Mode-shift impacts on safety

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[1] This research was conducted September 2023 to February 2024.

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Abbreviations and acronyms

ACC	Accident Compensation Corporation
CAS	Crash Analysis System
CQOS	Cycling quality of service
DSI	Death and serious injury
HTS	Household travel survey
ICD	International Classification of Diseases
MUA	Main urban area
NHI	National Health Index
NPS-UD	National Policy Statement on Urban Development
NZTA	NZ Transport Agency Waka Kotahi
OSM	OpenStreetMap
PCCL	Patient clinical-complexity level
PLOS	Pedestrian level of service
TDM	Travel demand management
TLA	Territorial local authority
VKT	Vehicle-kilometres travelled

Contents

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Executive summary

There are many possible ways to reduce vehicle travel, collectively called travel demand management (TDM), including 'smart growth' development policies that reduce travel distances between destinations, improvements to non-auto modes (walking, bicycling and public transport), pricing incentives (fuel tax increases, road tolls, parking fees, etc), commute-trip-reduction programmes, and TDM marketing campaigns.

Reducing motor-vehicle-kilometres travelled is a potential means to help address safety and emissions reduction goals. However, we currently have a limited understanding of how mode shift might impact our road-safety outcomes. There are several competing effects from the interactions between the different travel modes, particularly when the distances travelled by new modes are also changed. Other related changes to transport infrastructure at the same time can also affect the underlying risks of deaths or serious injury.

Travel mode casualty data sources and issues

In practice, this analysis depends on how risks are defined and measured, and is often limited by inadequate or biased data. Traffic risk can be measured by total crashes, most of which are property-damage-only crashes or casualty crashes (crashes that result in a serious injury or death). Although all crashes impose costs, property damage costs are largely compensated for by vehicle insurance and therefore internalised by motorists. However, human injuries and deaths impose very high costs, much of which cannot be compensated for with money, so reducing casualty crashes is generally considered the highest traffic safety priority.

Traffic risks can be measured per capita, as with other health risks, per hour of travel, or per unit of travel, for example as crashes or deaths per billion kilometres of travel. Measuring risk per unit of travel does not account for the additional risk that results when people travel more annual kilometres or the reductions in crash risk provided by vehicle-travel reductions. When measured per unit of travel, motor-vehicle travel is considered much safer than walking and bicycling (together called *active modes*), but because motorists tend to travel more annual kilometres than non-drivers, and therefore bear and impose more risk exposure, per-capita crash rates tend to increase with per-capita annual vehicle kilometres.

Data from the Crash Analysis System (CAS) provides the most straightforward way to access information about road transport crashes. However, it suffers from:

- significant under-reporting rates, particularly for crashes of lower severity or involving active modes
- virtually no capturing of crashes not involving motor vehicles
- inconsistent categorisation of small-wheeled devices, and no useful differentiation of their powered or unpowered status
- limited mode, demographic and geographic detail, making it difficult to determine the crash rates for specific groups and conditions.

Ministry of Health and Accident Compensation Corporation (ACC) datasets can help to improve our understanding of the overall scale of the transport injury problem (particularly for those injuries not involving a motor vehicle), with the limitation that these datasets provide only information on where the people injured in crashes live, not where the crash took place.

Relative risk per travel mode

Many studies have investigated the relative risk between modes of transport, with good agreement on the safety of individual modes of transport in terms of the people travelling by that mode. In general, most have found the following order of modes by crash casualty rates per passenger-kilometre, from highest to lowest:

- motorcycles

- bicycles and other two-wheeled devices
- pedestrians
- general motor traffic
- public transport.

When evaluating modal crash rates, it is important to consider both internal (risk to users of that mode) and external risks (risk to other travellers), and the attribution of this risk, and how this is considered in crash data. Notably, while motor-vehicle occupants generally have lower passenger-kilometre casualty rates than walking, bicycling and motorcycling, they impose more risk on others, and they tend to travel far more annual kilometres; when risk to other road users is included, the risk profile of this mode changes significantly. As a result, research indicates that total per-capita traffic casualty rates tend to decline in a community as motor-vehicle mode shares decline, and walking, cycling and public-transport usage increase, an effect that is often called 'safety in numbers.'

Various demographic, geographic, vehicle and facility design factors affect crash rates. For example, motorcycles tend to have high crash rates in part because they tend to attract risk-taking operators, such as young males, who also tend to have high crash rates when driving cars. Similarly, young men tend to bicycle more than average, which may contribute to higher crash rates. As a result, a cautious adult bicyclist with a reliable bike and safety equipment (such as helmets and lights) who observes traffic rules may have significantly lower crash risk than average bicyclists who include more risky demographics.

Quality of modal facilities

Per kilometre crash rates can vary widely depending on travel conditions, including facility type. While research linking the quality of facilities to safety is limited, there are some key themes and indications of what the most instrumental factors are. These key themes are broadly as follows.

- A dense network of high-quality, physically separated cycling facilities is the most effective in reducing injuries and deaths related to bicycle crashes with motor vehicles.
- Single-bicycle crashes make up a significant proportion of crashes at all severities and levels of mode share, and ensuring a high quality of separated facility is important for ensuring that increased cycling mode share results in improved overall safety outcomes.
- The safety-in-numbers effect for cycling appears to apply both to crashes with vehicles and single-bicycle crashes.
- Installation of bus-priority measures, particularly physical space allocation, appears to improve safety outcomes for all users, though research in this area is very limited.
- On-street parking has a significant impact on safety outcomes with adjacent road users, particularly when poorly designed.
- Installation of modal facilities for any mode often results in improved safety for all modes.

Travel mode changes

Travel mode changes affect these factors in different ways, and some factors have conflicting evidence on their safety impacts. The studies suggest that increases in fuel prices reduce the amount of driving, and therefore risk, however the level of reduction depends heavily on context. Other price impacts, such as congestion charging, are generally effective in reducing risk overall. Transport modes have different risks to external users, though this also depends heavily on the context – road design, demographics, and other factors play a role.

Some specific work on single-bicycle crashes seems to suggest that the safety-in-numbers effect applies both to crashes with motor vehicles and single-bicycle crashes, though this conclusion was reached by comparing geographies, rather than comparing one location through time.

Requirements for comprehensive analysis

To be sufficiently comprehensive for evaluating vehicle-travel-reduction safety benefits, analysis should account for the following factors:

- internal and external risk
- distance-based and per-capita casualty rates
- differences in geographic location (urban, suburban, rural) and facility type (sidewalk, path, street, arterial, highway)
- demographics (age, ability, etc).

Model development

An Excel-based model without macros that can be hosted by the NZ Transport Agency Waka Kotahi has been developed using 6 years of CAS, Ministry of Health, and ACC data. The model enables testing of changes in overall vehicle-kilometres travelled (VKT), changes in mode share, and different walking and cycling network levels (qualities) of service.

Model application

This analysis reflects only changes in distance-based risks. Travellers often reduce their total travel when they shift modes; for example, walking or bicycling to a local shop rather than driving across town to a regional shopping centre, or a non-driver walking or bicycling for a trip that would otherwise be a chauffeured vehicle trip that generates twice the VKT due to empty backhauls (motorists driving empty to or from a passenger drop-off).

Because this model predicts only changes in distance-based crash casualty rates, it is likely to significantly underestimate the reductions in crash casualties per capita, taking into account differences in per-capita annual VKT. As a result, policies and programmes that improve and encourage shifts from driving to active modes are likely to reduce total crash injuries and deaths much more than this model indicates.

Abstract

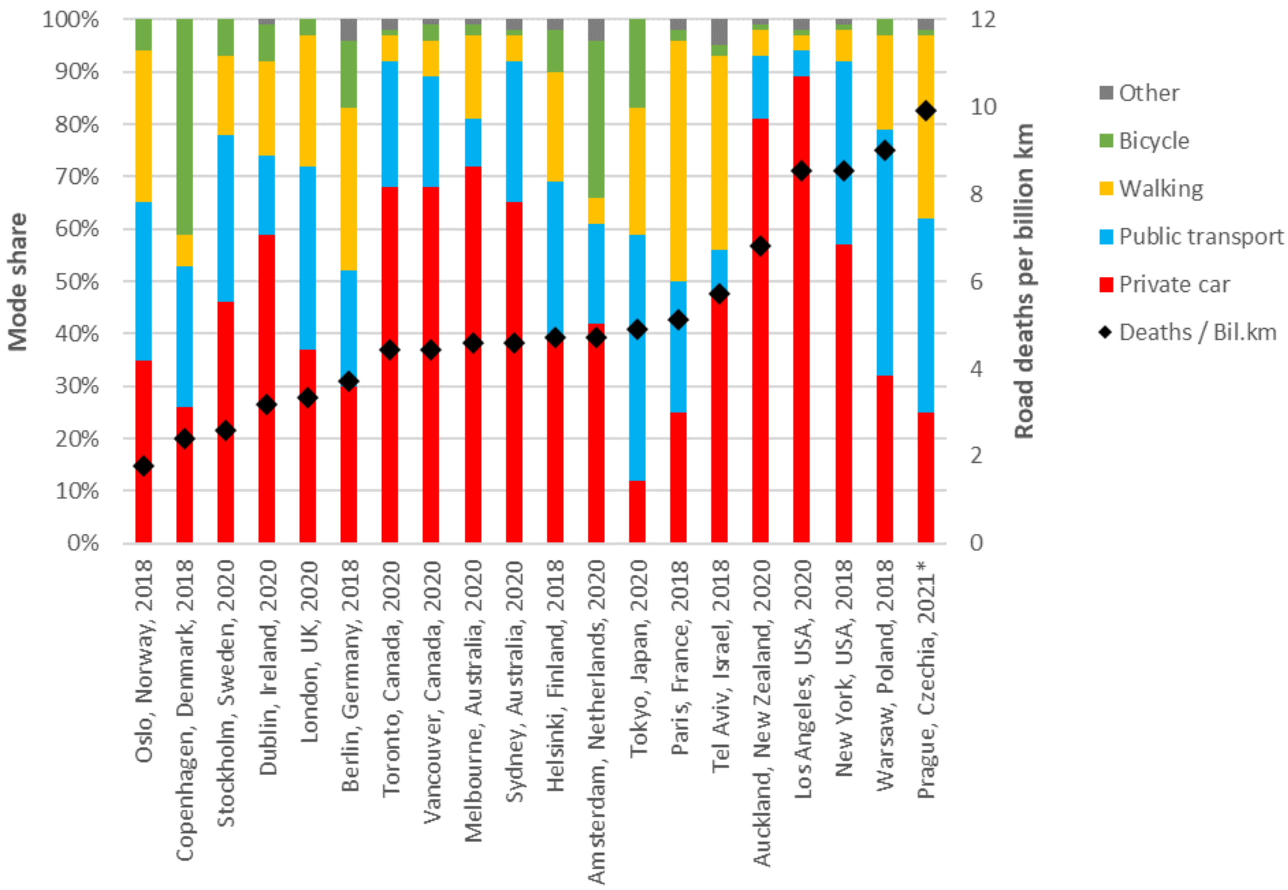
Many jurisdictions have targets to reduce vehicle travel and crashes. This study examines how these efforts can be integrated. Reducing motor-vehicle-kilometres travelled can reduce crash risk in addition to emissions. However, our current understanding of these impacts is limited, due to the complex interactions between the various risk factors plus inadequate data. This study examined research concerning the effects of mode shifts on casualty crash rates. It found that most risk factors have been studied individually, with many areas nearing academic consensus on relationships. Most studies only considered a few modes and did not explore multiple interactive relationships, and so tend to underestimate the full safety benefits of community-wide shifts from driving to walking, bicycling and public transport. This research has collated recent police crash report and hospital data, and produced a spreadsheet model that enables testing of various mode-shift scenarios. However, more research is needed to evaluate how mode changes are likely to affect crash casualties when other infrastructure and policy factors are taken into account.

1 Introduction

1.1 Background

New Zealand has one of the worst rates of road fatalities in the OECD (International Transport Forum, 2023), and New Zealand cities also have a higher share of private motor-vehicle use for journeys to work compared to other major cities worldwide. The bars in Figure 1.1 show the mode split for major cities worldwide (Deloitte, 2020; TSK, 2022), including Auckland, New Zealand; while the black diamonds show road death rates (per billion kilometres travelled) for the corresponding city (noting that the profile of a particular city may not be representative of the country as a whole). It is evident that the very high car use in Auckland results in a higher road death rate compared with many other cities where use of active transport and public transport[2] modes is higher.

Figure 1.1 Road deaths per billion vehicle-kilometres and mode share for major cities (International Transport Forum, 2023; Deloitte, 2020; TSK, 2022)



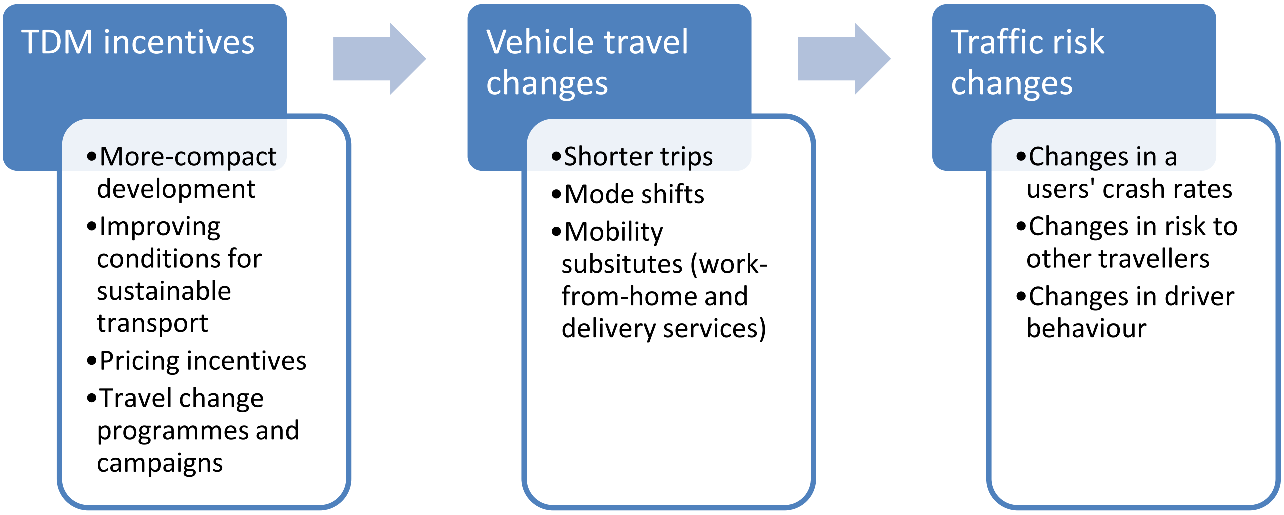
At the time this research was carried out, New Zealand had targets to reduce light vehicle travel by 20% by 2035 (Waka Kotahi NZ Transport Agency, 2023d) and also to reduce deaths and serious injuries by 40% from 2020 to 2030 (New Zealand Government, 2019). This study investigates how to integrate the planning to reach these two targets. Achieving them would require significant changes, including more compact and

[2] Public transport is also referred to as passenger transport (historic) or public transit (North America).

multimodal community design, and a shift from using private motor vehicles (eg, cars, SUVs, vans, light trucks and motorcycles) to more resource-efficient modes, such as walking, cycling and public transport. We currently have limited understanding of how mode shift might impact road-safety outcomes.

Various methods are used to reduce vehicle travel. These are often called travel (or transportation) demand management' or TDM. Figure 1.2 summarises common categories of TDM strategies and ways that they tend to affect crash risks.

Figure 1.2 How travel demand management affects risks



TDM incentives reduce vehicle travel by shifting travel to closer destinations or sustainable transport modes (walking, cycling and public transport), or replacing travel with mobility substitutes (eg, work from home or delivery services). These changes affect risk to the people who change their travel, and to other travellers on the network.

New Zealand has a high share of travel by private motor vehicles, and most road deaths and serious injuries (DSIs) involve cars, vans, motorcycles and trucks. Population growth and other correlated trends, such as increasing levels of vehicle ownership and gross vehicle-kilometres travelled (VKT) are making it more difficult to achieve the Road to Zero vision (New Zealand Government, 2019).

Evidence shows that public transport has lower rates of DSIs per passenger kilometre than other travel modes (Frith et al., 2015). Regions in New Zealand with higher public-transport ridership have both lower VKT and lower road deaths. Though the extent to which these two trends are linked is unproven, it seems reasonable to hypothesise that the more we switch from private vehicle travel to public transport, the more DSIs will reduce.

It is more difficult to evaluate the safety impacts of shifts from driving to active modes (walking, bicycling and their variants such as wheelchairs and e-bikes). Although walking and cycling tend to have higher DSIs per-kilometre, they pose much less road-safety risk to others due to their lower mass and average speeds, people who shift often reduce their total travel (for example, walking or bicycling to a local shop rather than driving further to a shopping mall), and because drivers tend to be more cautious when they expect active-mode traffic. As a result, total per-capita traffic casualty rates tend to decline as active travel mode shares increase in a community, a phenomenon called 'safety in numbers.'

A growing subset of active modes is 'low-powered vehicles', which include e-bikes and e-scooters. These are relatively new to New Zealand and there is limited data about their impacts on safety, apart from Accident Compensation Corporation (ACC) claims data, but their potential impact on safety is large (Accident Compensation Corporation, 2021).

Most existing TDM programs focus on objectives such as reducing traffic congestion and greenhouse gas emissions, and increasing urban vibrancy and public health; traffic safety is not generally considered. This may stem from a lack of knowledge about the actual safety impacts of specific vehicle travel reduction strategies. If TDM is demonstrated to reduce crashes, Road to Zero safety goals can justify additional vehicle travel reduction efforts.

However, current traffic safety analysis methods and data sets in New Zealand are not structured for evaluating the safety impacts of TDM strategies, particularly mode shift from driving to active modes, as shown in the following examples.

- Traffic risk analysis is often considered separate to mode share, with metrics such as crash rates per million vehicle-kilometres. This does not account for systemic effects, such as a reduction in traffic volumes resulting in a reduced risk imposed on other road users, or the effects of changes in total distances travelled.
- The crash reporting system captures only crashes where police attend. Police often do not attend non-fatal crashes associated with walking, cycling and micro-mobility, so these crashes are under-reported. The 2014 Cycling Safety Panel report used data from hospital admissions and ACC data because, for a long period of time, police did not report cyclist-only crashes (Cycling Safety Panel, 2014).
- Crash reporting systems do not capture ‘perceived safety’, which can relate to road safety or personal security and can be a significant factor for cycling, public transport, micro-mobility and walking. Such issues are a barrier to uptake of these modes (especially cycling and public transport), which can inhibit a step change occurring through a safety-in-numbers phenomenon (Turner et al., 2006).
- Crashes associated with accessing public transport are likely to be coded in terms of the access mode used (eg, walking/cycling) even though they’re part of a public-transport journey. Frith et al. (2015) suggested that mode shift to public transport should therefore take into account the whole journey in considering safety impacts.
- Not all mode-shift results in positive safety outcomes, at least not immediately. Some mode shifts may increase some crash risks, the impacts of which can depend on analysis perspective and data. For example, shifts from driving to cycling may increase risk to those travellers, particularly if they are new users with limited experience and training in cycling, or have limited options for safe routes to ride on. They might also increase risk to other users, for example pedestrians, where infrastructure for walking and cycling is not separated, such as on shared paths, or where no cycling infrastructure is available and cyclists ride on footpaths.
- Conversely, active-mode improvements support more compact and mixed development, which reduces the distances that people must travel to destinations, further reducing per-capita VKT. More comprehensive analysis consistently indicates that large shifts from driving to active modes reduces per-capita traffic casualties.

Depending on factors such as surrounding physical infrastructure, there are risks associated with active modes and these factors need to be considered in a system-wide view of mode shift and safety.

Previous research and other experience

The literature review (Chapter 2) details several sources relevant to this research. Previous investigations commissioned by the NZ Transport Agency Waka Kotahi (NZTA) include the following.

- NZTA Research Report 581 (Frith et al., 2015), which describes the role public transport can play in advancing the safe systems approach. This research indicates that increasing public transport tends to increase safety overall, including for users when travelling to and on public-transport vehicles, and for other travellers.

- Other research has valued the health benefits of active transport modes and included findings on injury risk, such as NZTA Research Report 359 (Genter et al., 2008). There is also existing research and reports (see for example NZ Transport Agency, 2024) to support making cycling a safer and more attractive transport choice.
- NZTA Research Report 537 (Wedderburn & Buchanan, 2013) developed an evaluation framework for estimating the cost-benefit analysis of integrating public transport with walking and cycling, and produced a spreadsheet evaluation tool that could be employed to estimate the dollar value of making improvements (including road safety benefits) to the integration of public transport, walking and cycling.

1.2 Purpose and objectives of research

This research seeks to determine the actual and potential safety impacts of achieving mode shift from private motorised vehicles to public transport, active modes and micro-mobility[3], in conjunction with making changes to the overall volume of travel by all modes. It aims to identify the individual and collective safety profiles of different travel modes, and the potential safety outcomes for different demographic groups that could arise from mode shift away from private, motorised vehicles in New Zealand.

The objectives are to:

a. identify and examine New Zealand and relevant international literature, especially in relation to countries whose transport systems are comparable to New Zealand's, to summarise what is known about the overall safety impacts of mode shift away from private motorised vehicles to whole journeys involving public transport, active travel or micro-mobility
b. determine the personal and collective safety impacts of different non-private vehicle travel modes across whole journeys and for different demographic groups in New Zealand
c. develop a model that will enable mode-shift 'scenario testing' to calculate the potential road-safety outcomes of different levels and configurations of mode shift in New Zealand:
   - at a national level; and
   - for a diverse sample of urban areas and demographics.

1.3 Scope definition and constraints

This research builds on previous research and complements *Safety Interventions and Their Contribution to Mode Shift* (NZ Transport Agency research report 701) (Thomas et al., 2022). Given the current distribution of provision in New Zealand, public transport is within scope for 'Tier 1' cities only (as defined in Appendix A.1).[4]

Drivers and enablers of mode shift are largely out of scope (eg, improvements to sustainable transport options, 'smart growth' development policies, transportation pricing reforms and other TDM incentives, etc),

[3] For this study, the term 'micro-mobility' generally refers to any lightweight low-powered or unpowered small-wheeled devices, the most visible of which are electric kick-scooters (or 'e-scooters'), but could also include skateboards, rollerblades, self-balancing devices, and the like. Electric cycles ('e-bikes') are covered separately under cycling for data analysis purposes, although some studies referred to also include cycles under micro-mobility.

[4] Tier 1 and Tier 2 are classifications used for cities in New Zealand, based on their size and relative growth. Tier 1 cities are Auckland, Hamilton, Tauranga, Wellington and Christchurch. Tier 2 cities are Whangārei, Rotorua, New Plymouth, Napier-Hastings, Palmerston North, Nelson-Tasman, Queenstown, and Dunedin.

except for walking and cycling, where a simplified model using level of service as a variable will be used to evaluate mode-shift potential. These may be the focus of subsequent research, depending on findings.

The focus of this research is also on the direct injury outcomes of existing and possible travel by various modes. It does not consider any of the other potential impacts to travellers and other parts of society from these modes, including health effects (eg, changes in cardiovascular fitness), environmental effects (eg, changes in pollution levels or noise), and societal effects (eg, changes in social severance). These may be addressed by other research.

While for this project, the term ‘crashes’ is commonly used in this report, there are times where ‘accidents’ has been chosen to describe transport incidents that lead to injuries or property damage. The authors recognise the road transport industry’s current preference to refer to ‘crashes’, to emphasise the responsibility of road users to travel safely. However, in many instances, ‘accident’ seems a better fit; for example, it also covers a cyclist slipping on a wet road surface, or a person tripping on a footpath, where there was no other party or object that the road user ‘crashed’ into. Similarly, most rail and maritime incidents are referred to in the industry as ‘accidents’. Some references (particularly international or older ones) also use the term accident in their titles, which we have not altered. The authors do not intend that the term ‘accident’ implies that no party was at fault in any way, but it is assumed that there was generally no specific intent to cause harm.

Although the report largely refers to VKT, in practice a change in mode from driving to active or public transport is a change of one person’s movement and should arguably be reflected as a change in ‘person-kilometres travelled’. The household travel survey (HTS) data used in this study is based on individual movements, so the resulting values presented later are effectively person-kilometres travelled per mode. This could have some slight implications for risks imposed on others; for example, a person could switch to taking a bus, but that doesn’t increase the amount of bus travel (and the resulting risk on surrounding users) because they just occupy a seat on an existing bus. However, for the purposes of this exercise we have assumed that any transfer of people between modes collectively results in an equivalent change in the relevant amount of exposure risk by those modes.

1.4 Report structure

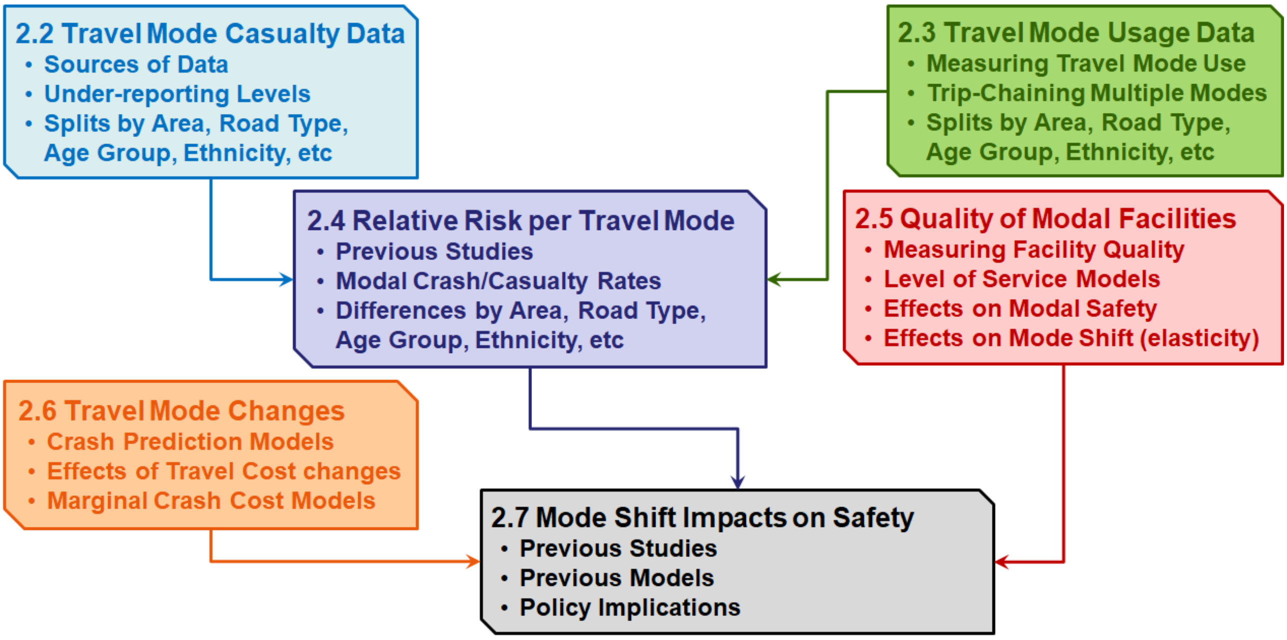
Section 2 of this report is a review of previous research on casualty data, travel mode usage data, risks per mode, the relationship of safety risk to quality of modal facilities, and the impact of mode shift on safety. Section 3 analyses personal and collective risks using updated New Zealand datasets collated for this research. Section 4 summarises the model, and outlines initial scenarios tested by the model. Section 5 summarises the research with conclusions and recommendations, including areas for further research.

2 Literature review

2.1 Approach

The literature review is structured around the key components that will ultimately contribute to answering the main research questions, that is, the aspects of usage and safety for the various travel modes. Figure 2.1 outlines the structure of this review, with the relevant chapter sub-sections noted.

Figure 2.1 Structure of literature review topics



2.1.1 Key inputs

The review was informed by a collation of previous research projects, particularly:

- the *Domestic Transport Costs and Charges (DTCC) Study* (Ministry of Transport, 2023), which determined the 'marginal accident cost' of changing travel mode use
- Auckland Transport's vulnerable road-user deep dive (ViaStrada, 2021), which identified under-reporting factors for the NZTA's Crash Analysis System (CAS) relative to Ministry of Health hospital data
- Auckland Transport's micro-mobility risk study (Martin et al., 2021), which estimated some key crash/injury factors for micro-mobility devices
- NZTA research on regulations and safety for e-bikes and other low-powered vehicles (Lieswyn et al., 2017), which investigated safety characteristics of e-bikes and mobility devices
- University of Canterbury research on the risk of cycling relative to other modes (Koorey & Wong, 2013), which compared the safety risk of different modes by age and road type.

Other relevant research identified includes research on:

- the role public transport can play in providing safer journeys and, in particular, to advance the safe systems approach (Frith et al., 2015)
- predicting accident rates for cyclists and pedestrians (Turner et al., 2006)
- regulations and safety for electric bicycles and other low-powered vehicles (Lieswyn et al., 2017)

- cycle safety and reducing the crash risk (Turner et al., 2009)
- improving the cost-benefit analysis of integrated public transport, walking and cycling (Wedderburn & Buchanan, 2013)
- mode shift to micro-mobility (Ensor et al., 2021)
- safety interventions and their contribution to mode shift (Thomas et al., 2022)
- the gig economy and road-safety outcomes (Raja et al., 2023)
- safe micro-mobility (International Transport Forum, 2020)
- the road-safety consequences of changing travel modes (Cairney, 2010).

The literature review explored policy documents, academic and research programme publications nationally and internationally. The focus was on studies with measured safety impacts from changes in mode shift.

Keywords used in the literature search include mode shift, travel modes, safety, safety impact, elasticity, data, New Zealand, travel demand management, and TDM.

After the initial search, the literature collection was filtered to determine what pieces of work are most relevant to the work, and whether their learnings can be applied in a New Zealand context, or not, and why. Literature was rated in terms of both quality of evidence and relevance to New Zealand.

2.1.2 Out of scope – health and social impacts and other travel reduction strategies

While potentially relevant to the broader question of mode shift, some topics have not been explored further in this study because they are not focused on safety impacts, such as the social and health impacts of mode shift. There are also other travel reduction strategies (in terms of policy, pricing and infrastructure) that can have an impact on mode safety and would inform modelled scenarios in this research. This section briefly summarises some research that did investigate these other impacts.

Health benefits research for the NZTA (Genter et al., 2008) showed that the evidence of links between insufficient active transport use and medical problems were strongest for chronic diseases (especially cardiovascular disease, type 2 diabetes and cancer – colon, breast and lung) and depression. The research used two methods to calculate the value of health benefits – disability-adjusted life years, and mortality ratios combined with years lost to (severity adjusted) disability. These methods generated annual per person values for active-mode usage in the range of $2,289 to $3,854 (2007 dollars). These values were translated into per kilometre benefits of up to $5 for walking and up to $2.50 for cycling – values that underpinned economic analysis of the relative speeds and time taken for each mode. The research suggested a longitudinal study to determine values for mental health, stress reduction, time savings due to not having to do dedicated exercise, increased productivity (fewer sick days), and the health benefits of less traffic noise and air-quality improvements. These benefits were not included in cost-benefit analysis procedures of the time, and most still are not.

Lindsay et al. (2011) showed that the health benefits of moving from cars to bikes heavily outweigh the costs of injury from road crashes. The effect of shifting short (≤7 km) urban driving trips to cycling trips (incorporating the safety-in-numbers concept) was calculated for motor vehicle versus cyclist injuries and fatalities, as shown in Table 2.1. The authors concluded that the benefits of a transport mode shift from car to bicycles outweighs the harms, and stressed the need to consider both the change in harms (deaths and serious injuries) and the change in benefits (air pollution and other health) in decision-making processes.

Table 2.1 Effect on health of moving short urban car trips to cycling from 1% to 30% of vehicle-kilometres shifted

Parameter	1%	5%	10%	30%
Hospital discharge rate per million km cycled	0.48	0.29	0.21	0.12
Discharges annually (number)	77.5	108.9	135	200.1
Cyclist fatalities per 100 million km cycled	2.19	1.32	0.95	0.53
Cyclist fatalities annually (number)	3.5	5	6.1	9.1
Cost of fatalities (at 2008 value of statistical life of $3.35 million)	$11,725,000	$16,750,000	$20,435,000	$30,485,000
Air pollution reduced annual deaths	-1.1	-5.6	-11.3	-33.9
Health mortality reduced annual deaths	-20.5	-116.5	-165.3	-716.2

In a wide-ranging review of various travel demand management measures, Litman and Fitzroy (2023) assess the relative impacts on safety to different travel modes. Table 2.2 summarises how various types of travel reduction strategies affect safety. These are general conclusions and may be different in particular situations.

Table 2.2 Travel demand management safety impacts summary (adapted from Litman & Fitzroy, 2023)

Category	Travel changes	Safety impacts
Pricing reforms (road and parking pricing, increased fuel taxes, etc)	Reduces vehicle mileage	Moderate-to-large safety benefits. Vehicle mileage reductions generally cause proportional or greater reductions in total crash damages.
Pay-as-you-drive insurance	Reduces mileage in proportion to motorist risk class	Large potential safety benefits. Reduces total traffic and gives high-risk motorists an extra incentive to reduce mileage.
Public-transport improvements, high-occupancy-vehicle priority, park and ride	Shifts automobile travel to public transport	Moderate-to-large safety benefits. Shifts from automobile to public transport reduce per-mile crash rates, and tend to reduce total vehicle travel.
Ridesharing, high-occupancy-vehicle priority	Shifts single-occupant travel to ridesharing	Moderate safety benefits. Reduces total vehicle traffic, but crashes that occur may involve more victims.
Walking and cycling improvements, traffic calming	Shifts motorised travel to active modes	Mixed safety impacts. Can increase per-mile to users, but reduces risk to others, reduces total person-miles and increases driver caution.
Telework, delivery services	Reduces total vehicle travel	Modest benefits. Reduced vehicle travel reduces crashes, but benefits may be offset by rebound effects.
Flexitime, congestion pricing	Shifts travel from peak to off-peak	Mixed. Reducing congestion tends to reduce crashes, but increased speed increases crash severity.
Streetscaping, traffic calming, speed enforcement	Reduces traffic speeds	Large safety benefits where applied. Increases safety by reducing crash frequency and severity, and reducing total vehicle mileage.
Time and location driving restrictions	Vehicle use restrictions	Mixed. Provides safety benefits if total vehicle travel declines, but not if vehicle travel shifts to other times and routes.
Land-use management (smart growth, new urbanism, etc)	Reduces per-capita vehicle travel and traffic speeds	Large safety benefits. Increases safety by reducing per-capita vehicle travel. Increases congestion, which increases crash frequency but reduces crash severity.

Another NZTA research report (Curl et al., 2020) found that, at present, social impacts are generally ascribed based on who uses modes more. Mode-shift policies, such as fare increases to expand service provision, were shown to potentially widen social inequities. They concluded that policies 'which reduce the need to travel (by car) … are best able to address transport inequities' and must be customised to different social conditions rather than 'one size fits all'.

While the above findings are useful in the broader context of sustainable land use and transport planning, many of these interventions are precursors to the resulting changes in travel mode usage (and subsequent changes in safety) that are being explored in this research. Some of these interventions (such as infrastructure and speed management changes) could be added to a future version of this model; further discussion of these intervention impacts is covered in section 3.6.

Overall, these different impacts point towards the complex and multidisciplinary nature of mode shift and show the need for other considerations aside from road safety.

2.2 Travel mode casualty data sources and issues

To be useful for multi-modal safety analysis, the following crash data is ideally required:

- date and time of each incident
- location of each incident (either specific site or general locality)
- the travel mode of the casualty and that of other travellers involved (if any); for example, a pedestrian may be injured as a result of a collision with a person driving a car (who themselves may be uninjured)
- identification of emerging travel modes including e-bikes and e-scooters
- casualty severity (death or level of severity of injury)
- demographic data (eg, age, gender, ethnicity) of the casualties
- contributory factors to the incident (eg, alcohol or drugs, human error, environmental hazards)
- travel conditions at the time of the incident, such as light levels and weather.

While this information is generally present in New Zealand casualty data, the following sub-sections outline some of the challenges identified in these datasets.

2.2.1 Under-reporting

Traditionally in New Zealand, road transport crashes and casualties have been reported and collected through NZTA's Crash Analysis System (CAS). However, it is acknowledged that this data (captured in general from police reporting) does not pick up all crashes, particularly those of lesser severity or involving non-motorised users (Koorey et al., 2023). This becomes even more problematic for incidents not involving motor vehicles, which are typically not captured by CAS at all.

Two recent local studies illustrate the potential scale of the transport harm problem in New Zealand away from conventional road safety metrics.

- ViaStrada (2021) looked at the safety of people walking, biking, motorcycling and using other transport devices in Auckland, and identified from hospital data that many more people are suffering serious injuries on roads and paths from incidents not always involving other vehicles. The analysis compared CAS data with Ministry of Health hospital admission data and ACC injury claim data (not including data from those undertaking recreational activities, like mountain-biking or tramping) and found considerable under-reporting across the non-motor-vehicle modes compared with CAS numbers, with typically six to eight times as many 'serious' injuries (defined as at least one night stay in hospital) being recorded by Ministry of Health data. By far, most of these incidents were user-only ones that did not involve a motor vehicle or other party (and thus were deemed not to require reporting in CAS). Most people suffered some kind of slip or trip, typically due to loose or wet surfaces, or uneven or stepped surfaces (including kerbs and tree roots), underlining the importance of good maintenance of paths and crossings. People aged over 60 were much more over-represented in serious injuries, highlighting the relative fragility of the older population when it comes to simple falls.

