_vkm) and the total combined traffic volume (Tot_vkm), the VIF was examined to determine which variables were problematic. The total combined traffic volume (Tot_vkm) variable was selected as the most appropriate traffic exposure measure to include in the model.

[27] *The VIF describes multicollinearity, low levels under five are acceptable, high levels over five and a maximum of eight should be removed.*

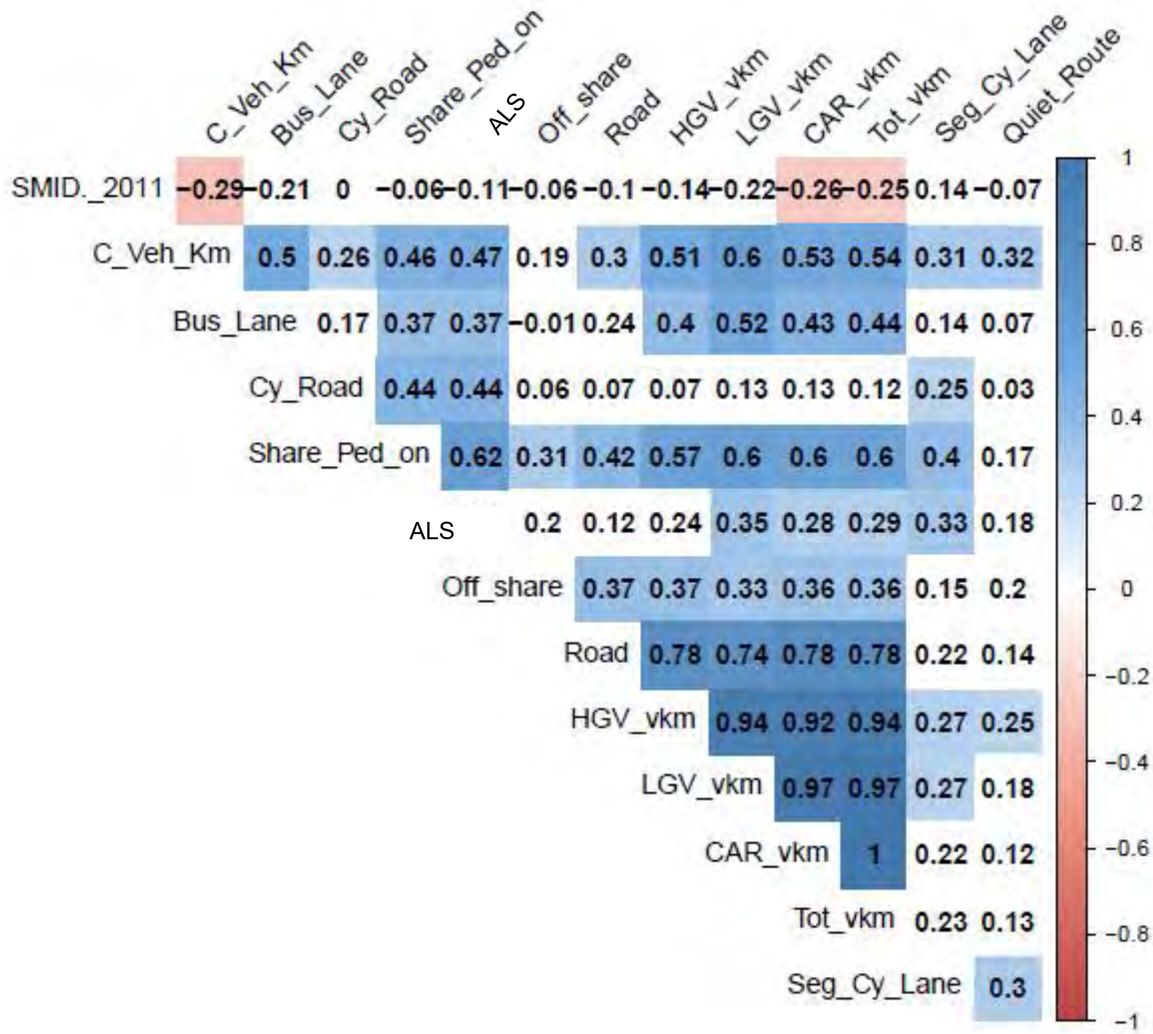

Figure 8-4 Exposure and Dependent variable correlation matrix and significant values (Blue and Red cells are significant correlation coefficients).

The next section discusses the modelling and results of the global GLM-NB and spatial GWPR models fitted to the data described in Table 8.1 above.

8.3 Multivariate Models for Edinburgh

This section examines local factors that may be associated with *SiN*; to consider these we will examine the influence of spatial variation and compare two modelling methods, previously discussed in Chapter 6, the prevailing GLM-NB model and the GWPR model.

Three cases were fitted for each model type: all injury collisions (ALL), KSIs (KSI) and slight collisions (Slight) to examine the *SiN* effect and explanatory cyclist infrastructure variables. In Chapter 6 it was not possible to fit a multivariate GWPR due to data limitations, the multivariate GWPR is feasible in this case study due to data availability. The next section describes the GWPR model fitted process followed by a discussion about the results.

8.3.1 GWPR MODEL FITTING PROCESS

The first explanatory variable permanently included in the GWPR model was the cyclist flow (C_Veh_Km), the second was total vehicle traffic (Tot_vkm) and so on until the last explanatory variable, bus lanes (Bus_Lane), was included (see Figure 8-5 below). In the model selection process, pseudo-stepwise[28], to optimise the AICc (see Figure 8-6 below), was completed after performing 55 iterations.

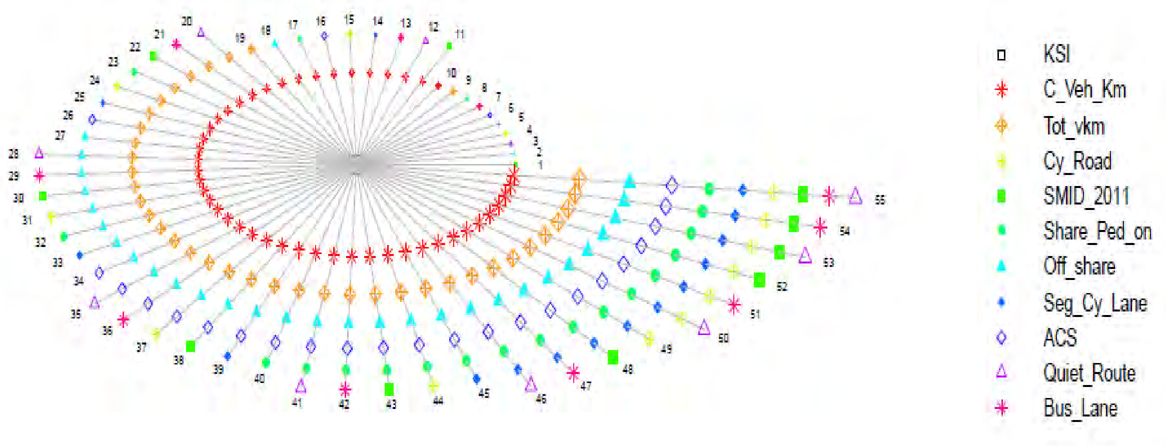

Figure 8-5 Illustration of the GWPR pseudo-stepwise 'forward' variable selection process.

The next part of the model fitting process examines local collinearity between the area units, the Scottish intermediate data zones (N=111). The models to be fitted in this section are multivariate models with ten explanatory variables that are likely to have individual patterns of collinearity between and among them.

Measuring the degree of collinearity that exists in the data (Brunsdon et al., 2012) is a key part of GWPR modelling, the local condition numbers (CN) are used evaluate the levels of collinearity. Gollini et al. (2012) suggests that the CN should be around 30 and that an adaptive method should be used to find the bandwidth to compensate for local collinearity. Furthermore, examination of the VIF is recommend as a diagnostic tool to identify problematic explanatory variables (Brunsdon et al., 2012; Fotheringham et al., 2002).

[28] *See Chapter 3 for a description of the pseudo stepwise regression process for GWPR.*

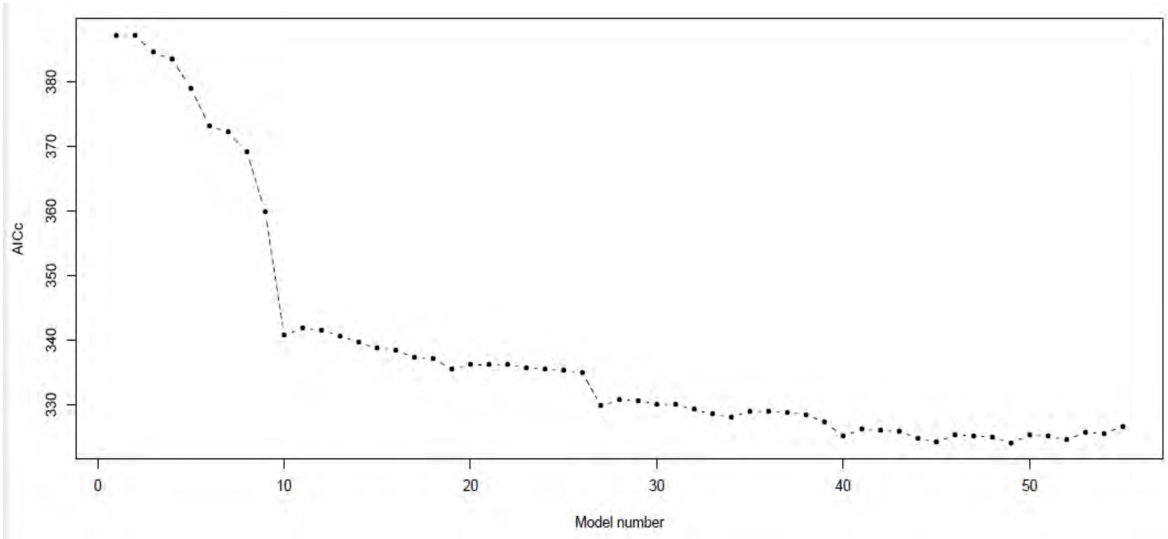

Figure 8-6 GWPR variable selection based on AICc optimisation, KSI model.

The results of the global model VIF were used as a guide to identify important variables and remove problematic ones. An adaptive bandwidth selection was used to calibrate the model bandwidth and finally manual selection was carried out until the CN was reduced to within the acceptable recommended range. The three full models, containing all ten explanatory variables, had high local CN but removing variables guided by the VIF reduced the CN value until the final model (CN Optimised) was achieved, shown in Table 8.3 below. The CN optimized GWPR model coefficient estimates and their respective significance is plotted in Figure 8-5 above. The model for All injuries and Slight injuries were fitted in the same way.

8.4 Multivariate model results for Edinburgh case study

The (global) GLM-NB model results are presented in Table 8.2 and the (spatial) GWPR model results are presented in Table 8.3. The GWPR model estimates and significance results are plotted for each of the intermediate data zones (n=111) and are illustrated in Figure 8-7, Figure 8-8 and Figure 8-9 below.

The *pseudo* R^2 values of the GLM-NB models are only slightly lower than the GWPR models, however the AIC values are significantly better in the GWPR. Similar to the univariate results in Chapter 6, this confirms that the spatial GWPR provides a superior model fit over the traditional GLM-NB models. The next section discusses and compares the model results.

Table 8.2 GLM Negative Binomial model results for KSI, ALL and Slight injury models.

	KSI		**KSI**		**ALL**		**ALL**		**Slight**		**Slight**	
Predictors	*IRR*	*std. Error*	*IRR*	*std. Error*	*IRR*	*std. Error*	*IRR*	*std. Error*	*IRR*	*std. Error*	*IRR*	*std. Error*
(Intercept)	-8.21 ***	1.9	-8.18 ***	1.08	-2.39 *	0.99	-2.22 ***	0.43	-1.75	1.02	-2.09 ***	0.45
	(-11.93 – -4.49)		(-10.30 – -6.06)		(-4.33 – -0.45)		(-3.07 – -1.37)		(-3.76 – 0.25)		(-2.97 – -1.21)	
C Veh Km	0.87 ***	0.19	0.90 ***	0.14	0.64 ***	0.09	0.68 ***	0.08	0.61 ***	0.09	0.63 ***	0.09
	(0.49 – 1.25)		(0.62 – 1.18)		(0.46 – 0.82)		(0.51 – 0.84)		(0.43 – 0.80)		(0.45 – 0.80)	
SMID 2011	0.02	0.29			-0.1	0.14			-0.13	0.15		
	(-0.55 – 0.58)				(-0.38 – 0.17)				(-0.42 – 0.16)			
Cy Road	0.02	0.05			0.04	0.03			0.05	0.03	0.05	0.03
	(-0.08 – 0.12)				(-0.01 – 0.09)				(-0.00 – 0.11)		(-0.00 – 0.11)	
Share Ped on	0.07	0.09			-0.02	0.05			-0.07	0.05	-0.07	0.05
	(-0.11 – 0.25)				(-0.12 – 0.07)				(-0.17 – 0.03)		(-0.16 – 0.02)	
Off share	-0.07 *	0.04	-0.07 *	0.03	-0.10 ***	0.02	-0.10 ***	0.02	-0.11 ***	0.02	-0.11 ***	0.02
	(-0.14 – -0.00)		(-0.13 – -0.00)		(-0.14 – -0.06)		(-0.14 – -0.06)		(-0.15 – -0.07)		(-0.15 – -0.07)	
Seg Cy Lane	0.01	0.04			0.05	0.03	0.05	0.02	0.06 *	0.03	0.05 *	0.02
	(-0.08 – 0.09)				(-0.00 – 0.10)		(-0.00 – 0.09)		(0.01 – 0.11)		(0.00 – 0.10)	
ACS	0.01	0.14			0.18 *	0.08	0.19 **	0.07	0.24 **	0.08	0.25 **	0.08
	(-0.26 – 0.29)				(0.02 – 0.33)		(0.06 – 0.33)		(0.08 – 0.41)		(0.09 – 0.41)	
Quiet Route	-0.01	0.03			-0.02	0.02	-0.02	0.02	-0.03	0.02	-0.03	0.02
	(-0.06 – 0.05)				(-0.05 – 0.01)		(-0.06 – 0.01)		(-0.06 – 0.00)		(-0.06 – 0.00)	
Bus Lane	-0.02	0.04			0.04	0.02	0.04	0.02	0.05 *	0.02	0.05 *	0.02
	(-0.10 – 0.07)				(-0.00 – 0.08)		(-0.00 – 0.08)		(0.01 – 0.10)		(0.01 – 0.09)	
Road	0.07	0.33			-0.03	0.17			-0.02	0.17		
	(-0.57 – 0.72)				(-0.35 – 0.30)				(-0.36 – 0.31)			
Tot vkm	0.21	0.26	0.29 **	0.11	0.06	0.13			0	0.14		
	(-0.29 – 0.72)		(0.07 – 0.50)		(-0.20 – 0.32)				(-0.28 – 0.27)			
Observations	111		111		111		111		111		111	
Cox & Snell's R^2 / Nagelkerke's R^2	0.48/0.51		0.47/0.51		0.69/0.69		0.68/0.68		0.68/0.68		0.67/0.67	
AIC	258.57		243.95		539.74		532.41		509.93		504.74	

** p<0.05   ** p<0.01   *** p<0.001*

Table 8.3 GWPR model results for KSI, ALL and Slight injuries.

	KSI			ALL			Slight		
Explanatory Variables	*min*	*Median*	*max*	*min*	*Median*	*max*	*min*	*Median*	*max*
(Intercept)	-9.07	-7.81	-7.72	-5.31	-3.89	-2.57	-5.21	-3.61	-1.46
C Veh Km	0.86	0.91	1.08	0.54	0.65	0.89	0.53	0.64	0.87
Cy Road									
Share Ped on				-0.23	-0.18	0.10	-0.25	-0.19	0.08
Off share	-0.08	-0.07	-0.05	-0.16	-0.15	-0.08	-0.17	-0.15	-0.09
Seg Cy Lane				0.02	0.08	0.10	0.03	0.08	0.12
ACS				0.12	0.28	0.42	0.19	0.32	0.47
Quiet Route				-0.06	-0.04	-0.03	-0.07	-0.04	-0.03
Bus Lane									
Tot vkm	0.18	0.26	0.31	-0.07	0.28	0.45	-0.15	0.25	0.47
Observations		111			111			111	
Cox & Snell's R^2		0.51			0.80			0.79	
AIC		104.68			194.91			189.44	
AICc		105.45			202.92			197.89	

All results are significant

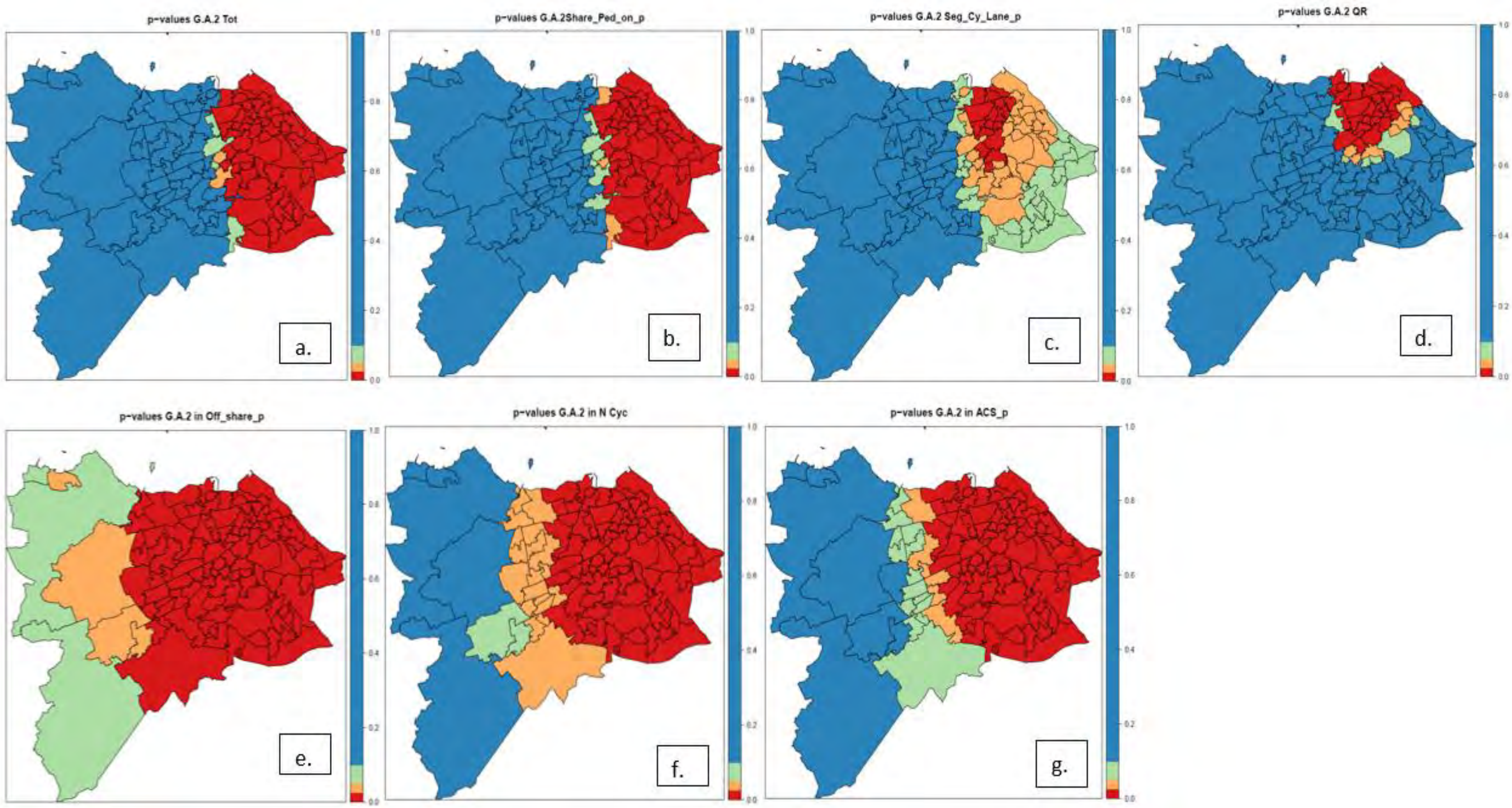

Figure 8-7 Slight cyclist collision GWPR model illustrating the significant local p-values (a) Traffic volume, (b) Shared footways adjacent to road carriageway, (c) Segregated cycle lanes, (d) Quiet Routes (circa.2011/12), (e) Unsegregated Off-road shared paths, (f) Cyclist traffic volume, and (g) the number advanced stop lines for cyclists at controlled junctions.
(*Significant zones, p-value < 0.01, are shown in red*)

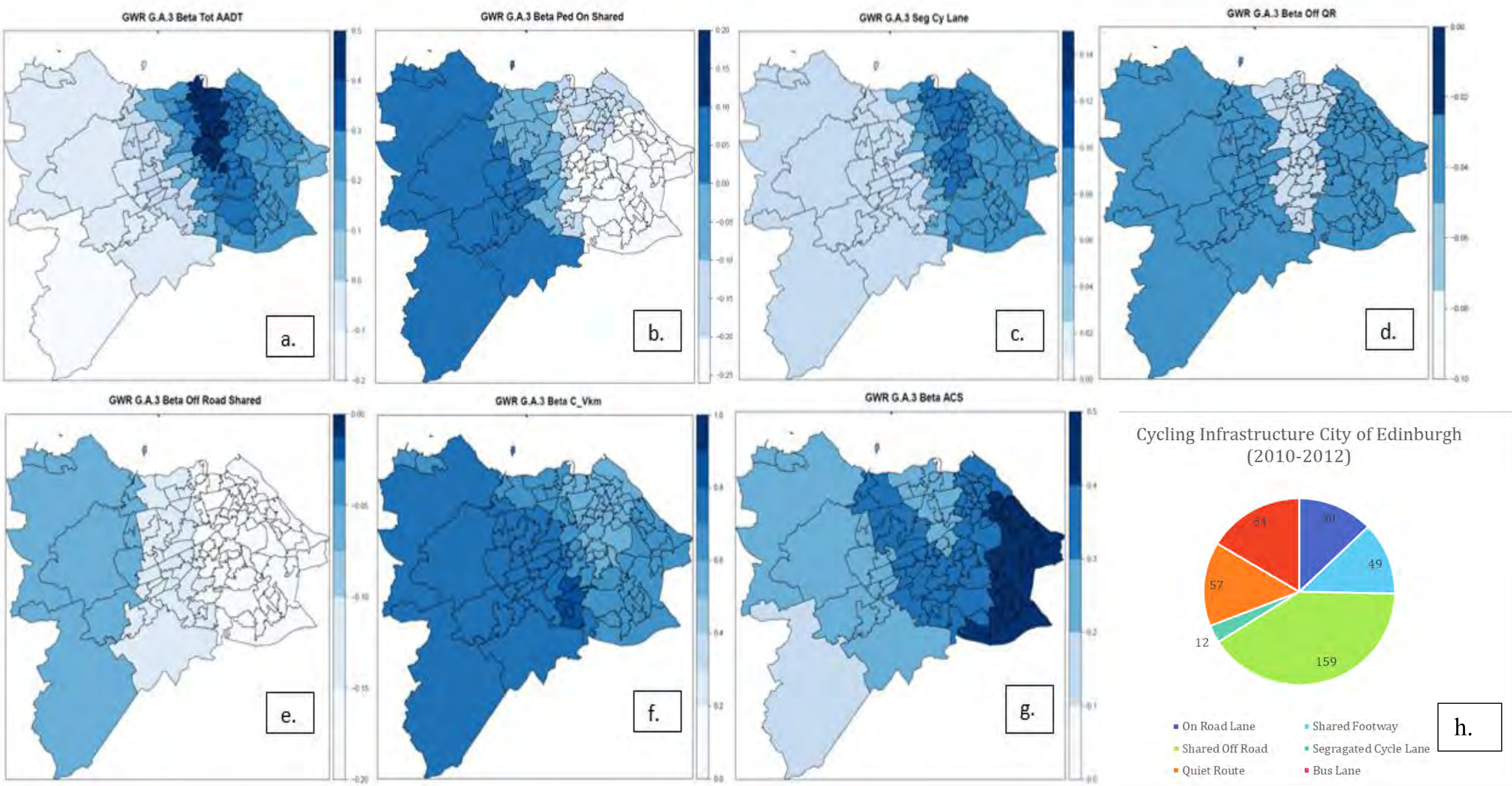

Figure 8-8 Slight cyclist collision GWPR model illustrating the estimated *SiN* coefficient values at each intermediate data zone, (a) Traffic volume, (b) Shared footways adjacent to road carriageway, (c) Segregated cycle lanes, (d) Quiet Routes (circa.2011/12), (e) Unsegregated Off-road shared paths, (f) Cyclist traffic volume (***SiN***), and (g) the number advanced stop lines for cyclists at controlled junctions, (h) proportions of cyclist infrastructure types.

