EVALUATING CHANGES IN DRIVER BEHAVIOUR FOR ROAD SAFETY OUTCOMES: A RISK PROFILING APPROACH

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Dedicated to my four grandparents

Abstract

Road safety continues to be an important issue with road crashes among the leading causes of death accounting for more than 1.2 million fatalities and 50 million injuries globally each year. Of these casualties, speeding is a major contributor and considerable effort has been put into improving our understanding of the factors that influence drivers' driving behaviour with a view to devising more effective road safety strategies. Within this body of literature, demographics, social norms, personality, legislation, enforcement and characteristics of the road environment have all been identified as possible influencers of risky – and safe – driving behaviour. However, existing research largely relies on drivers' self-reported behaviour and only incorporates a limited range of factors within each study. What is missing is an integrated empirical approach which examines the relationship between these factors and drivers' awareness of their speeding behaviour to a measure of drivers' day-to-day risky driving behaviour. This research employs demographic, psychological, vehicle, trip, Global Positioning System (GPS) driving data and a post-study exit survey collected from 106 drivers in Sydney, Australia during a 10 week pay-as-you-drive (PAYD) study. This is combined with supplementary spatial data used to represent the road environment.

The main contributions of this research are three-fold. First, a methodology is developed to control for the influence of spatiotemporal characteristics on driver behaviour and to allow for the isolation of specific road environments such as school zones. This deals with the inherent variability introduced to driving behaviour from road environment factors external to the driver which would otherwise lead to misleading or insignificant results. Second, the creation of a composite measure of drivers' speeding, aggressive acceleration and aggressive braking behaviour is designed to allow driver behaviour to be described using a single measure whilst accounting for the variability and multitude of aspects embedded within the driving task. This measure allows drivers to be compared to each other and for the same driver to be compared across time and space and thereby permit empirical testing of interventions in a before and after study. Lastly, this research reveals the potential for reducing the extent and magnitude of risky driving behaviour by making drivers aware of their own behaviour. The results indicate that drivers can be grouped into

three categories which can be predicted through risk perception and personality characteristics: drivers requiring a monetary incentive to change speeding behaviour, drivers requiring information alone to change their speeding behaviour and drivers that appear unresponsive to both monetary incentives and information.

Statement of Originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all assistance received in preparing this thesis and sources have been acknowledged.

Adrian B. Ell

Adrian Bachman Ellison

Executive Summary

Road safety continues to be an important issue with road crashes among the leading causes of death accounting for more than 1.2 million fatalities and 50 million injuries globally each year. Driver behaviour is a factor in over 90 percent of crashes, with speeding as one of the major contributors. Considerable effort has been put into improving our understanding of the factors that influence driver behaviour with a view to devising more effective road safety strategies. Nonetheless, drivers continue to engage in risky driving behaviour – such as speeding, distracted driving, rapid acceleration and braking – on a frequent basis. With this in mind, this thesis examines how drivers' risk perceptions, concern of injuries, driving confidence and personality relate to speeding, acceleration and braking behaviour before and after the introduction of a pay-as-you-drive (PAYD) intervention. The intervention comprised a financial incentive *and* a mechanism for making drivers aware of their speeding behaviour permitting both aspects to be investigated. This knowledge can be applied to develop more effective road safety interventions resulting in better societal outcomes.