- ViaStrada (2022) investigated the cost of road crashes nationally for the Ministry of Transport and found similarly large social costs from non-motorised road-user incidents. The investigation of transport-related accidents included calculating estimates of the total and average (social) costs per year, based on willingness-to-pay to avoid pain, grief and suffering. For cycle and pedestrian crashes involving motor vehicles, conventional costs were calculated using CAS data and standard under-reporting factors. Depending on how these costs were allocated to the parties involved (based on fault or suffering), the annual costs to these two modes ranged between $286 to $636 million a year. A separate calculation of accident costs involving these users only (ie, no motor vehicles involved) was determined using a combination of CAS and ACC data, and it was estimated that the social costs of these crashes was at least an additional $830 million a year, that is, much more than the figures for those involving motor vehicles.

Some years prior, Turner et al. (2006) investigated accident-prediction models for pedestrian and cyclist crashes. They used HTS, CAS, ACC and St John ambulance data focused on Christchurch to estimate actual crash numbers. Under-reporting factors were created for walking and cycling (roughly 1.5 and 1.8 respectively) and then applied to crash rates. This research concluded that the number of crashes in the CAS database was low, with further research suggested to confirm the exact proportion of under-reporting.

2.2.2 Accessibility and practicality of datasets

While Ministry of Health and ACC provide additional useful information about the true scale of transport injuries in New Zealand, the datasets suffer from a few practical problems.

- Unlike CAS, which can be readily accessed by registered transport practitioners, access to these other datasets requires specific requests to the relevant government agencies, which can introduce delays.
- Because their scope encompasses all kinds of medical incidents (ie, mostly non-transport), filtering of the data is needed to identify those cases related to land-transport injuries.
- The focus on these datasets is on the nature of the injuries suffered (and relevant medical treatment data). Unlike with the CAS, there is generally no specific location information about where each incident occurred, other than at a district level.

As a result, only transport-specific datasets like CAS are useful for helping to identify potential safety issues with particular locations in the transport network, and possible infrastructure improvements to these sites. Health-specific datasets like the Ministry of Health's and ACC's are more useful for establishing the relative size of the transport casualty problem in New Zealand, which is sufficient for an exercise that is focused on changes at an area-wide level such as a whole city or larger – such as this research.

2.2.3 The advent of new vehicle types

The introduction in recent years of various wheeled recreational devices (such as skateboards and kick-scooters) has also introduced new challenges in identifying and classifying the types of small vehicles (powered or otherwise) that are involved in crashes. Lieswyn et al. (2017) investigated safety characteristics of e-bikes, mobility scooters, and other low-powered devices, such as e-scooters, and found considerable inconsistencies in how they were often recorded in CAS in terms of vehicle type. It was noted that CAS is not able to currently distinguish between powered and unpowered small vehicles (eg, e-bikes vs un-powered bicycles), making it difficult to ascertain differences in crash risk. However, the Ministry of Health and ACC datasets used in ViaStrada (2021) may be able to differentiate between these user types, as they have more detailed user-type codes to capture this information (although again, occasional inaccuracies in these classifications have been noted).

Waka Kotahi NZ Transport Agency (2023c) reviewed the safety aspects of e-scooters since their widespread introduction to New Zealand in 2018. From ACC data, they noted there were over 10,000 e-scooter injury claims over a 4-year period to December 2022, costing around $30 million in injury treatment costs, or an average of around $3,000 per claim. The data also noted a peak in claims in 2019 (of around 3,180 claims), dropping to around 2,570 claims in 2022, despite an increase in scooter usage, as well as a drop in average cost per claim (to under $2,000). This data suggests that, as the novelty of riding e-scooters diminishes and people get more experienced at using them (especially regular riders who may purchase their own), both the number and relative severity of e-scooter crashes have reduced. Of note also is that only around 2% to 4% of e-scooter injury claims also involved a pedestrian – despite the common media concern around their use on footpaths, most e-scooter injuries would appear to be either stand-alone or involving other vehicles.

Should New Zealand adopt light-electric vehicles, then another category would be required. Edwards et al. (2023) examined safety data for the UK, France and Germany and found ‘there is limited data available from the small fleets in these countries, however the casualty rates indicate that they’re less safe than passenger cars but safer than motorcycles.’

2.2.4 Matching of datasets

There have been preliminary attempts to try to match data from the various transport-injury datasets in New Zealand, such as the SORTED (Study of Road Trauma Evidence and Data) study, which looked at seven different datasets from 2017 to 2019 (Te Manatū Waka Ministry of Transport, 2022). Table 2.3 shows the relative breakdown of hospitalised patients, identified by travel mode and gender, from that study. After light-motor-vehicle injuries, cycle crashes contribute a significant proportion of those hospitalised. It is also evident that males are over-represented, particularly in motorcycle and cycle injuries.

Table 2.3 Hospitalised patients by mode of transport and gender, 2018/2019 (reprinted from Te Manatū Waka Ministry of Transport, 2022, p. 14)

Mode of transport	Female	Male	Total	% Male
Car	2,752	2,840	5,592	51%
Motorcycle	303	1,572	1,875	84%
Bicycle	434	1,112	1,546	72%
Pedestrian	368	458	826	55%
Bus/truck/van	201	467	668	70%
Other	205	478	683	70%
Not recorded	611	207	818	25%
Total	4,673	6,685	11,358	59%

While the SORTED study is a promising way to capture a more detailed picture of transport injuries, the effort required to do this data matching is considerable.

2.2.5 Summary of findings

CAS data provides the most straightforward way to access information about road transport crashes. However, it suffers from some issues, notably:

- significant under-reporting rates, particularly for crashes of lower severity or involving active modes
- virtually no capturing of crashes not involving motor vehicles
- inconsistent categorisation of small-wheeled devices, and no useful differentiation of their powered or unpowered status.

Ministry of Health and ACC datasets can help to improve our understanding of the overall scale of the transport-injury problem (particularly for those injuries not involving a motor vehicle), with the limitation that these datasets only provide information on where the people injured in crashes live, not where the crash took place.

This means that there is no single dataset that provides the high level of detail required for the most robust crash analysis.

2.3 Travel mode usage data

2.3.1 Census and New Zealand Household Travel Survey data

In New Zealand, two main national-level data surveys capture travel mode usage. The national Census, undertaken by Stats NZ, provides mode share for individual journeys to work and journeys to education at a granular level over time, typically every 5 years. Mode share by time, distance and trip for other journey types is not as granular through the more frequent New Zealand Household Travel Survey (HTS), undertaken by the Ministry of Transport. The Census surveys also only focus on what is a person's 'main' mode of travel (typically in terms of the longest time or distance), which ignores journeys that may encompass multiple modes along the way (ie, trip chaining).

Locally, the small sample size of the HTS requires several years to be merged to present statistically valid results. This is unsuitable for monitoring local changes associated with increased mode-shift investment. Due to the small local HTS sample size, local authorities sometimes commission their own travel surveys, or ad-hoc boosters to the HTS, which helps improve local accuracy but does not create a consistent national dataset. In the future, NZTA will be funding a boosted sample size for the HTS, which will reduce the time for getting enough samples for regional estimates to about 1 year.

Internationally, there are a variety of censuses undertaken by other countries, although not all of them capture travel data, such as journeys to work. Typically, their frequency can range between every 5 to 10 years (or longer), often depending on the size of the country and available administrative resources. It is notable that, rather than collecting data from households, either physically or electronically, a growing number of countries are switching to using existing administrative data to collect the relevant information, including Netherlands, Norway, Sweden, Switzerland, Denmark, and Finland.

Similarly, several countries undertake HTSs, capturing information on trips made, by what modes and for what purposes. For example, the US National HTS uses a random sample of residential addresses to record household travel patterns across one 24-hour period (Ipsos Public Affairs, 2023). However, fewer than 17,000 people completed the 2022 US Travel Survey, making it difficult to disaggregate the dataset too far.

Meanwhile in Europe, a study surveyed 30 different countries and noted considerable variation in what travel data was collected and by which methods (Ahern et al., 2013). Only 15 countries had undertaken a travel survey within the past 10 years that captured national data across a range of different motorised and non-motorised modes, and covered all types of trip purpose and length.

2.3.2 Public count statistics

With the introduction of public shared (rental) e-scooter and bike services to New Zealand from 2018 onwards, additional data is now available to monitor trends in usage. One service is via Ride Report, a company that aggregates ride data from multiple commercial public ride-share operators to determine trip usage and distances travelled. In New Zealand, over 17 million trips spanning over 28 million kilometres have been recorded from public e-scooter and e-bike operators over the past 5 years (Ride Report, 2024). It is evident from the data that there has been growth in usage (ignoring the Covid lockdown periods), as more cities and operators have come on board. In 2023 alone, there were about 5.5 million trips (covering around 8.8 million kilometres) made on public e-bikes and e-scooters.

Waka Kotahi NZ Transport Agency (2023a) reviewed recent usage statistics for e-scooters as part of a legislative review of their continuation in New Zealand. They noted that people riding rental e-scooters had travelled around 23.38 million kilometres between January 2019 and June 2023, with an average trip length of 1.62 km. However, it was also observed that more people are using e-scooters for longer journeys (eg, around 20% of trips are of 4 km or more), which suggests that some people are substituting longer-distance modes (like car travel) with e-scooters, rather than just using e-scooters as a ‘first/last-mile’ connection device.

Unfortunately, there is more limited data available regarding private e-scooter usage. Waka Kotahi NZ Transport Agency (2023a) notes that import data for e-bikes and e-scooters is combined, so that it is difficult to differentiate sales of the two modes. The Ministry of Transport’s HTS introduced an e-scooter code in 2018, so in future it may be possible to establish the approximate amount of usage in New Zealand from years since then.

2.3.3 Other sources

Mobile phone data and lower quality surveys with limited local coverage do exist (eg, mode share estimated for the five main cities from monitoring of attitudes to walking and cycling), but these are not a robust measure of mode-share. Counting per mode (such as that undertaken by TMS, the traffic monitoring system used for New Zealand state highways to establish road, public-transport patronage, walking and cycling counts) is useful for understanding within-mode trends, but cannot allocate total travel between modes and doesn’t consistently report journeys by individuals as opposed to vehicles.

A combination of existing solutions may also provide an integrated picture of mode share. This approach builds on existing data, but is labour intensive and requires clear documentation to minimise analyst-induced variability. Examples of existing solutions, their limitations, and opportunities to overcome these limitations are presented in Table 2.4.

Table 2.4 Various measurement resolutions and associated methodologies

Resolution	Limitation(s)	Opportunity
Intercept or travel diary surveys *Area-wide, but not related to project level investments*	Costly to implement. NZTA is funding boosted HTS sample sizes. However, as stated in paragraph 2.3.1, this is unlikely to assist with mode-shift estimation. As discussed in 2.3.1, some local authorities also commission their own ad-hoc HTS boosters.	Can provide a national standard for questions based on the HTS and funding support for implementation.
National before and after project database *Currently active-mode focused*	Not currently multi-modal, but cross-tabulations with existing motor-vehicle counts and assumed vehicle occupancy could enable estimation of mode share. Without parallel route monitoring, route choice cannot be fully explored.	Expand existing database used in Latent Demand for Walking and Cycling research (Beetham et al., 2021) and *Monetised Benefits and Costs Manual* (Waka Kotahi NZ

Resolution	Limitation(s)	Opportunity
		Transport Agency, 2023b) simplified procedures 11 (SP11)
Monitoring of Bluetooth and Wi-Fi devices carried by travellers	Identification of likely travel mode being used is not 100% accurate. May be some sample bias depending on who has access to various devices. Requires development of an extensive network of monitoring devices for nationwide coverage.	Identification of route choices and travel times. Continuous monitoring of trip patterns over time.
Manual observation at urban centre cordons *Work-trip orientated*	Excludes trip making across suburban, ex-urban and rural areas; high coefficient of variation due to small sample size and small numbers issue for active modes; requires observation of all modes, which many road controlling authorities do not currently do. Not representative of urban area as a whole.	Replace manual count methods with automatic multi-modal count methods. Requires the algorithm and sensor technology to be able to estimate occupancy per private vehicle (this has been proven to work for high-occupancy-vehicle lane monitoring). Not likely to be implementable nationally in the near term.
Continuous automatic multi-modal counters across a sample of sites *All trips and spatial geographies*	Few road controlling authorities currently have a network of multi-modal counters that utilise algorithmic processing of LiDAR, video or thermal sensors. Whangārei, Wellington, Dunedin and Palmerston North are known to have small networks of multi-modal counters. Sites are often chosen based on high multi-modal use and are not necessarily representative of mode share for the entire city or region.	Leverage the expanding networks of security cameras in urban areas. Work with Intelligent Transport Systems New Zealand to assess data collection methods.
School travel mode surveys *Education-trip purpose, all spatial geographies*	Requires buy-in from school principals. Limited to the day of survey (small sample size per school, but robust when aggregated) unless we can get touchscreens installed at school gate or in classrooms.	Can develop easy and fun to use geo-spatial web tools for children (tamariki) and youth (rangatahi) to log their travel mode. These can easily be extended nationally.

2.3.4 Trip chaining

One of the attributes of journeys not always captured by simple travel mode surveys is the concept of 'trip chaining', that is, where a person's journey uses multiple travel modes along the way. For example, someone could ride an e-scooter to a train station, travel on a train, and then walk at the other end to their final destination. A trip chain could also comprise using a single mode for multiple purposes along a journey, for example travelling from work to home by car but stopping along the way at the shops.

The Ministry of Transport's HTS provides an insight into trip-chaining patterns in New Zealand, with the data being collated into 'journeys' that may be made up of multiple 'trip' records. Earlier studies have explored typical travel patterns. For example, O'Fallon and Sullivan (2009) analysed the 2004 to 2007 HTS dataset. They noted that only about 55% of journeys involved a single-trip mode leg, with 29% featuring two trip legs, 9% three legs, and 7% four or more legs. New Zealanders also typically made about 1.3 'tours' a day (averaging about 3.1 trip legs within them), where a journey started and ended at home. Not surprisingly, driving (or being a vehicle passenger) and walking were the most common single-trip journeys, with combinations of the two modes being the most common multi-trip journeys, followed by catching a bus and walking.

Milne et al. (2011) examined differences in travel patterns between 2003 and 2010 using HTS data across different urban areas in New Zealand. The highest levels of trip chain 'complexity' (ie, numbers of trip legs per journey) were from trips involving bus or rail (typically with around two to three trip legs per journey), followed by those involving motor vehicles. Journeys with cycling had the least complexity (involving 1.4 to 1.5 trip legs). Of the major urban areas, Wellington had the lowest proportion of single-trip journeys, reflecting the much greater use of public transport in the region. It was observed that, as trip chains become more complex by involving more trips and having longer distance, people were less likely to choose to walk or bicycle and more likely to use motorised forms of transport. As transport technology continues to evolve and the proliferation of e-bikes continues, this dynamic may change. However, many New Zealand datasets combine regular bikes with e-bikes, making assessing this shift challenging – changes to our data collection methods may be required to test this hypothesis in the New Zealand context.

One of the potential challenges of trip chaining is that increasing the use of relatively low-risk travel modes like public transport may lead to additional walking, cycling and scootering trips to connect to these services, which typically have higher travel risks. Therefore, a shift from (say) driving to public transport may not necessarily reduce the overall DSI risk of the total journey, unless considerable improvements are made to the walking and cycling infrastructure that connects to the public-transport terminal points.

Interestingly, Phan et al. (2022) investigated the impacts of Melbourne train commuters' access modes (pedestrian, cycling, driving, tram and bus) on safety and found that commuting with active transport as the first/last-mile mode would lead to an improvement in road safety. Unfortunately, the authors only compared modes to each other, rather than before and after improvements to a particular access mode.

2.3.5 Summary of findings

Census travel data is limited to journeys to work and study, and only captures a single 'main' travel mode for these journeys. The HTS provides more depth by monitoring all types of travel for all trip purposes, and capturing multi-leg trip chains, but is scaled up to national or district-wide figures from relatively small samples, limiting its precision and not allowing for highly localised analysis.

In considering journeys made by people, a considerable proportion of them involve using more than one travel mode or making intermediate stops along the way. Therefore, any consideration of changes to trip patterns (eg, switching from driving to public transport) may need to consider the likely sub-components of a new trip pattern.

2.4 Relative risk per travel mode

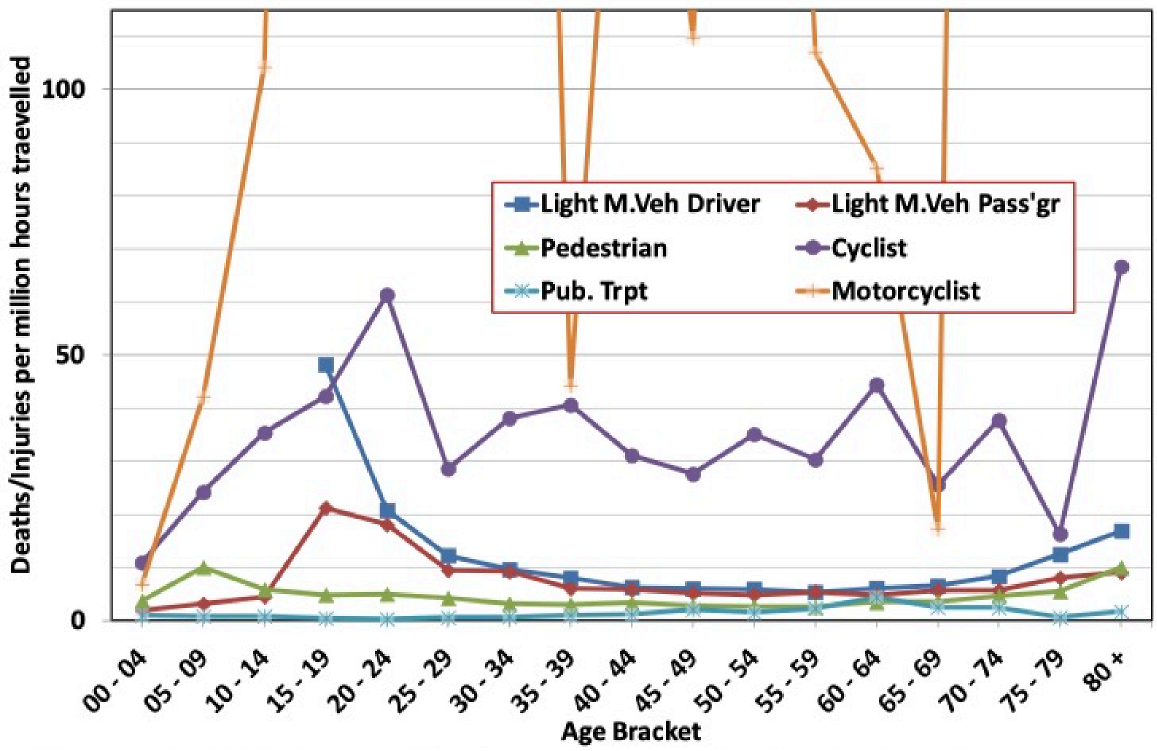
The aim of this study is to better understand how mode shifts will affect crash frequency, especially those crashes resulting in DSIs. To do this, it uses disaggregated local travel and crash data to estimate the relative risks of the different travel modes, along with best-practice crash-prediction models that can be used to predict future impacts.

As expected, different travel modes have different risks, levels of exposure and experiences in New Zealand and across the world. Some studies have measured the comparative risk and crash rates for various modes, while others have just attempted to gauge the risk of less understood modes, particularly active transport and new transport devices. Few of these studies include detailed gender, age, ethnicity, and geography data.

2.4.1 Comparing different modes

New Zealand crash and HTS data from 2003 to 2009 was analysed (Koorey & Wong, 2013) and showed the relative risks (deaths/injuries per million kilometres or hours) by travel mode for each age cohort and across different road types. Figure 2.2 for example shows the relative risks nationally for each mode by age (note that some motorcycle risk rates are well in excess of 100 DSIs per million hours travelled, with an average overall rate of 146 DSIs per million hours travelled, so the graph has been capped for comparative readability). The authors note that '…the crash rate for cycling is actually slightly better than that for driving for the 15-to-19-year age bracket. The two crash rates are also very comparable for the 75-to-79-year age bracket, as the relative risk of driving starts to climb up.'

Figure 2.2 Deaths and injuries per million hours travelled by age bracket for each mode (reprinted from Koorey & Wong, 2013, p. 6)



Notably, this graph shows casualty rates by duration, which is less typical than measuring by distance. Table 2.5 summarises the overall casualty rates for each mode analysed in the above study, in terms of both kilometres and hours travelled. Note that the rates per distance were so small that a denominator of per 100 million kilometres has been used for reasonable comparison.

Table 2.5 Comparison of New Zealand travel mode risk 2003–2009 (adapted from Koorey & Wong, 2013)

Travel mode	Deaths or injuries per million hr	Deaths or injuries per 100 million km
Car/van driver	10.2	27.5
Car/van passenger	7.3	18.3
Pedestrian	4.5	111.7
Cyclist	34.4	285.6
Public transport (bus, train, ferry)	1.0	4.5
Motorcyclist	146.0	485.3

As can be seen from Table 2.5, the analysis perspective taken has a significant impact on the conclusions. For example, when measured on a per-kilometre basis, both walking and cycling become relatively riskier than on a per-hour basis. This not surprisingly reflects the relative differences in average travel speeds (particularly when it comes to walking) compared with motorised modes. It is important to note however that the average trip distance for trips by cycle or walking is typically lower than by motor vehicles, suggesting that the per-trip crash rate for these active modes is also lower than the per kilometre rates might indicate.

Koorey and Wong (2013) also noted differences in relative risks when comparing travel on six different types of roads, such as rural state highways, minor urban roads, etc. The data suggested that the relative risk of cycling to driving was much closer on lower-volume roads, suggesting the safety influence of lower traffic volumes. Unfortunately, the current HTS no longer captures the type of road(s) travelled on as part of its data, so this type of analysis can't easily be made for this study.

Curl et al. (2024) undertook a systematic review of published academic literature (n=29) on how DSI rates vary by mode of transport, utilising studies that measured DSIs by distance (per million kilometres), DSIs by duration (per million hours), and DSIs by number of trips taken (per trips taken). As discussed above, DSIs by distance are dependent on speed, meaning slower modes such as pedestrians have worse safety outcomes. Notwithstanding this, this review found similar relativities between the travel modes, with public transport typically the safest and motorcycles typically the least safe. There was some variation however, with the relative rankings of the other modes in the middle (motor car, cycles, pedestrians), again dependent on the risk metric used and the different jurisdictions studied.

A study completed by Te Manatū Waka Ministry of Transport (2022) did further assessment of road trauma in New Zealand during the 2017/2018 and 2018/2019 financial years. It used health-system sources (including hospital admissions) alongside CAS. The study showed a similar pattern of road trauma by age as that found by Koorey and Wong (2013), with the highest levels of trauma being experienced by teenagers and young adults. The study also found that Māori had a higher rate of road trauma than non-Māori, with nearly double the rate of serious injuries per 100,000 people. The Māori road-safety outcomes report (Waka Kotahi NZ Transport Agency, 2021a) concurred, finding that although Māori travel less VKT than non-Māori, Māori experience higher rates of DSIs than non-Māori as vehicle occupants and pedestrians. From 2013 to 2017, the average rate of DSIs per 100,000 population for all Māori men was 87.0, much higher than the average rate of 61.5 for all men. For all Māori women, the average rate was 40.5, much higher than the average rate for non-Māori women of 29.0. Māori tamariki (children) have fatality rates twice that of non-Māori. This increased likelihood of DSIs for Māori in Aotearoa, compared to non-Māori, shows systemic inequities in road safety.

The systematic review undertaken by Curl et al. (2024) found ethnic disparities between Black and Hispanic Americans and white Americans in multiple published studies from the United States. Raifman and Choma (2022) found that cyclist fatality rates for Black and Hispanic Americans (per million miles) were four times the rate of white Americans. Similarly, pedestrian fatalities for Black and Hispanic Americans (per million miles) were twice the rate of white Americans. In the state of Wisconsin, McAndrews et al. (2013) found that 'American Indian' and 'Black Americans' face higher transportation injury risk than white travellers across all three measures: distance, time, and number of trips (DSIs per million miles or minutes or trips).

A study of crash records from the City of Toronto (Bassil et al., 2015) between the years 2008 to 2012 showed that 'compared with cyclists, motor-vehicle crashes involving pedestrians are more likely to result in hospitalisation or injury'. However, the injury rate (per million trips) was roughly double for bicycle trips than pedestrian ones (see Table 2.6). Consistent with the body of literature and human kinematics, youth and seniors were over-represented in injury statistics. Major arterial roads with higher traffic volumes and speeds accounted for 64% of cyclist injuries and 70% of pedestrian injuries. The authors found that the only type of cycling infrastructure associated with a reduced risk of crashes was separated cycle lanes.

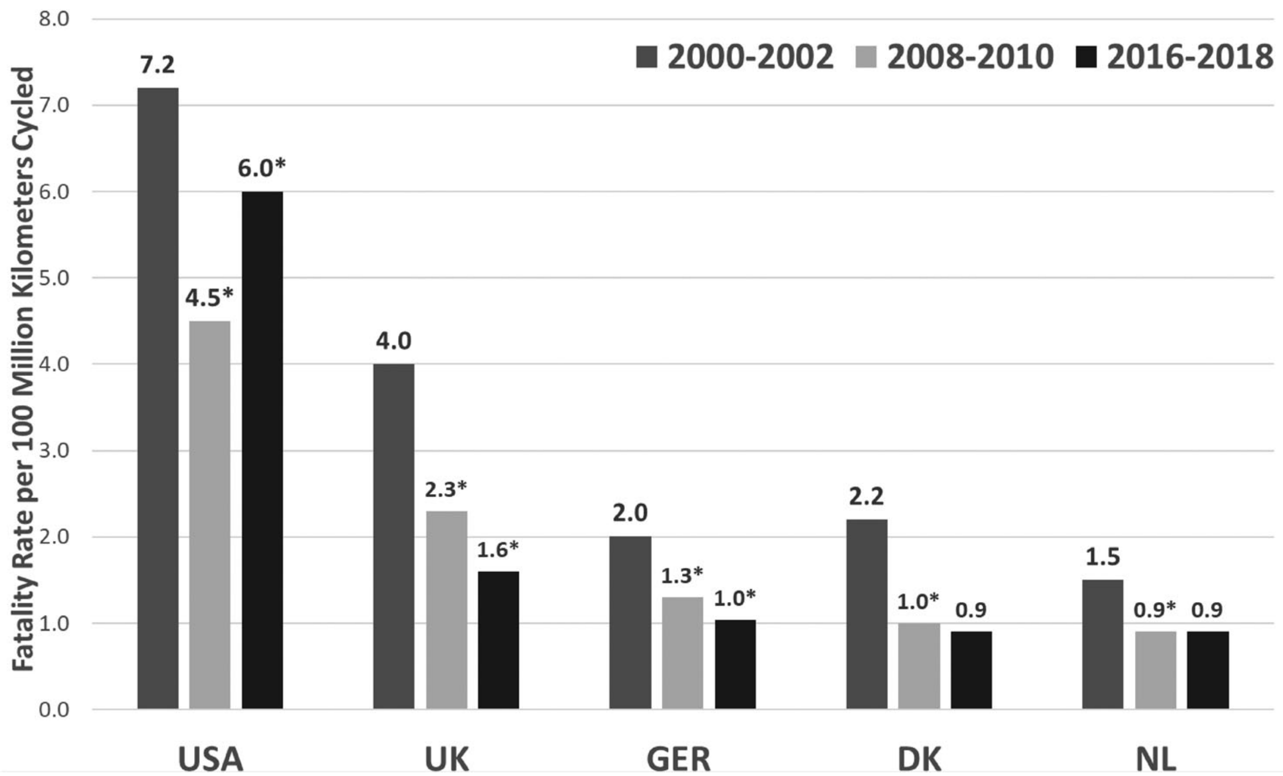
Table 2.6 Rate of pedestrian and bicycle injuries per million trips (Toronto) (adapted from Bassil et al., 2015)

Severity	Pedestrian	Bicycle
Minimal	6	17
Minor	8	15
Serious (Major)	1	1

Severity	Pedestrian	Bicycle
Fatalities	0.2	0.1
All severity levels	**16**	**34**

Buehler and Pucher (2021) found that the traffic fatality rate for people walking and cycling is significantly higher in the United States than in four European countries, and that this gap is widening with time. Notably, bike and walk fatality rates are decreasing at a faster rate in European countries than in the United States on a per-capita basis, with the United States even measuring an increase between 2010 and 2018 (Figure 2.3). This is despite bicycle usage increasing in the European countries, but generally decreasing in the United States. The authors also note that in 2018, the United States had roughly double the distance travelled by car per capita than Germany, Denmark, and the UK, and three times higher travel than the Netherlands. On a per-kilometre basis, the Netherlands has the lowest, and decreasing fatality rates.

Figure 2.3 Cyclist fatality rate per 100 million kilometres cycled (Buehler & Pucher, 2021)



Beck et al. (2007) used crash and travel survey data from the United States to calculate injury rates for various modes, separated by gender and age group; their overall results are summarised in Table 2.7.

Table 2.7 Rate of injuries per 100 million person-trips – United States (adapted from Beck et al., 2007)

	Passenger vehicle	Motorcycle	Pedestrian	Bicycle	Bus	Other
Injuries	803	10,336	216	1,461	160	1,020
Fatalities	9.2	536	14	21	0.4	28

Savage (2013) assessed the fatality risks in the United States across a longer time period, stretching back to the 1970s. The author found that all modes were now significantly safer than decades ago. However, commercial aviation and public transport were found to have significantly lower fatality rates than cars and light trucks. The results are summarised in Table 2.8. The fatality rate per mile had also decreased at a faster rate for all non-car modes since 1975. Notably, this analysis did not include any active modes, but did show the trend of 'trespasser' fatalities associated with rail, which showed a much slower decline than all other fatalities associated with rail.

Table 2.8 Passenger fatalities per billion passenger miles 2000–2009 in the United States

	Motorcycle	Car or light truck occupant	Ferry	Rail	Mass transit rail	Bus	Aviation
Fatalities (per billion passenger miles)	212.57	7.28	3.17	0.43	0.24	0.11	0.07

2.4.2 Micro-mobility travel risk

Micro-mobility modes, such as e-scooters, are relatively new to the transport space and thus still being evaluated in regard to their relative safety. A study in Liverpool, UK (Bodansky et al., 2022) used hospital data for an 8-month period in 2021 and 2022, during an e-scooter trial, and found the rates of injuries for bicycle and e-scooter riders are quite similar, as shown in Table 2.9. No comparison with other modes was included.

Table 2.9 Rate of orthopaedic injuries per million kilometres – Liverpool

	Bicycle	E-scooter
Orthopaedic injury rate	24.1	26.1

Chatterjee et al. (2023) conducted a meta-analysis of literature on e-scooter safety. However, all their sources were of early generation e-scooter share systems that (a) had a novelty effect and (b) did not include recent refinements in the apps that underpin usage and the scooter suspension, wheels and tyres. They used a larger dataset from an e-scooter trial that ran in Bristol and Bath cities, with data collected between July 2020 and December 2021. Data sources included surveys of users and non-users of e-scooters, e-scooter operator data on incidents reported by users, police crash records (STATS19), and hospital data. The results indicated a substantially higher rate of injury for e-scooter trial users than for bicyclists, and the authors calculated that there are 1.8 operator-reported injuries and 10 hospital admissions for each STATS19 police-reported injury: see Table 2.10.

Table 2.10 Injury rates for e-scooter riders in the Bristol area trial, compared to UK bicycle injury rate

Injury rates per 100,000 km	Bicycle (severity levels not stated)	E-scooter – all injury severities	E-scooter – level 2 and 3 injuries (more serious)
Trial operator data		9.25	1.43
STATS19 police data	0.294	-	0.52
Hospital admissions data (calculated)			7.9

Both of the UK e-scooter trial evaluations suffer from differences in exposure data sources, as Chatterjee et al. (2023) note (p. 53):

While the numerator has been collected based on the same protocol, the denominator for the e-scooter rides was derived from trial data, and the distance cycled was derived from the Department of Transport vehicle count data. This study therefore also suffers from the same issue that it has not been possible for the researchers to derive numerator and denominator for the comparison of the two modes from a single study with a common protocol.

Analysis of 36 hours of video from eight sites around Bristol revealed near-miss and trip patterns.

- A high proportion of people cycling, scooting and walking had been in a near-miss situation, which was defined as passing a parked car within a door's width, close overtaking passes by a motorist, or their trajectories crossing with another street user resulting in swerving, slowing or stopping to avoid collision.
- E-scooter riders are significantly less likely to have near-misses with motor-vehicles than cyclists, and possibly this lower pattern of near-misses is repeated with pedestrians.
- Walking and driving 'are important modes for both leisure trips and utility journeys, whereas e-scooters and cycles are relatively more important for the utility role they play'.

Chatterjee et al. (2023) used surveys to determine mode shift. Respondents were asked to indicate their most likely alternative to their last e-scooter ride (multiple answers were allowed). Walking was mentioned by 53%, public transport 41% to 58%, and car by 16% to 21% of respondents. The ranges correlate to younger to older respondents, respectively. E-scooters are also used as part of trip chains (modal integration). Respondents reported combining e-scooters with car (39%), bus (23%) and train (20%) trips.

In 2020, the International Transport Forum summarised 16 studies that used hospital admissions data from a range of cities in eight countries, and that estimated either e-scooter or cycle injury rates per billion trips (Table 2.11) (International Transport Forum, 2020).

Table 2.11 Rate of injuries per billion trips (order-of-magnitude level estimates)

	E-scooters	Bicycles
Emergency department visits (serious or minor)	87,000 to 251,000	110,000 to 180,000
Hospital admissions (serious)	29,000 to 62,000	1,000 to 10,000
Fatalities	78 to 100[5]	21 to 257[6]

The authors found only two reports of pedestrian fatalities involving e-scooters (ie, a pedestrian struck and killed by an e-scooter rider).

Lieswyn et al. (2017) looked at the actual and perceived safety impacts of low-powered devices and electric bikes to inform potential regulatory approaches. After the collation of international literature, some trends were agreed on, while others were not clear across different countries. Some relevant conclusions included:

- both safety risks and benefits are created by the introduction of e-bikes (due to their increased speed and weight, and the associated decrease in the use of vehicles)
- some studies showed e-bikes tended to be involved in more crashes than traditional bicycles, while others found no difference in the number of critical incidents (this was likely to be related to multiple external factors)
- crashes resulting in injuries involving mobility scooters were often caused by collisions with other objects (not vehicles)

[5] Based on Lime scooter data from the United States and Europe, and converted from nine known fatalities over an estimated 90 million trips.

[6] Based on the International Transport Forum's safer city streets network database.

- e-kick scooters were three times more likely to be involved in severe injury crashes then non-motorised scooters (note that these latter were often used by children)
- users of self-balancing devices showed less severe head injuries compared to pedestrian crashes.

Research on e-bike and e-scooter safety for Auckland Transport (Martin et al., 2021) found that collisions were often attributable to the behaviour of e-scooter riders, while falls or crashes with non-moving objects were mainly a result of road features such as surface quality. The researchers used ACC and CAS data to find that:

- e-bike riders were roughly twice as likely to suffer head injuries than unpowered cyclists
- there are eight times as many e-scooter injury claims as e-bike injury claims.

The Auckland research did not attempt to calculate injury rates using any form of exposure data. However, Waka Kotahi NZ Transport Agency (2023c) referred to a study of e-scooter admissions to Auckland City Hospital (McGuinness et al., 2021) and estimated a hospitalisation rate of 326 per million hours scooted. It should be noted, however, that this dataset was from the first year only of introduction of e-scooters to Auckland, when they were still somewhat of a novelty, and so the relative risk is likely to have dropped since then. In looking at this data and other sources from around the world, Waka Kotahi NZ Transport Agency (2023c) estimates that the typical relative risk of death or injury per hour of e-scooting is at least double that of cycling.

The potential for mode shift from cars to micro-mobility (Ensor et al., 2021) was modelled to be up to 5.7% of trips, which could be made by e-scooters, and up to 8.1% of trips, which could be made by e-bikes, depending on the urban land-use context. The safety impacts were described as follows (pp. 83–84).

> *From a safety perspective, micromobility has the potential to introduce a range of new risks. Some of these risks are a product of the modes themselves (higher speeds, device balance), some are linked to the specific road/pavement environment (steepness, camber, surface quality), and others may arise as a result of different modes sharing the same physical space. These impacts will be able to be managed to an extent through infrastructure design and carefully considered separation of micromobility from other modes. Policy interventions would also be beneficial in this area; speed restrictions (potentially digitally reinforced in key locations) are examples of this. Work in the infrastructure and policy space here could also have additional safety benefits for those already cycling and walking.*
>
> *There are likely to be transitional impacts on safety, as some new micromobility users may initially lack good handling skills, as well as more general 'active travel' skills such as spatial awareness. This is particularly relevant for uptake of e-scooters and e-bikes. These transitional safety impacts will be particularly apparent if there is a period of lag between when an observable increase in micromobility uptake takes place, and when micromobility-specific policy or infrastructure is implemented.*
>
> *Although mode shift to micromobility will likely reduce the volume of cars on the road on average, it is unlikely that this will result in a proportionate reduction in vehicle-related casualties because micromobility tends to replace suburban or urban trips, rather than higher-risk travel such as higher speed rural travel. Any benefits in a reduction of car transport-related injuries are likely to be at least balanced, if not outweighed, by the safety risks associated with micromobility travel itself.*

2.4.3 Risk and crash-rate measurement methods, challenges, and issues

The evaluation of options and investment through cost-benefit analysis is a key stage of transport sector decision-making processes. Wedderburn and Buchanan (2013) developed a framework for evaluating walking and cycling connections to public transport. To understand the monetary impacts of public-transport access and egress, they reviewed international literature and HTS data. This allowed the analysis of trip chaining, public-transport use and access, mode shift and the trip generation impact of improving public-transport access.