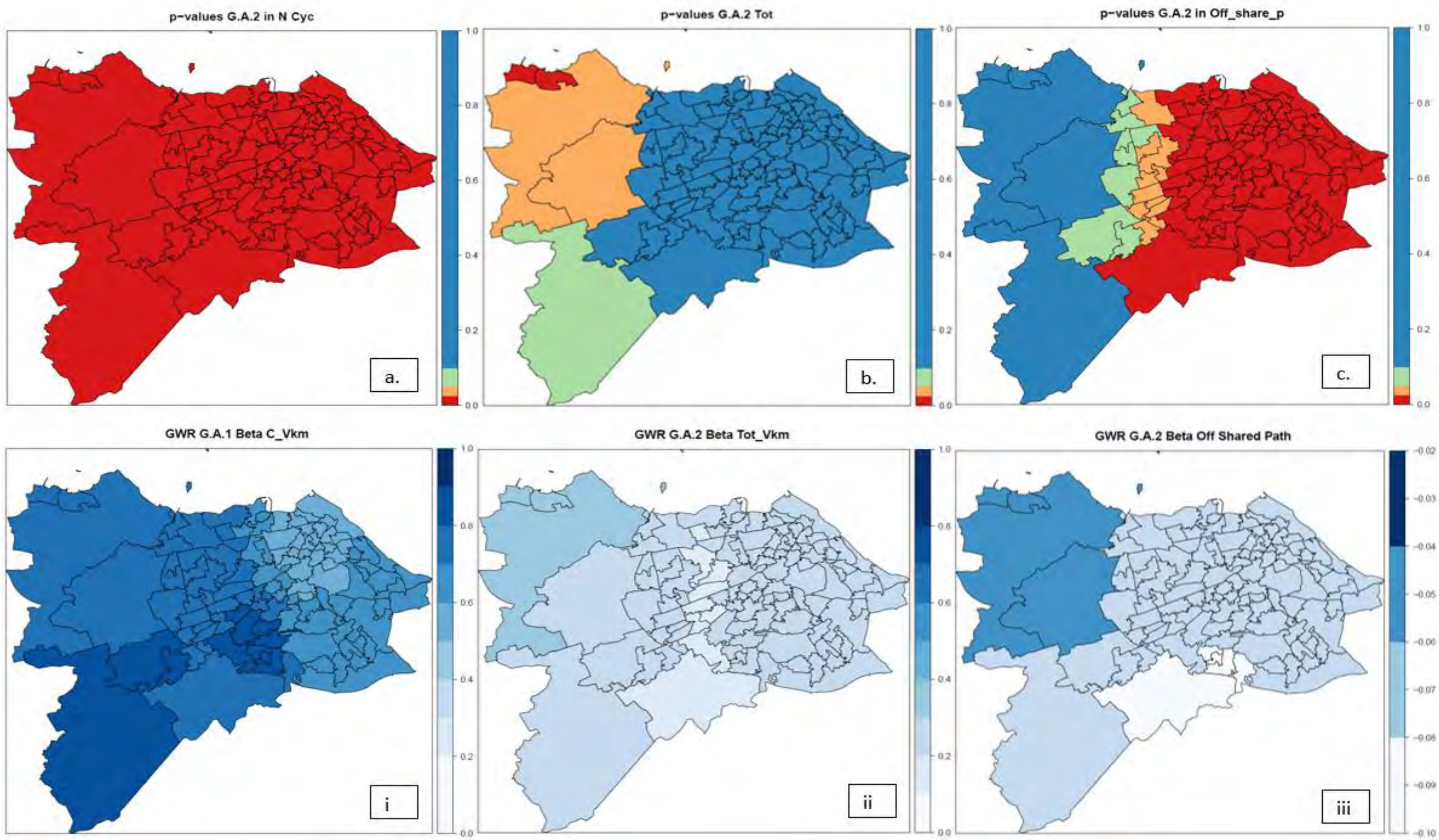

Figure 8-9 KSI GWPR model illustrating the significant local p-values (a) Cyclist traffic volume, (b) Traffic volume, and (c) Unsegregated Off-road shared paths. (*Significant zones, p-value < 0.01, are shown in red*).
2. KSI cyclists' collision GWPR model illustrating the estimated coefficient values at each intermediate data zone, (i) Cyclist traffic volume, (ii) Traffic volume, and (iii) Unsegregated Off-road shared paths.

8.4.1 Multivariate model results comparison

This section will compare the GLM-NB and GWPR model results for each of KSI, ALL and Slight cyclist injury collisions and the final part of this section will discuss the results with respect to *SiN* in Edinburgh. This section should be read in conjunction with the ArcGIS maps illustrating the location and quantity of the cycling infrastructure, Figure 8-2 and Figure 8-3 above, and the GWPR results of the coefficients and the significance plots, illustrated in Figures 8-7 to Figure 8-9 above.

The only significant cycling infrastructure variable in both the global GLM-NB and spatial GWPR KSI models was the <u>off-road shared unsegregated cycle paths</u>. The estimated coefficient sign was negative, so it has a beneficial effect (i.e. reduces cyclist KSIs). The GWPR KSI model also estimated coefficients that indicated a stronger effect than the GLM-NB, ranging from -0.16 to -0.08, however the beneficial effect was only significant within the central and eastern zones of the city, Figure 8-9 (c) above. This result is expected because shared off-road cycle paths, that are traffic-free, comprise the largest proportion (159 km) of the cycling infrastructure (159 km) in Edinburgh, see Figure 8-2 (a) and Figure 8-7 above.

The <u>total volume of motorised traffic</u> was included in both the GLM-NB model and the GWPR model, however the GWPR model shows that it is only significant in two zones in the north west of the city, see Figure 8-9 (b). The <u>cyclist traffic volumes</u> were significant in both the GLM-NB and GWPR models and will be discussed separately at the end of this section with respect to *SiN*.

Unlike the KSI model, the ALL and Slight injuries models included a number of significant explanatory variables. These explained a high proportion of the model variance with *pseudo* R^2 values of 0.8 and 0.8 in the GWPR models and *pseudo* R^2 values of 0.7 and 0.7 in the GLM-NB models, respectively. The ALL and the Slight GLM-NB models had very similar results and the GWPR model results were almost identical. The GLM-NB ALL and Slight models did not include the explanatory variables for Shared pedestrian footways and Quiet Routes as they were not significant, these variables were however significant in the GWPR models.

Segregated cycle lanes (see Chapter 2, Section 2.2.3.2.2 for an illustration) were positively associated with cyclist Slight/All injury collisions with coefficient estimates ranging from 0.02 to 0.12. This variable was not included in the KSI models (as it was not significant), so the result relates to slight cyclist injuries only and the result is only significant in a small number of zones to the north east of the city, see Figure 8-7 (c) above. There is a very limited amount of this type of infrastructure in Edinburgh, and nearly half of it is in the area identified. Segregated cycle lanes should ideally offer increased safety, but the implementation of the facility is often poor due to lack of continuity. Cyclists are required to dismount to cross at pedestrian controlled and uncontrolled crossing facilities which may contribute to its less than optimal performance. Furthermore, the amount of the infrastructure included in the model is small and therefore the results, while statistically significant, may be unreliable.

The shared pedestrian footway coefficient results ranged from -0.23 to 0.08 in the GWPR model. The negative sign indicates a positive safety effect, but the existence of some areas with a positive sign (i.e. negative safety effect) is interesting. An examination of the location of the relevant zones sheds some light on this. First, the result is significant in most zones except the zones to the west of the city, Figure 8-7 (e), and zones showing a beneficial effect correspond to the significant zones. Thus, the negative impact is not significant. This type of facility is available when an existing footway, beside the road carriageway, is re-allocated by CEC to be used as a shared cycle and pedestrian path. Here, pedestrians and cyclists are not segregated, and a posted blue sign is used to denote its presence (see Chapter 2, Section 2.2.3.2.1 for an illustration) and the results show that they have a beneficial safety effect.

The concentration of advanced stop lines (ASL) at signal-controlled junctions in an IZ has estimated ranging from 0.12 to 0.47, meaning that cyclists have an increased risk of a slight collision injury where this facility is provided. This result is attributable to the fact that ASL are located at junctions where most cyclist collisions occur, nonetheless some safety effect would have been expected given their prevalence of use (there are over 600 provided across the City of Edinburgh) and the fact that they are recommended in the guidance documents

[29].

However, most of the ASL provided lack adequate feeder lanes on the approach to the junction, the feeder lanes are not mandatory (i.e. may be legally traversed by motorised vehicles) and they are provided as a standalone measure (i.e. do not connect to other facilities before/after/through the junction). The effect is significant in the zones where the ASL are most prevalent, Figure 8-7 (g) and Figure 8-2 (b) above. As discussed above, most of the ASL are provided as a standalone measure, this likely contributed to their lack of effectiveness and the results would seem to confirm this because the worst effected zones, to the south and east of the city illustrated in Figure 8-8 (g), show that the ASL provided in these areas lack on-road cycle lanes. While the on-road cycle lanes (i.e. cycle lanes marked on the road carriageway with a dashed white line) were not significant in any model, their presence seems to have some beneficial effect associated with the ASL. This may be due to drivers being more aware of cyclists on the approach to a junction.

The last explanatory variable included in the GWPR models was the Quiet Routes and the results show that they represent a positive safety effect on slight injury collisions, the coefficient estimates range from -0.07 to -0.03. The beneficial effect is strongest in zones through the central north of the city and is only significant in a small number of zones, see Figure 8-7 (d) and Figure 8-8 (d) above, which is where a number of Quiet Routes cross and where they are most prevalent in the city, see Figure 8-2 (d).

Since 2011/12 there have been a number of new routes added to the network and several more are planned which should help to reduce slight injury collisions in the areas where the network is extended into. See Appendix A 8.1 for a map of the planned route extensions as part of the CEC ATAP 2017-2020 strategy to improve cycling numbers and cycling safety.

As mentioned above, in relation to ASL, on-road cycle lanes were not found to be significant in any model and this confirms the results presented in Chapter 5 that found that this type of infrastructure does not provide any safety benefit compared to cyclist collisions where these facilities are not provided (i.e. mixing with traffic). This is not unexpected because the lanes are implemented on a non-mandatory basis such that they are not subject to a Traffic

[29] *Handbook for Cycle-Friendly Design, Sustrans, 2014, pg.13); Local Transport Note LTN 2/08 Cycle Infrastructure Design, DfT, 2008, pg.56); Cycling by Design, (Scottish Executive, 2010, pg.90)*

Regulation Order and therefore vehicles may legally park in (subject to parking regulations in force) and travel on the cycle lane. Chapter 5 identified some of the negative safety impacts of this combination such as dooring and cycles colliding with a parked vehicle in a cycle lane. Therefore, the potential beneficial safety effect is eroded due to:

i) Parking regulations that hinder the safe function of the lane,

ii) Lack of stronger regulation of traffic because the lanes are provided in a non-mandatory capacity (this is due to authorities prioritizing parking over the cyclists), and finally

iii) the space is not protected and can't be if i) and ii) are permitted.

Therefore, these spaces are multi-functional and while the paint may suggest a place for cyclists to occupy the reality is that this space is double booked due to permitted parking and vehicles using and encroaching the lane legally.

The <u>deprivation variable</u>, unlike the results in Chapter 6, was not significant. However, this is not surprising given that Edinburgh is one of the least deprived areas in Scotland according to the Scottish Index of Multiple Deprivation 2012.

The <u>bus lane variable</u> was not significant in any of the models tested, however the GLM-NB KSI model coefficient sign was negative which may suggest some positive beneficial safety impact. In a similar way to the on-road lanes discussed above, bus lanes offer a compromised space for cyclists.

Finally, this section discusses the <u>volume of cyclists</u> in relation to cyclist collisions with specific reference to *SiN* (i.e. a doubling in cyclists results in a reduction in cyclist casualties by a third, see Chapter 2 – Part B for details). The KSI models and then the ALL and Slight models with be discussed in turn.

The KSI GLM-NB model coefficient for cyclist traffic volume (C Veh Km) is 0.9 which indicates that there is little to no *SiN* effect for KSI collisions in Edinburgh. The GWPR model coefficient estimates however range from 0.9 to 1.1. Coefficients greater than 1 indicate that increased cycling volumes will result in more KSI collisions, and at a more than proportional rate, therefore there is no *SiN* effect evident in Edinburgh for KSI cyclist collisions.

The GWPR significant results, Figure 8-9 (a) above, shows that cyclist traffic volumes are significant in all zones across Edinburgh. The coefficient estimates, illustrated in Figure 8-9 (i), show that there appears to be some *SiN* effect among the zones to the north east of the city. As discussed above, this is where Quiet Routes and off-road unsegregated cycle routes are most available, and while these variables were not significant in the GLM-NB or GWPR models they appear to have some beneficial effect on cyclist's KSI collision reduction. This is reflected in the results of the ALL model where these explanatory variables were significant, but this result is biased towards slight injuries because they make up the majority, see Table 8.1 above (Slight = 582, KSI = 109).

As noted above, the results of the ALL and Slight models were very similar. The GWPR Slight model coefficient estimates range from 0.53 to 0.87, coefficients less than 1 indicating that increased cycling volumes will result in proportionally fewer slight collisions, therefore there does appear to be a *SiN* effect evident in Edinburgh for slight cyclist collisions. This result is significant in the central and eastern zones, Figure 8-7 (f), and the strongest *SiN* effect occurs in the north of the city that benefits most from the presence of cyclist infrastructure, as discussed above.

In summary, the *SiN* effect which is evident in Edinburgh relates to ALL (slight) collisions and is not apparent nor absent when considering KSIs. The next section will discuss the results of an injury severity logistic regression model fitted for KSI cyclist collisions in Edinburgh. The aim of this model is to expand our understanding of the KSI cyclist injuries because the results above found that there was no apparent *SiN* effect.

8.5 Results: Multivariate Logistic Regression

In the previous section, the KSI models for the GWPR and the GLM-NB explained approximately half of the model variation and the model fitting process found a limited number of significant explanatory variables compared to the GWPR and the GLM-NB models for all injuries (ALL) and slight injuries (Slight). Based on the results discussed in Chapter 5, where it was found that speed was a significant explanatory variable and that controlled pedestrian crossing facilities were significant, an injury severity binary logistic model was fitted for the sample of the cyclist's collision data in Edinburgh (n=198).

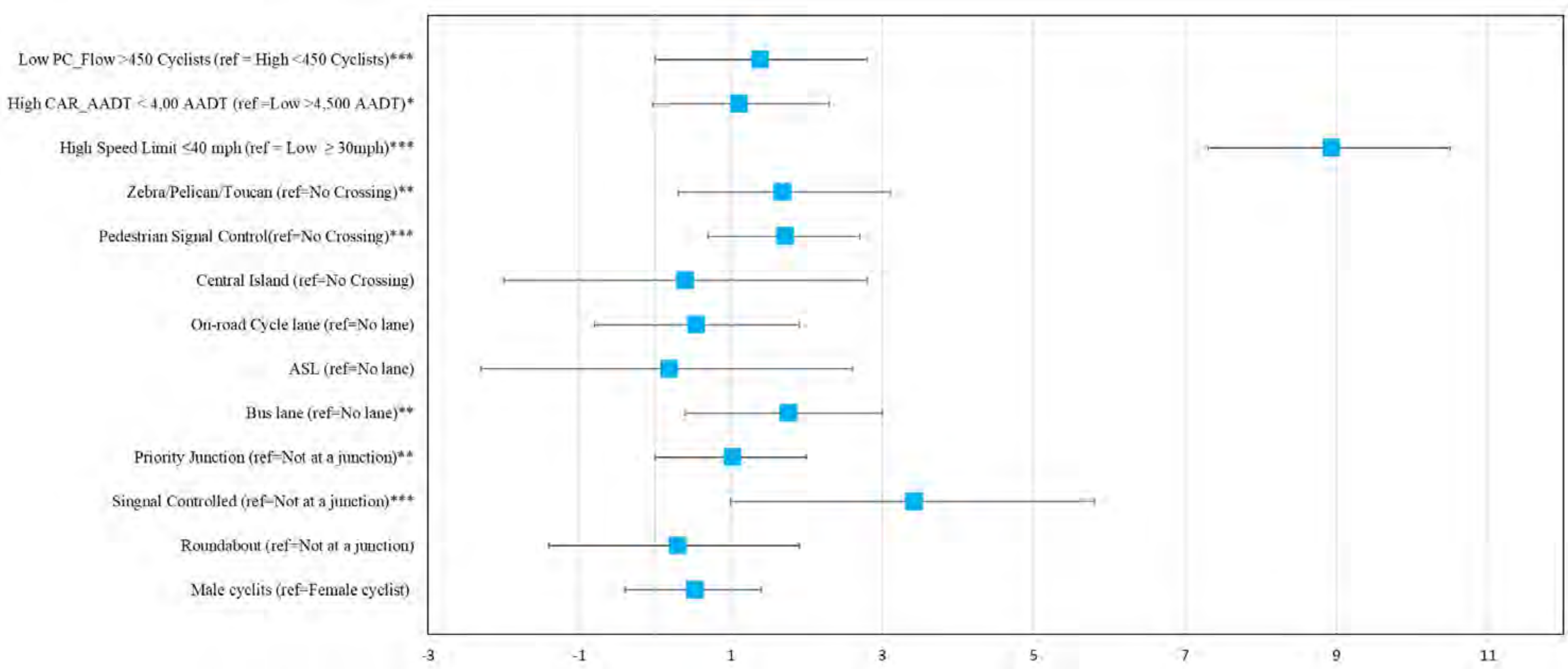

Figure 8-10 The logistic GLM and Odds Ratio plot of cyclist collisions in Edinburgh. (Odds ratio reference level in parenthesis, significance *p<0.10, **p<0.05, ***p<0.01).

The speed data was derived from the posted speed limit recorded in the STATS19 data, the cyclist volumes and the traffic volumes were extracted from the ArcGIS model, discussed and illustrated in Figure 8-1, speed was classified as either Low (≤30mph) or High (≥40mph). The binary threshold for low and high traffic volumes was determined from cycling guidance document classification (Sustrans, 2014; Fig 2.1) and low cycling flow was estimated at 10% of this figure. The model results and the odds ratio plot are illustrated in Figure 8-10 above.

In Chapter 5, the female models for cyclist KSI collisions and all injury cyclist collisions had the highest coefficient estimates of 0.85 and 0.9, both close to 1 which suggests that there is no *SiN* effect. In contrast, the male KSI cyclist collisions model coefficient estimate was 0.41, less than half that of the female estimate, which indicates that they do benefit from a *SiN* effect. Nearly twice as many men cycle in Edinburgh cycle than women (TS,2016b; Table 25b) and according to the report published by Sustrans (2018), highlighting the gender gap in cycling, only 27% of women think that cycling is safe (Edinburgh is one of the seven cities included in the report). Based on the risk differential between male and female cyclists, their perceived risk aligns with observed risk, firstly compared to male cyclists and secondly compared to other modes of transport. In terms of transport equity, road safety risk disproportionally impacts women, Aldred (2015) suggested that road safety is a gendered issue when it comes to cycling based on the near misses' research carried out in London that found that women reported twice as many '*frightening near misses'* on the road than men.

The results above show agreement with the Scotland results found in Chapter 5, women in Edinburgh have twice the risk of having a KSI collision then men, however this result was not significant and a larger sample size over a longer time period may provide a more conclusive result.

In Chapter 5, the female models showed that pedestrian controlled crossings were associated with higher KSI risk, the results in this chapter show that pedestrian controlled crossings at signalised junctions and zebra/pelican/toucan crossings were significant and had higher odds ratios for cyclist KSIs. This indicates that cyclists may be using these facilities or that there is some ambiguity related to their use between cyclists and drivers interactions which is beyond the scope of this research. However, it does highlight a risk factor and there is evidence within the contributory factors that suggests that this is a prevalent problem, the second most cited contributory factor involved in 20% serious collisions attributed to cyclists was ‘entering the road from the pavement’(including when a cyclist crosses the road at a pedestrian crossing) (RoSPA, 2017).

As discussed previously, some of the pedestrian footway in Edinburgh have been re-allocated to provide shared unsegregated paths that are signed at the start and end of the applicable section, the total length of re-allocated footway in Edinburgh is 49 kilometers, about 12% of cyclist facilities and only 3% of the total road network (see Appendix 8.2 for detailed breakdown of cyclist facilities in Edinburgh taken from the ArcGIS model developed for this research) which is why the sample did not include enough data to draw any conclusions about the KSI risks in this model. Similarly, the total length of on-road cycle lanes was 50 km but as with the re-allocated footways they only make up 3% of the entire road network in Edinburgh so the sample did not include enough data to draw conclusions and while the bus lane result is significant in the model it also only represents a very small sample.

From the sample (n=190) involved a cyclist collision, 37% occurred at a pedestrian controlled facility, 23% at a pedestrian phase at junction signals, 9% at zebra/pelican/toucan and 5% at central islands and the odds ratio showed that these locations were associated with higher KSI risk for cyclists. Therefore, there is evidence that cyclists may be using pedestrian facilities which suggests a need to provide facilities for cyclists.

The odds ratio for the posted speed limit, on the road where the cyclist collisions occurred, was nearly 9 times higher on road with a posted speed limit of 40 mph or more compared to 20 mph and 30 mph roads. Therefore, this result aligns with previous research concerning the association of speed with higher KSI risk (Elvik, 2009). The data examined in this research relates to the time period 2010 to 2012, in 2011 the first 20 mph pilot scheme was introduced in Edinburgh. Therefore, this research does not include results specific to 20 mph roads because the implementation of the 20 mph schemes postdated the sample data analysed – additional research to replicate this analysis when the next census data is available is recommended to further consider the impact of low speed zones.

The next section provides the main results and conclusions for this chapter and discusses how they address and answer specific research objectives and questions.

8.6 Discussion and Conclusions

The overall aim of this Chapter was to investigate whether there was evidence of localised cyclist *SiN* effect in Edinburgh, to examine what part the road environment played and to look at road safety policy with respect to cyclist infrastructure. This chapter gathered results from global GLM-NB and spatial GWPR models in Section 8.4 and a binary logistic regression to further assess KSI risk in Section 8.5. The following section discusses the main findings and how they address the research objectives and research questions.

OB-01: *Examine the processes used to implement road safety policy and investigate how this has had an impact on cyclist road safety in Scotland.*

The results found that on-road cycle lanes have no safety benefit over the status quo (i.e. cyclists mix with traffic in the main road carriageway). This form of infrastructure is installed on 3% of the total road network in Edinburgh and the total length provided is 50 km. The potential expected benefit however appears to be eroded or hindered by existing parking policies and the non-mandatory implementation of most of the lanes provided. As previously discussed, they are "double booked". The results for all of Scotland, from Chapter 5, also found that on-road cycle lanes were ineffective. Similarly, cyclists are permitted to use bus lanes, but no safety benefit was found in Edinburgh in this research, which was also the finding for Scotland, in Chapter 5.

Advanced stop line areas at junctions are also a recommended provision to improve cyclist safety and priority at controlled junctions, however the results did not find a benefit in terms of road safety.

In addition to the on-road facilities, local councils also provide Quiet Routes, re-allocated pedestrian footways into shared pedestrian and cycle routes, shared off-road paths and, to a lesser extent, segregated cycle lanes (physically separated from the carriageway and pedestrians). The results above show that these facilities do have an overall beneficial effect for cyclist safety, however that effect does not extend to KSI cyclist collisions.