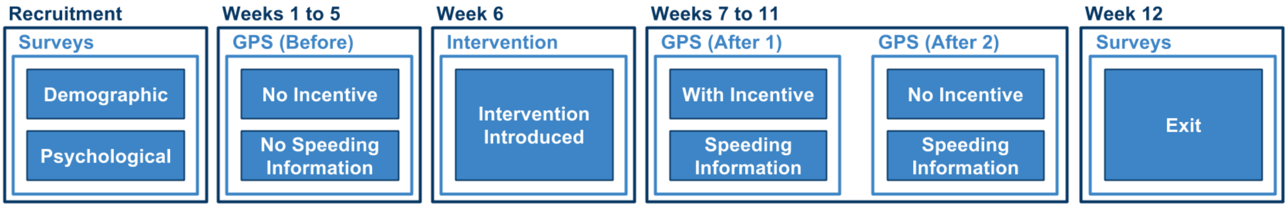
Background

Within the road safety literature, demographics, social norms, personality, legislation, enforcement and characteristics of the road environment have all been identified as possible influencers of risky – and safe – driving behaviour. However, there are four main limitations of this existing body of research. First, a small number of factors are included within each study. This means that interactions such as those between the road environment and personality, and how they relate to driver behaviour have not been adequately explored. Second, existing research largely relies on self-reported, crash and enforcement data as a proxy for the frequency of particular driving behaviours, which, while useful is known to both over and understate the extent to which drivers engage in risky driving behaviour. Although a small but growing number of naturalistic driving studies (using instrumented vehicles) have helped to reduce the reliance on these sources we still know surprisingly little about the frequency and magnitude of risky driver behaviour in day-to-day driving across time and space. Third, both frequency and magnitude of risky driving behaviour are important contributors to risk and – yet – most measures of driver behaviour (and speeding in particular) do not account for this meaning that results potentially under-state the contribution of higher magnitudes to casualty crash risk. Lastly, designing and targeting of road safety campaigns have largely focused on demographics (age and gender primarily), reflecting the disproportionate representation of different demographic groups in casualty crashes. Evidence suggests that demographic groups are not homogenous, affecting how they are (or are not) influenced by road safety campaigns. More precise and effective targeting would appear to enhance the effectiveness of future campaigns.

These research gaps suggest that what is missing is an integrated empirical approach, which examines the relationship between a range of factors – including demographics, personality, risk perceptions and the road environment – and a measure of drivers' day-to-day risky driving behaviour within the context of behavioural responses to a road safety intervention.

Methodology

This research employs demographic, psychological, vehicle, trip and Global Positioning System (GPS) driving data collected from 106 drivers in Sydney, Australia during a 10 week pay-as-you-drive (PAYD) study (illustrated in Summary Figure 1). This is combined with supplementary spatial data used to account for interactions with the road environment. During the PAYD study, drivers drove for a five week period during which baseline data on their driving was collected. From this, a financial incentive was calculated based on the distance driven, the distance driven at night and the distance driven over the speed limit. Subsequently, drivers were invited to participate in the after phase for a further five weeks. During this time their financial incentive was depleted for every kilometre driven (at any speed) with higher amounts levied for every kilometre of night-time driving and speeding. Drivers that reduced the combined effect of these three components received their remaining incentive.



Summary Figure 1: Study phases

Exploratory analyses performed at various levels of aggregation revealed that the road environment was the strongest predictor of speeding behaviour. As a consequence, models run using aggregate data that did not include these factors had no predictive power. Given the focus on driver characteristics, it was necessary to develop a method that controlled for the road environment thereby isolating the effects of driver characteristics while simultaneously allowing some aggregation to be performed to reduce the original dataset – of over 80 million observations – to a manageable size. This was accomplished using Temporal and Spatial Identifiers (TSI), which uniquely identify the characteristics of the road environment associated with each observation. The dataset could then be aggregated by TSI without losing information on the road environment.

These analyses also pointed to the hierarchical nature of the dataset and that the complexity of the driving task meant that a single measure of driving behaviour (such as the distance speeding by 1 km/h or more) was insufficient to adequately describe behaviour. To deal with this, a composite measure of drivers' speeding, aggressive acceleration and aggressive braking behaviour was developed. This driver behaviour profile (DBP) was designed to allow driver behaviour to be described using a single measure whilst accounting for the variability and multitude of aspects embedded within the driving task. This measure allowed drivers to be compared to each other and for the same driver to be compared across time and space facilitating empirical testing of the effects of the intervention. These profiles included a speeding risk score, acceleration risk score, braking risk score and a total risk score that combined all three behaviours. These scores relate to the risks of a casualty crash and were used as the dependent variables in the models used to test the hypotheses.

Results and discussion

A relationship was not found between driver characteristics and their acceleration and braking behaviour. As such, the remainder of this summary discusses speeding alone.

The results show that, in the before period, higher perceptions of the risk associated with a variety of driving behaviours – including speeding – were associated with higher speeding risk scores. In terms of personality, more excitable drivers were associated with higher speeding risk scores while more altruistic drivers were associated with lower scores. Personality exhibited the strongest effect of all the driver characteristics. Contrary to expectations, drivers with a greater concern for their passengers' safety were not associated with lower speeding risk scores. However, drivers with more concern for their own safety did exhibit lower speeding risk scores and, in addition, drivers that self-identified a higher likelihood of involvement in a crash also exhibited higher speeding risk scores. This suggests that changing drivers' risk perceptions has the potential to reduce speeding behaviour but it also reveals that the most dangerous drivers may be more aware of the risks they face.