The origin of public-transport trips showed considerable mode share variation in different cities. Motor vehicles had higher mode shares in rural areas compared to cities, where walking often accounts for 50% of public-transport access due to higher population densities and better public-transport services. Cycling varied depending on the quality of facilities provided; in cities with high-quality facilities at stations and city wide, and where cycling was prevalent in the wider culture, cycling accounted for around 20% of public-transport access trips. Walking was the most prominent mode of transport for destination end-trips in all locations.

In terms of distance travelled to access public transport, trends observed in New Zealand were similar to international trends. The distance people walked to buses in New Zealand was 200m (median) compared to 400 m to 800 m (mean) internationally. To access ferries or trains, walking 1,000 m or more was the average nationally. People who cycled to public transport were less common, but travelled a mean distance of 1,400 m. The result of this research was an evaluation tool, in the format of a spreadsheet, that presented improvements made in public-transport access in dollar values, through the use of the following data (at a minimum):

- daily boarding volumes at the station or stop
- number of passengers interchanging between public-transport modes
- population and employment data for surrounding areas
- cost estimates of the proposal.

Crashes are discussed briefly in research by Wedderburn and Buchanan (2013), that referenced NZTA crash-reduction evidence as follows (p. 77).

> *At a more localised level the original proposal estimated that the introduction of cycle lanes would result in a 10% reduction in bicycle crashes (from the seven bicycle crashes recorded over the previous five years), valued at $260,000 per collision (EEM1, NZ Transport Agency 2010, updated to the 2011 price base year). The resulting annual localised safety benefit was entered into the evaluation tool.*

The research applied overseas literature and methods to a local issue using existing data. This method is very relevant to this report thanks to a similar amount of data being available and previous research to review.

2.4.4 Internal versus external risk

A theme that appeared in some studies was the attribution of risk to different modes, in which both internal (ie, the mode of the victim of the death or injury) and external (ie, the mode of any other vehicle or road user involved) deaths and injuries were considered.

In their assessment of road-transport accident costs, ViaStrada (2022) identified three different ways to allocate the resulting costs.

- (Neutral) costs ‘shared’: Allocation of the estimated cost for each accident type (by number and type of vehicles involved) evenly across the vehicle types involved (eg, for an accident involving two cars and one truck, two-thirds of the cost would be allocated to cars, and one-third to trucks).
- Costs ‘imposed’ or ‘caused’: Allocation of total costs across vehicle types according to the vehicle type judged to be primarily at fault, with fault allocation based on movement types.

- Costs ‘borne’ or ‘suffered’: Allocation of total costs across vehicle types in proportion to the people experiencing the cost (in terms of injuries received).

Using this approach, less protected modes, such as walking and cycling, were likely to generate higher costs ‘suffered’ than if they had been calculated on a cost ‘shared’ basis, and less again if considering costs ‘caused’. Table 2.12 summarises the different annual costs for each of the travel modes studied.

Table 2.12 Yearly costs and usage rates for road accidents involving motor vehicles – by user type (ViaStrada, 2022)

	Bicycle	Pedestrian	Cars, light commercial, other	Motorcycle including moped	Bus	Truck
Costs shared ($million/yr)	110	219	4,349	511	77	380
Cost shared per distance travelled by person (cents/PKT)	35.7	31.0	6.3	123.1	2.8	12.6
Costs caused ($million/yr)	87	199	4,459	520	65	315
Cost caused per distance travelled by person (cents/PKT)	28.3	28.2	6.5	125.4	2.4	10.4
Costs suffered ($million/yr)	201	435	4,123	705	43	137
Cost suffered per distance travelled by person (cents/PKT)	65.1	61.7	6.0	170.1	1.6	4.5
Ratio: cost suffered/caused	2.30	2.19	0.92	1.36	0.66	0.43

Note: PKT = person-kilometres travelled.

The above results are largely in line with what has been seen elsewhere in terms of average costs by modes. The main motor-vehicle modes (car, truck, bus) are relatively safer than the more vulnerable modes (motorcycle, cycle, pedestrian) on a cost per person-kilometres-travelled basis. However, motor vehicles also tend to be the parties who *cause* more crash costs than they suffer themselves, compared with the more vulnerable modes, where the average costs suffered are often double those caused.

A study conducted in the United States (American Public Transportation Association, 2016) found that between 2000 and 2014, all modes of public transport had significantly lower death rates per passenger mile, with bus passengers found to be 30 times safer than car occupants. The study also found a strong negative correlation between the per-capita rates of public-transport use and traffic fatalities for all age groups for all cities in the country. Notably, even when fatalities from non-passengers (ie, people hit and killed by the vehicle) are included, all modes of public transport have lower fatality rates. The researchers suggest that not only is public transport a safer mode for an individual user, but that having higher public-transport usage and implementing policies that increase public-transport usage have a synergistic effect on road safety and create a safer transport environment for all modes.

Research carried out by Frith et al. (2015) looked at identifying and predicting the impact of public transport (including road-based public transport, ferries and trains) on the safe systems approach. The safe systems approach works to identify and eliminate all causes of crash trauma, recognising that all drivers will make mistakes. By reviewing the literature, practice and data (both nationally and internationally) on DSIs, including unreported injuries, a more comprehensive understanding of injuries occurring on public transport was developed.

This research collated a significant amount of national and international data on crash occurrences across different transport modes. The HTS was used for New Zealand data – this has been since updated and thus, the data in this research is no longer accurate. Overseas data and data from sources other than the HTS have been recorded in a spreadsheet for analysis.

The study noted that when reporting crash statistics, the mode of the user who has been injured is usually counted, however, the involvement of other vehicles is often not shown. The study shows an alternative for presenting both statistics simultaneously, and has been reproduced more recently by Litman and Fitzroy (2023, p. 30), as shown in Figure 2.4.

Figure 2.4 User compared to non-user fatalities (adapted from Litman & Fitzroy, 2023, p. 30)

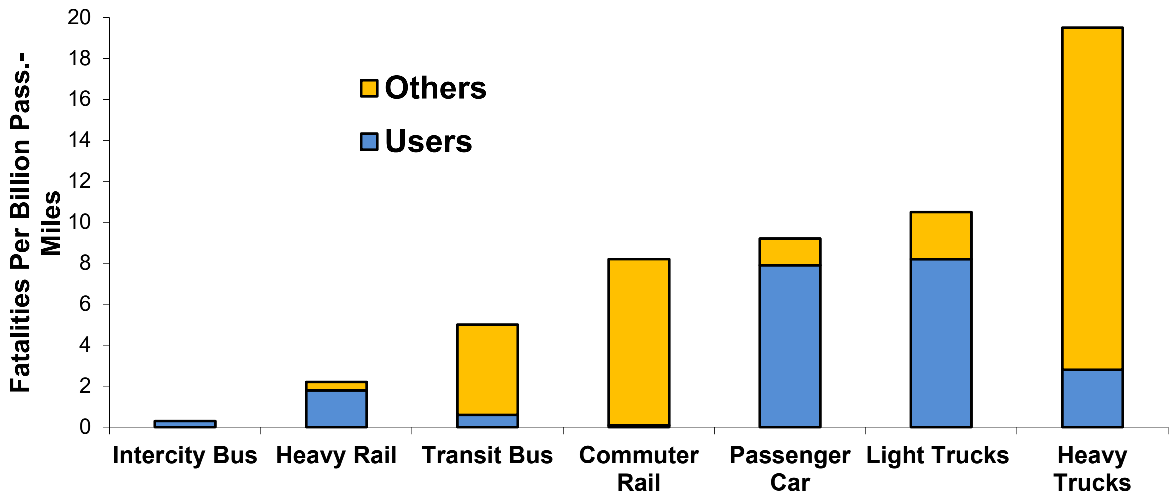


Figure 2.4 suggests that motor-vehicle travel imposes risks on both occupants and other road users. As vehicle weight increases, their internal risk tends to decline and their external risk tends to increase.

The research by Frith et al. (2015) indicates that increasing public transport tends to increase safety overall, including for users when travelling to and on public-transport vehicles, and for other travellers. The results also warn that trips to and from public transport, as well as injuries obtained when boarding or leaving public transport, should be considered more when drawing conclusions.

The above research is particularly relevant to this report, and the data and estimation methods used in that research can be adapted for use in the production of this new report. Safe systems can also be incorporated into the ethos, methods and results of this report.

A Canadian study (Morency et al., 2018) took a more disaggregated approach to assessing the safety impact of public transport. It individually assessed 10 bus routes in Montreal along major arterials using vehicle occupancy and individual crash data. The study found that the per-passenger-kilometre rates of injury and fatality were significantly higher for private vehicles than for buses. This applied both to vehicle occupants and people walking and cycling injured by the vehicles, with the ratio between car-based and bus-based injuries and fatalities per passenger-kilometre varying from 3.0 to 4.8 depending on the bus route. Notably, when only considering DSIs, this ratio was similar for pedestrians, but significantly higher for cyclists, with nine times more cyclist DSIs per passenger-kilometre for private vehicles. Another key finding is that both car-based and bus-based injury rates varied similarly between routes – that is, where injuries associated with cars were higher on a particular route, injuries associated with buses also tended to be higher. The authors suggest that while mode shift to buses will likely improve safety outcomes, the context and road design still play a decisive role in overall safety outcomes.

2.4.5 Data sources and quality

Ensor et al. (2021) reviewed the literature, and modelled the effect and usage of micro-mobility using survey counts, trip data, sales data, injury statistics and stated preferences. Issues were found with many of these data sources including significant regional variation and a lack of detail. The authors based their model off the existing Auckland Macro-Strategic Model and the Strategic Active Modes Model, (both developed by the Auckland Forecasting Centre) due to their level of detail and inclusion of a wide range of geographies, densities, and land-use types. Ensor et al.'s research works towards estimating the mode shift to micro-mobility. However, it does not look at crashes as an outcome of this shift. The authors suggested that ACC data sets be further investigated to form an understanding of injury rates.

A study completed by Waka Kotahi NZ Transport Agency (2021a) further investigated Māori road-safety outcomes. A notable challenge found during the study was the differences in how ethnicity data is captured across different datasets, with Census data being self-reported, but crash data, including ethnicity, being captured at crash scenes, and hence the potential for this data to differ from self-identified ethnicity. While this study only noted this for Māori, it is likely to have wider impacts on the quality of ethnicity-based analysis.

2.4.6 Summary of findings

Many studies have investigated the relative risk between modes of transport, with good agreement on the safety of individual modes. The following list ranks modes by DSI per unit of travel from highest risk (top) to lowest risk (bottom):

- motorcycles
- bicycles and other two-wheeled devices
- pedestrians
- general traffic
- public transport.

One key distinction between studies is their consideration of internal and external risk and the attribution of this risk, and how this is considered in crash data. Notably, while the occupants of personal vehicles are generally safer than many other modes (except for public transport), when risk to other road users is included, the risk profile of this mode changes significantly.

In addition, there may be differences in demographics and travel behaviour that affect risks. For example, cycle and motorcycle travel often tends to be overrepresented by young males, a relatively risky group. As a result, a skilled and responsible rider who uses proper safety equipment, follows traffic laws and avoids high-risk driving conditions is likely to have much lower crash rates than the overall average for these modes.

Also, most of these studies measure risk per unit of travel (such as billion passenger-kilometres) or time (per million hours of travel) and so fail to account for differences in annual kilometres travelled. Rankings may change if risk is measured per capita (ie, based on population), taking into account differences in demographics and annual travel by different types of travellers.

There are notable differences in the relative risks determined for each mode in terms of distance travelled versus time spent travelling; both have their merits for safety analysis. Therefore, this study will incorporate both metrics in the final model.

2.5 Quality of modal facilities

Improving the relative quality of transport facilities typically results in improved safety outcomes for the relevant modes of transport. This becomes particularly critical for those modes that are traditionally poorly served and as a result typically suffer higher crash and injury rates. Walking, cycling and other wheeled device users can see increased casualty numbers if increased usage is not accompanied with improved facilities for them.

2.5.1 Building a cycling network

Turner et al. (2009) looked at crash risk reductions caused by lowering traffic speed and installing cycling facilities (ranging from cycle lanes and paths to intersection cycle facilities). This research collected data from Christchurch, Hamilton and Palmerston North using before and after studies and crash-prediction modelling.

The risk of crashing while cycling was acknowledged as being typically higher than the equivalent risk when in a car; hence, the need to focus on increasing safety for these vulnerable users. Changes to increase safety looked in this study at included:

- reducing vehicle traffic volumes and speeds
- intersection treatments and traffic management
- reallocation of road space
- separating facilities.

Based on this research, the installation of standard on-road cycle lanes has been found to reduce cycle crashes by around 10% in New Zealand, or 20% if wider ones are installed (NZ Transport Agency, 2018). However, there is currently no suitable New Zealand data for assessing the safety impacts of other cycle facility interventions.

The decrease in cycle crashes measured is an example of how raising the cycling level of service can impact on crashes in a New Zealand context. This is highly relevant, as it can be directly applied to the impact that increasing cycling safety and levels of service will have on crash frequency. An improved cycling level of service also improves perceived safety, leading to increased uptake of cycling and then the safety-in-numbers effect in a 'feedback loop'.

Thomas et al. (2022) investigated the impact of safety interventions on mode shift by monitoring indicators, interviewing experts and reviewing literature and New Zealand case studies. Crash safety interventions (such as infrastructure and managing speeds), personal security interventions (such as real-time public-transport information) and slip, trip and fall interventions were all looked into. Results indicated that safety interventions did impact on mode shift and theorised that this could be used to improve decision-making beyond safety.

> *Infrastructure that physically separates vehicles and cyclists, speed reductions with traffic calming, lighting and real-time public transport information were identified as effective interventions. However, a fundamental aspect of successful safety interventions in achieving mode shift is that they must not be done in a piecemeal or isolated way. The best evidence supports the Safe System approach, looking at entire routes or areas to develop a complete package, looking at the needs and limitations of who is using and avoiding travel, and ultimately looking at whole-of-journey safety.* (Thomas et al., 2022, p. 11)

The authors suggest that while individual interventions do have a positive impact on mode shift, the highest levels of success come when these interventions are coordinated and applied at a network level. While crash frequency is not discussed by these authors, understanding the impact that safety interventions have on mode shift could contribute to the estimation of mode shift change.

Marques and Hernandez-Herrador (2017) investigated how the development of a network of separated cycleways impacted on safety. Between 2000 and 2013, a network of separated cycleways was built in

Seville, and bicycle use rose significantly; however, crashes per bicyclist reduced. The authors found that the lengthening of the network over time had a positive impact on safety. However, the authors also tested a ‘network’ variable to see whether the implementation of a more comprehensive and connected network of facilities was a suitable predictor of crash risk or usage. The authors found that the ‘network’ indicator was a better predictor of crash risk than the length-based measure.

Lusk et al. (2011) investigated the relative risk of cycle crashes in streets with separated cycle tracks, compared with normal untreated streets in Montreal, and found that the separated cycleways had a 28% lower crash rate. Other studies have suggested even greater reductions in crash rate for protected cycle facilities. For example, Teschke et al. (2012) suggested the reduction could be as much as 89% less than on busy untreated streets in Vancouver. However, the ‘case-crossover’ method of analysis used in that study has some potential for over-estimation of actual observed effects, especially with a small sample of injury cases. The same study also suggested that neighbourhood greenway-style ‘local bike routes’ might see a roughly 50% reduction in crash risk.

2.5.2 Level of service

Bowie et al. (2019) propose a rating method for measuring cycling levels of service and the impact of these levels on perceived safety. This research does not reference crash frequency. However, the improvements in perceived safety and peoples’ ‘willingness to ride’ if the environment were improved, suggest that safety benefits may be realised through both actual safety improvements to the network and the safety-in-numbers effect (refer section 2.6.3).

Myhrmann et al. (2021) further investigated how the quality of facilities affected the likelihood and severity of single-bicycle crashes in Aarhus, Denmark. The authors found that single-bicycle crashes were more frequent and severe on road sections where a poorly maintained bicycle lane was in place, and lower on separated, well-maintained cycling infrastructure.

Schepers and Wolt (2012) also found that infrastructure has a significant impact on single-bicycle crash rates, finding that approximately half of single-bicycle crashes are influenced by infrastructure quality. Particularly, surface quality was found to cause a significant number of crashes due to uneven or slippery surfaces.

Beck et al. (2019) completed similar research in Melbourne, Australia, finding that a variety of infrastructure- and context-related factors created the conditions for single-bicycle crashes to occur. This included striking potholes or other objects, loss of control due to surface quality or avoiding other road users, and interactions with tram tracks. The authors suggest mitigations, such as improved maintenance, to remove potholes and other hazards, and banning parking where other hazards (such as tram tracks) were present.

Marshall and Ferenchak (2019) investigated why cities with high bicycling mode share had better overall safety outcomes for all modes. While they found additional evidence for the safety-in-numbers effect, they found that the prevalence and quality of protected or separated cycling infrastructure had a much larger impact on safety outcomes. The authors suggest that the safety impacts on modes other than cycling may be due to separated infrastructure creating slower and safer adjacent road environments. They note that the relationship between levels of cycling and overall safety outcomes may be bi-directional: safer roads result in higher bicycle use, and higher bicycle use may result in safer roads.

Goh et al. (2013) investigated the safety impact of implementing different types of bus-priority measures in Melbourne. The authors found that the number of crashes reduced by 14% on average after implementation of bus lanes, and showed reductions regardless of whether the road was widened to add bus priority. Non-traffic-signal priority treatments (bus lanes) yielded a stronger positive safety effect (18.2% reduction in crashes) than traffic-signal priority treatments (11.1% reduction). The authors do not make a link to mode shift; however, this research implies that the way mode shift is achieved will have safety implications. Another paper from Goh et al. (2013) found that the provision of bus lanes (regardless of whether created through space reallocation or space creation) acted to lower the number of conflicts at intersections and bus stops. Again, the authors do not make the link to the co-benefit of mode shift by improving bus frequency and reliability with dedicated lanes, alongside safety improvements.

The report on the quality of life in 83 European cities (European Commission, 2023) showed that providing more infrastructure is linked to more cycling. The European Cyclists' Federation (Haubold, 2023) linked this data to their own data on cycling infrastructure, showing the correlation between cycling infrastructure (ratio of the main road network covered by separated infrastructure) and quality of life (R^2=0.572)

2.5.3 On-street parking

Ward et al. (2024) investigated the road safety and multi-modal impacts of on-street parking in New Zealand. The authors found that between 2017 and 2021 there were 14,030 crashes involving parking or as a result of parking. This included nine fatal crashes and 286 serious-injury crashes, with two-thirds of the fatal, and half of the serious-injury crashes involving pedestrians, cyclists or motorcyclists. They recommended ensuring that designs to reduce or remove on-street parking are not influenced by stakeholders to the extent that road-safety outcomes and multi-modal outcomes are compromised, and alluded to the need for a legislative approach to ensure what has been approved for implementation has been subject to a safe systems audit.

Although not alluding to mode-shift directly, this recommendation speaks to the ability (or lack there-of) of road-controlling authorities and transport practitioners to remove on-street parking to directly reallocate road space to encourage mode shift away from private motor vehicles, and therefore improve road-safety outcomes. These findings also support those found by Turner et al. (2009), who determined that the removal of adjacent on-street car parking was found to reduce cycle crash rates by about 75%.

2.5.4 Summary of findings

While the research linking the quality of facilities to safety is limited, there are some key themes and indications of what the most instrumental factors are. These key themes are broadly as follows:

- a dense network of high-quality, physically separated cycling facilities is most effective for reducing injuries and deaths related to bicycle crashes with motor vehicles
- single-bicycle crashes make up a significant proportion of crashes at all severities and levels of mode share, and ensuring a high-quality of separated facility is important for ensuring that increased cycling mode share results in improved overall safety outcomes
- the safety-in-numbers effect for cycling appears to apply both to crashes with vehicles and single-bicycle crashes
- installation of bus-priority measures, particularly physical space allocation, appears to improve safety outcomes for all users, though research in this area is somewhat limited and inconsistent
- on-street parking has a significant impact on safety outcomes, particularly when poorly designed
- installation of modal facilities for any non-motor-vehicle mode often results in improved safety for all modes.

Notably, limited research was found on the impacts of separate modal infrastructure on safety in New Zealand, though some work has been done in Australia, which could be considered more comparable than other international examples.

2.6 Travel mode changes

While not the key focus of this research, several factors can influence short-term and long-term changes in travel patterns, leading to greater or lesser use of particular travel modes. Some are policy-related factors (eg, pricing or regulatory changes), while others are physical or environmental factors (eg, land-use or infrastructure changes).

Changes in absolute numbers of people using different modes (or the equivalent exposure metrics of person-kilometres or person-hours) do not necessarily lead to a similarly linear change in casualty numbers. Various other factors influence the expected change in safety, and different models have been developed to attempt to explain and predict these changes.

2.6.1 Demographics

With a similar research question, Stroombergen et al. (2018) investigated the impact of socio-demographic changes on transport, and used literature and data from overseas, adapting it to New Zealand. Starting with a literature review of internationally available and related local research, a decomposition analysis of private VKT was developed. Future travel demand estimates were then integrated into this analysis and their implications discussed.

A section focusing on reviewing New Zealand-specific literature was a part of the authors' research, which is particularly relevant to the research questions. Data from the HTS showed the region someone lived in, their living status (if someone lives alone or has a family), and decreasing speeds limits all have impacts on the number of journeys taken.

While the findings of this research are not particularly relevant to mode shift's impact on safety, the underlying theory of socioeconomic impacts on transport is one of the underpinning ideas of mode shift. Stroombergen et al. (2018) noted that a person's socioeconomic status may be one of the drivers towards or away from mode shift. For example, a 10% increase in the cost of driving per dollar of household income causes a 0.2% reduction in driver trips on average.

Curl et al. (2020) considered the social and distributional impacts of policies leading to mode shift. International literature was reviewed with a focus on its applicability to New Zealand. The authors focused on the impact these policy levers had on people of different socio-economic status and geographic distribution, and how to determine the social impact of mode shift. Mode-shift levers examined included those:

- affecting urban shape and form
- making shared and active modes more attractive
- influencing travel demand and transport choices.

Meta-analysis included in the authors' research showed that areas with lower income tended to have higher levels of both air pollution and crashes, suggesting higher frequency of vehicle use.

2.6.2 Crash-prediction models

Crash and injury numbers typically do not vary in a linear manner with changes in traffic flows; other factors such as vehicle speeds and crash types (due to levels of vehicle interaction) also have a significant effect. Therefore, current crash rates may not necessarily reflect the costs of making any changes to the current traffic patterns.

In economic terms, the 'marginal costs' for road crashes represent the extra costs (in terms of the social cost of road crashes) that adding an extra vehicle-kilometre (or deducting a vehicle- kilometre) to the traffic-flow pattern brings. The main input values for the assessment of marginal crash costs are the crash risk per vehicle type and road type, the costs per casualty (generally assumed to be unchanged from average cost calculations) and the ‘risk elasticity’ (the change in crash risk relative to change in traffic flows). Therefore, an understanding of appropriate crash-prediction models is required first.

Typically, most crash-prediction models used assume a key relationship between traffic ‘exposure’ (ie, the amount of relevant at-risk traffic present) and the resulting number of crashes (or related metrics, such as the number of casualties or total crash costs) (Elvik et al., 2009). The basic form of these models tends to be:

$$[Crash\ metric] = b_0 \times [VKT_1]\ b_1 \qquad \text{(Equation 2.1)}$$

where $[VKT_1]$ is the total VKT by the exposed (at-risk) traffic, and b_0 and b_1 are coefficients to be determined.[7] Models for two conflicting flows (eg, at intersections or with two different conflicting travel modes) often feature two separate VKT values for each flow, each with a different exponent coefficient, multiplied together, that is:

$$[Crash\ metric] = b_0 \times [VKT_1]^{b1} \times [VKT_2]^{b2} \qquad \text{(Equation 2.2)}$$

More complex models also apply additional modification factors (usually multiplicative) to account for the effect of various road attributes present at the site(s) of interest.

Crash-prediction models are generally used to estimate the number of crashes (or a subset of them, like injury crashes). For this exercise we are interested in the overall numbers of DSIs. In principle, we could simply use an adjusted b_0 coefficient to calculate total DSIs instead of total crashes. However, in a study of national crash costs for different travel modes and road types, ViaStrada (2022) noted that consideration has to be given to the variation in average severity of crashes in three key dimensions.

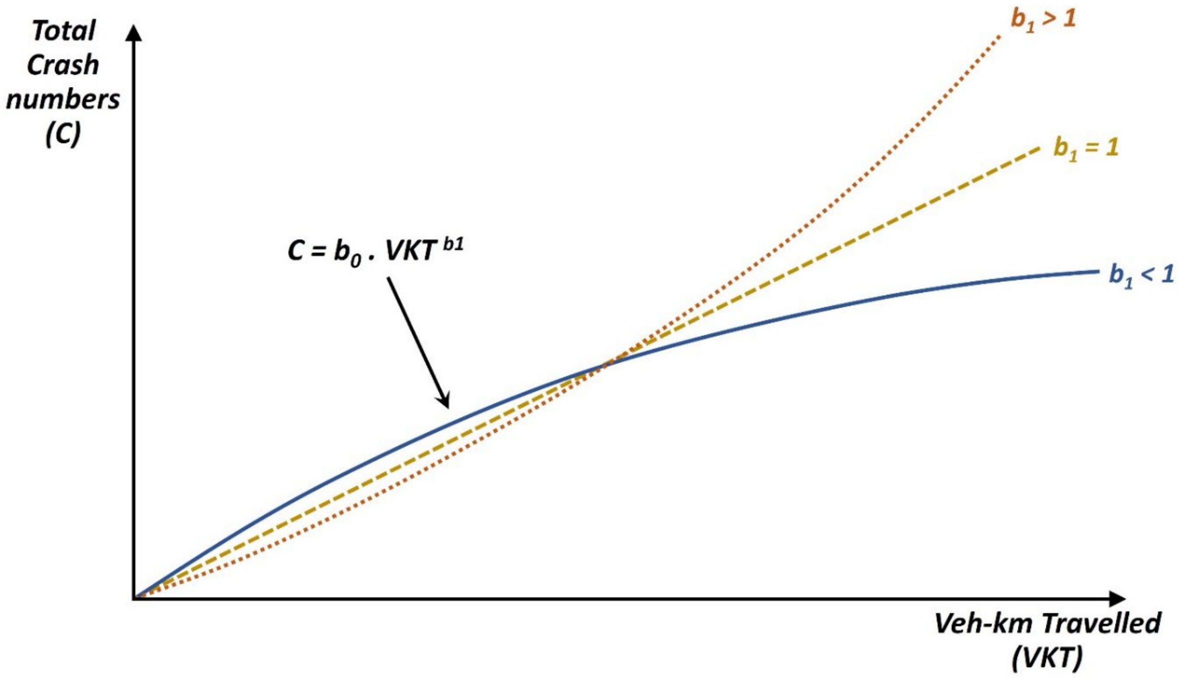
- Higher **speeds** are typically associated with more serious injuries (and a greater likelihood of deaths). Therefore, separate models with different coefficients could be needed for rural or motorway crashes compared with urban crashes. Adjustments could also be made to the DSI estimates if future changes to speed limits were introduced (eg, lower urban and rural posted speeds).
- **Intersections** involve typically different crash types than mid-block sections, again with different likelihoods of DSI. Therefore, separate models with different coefficients could be produced for intersection crashes compared with mid-block crashes.
- In **congested** situations (eg, rush hour), traffic speeds are typically slower than at uncongested times (eg, middle of the night), reducing the average crash severity. Therefore, some means of accounting for the speed/severity reduction effect with increasing VKT could be determined (in practice this is only likely to be a major issue for urban roads and motorways).

For this exercise, due to the global nature of the calculations (ie, either all crashes in New Zealand or some specific urban area), it will be assumed that single parameters for b_1 and b_2 in each mode will capture the overall nature of the model with sufficient precision (knowing b_0 is not critical, as the model is only interested in the *rate of change* of crash rates). Ideally, any potential inaccuracies in this approach would be mitigated somewhat in a future model version by introducing different model parameters for different road situations (for example, urban versus rural, or intersection versus mid-block crash models).

[7] Many crash-prediction models developed are presented as a confidence interval of possible values, reflecting the inherent random nature of crash occurrences. For this exercise, we will simply assume a ‘most likely’ value.

The coefficient b_0 determines the relative 'scale' of each model; that is, doubling b_0 will result in a doubling of the crash metric being investigated. The coefficient b_1 determines the relative 'shape' of the crash relationship in the model. A b_1 coefficient less than 1 implies a decreasing or logarithmic (but still ever-increasing if greater than 0) function where, for example, a doubling of VKT results in a crash metric increase that is less than double. A b_1 coefficient of exactly 1 implies a constant linear relationship (ie, a doubling of VKT produces a doubling in the crash metric). Finally, a b_1 coefficient greater than 1 implies an increasing or exponential relationship where a doubling of VKT results in a more-than-doubling of the crash metric. Figure 2.5 illustrates the different types of relationships when comparing total crashes against changes in VKT.

Figure 2.5 Different types of crash model relationships



All three types of relationships have been found in crash models to date (NZ Transport Agency, 2018), typically depending on the nature of the crashes being investigated. For example, crashes from greater interactions between motor vehicles (such as rural overtaking crashes) often increase exponentially (b_1 > 1) as the total traffic volumes increase. However, exponents less than 1 are most common.

Turner et al. (2006) included an international literature review on crash-prediction models. The authors found few studies focused on pedestrian and cyclist crash rates. No other New Zealand-based studies were found during this review. Based on the literature, they concluded that linear, multiplicative models including at least two variables (such as traffic and pedestrian volumes) were the preferred technique. The research also suggested that their crash rate is more dependent on the change in conflicting motor-vehicle volumes than the volumes of the active mode itself, and that therefore, a model featuring both modal VKT values would be sensible.

Generalised crash-prediction models have been used to determine the additional cost of adding one vehicle-kilometre travelled (per year) to the network, in terms of the likely crash implications. For travel on the road network, the crash-prediction models have been taken from the *Crash Estimation Compendium: New Zealand Crash Risk Factors Guideline* (NZ Transport Agency, 2018), with some additional guidance from earlier related research (Turner et al., 2006; Turner et al., 2009).

The Ministry of Transport's *Domestic Transport Costs and Charges (DTCC) Study* (Ministry of Transport, 2023) provided a comprehensive overview of all costs incurred in the transport system, including the marginal accident cost of additional kilometres travelled by different modes of transport. For motor vehicles, the costs were differentiated between where additional kilometres occur, recognising that rural crashes have worse severities, and walking and cycling crashes tend to have worse safety outcomes on a per-kilometre-travelled basis. These costs formed a key input into the crash-prediction models used in that study.

In developing crash (or accident) model relationships with traffic volume for the Domestic Transport Costs and Charges Study, ViaStrada (2022) noted that three different types of road environment contribute to New Zealand's road crashes:

- crashes on urban streets (speed limit of 70 km/hr and less)
- crashes on rural roads (speed limit of 80 km/hr and more)
- crashes on limited-access motorways and expressways.

Within urban and rural environments, crashes could be further split into those occurring at intersections and those occurring at mid-block sections (it was assumed that all motorway crashes are mid-block, with no at-grade intersections present). Therefore, the total motor-vehicle-crash costs for New Zealand could be represented by five sub-models, based on changes in total VKT. The intersection models required a bit more thought, as total VKT needs to be assigned to the various conflicting legs, which typically have unequal traffic volumes.

Pedestrian and cycle crashes do not have the same level of data breakdown available (eg, urban vs rural VKT). As discussed above, their crash rate is also more dependent on the change in conflicting motor-vehicle volumes than the volumes of the active mode itself, and therefore, a model featuring both modal VKT values (with a form somewhat like an intersection model) could be of value. However, for simplification, a single-factor model simply based on the active-mode VKT was used only for the domestic transport costs and charges exercise, with a recommendation that future improvements to the model should include a component for adjacent traffic volumes as well.

From the above discussion, and a review of various traffic models, Table 2.13 shows the final coefficients b_1 and b_2 applied to the marginal cost crash-prediction models in the Domestic Transport Costs and Charges Study (with b_1 being the coefficient for the primary travel mode or main road traffic at an intersection).

Table 2.13 Assumed Domestic Transport Costs and Charges Study crash prediction model coefficients (ViaStrada, 2022)

Sub-model	b1	b2
Urban mid-block	1.0	
Urban intersection	0.5	0.3
Rural mid-block	0.8	
Rural intersection	0.5	0.3
Motorway mid-block	1.4	
Cycle all	0.2	0.5*
Pedestrian all	0.4	0.6*

Note: *Inclusion of motor-vehicle VKT was not considered in the pedestrian and cycle models presented. If they had been, these b_2 values were considered the best estimate of the likely crash model coefficients.

Ensor et al. (2021) found that there are significant gaps in assessing the safety of micro-mobility, with limited research having been done to date. The authors also identify the limitations in data collection discussed in section 2.2, with many sources of crash data not correctly differentiating between types of micro-mobility, and many lower-severity crashes not being reported. Though some collections of data (such as the New

Zealand HTS) now include categories for these modes, this is a recent development, and long-term data (for both usage and crashes) is not yet available.

It is more difficult to find crash-prediction models for specific subsets of motor vehicles (eg, light vehicles versus heavy vehicles, motorcycles) or for particular public-transport modes (although their relatively low crash risk mitigates the need for a lot of research in this space). However, NZ Transport Agency (2018) does note a crash relationship for train versus motor-vehicle crashes at level crossings of:

$$[\text{Hit train and rear-end injury crashes / year}] = b_0 \times [\text{Trains per day}]^{b1} \times [\text{Crossing traffic volume}]^{b2}$$

(Equation 2.3)

where the factors b_0, b_1 (0.27 – 0.61), and b_2 (0.32 – 0.36) vary with the type of level crossing. While this is likely to only capture some of the injuries involving trains (for example, not those involving passengers who injure themselves while onboard), it provides an indication of the likely effect on casualties when either train or traffic volumes change.

2.6.3 Impacts of mode shifts

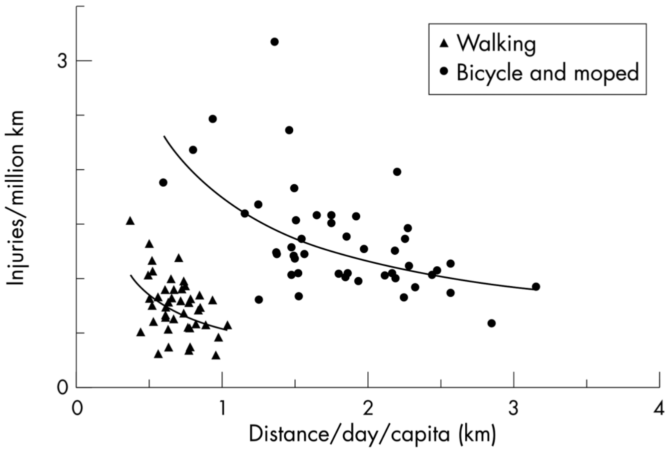
Per-capita traffic casualty rates tend to increase with automobile dependency and decline as a community becomes more multimodal with increased walking, bicycling and public transport (Ahangari et al., 2017; Ewing et al., 2015). While active modes have relatively high crash-casualty rates per kilometre of travel, a large body of evidence indicates that total crashes by all travellers tend to decline as walking and bicycling mode shares increase in an area; an effect called 'safety in numbers', whereby more people walking or cycling helps reduce the individual risk. In an update of their seminal 2003 work, Jacobsen et al. (2015) summarised this effect, using a series of North American and European examples that compared different towns or countries to demonstrate the effect's reliability (p. 217).

> *Where more people walk or bicycle, it seems likely that more vulnerable populations, such as older adults and children, would also walk or bicycle more, which would tend to increase the average injury risk. Yet that is the opposite of what we observe in Safety in Numbers.*

The safety-in-numbers effect occurs because walking and bicycling impose less risk on other road users; related improvements that encourage active travel, like compact development and lower traffic speeds, also reduce travel distances and increase traffic safety. Motorists also typically adjust their behaviour in the presence of greater numbers of pedestrians or cyclists. It may also be that as more and more people take up these active modes, political pressure for favourable laws, regulations and infrastructure grows and reinforces the effect. A greater proportion of people driving cars will also walk and bicycle at other times, so may be more conscientious of pedestrian and cyclist safety needs.

Figure 2.6 from Jacobsen et al. (2015) shows the non-linear safety-in-numbers effect, where the number of injuries per million kilometres travelled decreases as the distance per day per person increases.

Figure 2.6 Walking and bicycling in 47 Danish towns in 1993 to 1996 (Jacobsen et al., 2015)



More locally, Turner et al. (2006) developed some crash-prediction models for pedestrian and cyclist crashes and tested them against various road-user volumes. The safety-in-numbers effect was observed in crash data from traffic signals, roundabouts and mid-block sites for cyclists. No conclusion on safety in numbers for pedestrians was possible due to limited data.