OB-02: *Critically analyse road safety evidence, focusing on cyclists, to develop an understanding of the wider factors involved.*

The main finding in this chapter is that there little or no *SiN* for cyclist KSIs in Edinburgh but there is evidence that the *SiN* effect is stronger for slight injury collisions. As discussed above, on-road cycle lanes that are not protected physically and hindered by parking policies are ineffectual infrastructure interventions in terms of cyclist safety. Physical infrastructure matters, the results from this research demonstrate that cycle lanes offer little safety and when combined with on-street linear parking exacerbates cyclist safety risk (Beck et al., 2019).

The only infrastructure explanatory variable in the GWPR and the GLM-NB model that had a significant effect were higher lengths off-road shared cycle lanes. These results suggest to reduce KSIs, segregated facilities to improve safety are needed whereas the CEC cycle friendly measures (i.e., Quiet streets and widespread use of isolated ASL and non-mandatory on-road lanes) will reduce slight injuries but not KSIs. Further, zones that had higher concentrations of significant explanatory variables had stronger *SiN* effects and they were also associated with higher levels of cycling too.

RQ-01: *At a global level, is there a SiN effect evident among cyclists in Scotland?*

The aggregate answer to this question is yes, however as the results above clearly demonstrate the *SiN* effect is present for slight cyclist injury collision only and there is no apparent *SiN* effect for KSIs. Furthermore, the spatial GWPR plotted results show that the strength of the *SiN* effect corresponds with the levels of beneficial cycling infrastructure present in a zone. (i.e. Quiet Routes, shared pedestrian footways and off-road shared paths)

RQ-02: *Is there a reduction in cyclist's injury because of increasing cycling evident at a local population level?*

The results in this chapter demonstrate that while the overall cycling levels in Edinburgh are relatively high, the *SiN* effect varies by zone across the city and it is associated with both higher levels of cycling and the provision of infrastructure. The results and research presented in this chapter provides a means to evaluate cycling policy or infrastructure based on road safety evidence.

It is interesting to compare the infrastructure planned for the city with the findings in this research, first in terms of the type and concentration of infrastructure provided across the city and second, to look at the safety performance at a zonal level. As discussed previously, the zones with more infrastructure had stronger *SiN* effect and they were located to the north east and centre of the city. The zones with the weaker *SiN* effects were located in the south west of the city and therefore improving infrastructure and reducing speeds in this sector of the city would reduce the number of cyclist injuries. However, the new infrastructure or proposed improvements contained in the CEC development plans, see Appendix A 8.1 for a detailed map, notably is largely omitted from this area which highlights the need for evidence-based information on factors and exposure that effect cyclists which this research addresses.

RQ-04: *Are the prevailing national road safety policies a good fit for cyclists, if not, why? Can we provide better cyclist specific accident and safety evidence at a local level?*

The two-prong approach to cycling infrastructure and safety in Edinburgh consists of Cycle Friendly measures and extending and upgrading 'Quiet Routes' but this research shows that some cycle friendly measures such as on-road cycle lanes and ASL are ineffectual in terms of safety benefit. While the concept may be sound, they need complementary measures to allow them to work as intended, such as prohibiting parking and providing physical and regulatory protection (i.e. make mandatory through a Traffic Regulation Order) of on-road cycle lanes.

The results in Chapter 6 found that, although Edinburgh had the highest proportion of cyclists among the local council areas, it did not have a stronger *SiN* effect for KSIs. The results presented in this chapter agree with this result and show that KSIs in Edinburgh have little or no *SiN* effect, furthermore the logistic regression showed that speed reduced the odds ratio of a cyclist having a KSI collision. Chapter 5 discussed how urban area low speed roads (i.e. 20 mph and 30 mph) may not benefit from the deterrence that police presence or enforcement provides because police consider these roads to be 'self-enforcing' roads and therefore focus enforcement on roads with speeds over 40 mph. Therefore, urban speeds may be higher than expected and contribute to more severe injuries.

The odds ratio of a female cyclist having a KSI collisions is twice as high as male cyclists. The gender gap in Edinburgh persists despite the sustained long-term growth in the numbers of people cycling in the city today and road safety is a concern women still have. The measures implemented to date do not address ways to mitigate their concerns and the real risk imbalance between men and women. Women want segregated infrastructure and more off-road routes, and both are needed to mitigate KSI collisions generally. Without addressing women's needs, our transport system will continue to exclude women from participating in this activity which impacts their rights and freedoms, for example women with children need to be able to travel with their children safely. In the UK, fewer women than men meet the recommended physical activity levels, contributing to ill-health, early death and impeding mobility which can exacerbate existing inequalities in society.

Transformative examples include Seville where gender balance materialised when separated cycling infrastructure was implemented dating from the 1990s when transport authorities asked women what they needed (infrastructure) and in providing this, transformed the city. Also, in the 1990s in Vienna, a public survey on transport was undertaken by city planners. They realised responses differed between men and women. Simple steps were subsequently taken to better design Vienna for women, including better street lighting to make streets safer after dark, or widening pavements to make it easier to walk about with strollers and buggies. Vienna is now widely known as one of the most livable cities in the world. Transport equity, as discussed in Chapter 2, still needs to be addressed.

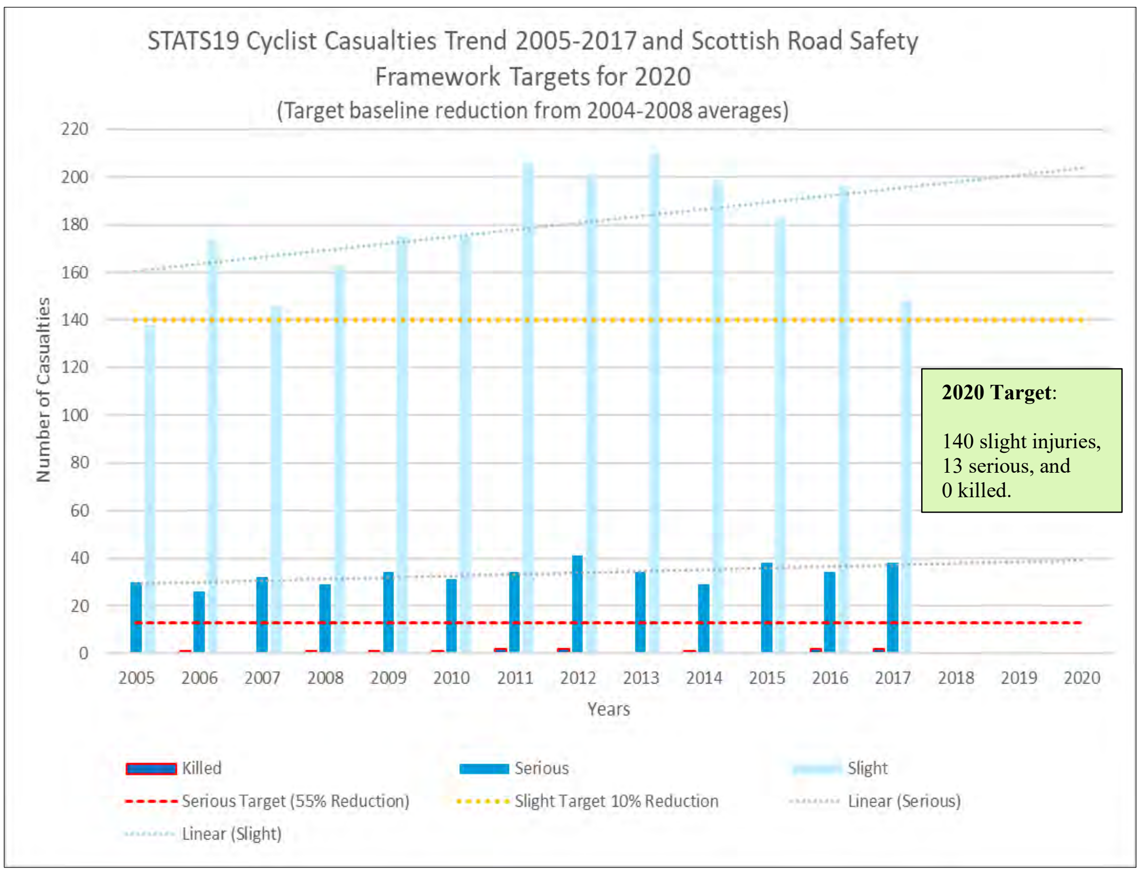

Figure 8-11 Edinburgh roads safety performance 2005 to 2017 against the Scottish Road Safety Targets for 2020.

Therefore, the current infrastructure offer does not entice or encourage the levels of women to cycle that policy may have hoped to achieve. While this is in part due to external factors such as working patterns and other time and family commitments, the research in this chapter shows that women have a higher risk of KSIs in Edinburgh. Off-road cycling infrastructure was the only infrastructure type that was significantly associated with less KSI risk. Furthermore, Figure 8-11 above illustrates that cyclist road safety performance against the Scottish Road Safety Framework targets are not likely to be achieved and they are continuing to increase.

To conclude, a *SiN* effect was found in Edinburgh, but it was concentrated where cycling flows were higher and cycling infrastructure was present. Little to no *SiN* effect was found for KSIs in Edinburgh. This chapter presented the final section of analysis and results. The next chapter draws together the results and discussion from all four research chapters to discuss the final conclusions and contributions.

CHAPTER 9

Conclusions

9.1 Introduction

This chapter begins by providing a summary of how the research objectives were achieved and answers the subsidiary research questions, as posed in Chapter 3. The next section compiles the research results from Chapters 5 to 8 and draws them together to present the main findings. Then the following section will include the most recent cyclist casualty trends, targets and road safety policies to frame the significance of the research. The evidence from all the sections is then used to provide recommendations for future policy and safety (or key) performance indicators pertaining to cyclists. Finally, the chapter discusses the limitations of the research, future work and research, and closes with the final thoughts and conclusions.

9.2 Objectives, Research Questions and Contribution

This section combines the detailed analysis presented and discussed previously, in Chapters 5 to 8, to demonstrate how each part of the research addressed the stated objectives and research questions. This section provides a summary of how each of the research objectives were addressed and research questions answered by drawing together all the research findings into a single commentary below. First the three research objectives will be discussed and then the five subsidiary research questions will follow.

OB-01: Examine road safety policy and investigate how this has had an impact on cyclist road safety in Scotland.

This objective was addressed in Chapter 6 and Chapter 8. The results show that *SiN* has not materialised as one would "expect", which has been described as worrying (Aldred et al., 2017). The results in Chapter 8 however, show that there is a positive *SiN* impact when considering slight cyclist casualties but that the effect has not extended to KSIs. This reflects the observed trends in cyclist casualties because KSI numbers have steadily crept upward since 2005 and particularly in the last decade as cycling has increased (see Figure 9-1 below). This trend is counterproductive to achieving Vision Zero (see Appendix 9.1) which the Scottish Government aims to achieve.

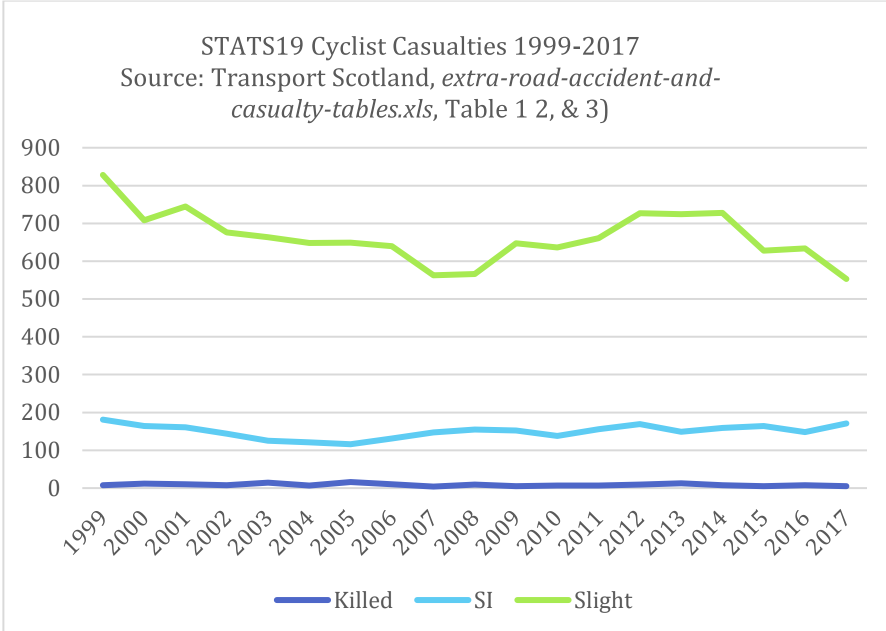

Figure 9-1 Cyclists killed, serious injury (SI) and slight injury casualty trend from 1999 to 2017.

This is strong evidence that *SiN* should not be used in cycling safety discourse by the Scottish Government or its partners. The current policies take *SiN* as a given positive and safety inducing effect achieved through encouragement to cycle. However, despite the great work and extent of measures that support, promote, and encourage cycling, the numbers speak for themselves. Furthermore, where the *SiN* effect is apparent, women do not benefit from it and therefore road safety policies fail to address gender.

OB-02: Critically analyse road safety evidence, focusing on cyclists, to develop an understanding of the wider factors involved.

This objective was addressed in Chapters 5, 6 and 7. The results demonstrate that cycle lanes offer little safety benefits when modelled using national level, data from the STATS19, or in the Edinburgh models, that included more detailed infrastructure variables and cycling flows.

In Chapter 5, the results highlighted two policy areas that impact cyclist road safety. The first is parking policy. On-road cycle lane safety odds were not significantly different to a road carriageway without on-road cycle lanes or bus lanes and this is probably due to parked vehicles and dooring causing cyclist injuries in cycle lanes. Their non-mandatory status means that parking may be provided by the local authority as part of the city's transport planning. Physical infrastructure matters but in combination with on-street linear parking it exacerbates cyclist safety risk (Beck et al., 2019). Parking policy needs to be made part of sustainable transport measures to increase cycling and improve safety in Scottish cities and towns to free up urban space for cyclists so that parking related injuries can be mitigated, safety perceptions improved and thence remove barriers to more cycling participation.

Secondly, police attended less cyclist injury collisions than car driver injury collisions: 76.6% of cyclist KSI collisions are attended compared to 96.3% of car KSI collisions. The decision to attend a road traffic collision is discretionary, therefore the availability of evidence (e.g. evidence that may be required for criminal or civil action, post collision) may not be available, which hinders the injured cyclist's ability to gain a legal decision in the courts if they were not at fault. Therefore, the legal system and policing policies in place need to be more supportive so that cyclists, when injured, have equitable response and legal strength.

In Chapter 6, women were found to have a lower *SiN* effect compared to men. Firstly, this demonstrates that women do not appear to benefit from *SiN* while men do; and secondly, that two previously hypothesised reasons for the manifestation of *SiN* do not appear to hold, i.e. that more cyclists on the road leads to drivers becoming more aware of them and adjusting their driving behaviours which results in fewer cyclist collisions, and that increased numbers stemming from better infrastructure creates a safer environment. Furthermore, female cyclists were found to be at greater risk than men of having KSIs at infrastructure types such as pedestrian crossing facilities.

At present, the national and regional transport models do not include cycling, walking or motorcycling, the vulnerable road user group: the models only provide estimates for motorised transport. Similarly, the City of Edinburgh does not have a transport model that provides cyclist flow estimates and when models have been developed their purpose was to assess major infrastructure changes, such as the Edinburgh Tram extension. Therefore, policy planning, monitoring, and evaluation against targets is very limited in comparison to motorised transport. Bespoke micro-simulation type network models are typically required to provide a mobility-based measure of 'exposure'. To combat these discrepancies, this research developed a model using census data, open source software 'stplanr', and routing engine data from CycleStreet.net, as well as combining several existing sources of raw observed cycling data from traffic counters and cycle counters.

This combined approach offers policy makers and planners empirical information – how much cycling happened and where – to monitor cycling numbers and safety more effectively using a normalised risk metric based on 'exposure' rather than merely the frequency of cyclist collisions and static count information or travel surveys. When cycle flow data is not available, a proxy 'exposure' measure based on aggregate population mode choice is used, but this research demonstrates that this can misrepresent where cycling intensity (i.e. flow density) occurs on the network resulting in unreliable risk estimates. Therefore, the ability to accurately estimate mobility-based exposure, as demonstrated in Chapter 7, is essential to our understanding of cycle safety and to our understanding of where cycling infrastructure is most needed and used. Taking a safe systems approach, cycling network exposure is an essential component, not only for risk evaluation, but also for monitoring of maintenance, evaluating the potential impacts on shared pedestrian routes and future changes to parking policy such as additional infrastructure.

Finally, as transport planning and funding moves towards greater prevalence and support of cycling as a transport mode, the analysis and results from the model validations suggests that the current transport model validation methods may need to be updated to include cyclist specific validation methods. The existing transport assessment thresholds for validating transport models are geared toward motorised transport models. This research demonstrated that the GEH[30] statistic and thresholds contained in the current transport modelling guidelines need to be re-examined in order to be fit for purpose for cyclist transport models. As more authorities implement larger and more extensive cycling schemes, funding and appraisal rules[31] determine that they must be appraised under cost-benefit and wider impacts, and a transport model traditionally plays a central role in appraisal.

OB-03: Use the understanding gained, from the first and second research objectives, to develop specific performance indicators for cyclists.

[30] *GEH (Geoffrey Edward Havers) statistic is a modified Chi² statistic used to calculate a value for the difference between observed and modelled flows, it is the validation method used in the Design Manual for Roads and Bridges, Volume 12 Traffic Appraisal of Road Schemes, Section 2 Traffic Appraisal Advice, Part 1 Traffic Appraisal in Urban Areas, Table 4.1. This is the requirement for the Transport Appraisal Guidelines*

[31] *Scottish Transport Appraisal Guidance (Scot-TAG).*

This objective was addressed in Chapters 5, 6, 7 and 8 where what matters is the pre- and post-collision enforcement context, the type of infrastructure, what and how cycling activity is measured, deprivation, disaggregation of cohorts within cyclists, visualisation of statistical results and finally, context-based evidence. These factors matter because evidence changes from place to place and research transferability from other states, and even regions within a country, should be treated with caution.

This research identified key performance indicators that can be used to monitor the performance of important aspects of the cycling infrastructure: police attendance; prevalence of dooring; parking enforcement; and infrastructure performance. This research also quantified *SiN*, both numerically and spatially, following the development of cycling flow models for on- and off-road cycling and built up a strategic model for the cycling offer (asset) in Edinburgh. The identified performance indicators are based on aspects of cycling safety that need to be addressed and should be monitored, but available data are not currently used for this purpose. In addition, the prevalence of some undesirable impacts or impacts on cycling (e.g. increased dooring) is difficult for local authorities to assess because they do not have cycling flow models from which to determine if these problems are localised, systemic or if they change over time. This research therefore provides knowledge and the means to implement better monitoring and evaluation of cycling safety performance for local authorities and therefore represents a significant contribution to knowledge.

The objectives discussed above draw together the results and discussions detailed in Chapters 5 to 8. This next section will turn to a discussion about the research with respect to the subsidiary research questions.

RQ-01: Is there a *SiN* effect evident among cyclists in Scotland?

The disaggregated GLM-NB global models (see Chapter 6) examined the relationship between the number of cyclists and cyclist collisions at the population level in Scotland. The results found that for all injury severities and cyclist sub-groups (male, female, under 16 years of age, over 60 years of age, urban and rural, different posted speed limits) there was a *SiN* effect, but more interestingly this research showed that the magnitude (strength) of the effect varied. Female cyclists were only found to have a marginal *SiN* effect, coefficient estimate of 0.91 and 0.85 for KSI and slight injury categories, respectively.

The results in Chapter 6 also showed that the *SiN* effect was also very similar to the results reported in original research (0.41 by Jacobsen, 2003) at 0.48 for killed and serious injuries and 0.55 for all injury severities (i.e. slight, serious and killed injuries). As discussed in Chapter 5, male cyclists represent most of the record in the STATS19 data which creates bias. Therefore, this research shows that within *SiN* there maybe 'Hazard in Scarcity' due to a lack of women participation in cycling for transport.

A key contribution of this research is firstly that traditional GLM-NB models, used to model road safety, need to account for spatial dependence because the presence of this variation in panel models may exaggerate the *SiN* effect whereas the GWPR model provides local estimates for each location in the model. Secondly, the research demonstrated the ability of the GWPR model specification to model cyclists' collisions more accurately and that local model estimates can be mapped to compare outcomes with other policy impact areas such as health, deprivation, transport poverty, etc. This research contributes to the understanding and mechanisms associated with *SiN* which is a significant contribution to knowledge in this research area.

RQ-02: Is there a reduction in cyclist injury because of increased cycling, evident at a local population level?

Chapter 7 illustrated the importance of using flow data (million vehicle kilometres, mvkm) as an 'exposure' measure because population-based do not accurately reflect the level of activity within an area, as it only counts the number of people who cycled. The two measures of 'exposure' (population and distance) differ considerably, using population as a proxy measure is likely to misrepresent activity because the spatial distributions differ: one measures cycling flow volumes (i.e. activity intensity) and the other measures population-based count per head of population at a location by average distance cycled.

The average casualty risk in Edinburgh for any severity or mode was 0.47 per mvkm in 2011 and improved slightly to 0.44 per mvkm in 2016 (TS, 2017). The KSI average casualty risk was 0.06 and 0.057 per mvkm over the same period. Over this period, cycling in Edinburgh has grown and increased but the overall change in safety has not changed considerably.

Chapter 8 elaborates on the findings in Chapter 7. The levels of risk and *SiN* varied across Edinburgh which demonstrated that increased cycling was associated with better safety. However, the areas with better safety, higher cycling and the best *SiN* effects were locations that had more cycling infrastructure present, which contributed to the effect. The results in Chapter 8 demonstrate that, while overall cycling levels in Edinburgh are relatively high (compared to the national average across Scotland), the *SiN* effect varies across the city, in other words the effect is localised.

RQ-03: What are the local level factors that influence the likelihood that a cyclist will be involved in an accident and do they accord with local safety perceptions?

The cycle design guidance documents[32] recommend a variety of cycling infrastructure options for local authorities to implement. The on-road cycle lanes re-allocated existing road carriageways for use by cyclists and they can be for the exclusive use of cyclists if they are mandatory through implementation of the Traffic Regulation Order[33]. However, the normal and more prevalent version is the non-mandatory, where vehicles may legally use or enter the lane and where there is parking and loading provision. The other type of on-road lane allocated for cycling use are bus lanes and advanced stop lines. The logistic models examined in Chapter 5 did not find any statistical safety benefit for either bus lanes or on-road cycle lanes. These results were echoed in the Edinburgh case study that examined more detailed infrastructure data than that provided in the STATS19 alone and, in addition to the bus lanes and on-road cycle lanes, advanced stop lines did not prove to have beneficial or significant safety benefit in any model tested.

Safety expectations of the infrastructure discussed above can be viewed from three different perspectives, the policymaker, the driver and the cyclist. From the cyclists' viewpoint (cyclist logic), the expectation is for a safe, convenient and comfortable journey. However, the potential beneficial safety effect (comfort and convenience) is eroded due to:

i) parking regulations that hinder the safe function of the lane;

ii) lack of stronger regulation of traffic because the lanes are provided in a non-mandatory capacity; and

iii) the space not being protected which is cannot be if *i*) and *ii*) are permitted.

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[32] *Handbook for Cycle-Friendly Design (Sustrans, 2014); Local Transport Note LTN 2/08 Cycle Infrastructure Design, (DfT, 2008); Cycling by Design, (Scottish Executive, 2010).*

[33] *Under the Road Traffic Regulation Act 1984, Local Authorities' Traffic Orders (Procedure) (Scotland) Regulations 1999 (SI 1999/614).*

Therefore, these spaces are multi-functional and while the paint may suggest they are places for cyclists to occupy, the reality is that this space is “double-booked” and cannot deliver on safety, as the evidence presented in this research demonstrates, or on comfort or convenience.