These same relationships were observed after the introduction of the PAYD scheme with those factors observed in the before period to be related to lower scores being associated with greater (beneficial) changes in speeding behaviour relative to their behaviour prior to its introduction. These results suggest that while the intervention was successful in reducing speeding behaviour overall, these changes were made disproportionately by those who are already (relatively) safer drivers with significantly smaller changes observed in those drivers who are of greatest concern. This mirrors the relationship between self-reported likelihood of a crash and speeding behaviour – observed in both the before and after periods – adding further evidence to the existence of a significant minority (approximately 20 percent) of drivers that appear to be knowingly engaging in considerable speeding behaviour.

In terms of the intervention aspects themselves, the results show speeding risk scores were reduced substantially following the introduction of the PAYD scheme when both a financial incentive and information on their speeding behaviour were available to participants. For some drivers, the financial incentive was depleted prior to the completion of the after phase. As such, these drivers continued to be exposed to information on their speeding behaviour but no longer benefited from a financial incentive. Speeding behaviour during this period ("after two") was higher than their speeding behaviour when they were receiving a financial incentive ("after one") but remained (for most drivers) substantially lower than during the before (baseline) period. This suggests that while the combination of the financial incentive and information provide the largest benefit, making drivers aware of their speeding behaviour (on its own) could lead to substantial reductions in speeding behaviour, at least in the short term. However, some drivers were unresponsive to both elements of the intervention and, unfortunately, these were also the highest risk drivers.

Over and above the examination of the hypotheses and intervention, a significant finding has been that driver characteristics alone only partially explain risky driving behaviour, with the majority of differences explicable by external constraints associated with the road environment, such as congestion and road conditions. This is the case in all phases of the study and across the sample. Not accounting for this appropriately results in models with poor predictive power and (potentially) leads to misleading conclusions.