Marshall and Ferenchak (2019) noted various factors that help explain the large total crash reductions associated with more active and public transport.

- Safer travel conditions – both active safety and travel tend to increase with improved footpaths, crosswalks, cycling facilities, streetscaping, traffic speed control and education programmes.
- Complementary factors – many factors that encourage walking and cycling, such as connected streets, higher parking and fuel prices, and compact development, also tend to increase traffic safety.
- Reduced total travel – residents of more walkable and bikeable communities tend to drive less, reducing risk exposure. Shorter active-mode trips often substitute for a longer motor-vehicle trip, for example, walking or biking to local shops rather than driving to regional shopping centres. Improving walking and cycling conditions also reduces chauffeured trips. Since most public-transport trips involve walking and cycling links, improving their conditions can increase public-transport travel.
- Reduced risk to other road users – being smaller, slower and lighter, pedestrians and bicyclists impose less risk on other road users.
- New users may be more cautious than current users – walkers and cyclists who observe traffic rules and use protective gear (such as helmets and lights) can have lower-than-average casualty rates.
- Increased driver caution – as walking and bicycling increases in an area, drivers are likely to become more aware and cautious.
- Less high-risk driving – improving non-auto modes allows young, old, impaired and distracted travellers to reduce driving, increasing the effectiveness of safety programmes, such as graduated licences, senior driver testing, and anti-impaired and distracted driving campaigns. For example, ride-hailing and public-transport availability can help reduce post-drinking driving.
- Stronger traffic enforcement – in automobile-dependent communities, courts are less likely to restrict the licences and confiscate the vehicles of high-risk drivers.

Ahangari et al. (2017) also found that higher levels of walking are associated with reduced traffic fatalities in a study looking at differences in crash rates between states in the United States. The authors found a similar relationship with urban density, suggesting that creating urban places that enable the use of modes other than motor vehicles, and thus reduce the amount of travel, is important for improving traffic safety overall.

Schepers (2012) found that people cycling are less likely to have bicycle-only crashes in regions where bicycle use is high, for all crash severities, though the effect lessens the greater the severity of the crash. While many studies on safety in numbers focus on car and bicycle crashes, the author suggests that the safety-in-numbers effect may also affect bicycle-only crashes. This is worth noting, as other studies have found that increases in cycling mode share come with a resultant increase in single-bicycle crashes, sometimes offsetting the safety gains from crashes involving motor vehicles (Schepers et al., 2017; Stipdonk & Reurings, 2012).

Schepers et al. (2015) completed a review of the literature regarding single-bicycle crashes and found that while an increase in cycling mode is not associated with a change in the proportion of crashes that are single-bicycle crashes, the number of single-bicycle-crash serious injuries increases 'proportionally less than the increase in bicycle modal share'.

Wei and Lovegrove (2013) developed models to test the safety-in-numbers effect in Canada, focusing on the impact of bicycling mode share increase in places where the current mode share is particularly low. They found that their models predicted an initial increase in bicycle crashes, but suggested that at some unknown critical mode share percentage bicycle crashes would decrease again.

As public-transport travel increases in a community, total (pedestrian, cyclist, motorist and public-transport passenger) per-capita traffic casualty rates tend to decline (Litman & Fitzroy, 2023). For example, using sophisticated statistical analysis, Ewing et al. (2015) found that more compact communities had significantly higher public-transport ridership, slightly higher total crash rates, but much lower fatal crash rates than sprawled communities: each 10% increase in their compact community index is associated with an 11.5% increase in public-transport commute mode share, a 0.4% increase in total crashes, and a 13.8% reduction in traffic fatalities.

In a study of crash rates in Melbourne, Australia, Truong and Currie (2019) found that shifts from private-vehicle to public-transport (ie, train, tram and bus) commuting tend to reduce both total crashes and severe injury crashes. They estimate that, holding all other variables (including proportions of commuting by tram, bus, walking, cycling and motorbike) constant, each percentage point increase in the proportion of commuting from a zone by train reduce 2.2 total crashes and 0.86 severe crashes, and a percentage point increase in bus mode share reduces an even larger 5.7 total crashes and 1.8 severe crashes. Increases in walking, bicycle and motorcycle mode shares, higher speed roads and industrial areas all tend to increase crashes in a zone.

Analysing 29 years of traffic data for 100 United States cities, Stimpson et al. (2014) found that a 10% increase in the portion of passenger-miles made by public transport is associated with a 1.5% reduction in total traffic deaths. Since only about 2% of total person-miles were currently by public transport, this means that a 1% increase in public-transport mode share was associated with a 2.75% decrease in fatalities per 100,000 residents, which translated into a 5% decrease in total traffic fatalities in the 100 cities included in their study.

Lichtman-Sadot (2019) found that the introduction of night buses in Israel had a significant impact on the frequency of crashes for young drivers while they operate, reducing them by 37%. Injuries from crashes also reduced by 24%.

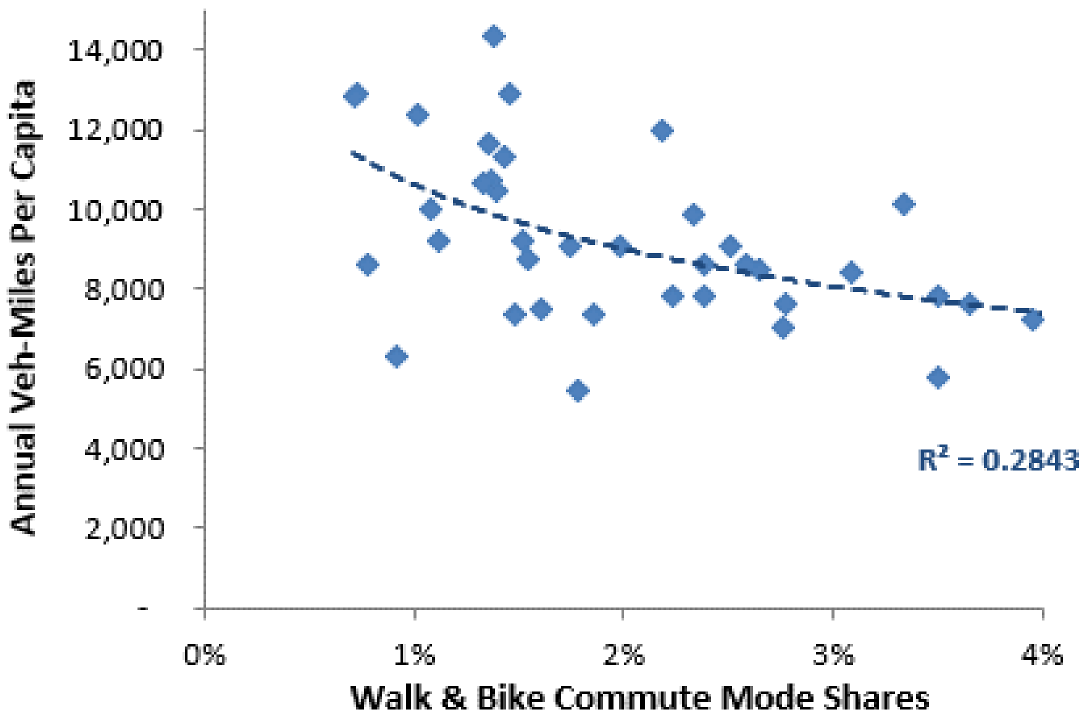
2.6.4 Per-capita vehicle travel and risk exposure

As touched on in section 2.6.3, changes in mode can often be accompanied by changes in the distance travelled using the new mode; for example, a person might now walk or bike to local shops rather than driving to a regional shopping centre further away. This has implications in terms of the relative exposure to risk faced by the traveller in each case. Instead of a straight swap to a 'riskier' mode on a per-kilometre or per-hour basis, the resulting DSI risk may change very little due to the reduced distance or time travelled.

One hypothesis is that these effects can be evaluated by using a 'fixed travel-time budget', which recognises that people typically devote an average of 60 to 80 daily minutes to out-of-home travel, regardless of mode(s) taken. If they shift from faster to slower modes, they find ways to travel shorter distances. Since driving is typically 3 to 10 times faster than active modes, one theory is that each kilometre shifted from driving to active modes generally reduces 3 to 10 vehicle-kilometres as travellers maintain their total daily travel-time target.

Figure 2.7 illustrates this effect, based on the relationship between active commute mode shares and per-capita vehicle-miles for the 40 largest United States cities (Litman, 2021). Each 1 percentage-point increase in active-mode share (indicating around 100 to 200 more average annual walk- and bike-miles) is associated with a 5% to 10% reduction in vehicle-miles (indicating around 500 to 1,000 fewer motor-vehicle miles), signifying a five- to ten-old 'leverage' effect (ie, 5 to 10 fewer vehicle-miles for each additional active-mode mile).

Figure 2.7 Active-mode shares and per-capita vehicle-miles travelled (reprinted from Litman, 2021, p. 11)



Other studies have found similar results. Guo and Gandavarapu (2010) found that installing sidewalks on all streets in a typical North American community would increase daily walk- and bike-miles by 0.097 on average per capita and reduce vehicle-miles by 1.142, equating to about 12 miles of reduced driving for each additional active-mode mile. Similarly, Wedderburn and Buchanan (2013) found that in New Zealand cities, each additional daily public transport trip by driving-age residents increases average daily walking (in addition to public transport access walking trips) by 0.95 trips and 1.21 km, and reduces two daily car driver trips and 45 vehicle-kilometres. Other international data indicates that each mile of increased active travel is associated with a reduction of 7 motor-vehicle-miles (Kenworthy & Laube, 1999).

Although many demographic, geographic and travel factors can affect crash risk, they tend to be stable, so for an individual and group, a change in per-capita vehicle travel tends to cause approximately proportional changes in crash risk (Ahangari et al., 2017; Litman & Fitzroy, 2023). For example, a high-risk driver may average one crash every 50,000 kilometres and a low-risk driver may average a crash every 500,000 kilometres, but if they reduce their annual travel by 30% their chance of a crash will decline about that amount, provided that the kilometres they reduce are of about average risk.

Ahangari et al. (2017) found that the strongest impact on per-capita traffic fatality rates comes from vehicle-miles travelled and vehicle ownership rates, suggesting that reducing vehicle travel overall would improve safety outcomes. However, this has to be considered against the backdrop of existing traffic congestion levels. For example, Stiles et al. (2023) found that during the Covid-19 pandemic, total United States vehicle traffic declined, leading to reduced congestion, which increased traffic speeds, crash severity and traffic deaths. However, that finding was unique, traffic deaths declined in most other countries (Yasin et al., 2021).

2.6.5 Transportation pricing measures

Section 2.1.2 noted a number of travel demand management (TDM) measures that can affect traveller risk, although they are arguably out of scope for this project. TDM includes a variety of transportation pricing reforms including fuel tax increases, cost-recovery highway and bridge tolls, congestion pricing intended to reduce urban congestion problems, parking pricing intended to recover parking facility costs and manage demand, and distance-based vehicle fees (converting fixed vehicle taxes, registration fees and insurance premiums into distance-based charges). All of these can cause significant changes in vehicle travel and therefore crash risk. While it is not likely that this project’s initial model will capture these effects, it is useful to consider how they may indirectly affect safety.

Several researchers have performed regression analyses of fuel prices and traffic crash data. Best and Burke (2019) analysed 1989 to 2017 data in New Zealand and found a negative relationship between fuel prices and key road-risk outcome variables, including the number of road deaths. However, the number of serious injuries to cyclists tends to increase when fuel prices are high. A potential explanation for the cyclist safety finding is that high fuel prices lead to mode shift and a greater number of injured cyclists as a result. Without exposure data, there is no way to draw further conclusions.

Chi et al. (2012) analysed data between 1999 and 2009 in the state of Alabama in the United States, and found that higher gasoline prices decrease the incidence of all traffic crashes due to people driving less and reducing their trip frequency and distance (p. 476).

> *The results show that gasoline prices have both short-term and long-term effects on reducing total traffic crashes and crashes of each age, gender, and race/ethnicity group (except Hispanic due to data limitations). The short-term and long-term effects are not statistically different for each individual demographic group. Gasoline prices have a stronger effect in reducing crashes involving drivers aged 16 to 20 than crashes involving drivers aged 31 to 64 and 65+ in the short term; the effects, however, are not statistically different across other demographic groups.*

In contrast, Chi et al. (2013) found that fuel prices had a negligible effect on fatal crashes, although they concurred that higher fuel prices did result in a reduction in crashes of lower severities.

Both of the above studies looked at the effects of fuel prices within an individual state. Ahangari et al. (2017) tested many variables (including fuel prices) to determine their effects on variations in traffic fatalities between states. They found that fuel prices had a weak explanatory power on traffic fatalities, agreeing with Chi et al. (2013) that effects on serious crashes are minimal.

London's congestion-pricing programme reduced traffic crashes in the charging zone by 46%, and in adjacent areas, while other cities with congestion pricing, such as Oslo and Stockholm have some of the world's lowest per-capita crash rates (Ding et al., 2021). Raftery (2023) observed that (p. iii–iv):

> *In 2003 the city of London in the UK introduced a congestion charge (the London Congestion Charge or LCC) as a measure to reduce traffic delays associated with congestion. Following the introduction of the LCC, car trips reduced while trips by bicycle, motorcycle, taxi, and public transport increased, and congestion reduced by 30%. A general reduction in crashes was reported by studies examining the effect of the LCC, but findings regarding the effect on cycling casualties are less clear, with studies reporting a reduction, no change, or an increase. Reduction in traffic congestion has also been associated with increases and greater variation in travel speeds, which, while good for travel time, can increase the likelihood of crashes and the severity of injuries in those crashes, particularly for vulnerable road users. The reduction of crashes observed in the LCC studies are likely due to reduced vehicle volumes.*

Other studies on the London congestion charge (Green et al., 2016; Li et al., 2012; Noland et al., 2007) also commented on its impact on crash frequency. Noland et al. (2007) analysed the safety impacts of the charge, but found no significant changes to crash rates aside from a slight decrease in minor injuries to passengers. The authors theorised this may be due to the limited change in mode shift observed at that stage of the congestion charge. Li et al. (2012) modelled the changes caused by the London congestion charge, showing its significant impact on road casualties. These authors all looked at similar trends, but came to different conclusion; this may be due to the investigation of crashes compared to casualties, and the timeframes of data used to model the changes observed in London. Green et al. (2016) hailed the London congestion charge as a triumph of economics and, being the first congestion charge of its kind, an example for other cities. The authors noted that the charge could result in a reduction in traffic incidents. However, they only looked at it from a theoretical point of view.

In some cases, while the crash may have involved a person using active transport (a person cycling, walking or using buses), the other vehicle involved could have been a car (as shown in Figure 2.4). If this car was not present, a crash may not have occurred. Thus, the impact of mode shift may decrease crash rates through decreasing people's exposure to vehicles (Frith et al., 2015).

A systematic literature review of congestion-pricing impacts on crashes found that, while some studies found short-term increases in cyclist and motorcyclist crashes and injuries, virtually all studies found overall reductions in crashes and injuries over the long run (Singichetti et al., 2021). To the degree that they reduce vehicle travel, parking fees probably provide similar crash reductions, and because they are more common and easier to implement, they are probably a better vehicle-travel-reduction strategy than roadway fees in most communities.

Distance-based pricing converts existing vehicle fees into distance-based charges, which gives motorists a new financial incentive to drive less. For example, a motorist in a 20,000 annual kilometre rate class who currently pays $1,000 annually for vehicle insurance would instead pay 5 cents per kilometre ($1,000/20,000 km), and so would save $50 for each 1,000 km reduced, reflecting the reduction in claim costs that result from reduced crash exposure. Because per-kilometre premiums incorporate all other rating factors, motorists' incentive to reduce driving increases with their risk profile, so a lower-risk driver may only pay 2 cents per kilometre and reduce driving by 10%, but a higher-risk driver who pays 10 cents per vehicle-kilometre would reduce driving by 30%, providing proportionately larger crash reductions.

Table 2.14 summarises various pricing reforms and their impacts. Total safety impacts depend on the amount and type of travel reduced. These reforms tend to be most effective and acceptable if implemented as an integrated programme that includes improvements to alternative modes, encouragement programmes, and smart-growth land-use policies. Comparisons between otherwise similar geographic areas indicate that those with more efficient transport pricing (ie, road, parking and insurance prices that reflect marginal costs) have significantly less per-capita vehicle travel and traffic casualties (typically 40% to 60% lower) than those where fuel, road and parking are significantly underpriced relative to costs (Buehler, 2010).

Table 2.14 Transport pricing reform impacts (adapted from Litman, 2014)

Pricing type	Description	Travel impacts	Traffic-safety impacts
Higher fuel prices	Increase fuel prices to finance roads and traffic services, and to internalise fuel economic and environmental costs.	European-level fuel prices reduce per-capita vehicle travel 30% to 50% compared with North America. Affects most vehicle travel.	Reducing vehicle travel provides about proportionate or greater crash reductions (ie, a 30% mileage reduction provides a 30%+ fatality reduction).
Road pricing	Tolls to reduce congestion and generate revenue.	Typically reduces affected vehicle travel by 10% to 30%. Usually applied on a limited number of highways and in large city centres.	Decongestion fees that increase urban traffic speeds could theoretically increase risks, particularly to pedestrians, but in practice they generally reduce per-capita crash rates by 20% to 40%.
Parking pricing	User fees to finance parking facilities. Can also include parking cash out and unbundling.	Typically reduces affected vehicle trips by 10% to 30%. Most common in city centres, campuses and hospitals.	Can significantly increase safety where applied. Because it is relatively easy to implement, can be widely applied.
Distance-based pricing	Pro-rates vehicle insurance premiums and registration fees	Fully pro-rated pricing typically reduces affected vehicle travel by 8% to 12%, although most current examples have smaller price and travel impacts.	Potentially large safety benefits for affected vehicles. If widely applied, can provide large total safety benefits.
Public-transport fare reductions	Reduce fares and provide other commuter public-transport benefits to make public-transport travel more attractive and affordable.	A 10% fare reduction typically increases ridership by 3%, although only a portion of this substitutes for driving.	Fare reductions alone have modest impacts, but integrated programmes can provide large safety benefits.

2.6.6 Summary of findings

Many demographic, geographic, and economic factors can affect how and how much people travel, and the resulting crash risks. Mode shifts can have various safety impacts, depending on specific factors related to who, what (mode), where, how, when and why travel changes. The research reviewed in this study suggests that mode shifting that reduces total per-capita vehicle-kilometres generally reduces total per-capita crash casualties, considering all road users. Several factors can contribute to this including reduced total traffic-risk exposure where traffic density declines, reduced external risk that motor vehicles impose on other travellers, increased caution if drivers expect more vulnerable road users, and reductions in driving by higher-risk (young males, seniors and impaired) groups where there are better non-auto alternatives. However, the level of driving reduction depends on context; any short-term uncertainty about safety improvements is only likely to result in mode changes and subsequent crash reductions in the longer term.

The United States' experience during the Covid-19 pandemic suggested that reductions in traffic congestion could increase serious crashes, but that was a unique event. In most other situations, reductions in per-capita vehicle travel result in comparable or larger reductions in total (all traveller) per-capita crash casualties. To the degree that congestion reductions can increase crashes, congestion-reduction programmes should be implemented with targeted speed-management policies and programmes.

Research on single-bicycle crashes suggests that the safety-in-numbers effect applies both to crashes with motor vehicles and single-bicycle crashes, although this conclusion was reached by comparing geographies, rather than comparing one location through time.

2.7 Modelled mode-shift impacts on safety

As noted in section 1.2, the key objective of this research is to better understand the impacts on safety of changes to travel mode usage. However, there have been some efforts previously to attempt to address this question.

Although based on 20-year-old data, Austroads research (Cairney, 2010) is highly relevant in that it focused on the extent and impact of mode shift on DSIs. Impacts were looked at Australia-wide through a lens of Australia's national road safety strategy targets. This research developed a model to estimate the impact of mode shift using the following data sources:

- surveys of day-to-day travel in Australia, from Socialdata (including Australia-wide estimates of the exposure, travel by state, mode, gender, age group and time of day and crash rates)
- a 2004 survey of motor vehicle use
- 2003 Census data from the Australian Bureau of Statistics estimating travel by car drivers, car passengers and motorcyclists
- crash data from data sets provided by Austroads member authorities.

DSI rates were estimated for different modes using corresponding travel estimates as two different models, a 'power model' only and a power model combined with a linear model.

Results of this research indicated that traveling as a passenger in a car is the safest mode of transport followed by traveling as a driver. This seems slightly at odds with other studies that found buses to be safest. Motorbikes were the least safe mode with around 30 times the injury rates of travel by car. Possible mode-shift impacts were estimated as shown in Table 2.15 (using one or a combination of models).

Table 2.15 Impact of mode shift, as reported by Cairney (2010)

Mode shift from driving a car to	Model	Impact on the party shifting modes
Biking	Power	Reduced DSIs
Walking	Power	Increased fatalities and decreased serious injuries
Using the bus	Power	Moderate reduction in crashes
Being a passenger	Power and linear	Reduced deaths and injuries
Using a motorcycle	Power and linear	Increased deaths and injuries

Raftery (2023) conducted a literature review in 2017 and found that (p. iii):

> *Several studies have sought to calculate the risk for different modes of transport using either the number of trips, distance travelled, or time spent travelling as exposure variables (i.e., the number of casualties per 100 million trips, per billion kilometres, or per million hours travelled). While there is some variation in the risk rates across studies there is a general trend suggesting a hierarchy such that the order of risk from greatest to least is motorcycle/moped/scooter > bicycle > walking > passenger vehicle > bus.*

Elvik (2009) modelled the safety effect of various reductions in car traffic, finding that significant levels of mode shift (resulting in a 50% reduction in vehicle volumes) is required for safety to start improving.

Schepers and Heinen (2013) modelled the effect of shifting 10%, 30% and 50% of short car trips to cycling, assuming constant casualty rates per kilometre. The authors found that cyclists' risk of fatality decreased significantly at all levels of mode shift, but that the overall raw number of fatalities remains static, while for serious injuries, the raw numbers increase. When risk is reduced by 20%, numbers decrease, suggesting that investing in safer infrastructure alongside a mode shift to cycling will likely improve overall safety outcomes, while increasing cycling mode share without associated safe cycling infrastructure leads to worsened safety outcomes.

Marques and Hernandez-Herrador (2017) investigated the safety impacts of the rapid expansion of Seville's bicycle network. Their findings showed that crash risk for cyclists significantly reduced after the extension of the network, and found that the safety-in-numbers effect was modelled at the same rate as Jacobsen (2003).

2.8 Summary of literature review

The literature review found that most areas of input to the model have been studied, with many areas nearing academic consensus on relationships. Most studies only considered a few modes and did not explore multiple relationships, and many failed to consider interactive effects, such as external risks to other travellers. Research in New Zealand is limited, particularly when it comes to non-motor-vehicle modes of transport. Newer modes of transport (such as micro-mobility) have been covered less, though there is a growing body of research in the New Zealand context.

2.8.1 Key findings

Some key findings from the literature review include the following.

- Census data is inadequate because it only measures the primary commute modes. The HTS provides a good base for deriving modal usage.
- All sources of crash data have advantages and disadvantages, though all tend to have problems with under-reporting crashes that are lower in severity, and crashes not involving motor vehicles.
- Micro-mobility is a newer mode of transportation, and many datasets (for both usage and crashes) have only recently begun collecting data for these modes, or differentiating between them and related modes (eg, regular bicycles versus e-bikes).
- In almost all cases, on a per-kilometre basis, the least safe modes of travel are by motorcycle, bicycle and other two-wheeled devices, and walking, while the safest tends to be public transportation.
- Conversely, if considering external risk (ie, traffic fatalities caused by a mode), motor vehicles tend to have the worst safety outcomes, with public-transport risk being highly dependent on the context.
- While walking and cycling tend to have some of the highest per-kilometre risks of all modes, higher walking and cycling mode share correlates strongly with better safety outcomes overall. This probably reflects the combination of reduced risk to other road users, reductions in total travel and risk exposure, and more caution by drivers when they expect more active-mode users.
- Providing safer mode-specific infrastructure (eg, complete sidewalk networks, separated bicycle paths, lower roadway traffic speeds) improves safety, both for the mode in question and for all other modes.
- The safety-in-numbers effect has been confirmed by multiple studies, finding that increases in cycling result in reduced crash risk at an individual level. Some research also suggests that this may occur at a certain threshold.

- In almost every case studied, reductions in total motor VKT causes similar magnitude reductions in crash casualties. Where infrastructure changes have been made, VKT reductions are associated with improved safety outcomes.

While many studies have looked at the impacts of infrastructure on mode shift (to cycling in particular), and some studies use modelling techniques to estimate the safety impacts of cycling mode share increases, none were found that link all three together. That is, no research was found that answers the question of: when improved safe infrastructure is the cause of an increase in cycling mode share, is there a negative or positive overall safety impact on the transport system? This question is pertinent to this study, as cycling mode share increase tends to be a result of other factors that impact safety.

2.8.2 Data limitations

All of the research reviewed has its own limitations. Some of the more significant recurring patterns of limitations include:

- under reporting of crashes
- long-term improvements in safety as newer models are adapted to (by both infrastructure and people) making prediction models inaccurate
- limited data on distances travelled using active modes
- the use of estimations to calculate the number of collision and injuries involving active modes
- limited data on the modes used to chain trips together (eg, walking to use public transport).

New Zealand data was limited to three primary sources, which were used in almost every study: the Ministry of Transport's HTS, ACC claims data and CAS data. These datasets have been used to calculate under-reporting rates for different travel modes, such as by Turner et al. (2006) and Koorey et al. (2023). Both studies show that under-reporting rates are higher for lower-severity crashes and show differences in under-reporting rates by travel mode.

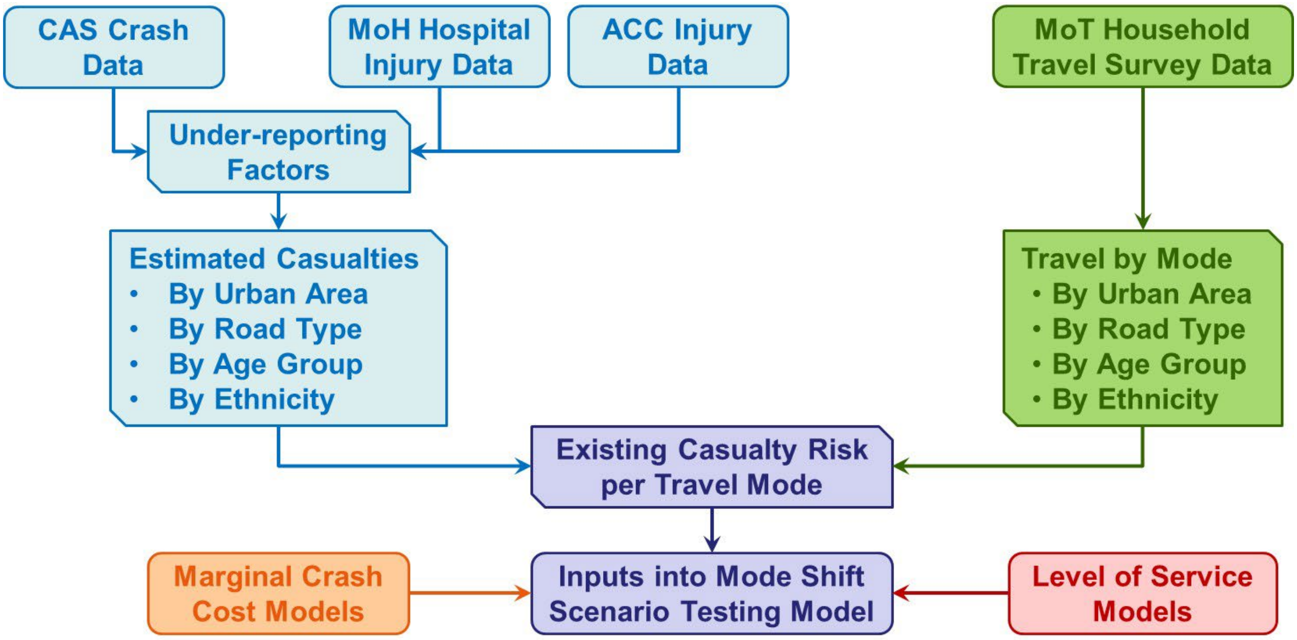
3 Analysis of personal and collective safety impacts

To understand the safety impacts of mode shift, existing crash and casualty risk rates (per kilometre or hour travelled) will be included in the model database. This requires several data sources:

- existing crash and casualty data (scaled for under-reporting)
- existing travel mode usage (kilometres or hours travelled)
- predictions of how risks change by exposure (marginal cost models)
- predictions of how risks change with improved environments or levels of service.

Figure 3.1 illustrates how the various data sources have been combined to better understand how mode-shift impacts safety outcomes. Note that we were unable to estimate casualties or travel usage by road type, due to limitations in the available datasets.

Figure 3.1 Data sources and combination process



Other factors considered include:

- the level of under-reporting of crashes, which depends on travel mode, severity, and motor vehicle involvement
- risk differences in different environments – the average crash rates nationally may not reflect individual locations of travel, including different urban areas
- differences within populations – different age, gender and ethnicity groups may have different risks, which may have implications if they change modes (unfortunately estimation of crash rates by disability groups was not possible)
- the risk associated with 'linking journeys' between modes, for example walking, cycling, wheeling or driving to or from public transport, where these parts of the journey may be riskier than the public-transport component of the trip
- the effect of changes to transport environments; for example, the possibility of improvements being made to facilities while mode shift occurs

- the proportion of all reported transport-related injuries that involved a motor vehicle, in other words, if there was a mode shift from private vehicles to public transport then the exposure to harm is decreased by there being fewer vehicles in the system that can cause injury to people outside of vehicles.

This chapter briefly discusses the key matters investigated in this study regarding safety impacts. Full details are referred to in the various appendices. Note that a number of the values determined are provisional estimates to provide a placeholder value in the model, but are subject to further research confirming these values.

Broadly speaking, for each travel mode analysed, the estimated change in the number of DSIs with a change in mode shift has been calculated in the following manner:

$$[\textit{Predicted DSIs}] = [\textit{Existing DSIs}] \times [\textit{Future VKT}] / [\textit{Existing VKT}] \times \pi_j [\textit{Infra}_j] \times f(\textit{Marginal-Crash-Rate}) \quad \text{(Equation 3.1)}$$

Where:

$\pi_j [\textit{Infra}_j]$	= a multiplicative combination of factors to improve crash rates, associated with improvements to pedestrian or cycle infrastructure, as described in sections 3.4 and 3.5
f(Marginal-Crash-Rate)	= a correction of the marginal crash rate, based on changes to relevant travel mode volumes, as described in section 3.2.

Prior to any further self-determined changes to future VKT volumes, the existing VKT volumes of car, bike or scooter, pedestrian and bus trips are also initially increased when they form part of a trip-chain with any increases in public-transport usage, as described in section 3.3.

3.1 Travel mode usage and crash risk

The Ministry of Transport's HTS data in conjunction with crash and casualty data from CAS and the Ministry of Health and ACC has been used to understand travel risk by mode and other demographic sub-groups (gender, age and ethnicity). Appendix A provides more detail about the different demographic groups used for this study.

Data from the NZTA's CAS involves a high degree of under-reporting, especially when no motor vehicles are involved and for lower-severity crashes. Hospital and ACC data can give a better idea of the scale of the problem for different road users. As the focus of this study is on DSIs (which are most likely to result in a hospital admission), the Ministry of Health hospital dataset has been employed as the key source of relevant transport injuries and deaths. Appendix G outlines the preparation and analysis involved to identify the relevant transport modes, injury severity, and other information from this dataset.

As a starting point, the model assumes a straight linear relationship between travel mode VKT and resulting DSI numbers (eg, a doubling of VKT would lead to a doubling of DSIs) before other factors described in the following sub-sections are introduced.

3.2 Marginal crash risks

As noted in section 2.6.1, transport mode crash numbers do not typically operate linearly relative to usage. It is important therefore that the relative risk of each travel mode is adjusted to allow for likely changes when volumes change – this also includes adjusting for any concurrent changes in interacting travel mode usage levels as well.

Based on the crash-prediction models outlined in section 2.6.1, factors were built into each of the future-crash-rate estimates to account for likely changes in risk. These used coefficients determined following a review of the various traffic models described in the relevant literature, and summarised in Table 3.1.

Table 3.1 Assumed crash-prediction model coefficients

Travel mode	VKT variables	Main mode b1	Motor vehicle b2	Sources and section of report where cited
Motor vehicles	[M.Veh Mode VKT] ^{b1} × [All motor traffic VKT] ^{b2}	0.8	0.8	ViaStrada (2022), section 7.2
Cycling	[Cycle VKT] ^{b1} × [Adjacent traffic VKT] ^{b2}	0.2	0.4	ViaStrada (2022), section 7.2 NZ Transport Agency (2018), section 7.1 and 7.2 Turner et al. (2009), section 5 Turner et al. (2006), section 6
Pedestrian	[Pedestrian VKT] ^{b1} × [Adjacent traffic VKT] ^{b2}	0.4	0.6	ViaStrada (2022), section 7.2 NZ Transport Agency (2018), section 4.2 Turner et al. (2006), section 6
Trains	[Train VKT] ^{b1} × [Adjacent traffic VKT] ^{b2}	0.4	0.3	NZ Transport Agency (2018), section 6.5

The above coefficients were determined by inspecting a selection of relevant studies for each model type and assessing appropriate best-estimate values. These coefficients could be adjusted in the final model to test other values. However, it is likely that some would need to vary greatly to get a big difference in the resulting marginal costs.

It is notable that in all cases the model exponents are less than 1, that is, a doubling of VKT would lead to less than a doubling in crashes. This illustrates the safety-in-numbers effect commonly found in most crash relationships.

Note that the b_2 coefficient is applied to the combined total change of VKT in all motor vehicles (VKT_{MV}), namely cars and light vehicles, trucks, motorcycles and buses. This reflects the fact that it is likely that all adjacent motor traffic contributes to the relative crash risk of other modes.

The effect on the resulting crash rates can be calculated thus for each mode M with a VKT of VKT_M:

$$[DSIs_{New}] = [DSIs_{Existing}] \times ([New\ VKT_M] / [Existing\ VKT_M])^{b1} \times ([New\ VKT_{MV}] / [Existing\ VKT_{MV}])^{b2}$$

(Equation 3.2)

For example, if cycling VKT increased by 50% (relative), while motor-vehicle VKT is reduced by 1%, then the resulting change in cycle DSI numbers would be $(1.50 / 1.00)^{0.2} \times (0.99/1.00)^{0.4} = 1.08$ higher. However, because cycle VKT have increased by 50%, the effective change in the cycle DSI rate would be (1.08 / 1.50) = 0.72 or a 28% reduction.

3.3 Trip chains associated with public transport

As discussed in section 2.3.4, trip chaining occurs when a person's journey comprises using multiple travel modes along the way. This is particularly a common issue with public-transport trips, where the travel to and from the public-transport leg may be made by other travel modes, such as driving and walking, but potentially also by cycles and other wheeled devices and even buses feeding into ferry or train trips.

Appendix B summarises the key analysis work undertaken to establish trip-chaining patterns for New Zealand public-transport trips. Section B.4 is a particularly useful component to the model, as it analyses the relative use of modes supporting public-transport trips, in terms of relative distances travelled, and is thus used to predict the increase in supporting modes, such as walking and cycling, when use of buses, trains or ferries increases.

For example, every additional kilometre of bus travel undertaken in Auckland is likely to be associated with an average of an extra 0.19 km driven, 0.01 km cycled, and 0.07 km walked. Therefore, the base VKT amounts for car and light vehicles, cycling and walking are adjusted accordingly to take these into account.

Although not strongly reflected in the HTS data yet (there was only one trip recorded), there is growing evidence that wheeled devices such as e-scooters are likely to also feature in first/last-mile journeys associated with public transport. For example, in their review of micro-mobility use in Auckland, Martin et al. (2021) cited evidence that one in five users said they currently rode shared e-scooters to and from public-transport stations. It is likely that these trips may be replacing both existing walking and cycling trips to and from public transport, and possibly other traditional linking modes, such as driving and busing. Therefore, for now, we have made an assumption that 20% each of the increased VKT attributed to cycling and walking to and from public transport should be added to e-scooters instead. This will require further future research to confirm more accurate estimates.

3.4 Effects of improvements to walking and cycling levels of service

Section 2.5.2 reported on numerous studies where increased quality of pedestrian and cycling facilities were shown to reduce crash rates and the severity of crashes. As well as safety impacts, the quality of infrastructure is also associated with higher levels of active mode use such as cycling, as discussed in section 2.5.2.