From the drivers’ point of view (driver logic), their expectation is that cyclists keep to their lane and stay out of their way. This expectation or perception is not met due to poor design, lack of continuity and the need to avoid hazards such as dooring and parked cars and so forth. Finally, the policymaker expectations are that this type of infrastructure will be implemented with good judgement on the part of local authorities and do not expect competing pulls on decision making that does not prioritise cyclists. Therefore, perceptions and expectations of the interactions are not met. The result is a system of on-road cycle lanes that do not provide safety benefits for cyclists.

The results in Chapter 5 show that the odds of having a KSI collision on roads with a posted speed limit of 60mph are 2.4 times higher than a 20mph posted speed limit. However, there was no statistical difference between 20mph and 30mph posted speed limits in Scotland. Despite the similar risk of a KSI between 20mph and 30mph, the result aligns with other research findings that also did not find a significant difference. For example, a before and after study of casualties on residential roads that were changed from 30mph to 20mph (Atkins and Maher, 2018) found little evidence of a significant difference. 20mph results were not obtained for the Edinburgh case in this study because there was not enough data within the time period to examine. However, the research did find that 30mph roads had a lower odds ratio for a KSI collision than roads with a 40mph or higher speed limit. While this research does not present evidence to support the 20mph speed limits, there is clear evidence that speed reduction is beneficial. Therefore, further research is needed to fully assess the impact of 20mph zones.

This research did find that quiet routes, off-road shared paths and shared pedestrian footways had a positive safety effect that reduces the risk of cyclist collisions. This was true for slight injury collisions, but only off-road shared paths affected KSI cyclist collisions. The spatial GWPR models confirmed that these benefits of infrastructure stay local to the zones where such infrastructure are provided.

Finally, *SiN* was identified as having a local effect, the effect was found to be local to Scottish Council areas and the Scottish intermediate zones examined in the Edinburgh case study.

RQ-04: Are the prevailing national road safety policies a good fit for cyclists, and if not, why? And, can we provide better cyclist specific accident and safety evidence at a local level?

The current Scottish road safety framework to 2020 set out the road safety improvement targets for killed, serious and slight injury categories to achieve *A steady reduction in the numbers of those killed and those seriously injured, with the ultimate vision of a future where no-one is killed on Scotland's roads, and the injury rate is much reduced.*[34] The progress to date against this overarching vision and the targets are illustrated in Figure 9-1 above, and the respective targets are shown in Table 9.1, below. The data below shows that serious injuries have been increasing at a slow but steady pace since 2005 and that slight injuries have improved but the numbers of cyclists killed remains largely unchanged.

Cyclist incidents have not reduced across any injury severities but instead have risen slight casualties increased by 7%, serious casualties by 18% and killed showed a change from 8% to 9% of cyclists. The lack of progress against the strategy targets for cyclists compared to the overall transport casualty reduction is stark. Slight injuries increased above the target by 18%, serious injuries by 162% and killed by 45%, whereas the overall change across all modes was a 46%, 39% and 50% reduction compared to the target, respectively. Compared to the overall KSI casualty rate of 0.06 (per mvkm), cyclists are 10 times higher at 0.6 (per mvkm).

The lack of performance demonstrates that a serious rethink of how to address cyclist road safety performance is required. The evidence discussed in the previous section highlights several areas where cyclist safety is either not performing or external factors hinder implementation. The road safety framework is underpinned by the traditional road safety three E's (Education, Enforcement and Engineering), plus the additional Encouragement, and all actions are underpinned by Evaluation, shown in Figure 9-2 below.

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[34] *Scotland's Road Safety Framework to 2020: Go Safe on Scotland's Roads it's Everyone's Responsibility, The Scottish Government Edinburgh, 2009, pg.16.* *(file:///C:/Users/Owner/Downloads/ScottishRoadSafetyFramework.pdf)*

Table 9.1 Cyclists progress against Scotland's Road Safety Framework to 2020 targets[35]

Year	Slight	Serious	Killed
2004-08 average (*benchmark*)	613.2	134	9.2
2010	636	138	7
2011	661	156	7
2012	727	169	9
2013	724	149	13
2014	728	159	8
2015	628	164	5
2016	634	148	8
2017	553	171	5
2020 targets	**10%**	**55%**	**40%**
Target to be attained (below *benchmark*)	552	60	6
2013-2017 average	653	158	8
% Change	7	18	-13
% over target	**18**	**162**	**45**

The framework outlined above also contains a selection of commitments that are delivered in partnership with other stakeholders. In the case of cycling, the stakeholders are Sustrans, the local authorities, living streets, and Cycling Scotland. According to Wegman (2016, pg.96), we need to move away from the traditional road safety 'playground' of the three E's because their only goal is to improve road safety. While the Scottish road safety framework version of the three E's is making progress towards its overall goal, a wider range of opportunities such as planning, public health and environmental policies are missing. This requires integration of road safety policy where road safety policymakers and professionals actively work across all policy areas to meet goals other than road safety. The evidence presented in this research shows that, for cycling at least, this has yet to be developed: for example, parking policy preventing mandatory cycle lanes and dooring continuing to cause serious injuries and a lack of speed enforcement in urban areas

Cyclist road safety improvement is inextricably linked to encouragement within active travel policy goals. One of the prevailing discourses surrounding cyclist safety is the acceptance of the Safety in Numbers theory, first described by Smeed (1947) but popularised by the work of Jacobsen (2003).

[35] *Scotland's Road Safety Framework to 2020: Go Safe on Scotland's Roads it's Everyone's Responsibility, The Scottish Government Edinburgh, 2009, Table One. (file:///C:/Users/Owner/Downloads/ScottishRoadSafetyFramework.pdf)*

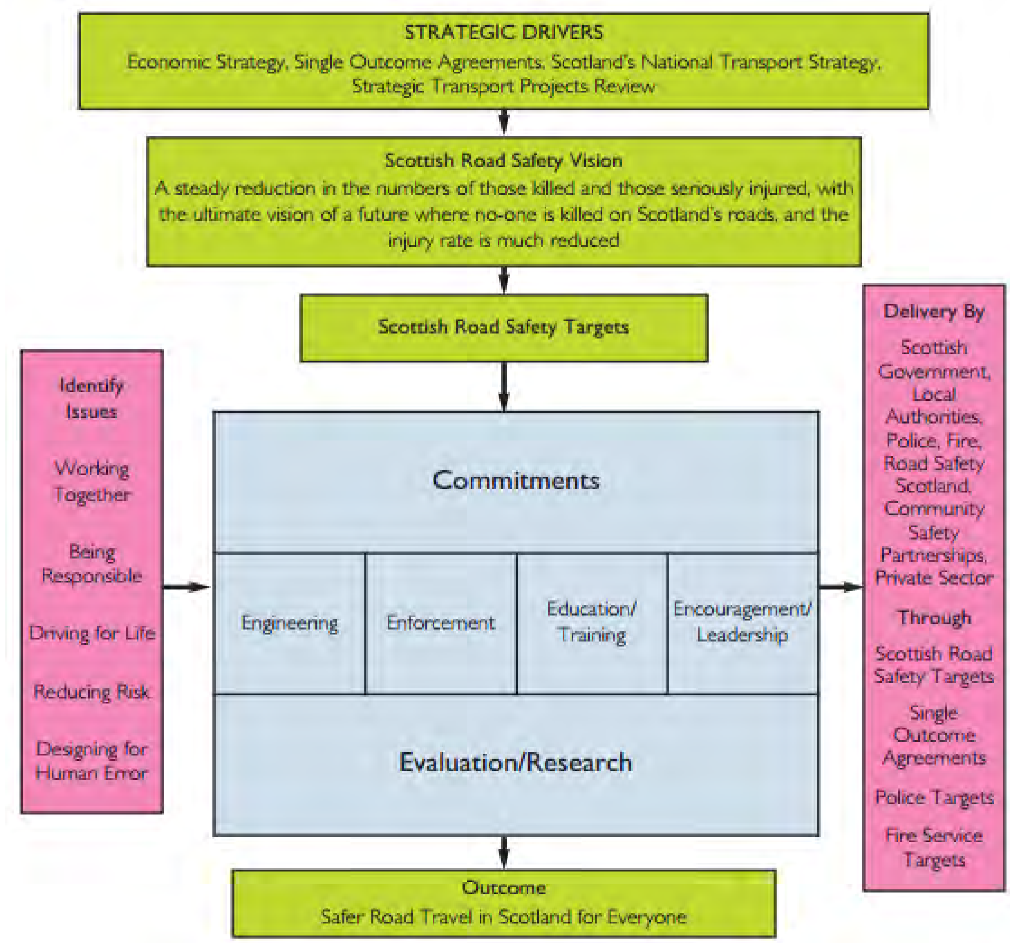

Figure 9-2 Figure two: Road safety strategic diagram. Scotland's Road Safety Framework to 2020, Pg.20.

In the UK and Scotland, policymakers hope that by increasing cycling in low cycling contexts, through encouragement and what they regard as better facilities, injury risk reduction will follow at a less than proportional rate than the cycling increase (Aldred et al., 2017).

An increase in cycling has been achieved in Scotland over the last two decades but *SiN* has not materialised as predicted by those responsible for the allocation of road safety funding and in decision making positions for the design process. The belief in *SiN* has shaped current policies whereby the focus has not been the large-scale construction of separated or protected high quality infrastructure or the re-organisation of road space, but rather minimal re-allocation of space and sharing with pedestrians and a lot of encouragement actions and activities. The organisations engaging in discourse about *SiN* are many of the same road safety strategy partners responsible to delivering parts of the strategy such as the Cycling Action Policy (CAPS).

At a more local level, the current City of Edinburgh council's (CEC) policy that aims to promote cycling, provide cycling infrastructure and improve safety follows a parallel approach. In the first instance, CEC policy promotes the extension of the network of 'Quiet Routes' to cater for less confident cyclists and secondly, move towards a Cycle Friendly City through reduced traffic and traffic speeds. However, the main reason cited by Scottish people for not cycling to work is "*too far to cycle*" (TS, 2017) rather than the perceived quietness of the route, and as previously discussed both the 'quiet' and 'balanced' route options (as presented in Chapter 7) involved longer distances. Recent research shows that reduced speeds only entice 25% of people to change their route (Atkins and Maher, 2018). Therefore, the current policy may not change the current situation and the research presented in this study demonstrates that while these policies will have an impact on slight injury collisions, they are unlikely to significantly reduce KSI collisions among cyclists. Table 9.1 above shows that slight casualties have had the lowest overall increase but, as this research has demonstrated, current strategies have not successfully targeted KSI casualties.

Two final points, the first of which relates to the difference between police attendance rates for cyclists and drivers because police enforcement and targets are part of the road safety framework (Figure 9-2); and the second which relates to gender, as women were found to be twice as likely to be involved in KSI collisions than men. These matters are not currently addressed in the road safety framework. In conclusion, the prevailing national road safety polices are not a good fit for cyclists because the numbers of casualties across all injury severities have increased.

RQ-05: *What should Safety Performance Indicators measure to ensure cyclists benefit from road safety investment and the road safety system equitably?*

This research demonstrates that *SiN*, where present, does not benefit inhabitants equally: it varies spatially, and women do not appear to benefit to the same extent as men. Furthermore, with increased urbanisation the gap between urban and rural areas will widen and more cycling will not have such an impact in rural areas.

Gender differences were identified in the global models for Scotland where the female KSI model suggests that women do not benefit from a *SiN* effect. The binomial logistic model showed that women are more likely than men to be involved in a KSI collision and it was also found that the models developed for women have different significant explanatory variables. Safety evaluation should therefore disaggregate by gender to identify gender patterns.

Safety Performance Indicators (SPIs) are measures reflecting those operational conditions of the road traffic system that influence the system's safety performance (Wegman, 2016). The two-prong approach to cycling infrastructure and safety in Edinburgh consists of Cycle Friendly measures and extending and upgrading 'Quiet Routes'. However, as previously discussed, some supposedly cycle-friendly measures such as on-road cycle lanes and ASL are ineffectual (in safety terms) and while the concept may be sound, they then need complementary measures to allow them to work as intended, such as prohibiting parking and providing physical and regulatory protection (i.e. implement mandatory cycle lanes using a Traffic Regulation Order) of on-road cycle lanes.

The cycling gender gap in Edinburgh persists despite the sustained long-term growth in the overall numbers of people cycling in the city today; road safety remains a particularly serious concern for women. The measures implemented to date do not address ways to mitigate their concerns and the real risk imbalance between men and women. This research demonstrated that men are 50% less likely to have a KSI than women, therefore women have a higher than 10-fold risk rate compared to motorised travel because the majority of the distance travelled is by men (who comprise the majority of cyclists). Women's activities and travel needs are more complex than men because of their "*double duties*" (Hasson and Polevoy, 2011) and women make more multi-stop trips than men (Barker, 2009).

While this research found that 'Quiet Routes' and off-road paths were positively associated with reducing cyclist collisions and contribute to a *SiN* effect, these are mostly located away from the shops and services that women need access to in the course of their day. Therefore, women want and need segregated infrastructure and providing this should mitigate KSI collisions more generally. Without addressing women's needs the transport system will continue to exclude women from participating in this activity which impacts their rights and freedoms: for example, women with children need to be able to travel safely with them. Transformative examples such as Seville[36] show that gender balance can be achieved through separated cycling infrastructure.

9.3 Main Findings and recommendations

This section describes the main research findings and the following section outlines recent casualty trends and current government policy in terms of road safety. The final part of this section, drawing on the content of the research, makes recommendations for policy and finally discusses the main research contributions. This section focuses on the key findings from this thesis that potentially have the most significant implications for the future targeting of interventions.

"[On-road] cycle lanes don't work as intended: in addition to parking and lack of exclusivity the lanes are retrofitted onto roads which often have many driveways and side roads, and this makes them unlikely to be a success" (Wardlaw, 2014, pg.9). The research presented in Chapters 5 and 8 provides evidence for this statement, demonstrating that on-road cycle lanes are no safer than the main carriageway when they are retrofitted and are non-mandatory. This evidence should be used to justify the provision of better infrastructure and design.

Sharing the main carriageway is the recommended alternative, subject to low speeds and traffic volumes, but this is not always practical from a cyclist's point of view and from a convenience point of view if they are installed along roads with many driveways and side roads. Dutch urban areas have been developed so that main roads generally do not have driveways or lanes emerging onto them (International Transport Forum, 2013). Where this would be a problem, as in suburban streets or old town centres, the solution is to allow sharing of road space with calmed traffic. This should be adopted in UK, too.

This research illustrated the benefits to be gained from the use of spatial GWPR over the traditional global GLM-NB models. The GWPR model specification provides a better statistical fit and the local nature of the modelling algorithms allow comparison at smaller scales, whereas global models provide aggregated population level results that are of little use to local authorities.

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[36] *Between 2007-2013 segregated lanes increased from 12km to 152km, cyclist risk fell 50% and SiN materialised (Marques Hernández-Herrador, 2017).*

As per Wegman's idiom of: "*You can't manage what you can't measure*" (2016), this research found that mobility-based 'exposure' provides a better measure for evaluation of cyclist risk compared to population-based proxy measures. There is therefore a need to persuade transport planners to adopt analytical methods which utilise appropriate exposure metrics and to ensure that cycle flow monitoring is more generally undertaken by local authorities to facilitate such analyses.

Engineering intervention can be an effective part of both active travel and road safety, by encouraging more cycling with safe and attractive facilities and by changing the road environment so that using it is safe for all users. The empirical data and analysis conducted at national scale in Scotland (Chapters 5 and 6) and at local level in the City of Edinburgh (Chapter 8) clearly suggests that the existing on-road cycle lanes and bus lanes, fails to provide a safer road environment compared to not providing any on-road facilities.

9.3.1 Safety in Numbers

In Chapter 2 Part B a number of theories were discussed in relation to the *SiN* effect, spatial effects, Risk-in-Scarcity (Tin Tin et al., 2011; pg. 362), co-existence of *SiN* with increased cyclists risk (Aldred et al., 2017) and others claim that *SiN* is an artefact (Elvik, 2013) and that simply adding numbers to the system without adding quality may be wrong (Wegman et al., 2013).

To promote more walking and cycling and dispel safety concerns, both transport policymakers and advocacy groups refer to the *SiN* effect, see Chapter 2 Section 2.3.11. Pike and Christie (2015) make the argument that Jacobsen's paper and the popularisation of *SiN* has led to a paradigm shift among planners and engineers approach to pedestrians and cyclists, allowing them to allow for increased numbers without the fear that the increase would result in more traffic collisions and casualties. A significant point to consider is the fact that some of the research, used as policy evidence and promoted by advocacy groups, could be founded on erroneous data (Elvik, 2013; Elvik and Bjornskau, 2016).

The *SiN* effect, for either pedestrians or cyclists, has been queried from a number of different perspectives, namely to establish causal links, safe systems and infrastructure perspectives (Wegman et al., 2012; Luukkonen and Vaismaa, 2015), behavioural changes (Bhat and Wire, 2013; de Goede et al., 2014), spatial differences (Vendenbulcke, 2011;

Kaplan and Prato, 2015) and demographic variation (Christie and Pike, 2015) all without conclusive agreement on the nature of the effect mechanisms.

Furthermore, the current *SiN* research does not answer the question ’who is safe in numbers?’, because the *SiN* effect does not extend to deprived areas despite having relatively higher numbers who walk or cycle in comparison to more affluent neighbourhoods (Christie and Pike, 2015). This is another potential ‘flaw’ in the *SiN* concept (Edwards et al., 2006; Christie et al., 2010), such that it appears to be selective in terms of deprivation level.

Finally, two studies (Elvik, 2013 and Tin Tin, 2011) suggest that *SiN* may co-exist with hazard-in-scarcity or hazard-in-numbers, due to low cycling activity, but there are no mechanisms available to measure where either effect manifests. Most previous studies have been cross-sectional, and there has been one longitudinal study by Aldred et al., (2017) however the *SiN* effect has not been explored spatially. This research has confirmed several of the gaps discussed above and also provided a mechanism to measure *SiN* more accurately and allow spatial comparison.

9.3.1.1 Safety in Numbers research contributions

SiN can co-exist with hazard-in-scarcity, the results presented in Chapter 8 demonstrates that while Edinburgh enjoys relatively high levels of cycling mode share only limited zones of the city have a *SiN* effect. The co-existence of *SiN* with increased cyclist risk may be explained by the use of traditional regression models because this research demonstrated that the presence of unaccounted spatial dependence in these models exaggerates the *SiN* effect results.

This research supports Wegman et al. (2013) such that simply adding numbers to the system without adding quality does not provide safety benefits for cyclists. This research answers the question ’*who is safe in numbers?*’, the result in Chapter 5 and Chapter 8 demonstrates that male cyclists have lower cycling injury risk than female cyclists, as discussed female cycling patterns differ from male cyclists and form the minority and Chapter 6 demonstrated that female cyclists have little or no *SiN* effect compared to male cyclists which had a *SiN* effect similar to the Jacobsen (2003) results. This is another potential ‘flaw’ in the *SiN* concept such that it appears to be selective in terms of gender, this adds to the work by Edwards et al. (2006) and Christie et al. (2010) who showed that *SiN* was selective in terms of deprivation level. This research identified that the *SiN* effect is the relationship between the number of accidents and exposure, called the 'safety performance function'(SPF) an SPF it is seldom linear (Hauer, 1995) and hence the *SiN* effect is the SPF not an effect as such.

Finally, this research identified and demonstrated that the GWPR models can be applied to visualised and measure the spatial magnitude of *SiN* and analyses multivariate date to evaluate causal factors.

9.3.2 Deprivation

Deprivation should be analysed in conjunction with active travel policies to ensure that deprived individuals are not exposed to double the risk. The deprived area and use of an active mode have a disproportionately higher risk rate per kilometre travelled than for motorised transport which they may not be able to afford; this is particularly pertinent in rural areas where public transport services may not meet social and accessibility needs. Thus, they are hit twice (Gough, 2017) through both transport inequity and transport poverty (Motherwell, 2018).

9.3.3 Design and Appraisal Guidelines (GEH)

As discussed above, the existing methods for validating transport models should be changed or include new thresholds for cyclist flow model validation. The GEH statistic and threshold were designed to evaluate and validate large volume motorised flows, and these are not suitable for the considerably lower cyclist flows.

9.3.4 Parking Policy

Even though good parking management has proven to be beneficial in delivering sustainable urban mobility in our cities, it is still one of the most underdeveloped sections within the Sustainable Urban Mobility Planning (SUMP) policies. The Horizon 2020 project Park4SUMP[37] aims to reverse this status by considering parking management as part of a wider strategy that can benefit urban mobility but also the overall quality of life in cities. In fact, good parking management can help in freeing up public space, supporting local businesses, generating revenues, and making our cities more attractive.

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[37] *Park4SUMP aims to help cities integrate innovative parking management solutions into Sustainable Urban Mobility Plans (SUMPs) for better mobility and quality of life. European Union's Horizon 2020 research and innovation programme 2018 – 2022. (Source: https://park4sump.eu/).*

Cities in Europe are aggressively removing on-street parking and using parking fare structures and other supporting policies to achieve their sustainable urban mobility plans (SUMPs). For example, Rotterdam[38] plans to remove 3,000 parking spaces by 2020 to create urban green space for its inhabitants, which includes widening their footways and cycle lanes to improve the liveability of the city.

The results of this research may seem rather negative to those advocating investment in cycling. However, it is only by identifying barriers accurately that they can be overcome. If barriers to cycling are tackled effectively, based on the best available evidence, this could lead to an equivalent 'virtuous circle', in which money well spent leads to better facilities that get used, leading to political support and more money (Alder et al., 2017). Further, *designing an effective road safety strategy and conducting good quality road safety studies is impossible without good data to lead to the identification of the main problems or sub-problems* (Wegman, 2016).

9.3.5 Integrated transport policy and health policies

There are two facets to cyclists' safety that affects public health policies. The first is the direct impact of reported or unreported cyclists with road traffic-related injuries presenting in hospital emergency units or their local health clinics for treatment. The second relates to a more widespread and long-term impact of the population failing to move from motorised transport into active modes because one of the persistent barriers to cycling for many, particularly women, is safety, despite encouragement and attempts to improve infrastructure.

According to Grant et al. (2017), public health policy needs to actually create health and the authors point out that public health needs to explore and understand how to create the best conditions for good health to ensure humans can flourish with equal access to such health-creating conditions. This research has highlighted several forms of 'cycle-friendly' infrastructure that is no more friendly than the average road, which is not conducive to creating better health because they do not entice people to use them. Therefore, they do not represent a health-creating aspect of the transport system and thus local authorities need to re-evaluate the evidence.

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[38] *Rotterdam has a population of 650,000 and is a Partner in the Park4SUMP Project. (https://park4sump.eu/news-events/news/parking-management-advantages-all).*

9.3.6 Cycling policies

In the UK and Scotland, policymakers hope that by increasing cycling in low cycling contexts, through encouragement and what they regard as better facilities, injury risk reduction will follow at a less than proportional rate than the cycling increase (Aldred et al., 2017). One of the prevailing discourses surrounding cyclist safety is the acceptance of the Safety in Numbers theory, first described by Smeed (1947) but popularised by the work of Jacobsen (2003).

An increase in cycling has been achieved in Scotland over the last two decades but SiN has not materialised as predicted by those responsible for the allocation of road safety funding and in decision making positions for the design process. The belief in SiN has shaped current policies whereby the focus has not been the large-scale construction of separated or protected high quality infrastructure or the re-organisation of road space, but rather minimal re-allocation of space and sharing with pedestrians and a lot of encouragement actions and activities. The organisations engaging in discourse about SiN are many of the same road safety strategy partners responsible to delivering parts of the strategy such as the Cycling Action Policy (CAPS). Therefore, cyclist road safety improvement is inextricably linked to encouragement within active travel policy goals. The research presented in this study demonstrates that the physical environment has more influence over safety than the number of cyclists. Therefore, policies for encouragement and safety should not be linked, safety should be re-allocated back to national safety strategy.

At a more local level, the City of Edinburgh council's (CEC) current policy is to promote cycling and provide cycling infrastructure and improve safety. It follows a parallel approach, first instance the CEC promote the extension of the 'Quiet Routes' network (See Appendix 8.1) to cater for less confident cyclists and secondly provide a Cycle Friendly City through reduced traffic and traffic speeds. As discussed above parking policy can have an impact on the quality and safety of the urban space by seeking to remove parking spaced and using the space for pedestrians and cyclists. There is no specific policy to do this in Scotland or Edinburgh, furthermore the parking policy in Edinburgh is not integrated with the provision of cycle lanes. As discussed in Chapter 5 and 8 cycle lanes have little safety benefit for cyclists and because cycle lanes are mainly non-mandatory in Scotland parking is permitted. There are not policies in place to address this currently in Scotland or Edinburgh, based on the research presented her this should be addressed.