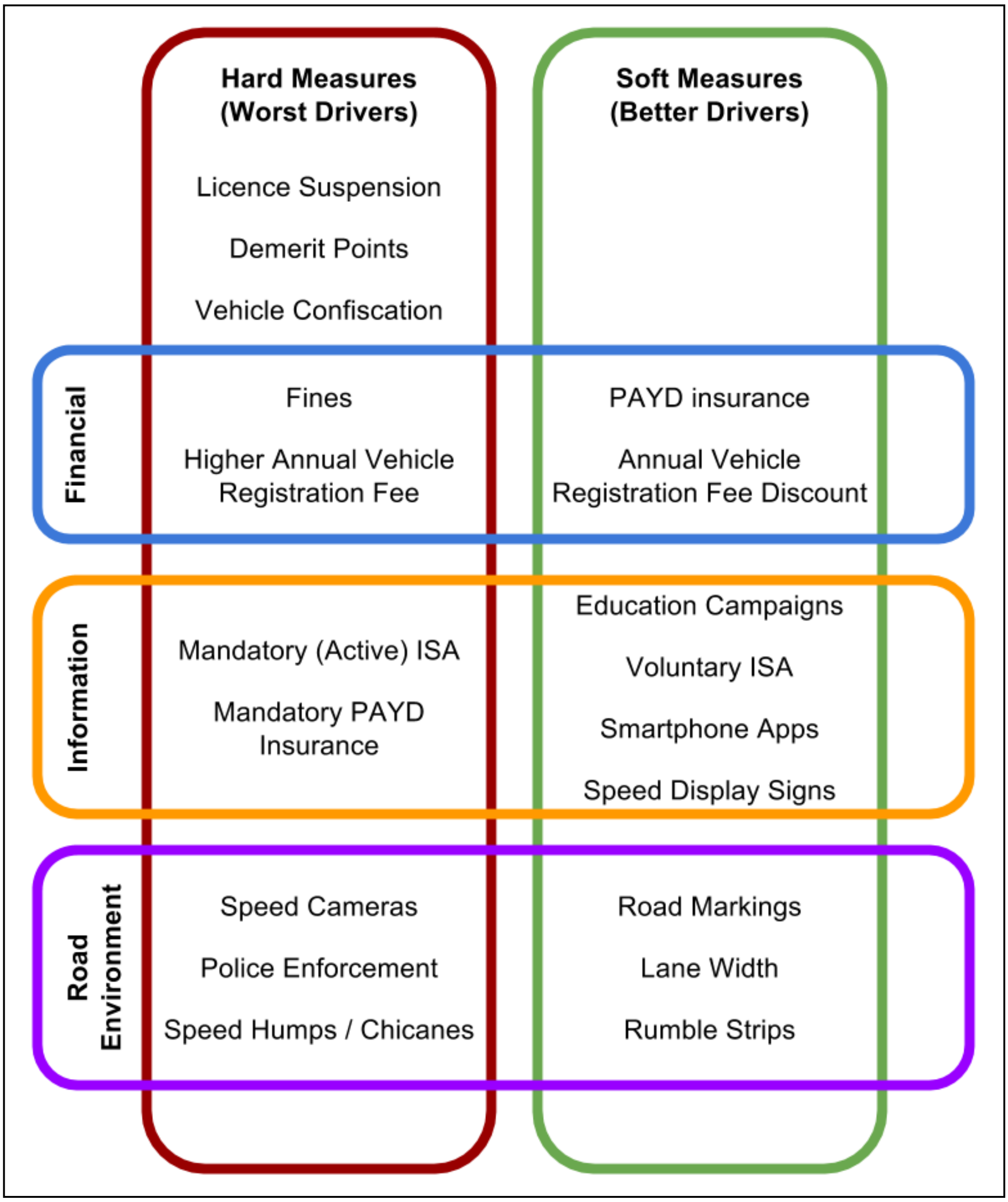
Conclusions and recommendations

A number of conclusions can be drawn from this research. First, the road environment is the strongest predictor of driver behaviour and appears to constrain the behaviour of (particularly) the most dangerous drivers. Second, personality (and to a lesser extent) risk perceptions are predictors of speeding behaviour and appear to perform better than demographic attributes within the constraints of the sample used in this study. Lastly, the combined effects of a financial incentive and increasing awareness substantially reduce speeding behaviour – however increasing awareness on its own could have significant benefits in reducing speeding.

These conclusions lead to two sets of recommendations for policy makers, summarised in Summary Figure 2, which are comprised of differentiated policies for drivers that do and do not respond to soft measures.

The drivers that engage in the most speeding behaviour appear to be relatively unresponsive to soft (voluntary) measures. These drivers require hard measures which remove their choice to speed. This includes changing the road environment to constrain driver behaviour, heavier enforcement and penalties, and possibly mandatory (active) Intelligent Speed Adaptation (ISA) to prevent drivers from pressing the accelerator pedal when they are speeding. Since financial penalties alone do not appear to be effective they should be used in conjunction with harsher penalties including licence suspension and vehicle confiscation.

In contrast, the majority of drivers appear responsive to soft measures. These may include education campaigns designed to change risk perceptions based on personality traits. More comprehensively, wider availability of PAYD insurance, which may include (passive) ISA that provides an audible or visual warning to drivers when they exceed the speed limit would be beneficial as it raises awareness of a driver's own speeding behaviour. In addition, the relatively safer drivers were also influenced by the road environment and, therefore, changes to the road environment such as reducing lane width and adding rumble strips could be beneficial in reducing speeding behaviour by these drivers.



Summary Figure 2: Policy measures for speeding behaviour change

Acknowledgements

Twenty years before I started this thesis[1], I thought that cars were best experienced standing (not sitting) in the back row while driven (fortunately, by someone else) at speed. I now prefer to be a seated, belted passenger in a car travelling at the more reasonable – yet perhaps still a bit high – speed limits found in American Samoa, Niue and Norfolk Island. Although this shift in preference has occurred over a longer period than this thesis took to complete, it has undoubtedly been influenced (and will continue to be influenced) by what I have experienced and learned during my PhD candidature. This experience has, however, benefited (statistically) significantly by the contribution of a number of people.