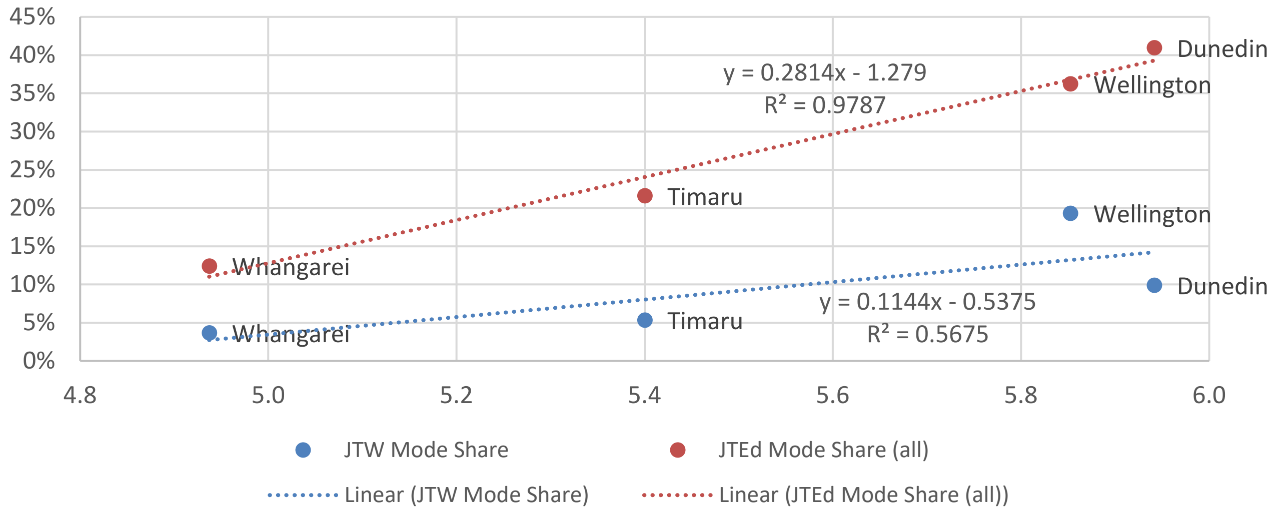
There are numerous pedestrian or cyclist level of service tools. However, few have been developed for evaluating more than a single corridor (eg, a neighbourhood, city or nation), and most are not quantitative in their outputs. Two recent models (unpublished), developed for evaluating the Whangarei District Council and Dunedin City Council's urban active-mode networks were utilised to create a model for New Zealand. The two models have been further refined with data from other cities to estimate the mode shift resulting from changes in infrastructure that improves pedestrian level of service (PLOS) and cycling quality of service (CQOS).

Appendix C describes the work undertaken to determine CQOS scores for different urban areas, and the resulting impact on cycling usage levels and (provisionally) cycle safety risks. The resulting model allows one to assess the effect of hypothetically adding additional cycling infrastructure to any major city in New Zealand (in terms of kilometres of facility).

A separate, less detailed analysis has been undertaken looking at the effect on usage of journey to work and education and study walking trips (from the 2018 Census data) compared with the relative PLOS in four New Zealand cities.

Figure 3.2 shows the resulting relationship. Although the sample is limited, the correlations are reasonably strong. Ideally over time, a large sample of data points would be collected, and other potential factors also incorporated (eg, terrain and climate).

Figure 3.2 Relationship between journey to work or study walking share and pedestrian level of service



Note: JTW = journey to work; JTEd = journey to education and study

The findings suggest that for every 0.1 improvement in PLOS there is a 2.81% (absolute) increase in journey-to-education walking trips and a 1.14% increase in journey-to-work trips. HTS data for 2015 to 2021 (Ministry of Transport, 2021) indicates that the numbers of these walking trips are roughly even (about 52% and 48%, respectively), so a trendline interpolated halfway between the two in the figure is assumed as representative of the growth in pedestrian trips overall. If the PLOS values around the mid-point of the dataset are assumed as a base (ie, 5.4), then every 5% relative improvement in this score would see a 33% increase in walking trips. For this model, a conservative estimate has been applied of a 25% increase in walking trips for every 5% improvement in PLOS.

At present, no clear research has been identified that shows a relationship between PLOS and changes to pedestrian crash risk. However, it would seem logical that an improvement in walking conditions should also result in a corresponding improvement in pedestrian safety. As a conservative estimate for the model at this point, it has been assumed that every 5% improvement in PLOS would correspond to a 5% reduction in pedestrian DSI risk.

3.5 Effect of improvements in pedestrian access to public transport

As noted in section 2.3.4, additional public-transport trips can lead to additional risks for other more vulnerable travel modes that connect to these services. Therefore, ideally efforts should be made to improve the relative safety of these first/last-mile journeys as well.

Previous research from Auckland focussed on the safety of people travelling outside vehicles (ViaStrada, 2021) and identified that a reasonable proportion of total pedestrian injuries involved people trying to access public transport. Not all of these public-transport journey injuries involved a motor vehicle either; many involved a person tripping or slipping when running for the bus or on an uneven surface while catching the bus, or when boarding. The authors hypothesised that improved pedestrian access to public transport may reduce the number of these injuries. Interventions to achieve these safety gains may include those that reduce the likelihood of tripping and falling, such as raised pedestrian crossings, or other raised platform crossing types from the standard safety intervention toolkit (Waka Kotahi NZ Transport Agency, 2021b) where the crossing tripping hazard is effectively mitigated.

Few studies have examined the access modes to public transport, and the percentage decrease in DSIs from improving pedestrian access to public transport. A before and after comparison crash study using a substantial number of bus stops would need to be undertaken to gather statistically meaningful data on the effect that access to public transport has on safety. The level of service or quality of service of each bus stop would need to be quantified.

For the purposes of this model, we have made a simple assumption that any pedestrian improvements to accessing train or bus services would improve the DSI risk of those trips by 20%. These savings have only been applied to the pedestrian trips directly associated with any train or bus journeys.

3.6 Safety impacts not explored in this research

There are a number of impact interventions not directly explored in this study, which probably warrant further investigation for an updated version of the model. Section 5.2.1 summarises some of these (and other) recommendations for consideration in further developments of the model.

One such factor is the effect of speed management on safety. This could be separated into improving speed management at a network level, and at the corridor level. There is good evidence about the safety effects of speed reductions on all travel modes, and also some evidence that lower speeds can encourage greater take-up of active modes. The effect on mode shift of posted speed-limit changes only, and the effect of physical interventions, could be investigated separately.

Given that speed is a key function of safety, the effect of congestion (where speeds are usually decreased) on crash frequency and DSIs could also be investigated. The introduction of some improvements to walking, cycling and public-transport infrastructure networks (such as raised crossings, reallocated traffic lanes and reprioritised signal timings) often also lead to reductions in motor-vehicle speeds, which can have the side effect of reduced DSIs. The links between the use of congestion pricing, mode shift, crash frequency and DSIs could also be better understood.

Another issue that was unable to be developed in this version of the model was the separation of DSIs for each mode into those involving other parties and those involving the traveller alone. For example, a pedestrian could be involved in a collision with a motor vehicle, or they could be injured from a slip on a footpath. Different interventions may affect the relative DSI risk of each type of incident, for example a reduction in the amount of motor traffic would probably improve the former risk, but have very little impact on the latter risk (which may be better served by level-of-service improvements to the walking network).

Section 2.6.4 highlighted considerable evidence suggesting that mode shift from driving is often accompanied by a reduction in the amount of motor-vehicle VKT that is greater than the increase in corresponding VKT by the substituted mode, and that this is often due to people having a relatively fixed travel-time budget. This could mean, for example, that each kilometre shifted from driving at (say) 40 km/hr to walking (typically 4 km/hr) actually reduces about 10 vehicle-kilometres of driving (=40/4), and each kilometre shifted to biking (typically 20 km/hr) reduces about 2 vehicle- kilometres (=40/20). The actual values to use require further investigation, but could be a useful enhancement to a future version of the model.

The data for the model currently includes both urban and rural travel and casualty data. While the focus of much of this study is on potential changes to mode shift in urban areas, DSIs typically have different risk profiles in urban vs rural environments, largely due to the difference in travel speeds and resulting crash severity. It could be worth exploring these differences further in the future.

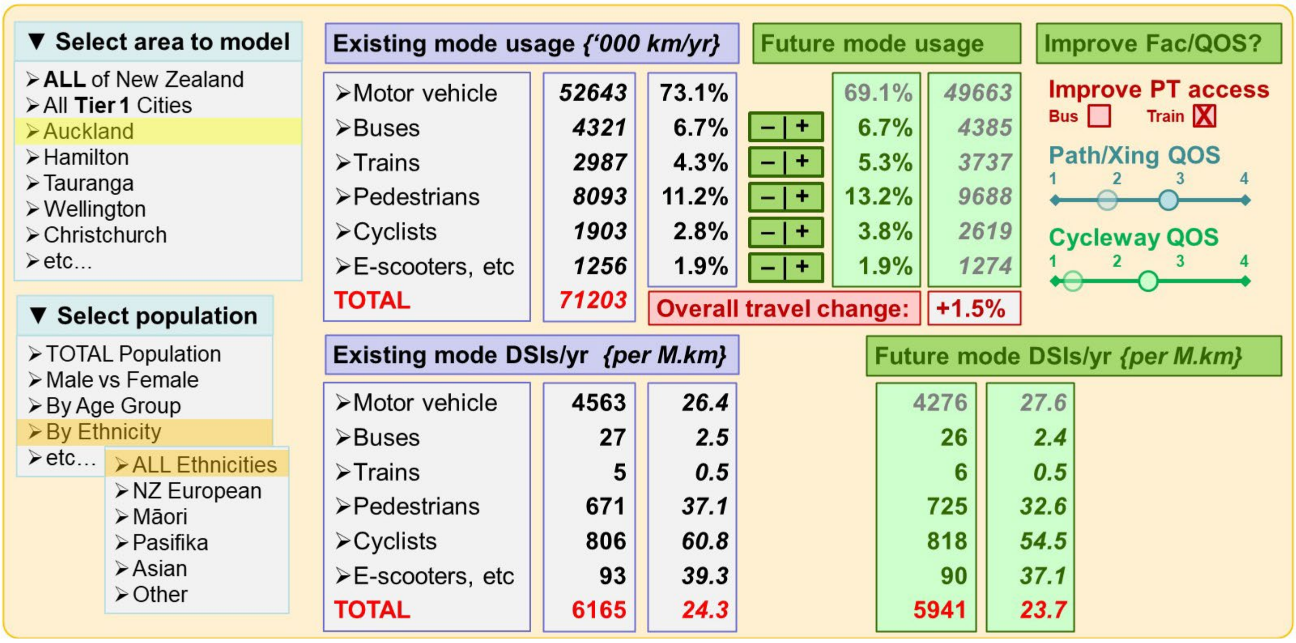
4 Model for mode-shift scenario testing

Building on the findings from the above analysis, an Excel spreadsheet-based model was developed to enable mode-shift scenario testing for various situations. The model[8] allows users to select a combination of region and demographics, and adjust the future mode usage for this combination. From this, the potential road-safety outcomes will be calculated, both in total terms, and by exposure (per kilometre or hour travelled).

4.1 Model overview

The original mock-up structure proposed for the final model (following some feedback from the steering group) is presented in Figure 4.1.

Figure 4.1 Mock-up of proposed spreadsheet tool



The final model had some changes made to this draft version, namely:

- all inputs used drop-down lists rather than push buttons, to avoid having to include macros in the final spreadsheet tool
- the tool was set up to only allow one demographic group (age, gender or ethnicity) to be sub-selected at any one time
- the motor-vehicle mode was split into cars and light vehicles, trucks, buses, and motorcycles
- additional rows were provided for travel by passenger train and ferry
- a more comprehensive means of specifying additional cycle facilities to be built was added
- more explicit information was provided about the impact of different improvements on changes to travel mode trips and DSIs.

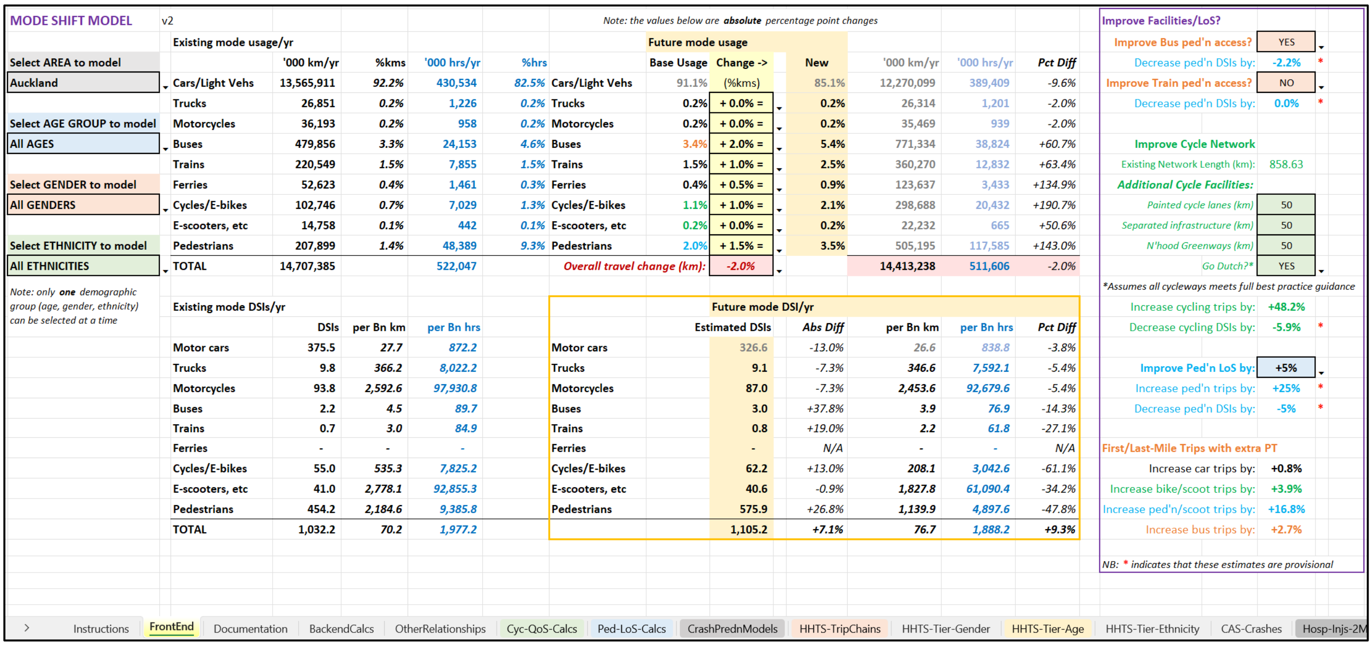
The final structure has:

[8] The model can be found at this link: www.nzta.govt.nz/resources/research/reports/728

- a front-end tab where all inputs and outputs are presented – this is the only tab the end-user is required to interact with
- a back-end tab that performs the bulk of the underlying calculations
- further intermediate step tabs that are used to calculate various sub-elements of the models for trip usage, modal shift, and resulting DSI figures
- various background tabs that provide the model with the processed usage (HTS) and casualty (CAS and Ministry of Health) data.

Figure 4.2 illustrates the front-end tab of the final spreadsheet tool produced.

Figure 4.2 Final mode-shift spreadsheet tool



MODE SHIFT MODEL v2

*Note: the values below are **absolute** percentage point changes*

Select AREA to model	Auckland
Select AGE GROUP to model	All AGES
Select GENDER to model	All GENDERS
Select ETHNICITY to model	All ETHNICITIES

*Note: only **one** demographic group (age, gender, ethnicity) can be selected at a time*

Existing mode usage/yr	'000 km/yr	%kms	'000 hrs/yr	%hrs
Cars/Light Vehs	13,565,911	92.2%	430,534	82.5%
Trucks	26,851	0.2%	1,226	0.2%
Motorcycles	36,193	0.2%	958	0.2%
Buses	479,856	3.3%	24,153	4.6%
Trains	220,549	1.5%	7,855	1.5%
Ferries	52,623	0.4%	1,461	0.3%
Cycles/E-bikes	102,746	0.7%	7,029	1.3%
E-scooters, etc	14,758	0.1%	442	0.1%
Pedestrians	207,899	1.4%	48,389	9.3%
TOTAL	14,707,385		522,047	

Future mode usage	Base Usage	Change ->	New	'000 km/yr	'000 hrs/yr	Pct Diff
Cars/Light Vehs	91.1%	(%kms)	85.1%	12,270,099	389,409	-9.6%
Trucks	0.2%	+ 0.0% =	0.2%	26,314	1,201	-2.0%
Motorcycles	0.2%	+ 0.0% =	0.2%	35,469	939	-2.0%
Buses	3.4%	+ 2.0% =	5.4%	771,334	38,824	+60.7%
Trains	1.5%	+ 1.0% =	2.5%	360,270	12,832	+63.4%
Ferries	0.4%	+ 0.5% =	0.9%	123,637	3,433	+134.9%
Cycles/E-bikes	1.1%	+ 1.0% =	2.1%	298,688	20,432	+190.7%
E-scooters, etc	0.2%	+ 0.0% =	0.2%	22,232	665	+50.6%
Pedestrians	2.0%	+ 1.5% =	3.5%	505,195	117,585	+143.0%
Overall travel change (km):		-2.0%		14,413,238	511,606	-2.0%

Existing mode DSIs/yr	DSIs	per Bn km	per Bn hrs
Motor cars	375.5	27.7	872.2
Trucks	9.8	366.2	8,022.2
Motorcycles	93.8	2,592.6	97,930.8
Buses	2.2	4.5	89.7
Trains	0.7	3.0	84.9
Ferries	-	-	-
Cycles/E-bikes	55.0	535.3	7,825.2
E-scooters, etc	41.0	2,778.1	92,855.3
Pedestrians	454.2	2,184.6	9,385.8
TOTAL	1,032.2	70.2	1,977.2

Future mode DSI/yr	Estimated DSIs	Abs Diff	per Bn km	per Bn hrs	Pct Diff
Motor cars	326.6	-13.0%	26.6	838.8	-3.8%
Trucks	9.1	-7.3%	346.6	7,592.1	-5.4%
Motorcycles	87.0	-7.3%	2,453.6	92,679.6	-5.4%
Buses	3.0	+37.8%	3.9	76.9	-14.3%
Trains	0.8	+19.0%	2.2	61.8	-27.1%
Ferries	-	N/A	-	-	N/A
Cycles/E-bikes	62.2	+13.0%	208.1	3,042.6	-61.1%
E-scooters, etc	40.6	-0.9%	1,827.8	61,090.4	-34.2%
Pedestrians	575.9	+26.8%	1,139.9	4,897.6	-47.8%
	1,105.2	+7.1%	76.7	1,888.2	+9.3%

Improve Facilities/LoS?		
Improve Bus ped'n access?	YES	
Decrease ped'n DSIs by:	-2.2%	*
Improve Train ped'n access?	NO	
Decrease ped'n DSIs by:	0.0%	*
Improve Cycle Network		
Existing Network Length (km):	858.63	
Additional Cycle Facilities:		
Painted cycle lanes (km)	50	
Separated infrastructure (km)	50	
N'hood Greenways (km)	50	
*Go Dutch?**	YES	
**Assumes all cycleways meets full best practice guidance*		
Increase cycling trips by:	+48.2%	
Decrease cycling DSIs by:	-5.9%	*
Improve Ped'n LoS by:	+5%	
Increase ped'n trips by:	+25%	*
Decrease ped'n DSIs by:	-5%	*
First/Last-Mile Trips with extra PT		
Increase car trips by:	+0.8%	
Increase bike/scoot trips by:	+3.9%	
Increase ped'n/scoot trips by:	+16.8%	
Increase bus trips by:	+2.7%	

*NB: * indicates that these estimates are provisional*

It is important to note that the model should *not* be used solely to justify or target any particular modal mix. Mode shares affect many different societal factors, including travel time, travel reliability, greenhouse gas emissions, accessibility, public health, and community severance. All of these effects – together with safety effects – need to be considered in a comprehensive cost-benefit analysis before policymakers implement measures to target a particular modal profile.

4.2 Model input data

In the spreadsheet tool, the user can select a geographic urban area (or all of New Zealand), plus up to one demographic breakdown (multiple selections are not possible due to dataset limitations). The model includes checks for when values are zero, to avoid divide-by-zero errors in the results presented.

4.2.1 Data preparation and classification

The geographic breakdown is derived from the Tier 1 and 2 urban environments listed in the *National Policy Statement on Urban Development 2022* (Ministry for the Environment, 2022). All other areas of New Zealand are aggregated into a broad 'rest of New Zealand' category, which contains smaller urban areas and all rural areas. Further detail on the geographic classifications used can be found in Appendix A.

Demographic breakdown is available for either gender, age or ethnicity. Further detail on demographic, geographic and travel mode classification can be found in Appendix A. These data classifications apply to

CAS, HTS and Ministry of Health data. Appendix D gives the HTS mode classification, and data cleaning of the public-transport trip data. The method of weighting HTS data using Stats NZ Census data is covered in Appendix E. Appendix F and Appendix G provide information on CAS data preparation and Ministry of Health data preparation, respectively. Finally, Appendix H reports on differences in the CAS and Ministry of Health datasets in terms of crash severity, multi-party crash rates and the geographic analysis of DSIs.

4.2.2 Usage data

Usage data has been derived from the HTS, with data from 2015/2016 to 2021/2022 (ie, 7 years). Depending on the scenario selected, weighting factors are used to estimate national usage statistics for a given combination of geography and demographic factors.

Note that the data does include a small proportion (<1% of VKT nationally) of trips made by trucks; while most truck traffic is considered commercial in nature, the HTS (which ostensibly focuses on personal travel) does record some truck journeys. For a more accurate picture of truck safety, other data sources are probably necessary to determine overall truck VKT in New Zealand and sub-areas. For example, the Ministry of Transport (2023) suggests that annual heavy and medium commercial vehicle usage in New Zealand totals over 3 billion vehicle-kilometres.

Arguably, to simplify the current exercise, truck usage and casualties could be removed altogether from the model. However, they are a key factor in the relative safety of all other travel modes due to the (often serious) risk they impose on other travellers.

For this research, no attempt has also been made to differentiate between private light-motor-vehicle journeys (ie, people using their own vehicles for personal trips), and other light vehicle use associated either with business (eg, company cars or rental cars) or passenger transport (eg, taxis and ride-share services). However, in its review of the costs of personal (for hire) transport, the Ministry of Transport (2023) noted that taxis and ride-hail services are estimated to account for <1% of total VKT for light vehicles in New Zealand.

4.2.3 Casualty data

The primary source for DSI data in the model is the Ministry of Health’s hospital admission data, with ACC and CAS data being used as a sensitivity and sense-check. Appendix G summarises the analysis undertaken to establish which hospital records were equivalent to CAS’s ‘serious’ injury rating, with Appendix H providing a comparison between CAS and Ministry of Health numbers.

Subsequent checking of the DSI numbers suggests that some miscoding of vehicle types was evident in the Ministry of Health data (for example, classifying light truck injuries as being associated with ‘trucks’). Therefore, some further adjustment of the underlying casualty database may be required.

4.2.4 Baseline usage and risk data

Notwithstanding some of the potential data accuracy issues in the first cut of the data analysis, Table 4.1 summarises the overall personal usage and travel risk for each mode across all of New Zealand. Note that, for ease of meaningful comparison between modes, travel usage by mode is presented in thousand kilometres or hours per year, while DSI risk rates are presented per billion kilometres or hours travelled.

Table 4.1 Travel mode usage and injury risk for all of New Zealand

	Existing mode usage per year				Existing mode risk per year		
Travel mode	**'000 km/yr**	**% km**	**'000 hr/yr**	**% hrs**	**DSIs**	**Per billion km**	**Per billion hr**
Cars/light vehicles	52,209,992	93.7%	1,337,590	83.1%	1,399.7	26.8	1,046.4
Trucks	463,187	0.8%	11,242	0.7%	77.3	167.0	6,879.0
Motorcycles	154,595	0.3%	4,100	0.3%	380.8	2,463.4	92,886.7
Buses	1,126,479	2.0%	50,605	3.1%	7.5	6.7	148.2
Trains	519,567	0.9%	14,612	0.9%	6.2	11.9	422.0
Ferries	119,595	0.2%	3,537	0.2%	-	-	-
Cycles/e-bikes	388,160	0.7%	29,172	1.8%	207.7	535.0	7,118.6
E-scooters, etc	17,281	0.0%	621	0.0%	121.3	7,021.3	195,381.6
Pedestrians	696,050	1.2%	158,041	9.8%	1,300.8	1,868.9	8,231.0
Total	**55,694,905**		**1,609,520**		**3,501.3**	**62.9**	**2,175.4**

Some key observations from these results include:

- Not surprisingly, private motor cars and other light vehicles currently dominate usage statistics in New Zealand, with over 93% of all vehicle kilometres travelled. However, the slower speeds of other transport modes mean that, on a duration basis, the proportion of all time spent travelling by cars and light vehicles is only ~83%.
- In comparison with the data on public e-scooter usage presented in section 2.3.2, the above usage data would suggest that there could be a similar proportion of vehicle kilometres also made by private e-scooters in New Zealand.
- As found in other literature, public-transport modes are the safest in terms of DSI risk (in fact, no DSIs were identified as being associated with passenger ferry travel).
- Although truck DSI risk is shown as much higher than the equivalent for cars & light vehicles (in contrast with the data in section 2.4.4 that suggested roughly a doubling of risk), that may possibly reflect an under-estimation of the amount of truck travel captured in the usage data and an over-estimation of casualties assigned to the truck category.
- Perhaps surprisingly, pedestrian DSI risk is quite high, higher than cycling and even close to motorcycle risk on a per-kilometre basis. However, this probably reflects the finding from ViaStrada (2021) (discussed in section 2.2.1) that found considerable under-reporting of non-motor-vehicle injuries to pedestrians due to other mechanisms such as slip, trip and fall.
- E-scooters and other similar wheeled devices appear to be the riskiest travel mode by some distance, although there could be some issues with proper categorisation of both usage and casualty statistics. The relative novelty factor of this travel mode (as alluded to in section 2.4.2) may also be skewing current risk rates.

The focus of much of this study is on potential changes to mode shift in urban areas. Therefore, Table 4.2 provides a similar summary for just the Tier 1 cities (Auckland, Hamilton, Tauranga, Wellington, Christchurch).

Table 4.2 Travel mode usage and injury risk for Tier 1 cities only

Travel mode	Existing mode usage per year				Existing mode risk per year		
	'000 km/yr	% km	'000 hr/yr	% hrs	DSIs	Per billion km	Per billion hr
Cars/light vehicles	25,139,662	92.1%	746,737	80.4%	637.0	25.3	853.0
Trucks	96,235	0.4%	3,299	0.4%	20.7	214.8	6,264.8
Motorcycles	90,969	0.3%	2,605	0.3%	172.0	1,890.8	66,033.4
Buses	761,829	2.8%	38,794	4.2%	4.7	6.1	120.3
Trains	405,388	1.5%	12,167	1.3%	3.0	7.4	246.6
Ferries	87,346	0.3%	2,500	0.3%	-	-	-
Cycles/e-bikes	242,410	0.9%	17,228	1.9%	114.7	473.0	6,655.8
E-scooters, etc	16,297	0.1%	586	0.1%	81.0	4,970.4	138,117.2
Pedestrians	458,333	1.7%	104,678	11.3%	779.3	1,700.4	7,445.1
Total	**27,298,469**		**928,595**		**1,812.3**	**66.4**	**1,951.7**

The data for Tier 1 cities is similar to the national data, but shows slightly lower usage of cars and light vehicles and corresponding increases in other travel modes. The DSI rates for almost all modes are also slightly less than the national averages, probably reflecting the lower speeds involved in urban areas.

The model assumes that, where an existing crash rate does not currently exist (possibly due to relatively low existing mode usage and hence no crashes), the average Tier 1 city rate from above will be used for future DSI risk estimates; with the exception of e-scooters and other wheeled devices, where a rate three times that of the cycling rate has been assumed.

Note that, at the Tier 2 city level, many locations did not have sufficient usage or casualty data for modes like ferries, trains, and e-scooters (either because such services do not operate there, or the HTS data did not capture any travel by these modes).

4.3 Scenario development

Once a geographic area and (if desired) a demographic group has been selected, modal usage statistics (up to +10% absolute mode shift in non-car modes) and total overall travel (up to +/- 20% relative change) can be adjusted to generate a future scenario. Future enhancements to the model could be considered later to allow modal shift changes to be expressed both in terms of absolute or relative percentage changes.

Other adjustments can also be made, including:

- cycling infrastructure can be added to adjust the cycling mode share and improve safety outcomes
- pedestrian quality of service can be adjusted to adjust the walking mode share and improve safety outcomes
- public-transport access can be enhanced to improve safety outcomes for those walking to public-transport services.

Once the future scenario has been set, new crash statistics are generated (both per kilometre and per hour travelled) for the selected geography and demographic breakdown, using the crash-prediction models derived from the existing crash statistics and relationships identified in section 3.

4.4 Scenario examples

Three example scenarios are provided, as a way of indicating the tool's capabilities based on existing mode-shift plans, as outlined in Table 4.3. For practicality reasons, we decided that the model would allow up to a 10% increase in mode share, apart from the additional gains from improved level of service or trip-chaining effects; hence at this point, it is not always possible to model the targeted mode share values, in which case the highest possible value is applied, as shown in the 'modelled' columns. Future enhancements to the model could look into extending the potential range of mode share increases provided or allowing for manual entry of target mode shares.

Table 4.3 Scenario examples

Location, plan and target year		Auckland: Transport emissions reduction pathway, 2030			Christchurch: Regional mode-shift plan, 2028			Wellington: Regional mode-shift plan, 2030		
Demographics		All ages, genders, ethnicities			All ages, genders, ethnicities			All ages, genders, ethnicities		
Mode share (% km)		Existing	Target (2030)	Modelled	Existing	Target (2028)	Modelled	Existing	Target (2030)	Modelled
Travel modes	Motor cars	92.2%	50.4%	54.3%	93.2%	90.6%	89.9%	86.3%	54.4%	53.5%
	Trucks	0.2%	0.2%*	0.2%	1.1%	1.1%	1.1%	0.3%	0.2%	0.3%
	Motorcycles	0.2%	0.2%*	0.2%	0.4%	0.4%	0.4%	0.7%	0.4%	0.7%
	Buses	3.3%	13.1%	14.1%	1.8%	3.6%	3.8%	3.9%	13.6%	13.3%
	Trains	1.5%	16.4%	11.5%	0.0%	0.0%	0.0%	4.0%	14.1%	14.0%
	Ferries	0.4%	2.2%	2.4%	0.1%	0.1%	0.1%	0.7%	2.5%	2.7%
	Cycles/e-bikes	0.7%	5.5%	5.6%	1.7%	2.0%	2.2%	1.0%	3.6%	3.6%
	E-scooters, etc	0.1%	8.7%	8.5%	0.0%	0.0%	0.1%	0.0%	0.0%	0.4%
	Pedestrians	1.4%	3.3%	3.4%	1.8%	2.2%	2.5%	3.1%	11.1%	11.5%
Total VKT reduction			-5%	-5%		0%	0%		0%	0%

Note: *Target for mode is not stated in the plan, and assumed to remain at existing (base) levels.

The further assumptions made in modelling the mode-shift plan targets are given in Table 4.4.

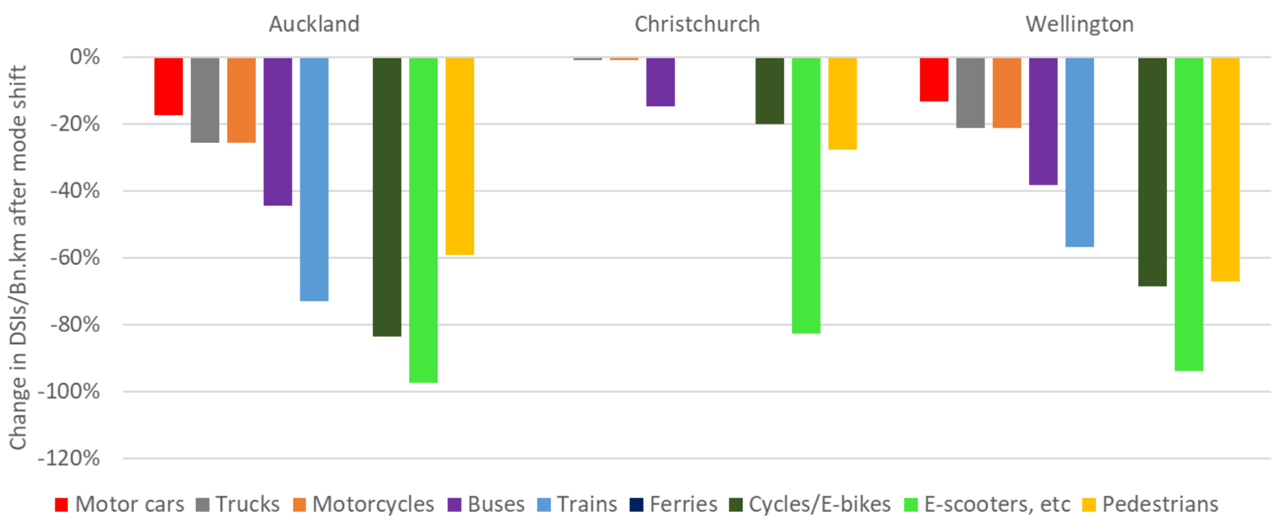
Table 4.4 Mode-shift plan assumptions made in modelling

Mode-shift plan	Assumptions
Auckland	Target percentages stated in the plan have been adjusted so that the modes studied sum to 100%. Assume improvement to bus and train access for pedestrians, in line with the plan's targets to increase public transport. Bus use increased further than target, to compensate for the model not being able to achieve the desired increase in train use (currently limited to a 10% absolute increase, as described above). Assume 4.5% increase in the three types of cycle facilities, corresponding to desired increase in cycling (excluding gains from trip chaining etc). Assume 5% increase in PLOS, corresponding to desired increase in walking.
Christchurch	Cycling and pedestrian targets have been adjusted linearly to accord with the same target year as public transport.

Mode-shift plan	Assumptions
	Remaining modes have been apportioned relative to their existing mode share. No VKT reduction stated in the plan – has been assumed to be held constant. Assume improvement to bus access for pedestrians, in line with targets to increase public transport. Assume 0.5% increase in the three types of cycle facilities, corresponding to desired increase in cycling (excluding gains from trip chaining etc). Assume 5% increase in PLOS, corresponding to desired increase in walking.
Wellington	Target percentages have been calculated to factor up public transport, walking and cycling according to their current proportions, so that they sum to 45%, with remaining modes summing to 55%. No VKT reduction stated in the plan – has been assumed to be held constant. Assume improvement to bus and train access for pedestrians, in line with the plan's targets to increase public transport. Assume 2.5% increase in the three types of cycle facilities, corresponding to desired increase in cycling (excluding gains from trip chaining etc). Assume 10% increase in PLOS, corresponding to desired increase in walking.

The predicted safety gains of applying the modelled mode shares (Table 4.3), represented as a percentage decrease compared to the base case, are shown in Figure 4.3.

Figure 4.3 Predicted safety improvements from mode-shift plan scenarios



The model predicts that the mode-shift targets from the three plans considered will have safety benefits, especially for pedestrians, cycles and wheeled devices. Public-transport modes also see moderate safety gains, while motor-vehicle modes have smaller safety improvements again.

4.5 Data limitations of the model

This model has the potential to provide considerable flexibility to assess many different mode-shift scenarios, based on existing New Zealand evidence and indicative trends from associated research.

A brief summary of the model's data limitations follows.

- The model does not automatically adjust distances travelled for each travel mode, so it doesn't account for any reductions in kilometres travelled when people shift from motorised to active modes. As a result, it is likely to significantly underestimate total reductions in per-capita crash casualties, particularly over the long run if, for example, active-mode improvements induce more shifts to public transport and provide a catalyst for more compact, transit-oriented development.
- Weighting factors for each geographic and demographic breakdown are derived from the 2018 Census, while both usage and crash statistics cover years before and after 2018.
- Hospital crash data is geographically categorised by the area in which the patient resides – it is assumed that the crash occurred within the same urban environment.
- Datasets have different methods of categorising vehicle types – the model uses the most detailed breakdown of mode possible; however, some modes are still grouped together (eg, bike and e-bike, private and public-hire e-scooters, trucks of all types).
- Geographic boundaries set during the 2018 Census have been used; however, boundaries have changed over time.
- CQOS is based on open-source data, which has varying quality and has been calculated through a process that makes assumptions about facility quality that may not reflect real-world conditions.

While none of these factors are likely to greatly affect the overall ranking of the relative personal-risk profile or the collective-risk profile across modes, they do mean that any specific instance of mode shift could have markedly different effects on DSI than is observed on average. For this first iteration of the model, a single value has been selected for each of the factors affecting overall modal shift and safety impacts. However, a model with a range of possible high and low values (ie, error margins) would be a useful improvement, to highlight the likely range and uncertainty in some of the estimates.

Some recommendations for future research and initiatives related to these limitations are discussed further in section 5.2.1.

4.6 Discussion of model results

The output results of the model may show an increase in the number of deaths and serious injuries occurring. However, the amount of travel for each mode must be taken into account. For example, the number of cyclists DSIs may have increased when more people choose to cycle, but the risk may have decreased through people cycling more.

To illustrate this, in the Netherlands, around 18.4 billion kilometres or around 1.7 billion hours are travelled by bike each year (Statistics Netherlands (CBS), 2023a), and around 230 cyclists are killed in traffic each year (Statistics Netherlands (CBS), 2023b). The total number of cycle deaths in the Netherlands is much greater than in New Zealand (approximately 12 cycle deaths per year), but the crash rates there (deaths per billion kilometres or per billion hours travelled) are relatively low, given the substantial amount of cycling that takes place. Table 4.5 shows the comparison.

Table 4.5 Cyclists killed by distance and time travelled

Country	Cyclists killed/yr	Million km travelled/yr	Million hr travelled per yr	Cyclists killed per billion km travelled	Cyclists killed per billion hr travelled
Netherlands	~232	18,411	1,679	12.6	138.2
New Zealand	~12.7	388.2	29.2	32.7	434.9

This example highlights how reductions in absolute numbers of DSIs may not always be achievable if there are substantial increases in some travel modes.