9.3.7 Contribution to Theory, Methods, Practice and Policy

This research contributes to the theory, methods, polices and practice in the field of cycling research. The following sections details how the research has contributed to each as follows:

Contribution to Theory

1) The *SiN* effect for cyclists is a widely referenced and observed, but it is a poorly understood phenomenon (Bhatia and Wier, 2011; Christie and Pike, 2015; Elvik and Bjørnskau, 2017), this research has added to the understanding of the theory on this topic by using geographically weighted regression to estimate local level *SiN* effects which also facilitated mapping the effects spatially. Thus, by demonstrating that the *SiN* effect varies spatially and within an urban area the research provides further insight into the manifestation of *SiN* and furthermore linked the strength or weakness of the effect to cyclist's infrastructure in each spatial unit. Therefore, future work into *SiN* should take spatial variation into account because the dependent and explanatory variable are not spatially homogeneous or independent. This research has demonstrated that failure to account for spatial dependence exaggerates the apparent *SiN* effect and this maybe the reason why *SiN* has been found but it does not accord with the observed increase in cyclists' collisions despite its presence.
2) This research also demonstrated that the *SiN* effect does not simply follow from increased numbers of cyclists alone. The multivariate analysis provided evidence about the effectiveness of various forms of cycling infrastructure in Edinburgh.
3) In Chapter 2 Part B several theories have been put forward to describe *SiN*. This research has identified that the *SiN* effect is the previously described non-linear relationship between accidents and traffic volumes called the Safety Performance Indicator (SPF). As such *SiN* is not an effect. Therefore, as with motorised transport modelling, multivariate analysis is required to evaluate cyclist's safety. The SPF can however be used to monitor safety, as such *SiN* should be monitored and used as a SPF in this meaning and not as a phenomena or effect.

Contribution to Methods

1) A key contribution of this research is firstly that traditional GLM-NB models, used to model road safety, need to account for spatial dependence because the presence of this variation in panel models may exaggerate the *SiN* effect whereas the GWPR model provides local estimates for each location in the model. The geographically weighted regression models take account of spatial dependence, traditional transport models assume that dependent variables are independent, however this research demonstrated that this assumption is violated. As a result, the *SiN* effect predicted is exaggerated by the traditional models (without spatial correction). The comparison of the traditional generalised linear models and negative binomial models with the geographically weighted regression models demonstrated that the geographically weighted regression models provided a better statistical fit than the traditional transport models.
2) The research demonstrated the ability of the GWPR model specification to model cyclists' collisions more accurately and that local model estimates can be mapped to compare outcomes with other policy impact areas such as health, deprivation, transport poverty, etc. This research contributes to the understanding and mechanisms associated with *SiN* which is a significant contribution to knowledge in this research area. The GWPR models also facilitate exploring the *SiN* effect more deeply, and at local level to show that the effect varies both spatially and the magnitude. This is a new dimension that has not been researched previously which has contributed to providing answers to explain why *SiN* manifests and why *SiN* is present by cycling collisions increase despite its apparent presence.
3) This research has provided a way to quantify the *SiN* effect in a meaningful way using spatial analysis, facilitating analysis of confounding factors, and it has also highlighted that *SiN* therefore is, and can be, used as a safety performance indicator.

Contribution to Practice

1) As transport planning and funding moves towards greater prevalence and support of cycling as a transport mode. This research demonstrated that the GEH statistic and thresholds contained in the current transport modelling guidelines need to be

re-examined in order to be fit for purpose for cyclist transport models. The GEH statistic is a widely used criterion (Giuffre et al., 2017) that is specified in UK Highways Agency and Transport for London (TfL) for the validation of transport models. The results presented above illustrate some of the limitation of using the GEH validation statistic for cyclist flows. It was originally developed for use on much higher motorised flow volumes; The Pearson's correlation coefficient and linear regression were found to be more suitable for cyclist flows. As more authorities implement larger and more extensive cycling schemes, funding and appraisal rules determine that they must be appraised under cost-benefit and wider impacts, and a transport model traditionally plays a central role in appraisal.

2) This research combined two open source methods to provide new data and a new way to provide exposure measurements for cyclists using existing data, i.e. cyclestreets.net and geographically weighted poisson regression (GWPR). This combination allowed a simple and inexpensive way to provide a traffic model for cyclists and it allowed the simplification of how statistical model results are shown by mapping the effects and significance. This is a much more intuitive way to explain statistics, particularly to non-technical decision-makers and influencers and most importantly for public engagement.
3) The software used is open source unlike commercial products such as 'VISSIM' that can be cost prohibitive. Authorities should use new emerging research to aid policy monitoring and evaluation and in particular 'open' research because it is low cost and does not require procurement of services from external consultants and is therefore highly cost effective. Therefore, the use of stplanr and OpenStreet.net provide a viable method for estimating route flows to provide mobility-based exposure estimates, subject to sufficient count data availability. Furthermore, local authorities can use this method to develop strategic cycling models for their own urban areas at a fraction of the cost of a traditional transport model. While funding is increasing for cycling infrastructure the strategic monitoring and data collection for cycling infrastructure lags behind motorised transport and separate funding for background supporting information is under developed, This method offers a cost effective way for authorities to develop a cycling transport model compared to a traditional four stage transport model to

provide much needed support in monitoring and evaluation of cycling in urban areas.

4) This research investigated the link between cyclist's safety and cyclist's infrastructure by interrogating aerial photography at a cyclist's accident location. It was not possible to make this assessment with the information contained in the STATS19 data sets. They type of infrastructure present is collected for motorised transport and pedestrian, but it is missing for cyclists. The availability of this information would aid cyclist's accident investigation and monitoring.

Contribution to Policy

The policy contributions are listed below, and the policy recommendations are provided in Table 9.2 below.

1) This empirical research has demonstrated that on-road cycle paths, that have no legal or physical protection, do not offer improved safety for the user. Therefore, future policy should use this research as:

   a) evidence to support the provision of segregated cycling infrastructure, and

   b) used to inform design guidelines, existing guidelines recommend on-road cycle lanes and recommend that they may be non-mandatory if parking is required which does not offer improved safety for cyclists. .

2) Although a wide range of academic, applied studies and cycling guidance cite *SiN* as a potential solution to cyclist collisions (Elvik and Bjørnskau, 2017; Fyhri, et al., 2016; Jacobsen, 2003; Robinson, 2005; Tin Tin et al., 2011), there has been little definitive evidence to guide policymakers or transport planners as how to use *SiN* to create a safer cycling environment beyond simply encouraging 'more cyclists' into the system (Thompson et al., 2018). This research provides definitive and illustrated evidence, at a local level, that policy makers can use and easily understand by mapping results rather than using statistical or transport modelling language. Therefore, this research has provided theory that can be applied by practitioners in a meaningful way. Furth more, this research has provided evidence for policy makers that demonstrates that there is very little or no *SiN* effect in the absence of segregate cycle lanes even with higher levels of

cycling. *SiN* is a very cost-effective concept in policy terms, meaning that simply increasing numbers walking or cycling improves road safety, and as such it does not require, or at least requires very little, infrastructure investment. *SiN* is referenced in Scottish planning and policy documents to encourage active mobility, therefore confirmation of the effect under Scottish conditions is warranted. In the absence of an observed *SiN* effect, policy should move towards the harder choices that increase VRU infrastructure investment, i.e. implement parking and road space restrictions for motorists in urban centres so that more space is devoted to walking and cycling. Therefore, policy that advocated *SiN* as an effect, without providing supportive infrastructure, will not be successful.

3) This research demonstrates that cycling carries a higher risk than other transport modes, and is not preforming against national road safety targets, even in Edinburgh. There is therefore a higher risk associated with cycling if one chooses to travel or must travel to work, education etc. by bike. Injury risk is not equitably distributed within the transport system and transport planning decisions often have significant equity impacts (Litman, 2016). Leaving aside the large body of evidence on the health, social and environmental benefits that advocate increased activity, this research has identified the need to address cycling safety urgently. It is a sign that the system isn't working, because the vision of no injuries cannot be achieved and the very policy goals that it underpins will flounder as a result. Policy makers should use the evidence presented in this research to increase the funding provided for cycling infrastructure, to seek a road safety target for cyclists and to integrate transport with parking policy.
4) This research has identified that gender plays and important role in cyclist road safety. Due to the imbalance between male and female cyclist the data collection from counts or observational studies are likely to be biased towards men and therefore may miss trends applicable to women. In order to encourage cycling for all the existing knowledge on cycling needs to be inclusive of women and more research and policy orientation id required to address this to ensure equal access to services and to ensure women benefit equitably from transport investment and active travel policies.

5) This research identified a policy gap between parking and infrastructure provision. Currently parking policy and implementation does not evaluate or take the operation of cycle lanes into account. Where cycle lanes are provided and parking on the cycle lane is also permitted this is a policy clash that hinders cyclist's safety. Parking can be provided at the same location, but reconfiguration of the road should protect cyclists from dooring and from parked vehicles.

Table 9.2 Policy recommendation summary

Existing Policy	***Recommendation***	***Target outcome***	***Chapter***	***SPI***	***Wider policy area benefits***
Parking	Remove on-street parking and restrict loading and integrate with sustainable travel policy	Reduce cyclists hitting cars and dooring	5	"Dooring" casualties and "Hit object in the road" casualties	Climate, emissions, health, liveability, economic sustainability
Gender	Measure impacts relative to women rather than as an aggregate, one-fits-all approach	Safety is improved in tandem for all	5, 6, 8	Disaggregate safety from other SPI by gender	Provide infrastructure and environments so that more women cycle, improve level of physical activity in women to improve population wellbeing
Road safety	Integrate with sustainable travel policy and health policies and set a specific target with specific measures and outcomes	Reduce cyclists KSI	8	Cyclist KSI	Achieve active travel targets, reduce barriers caused by poor safety, reduce health burden from accidents and poor health. Achieve Vision Zero across all transport modes and sub-groups equally
National/Regional transport models	Develop cycling flow models at local authority level	Ability to monitor and evaluate cycling volumes and safety performance strategically	7	KSI/mvkm (this is a current action under CAPS, but it is not possible at present to measure this at local or link levels in Scotland)	Provide justification and evidence for increased spending. Ability to evaluate new infrastructure or measure more comprehensively to ensure better outcomes and to more accurately evaluate physical activity or exposure to pollution
Measure the rate of casualties per mvkm	Use the *SiN* co-efficient as a safety performance indicator/safety performance function (SPF)	Achieve *SiN* comparable to high cycling participation countries, e.g. Denmark	6, 8	*SiN* GWPR regression coefficient for the volume of cycling flow at small area or link level.	Use the *SiN* effect as a SPF to evaluate cyclin safety and factors.

9.4 Limitations

The traffic flow model, developed in Chapter 7 using the Census 2011 origin destination data to create a cycling flow model for Edinburgh, was validated using traffic and cycle counters. One limitation of this approach is that, while male and female origin and destination data may be desirable, the traffic counters do not capture this. A female cycle flow model could potentially shed light on the infrastructure types predominantly used and confirm whether women take avoidance routes or prefer to take direct routes. The research results in this study showed that the 'fast' (i.e. most direct routes) were the best fit to the counter data used to validate the model. However, due to the imbalance between male and female commuters, the results are likely to be biased towards men and therefore may have missed trends applicable to women. The results are consequently biased towards males.

The cycling flow model developed for this research was validated using observed cycle counts. However, the census origin destination data provided commuter trips only and as such it did not include the origin destination data for other trip purposes. Therefore, the model has limited scope to capture all cycling flows, however there is no limitation to adding this should it become available from additional data collection or crowd source data. A further limitation lies with the observed traffic count data; it does not record age, gender or trip purpose.

This research used R Project open software to conduct the analysis that compared the global GLM-NB to a spatial GWPR model. It is possible that a negative binomial version of the geographically weighted regression (GWR-NB) would provide a better model fit than the poisson (GWPR) which was used in this thesis. However, at the current time, a negative binomial for the GWR model is not available in any CRAN[41] package. Further modelling using GWR-NB is recommended to confirm this research, with an extension that deals with over-dispersion that may further improve the results. At the time of writing, the 'GWmodel' does not support the calibration of the GWR with the Negative Binomial structure or in any other GWR packages such as 'spdep', therefore it was not possible to apply a negative binomial GWPR using R. A comparison of GLM poisson and NB models showed that, while

[41] *The Comprehensive R Archive Network (https://cran.r-project.org/)*

there is over dispersion present in the data, it was not substantial; therefore, the poisson structure of the GWPR was deemed suitable.

The data timeframe, 2010 to 2011, was selected because it facilitated matching the census 2011 origin destination data to the STATS19 data. More recent STATS19 data and updating or extending the cycling flow model may yield more results, for example evaluation of the 20mph zone in Edinburgh. Therefore, the data presented in this research is limited to the years it evaluated.

Finally, this research was conducted under frequentist modelling beliefs because the researcher's own experience and knowledge most align with this method of statistical analysis, whereas Bayesian methods may provide differing outcomes and interpretations. In terms of the models, the explanatory variables tested, and therefore explanatory variables in the final models, are subjective, such that one modeller may deduce a completely different model from the way the models were structured and disaggregated. The element of subjectivity was minimised by using standard methods of significance and correlation testing as well as testing variables found in this or previous studies, such that their association and effects discussed were not completely by chance. Nevertheless, some subjectivity is present.

9.5 Future Research and ongoing Work

This research has demonstrated that the spatial GWPR models performed better than the traditional global GLM-NB models for explaining cyclist risk and that identifying it locally allows for greater insight. The model results are limited by the flow model which is biased towards male cycling patterns; as mentioned in the section above on limitations, the census provides a valuable and comprehensive source of flow data that can de disaggregated by gender, however the validation data cannot be. The next Census is an opportunity to examine gender patterns separately in Edinburgh by collecting data samples at each cycle counter location so that the proportions can be used to validate each model for comparison.

In Chapter 3, a Phase 3 is suggested where focus groups could be used to evaluate the use of the spatial GWPR models, particularly the visualisation of the statistical results to investigate if this represents a better way to disseminate and communicate results (frequently difficult to interpret, let alone discuss) with a wide variety of stakeholders and in layman terms. A series of stakeholder interviews to gather preliminary views on the visualisations are planned as part of ongoing work.

Further work to develop the models to include additional explanatory variables, such as discontinuities, parking restrictions, bus stops, tram lines and to examine off-road models for pedestrian flows and bike only casualties, is recommended.

The discussion surrounding how speed limits impact safety was limited by the research dataset that pre-dating the implementation of the 20mph zone for Edinburgh. Further work to re-evaluate the data for later years to evaluate the impact of the 20mph would be of interest. The finding in this research will inform new research being developed in consultation with Police Scotland into the effectiveness of 20mph Zones within the Transport Research Institute at Edinburgh Napier University.

Without a measurement of cycling flow and volumes at a local and link level it is very difficult to determine if cyclist casualties are increasing due to exposure or due to some other causal factor. This research demonstrated that appropriate flow measures can be derived from existing data and by using open data software. Further research is needed to develop and refine the model for morning and evening peak scenarios, future years and the addition of future planned cycle infrastructure to examine how cycle flows may change. Initial work had been conducted to calibrate a gravity model which will provide growth factors for future flows based on the 2011 census. Furthermore, the infrastructure associated with cycling, parking, bus lanes, etc. will also need to be updated in tandem.

The use of geostatistical techniques has grown over the last 30 years and has moved from the margins to the mainstream of applied econometrics and social science methodology (Anisin, 2010), and this has a wide range of applications across heath, ecology and human geography. The use of this methodology has facilitated unpicking the effect and mechanisms associated with *SiN* that have eluded researchers for some time and they explain why and how *SiN* co-exists with increased overall cyclist risk and the absence of *SiN*. These geostatistical methods can be used to re-examine *SiN* research to gain a better insight into *SiN* which may change the discourse, or more specifically in low-cycling countries, the 'hope' that safety will manifest simply through encouragement measures. Furthermore, it demonstrated that geographically weighted regression is a technique that contributes to the field of transportation that can be used by others. Finally, the fast-paced evolution of R project packages considered throughout this research suggest that the field has reached a stage of maturity, as illustrated by the general acceptance of both spatial statistics and spatial econometrics as mainstream methodologies.

9.6 Final Thoughts

The aim of this research was to investigate whether there is a *SiN* effect in Scotland due to increased cycling mobility and to examine if there are wider spatial, demographic and policy differences affecting cyclists. This overall aim was achieved as this research found that there is an overall, but weak, *SiN* effect in Scotland. It was also demonstrated that the effect varies between cycling cohorts and that models analysing *SiN* should take account of spatial effects. Local and spatial effects are masked by global modelling methods and leads to the identification of a global *SiN* effect and therefore an apparent *SiN* effect can co-exist with increased cyclist risk, as observed by Aldred et al. (2017). This is because it manifests in local pockets where complementary facilities and environments exist but that such effects are not evenly distributed geographically, and it is only possible to explore this using local spatial models. Further, it was found that the availability of data from a cycling flow model facilitated a more accurate analysis that revealed *SiN* was evident for slight casualties but not KSIs. Hence, this research was also able to clarify why the *SiN* effect can co-exist with increased cyclist risk.

Finally, this research mapped *SiN* so that the elusive effect and its confounding factors can be visualised uniquely when applied to *SiN* in this research. This final point will be a key mechanism to communicate some of the limitations of assuming *SiN* will naturally follow increased cycling and it may also be used to hopefully show future progress.

The results of this research may seem somewhat negative especially to those advocating investment in cycling and devoting much time and considerable effort into encouragement. The scale of the *SiN* effect was not found as perhaps advocates would have hoped despite the multi-agency investment and wide-ranging projects and initiatives to date

To answer the question posed in Chapter 3 – 'Why has cyclist road safety performance failed to improve in tandem with motorised modes over the past decade in Scotland?' – the research presented in this thesis points a lack of integrated sustainable transport police, policing focus lies elsewhere and the whole system benefits those who are fit, able and without restriction on their free time to choose cycling as their main mode of transport.

This research found that much of the infrastructure already in place to be ineffective in terms of road safety at a global and local level and particularly KSIs. However, this research has identified several areas that can be improved. It is only by identifying accurately what does not work and providing evidence that changes to policy and implementation barriers for better infrastructure can be made. *SiN* as a concept is neat and easily understood; however, road safety and cycling road safety is not straightforward. On a more positive note, the levels of *SiN* that were found can be mapped and quantified and infrastructure does indeed make an impact which means there is substantial scope for improvement through both soft and hard intervention measures.

Gaining a greater understanding into how the results found in this research play a part in cycling safety performance means that we can develop safety strategies or new national frameworks with specific relevance to cyclists. Consequently, cyclist injury and risk performance can begin to become more equitable (currently 10 times higher KSI risk) in tandem with achieving road safety targets. As such, this research provides strong evidence for the need to provide and invest in cycling infrastructure because we can't wait for *SiN*.

The evidence presented in this thesis contains findings that can be applied to improve and understand cycling throughout the UK, and perhaps other countries with low use, and in doing so this research has contributed to the deeper understanding of the *SiN* effect and how and when it should be utilised by policymakers.

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APPENDIX A 4-1

Methodological approaches	Previous research
Binary logit/probit models	Shibata and Fukuda (1994), Farmer et al. (1997), Khattak et al. (1998), Krull et al. (2000), Al-Ghamdi (2002), Bedard et al. (2002), Toy and Hammitt (2003), Ballasteros et al. (2004), Chang and Yeh (2006), Sze and Wong (2007), Lee and Abdel-Aty (2008), Pai (2008), Rifaat and Tay (2009), Haleem and Abdel-Aty (2010), Peek-Asa et al. (2010), Kononen et al. (2011), Moudon et al. (2011), Santolino et al. (2012)
Multinomial logit models	Shankar and Mannering (1996), Carson and Mannering (2001), Abdel-Aty and Abdelwahab (2004), Ulfarsson and Mannering (2004), Khorashadi et al. (2005), Islam and Mannering (2006), Kim et al. (2007b); Malyshkina and Mannering (2008), Savolainen and Ghosh (2008), Schneider et al. (2009), Malyshkina and Mannering (2010a, 2010b), Rifaat et al. (2011), Ye and Lord (2011), Schneider and Savolainen (2011), Eluru (2013), Yasmin and Eluru (2013), Ye and Lord (2014)
Nested logit models	Shankar et al. (1996), Chang and Mannering (1998, 1999), Lee and Mannering (2002), Abdel-Aty and Abdelwahab (2004), Holdridge et al. (2005), Savolainen and Mannering (2007), Haleem and Abdel-Aty (2010), Hu and Donnell (2010), Patil et al. (2012), Wu et al. (2013); Yasmin and Eluru (2013)
Sequential logit/probit models	Saccomanno et al. (1996), Dissanayake and Lu (2002a, 2002b), Helai et al. (2008), Yamamoto et al. (2008), Jung et al. (2010), Xu et al. (2013)
Heteroskedastic ordered logit/probit models	O'Donnell and Connor (1996), Wang and Kockelman (2005), Lemp et al. (2011)
Ordered logit/probit models	Khattak et al. (1998, 2002), Klop and Khattak (1999), Renski et al. (1999), Khattak (2001), Kockelman and Kweon (2002), Quddus et al. (2002), Abdel-Aty (2003), Austin and Faigin (2003), Kweon and Kockelman (2003), Zajac and Ivan (2003), Khattak and Rocha (2003), Yamamoto and Shankar (2004), Donnell and Mason (2004), Khattak and Targa (2004), Abdel-Aty and Keller (2005), Lee and Abdel-Aty (2005), Shimamura et al. (2005), Garder (2006), Lu et al. (2006), Oh (2006), Siddiqui et al. (2006), Pai and Saleh (2007), Das et al. (2008), Gray et al. (2008), Wang and Abdel-Aty (2008), Chimba and Sando (2009), Wang et al. (2009); Pai (2009), Xie et al. (2009), Haleem and Abdel-Aty (2010), Jung et al. (2010), Quddus et al. (2010), Ye and Lord (2011), Zhu and Srinivasan (2011), Ferreira and Couto (2012), Abay (2013a), Jiang et al. (2013a, 2013b), Eluru (2013), Mergia et al. (2013), Yasmin and Eluru (2013), Ye and Lord (2014)
Log-linear models	Chen and Jovanis (2000)
Generalized ordered outcome models	Srinivasan (2002), Eluru et al. (2008), Quddus et al. (2010), Castro et al. (2013), Eluru (2013), Abay et al. (2013), Yasmin and Eluru (2013), Yasmin et al. (2014)
Simultaneous binary logit model	Ouyang et al. (2002)
Bivariate/multivariate binary probit models	Winston et al. (2006), Lee and Abdel-Aty (2008)
Bivariate/multivariate ordered probit models	Yamamoto and Shankar (2004), de Lapparent (2008), Eluru et al. (2010), Rana et al. (2010), Abay et al. (2013), Chiou et al. (2013a), Yasmin et al. (2013), Russo et al. (in preparation)
Artificial neural networks	Abdelwahab and Abdel-Aty (2001), Delen et al. (2006), Chimba and Sando (2009)
Mixed joint binary ordered logit model	Eluru and Bhat (2007)
Mixed logit model (random parameters logit model)	Milton et al. (2008), Kim et al. (2008, 2010, 2013), Malyshkina and Mannering (2010b), Kim et al. (2010), Altwaijri et al. (2011), Anastasopoulos and Mannering (2011), Moore et al. (2011), Ye and Lord (2011), Morgan and Mannering (2011), Chiou et al. (2013b), Aziz et al. (2013), Abay (2013a); Manner and Wunsch-Ziegler (2013), Yasmin and Eluru (2013), Ye and Lord (2014)
Partial proportional odds model	Wang and Abdel-Aty (2008), Wang et al. (2009), Quddus et al. (2010)
Finite-mixture/latent-class and Markov switching models	Malyshkina and Mannering (2009), Xie et al. (2012), Eluru et al. (2012), Xiong and Mannering (2013), Xiong et al. (2013), Yasmin et al. (2014)
Heterogeneous outcome model	Quddus et al. (2010)
Mixed ordered probit (random parameters probit) model	Zoi et al. (2010), Paleti et al. (2010), Xiong et al. (2013)
Spatial and temporal correlations	Castro et al. (2013)

[a] *Source*: Updated from Savolainen et al. (2011).