However, beyond the benefits to safety from mode shift, there are substantial public-health benefits through active transport. It is important to consider the DSIs per kilometre (or hour) travelled alongside the associated health benefits for shifting to active transport or public transport modes (where public transport includes a component of activity when a person actively travels to or from a station or stop). Enabling people to walk and cycle provides public health benefits that include lowering cardiovascular disease risk, obesity and the adverse health effects of pollution. For example, as alluded to in section 2.1.2, Lindsay et al. (2011) found that a 5% shift of vehicle kilometres to cycling would produce health effects of about 116 deaths avoided annually from increased physical activity, and six deaths avoided due to improved air pollution, whilst simultaneously incurring an increase of an additional five cyclists' fatalities.

Further research could quantify this relationship of the change in the acute DSIs of a population (studied in this research), alongside the long-term health benefits of a population, through more use of active transport. The long-term health benefits from active transport are greater than solely cardiovascular disease risk, obesity, and air pollution. Health benefits (including preventable and premature deaths) include reductions in nitrous dioxide (NO_2) and noise too. Land-use changes to pedestrian-orientated neighbourhoods in Barcelona (known as Barcelona 'superblocks') tangibly show these public-health benefits, where around 700 premature deaths are prevented annually from reductions in nitrogen oxide (around 300), heat (120), green-space development (60) and physical activity (36) (Mueller et al., 2020). A reduction of VKT, changing to active modes and reallocating vehicle infrastructure to green infrastructure has a substantive effect on long-term health benefits. Further research could quantify how mode shift affects these further health impacts. As described in section 2.1.2, these health and social impacts were considered out of scope for this research.

5 Conclusions and recommendations

This research sought to determine the actual and potential safety impacts of mode shift from private motorised vehicles to public transport, active modes and micro-mobility, in conjunction with changes to overall volume of travel by all modes. The development of the related model has resulted in a means of testing the safety impacts of different mode-shift scenarios.

5.1 Conclusions

The literature review found that most areas of input to the model have been studied. However, most studies only considered a few modes and did not explore multiple relationships, and many failed to consider interactive effects, such as external risks to other travellers. Research in New Zealand was even more limited, particularly when it comes to non-motor-vehicle modes of transport. Newer modes of transport (such as micro-mobility) have been covered less, although there is a growing body of research in the New Zealand context.

Some key findings from the literature review include the following.

- Census data is inadequate because it only measures primary commute modes. The HTS provides a good base for deriving modal usage.
- All sources of crash data have advantages and disadvantages, though all tend to have problems with under-reporting crashes that are lower in severity, and crashes not involving motor vehicles.
- Micro-mobility is a newer mode of transportation, and many datasets (for both usage and crashes) have only recently begun collecting data for this mode (if at all), or differentiating between this and related modes (eg, regular bicycles versus e-bikes).
- In almost all cases, on a per-kilometre basis, the least safe modes of travel are by motorcycle, bicycle and other two-wheeled devices, and walking, while the safest modes tend to be public transportation. Light motor vehicles (cars, vans, etc) tend to have a risk somewhere in the middle.
- Conversely, if considering external risk (ie, traffic fatalities *caused* by a mode), motor vehicles tend to have the worst safety outcomes, with public-transport risk being highly dependent on the context.
- While walking and cycling tend to have some of the highest per-kilometre risks of all modes, higher walking and cycling mode share correlates strongly with better safety outcomes overall. This probably reflects the combination of reduced risk to other road users, reductions in total travel and risk exposure, and more caution by drivers when they expect more active-mode use.
- Providing safer mode-specific infrastructure (eg, a complete sidewalk network, separated bicycle paths, lower roadway traffic speeds) improves safety, both for the mode in question and for all other modes.
- The safety-in-numbers effect has been confirmed by multiple studies, finding that increases in cycling result in reduced crash risk at an individual level. Some research also suggests that this may occur at a certain threshold.
- In almost every case studied, reductions in total motor VKT causes similar magnitude reductions in crash casualties. Where infrastructure changes have been made, VKT reductions are associated with improved safety outcomes

Based on the available literature, various relationships were identified to understand the safety impacts of mode shift. This required several data sources:

- existing crash and casualty data (scaled for under-reporting)
- existing travel mode usage (kilometres or hours travelled)
- predictions of how risks change by change in exposure (marginal cost models)

- predictions of how risks change with improved environments or levels of service.

Transport mode crash numbers do not typically operate linearly relative to usage. Therefore, the relative risk of each travel mode was adjusted to allow for likely changes when volumes change. This also included adjusting for any concurrent changes in adjacent motor-traffic usage as well. In all cases, the chosen crash-prediction model exponents were less than 1, that is, a doubling of VKT would lead to less than a doubling in crashes. This illustrates the safety-in-numbers effect commonly found in most crash relationships.

Building on the above findings, an Excel spreadsheet-based model was developed to enable mode-shift scenario testing for various situations. The model allows users to select a combination of region and demographics, and adjust the future mode usage for this combination. From this, the potential road-safety outcomes can be calculated, both in total numbers of DSIs, and by exposure (DSIs per kilometre or hour travelled).

5.2 Recommendations

This piece of research has already identified a variety of different interacting components in the complex question of the safety impacts of mode shift, and only some of them have been incorporated into the resulting model at this stage (and even some of those with provisional estimates). While this provides a starting point in attempting to address the core research-brief question, further investigation is needed on some other factors to understand them better and add them as enhancements to this model.

5.2.1 Further research and model enhancements

The data analysis and model development exercise identified several potential issues with this first draft of the mode-shift model. It is recommended that further research investigates in more detail the topics listed in Table 5.1. A reference to the related discussion of the recommendation in this report is provided in the second column.

Table 5.1 Recommendations from this research

Topic	Reference	Recommendation
Trip chaining between modes	2.3.4	A greater investigation of the impacts of trip chaining on safety, an aspect not always captured in journey data.
External versus internal risk	2.4.4	A deeper assessment of the relationships between crashes involving multiple people or vehicles, including the neutral costs ‘shared’, costs ‘imposed/caused’ to others and costs ‘borne/suffered’.
Effect of cycle facility type on safety	2.5.1, C.4	It would be useful to further investigate the relationship between the measured CQOS scores in different cities and their equivalent cycle crash rates, to determine a more robust safety relationship. Alternatively, more cross-sectional studies could explore the crash rates of different types of cycle facilities in New Zealand.
Relationship between quality of facilities and single-user crashes	2.5.2, 2.5.4, 2.6.3	An investigation of the relationship between quality of walking and cycling facilities, and crashes that do not involve an external party (eg, bicycle-only or pedestrian-only crashes).
National cycling prediction models	2.6.1, 4.3, 4.5	Further development of cycling prediction models based on improved quality-of-service-based metrics for various cycle facility types.
Relationships between demographic groups and crash statistics	2.6	A deeper dive into relationships between demographic groups, travel behaviour, and crash statistics, although this will require additional data collection.

Topic	Reference	Recommendation
Inclusion of vehicle-occupancy factor	2.3.3	Investigate the effect of including a vehicle-occupancy factor for private motor vehicles, to allow for increased ridesharing that increases personal kilometres travelled without increasing VKT to the same extent.
Add toggle for improving quality of service for pedestrians or public-transport users or motorist	2.5, C.3	A 'go Dutch' option was added to allow users to see the impact of higher infrastructure quality (a higher CQOS) on mode share. This feature could also be added for: • pedestrian quality of service • public-transport quality of service • motorist quality of service.
Effect of congestion on crash frequency and DSIs	2.6	Incorporate the safety impacts of congestion (ie, possible increase in crashes, but reduction in average severity due to lower speeds).
Methods to achieve safety from VKT reduction or mode shift	2.6	Explore further the methods of achieving VKT reduction or modal shift that result in the best safety outcomes.
Changes in average trip lengths with mode shift	2.6.4, 3.6	Investigate likely changes in average trip lengths when people change modes (which may also involve changing to a new destination), and update the model to reflect these typical changes in VKT
Model validation from international statistics	2.7	Further validate model against other countries' mode share and crash and injuries outcomes.
Effect of pedestrian access to public transport on safety	2.4.3, 3.5, B.3	Determine the percentage decrease in DSIs from improvements to access to public-transport stations and stops. An investigation may include a substantial number of bus stops, categorisation of their existing or proposed levels of service, and a comparison crash study.
E-scooter substitution for walking and cycling trips to and from public transport	3.3	Investigate how many first/last-mile trips to public transport that were previously made by walking or cycling (and possibly other modes too) are now being made by wheeled devices such as e-scooters.
Effect of PLOS improvements on uptake of walking trips and their safety	3.4	Add further cities and other potential causative factors (eg, terrain, climate) to the PLOS model to improve its predictive ability. Also review pedestrian injury rates to assess the relative safety effects of different PLOS ratings.
Incorporate safe system improvements	3.6	Add to model the possibility of improving system safety for all road users (eg, by improving the standard of roads, installing safety barriers, or reducing travel speeds.)
Urban and rural split	3.6	Add the ability for the model to split out the safety effects of rural versus urban DSIs.
Understanding truck usage	4.2.2	Introduce more precise data on total truck travel, to improve the relative risk metrics.
Understanding the role of private and company vehicles, and taxis, ridesharing and rental vehicles	4.2.2	Investigate further the relative makeup (and relative risk) of non-personal travel by cars and other light vehicles, such as company cars, rental vehicles, taxis, and ride-share services.
Improvements to vehicle and user classification	4.2.3, G.2, H.2	Refine the Ministry of Health's International Classification of Diseases (ICD) code analysis to produce an improved breakdown of vehicle and user types involved in each incident.
Absolute versus relative mode-shift changes	4.3	Add to the mode the ability to model either absolute or relative mode-shift changes.

Topic	Reference	Recommendation
Introduce error margins for model estimates	4.5	Update the model with a range of possible high and low values (ie, error margins), to highlight the likely range and uncertainty in some of the estimates.
Non-acute health impacts from mode shift	2.1.2, 4.6	Consider the long-term health outcomes of shifting vehicle transport to active transport (or public transport), alongside the change in acute DSIs (what has been presented in this research). As discussed in section 2.1.2, Lindsay et al. (2011) presented the public health change in acute DSIs, alongside the change in long-term health impacts through mode shift. Presentation of non-acute alongside acute health impacts may be of high value and use to accurately portraying the substantive benefits of mode shift to government organisations, decision makers and the general public.

5.2.2 For all government transport agencies (data-collection improvements)

The data collection and analysis involved in this study also highlighted some of the inconsistencies between the various datasets used, especially when examining transport-related incidents. It is recommended that the NZTA continues the conversation with other relevant government agencies (including ACC, the Ministry of Health and the Ministry of Transport) to improve the alignment of injury data occurring in the transport system. Some of this is continuing as a follow-up to the original SORTED study (Te Manatū Waka Ministry of Transport, 2022), and this is to be encouraged. There are substantial potential benefits from standardising the approach for defining and measuring injury and crash data.

ViaStrada (2021) provided a list of recommended actions around data collection for Auckland Transport, Auckland road safety partners and government transport agencies. Some of these recommended actions are set out in Table 5.2.

Table 5.2 Recommended actions for all government transport agencies

Issue	Relevant organisation(s)	Recommendation
General standardisation of transport casualty data	All	Continue to link information from different agencies to provide an accurate picture of road trauma in New Zealand for all modes of transport.
Under-reporting scaling factors	NZTA (CAS)	Investigate methods for improving the under-reporting rate to allow analysts to not need to use specific scaling factors (eg, the pedestrian, cyclist and other vulnerable road-user scaling factors determined for Auckland by (ViaStrada, 2021)).
Recording of non-motor-vehicle incidents	NZTA (CAS)	Improve mechanisms for capturing transport incidents not involving a motor vehicle (eg, pedestrian fall, cyclist hit object) in CAS, perhaps by monitoring hospital admissions and initiating data entries for relevant patients.
Geospatial location to higher resolution than territorial local authority	Ministry of Health	The Ministry of Health assigns a patient's residential home address to their respective domicile codes. However, these do not relate to Stats NZ's SA2 area codes. Consider using Stats NZ SA2 areas instead.
	ACC	Encourage ACC to collect location data to a higher resolution than solely territorial local authority level. Consider using Stats NZ SA2 areas.
Field standardisation	Ministry of Health, ACC	Encourage the Ministry of Health & ACC to standardise free-field text entries to make analysis more efficient, especially regarding transport-related injuries.

Issue	Relevant organisation(s)	Recommendation
Injury severity	NZTA (CAS), Ministry of Health and ACC	CAS and the Ministry of Health currently identify 'serious injury' as typically an overnight stay in hospital at least. It is recommended that the NZTA aligns with the ACC definition of 'serious injury'. Ideally a more consistent approach for 'serious injuries' from all data sources would be helpful, including consideration of moving to the international MAIS scale for minor, moderate and severe trauma (ie, three, instead of two injury-severity ratings).
Vehicle and user categories	NZTA (CAS), Ministry of Health, Ministry of Transport, and ACC	Develop a more standardised approach to capturing vehicle and user types involved in transport casualty records (including other parties where present), and attempt to reduce the proportion of 'unknown' entries. In particular, develop a consistent way of capturing wheeled devices such as e-scooters and mobility scooters.
Demographic categories	NZTA (CAS), Ministry of Health, Ministry of Transport, and ACC	Develop a more standardised approach to capturing ethnicity as part of transport casualty datasets, and attempt to reduce the proportion of 'unknown' entries.
Injury location (private versus public locations)	ACC	ACC to consider how to better differentiate trips and falls on public paths (both next to or away from road corridors) from trips and falls in other private, commercial or recreational settings.
	Ministry of Health	Encourage the Ministry of Health to collect more specific location data (where incident occurred) as a free-text field to allow data to be used to identify localised issues that can be addressed by transport authorities.

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Appendix A Data classification and aggregation

A.1 Geographic classification

All data used in the study has been classified geographically based on the 'urban environments' defined in the *National Policy Statement on Urban Development 2022* (Ministry for the Environment, 2022) (also referred to as the NPS-UD). These areas are as defined in Table A.1.

Table A.1 Urban environments and corresponding local authorities (adapted from Ministry for the Environment, 2022)

Tier 1 urban environments	Territorial local authorities
Auckland	Auckland Council
Hamilton	Hamilton City Council, Waikato District Council, Waipa District Council, Waikato Regional Council*
Tauranga	Tauranga City Council, Western Bay of Plenty District Council, Bay of Plenty Regional Council*
Wellington	Wellington City Council, Porirua City Council, Hutt City Council, Upper Hutt City Council, Kāpiti Coast District Council, Greater Wellington Regional Council*
Christchurch	Christchurch City Council, Waimakariri District Council, Selwyn District Council, Environment Canterbury*
Tier 2 urban environments	**Territorial local authorities**
Whangārei	Whangārei District Council, Northland Regional Council*
Rotorua	Rotorua District Council, Bay of Plenty Regional Council*
New Plymouth	New Plymouth District Council, Taranaki Regional Council*
Napier-Hastings	Napier City Council, Hastings District Council, Hawke's Bay Regional Council*
Palmerston North	Palmerston North City Council, Manawatū-Whanganui Regional Council*
Nelson-Tasman	Nelson City Council, Tasman District Council
Queenstown	Queenstown Lakes District Council, Otago Regional Council*
Dunedin	Dunedin City Council, Otago Regional Council*

Note: *These regional councils are listed in the NPS-UD as authorities that have influence on urban development. However, the urban environments are entirely within the non-regional councils listed. For the purposes of defining the urban areas for this study, the regional councils are not mentioned hereafter.

The NPS-UD does not define the boundaries of each urban environment geographically, aside from referencing territorial local authorities (TLAs). In many cases, the TLAs associated with an urban environment extend far beyond the urban environment referenced, particularly when including regional councils. Initially, there were attempts to make connections between the urban environments contained in the NPS-UD and the 'functional urban area' classification (Stats NZ, 2021). However, this resulted in misalignment with the NPS-UD in some cases[9], and made accurate aggregations from the HTS data impossible.

[9] For example, Tuakau and Pōkeno are considered to be part of the Auckland functional urban area, while falling within the Waikato District Council boundaries, which under the NPS-UD is part of the Hamilton urban environment.

Ultimately, a combination of the 'urban rural' classification (Stats NZ, 2020) and the local territorial authority was used as the definition of an urban environment for this project. Every major, large, and medium urban area within the non-regional TLAs listed was considered to comprise the urban environment. Table A.2 summarises this relationship.

Table A.2 Classification of urban environments

Tier	Urban environment	Non-regional territorial authority	Urban area	Urban / rural classification
2	Whangārei	Whangārei District Council	Whangārei	Large urban area
1	Auckland	Auckland Council	Hibiscus Coast	Large urban area
			Auckland	Major urban area
			Pukekohe	Medium urban area
1	Hamilton	Waikato District Council	N/A*	N/A*
		Hamilton City Council	Hamilton	Major urban area
		Waipa District Council	Cambridge	Medium urban area
			Te Awamutu	Medium urban area
1	Tauranga	Tauranga City Council	Tauranga	Major urban area
		Western Bay of Plenty District Council	N/A*	N/A*
2	Rotorua	Rotorua District Council	Rotorua	Large urban area
2	New Plymouth	New Plymouth District Council	New Plymouth	Large urban area
2	Napier Hastings	Napier City Council	Napier	Large urban area
		Hastings District Council	Hastings	Large urban area
			Havelock North	Medium urban area
2	Palmerston North	Palmerston North City Council	Palmerston North	Large urban area
1	Wellington	Kapiti Coast District Council	Waikanae	Medium urban area
			Paraparaumu	Medium urban area
		Upper Hutt City Council	Upper Hutt	Large urban area
		Lower Hutt City Council	Lower Hutt	Major urban area
		Porirua City Council	Porirua	Large urban area
		Wellington City Council	Wellington	Major urban area
2	Nelson Tasman	Nelson City Council	Nelson	Large urban area
		Tasman District Council	Richmond	Medium urban area
1	Christchurch	Waimakariri District Council	Rangiora	Medium urban area
			Kaiapoi	Medium urban area
		Christchurch City Council	Christchurch	Major urban area
		Selwyn District Council	Rolleston	Medium urban area
2	Queenstown	Queenstown-Lakes District Council	Queenstown	Medium urban area
2	Dunedin	Dunedin City Council	Dunedin	Major urban area
			Mosgiel	Medium urban area

Note: *These council areas were included as part of the urban environment under the NPS-UD, but had no medium, large, or major urban areas within them.

Small urban areas were excluded from the urban environments, due to the HTS including these in the 'rural' category. These areas are included in the 'other-rural-blank' category – this is further explained in Appendix C.

Both TLA boundaries and urban–rural boundaries and classifications have changed over time as towns and cities grow. For the purposes of this work, the TLA and urban–rural boundaries from the 2018 Census have been used to maintain consistency and comparability between datasets and through time.

All datasets are categorised by geographies allowing for aggregation into the method described above, with the exception of the Ministry of Health hospital admission data. The approach to geographic categorisation of this data is further discussed in section G.4.

Maps of urban environments comprising multiple main urban areas (MUAs) are shown as follows (Figure A.1 to Figure A.7).

Figure A.1 Auckland main urban area

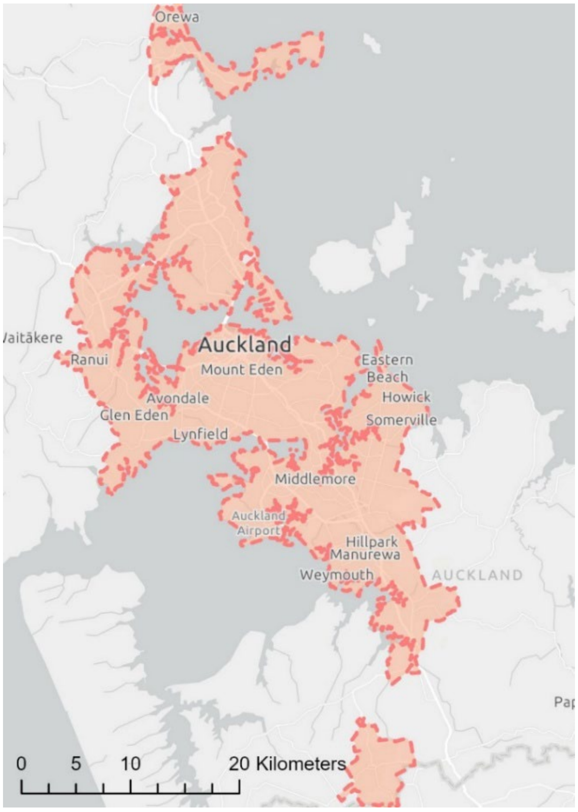


Figure A.2 Hamilton main urban area

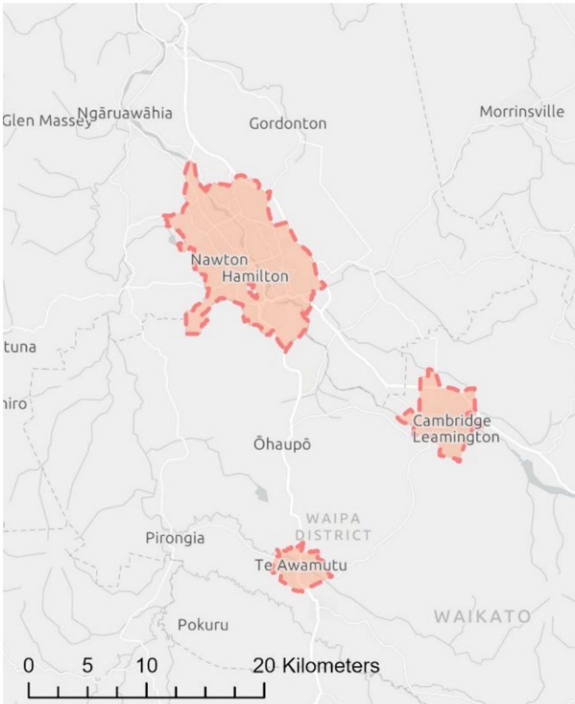


Figure A.3 Wellington main urban area

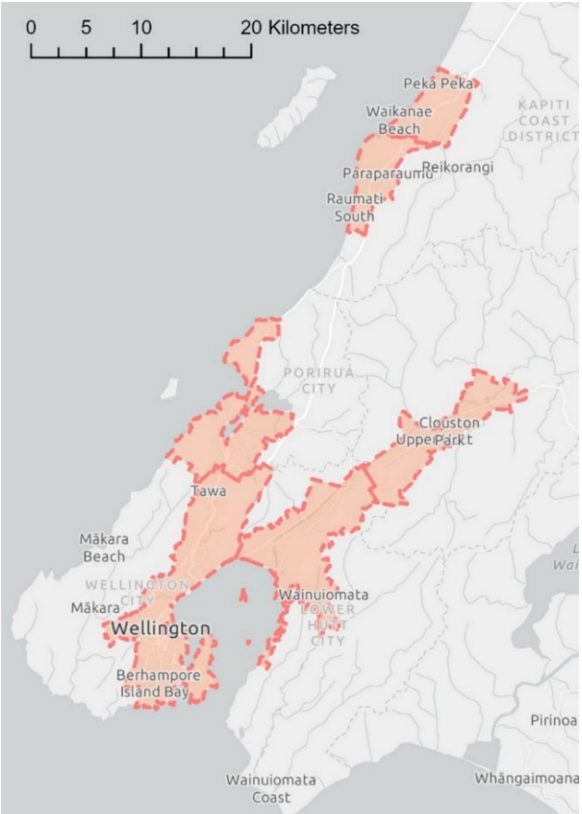


Figure A.4 Napier–Hastings main urban area

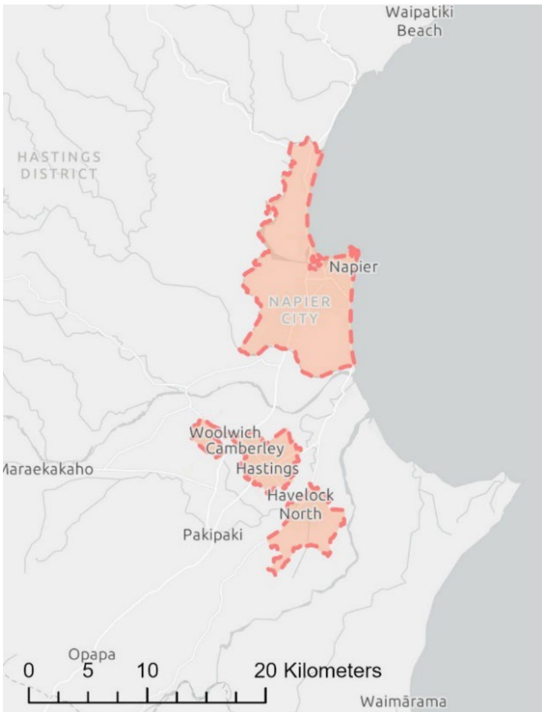
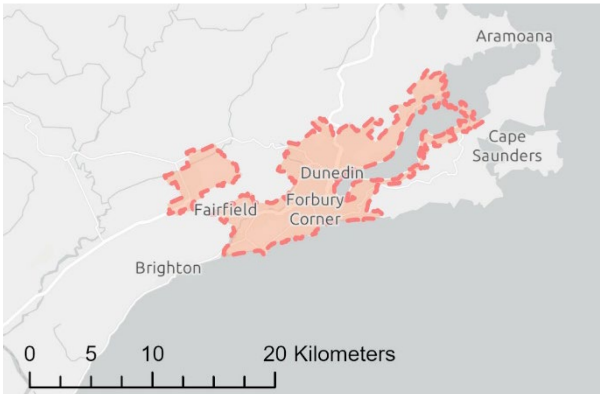


Figure A.5 Christchurch main urban area

Figure A.6 Nelson main urban area

Figure A.7 Dunedin main urban area



A.2 Ethnic classification

Five groups of ethnicities were applied:

- New Zealand European or European
- Māori
- Pacific people
- Asian, including Indian
- Other (including Middle Eastern, Latin American, and African).

For some datasets, for example the HTS and the Census, people have the option of selecting multiple ethnic groups from a long list of possible options, which results in a myriad of possible ethnicity combinations. This analysis, however, requires grouping people according to only one ethnicity. Where someone has selected more than one ethnicity, the ethnicity used has been determined according to the Ministry of Health level 2 ethnic group priorities[10]. This process could result in some discrepancies (eg, if someone considers themselves 'predominantly New Zealand European' but also has some Māori heritage they would be classified as Māori.

Given the HTS included the classification 'ethnicity unknown', these participants were filtered out of the weighting (scaling) factors data. This reduced the HTS dataset from 29,344 participants to 28,307 participants (a 3.53% reduction).

A.3 Age classification

People's ages were grouped in 10-year intervals, up to 70–79, with a final category for anyone 80 years or older. The HTS included the classification 'age unknown'; these participants were filtered out of the weighting (scaling) factors data. This reduced the HTS dataset from 29,316 participants to 29,305 participants (a 0.04% reduction).

A.4 Gender classification

The 2018 Census had two options for gender: male and female. Other data sources have introduced various additional options (eg, 'gender diverse' in later years of the HTS). However, the Census is critical in weighting the HTS data to reflect the entire population, and without these categories being included in the Census data, it is not possible to develop meaningful travel or exposure metrics for them. Therefore, a binary classification of gender has been retained.

The HTS included the classification 'gender diverse'. These participants were removed from the weighting (scaling) factors data to mirror the binary classifications of the 2018 Census. This reduced the HTS dataset from 29,344 participants to 29,315 participants (or a 0.1% reduction).

A.5 Travel mode classification

Modes of travel were categorised as:

- all-terrain vehicle, other or unknown vehicle
- bicycle (including e-bike)

[10] See 'Level 2 ethnic codes' table on page https://www.tewhatuora.govt.nz/our-health-system/data-and-statistics/nz-health-statistics/data-references/code-tables/common-code-tables

- bus occupant
- ferry passenger
- motor-car occupant (car, taxi, van, ute)
- motorcycle, motor-scooter or moped rider
- pedestrian
- pedestrian mobility device user (eg, wheelchair, mobility scooter)
- plane passenger (HTS only)
- train or tram passenger
- truck occupant
- wheeled device – e-scooter rider
- wheeled device rider – other (eg, skateboard, kick-scooter)

Appendix B Trip chaining and public transport

B.1 Overview

The HTS data has been merged (ie, containing information from people, households, trips and journeys) and adjusted (ie, converting unrealistically short public-transport trips to realistic values, as detailed above), but is unweighted (because this is a relative exercise), and the resulting data has been used to calculate:

- the number of modes per journey (Table B.1)
- the number of public-transport (bus, ferry or train) modes per journey (Table B.2)
- the journeys involving public transport without any supporting modes (Table B.3):
  - the type(s) of public transport involved
  - the distances travelled
- the journeys involving public transport plus a supporting mode(s) (Table B.4):
  - the types of public transport involved
  - the main public-transport mode
  - the types of supporting modes involved
  - the distances travelled
  - the proportions (by distance) of the supporting mode relative to public transport.

Note, the public-transport trips used in this analysis include both local and non-local. However, these subsets could be disaggregated if needed.

B.2 Modes per journey

Table B.1 shows the number of modes per journey; the vast majority (98.2%) of journeys involve one mode only. The remaining 2% involve some sort of trip chaining using different modes. Table B.2 shows that the vast majority (98.1%) of journeys did not involve any public transport, and those that did involve public transport were most likely to involve only one of either bus, ferry or train.

Table B.1 Number of modes per journey

Number of modes	Number of corresponding journeys
1	430,883
2	7,091
3	976
4	36
5	6
6	1
Total	**438,993**

Table B.2 Number of public-transport modes per journey

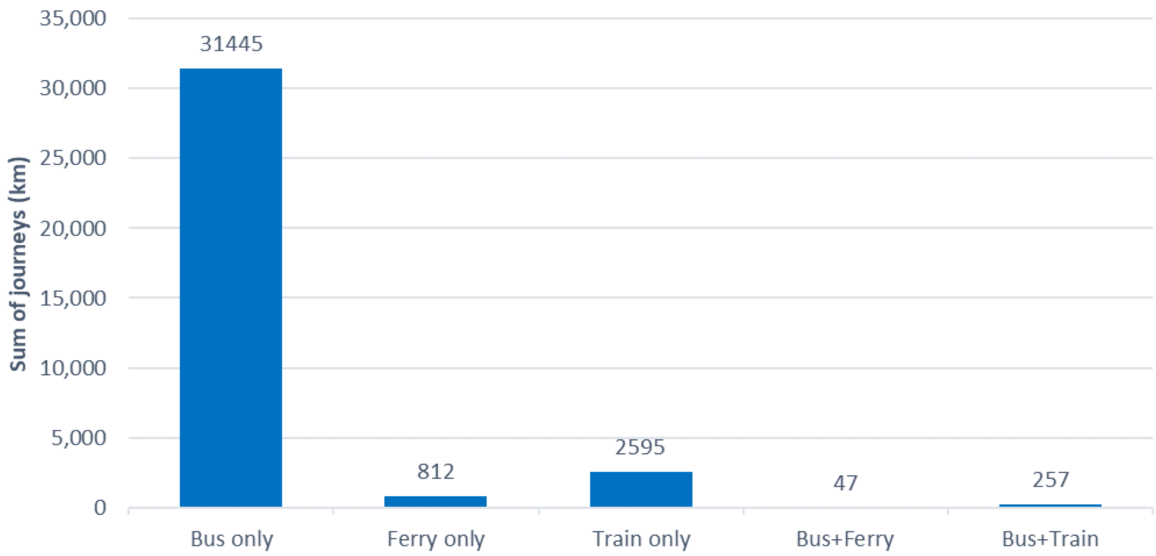
Number of public-transport modes	Number of corresponding journeys
0	430,535
1	8,230
2	226
3	2
Total	**438,993**

B.3 Relative use of modes supporting public transport (for all public-transport combinations)

Most public-transport users don't have a public-transport stop directly outside their house and again directly outside their destination, and therefore have to walk or travel by some other means between their public-transport stops and their origin and destination. However, the HTS does not include trips less than 100 m, unless there is a change in trip purpose or a street is crossed, which makes it possible for a trip to be coded as using public transport only, with no supporting modes.

Figure B.1 shows the sum of journey distances (km) for trips that only involve public transport, without any supporting modes by the different possible mode combinations.

Figure B.1 Total journey distance by mode combinations for journeys involving public transport only (no supporting modes)



It can be seen from Figure B.1 that the most common public-transport journeys without supporting modes involve buses. This is due to the prevalence of bus networks across the country and the extent of coverage across each city. People are much more likely to have a bus stop within a negligible walking distance of their home and destination, than for either of the other public-transport modes, although there are records for both ferry only and train only.

Figure B.2 shows the sum of journey distances (km) for trips that involved at least one public-transport mode plus at least one supporting mode (ie, modes used to get to the start of the public-transport trip, and then from the end of the public-transport trip to the final destination – these are often called 'first/last-mile' modes). Note that only the most common combinations (a total journey distance of 700 km or more) are shown in this figure.

Figure B.2 Total journey distance by mode combinations for journeys involving public transport plus supporting modes

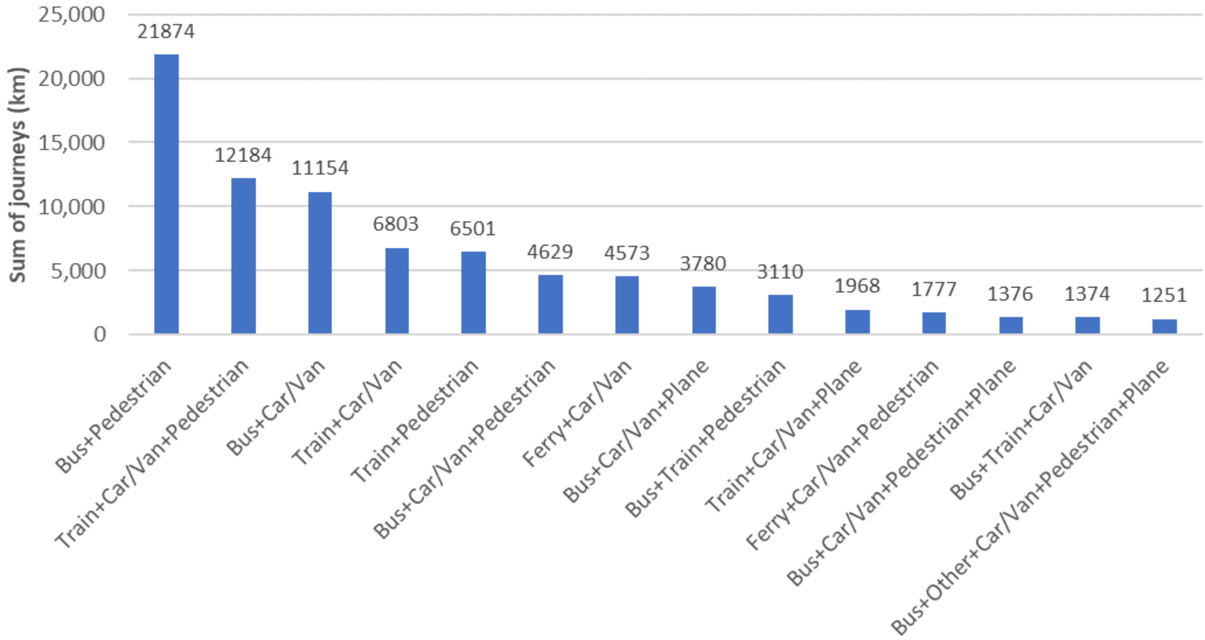


Figure B.2 shows that the greatest journey distances are covered by bus travel, with walking as the supporting mode. The next greatest are for train plus car and walk, and for bus plus motor vehicle. Again, this reflects the coverage of bus networks throughout New Zealand.

Table B.3 summarises the number of public-transport trips involving each of the supporting modes, and the average trip length of supporting modes relative to the public-transport trip length for a given journey. These numbers show that the term ‘first/last mile’ is inaccurate, as people are willing to travel long distances to access public transport. People who combine motor vehicles with public transport are likely to travel further in the supporting modes than the public transport itself. People who cycle in conjunction with public transport are, on average, willing to travel up to half of the public-transport trip length by bike (this average is affected by people like the St Heliers man and the Thorndon man in the examples discussed in section D.2 who travelled much further by cycle than by ferry or train).

Table B.3 Relative use of supporting modes in relation to public transport

Usage variable	Mode supporting public-transport journey					
	Car or van	Cyclist	Electric scooter	Mobility scooter or wheelchair	Motorcyclist	Pedestrian
Number of public-transport trip chains with mode	1,495	75	1	3	15	3,739
Average trip length of supporting mode trip (km)	15.4	9.3	2.4	1.9	13.0	2.1
Average supporting mode trip length relative to public-transport trip length	122.6%	50.7%	29.9%	37.7%	82.3%	26.5%

B.4 Relative use of modes supporting public transport (to main public-transport mode)

For each journey involving public transport, the main public-transport mode was identified. For journeys involving more than one public-transport mode, a hierarchy was assumed, as per Table B.4.

Table B.4 Hierarchy to determine main public-transport mode

Journey description	Main public-transport mode
Any journey involving a ferry trip	Ferry
Any journey involving a train or tram trip, but not a ferry trip	Train or tram
Any journey where bus is the only public-transport mode	Bus

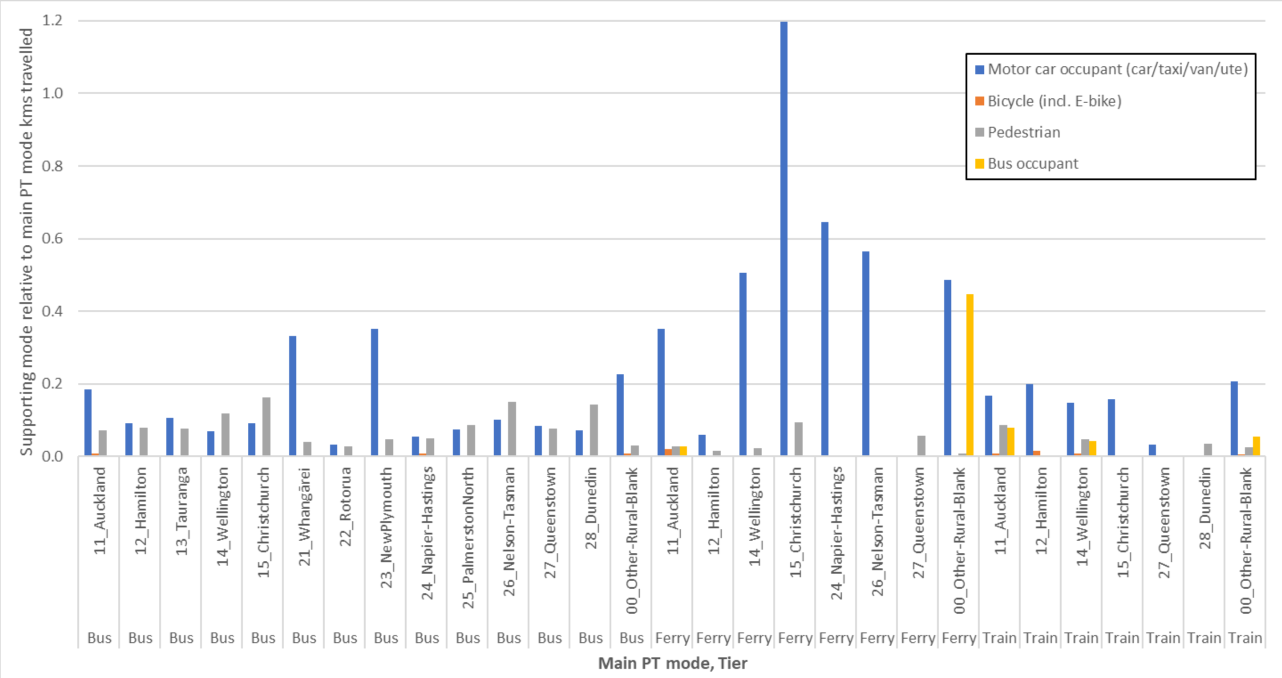
Only the main supporting modes were considered – car occupants, bicycles, pedestrians and bus occupants (if not main public-transport mode).

At this stage, one journey was removed from the dataset as it was the only journey from Queenstown that had bus as the main (ie, only) public-transport mode, plus a supporting motor-vehicle trip, and the ratio of supporting mode to public-transport mode was 62.5, which is two orders of magnitude greater than most others in the dataset. This was because it reportedly involved a very short bus trip (0.21 km, which is just over the defined threshold for unrealistically short bus trips defined in D.2) and a car trip of 12.9 km.

The average ratio of supporting mode to main public-transport mode has been calculated for each main public-transport mode and supporting mode combination, for each tier-based geographic area. These ratios are presented in Figure B.3 and are a direct input to the mode-shift tool.

In some cases, trips involving public-transport modes that are not available in a particular location were recorded, for example, train trips in Queenstown. This is a result of the location of residence of each HTS participant being used as a proxy for trip location, whereas in reality, participants may have travelled away from home during the survey period. These trips were removed from the trip-chain weightings.

Figure B.3 Ratio of supporting-mode kilometres travelled to main public-transport mode kilometres travelled, by main public-transport mode and tier



Appendix C Cycling quality-of-service model

C.1 Overview

The main output of this project (the spreadsheet tool) allows users to adjust the usage of each mode, to test the safety outcomes of this adjustment based on current crash rates. However, particularly for active modes, increases in usage are commonly the result of improved infrastructure (in conjunction with other initiatives). This increases the safety (real and perceived) of cycling or walking in a given place, leading both to increased usage and improved safety. If current crash rates were to apply to an increased amount of walking and cycling without the commensurate infrastructure, this could potentially result in worsened safety outcomes overall.

To address this, a CQOS metric (based on NZTA's SP11 cycling demand simplified procedure (Waka Kotahi NZ Transport Agency, 2023b)) has been developed to establish relationships between infrastructure quantity and quality, cycling mode share and safety outcomes. This has then been used in the final spreadsheet tool to adjust usage statistics, and to adjust the crash-prediction models.

C.2 Calculating existing cycling quality of service

C.2.1 Evaluating whole-of-network quality of service

To establish the level of cycling provision on and off the road network, two datasets were combined:

- NZTA MegaMaps road network – for road attributes
- OpenStreetMap (OSM) – for cycling provision.

OpenStreetMap was found to have the best available cycling provision data in terms of accuracy, detail and comprehensiveness, compared to other sources. National cycling maps tend to be out of date, and sources from individual local councils vary widely in quality, accuracy, detail and categorisation of facility type. MegaMaps contains the traffic volume, speed and number of lanes required for the quality of service calculation. These two datasets were combined using a geographic-information-system process to assign a facility type (from OSM) to each road segment (MegaMaps), with completely off-road paths being added to the dataset.

These networks were clipped to the areas of interest (larger urban areas within the Tier 1 and 2 TLAs). The Auckland Transport CQOS tool was then used to determine the quality of service of each road segment.

The cycling provisions considered were:

- separated cycleway
- shared path
- cycle lane
- neighbourhood greenway
- mixed traffic – this is the default where no specific provision is made for cycling.

The Auckland Transport quality-of-service tool has five principles (subsets of criteria) for evaluating cycle provision, but only the three principles directly relating to safety were evaluated. The other two principles, directness and comfort, were assumed to be consistent across facility types for a given locality. CQOS is scored between 1 (best possible provision) and 4 (worst possible provision).

Where data was available, metrics within each principle were evaluated for each individual street. Where individual street-level data was not available, some assumptions were made. For example, it was assumed that facility dimensions would be reasonable but not generally within the ‘gold-plated’, that is, the highest-scoring category.

Table C.1 shows the assumed parameters (value, CQOS score) for each metric for each facility type. To find a CQOS score for an entire urban area, the CQOS for each street segment is multiplied by its length, and then divided by the total network length, finding an average CQOS score.

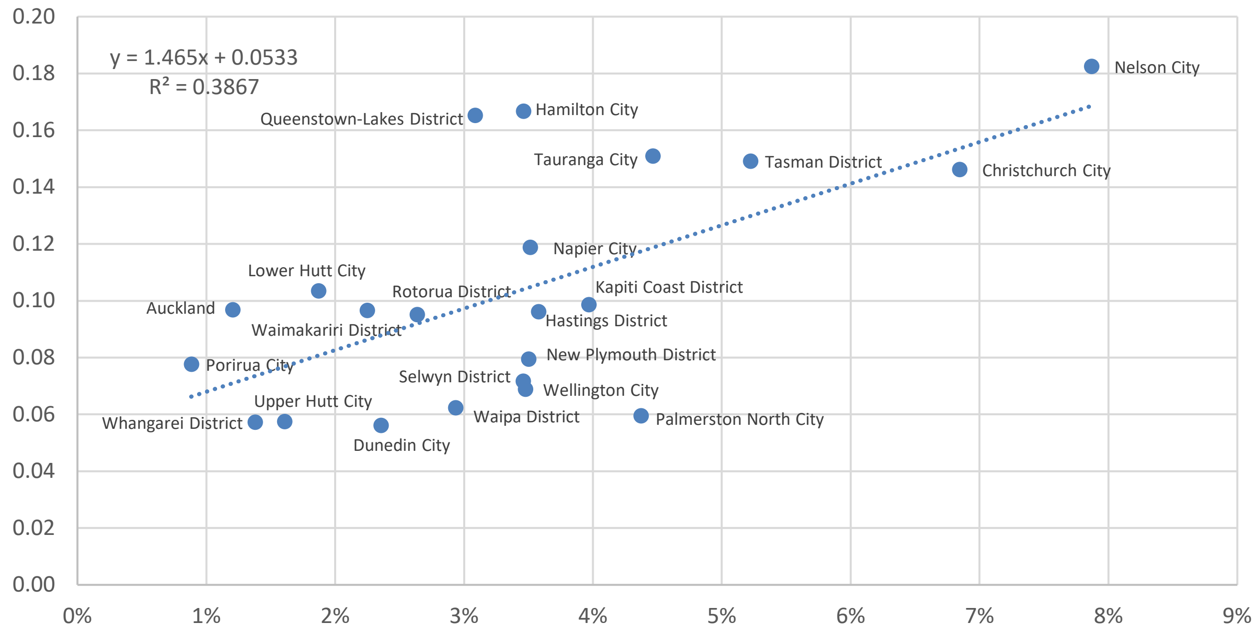
Table C.1 Mapping of cycling quality-of-service scores (in bold) to facility types

	Separated cycleway	Shared path	Cycle lane	Neighbourhood greenway	Mixed traffic
Traffic volume			Street data	Street data	Street data
Traffic speed			Street data	Street data	Street data
Number of street traffic lanes (per direction)			Street data	Street data	Street data
Cycle lane or path width	1.8–2.1 m **2**	3.0–4.0 m **2**	1.2–1.8 m **3**		
Facility blockage	Rare **2**	Not possible **1**			
Interaction with on-street car parking	Separated 0.8–1.0 m **2**	Separated 0.8–1.0 m **2**			
Interaction with public transport stops	Behind **1**	Behind **1**			
Treatment at driveway intersections	Marked and calmed **2**	Marked and calmed **2**			

C.2.2 Relationship between cycling quality of service and cycling mode share

To account for the ‘network effect’, a combined metric was used, multiplying the inverse average CQOS score of cycling infrastructure by the percentage of the network that has cycling infrastructure. The following relationship between the combined CQOS metric and cycling mode share is obtained and shown in Figure C.1. While still warranting further investigation and refinement, the R-squared value of 0.38 is considered acceptable for use in the research model.

Figure C.1 Coverage-weighted cycling quality of service vs cycling mode share



C.3 Estimating mode shift to cycling

C.3.1 Quality of service

For future provision, the user of the model tool enters the length of added cycling infrastructure by type: separated infrastructure (including shared paths and separated cycleways), cycle lanes and neighbourhood greenways. To assess the impact of this, an assumed CQOS is assigned to the added cycling infrastructure by its type. This assumed CQOS is derived from the national average CQOS for that facility type rounded down (ie, better), as it is assumed that newer cycling infrastructure will be, on average, higher quality than what exists today. A 'go Dutch' option has also been added, to allow users to see the impact of higher infrastructure quality on mode share. This option assumes a higher CQOS level for all facility types. Assumed CQOS scores for added infrastructure are shown in Table C.2 (scored 1 to 4, where 1 is best provision).

Table C.2 Cycling quality-of-service scores for different cycle facility types and 'go Dutch' options

Option selection	Separated infrastructure	Cycle lanes	Neighbourhood greenways
Standard quality of service	1.6	2.3	1.8
Go Dutch quality of service	1.2	1.6	1.0

The length of the facility at a given CQOS is then added to the total length of cycling network, providing both a new average CQOS value for cycling infrastructure, and a new value for the proportion of the network that has cycling infrastructure (the total network length is assumed to remain the same, ie, all new facilities are assumed to be built on the existing road network). The relationship established between the combined CQOS metric and the Census cycling mode share is then applied to the new network parameters, where the projected increase in cycling mode share is added to the existing measured cycling mode share.

C.3.2 Effect on safety

Section 2.5.1 identified some research elsewhere that has attempted to estimate the safety effect of introducing different types of cycle facilities to existing networks. Based on this literature, Table C.3 suggests estimates of DSI reductions that can be applied to any expanded cycle networks.

Table C.3 Estimated safety effects of different cycle facility types

Option selection	Separated infrastructure	Cycle lanes	Neighbourhood greenways
Standard quality of service	0.70	0.90	0.80
Go Dutch quality of service	0.50	0.80	0.50

The relative additional length of each type of cycle facility can be combined to form a weighted crash reduction factor (with the assumption that the existing cycle network has a factor of 1.0 reflecting the existing cycle crash numbers). This can then be applied to the existing cycle crash rate for the network to determine a future crash rate.

C.4 Limitations

There are limitations to this approach as follows.

OpenStreetMap-based cycle network

- While this data was better than other sources available, OSM relies on members of the public to update its data. Its quality and accuracy therefore varies – during the development of this model, errors were found and logged. Future revisions of this approach will likely involve making updates to OpenStreetMap where there are known issues.
- OSM does not explicitly define facility types – for the model, facility types were derived from OSM tags. While conventions for tagging exist, there are often regional differences in tagging convention, and grey areas for what tags constitute a certain facility type. While best efforts have been made to ensure that most edge cases have been accounted for, it is likely that some cycling infrastructure has been incorrectly included or excluded, even though it does exist in OSM.

MegaMaps road network

- This road network does not include private roads, even where these may be publicly accessible (eg, roads around many airports), and some smaller residential streets.
- A full list of assumptions and calculation methods for the values in this dataset can be found in the *User and Interpretation Guide: MegaMaps Road to Zero Edition 2* (Waka Kotahi NZ Transport Agency, 2023e).

Auckland Transport quality-of-service tool

- The tool is intended to be applied to specific road segments and does not provide any means of combining the quality-of-service scores for multiple segments to give an average score. The method of weighting the various quality-of-service scores by length seems to be a reasonable approach to producing an average score.
- The method is focused on midblock facility type, but did not consider intersections, which are generally more difficult to design and are where the biggest risks to cycling safety can occur. It was assumed that, if midblock facilities are provided, intersection provision will be at least to the same safety standard.

- The tool required 85th percentile speeds to be used. MegaMaps road network data has 50th percentile speeds (referred to as 'free flow speed') and posted speed limit – as the posted speed limit was generally higher than the 50th percentile speed, this was opted for as it was likely to be closer to the 85th percentile speed.
- Some metrics within the quality-of-service tool have not been used, such as gradient and social safety. In future, these could be incorporated by using digital elevation models to measure hilliness of road segments, and Land Information NZ or OSM datasets as proxies for street activity.

In addition, the cycle facility safety estimates suggested in Table C.3 are provisional, based on some indicative research elsewhere. Ultimately, it would be useful to further investigate the relationship between the measured CQOS scores in different cities and their equivalent cycle crash rates, to determine a more robust safety relationship.

Appendix D Household Travel Survey travel modes

D.1 Mode classification

The following fields in the HTS (Table D.1) were used to align the HTS data as best as possible with the desired mode classification system for the wider project.

Table D.1 Household Travel Survey fields used

HTS field	Use	Limitations
NewMode	Main means of identifying mode categories.	Separates ‘Local public transport’ versus ‘Non-local public transport’ but doesn’t include individual public-transport modes. Doesn’t distinguish mode for non-household travel (which includes the majority of truck use). Doesn’t distinguish e-scooters, mobility scooters, wheelchairs etc.
TrMode (travel mode)	Distinguish public-transport type. Distinguish plane, mobility scooter or wheelchair, and e-scooter from ‘Other household travel’ category in NewMode.	
VType (vehicle type)	Cross-reference with NewMode to identify trucks, taxis (car) and motorcycles that were ‘hidden’ in unknown or incorrect categories.	Includes ‘Other (specify)’ category.
VType Other (specifies ‘other’ vehicle types)	Identify mode of those indicated as ‘Other (specify)’ in VType.	

D.2 Data cleaning – public-transport trip lengths

Initial attempts to analyse the data yielded some anomalies with the stated lengths of some public-transport trips, particularly those involving ferries.

For example, the highest cycle/public-transport ratio in the dataset (using the HTS ‘best distance’ trip length) involved a 50-to-59-year-old man who lives in St Heliers[11] and who apparently cycled 6.3 km, then took a ferry for 0.15 km, then cycled 13.2 km; the timing suggests this was his evening commute home. A ferry trip length of 0.15 km is not available in Auckland (nor elsewhere in New Zealand). The journey pattern does, however, mirror the man's morning commute (10.3 km cycle, 2.9 km ferry, 7.7 km cycle); this trip had the second-highest cycle/public-transport ratio in the unadjusted dataset, but does have plausible distances for a cycle ride from St Heliers to the city ferry terminal, and a ferry trip to either Northcote, Bayswater or Devonport. Therefore, it seems more appropriate to leave both trips in the dataset, but to adjust the ferry leg for the evening trip to a more realistic value.

Another example of an apparent anomaly is the third-highest cycle/public-transport ratio in the dataset, which is for a man aged 40-to-49 years who lives in Thorndon–Tinakori in Wellington.[12] In the morning, he apparently cycled 1.3 km, then took the train for 2.9 km and then cycled another 13.4 km, for what appears

[11] Year 2017/2018, sample number 351, person 1, day 2, journey 2.

[12] Year 2019/2020, sample number 3819, person 2, day 2, journey 1.

to be his morning commute. In the evening, he cycled 14.7 km for what appears to be his evening commute. The morning trip seems strange – why would he take the train for such a short distance only to resume cycling again? However, the trip length is plausible. Perhaps he initially intended to take the train for longer but decided after a few stops that the weather was too nice, or he needed exercise, or the train was too slow, or the train was becoming too crowded etc, and he decided it would be better to get off and bike the rest of the way to work.

To address the problem of unrealistically short trips (eg, the evening trip for the man from St Heliers), one option would be to remove all journeys involving unrealistically short public-transport trips from the dataset. However, the number of public-transport trips is relatively small, and removing these this would also affect the trip distances of supporting modes, which typically include substantial proportions of pedestrians and cyclists (ie, vulnerable road users who are most at risk in traffic crashes). Therefore, it was decided to adjust the unrealistically short public-transport trips to more realistic values. Threshold values were set for each public-transport mode, below which a trip length was considered 'unrealistically short' (Table D.2).

Table D.2 Threshold values, number and average distance for unrealistically short public-transport trips, by public-transport mode

Public-transport mode	Threshold for short trips (km)	Realistic public-transport trips		Unrealistically short public-transport trips	
		Number of trips	Average distance (km)	Number of trips	Average distance (km)
Bus	0.2	7,309	8.9	113	0.1
Ferry	1.0	272	21.9	30	0.3
Train	0.5	1,424	19.8	39	0.2
All		**9,005**	**11.0**	**182**	**0.2**

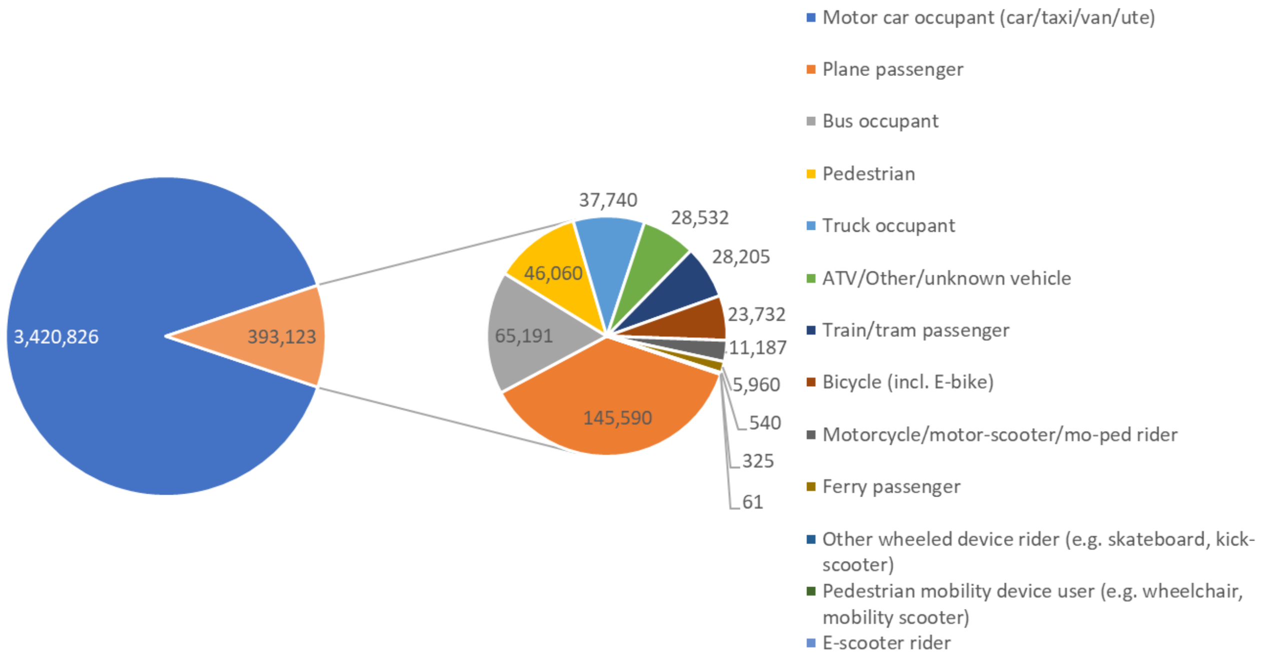
Once unrealistically short trips had been identified, their travel distance was adjusted to equal the average of the realistic trip distances for that public-transport mode for the person's hometown TLA.[13]

D.3 Trip distance travelled by mode

Figure D.1 shows the distance travelled for the HTS data, having applied the project mode classification and made the adjustments for unrealistically short public-transport trips.

[13] It is noted that some trips might have been made outside a person's hometown TLA, but that is a limitation of the dataset supplied, as exact trip addresses were not provided for this research.

Figure D.1 Household Travel Survey distance by project mode classification



Appendix E Household Travel Survey weighting

E.1 Overview

The HTS data has been provided for the years 2015/2016 to 2021/2022 (ie, 7 years of data). In the first 3 years, survey participants were surveyed for 7 days, but from 2018/2019 onwards, only 2 days of data were collected per participant, with different participants starting on different days of the week to cover all days of the week.

The person dataset comprised 43,841 people, but one-third (14,497) of these did not have any trips recorded in the trip dataset. People who were recorded in the person dataset but not the trips dataset were similarly represented across time and geographic location. It has been assumed that these people were included in the pool of potential survey participants but did not actually participate. The demographic data has been calculated using only people for whom trips were recorded.

The trip dataset included 453,066 trips. The data was provided in four different spreadsheets: ‘people’, ‘households’, ‘trips’ and ‘journeys’. These were linked together using the various identifier codes, to provide a comprehensive database of trips.

The HTS includes various weighting factors. The person weighting factors are based on age, gender and region, but do not include ethnicity, which is desired for this research.

E.2 Census dataset

The 2018 Census was used. This is the most recent Census for which ethnicity data is available, and it also occurred around the middle of the period for the HTS data provided. While we are aware that data collection for the 2018 Census was problematic, and may have produced some data of lower quality than previous years, the resulting population, age, gender and ethnicity variables were all assessed to be of a ‘very high’ or ‘high’ data quality.

The specific dataset used was the ‘Ethnic group (detailed single and combination) by age and gender, for the Census usually resident population count’[14] for 2018, by SA2 unit. Although downloaded from the same source, unfortunately all three datasets (gender, age, and ethnicity) had varying total populations. These discrepancies were considered unimportant given the slight change in total population was unlikely to substantially change the HTS weightings. The differences from the gender dataset to the age dataset and ethnicity dataset are shown in Table E.1.

Table E.1 Census dataset total number of people discrepancy, showing difference to the gender dataset

Dataset	Population	Difference
Gender	4,699,107	0%
Age	4,698,405	-0.015%
Ethnicity	4,698,273	-0.018%

The Census data provided by Statistics New Zealand was edited to:

- exclude the Chatham Islands (663 people in 2018), because the small population of this TLA triggers confidentiality clauses, meaning much of the data at a demographic-level breakdown is censored
- exclude people living in areas outside the defined TLAs (39 people).

[14] Available at https://nzdotstat.stats.govt.nz/wbos/Index.aspx#

The HTS and Census datasets were each categorised according to:

- location – grouped by Tier 1 or Tier 2 urban environments, and filtered for urban-only within each TLA; all other rural TLAs, or segments of urban TLAs with rural components were assigned a combined rural category
- gender – male vs female (the HTS also included a 'gender-diverse' option in later years)
- age – grouped in 10-year age brackets
- ethnic grouping.

E.3 Urban and rural areas

Within each TLA, the areas that were rural could be separated from the rest using the 'areatype2' classifications in the HTS, or the 'statistical standard geographic areas 2018' classification in the Census (SSGA18). The classifications were equated in Table E.2 using a linking field 'ViaStrada areas'.

Table E.2 Urban and rural classifications by population

Population	New Zealand Census (SSGA18)	Household travel survey (Areatype2)	ViaStrada areas
>100,000	Major urban area	Main urban area	MajorLarge
30,000–99,999	Large urban area	Main urban area	MajorLarge
10,000–29,999	Medium urban area	Secondary urban area	Medium
1,000–9,999	Small urban area	Rural	Rural
<1,000	Rural*	Rural	Rural

Note: *The rural classification includes water bodies.

TLAs with urban and rural separations were categorised into Tier 1 and Tier 2 urban environments (Table E.3) as per the NPS-UD. For all other areas (Tier 3 urban and all rural), these were classified as 'Other-Rural-Blank'.

Table E.3 NPS-UD Tier 1 and 2 cities (adapted from Ministry for the Environment, 2022)

Tier 1 urban environments	Territorial local authorities
Auckland	Auckland Council
Hamilton	Hamilton City Council, Waikato District Council, Waipa District Council
Tauranga	Tauranga City Council, Western Bay of Plenty District Council
Wellington	Wellington City Council, Porirua City Council, Hutt City Council, Upper Hutt City Council, Kāpiti Coast District Council
Christchurch	Christchurch City Council, Waimakariri District Council, Selwyn District Council
Tier 2 urban environments	**Territorial local authorities**
Whangārei	Whangārei District Council
Rotorua	Rotorua District Council
New Plymouth	New Plymouth District Council
Napier-Hastings	Napier City Council, Hastings District Council
Palmerston North	Palmerston North City Council

Nelson-Tasman	Nelson City Council, Tasman District Council
Queenstown	Queenstown Lakes District Council
Dunedin	Dunedin City Council

The ‘areatype2’ classification (from the HTS) did have two key irregularities.

- Incorrect areatype2 classifications (compared to the 2018 Census urban areas). An area of a TLA may have been classified in the HTS as ‘main‘ or ‘secondary’, but the corresponding Census classification of a TLA was not categorised as urban. As discussed below, these irregularities affected the mode statistics by TLA, but did not affect the mode statistics by tier-age, tier-gender and tier-ethnicity. This occurred for the following TLAs.
  - Waikato District Council (239 of 28,298 participants[15]) or 0.76% of the HTS participant dataset. It can be assumed that these participants are part of the Hamilton (Tier 1 urban area), and these participants were captured as part of Hamilton in the tier-age, tier-gender, and tier-ethnicity datasets. These participants were not captured by the ‘mode statistics by TLA’ dataset.
  - Western Bay of Plenty District Council (109 of 28,298 participants) or 0.35% of the HTS participant dataset. It can be assumed that these participants are part of the Tauranga (Tier 1 urban area), and these participants were captured as part of Tauranga in the tier-age, tier-gender, and tier-ethnicity datasets. These participants were not captured by the ‘mode statistics by TLA’ dataset.
  - South Taranaki District Council (52 of 28,298 participants) or 0.18% of the HTS participant dataset. These participants were captured as part of Other-Rural-Blank in the tier-age, tier-gender, and tier-ethnicity datasets. These participants were not captured by the ‘mode statistics by TLA’ dataset.
  - Grey District Council (280 of 28,298 participants) or 0.93% of the HTS dataset These participants were captured as part of Other-Rural-Blank in the tier-age, tier-gender, and tier-ethnicity datasets. These participants were not captured by the ‘mode statistics by TLA’ dataset.
- Forty-four of 29,344 HTS participants were not classified into an areatype2 classification (MUA, SUA or rural). This represents 0.15% of the relevant HTS participant dataset and these values were excluded.

E.4 Initial comparison of HTS vs Census data

Figure E.1 compares the ethnicities from the HTS and the Census data. The Census data includes only 0.01% of people of ‘unknown’ ethnicity, but over a quarter of the HTS respondents were in this category; either because these people refused to state their ethnicity, stated it only as ‘New Zealander’, or did not answer.

[15] The figure of 28,298 total participants was filtered in the mode statistics by TLA dataset from 29,344 participants to 28,298 participants by excluding gender unknown, age unknown and ethnicity unknown participants.

Figure E.1 Percentage of population by ethnicities, for New Zealand Household Travel Survey versus Census data

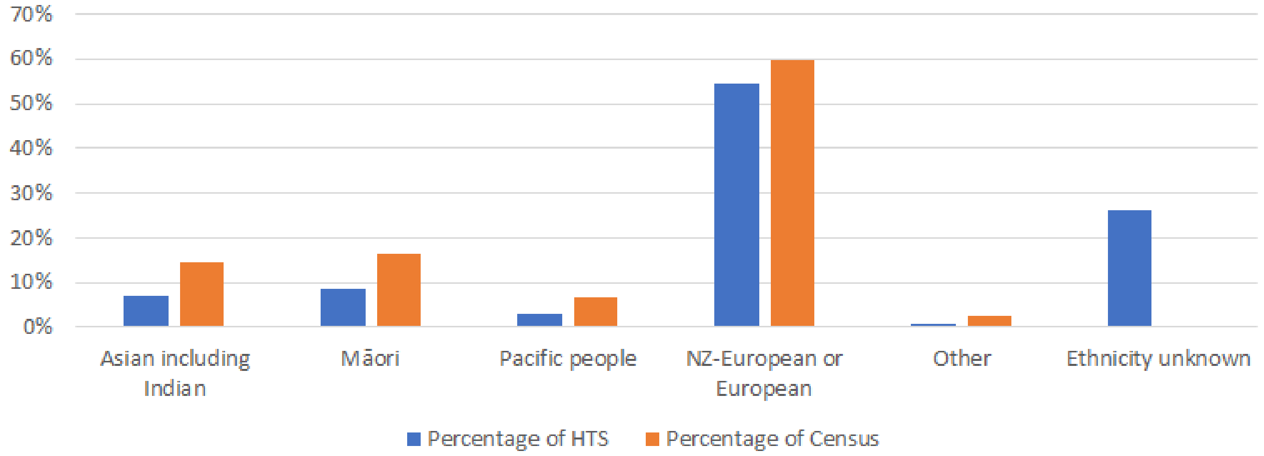
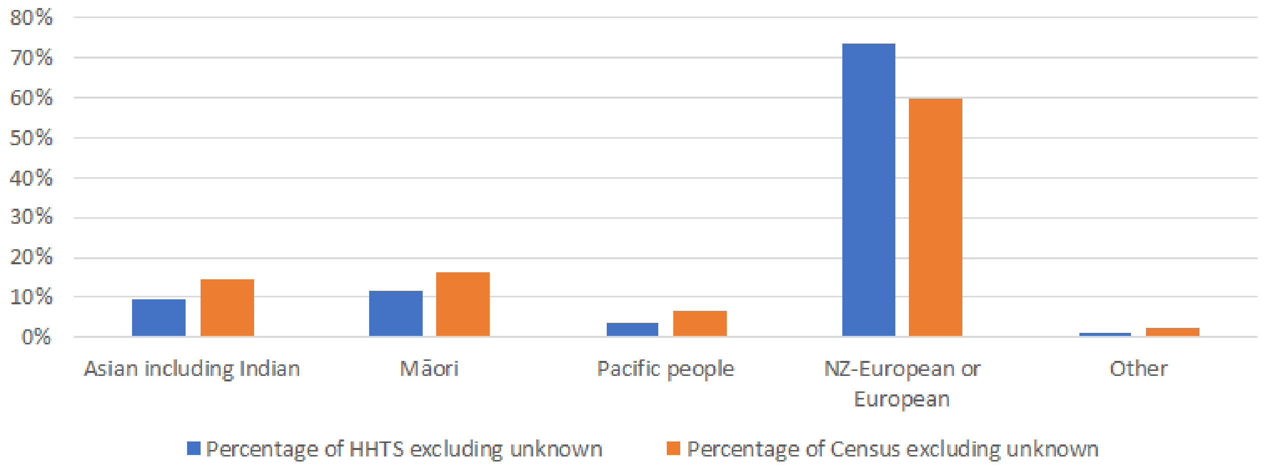


Figure E.1 also shows New Zealand European or other European ethnicities are by far the highest percentage in both data sources and have a similar percentage in each. However, the minority ethnicities (Asian / Indian, Māori, Pacific people and Other) have substantially lower percentages in the HTS compared with the Census, which suggests the 'ethnicity unknown' category includes a disproportionate number of minority ethnicities.

The second chart (Figure E.2) confirms that, when ignoring the 'unknown' category in the HTS, Europeans are over-represented and the minorities, especially Pacific people, are under-represented.

Figure E.2 Percentage of population by ethnicities for known ethnicities only, for New Zealand Household Travel Survey versus Census data



As a result, there is a significant difference between observed and expected for the various categories, resulting in a Chi-squared statistic of virtually 0, that is, well below the desired confidence level of 0.05 (95%).

Overall, the comparison of the HTS and Census ethnicities suggests the HTS is not a representative sample of the total population in terms of ethnicity, and therefore it is necessary to develop new weighting factors that include ethnicity.

E.5 Weighting method

E.5.1 Calculation

Weighting factors were developed in the person dataset based on:

$$\boldsymbol{W_{y,d}} = \frac{\boldsymbol{PopCensus_d}}{\boldsymbol{PopHHTS_{y,d}}} * \frac{\boldsymbol{DaysYear_y}}{\boldsymbol{DaysHHTS_y}}$$

(equation E.1)

where:

d = demographic (ie, tier/gender, tier/age, or tier/ethnicity)

y = survey year based on HTS ranges (ie, 2015/2016, 2016/2017 – note that the HTS does not run to calendar years)

$W_{y,d}$ = weighting factor for a given survey year and a given demographic

$PopCensus_d$ = 2018 Census population for the demographic, d

$PopHTS_{y,d}$ = Number of people in the HTS survey for the given survey year and given demographic

$DaysYear_y$ = Number of days in survey year, y

$DaysHTS_y$ = Number of days each HTS participant was surveyed (7 days for the first 3 years in the dataset, 2 days for the remaining years).

The total trip distances for an average year for the demographic were then estimated according to:

$$Dist_{m,d} = \frac{\sum_y^Y (DistHTS_{m,d,y} * W_{y,d})}{Y_{m,d}}$$

(equation E.2)

where:

$Dist_{m,d}$ = the annual distance (kilometres per year) travelled for the demographic, d, using mode, m

$DistHTS_{m,d,y}$ = the total distance travelled by participants in the HTS for the given combination of mode, demographic and survey year

$Y_{m,d}$ = the number of years surveyed in the HTS sample for the demographic, d, using mode, m (ie, 7 years for most combinations, but fewer for some combinations that did not have HTS data for all 7 years).

The total trip durations (in hours) for an average year were calculated by the same method as above.

E.5.2 Validation

Table E.4 shows the statistics provided by the Ministry of Transport (2022) for the whole of New Zealand, and the sum of the weighted distances computed by the analysis method described above, for each of the three demographic splits (tier-gender, tier-age and tier-ethnicity). As the Ministry of Transport figures excluded non-household travel, but this analysis attempted to assign non-household travel to the relevant mode categories, the proportion of non-household travel (1.1%) was deducted from the distances for this analysis.

Table E.4 Comparison of estimates with New Zealand Household Travel Survey statistics – whole of New Zealand

Source	Parameters		Time period	Total annual travel (billion km/yr)
Ministry of Transport: New Zealand HTS results – travel by people resident in New Zealand	Household travel only		2015–2018	51.3
			2019–2022	58.9
			Average 2015–2022	**55.1**
This analysis	Sum for all tier-gender demographics	Excluding 1.1% (proportion of non-household travel from total sample)	Average 2015–2022	57.3
	Sum for all tier-age demographics			55.3
	Sum for all tier-ethnicity demographics			56.5

This shows that the weighting method used in this analysis results in slightly different total estimates for the three demographic splits used; however, they are all within 4% of each other, which is considered acceptable. The differences are likely due to some HTS participants who provided information for some demographic fields but not others (eg, someone whose age was stated, but their ethnicity was unclear).

Most importantly, the three estimates from this analysis are all within 4% of the Ministry of Transport figure, with the most-accurate estimate – the one using the tier-age split – being within 0.4%.

Table E.5 compares the Ministry of Transport (2022) annual kilometres travelled given for key main urban areas (MUAs) with the estimates produced for this analysis (using the tier-age estimates) for the corresponding tier cities. Note that the MUAs and tiers do not have exactly the same boundaries, as discussed in A.1.

Table E.5 Comparison of estimates with New Zealand Household Travel Survey statistics – key main urban areas and tiers

HTS Auckland MUA annual average 2015–2022		This analysis: estimated annual average for tier		% difference
Location	Billion km/yr	Location and tier	Billion km/yr	
Auckland MUA	14.70	Auckland T1 city	15.27	3.9%
Hamilton MUA	1.77	Hamilton T1 city	2.10	18.4%
Tauranga MUA	2.13	Tauranga T1 city	1.60	-25.0%
Wellington MUA (incl. Kapiti)	4.31	Wellington T1 city	4.94	14.7%
Christchurch MUA	4.04	Christchurch T1 city	4.16	2.8%
Dunedin MUA	0.71	Dunedin T2 city	0.91	28.4%

The estimates for New Zealand's two largest cities, Auckland and Christchurch, by tier are close to the statistics provided by the Ministry of Transport for the corresponding MUAs. The differences for the other cities are likely due to the difference in geographical areas between the MUA and the tier definitions.