Figure A4-1 Review of previous methods for accident severity models by Bhat and Mannering (2014), Table 2.

APPENDIX A 5.1

Table A 5.1 Binomial Logistic Regression Results for the *Overall Model*

Dependent variable: Overall KSI Collisions	***β*** *(Std. Errors)*
dayMonday	0.244 (0.185)
daySaturday	-0.037 (0.215)
daySunday	-0.260 (0.222)
dayThursday	-0.085 (0.194)
dayTuesday	0.007 (0.192)
dayWednesday	-0.285 (0.198)
relevel(Road_Type, ref = "6")1	**1.182** (0.464)**
relevel(Road_Type, ref = "6")2	-0.230 (0.422)
relevel(Road_Type, ref = "6")3	0.286 (0.194)
relevel(Road_Type, ref = "6")7	**1.647** (0.776)**
relevel(Road_Type, ref = "6")9	-0.317 (0.650)
Urban_or_Rural_Area2	0.109 (0.383)
Speed_limit30	-0.002 (0.362)
Speed_limit40	0.598 (0.426)
Speed_limit50	0.488 (0.628)
Speed_limit60	**0.876** (0.423)**
Speed_limit70	**1.308* (0.667)**
Junction_Detail1	**-1.786*** (0.459)**
Junction_Detail2	**-1.590*** (0.594)**
Junction_Detail3	-0.213 (0.135)
Junction_Detail5	-0.209 (0.556)
Junction_Detail6	**-0.456** (0.219)**
Junction_Detail7	**-0.674* (0.404)**
Junction_Detail8	-0.479 (0.414)
Junction_Detail9	-0.334 (0.225)
Road_Surface_Conditions2	**-0.373*** (0.135)**
Road_Surface_Conditions3	-0.564 (1.143)
Road_Surface_Conditions4	-0.453 (0.475)
Road_Surface_Conditions5	1.537 (1.040)
Special_Conditions_at_Site1	0.078 (0.948)
Special_Conditions_at_Site3	-12.544 (535.411)
Special_Conditions_at_Site4	-0.488 (0.703)
Special_Conditions_at_Site5	0.092 (0.604)
Special_Conditions_at_Site6	0.353 (1.306)
Carriageway_Hazards1	0.329 (1.352)
Carriageway_Hazards2	**0.763* (0.413)**
Carriageway_Hazards3	0.982 (1.425)
Carriageway_Hazards6	-0.313 (1.125)
Carriageway_Hazards7	0.998 (1.054)
Did_Police_Officer_Attend_Scene_of_Accident2	**-0.805*** (0.149)**

Dependent variable: Overall KSI Collisions	***β*** *(Std. Errors)*
UR6FOLD2	0.159 (0.143)
UR6FOLD3	0.087 (0.481)
UR6FOLD4	-0.005 (0.522)
UR6FOLD5	-0.089 (0.409)
UR6FOLD6	-0.356 (0.468)
Pedestrian_Crossing.Physical_Facilities1	0.036 (0.410)
Pedestrian_Crossing.Physical_Facilities4	0.294 (0.192)
Pedestrian_Crossing.Physical_Facilities5	-0.096 (0.197)
Pedestrian_Crossing.Physical_Facilities7	-10.828 (535.412)
Pedestrian_Crossing.Physical_Facilities8	0.226 (0.377)
relevel(AGE_16.y, ref = "1")0	**0.260* (0.158)**
relevel(AGE_60.y, ref = "1")0	**-0.544*** (0.210)**
Light_Conditions4	**0.335** (0.153)**
Light_Conditions5	**0.814** (0.393)**
Light_Conditions6	-0.029 (0.406)
Light_Conditions7	-0.070 (1.097)
Urban_or_Rural_Area2:Did_Police_Officer_Attend_Scene_of_Accident2	0.156 (0.295)
Constant	-0.857* (0.463)
Observations	2,503
Log Likelihood	-1,137.141
Akaike Inf. Crit.	2,390.283
*Note: Significant Explanatory variables in **Bold** text.*	*p**p***p<0.01

Table A 5.2 Binomial Logistic Regression for *Female Model*

	β (Std. Errors)
Dependent variable: Female KSI Collisions	
relevel(day, ref = "Wednesday")Friday	0.391 (0.511)
relevel(day, ref = "Wednesday")Monday	0.598 (0.518)
relevel(day, ref = "Wednesday")Saturday	0.685 (0.588)
relevel(day, ref = "Wednesday")Sunday	0.826 (0.552)
relevel(day, ref = "Wednesday")Thursday	0.276 (0.538)
relevel(day, ref = "Wednesday")Tuesday	**1.206** (0.505)**
relevel(Road_Type, ref = "6")1	16.913 (1,468.056)
relevel(Road_Type, ref = "6")2	0.577 (0.978)
relevel(Road_Type, ref = "6")3	0.011 (0.533)
relevel(Road_Type, ref = "6")7	-17.268 (6,522.639)
relevel(Road_Type, ref = "6")9	-18.139 (2,636.579)
Urban_or_Rural_Area2	0.527 (1.182)
Speed_limit30	0.769 (0.905)
Speed_limit40	-0.449 (1.424)
Speed_limit50	0.716 (1.386)
Speed_limit60	0.342 (1.113)
Speed_limit70	-17.882 (6,522.639)
Junction_Detail1	-17.681 (1,468.056)
Junction_Detail2	-17.094 (1,468.056)
Junction_Detail3	**-0.845** (0.346)**
Junction_Detail5	0.055 (1.351)
Junction_Detail6	-0.726 (0.469)
Junction_Detail7	**-1.499* (0.838)**
Junction_Detail8	-17.327 (2,561.729)
Junction_Detail9	-0.438 (0.505)
Road_Surface_Conditions2	-0.144 (0.342)
Road_Surface_Conditions3	-33.058 (4,016.554)
Road_Surface_Conditions4	-16.430 (2,403.779)
Special_Conditions_at_Site1	-16.889 (6,522.639)
Special_Conditions_at_Site4	-18.105 (6,522.639)
Special_Conditions_at_Site5	18.608 (6,522.639)
Special_Conditions_at_Site6	-17.614 (6,522.639)
Carriageway_Hazards2	0.682 (0.849)
Carriageway_Hazards6	-18.483 (3,694.825)
Carriageway_Hazards7	19.761 (6,522.639)
Did_Police_Officer_Attend_Scene_of_Accident2	**-0.553* (0.332)**
UR6FOLD2	**0.736** (0.364)**
UR6FOLD3	-0.794 (1.424)
UR6FOLD4	0.900 (1.387)
UR6FOLD5	-0.296 (1.269)
UR6FOLD6	0.203 (1.354)

Dependent variable: Female KSI Collisions	*β (Std. Errors)*
Pedestrian_Crossing.Physical_Facilities1	0.119 (1.088)
Pedestrian_Crossing.Physical_Facilities4	**1.218*** (0.459)**
Pedestrian_Crossing.Physical_Facilities5	0.126 (0.436)
Pedestrian_Crossing.Physical_Facilities8	-0.937 (1.187)
relevel(AGE_16.y, ref = "1")0	**0.818** (0.406)**
relevel(AGE_60.y, ref = "1")0	-0.655 (0.604)
Light_Conditions4	-0.342 (0.410)
Light_Conditions5	1.159 (0.822)
Light_Conditions6	1.086 (1.584)
Light_Conditions7	-16.884 (4,610.024)
Urban_or_Rural_Area2:Did_Police_Officer_Attend_Scene_of_Accident2	0.436 (0.709)
Constant	-2.286* (1.269)
Observations	463
Log Likelihood	-199.828
Akaike Inf. Crit.	505.656
*Note: Significant Explanatory variables in **Bold** text*	*p**p***p<0.01

Table A5.3 2x2 contingency table to compare Urban Rural

2x2 (Df =1)	Urban	Rural	Totals	
Slight	151	335	486	χ^2 26.5
KSI	407	1615	2022	
Totals	558	1950	2508	

Table A5.4 2x2 contingency table to compare Cyclist and Car driver police attendance rates.

2x2 (Df= 1)	20mph	30mph	Total	χ^2
KSI	10	339	349	0.02
Slight	51	1704	1755	
Total	61	2043	2104	

Table A5.5 2x2 contingency table to compare Cyclist and Car driver police attendance rates for KSI and Slight injury collisions.

KSI 2x2 (Df= 1)	Cyclists	Car	Total	χ^2
Did Not Attend	95 (24.4%)	99 (3.73%)	194	185.33
Attended	389	2658	3047	
Total	484	2757	3241	

Table A5.6 2x2 contingency table to compare Cyclist and Car driver police attendance rates for KSI and Slight injury collisions.

Slight 2x2 (Df = 1)	Cyclists	Car	Total	χ^2
Did Not Attend	718 (55.15%)	2672 (14.7%)	3390	753.22
Attended	1302	18199	19501	
Total	2020	20871	22891	

Table A5.7 2x2 contingency table to compare cyclist KSI and Slight injury collision rates for *Cycle lane (on main carriageway)"*.

STATS19	KSI	Slight	Total	χ^2
Cycle lane (on main carriageway)	9	468	477	0.89
Main Carriageway	55	1890	1945	
Total	64	2358	2422	

Table A5.8 2x2 contingency table to compare cyclist KSI and Slight injury collision rates when cycle infrastructure is present or not present.

2x2 (Df = 1)	KSI	Slight	Total	χ^2
Present	33	154	187	0.4
Not present	468	1891	2359	
Total	501	2045	2546	

Table A5.9 2x2 contingency table to compare cyclist KSI attendance at roads with a posted speed limit of 40mph and over with 20mph and 30mph roads.

Police Attendance Cyclist KSI				
Speed Limit	Did	Did not	Total	χ^2
40/60/70	120	17	137	
20/30	269	78	347	
Total (KSI)	389	95	484	5.69
OR= (a/c)/(b/d)	**2.05**			CI 95%

APPENDIX A 5.2

Department for Transport statistics

https://www.gov.uk/government/publications/reported-road-casualties-great-britain-annual-report-2013

RAS50005

Vehicles in reported accidents by contributory factor and vehicle type, Great Britain, 2013

Number/ *percentage*

Contributory factor attributed to vehicle[1,2]	Pedal cycle Number	Pedal cycle Per cent	Motorcycle Number	Motorcycle Per cent	Car Number	Car Per cent	Bus or Coach Number	Bus or Coach Per cent	Van/Light goods Number	Van/Light goods Per cent	HGV Number	HGV Per cent	All vehicles[3] Number	All vehicles[3] Per cent
Road environment contributed	**470**	***3***	**2,253**	***13***	**11,862**	***8***	**122**	***3***	**670**	***7***	**347**	***6***	**15,853**	***8***
Poor or defective road surface	87	*1*	244	*1*	413	*0*	11	*0*	22	*0*	13	*0*	796	*0*
Deposit on road (eg. oil, mud, chippings)	56	*0*	467	*3*	950	*1*	7	*0*	46	*0*	23	*0*	1,560	*1*
Slippery road (due to weather)	209	*2*	1,253	*7*	7,969	*5*	50	*1*	428	*4*	187	*3*	10,156	*5*
Inadequate or masked signs or road markings	18	*0*	26	*0*	421	*0*	5	*0*	35	*0*	10	*0*	519	*0*
Defective traffic signals	4	*0*	11	*0*	179	*0*	3	*0*	10	*0*	2	*0*	209	*0*
Traffic calming (eg. road humps, chicane)	9	*0*	21	*0*	69	*0*	1	*0*	9	*0*	3	*0*	112	*0*
Temporary road layout (eg. contraflow)	5	*0*	17	*0*	187	*0*	5	*0*	14	*0*	19	*0*	251	*0*
Road layout (eg. bend, hill, narrow road)	82	*1*	314	*2*	2,293	*2*	43	*1*	137	*1*	100	*2*	3,023	*2*
Animal or object in carriageway	30	*0*	178	*1*	919	*1*	8	*0*	46	*0*	15	*0*	1,204	*1*
Slippery inspection cover or road marking	5	*0*	22	*0*	54	*0*	0	*0*	2	*0*	3	*0*	87	*0*
Vehicle defects	**314**	***2***	**181**	***1***	**1,197**	***1***	**19**	***0***	**136**	***1***	**106**	***2***	**2,003**	***1***
Tyres illegal, defective or under inflated	12	*0*	67	*0*	524	*0*	4	*0*	33	*0*	13	*0*	657	*0*
Defective lights or indicators	75	*1*	25	*0*	52	*0*	0	*0*	4	*0*	2	*0*	168	*0*
Defective brakes	214	*2*	72	*0*	364	*0*	11	*0*	45	*0*	25	*0*	743	*0*
Defective steering or suspension	16	*0*	26	*0*	216	*0*	4	*0*	8	*0*	10	*0*	287	*0*
Defective or missing mirrors	0	*0*	1	*0*	8	*0*	0	*0*	4	*0*	1	*0*	15	*0*
Overloaded or poorly loaded vehicle or trailer	8	*0*	8	*0*	84	*0*	0	*0*	51	*1*	59	*1*	227	*0*
Injudicious action	**1,853**	***14***	**2,497**	***15***	**19,506**	***13***	**193**	***5***	**1,456**	***14***	**588**	***11***	**26,254**	***13***
Disobeyed automatic traffic signal	187	*1*	107	*1*	1,664	*1*	25	*1*	98	*1*	27	*0*	2,121	*1*
Disobeyed 'Give Way' or 'Stop' sign or markings	167	*1*	105	*1*	2,996	*2*	17	*0*	229	*2*	40	*1*	3,577	*2*
Disobeyed double white lines	3	*0*	35	*0*	156	*0*	0	*0*	8	*0*	8	*0*	212	*0*
Disobeyed pedestrian crossing facility	92	*1*	29	*0*	337	*0*	14	*0*	23	*0*	6	*0*	509	*0*
Illegal turn or direction of travel	76	*1*	55	*0*	577	*0*	2	*0*	40	*0*	19	*0*	778	*0*
Exceeding speed limit	18	*0*	812	*5*	3,730	*3*	10	*0*	184	*2*	41	*1*	4,813	*2*
Travelling too fast for conditions	284	*2*	890	*5*	5,907	*4*	30	*1*	339	*3*	169	*3*	7,668	*4*
Following too close	186	*1*	711	*4*	5,897	*4*	102	*3*	653	*6*	335	*6*	7,920	*4*
Vehicle travelling along pavement	120	*1*	21	*0*	95	*0*	2	*0*	10	*0*	3	*0*	265	*0*
Cyclist entering road from pavement	882	*7*	2	*0*	27	*0*	0	*0*	0	*0*	0	*0*	916	*0*
Driver/Rider error or reaction	**4,915**	***37***	**7,652**	***45***	**65,844**	***44***	**1,474**	***38***	**4,814**	***48***	**2,435**	***44***	**87,882**	***44***
Junction overshoot	197	*1*	116	*1*	2,027	*1*	11	*0*	137	*1*	39	*1*	2,547	*1*
Junction restart (moving off at junction)	34	*0*	60	*0*	1,633	*1*	44	*1*	98	*1*	32	*1*	1,913	*1*
Poor turn or manoeuvre	753	*6*	1,603	*10*	12,285	*8*	229	*6*	959	*10*	538	*10*	16,517	*8*
Failed to signal or misleading signal	136	*1*	66	*0*	1,689	*1*	21	*1*	143	*1*	52	*1*	2,135	*1*
Driver/Rider failed to look properly	3,147	*23*	2,682	*16*	36,773	*25*	509	*13*	2,998	*30*	1,408	*25*	47,906	*24*
Driver/Rider failed to judge other person's path or speed	1,398	*10*	2,244	*13*	18,821	*13*	291	*8*	1,548	*15*	858	*15*	25,348	*13*
Too close to cyclist, horse rider or pedestrian	82	*1*	73	*0*	1,602	*1*	107	*3*	197	*2*	79	*1*	2,184	*1*
Sudden braking	173	*1*	1,099	*7*	5,802	*4*	595	*15*	377	*4*	166	*3*	8,246	*4*
Swerved	246	*2*	436	*3*	3,333	*2*	29	*1*	217	*2*	110	*2*	4,401	*2*
Loss of control	695	*5*	2,646	*16*	11,041	*7*	59	*2*	445	*4*	239	*4*	15,248	*8*
Impairment or distraction	**1,009**	***8***	**550**	***3***	**11,124**	***7***	**98**	***3***	**636**	***6***	**268**	***5***	**13,771**	***7***
Driver/Rider impaired by alcohol	276	*2*	285	*2*	3,874	*3*	6	*0*	194	*2*	19	*0*	4,679	*2*
Driver/Rider impaired by drugs (illicit or medicinal)	38	*0*	36	*0*	495	*0*	1	*0*	17	*0*	1	*0*	593	*0*
Fatigue	25	*0*	38	*0*	1,451	*1*	7	*0*	127	*1*	95	*2*	1,753	*1*
Uncorrected, defective eyesight	9	*0*	3	*0*	215	*0*	2	*0*	5	*0*	2	*0*	240	*0*
Driver/Rider illness or disability, mental or physical	44	*0*	46	*0*	1,927	*1*	20	*1*	87	*1*	46	*1*	2,191	*1*
Not displaying lights at night or in poor visibility	309	*2*	38	*0*	95	*0*	1	*0*	2	*0*	3	*0*	456	*0*
Rider wearing dark clothing	487	*4*	31	*0*	27	*0*	0	*0*	3	*0*	0	*0*	550	*0*
Driver using mobile phone	15	*0*	4	*0*	349	*0*	0	*0*	34	*0*	20	*0*	422	*0*
Distraction in vehicle	18	*0*	22	*0*	2,675	*2*	31	*1*	161	*2*	88	*2*	3,004	*2*
Distraction outside vehicle	43	*0*	82	*0*	1,344	*1*	38	*1*	93	*1*	43	*1*	1,655	*1*
Behaviour or inexperience	**1,269**	***9***	**3,292**	***20***	**19,771**	***13***	**218**	***6***	**1,359**	***13***	**508**	***9***	**26,613**	***13***
Aggressive driving	40	*0*	376	*2*	2,822	*2*	19	*0*	179	*2*	35	*1*	3,492	*2*
Driver/Rider careless, reckless or in a hurry	1,117	*8*	1,630	*10*	13,916	*9*	197	*5*	1,182	*12*	400	*7*	18,560	*9*
Driver/Rider nervous, uncertain or panic	41	*0*	167	*1*	1,511	*1*	4	*0*	34	*0*	13	*0*	1,786	*1*
Driving too slow for conditions or slow veh (eg tractor)	7	*0*	8	*0*	68	*0*	0	*0*	2	*0*	4	*0*	99	*0*
Learner or inexperienced driver/rider	92	*1*	1,439	*9*	3,036	*2*	2	*0*	35	*0*	11	*0*	4,638	*2*
Inexperience of driving on the left	7	*0*	32	*0*	288	*0*	1	*0*	14	*0*	64	*1*	421	*0*
Unfamiliar with model of vehicle	15	*0*	192	*1*	502	*0*	4	*0*	25	*0*	15	*0*	776	*0*
Vision affected by external factors	**540**	***4***	**878**	***5***	**9,826**	***7***	**115**	***3***	**678**	***7***	**576**	***10***	**12,719**	***6***
Stationary or parked vehicle(s)	337	*3*	460	*3*	3,142	*2*	28	*1*	187	*2*	37	*1*	4,212	*2*
Vegetation	40	*0*	15	*0*	285	*0*	5	*0*	21	*0*	11	*0*	384	*0*
Road layout (eg. bend, winding road, hill crest)	47	*0*	128	*1*	1,175	*1*	12	*0*	79	*1*	38	*1*	1,494	*1*
Buildings, road signs, street furniture	17	*0*	12	*0*	198	*0*	2	*0*	17	*0*	3	*0*	252	*0*
Dazzling headlights	6	*0*	12	*0*	332	*0*	2	*0*	9	*0*	4	*0*	370	*0*
Dazzling sun	44	*0*	136	*1*	2,514	*2*	22	*1*	158	*2*	65	*1*	2,958	*1*
Rain, sleet, snow, or fog	42	*0*	119	*1*	1,831	*1*	16	*0*	93	*1*	60	*1*	2,178	*1*
Spray from other vehicles	2	*0*	8	*0*	170	*0*	0	*0*	9	*0*	14	*0*	206	*0*
Visor or windscreen dirty, scratched or frosted etc.	0	*0*	12	*0*	123	*0*	1	*0*	8	*0*	1	*0*	145	*0*
Vehicle blind spot	19	*0*	15	*0*	828	*1*	35	*1*	139	*1*	375	*7*	1,436	*1*
Pedestrian only (casualty or uninjured)	**4**	***0***	**3**	***0***	**21**	***0***	**1**	***0***	**1**	***0***	**0**	***0***	**30**	***0***
Crossing road masked by stationary or parked vehicle	1	*0*	0	*0*	4	*0*	0	*0*	0	*0*	0	*0*	5	*0*
Pedestrian failed to look properly	0	*0*	2	*0*	9	*0*	1	*0*	1	*0*	0	*0*	13	*0*
Pedestrian failed to judge vehicle's path or speed	0	*0*	0	*0*	3	*0*	0	*0*	1	*0*	0	*0*	4	*0*
Pedestrian wrong use of pedestrian crossing facility	0	*0*	0	*0*	0	*0*	0	*0*	0	*0*	0	*0*	0	*0*
Dangerous action in carriageway (eg. playing)	3	*0*	1	*0*	2	*0*	0	*0*	0	*0*	0	*0*	6	*0*
Pedestrian impaired by alcohol	0	*0*	0	*0*	3	*0*	0	*0*	0	*0*	0	*0*	3	*0*
Pedestrian impaired by drugs (illicit or medicinal)	0	*0*	0	*0*	1	*0*	0	*0*	0	*0*	0	*0*	1	*0*
Pedestrian careless, reckless or in a hurry	0	*0*	0	*0*	4	*0*	0	*0*	0	*0*	0	*0*	4	*0*
Pedestrian wearing dark clothing at night	0	*0*	0	*0*	0	*0*	0	*0*	0	*0*	0	*0*	0	*0*
Pedestrian disability or illness, mental or physical	0	*0*	0	*0*	3	*0*	0	*0*	0	*0*	0	*0*	3	*0*
Special codes	**170**	***1***	**298**	***2***	**3,087**	***2***	**131**	***3***	**255**	***3***	**141**	***3***	**4,278**	***2***
Stolen vehicle	1	*0*	88	*1*	427	*0*	0	*0*	40	*0*	4	*0*	567	*0*
Vehicle in course of crime	4	*0*	42	*0*	314	*0*	0	*0*	28	*0*	1	*0*	391	*0*
Emergency vehicle on a call	3	*0*	12	*0*	456	*0*	1	*0*	34	*0*	12	*0*	648	*0*
Vehicle door opened or closed negligently	2	*0*	0	*0*	471	*0*	18	*0*	38	*0*	13	*0*	551	*0*
Other	160	*1*	171	*1*	1,549	*1*	113	*3*	128	*1*	111	*2*	2,283	*1*
Vehicles with no contributory factor	**6,672**	***50***	**6,123**	***36***	**60,654**	***41***	**2,059**	***53***	**3,843**	***38***	**2,342**	***42***	**82,434**	***41***
Total number of vehicles	**13,440**	***100***	**16,862**	***100***	**148,385**	***100***	**3,864**	***100***	**10,087**	***100***	**5,571**	***100***	**200,074**	***100***

1 Includes only vehicles in road accidents where a police officer attended the scene and in which a contributory factor was reported. Columns may not add up to 100 per cent as accidents can have more than one contributory factor.