Overall, the weighting method used for this analysis is considered to achieve a suitably reliable result. Some of the discrepancy with the Ministry of Transport's estimates may be due to:

- Additional non-household travel being inaccurately nestled in the ‘other’ category of the HTS (4.1% of the total HTS sample).
- The weighting method hinges on the population at the 2018 Census without recognising population changes over time. The HTS sampling fluctuates across geographic location and demographics from one year to the next, so there will be some inaccuracies in the weighted travel estimates for particular demographic subsets.
- The Ministry of Transport also had to make some assumptions in its scaling method and its exact methodology is not known.

Appendix F Crash Analysis System categorisation methods

F.1 Data preparation

The following fields from the CAS database (Table F.1) were used to align the CAS data as best as possible with the desired mode classification system for the wider project:

Table F.1 Crash Analysis System fields, uses and notes

CAS field	Use	Notes and limitations
‘Crash Identifier’	Used to merge ‘vehicle’, ‘person’, ‘crash’ data.	Classifies an individual crash event but does not include the separate crash severity of each individual involved in crash.
‘Road usage type’	To distinguish road user or vehicle type (eg, car, motorbike, cyclist) and to determine if a motor vehicle was involved in a crash.	Provides a detailed variable of what type of transport mode was taken during the crash. However, does not record e-scooters. This field was chosen over ‘road user types’ as it contained more unique variables that are more detailed. This field is limited to the accuracy of the input from the witness or police.
‘Codedcrashpersonid’	Individual record of an individual involved in a crash.	Contains the identification code of an individual involved in a crash, either a passenger, driver or third party.
‘Simple / complex crash’	To determine if a motor vehicle was involved in a crash, cross referenced with ‘vehicle type’ field.	
Crash severity	To determine the injury severity of a crash.	This field is potentially providing an inaccurate count of fatalities or injury types as each ‘crash severity’ classification for an individual reflects on the worst-case scenario of a party involved in a crash. It does not reflect their own circumstance or injury severity.

Seven years’ worth of data was extracted from CAS, where it was then cut down to six financial years (June 2017 to July 2023). The person data was extracted through the ‘query data download’ option and was used to conduct the analysis.

Within the period, CAS recorded a total of 210,882 crash events, with 369,394 vehicles involved and 455,962 road users affected, including cases of non-injury crashes.

F.2 Exploratory analysis of CAS data

Figure F.1 depicts the likelihood of different transport mode users being involved in crashes of various severities. Note that CAS classifies every user involved in a crash with the worst-case severity of anyone involved in the crash, regardless of their mode. It does not indicate whether that user is the cause or the recipient of the classified injury severity.

Figure F.1 Proportion of crash severity according to involvement of transport mode

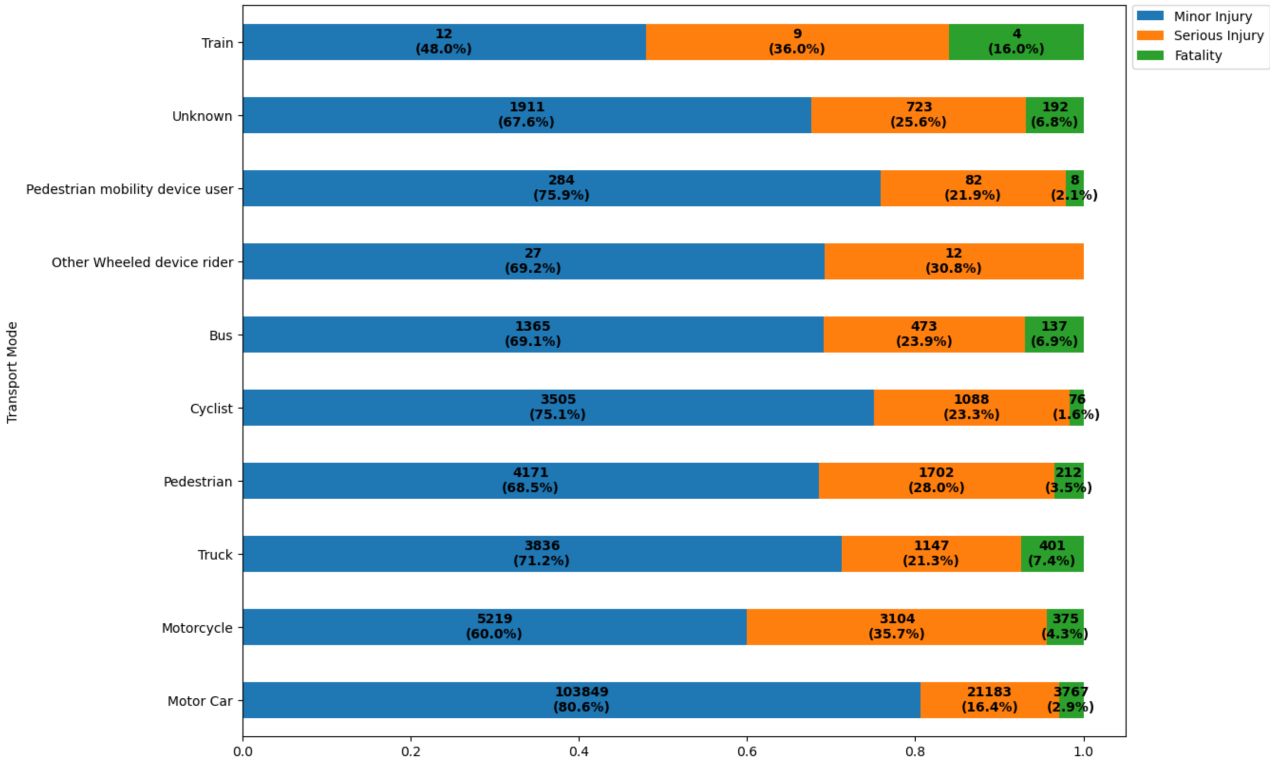
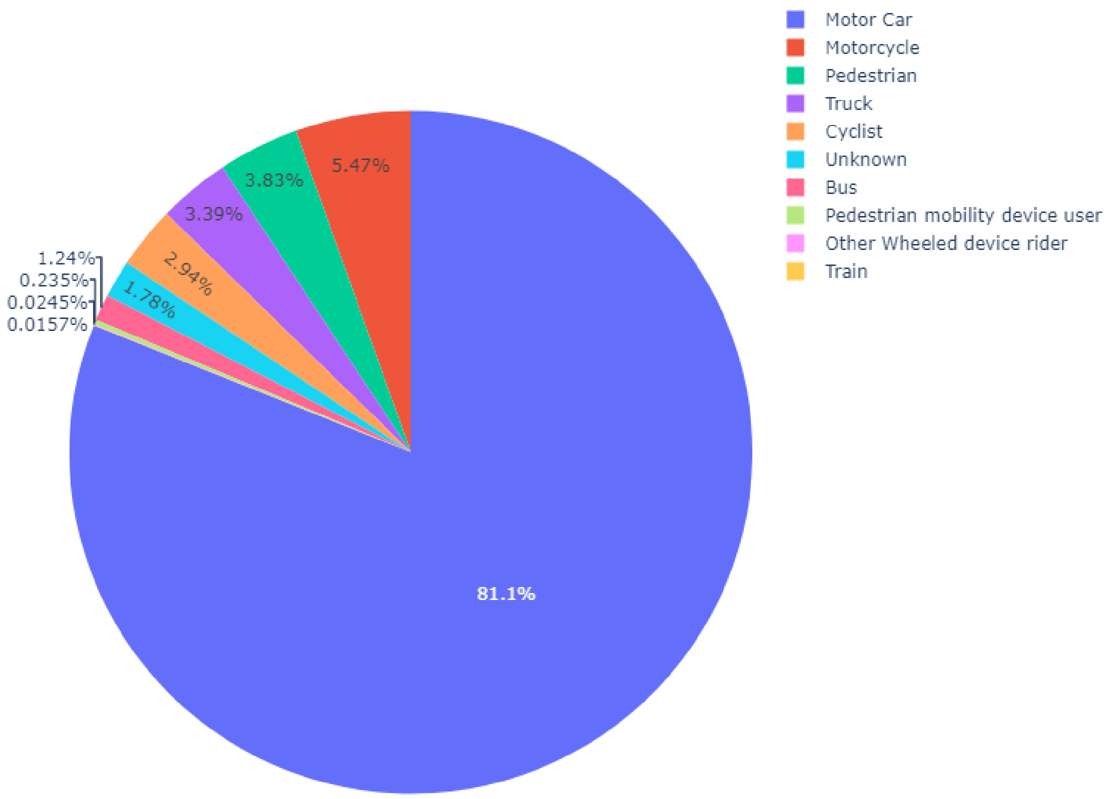


Figure F.2 shows that most recorded crashes involve a motor vehicle. This is unsurprising due to the popularity of the mode itself. Despite the high number of crashes recorded overall, CAS data shows that there is only a 2.9% chance of motor-vehicle users being involved in a fatal crash.

Figure F.2 Proportion of road users involved in a crash (excluding non-injury)



Trains and buses were among the top three mode-user categories to be involved with fatal road crashes. This is largely due to the vehicle sizes causing more severe collisions. Investigations of detailed reports show that most fatal crashes involving buses or trains often involve multiple parties and result in a more severe injury for the external party involved.

However, there are a total of 76 single-party cases of bus and train accidents (where no other party was involved) that resulted in a fatality; 72% of those incidents occurred in rural areas and were often tourist buses (see Figure F.3).

Figure F.3 Proportion of rural and urban areas in single-party crashes involving trains and buses

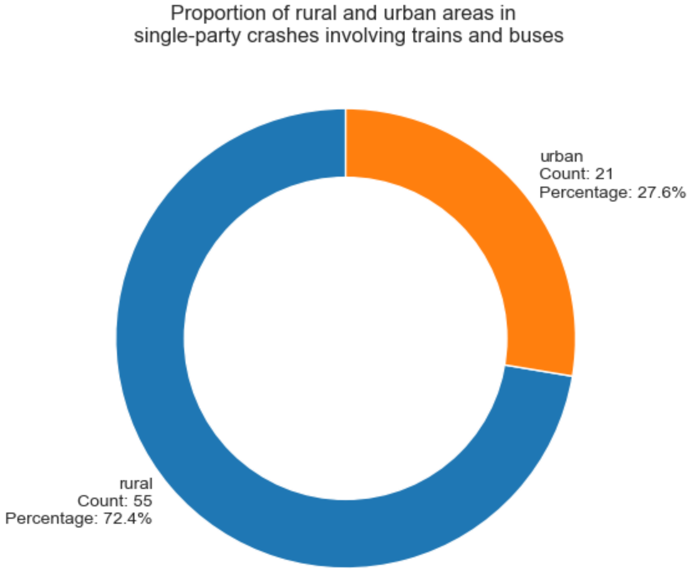


Table F.2 depicts the counts of each mode being involved with other modes in multiple-party crashes. CAS classifies vehicles in a crash numerically from 1 to 4, with vehicle 1 as the key vehicle.[16] Cars are the most common mode to be involved in crashes for all transport mode users, with a substantially large gap down to other modes. Refer to section H.2 for more information.

Table F.2 Transport-mode crash contingency tables

		Secondary vehicle					
		Bus	Cyclist	Car	Motorcycle	Train	Truck
Key vehicle	Bus	6	12	237	16	0	10
	Cyclist	20	54	657	4	0	60
	Car	369	489	21,676	1,340	12	2,727
	Motorcycle	48	0	5,246	570	0	384
	Truck	93	52	1,976	181	0	304

[16] The vehicle travelling in the direction indicated by the dark (bold) arrow on the CAS vehicle-movement coding diagrams.

Appendix G Ministry of Health hospital admission data injury-severity categorisation

To compare and merge multiple datasets (ie, CAS, ACC, Ministry of Health), it is essential to ensure that the variables are consistent across all the fields. This allows for a valid comparison of the data values and avoids errors or biases. To achieve this, some variables are altered to make them like other variables in other datasets.

G.1 Ministry of Health data preparation

The following fields from the Ministry of Health's National Minimum Dataset hospital admission database (Table G.1) were used to align the ministry's data as best as possible with the desired mode classes and crash severity for the wider project.

Table G.1 Ministry of Health National Minimum Dataset data fields used

National Minimum Dataset field	Use	Notes and limitations
'ecode1'	Used to classify relevant traffic incidents and transport modes.	Some injury mechanisms also recorded in ecode2 and ecode3.
'PCCL'	Patient clinical-complexity level (see section G.3.1).	One of the two ways to determine the severity of an accident.
'LENGTH_OF_STAY'	Length of stay by the patient at the medical facility (see section G.3.2).	One of the two ways to determine the severity of an accident.
'new_enc_nhi'	Encoded National Health Index (NHI); sub-field to a merged identifier key.	Merged with event dates and event type.
'EVENT_START_DATE'	Date and time of arriving at a health facility; sub-field to a merged identifier key.	Merged with NHI, event dates and type.
'EVENT_END_DATE'	Date and time of leaving a health facility; sub-field to a merged identifier key.	Merged with NHI, event dates and type.
'FACILITY_CODE'	Identifies each healthcare facility; sub-field to a merged identifier key	Merged with event dates and NHI.
'EVENT_TYPE'	The type of health event suffered; sub-field to a merged identifier key.	Merged with NHI, event dates and type.
'DOMICILE_CODE'	Location where the patient normally lives.	Used to merge with TLA table to identify TLAs.
'ETHNICGP'	Used to code and distinguish ethnic groups.	
'EVENT_END_TYPE'	Codes are used to identify fatalities or other discharges or transfer actions.	Used in conjunction with 'PCCL' or 'LENGTH_OF_STAY'.
'GENDER_CODE'	Used to determine gender.	

G.2 Ministry of Health transport mode classification

The Ministry of Health database does not have a particular query or field that contains information about the vehicles involved in an accident based on modes of transport. To determine this, we look at the International

Classification of Diseases (ICD-10-AM) coding, mentioned in each case, and assign the relevant ICD code to its respective transport mode. There are a total of 3,104 unique ICD codes, and 821 of those were considered relevant road-transport traffic injuries.

A combination of manual data manipulation and string searching algorithms were used to classify relevant ICD codes that were a result of land transport incidents, alongside what modes were involved. This led to a decrease in the overall Ministry of Health data from 143,135 records of unique patients to 64,276. Roughly 45% of patients recorded in the Ministry of Health admission database were admitted due to land-transport-related injuries.

The top 10 most common relevant ICD codes used in the Ministry of Health data are given in Table G.2.

Table G.2 Top 10 most common International Classification of Diseases codes

Code	Description	Occurrences
V4359	Car occupant injured in collision with car, pick-up truck or van, driver, traffic accident, unspecified car [automobile]	9,160
W011	Fall on same level from tripping	7,501
V4759	Car occupant injured in collision with fixed or stationary object, driver, traffic accident, unspecified car [automobile]	5,952
V031	Pedestrian injured in collision with car, pick-up truck or van, traffic accident	4,292
V4369	Car occupant injured in collision with car, pick-up truck or van, passenger, traffic accident, unspecified car [automobile]	4,185
V4769	Car occupant injured in collision with fixed or stationary object, passenger, traffic accident, unspecified car [automobile]	2,225
V134	Pedal cyclist injured in collision with car, pick-up truck or van, driver, traffic accident	2,153
W029	Fall involving other and unspecified pedestrian conveyance	1,975
W010	Fall on same level from slipping	1,828
W189	Unspecified fall on same level	1,735

G.3 Injury-severity classification

CAS data uses a four-level severity classification system (fatal, serious injury, minor injury, non-injury) that is used widely in studies and research. Thus, an attempt was made to align this metric with the Ministry of Health data. Two classification methods were used to determine the injuries based on the information provided by the Ministry of Health admission data – measuring the length of stay, and classifying the patient clinical-complexity level (PCCL) values.

G.3.1 Classifying by patient clinical-complexity level

The PCCL are integers that vary from 0 to 4, which indicate the clinical complexity of a case. The idea was to equate the clinical complexity with severity and therefore make it consistent with the severity classification system used in CAS. This is summarised in Table G.3.

Table G.3 Patient clinical-complexity level injury classification

PCCL value	Description	CAS severity equivalent
0	No clinical complexity effect	Minor
1	Minor clinical complexity effect	Serious

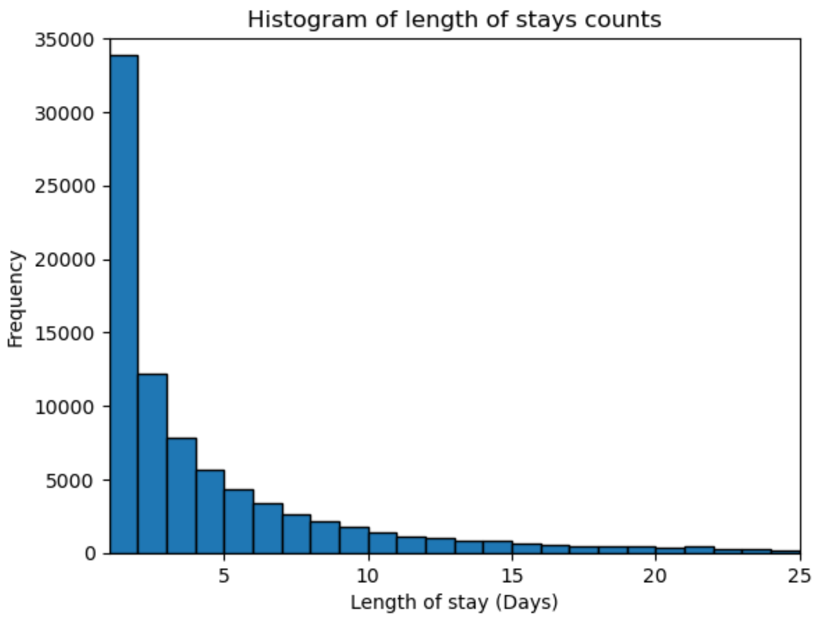
PCCL value	Description	CAS severity equivalent
2	Moderate clinical complexity effect	Serious
3	Severe clinical complexity effect	Serious
4	Catastrophic clinical complexity effect	Serious

Identification of a 'death' discharge code in each case was the superseding logical comparison to identify deaths.

G.3.2 Classifying by length of stay

Another method to translate severity to the metric used by CAS is to use the person's length of stay to determine the severity. Simplistically, if a person stays overnight, it could be considered 'serious'. If the person is treated as an outpatient (ie, discharged on the same day), it would be 'minor'. Like the alternative classification method, death was identified using that discharge code. The counts for the length of stays can be seen in Figure G.1.

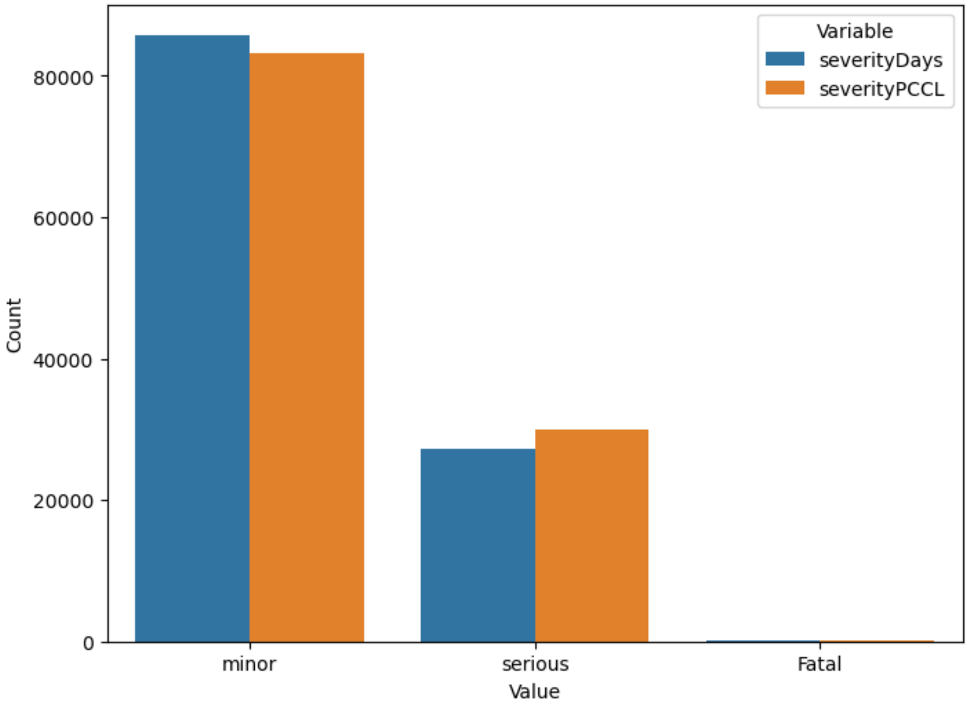
Figure G.1 Histogram of the length of stay frequencies



G.3.3 Comparing the severity classification methods

The proportions of severities are roughly the same from both classification methods (see Figure G.2). The injury rates used in the final model are values extracted from the PCCL value, as it reports more serious injuries and is derived from a pre-determined scaling system.

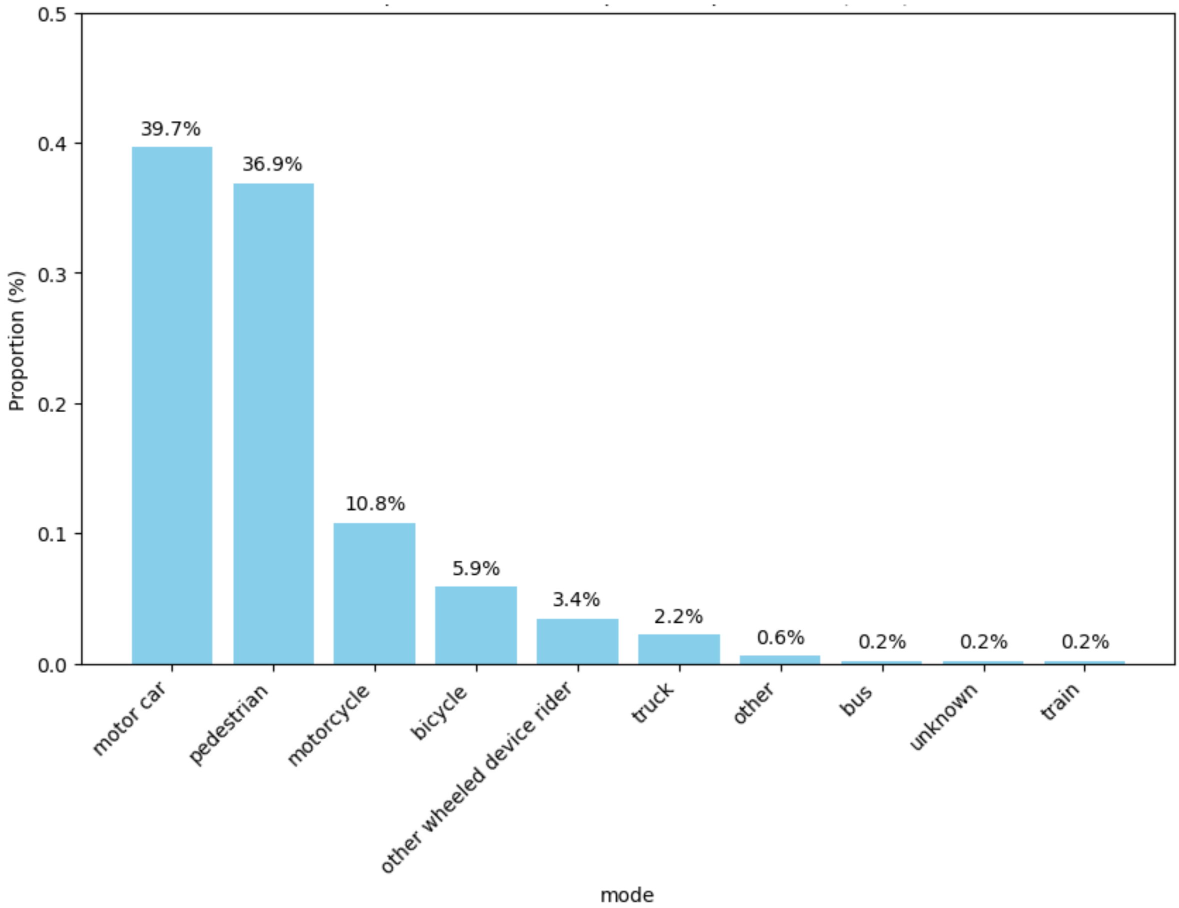
Figure G.2 Counts of severity categories based on patient clinical-complexity level versus length of stay



G.3.4 Exploratory analysis of Ministry of Health data

Figure G.3 shows the proportion of DSI incidents admitted by transport mode. It was found that most admitted patients are victims of injuries while they were in a car or walking. Hospital admittance due to injuries sustained in buses or trains were found to be rare and compromised of a total of 0.4% from all traffic-related incidents.

Figure G.3 Proportion of injuries sustained within various transport modes



G.4 Ministry of Health geographic classification

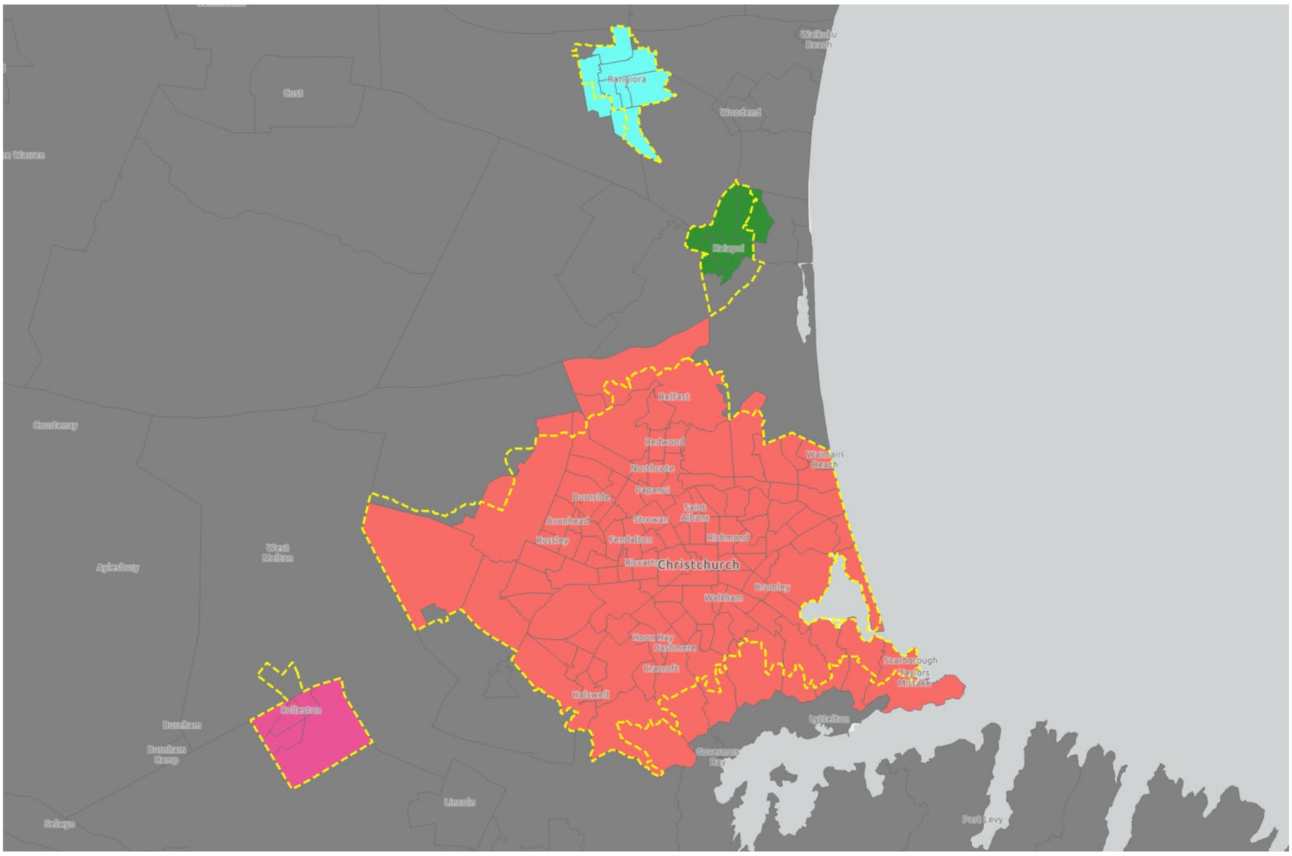
The Ministry of Health uses an automatic categorisation system to assign each NHI number a ‘domicile code’ based on the person’s normal residential address. Domicile codes are geographically based on Stats NZ’s Census area units, which have been discontinued. The most recent alignment between Stats NZ and the Ministry of Health’s geographies occurred in 2013, where domicile codes were aligned with the area units used during the 2013 Census.

As noted in Appendix A, all other datasets allow for categorisation into urban areas through SA2 units. However, the shapes and sizes of these units have adjusted through time to match changes in population and urban growth. As a result, domicile codes no longer align with any statistical geography currently in use, including the rural urban categorisation.

To enable categorisation of the hospital admission data into ‘urban environments’, a semi-automated geographic-information-system process was automated further, with any domicile code areas fully within or fully outside of an urban environment being categorised. The remaining areas were assessed manually, with domicile codes that had a significant majority of their area within an urban environment being attributed to that urban environment. For areas with a less clear attribution, a judgement call was made, taking into consideration the land-use profile of a given area and the distribution of residential addresses.

Figure G.4 shows the resulting comparison of urban environment boundaries (dashed yellow outline) with domicile codes after attribution to urban environments.

Figure G.4 Domicile code urban environment attribution



Appendix H Comparison of Crash Analysis System and Ministry of Health data

H.1 Crash-severity ratios

When it comes to crash severities, CAS captures significantly higher counts of crashes. This may be due to CAS being specifically designated and built to record crashes of all severities (including minor and non-injury), whereas hospitals typically involve only more serious types of cases and injuries. In both data sets, the proportions of minor, serious and fatal injuries were roughly the same (Table H.1), as minor injuries were the dominant type of injuries to have been recorded.

Table H.1 Comparison of Crash Analysis System versus Ministry of Health data

Field	CAS (excluding non-injury)	Ministry of Health
Individuals recorded	158,028	64,276
DSIs recorded	34,695 (22% from total)	21,174 (33% from total)

Ministry of Health data shows traffic crashes are often fatal before the victims can get medical attention. The data shows that 99% of the deaths caused by traffic crashes happen at the scene or before reaching the hospital. Fewer than 1% of the traffic-related cases that are admitted to the hospital result in subsequent death (see Figure H.1 and Figure H.2). Similarly, a reasonable number of lesser injuries are treated at medical facilities away from hospitals.

Figure H.1 Counts of injury severity recorded – Ministry of Health versus Crash Analysis System data

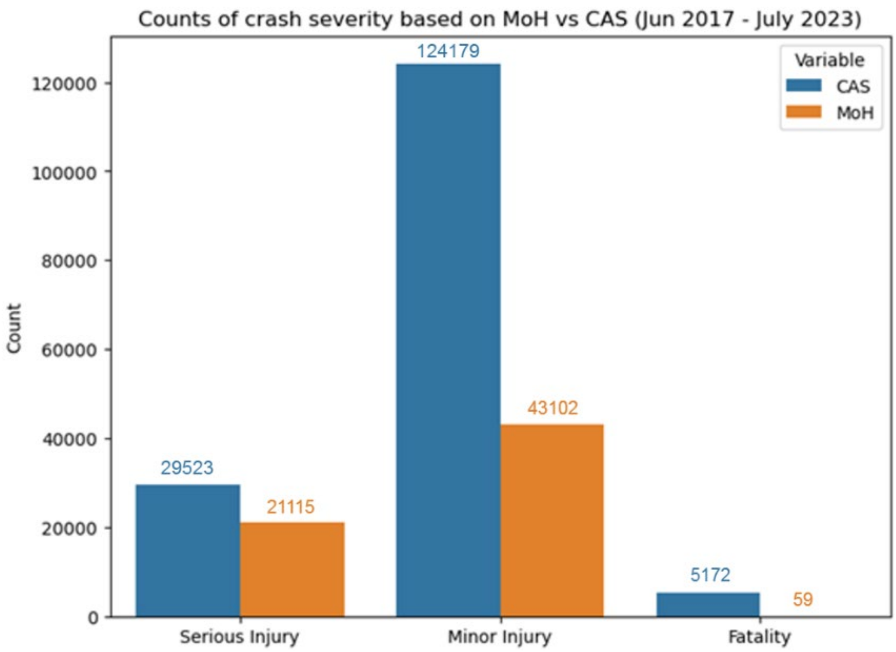
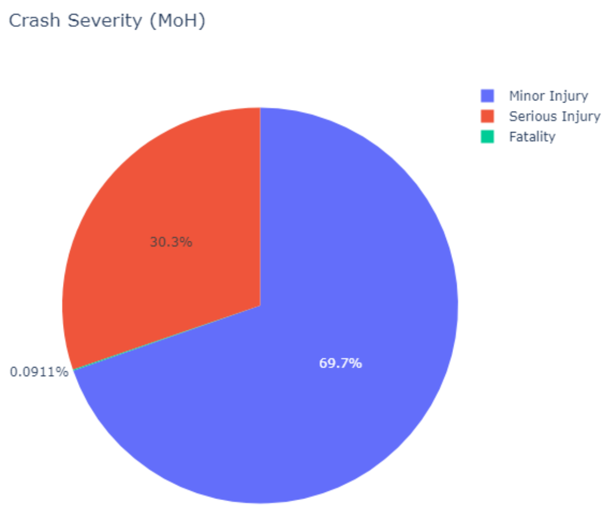
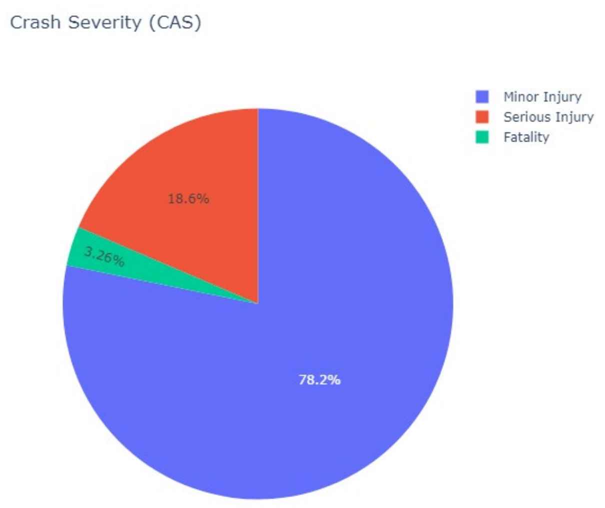


Figure H.2 Proportion of crash severities – Ministry of Health (left) versus Crash Analysis System (right) data





H.2 Multi-party crash rates

Table H.2 and Table H.3 show the counts of separate vehicle types crashing with various other vehicle types. The 'key vehicle' role definitions for CAS and Ministry of Health datasets are slightly different:

- CAS refers to the 'key vehicle' as the vehicle that is primarily being referred to in the crash movement diagrams (symbolised by the large bold dark arrow), while the 'secondary vehicle' is reported to be the other party (if any) that has been obstructed
- in the Ministry of Health data, the 'key vehicle' is referred to as the admitted patient's mode of transport during the time of the incident, whereas the 'secondary vehicle' is referred to as the type of vehicle that hit the admitted patient (if any).

Note that the 'key vehicle' role does not in any way indicate driver fault for both datasets.

Table H.2 Crash Analysis System multi-party crash contingency table

Key vehicle	Secondary vehicle					
	Bus	Cyclist	Car	Motorcycle	Train	Truck
Bus	6	12	237	16	0	10
Cyclist	20	54	657	4	0	60
Car	369	489	21,676	1,340	12	2,727
Motorcycle	48	0	5,246	570	0	384
Truck	93	52	1,976	181	0	304

Table H.3 Ministry of Health multi-party crash contingency table

Key vehicle	Secondary vehicle								
	Bicycle	Bus	E-scooter	Cars	Other wheeled device rider	Pedestrian	Pedestrian mobility device user	Train	Truck
Bicycle	95	43	0	12	213	18	0	2	620
Bus	0	0	0	1	0	1	0	0	14
Cars	2	1	0	45	0	33	0	5	4799
Motorcycle	2	77	0	98	5	23	0	0	1256
Other wheeled device rider	0	0	0	0	0	0	0	0	0
Pedestrian	24	0	14	276	5	2	1	5	1660
Train	0	0	0	1	0	0	0	0	0
Truck	0	0	0	16	0	5	0	2	283

The contingency tables show the same trend where buses and trains are the transport modes with one of the fewest counts of multi-party crashes. The Ministry of Health's data shows a high number of crashes involving trucks. This may be due to a coding problem in distinguishing between heavy vehicles (ie, trucks) and light trucks (ie, SUVs and vans). Despite this, it can be determined that cars and trucks are the main contributors to multi-party crashes.

H.3 Geographical analysis of death and serious-injury crashes

Figure H.3 shows the TLAs with the highest numbers of DSIs (red) alongside the TLAs with the lowest numbers of DSIs (blue). A majority of the TLAs with the lowest DSIs are in the South Island.

Figure H.3 Choropleth of death and serious-injury crashes according to territorial local authority area