2 Due to recording errors some vehicle specific factors may have been allocated to the wrong vehicle in some accidents.

3 Includes other vehicles types and cases where the vehicle type was not reported.

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Notes & Definitions

Source: STATS19

Last updated: 25 September 2014

Next update: September 2015

APPENDIX A 6.1

Table A6.1 Model Comparison Results											
						KSI					
	generalized linear mixed-effects		*Poisson*	*negative binomial*	*Poisson*	*negative binomial*	*Poisson*	*negative binomial*	*Poisson generalized estimation equation*		
	(1)	(2)	(3)	(4)	(5)	(7)	(9)	(11)	(13)	(14)	(15)
Constant	-3.42^{***}	-3.42^{***}	-3.78^{***}	-3.39^{***}	-5.40^{**}	-5.40^{**}	-3.89^{***}	-3.47^{***}	-3.78^{***}	-3.78^{***}	-3.75^{***}
	(-4.61, -2.23)	(-4.61, -2.23)	(-4.35, -3.21)	(-4.27, -2.50)	(-10.09, -0.72)	(-10.09, -0.72)	(-4.47, -3.31)	(-4.37, -2.57)	(-4.70, -2.86)	(-4.70, -2.86)	(-4.67, -2.83)
lnN_Cyc	0.70^{***}	0.70^{***}	0.76^{***}	0.71^{***}	0.94^{***}	0.94^{***}	0.76^{***}	0.71^{***}	0.76^{***}	0.76^{***}	0.76^{***}
	(0.53, 0.87)	(0.53, 0.87)	(0.69, 0.84)	(0.58, 0.83)	(0.34, 1.55)	(0.34, 1.55)	(0.69, 0.84)	(0.59, 0.83)	(0.64, 0.89)	(0.64, 0.89)	(0.64, 0.88)
factor(LA)911					0.20	0.20					
					(-0.52, 0.92)	(-0.52, 0.92)					
factor(LA)912					-0.20	-0.20					
					(-1.20, 0.81)	(-1.20, 0.81)					
factor(LA)913					-0.41	-0.41					
					(-1.72, 0.89)	(-1.72, 0.89)					
factor(LA)914					1.01^{**}	1.01^{**}					
					(0.07, 1.95)	(0.07, 1.95)					
factor(LA)915					1.21	1.21					
					(-0.37, 2.79)	(-0.37, 2.79)					
factor(LA)916					0.94	0.94					
					(-0.59, 2.47)	(-0.59, 2.47)					
factor(LA)917					-0.24	-0.24					
					(-1.09, 0.61)	(-1.09, 0.61)					
factor(LA)918					0.24	0.24					
					(-0.61, 1.09)	(-0.61, 1.09)					
factor(LA)919					1.15	1.15					
					(-0.31, 2.62)	(-0.31, 2.62)					
factor(LA)920					0.23	0.23					
					(-1.06, 1.51)	(-1.06, 1.51)					
factor(LA)921					0.17	0.17					
					(-0.70, 1.03)	(-0.70, 1.03)					

factor(LA)922	1.27*	1.27*
	(-0.07, 2.61)	(-0.07, 2.61)
factor(LA)923	0.09	0.09
	(-1.02, 1.19)	(-1.02, 1.19)
factor(LA)924	0.62	0.62
	(-0.25, 1.49)	(-0.25, 1.49)
factor(LA)925	0.03	0.03
	(-0.55, 0.61)	(-0.55, 0.61)
factor(LA)926	0.34	0.34
	(-0.34, 1.02)	(-0.34, 1.02)
factor(LA)927	-0.87**	-0.87**
	(-1.60, -0.14)	(-1.60, -0.14)
factor(LA)928	1.03	1.03
	(-1.20, 3.26)	(-1.20, 3.26)
factor(LA)929	0.27	0.27
	(-1.03, 1.57)	(-1.04, 1.57)
factor(LA)930	-1.43**	-1.43**
	(-2.66, -0.19)	(-2.66, -0.19)
factor(LA)931	-0.04	-0.04
	(-1.33, 1.26)	(-1.33, 1.26)
factor(LA)932	0.71	0.71
	(-0.39, 1.81)	(-0.39, 1.81)
factor(LA)933	-0.58	-0.58
	(-3.11, 1.95)	(-3.11, 1.95)
factor(LA)934	0.71*	0.71*
	(-0.10, 1.51)	(-0.10, 1.51)
factor(LA)935	1.27***	1.27***
	(0.37, 2.18)	(0.37, 2.18)
factor(LA)936	0.30	0.30
	(-2.61, 3.20)	(-2.61, 3.20)
factor(LA)937	0.16	0.16

					(-0.90, 1.21)	(-0.90, 1.21)					
factor(LA)938					0.85*	0.85*					
					(-0.13, 1.83)	(-0.13, 1.83)					
factor(LA)939					0.49	0.49					
					(-0.51, 1.49)	(-0.51, 1.49)					
factor(LA)940					0.83*	0.83*					
					(-0.06, 1.72)	(-0.06, 1.72)					
factor(LA)941											
1 | LA											
factor(YEAR)2011							0.12	0.09			
							(-0.11, 0.34)	(-0.23, 0.42)			
factor(YEAR)2012							0.19	0.15			
							(-0.03, 0.41)	(-0.17, 0.48)			
1 | YEAR											
Observations	96	96	96	96	96	96	96	96	96	96	96
Log Likelihood	-208.29	-208.28	-224.87	-215.45	-174.88	-175.89	-223.36	-215.02			
AIC	422.58	424.56	453.74	434.90	413.77	415.77	454.71	438.05			
BIC.	430.27	434.81									

Note: *p**p***p<0.01

APPENDIX A 6.2

Table A6.2 "ALL" cyclist injury collision results

	Dependent variable: All cyclists casualties			
	Code: ALL			
	(1)	*(2)*	*(3)*	*(4)*
lnN_Cyc		0.597***	0.574***	0.657***
lnmvkm_v		0.705***	0.346***	0.377***
lnRD_L		-0.110		
lnN0_Car		0.350		
lnRL_A		-0.076		
lnRL_B		0.214*		
lnRL_C		-0.132		
lnRL_U		-0.287		
SMID_15_N		0.082	0.084**	
Urban		0.005	0.010***	
factor(YEAR)2011		0.024		
factor(YEAR)2012		0.115		
Intercept	3.260***	-5.650***	-4.470***	-4.550***
Log Likelihood	-412	-288	-296	-325
theta	0.938***	28.3***	19.4***	6.5***
Akaike Inf. Crit.	826	602	601	657
Note:				*p**p***p<0.01

Table A6.3 "KSI" cyclist injury collision results

	Dependent variable:			
	KSI			
	(1)	(2)	(3)	(4)
lnN_Cyc		0.493***	0.472***	0.583***
lnmvkm_v		0.775***	0.362**	0.290*
lnRD_L		1.200		
lnN0_Car		-0.067		
lnRL_A		-0.409		
lnRL_B		-0.061		
lnRL_C		-0.192		
lnRL_U		-1.040		
		(0.902)		
SMID_15_N		0.063	0.032	
		(0.093)	(0.063)	
Urban		0.004	0.010***	
		(0.007)	(0.002)	

factor(YEAR)2011		0.103		
		(0.136)		
factor(YEAR)2012		0.171		
		(0.134)		
Constant	1.620***	-6.780**	-5.360***	-4.880***
	(0.107)	(2.800)	(0.986)	(0.968)
Observations	96	96	96	96
Log Likelihood	-261.000	-201.000	-204.000	-214.000
theta	1.110*** (0.193)	21.200 (18.900)	12.800* (7.570)	5.630*** (1.910)
Akaike Inf. Crit.	524.000	428.000	419.000	434.000
Note:				*p**p***p<0.01

Table A6.4 "SL" cyclist injury collision results

	Dependent variable:			
	SL			
	(1)	(2)	(3)	(4)
lnN_Cyc		0.643***	0.617***	0.698***
		(0.060)	(0.054)	(0.078)
lnmvkm_v		0.671***	0.333***	0.367***
		(0.154)	(0.097)	(0.125)
lnRD_L		-0.476		
		(0.794)		
lnN0_Car		0.507*		
		(0.291)		
lnRL_A		0.026		
		(0.212)		
lnRL_B		0.292**		
		(0.124)		
lnRL_C		-0.113		
		(0.184)		
lnRL_U		-0.092		
		(0.517)		
SMID_15_N		0.077	0.089**	
		(0.056)	(0.041)	

Urban		0.006	0.011^{***}	
		(0.004)	(0.001)	
factor(YEAR)2011		0.012		
		(0.081)		
factor(YEAR)2012		0.112		
		(0.079)		
Constant	3.050^{***}	-6.130^{***}	-4.940^{***}	-5.000^{***}
	(0.112)	(1.600)	(0.608)	(0.703)
Observations	96	96	96	96
Log Likelihood	-391.000	-268.000	-276.000	-305.000
theta	0.869^{***} (0.119)	35.200^{**} (15.200)	21.500^{***} (7.220)	6.320^{***} (1.320)
Akaike Inf. Crit.	784.000	561.000	562.000	617.000
Note:				*p**p***p<0.01

Table A6.5 “KSI_m” cyclist injury collision results

	Dependent variable:			
	KSI_m			
	(1)	(2)	(3)	(4)
lnN_Cyc		0.483^{***}	0.401^{***}	0.540^{***}
		(0.103)	(0.092)	(0.111)
lnmvkm_v		1.030^{***}	0.483^{***}	0.390^{**}
		(0.279)	(0.176)	(0.189)
lnRD_L		1.240		
		(1.540)		
lnN0_Car		-0.122		
		(0.510)		
lnRL_A		-0.477		
		(0.408)		
lnRL_B		0.009		
		(0.217)		
lnRL_C		-0.112		
		(0.336)		
lnRL_U		-1.400		
		(1.010)		

	(1)	(2)	(3)	(4)
SMID_15_N		0.077	0.021	
		(0.094)	(0.068)	
Urban		0.007	0.013^{***}	
		(0.008)	(0.003)	
factor(YEAR)2011		0.199		
		(0.141)		
factor(YEAR)2012		0.270^{*}		
		(0.139)		
Constant	1.390^{***}	-7.390^{**}	-6.260^{***}	-5.610^{***}
	(0.111)	(3.000)	(1.110)	(1.090)
Observations	96	96	96	96
Log Likelihood	-242.000	-183.000	-188.000	-201.000
theta	1.070^{***} (0.196)	38.900 (79.100)	11.900 (7.870)	4.560^{***} (1.540)
Akaike Inf. Crit.	486.000	392.000	387.000	407.000
Note:				*p **p ***p<0.01

Table A6.6 **"KSI_f" cyclist injury collision results**

	Dependent variable:			
	KSI_f			
	(1)	(2)	(3)	(4)
lnN_Cyc		0.731^{***}	0.865^{***}	0.905^{***}
		(0.232)	(0.160)	(0.142)
lnmvkm_v		-0.107	-0.109	-0.138
		(0.567)	(0.310)	(0.296)
lnRD_L		1.820		
		(2.900)		
lnN0_Car		0.085		
		(1.050)		
lnRL_A		-0.160		
		(0.750)		
lnRL_B		-0.341		
		(0.445)		
lnRL_C		-0.480		
		(0.650)		

lnRL_U		-0.705		
		(1.790)		
SMID_15_N		-0.001	0.015	
		(0.177)	(0.091)	
Urban		-0.001	0.002	
		(0.016)	(0.004)	
factor(YEAR)2011		-0.216		
		(0.250)		
factor(YEAR)2012		-0.118		
		(0.243)		
Constant	0.010	-8.010	-5.390***	-5.300***
	(0.154)	(5.960)	(1.820)	(1.730)
Observations	96	96	96	96
Log Likelihood	-134.000	-108.000	-109.000	-109.000
theta	0.772*** (0.228)	5,799.000 (79,466.000)	3,750.000 (51,991.000)	3,824.000 (55,128.000)
Akaike Inf. Crit.	271.000	242.000	228.000	225.000
Note:				*p**p***p<0.01

Table A6.7 “AGE” cyclist injury collision results

	Dependent variable:			
	AGE_16			
	(1)	(2)	(3)	(4)
lnN_Cyc		0.274***	0.176**	0.277***
		(0.085)	(0.077)	(0.088)
lnmvkm_v		0.783***	0.547***	0.528***
		(0.218)	(0.136)	(0.150)
lnRD_L		-4.350***		
		(1.160)		
lnN0_Car		-0.392		
		(0.427)		
lnRL_A		1.000***		
		(0.305)		
lnRL_B		0.312		

		(0.193)		
lnRL_C		0.593**		
		(0.291)		
lnRL_U		2.080***		
		(0.745)		
SMID_15_N		0.285***	0.149***	
		(0.081)	(0.056)	
Urban		-0.0003	0.005**	
		(0.006)	(0.002)	
factor(YEAR)2011		-0.074		
		(0.116)		
factor(YEAR)2012		-0.161		
		(0.118)		
Constant	1.500***	2.310	-4.550***	-4.710***
	(0.087)	(2.280)	(0.850)	(0.866)
Observations	96	96	96	96
Log Likelihood	-245.000	-191.000	-201.000	-209.000
theta	2.000*** (0.418)	27,267.000 (523,223.000)	24.700 (23.700)	9.000** (3.950)
Akaike Inf. Crit.	492.000	409.000	411.000	425.000
Note:				*p**p***p<0.01

Table A6.8 "AGE" cyclist injury collision results

	Dependent variable:			
	AGE_60			
	(1)	(2)	(3)	(4)
lnN_Cyc		0.259	0.299**	0.325**
		(0.173)	(0.143)	(0.150)
lnmvkm_v		1.170***	0.881***	0.652**
		(0.443)	(0.280)	(0.267)
lnRD_L		2.250		
		(2.380)		
lnN0_Car		1.690*		
		(0.872)		

lnRL_A		-0.552		
		(0.617)		
lnRL_B		0.050		
		(0.341)		
lnRL_C		-0.041		
		(0.530)		
lnRL_U		-1.800		
		(1.520)		
SMID_15_N		-0.780***	-0.470***	
		(0.261)	(0.173)	
Urban		0.011	0.009**	
		(0.013)	(0.004)	
factor(YEAR)2011		-0.025		
		(0.222)		
factor(YEAR)2012		0.218		
		(0.210)		
Constant	0.318**	-18.500***	-9.330***	-7.280***
	(0.132)	(5.050)	(1.780)	(1.590)
Observations	96	96	96	96
Log Likelihood	-156.000	-128.000	-132.000	-136.000
theta	1.060*** (0.309)	2,120.000 (34,690.000)	8.630 (8.910)	3.730* (2.050)
Akaike Inf. Crit.	314.000	281.000	274.000	279.000
Note:				*p**p***p<0.01

Table A6.8 "Urban" cyclist injury collision results

	Dependent variable:			
	KSI_u			
	(1)	(2)	(3)	(4)

lnN_Cyc		0.538***	0.583***	0.748***
		(0.112)	(0.092)	(0.152)
lnmvkm_v		0.522	0.178	0.080
		(0.328)	(0.201)	(0.247)
lnRD_L		0.716		
		(1.770)		
lnN0_Car		0.704		
		(0.623)		
lnRL_A		-0.662		
		(0.461)		
lnRL_B		0.185		
		(0.251)		
lnRL_C		-0.327		
		(0.370)		
lnRL_U		-0.203		
		(1.210)		
SMID_15_N		-0.039	0.039	
		(0.097)	(0.051)	
Urban		0.011	0.024***	
		(0.009)	(0.003)	
factor(YEAR)2011		0.080		
		(0.133)		
factor(YEAR)2012		0.178		
		(0.130)		
Constant	1.300***	-9.620***	-6.130***	-4.710***
	(0.140)	(3.440)	(1.260)	(1.370)
Observations	96	96	96	96
Log Likelihood	-230.000	-166.000	-169.000	-198.000
theta	0.622*** (0.108)	17,146.000 (271,210.000)	36.600 (60.300)	1.910*** (0.528)
Akaike Inf. Crit.	463.000	359.000	349.000	402.000
Note:				*p**p***p<0.01

Table A6.9 "Rural" cyclist injury collision results

	Dependent variable:

	KSI_r			
	(1)	(2)	(3)	(4)
lnN_Cyc		-0.040	-0.071	-0.152
		(0.227)	(0.169)	(0.158)
lnmvkm_v		1.900***	1.220***	1.050***
		(0.512)	(0.271)	(0.261)
lnRD_L		-0.330		
		(1.920)		
lnN0_Car		0.602		
		(1.010)		
lnRL_A		0.014		
		(0.539)		
lnRL_B		0.810*		
		(0.440)		
lnRL_C		-0.419		
		(0.555)		
lnRL_U		-0.634		
		(1.210)		
SMID_15_N		-1.140*	-0.955***	
		(0.634)	(0.349)	
Urban		-0.004	-0.004	
		(0.011)	(0.005)	
factor(YEAR)2011		0.210		
		(0.225)		
factor(YEAR)2012		0.241		
		(0.224)		
Constant	0.303**	-11.600**	-8.500***	-7.220***
	(0.123)	(5.920)	(1.580)	(1.530)
Observations	96	96	96	96
Log Likelihood	-155.000	-125.000	-129.000	-142.000
theta	1.400*** (0.475)	55.200 (246.000)	7.620 (6.180)	2.990** (1.490)
Akaike Inf. Crit.	311.000	275.000	269.000	290.000
Note:				*p**p***p<0.01

APPENDIX A 6.3

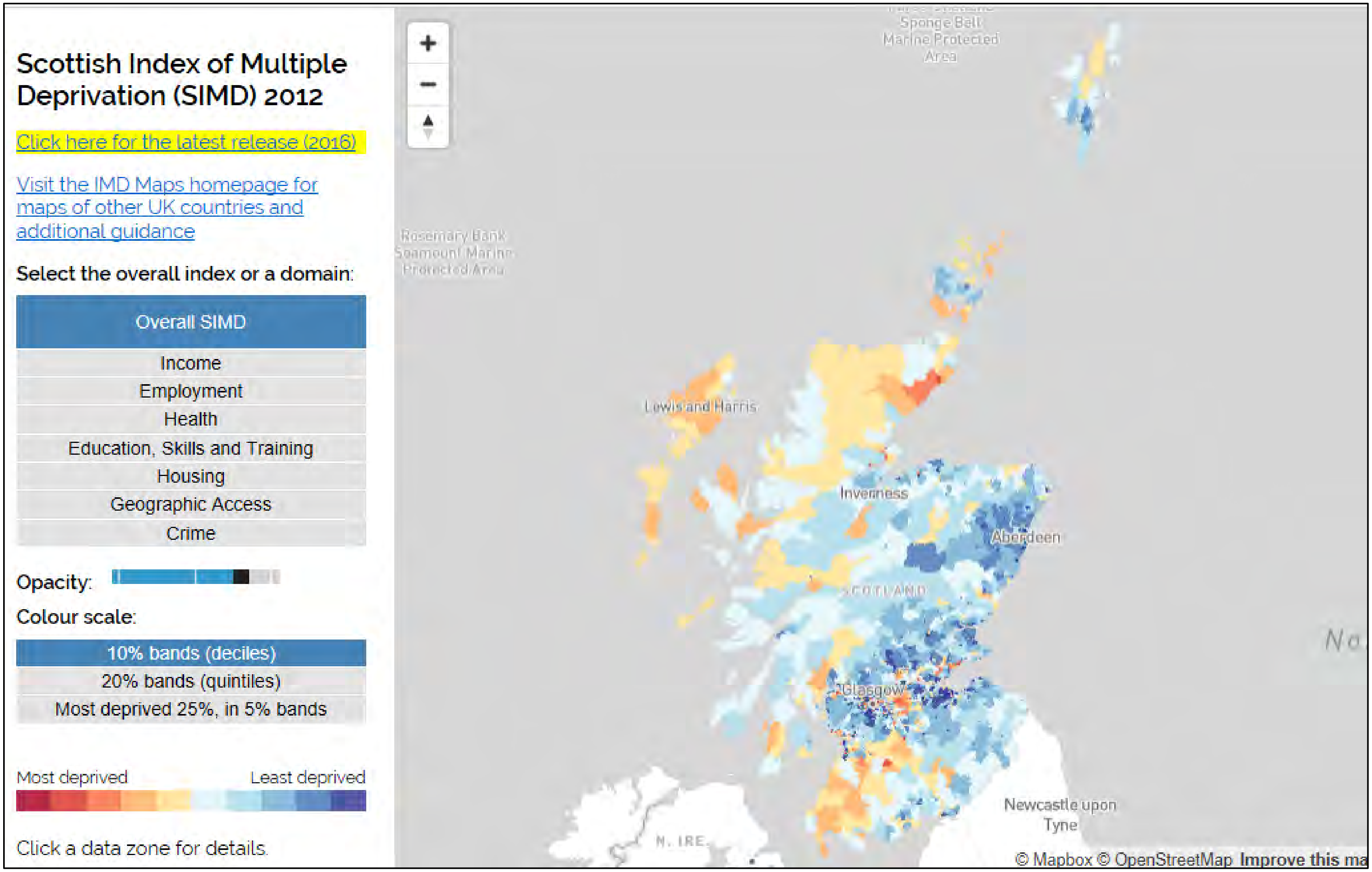

Figure A 6-1 SIMD 2012 (Source: https://jamestrimble.github.io/imdmaps/simd2012/

APPENDIX A 6.4

Table A 6.11 LA Name	ALL	KSI	SL	KSI_m	KSI_f	KSI_60	KSI_30	N_Cyc	mvkm_v	mvkm_Cyc	Pop	***(SiN)*GWPR Beta ksi**	% pop Cycles to work/school	KSI 1000 per pop	Slight 1000 pop
Highland	94	13	81	7	6	5	58	3681	7758	64	102091	**0.38**	3.61	0.13	0.79
Eilean Siar	7	1	6	0	1	1	2	96	609	2	12576	**0.58**	0.76	0.08	0.48
Moray	26	3	23	3	0	1	21	1394	2142	24	40062	**0.70**	3.48	0.07	0.57
North Lanarkshire	83	11	72	10	1	4	74	576	7536	10	145998	**0.71**	0.39	0.08	0.49
South Lanarkshire	70	15	55	10	5	7	51	687	4572	12	139188	**0.72**	0.49	0.11	0.40
Falkirk	62	15	47	13	2	2	53	876	2988	15	68732	**0.72**	1.27	0.22	0.68
Glasgow City	377	61	316	50	11	1	370	5227	6159	91	285693	**0.73**	1.83	0.21	1.11
West Lothian	79	17	62	12	5	3	54	806	3102	14	73398	**0.73**	1.10	0.23	0.84
East Dunbartonshire	32	6	26	6	0	4	26	505	1602	9	43473	**0.73**	1.16	0.14	0.60
East Renfrewshire	38	12	26	9	3	1	31	348	1674	6	37225	**0.73**	0.93	0.32	0.70
Clackmannanshire	21	8	13	5	3	1	19	241	984	4	22734	**0.73**	1.06	0.35	0.57
East Ayrshire	26	9	17	9	0	2	20	290	2700	5	53919	**0.73**	0.54	0.17	0.32
Stirling	57	11	46	11	0	3	33	728	2895	13	37566	**0.74**	1.94	0.29	1.22
Dumfries & Galloway	45	9	36	7	2	6	33	1269	3897	22	67980	**0.74**	1.87	0.13	0.53
West Dunbartonshire	18	7	11	6	1	1	11	279	1902	5	42167	**0.74**	0.66	0.17	0.26
Scottish Borders	41	18	23	15	3	3	18	704	3540	12	52498	**0.74**	1.34	0.34	0.44
Renfrewshire	77	24	53	21	3	6	67	723	2868	13	80902	**0.74**	0.89	0.30	0.66
Midlothian	34	6	28	6	0	1	26	484	1956	8	34978	**0.74**	1.38	0.17	0.80
Edinburgh, City of	691	108	583	80	28	31	653	12526	7794	218	223051	**0.75**	**5.62**	0.48	2.61
South Ayrshire	39	8	31	8	0	6	30	738	2937	13	51286	**0.75**	1.44	0.16	0.60
Inverclyde	21	3	18	3	0	2	16	103	1557	2	37434	**0.75**	0.28	0.08	0.48
North Ayrshire	43	5	38	4	1	3	34	551	2310	10	62498	**0.75**	0.88	0.08	0.61
Perth & Kinross	49	18	31	14	4	7	25	972	5559	17	64777	**0.75**	1.50	0.28	0.48
Orkney Islands	3	1	2	0	1	0	2	178	405	3	9725	**0.75**	1.83	0.10	0.21
East Lothian	62	11	51	7	4	4	50	1022	2565	18	42905	**0.76**	2.38	0.26	1.19
Argyll & Bute	29	4	25	2	2	3	18	648	2652	11	40125	**0.76**	1.61	0.10	0.62
Fife	105	22	83	20	2	7	78	2461	7785	43	160952	**0.77**	1.53	0.14	0.52
Dundee City	68	12	56	11	1	6	61	1037	2601	18	69193	**0.80**	1.50	0.17	0.81
Shetland Islands	2	1	1	0	1	0	2	70	606	1	9950	**0.82**	0.70	0.10	0.10
Aberdeenshire	61	15	46	12	3	8	35	1375	8148	24	104714	**0.82**	1.31	0.14	0.44
Angus	29	7	22	5	2	3	24	932	3225	16	51616	**0.82**	1.81	0.14	0.43
Aberdeen City	115	23	92	21	2	0	94	2666	3924	46	103371	**0.84**	2.58	0.22	0.89

APPENDIX A 8.1

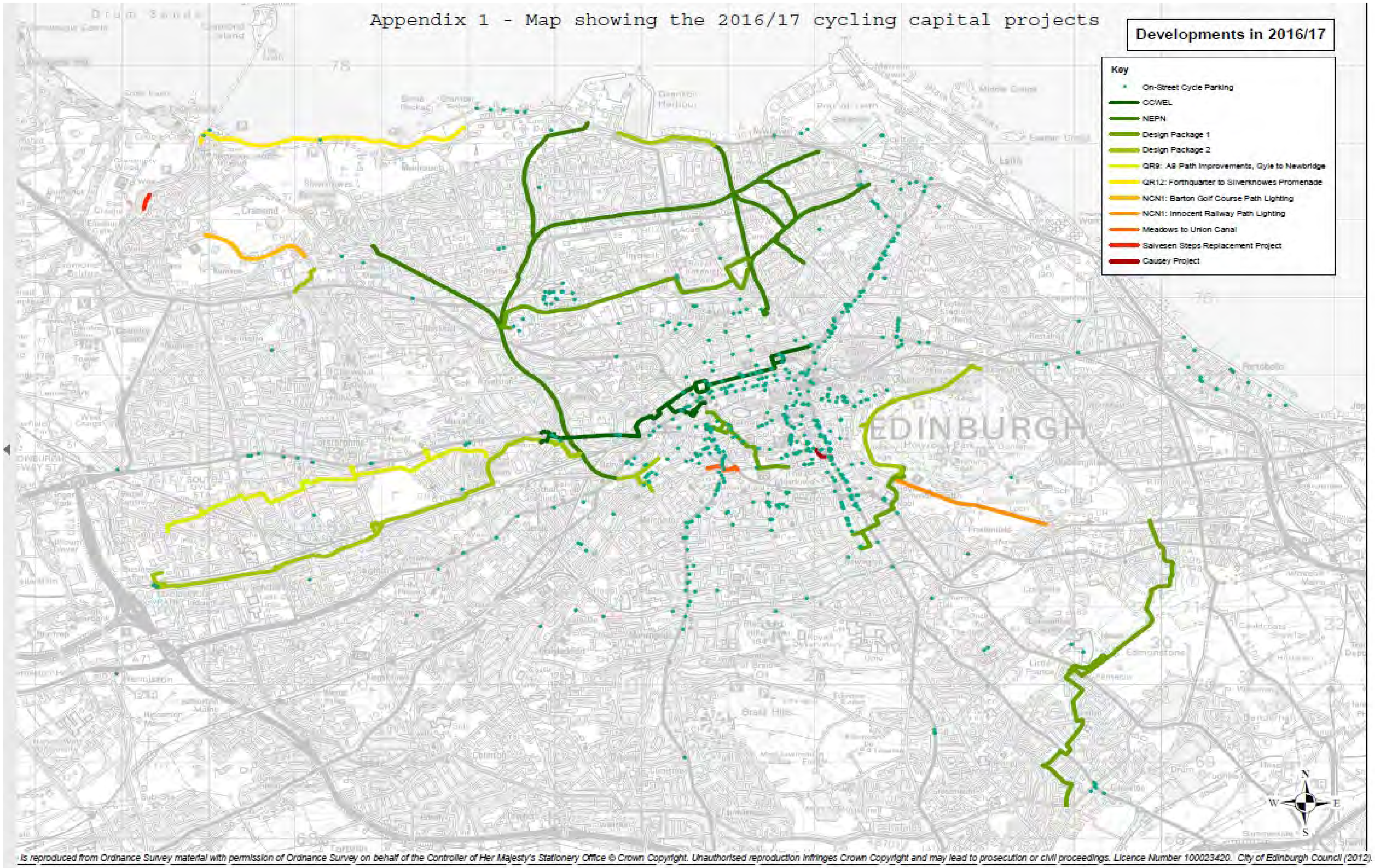

Figure A 8-1 Cyclist infrastructure City of Edinburgh Infrastructure activity delivery update 2017

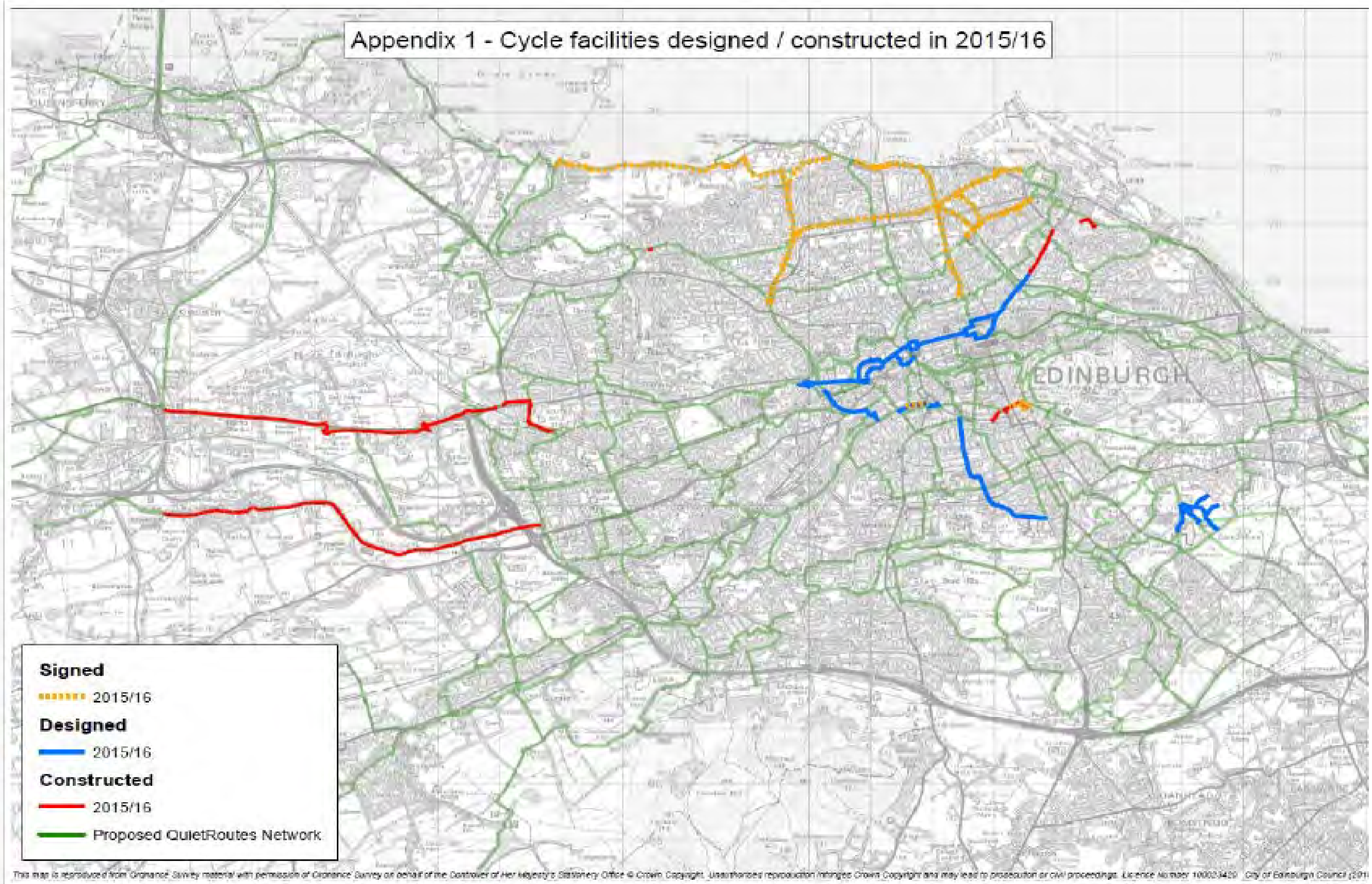

Figure A 8-2 Cyclist infrastructure City of Edinburgh Infrastructure activity delivery update 2016.

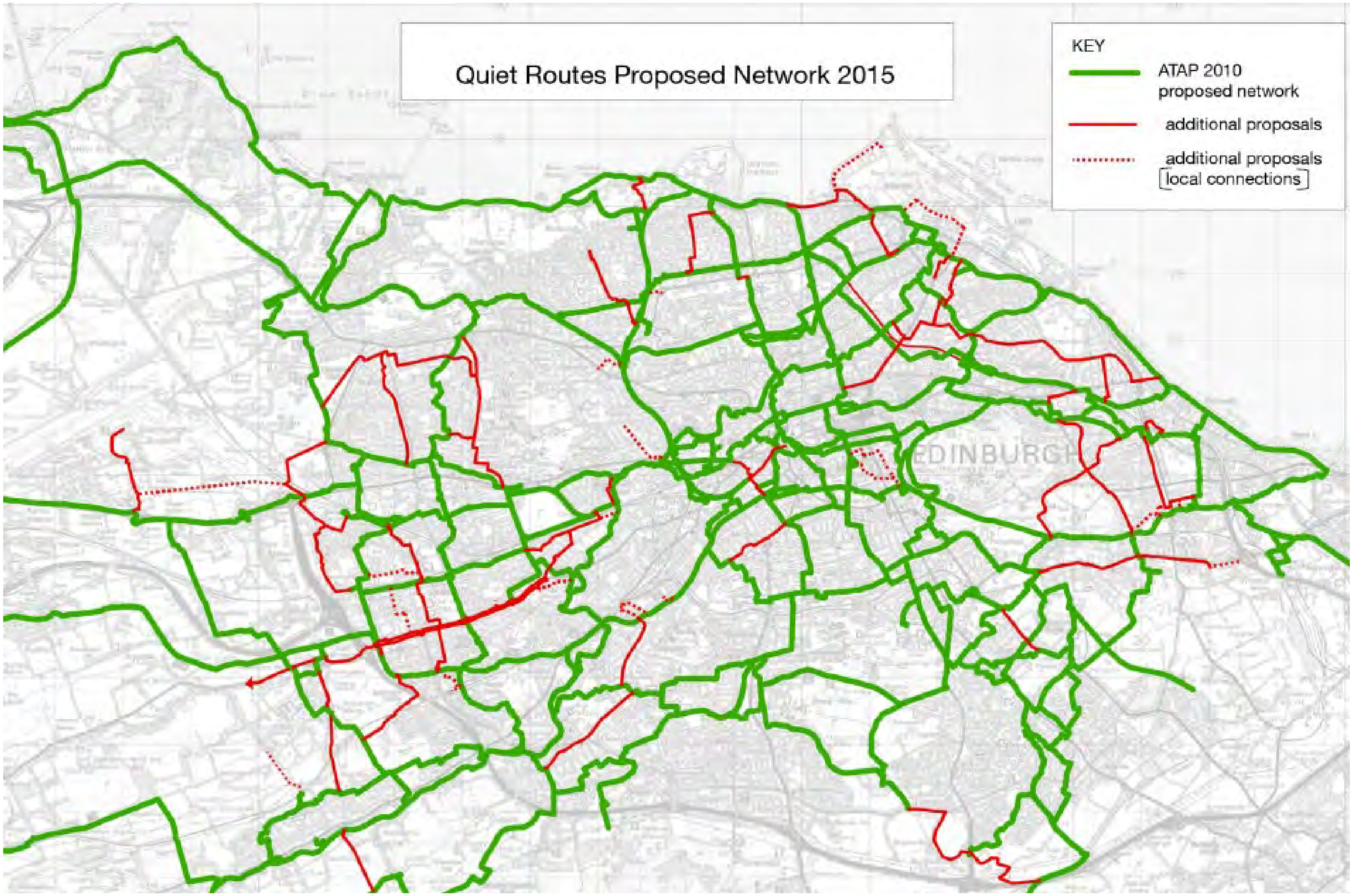

Figure A 8-3 Cyclist infrastructure City of Edinburgh proportions Quiet Routes ATAP 2016 planned extension.

APPENDIX A 8.2

Table A 8.1 Summary of cycling infrastructure, City of Edinburgh 2011 (from ArcGIS model).

	All facilities	On-road cycle lane	*(Re-allocated)* Shared unsegragated footway	Shared off-road path	Segragated cycle lane	Quiet Route	Bus lane
% of road network	17	3	3	10	1	4	4
Total length (km)	268	50	49	159	11	58	64
Total length (miles)	167	31	30	99	7	36	40
Total traffic free (km)	219		Total road network (km)			1537	
Total traffic free (miles)	136		Total road network (miles)			955	

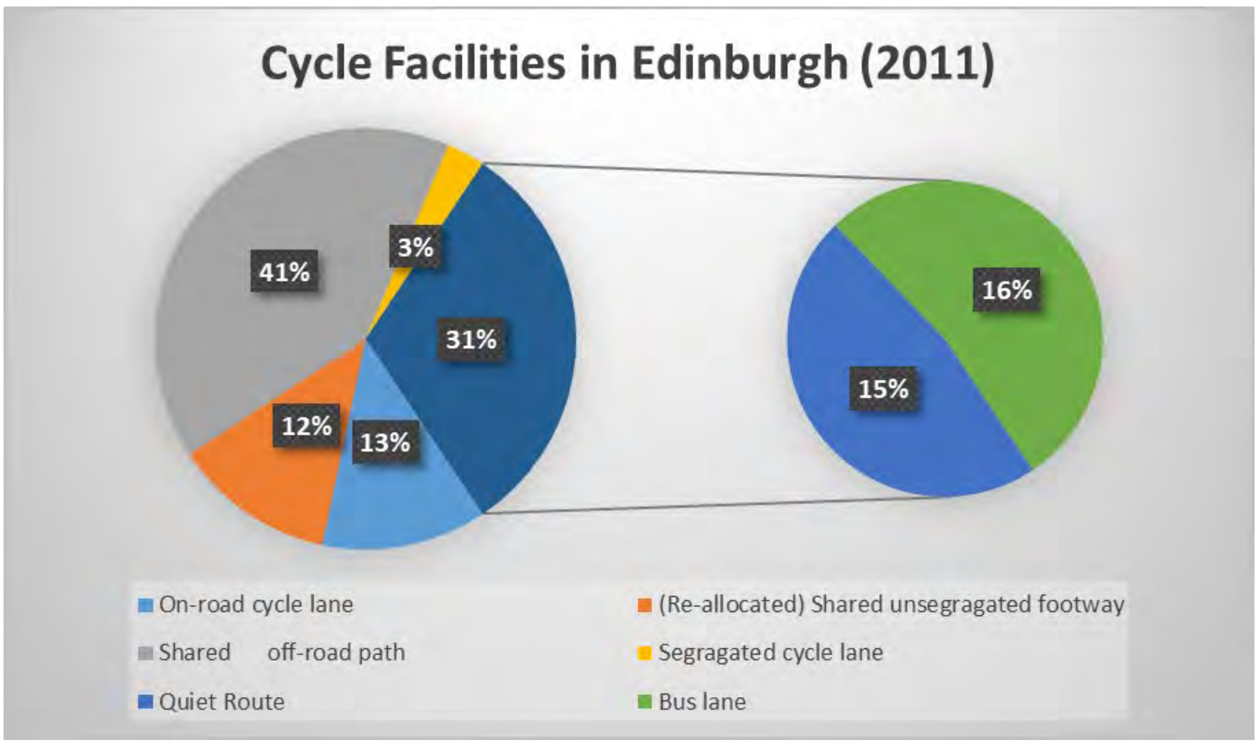

Figure A 8-4 Cyclist infrastructure City of Edinburgh proportions by type.

APPENDIX A 9.1

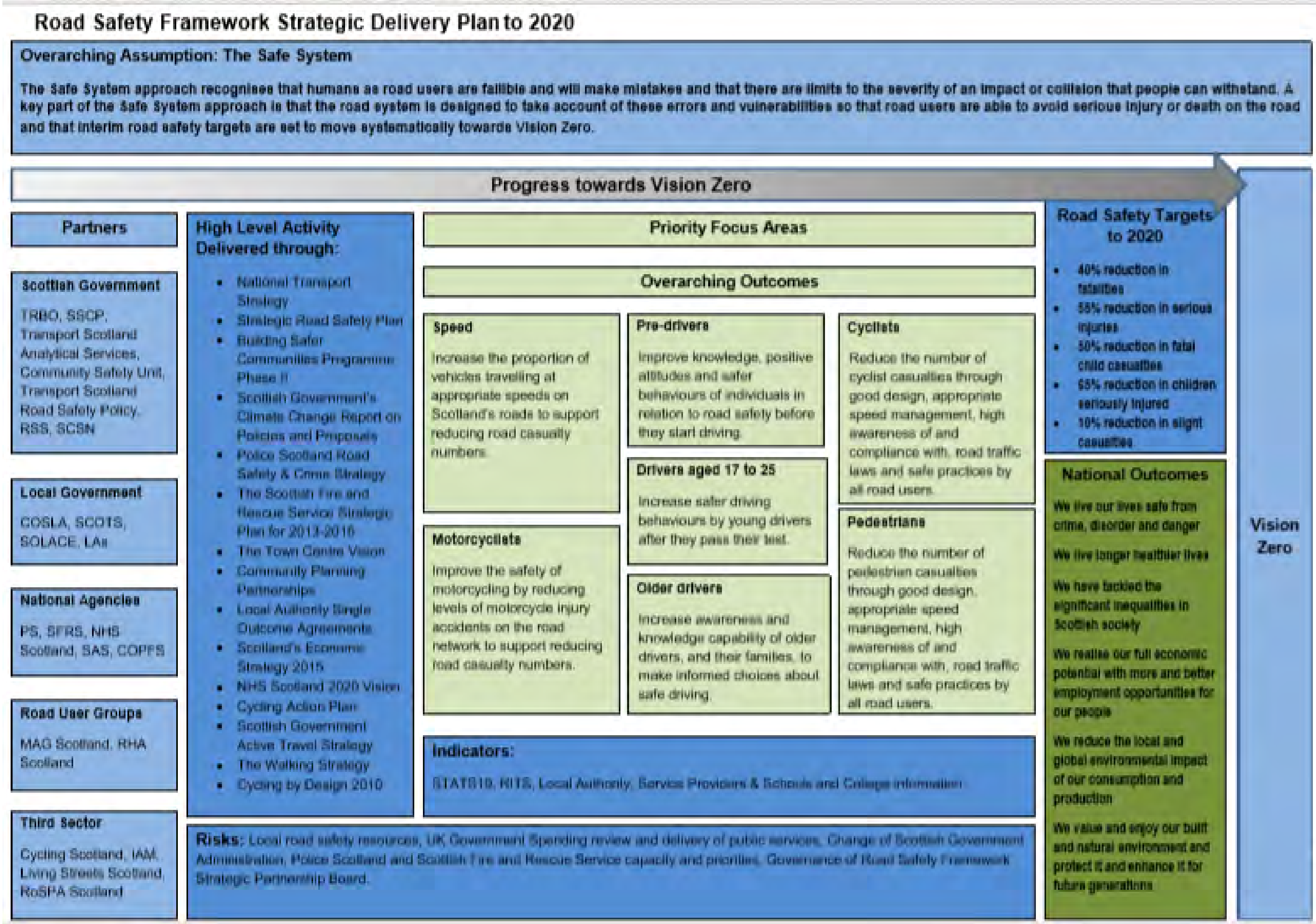

Figure A 9-1 Road Safety Framework Strategic Delivery Plan to 2020 (TS, 2009)

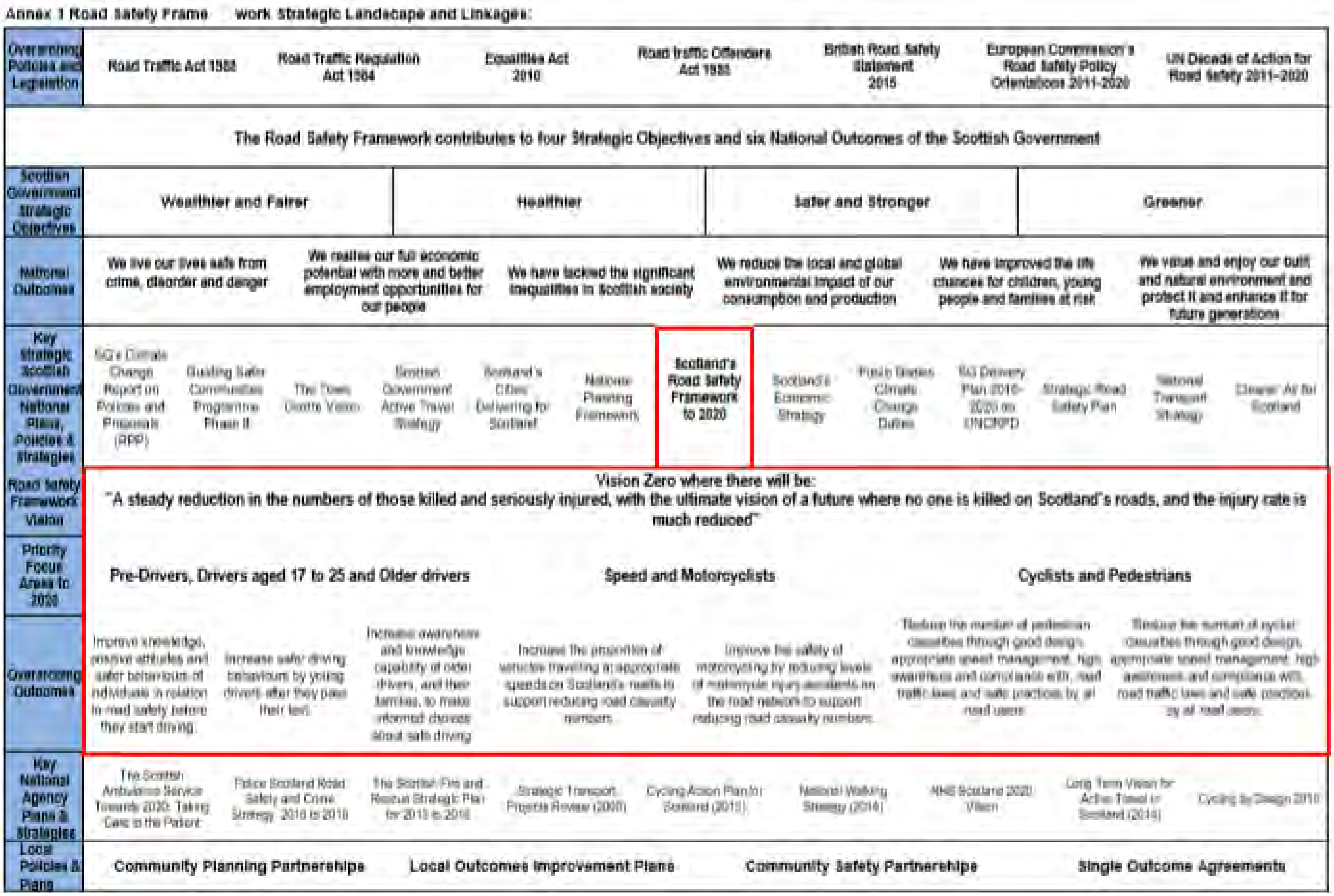

Figure A 9-2 Road Safety Framework Strategic links to other policies. (TS, 2009)