First and foremost, my supervisor A/Professor Stephen Greaves and my two associate supervisors Dr Rhonda Daniels and Professor Michiel Bliemer were instrumental at all stages of this thesis. Steve was the person that initially introduced me to road safety research and subsequently supervised my initial forays as a Master's student and then encouraged me to continue as a PhD student. His foresight in ensuring that my work was submitted (and accepted) for publication was also critical in me being awarded my PhD scholarship. It can, therefore, be reasonably concluded that this thesis would not exist without him. Rhonda ensured that I maintained my focus on the objectives of my research instead of going off on one of my very many technologically-led tangents. She also lent her experience in government and academia to shape and influence the direction and presentation of my research and thesis. Michiel became involved at a later stage but has, nonetheless, been immensely helpful in what became a very technical document. I am particularly grateful for his input into my driver behaviour profiles methodology and the writing of my (lengthy) results chapters.

Although it is sometimes stated that PhD theses are solitary projects, I cannot state that this is the case at the Institute of Transport and Logistics Studies (ITLS). All the staff contributed directly and indirectly to this thesis through formal and informal discussions, their own presentations and provided assistance in other ways. Informal

[1] Long before I was eligible for a driver's licence

discussions during lunch were especially useful and I encourage all current and future PhD students to take advantage of this. These took place regularly when we were at the Burren Street building for the majority of my PhD years and have, thankfully, mostly transferred to the St James building where ITLS now finds itself. A special thank you is reserved for Dr Russell Familar who introduced me to multilevel modelling, a technique that became a core component of my methodology. I am also grateful to the administrative staff at ITLS for helping me navigate through the waters (or roads?) of university processes and procedures saving me a substantial amount of time and energy that was instead spent on my research.

The majority of the data that was used in this thesis were sourced from a previous study undertaken at ITLS by A/Prof Stephen Greaves, Dr Simon Fifer and Dr Richard B. Ellison (among others). I must acknowledge the substantial effort that went into that process and the time spent answering many of my questions on the data collection process.

Outside of ITLS, my thesis examiners provided exceedingly helpful comments on my thesis, especially in terms of the psychological aspects, as did the anonymous reviewers of the papers I submitted to various conferences and journals.

It was a pleasure to undertake my PhD with many other excellent (past and present) PhD students – all of whom contributed in their own way. A number of PhD students stand out for a number of reasons. I want to thank Dr Tan Lin and Dr Chi-Hong Tsai for being excited/brave/foolhardy (select as appropriate) enough to join me (and Richard) on one of our whirlwind expeditions to Norf'k Ailen (Norfolk Island) and Te Ika-a-Māui (North Island, New Zealand) respectively. Dr Jyotirmoyee Bhattacharjya and Dr Wai Yan Leong provided substantial contributions to my afternoon biscuit breaks (and the discussions that took place during that time). Dr Chinh Ho has provided continual encouragement for me to finish my thesis – including asking me every day if I have finished my acknowledgements[2]. Dr Joe Fai Poon was kind enough to show me around Singapore on my visits there. Dr Claudine Moutou also deserves an honourable mention for accepting/tolerating/enjoying (select as appropriate) my

[2] A task I left till last

frequent travel and technical discussions completely unrelated to anybody's research. Lastly, I have shared my ITLS office with Dr Richard B. Ellison who in addition to cooking dinner every other night (at home) also provided occasional assistance with (the appropriately named) R-Project that I used extensively.

Further afield, I am grateful to friends and family for tolerating my increasingly fleeting visits (and other communication) over the past few years, although, as I have enjoyed it tremendously (the visits, not the lack of communication) I cannot promise that will end. Perhaps 96.63 percent of the time I will try to make my connections longer than 10.573 hours and my telephone calls longer than 8.318 minutes. There have been a number of (unobserved) drempels[3] along the way, which hopefully will be smoothed out at some point (in conjunction with a lower, enforced, speed limit). I also acknowledge the (perhaps unintentional) contribution of everybody who has driven me around in my lifetime for providing inspiration (in a good way) for this thesis. Last, but not least, my mother deserves credit for handling two children completing PhD theses at the same time who have (occasionally) got stuck in gear while going around the (global and scholarly) roundabout.

[3] Speed bumps

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Publications

The following publications were authored or co-authored on this thesis topic during my candidature.

2013

Journal Article/s

Ellison AB, Greaves SP and Bliemer MCJ (2013) 'Examining Heterogeneity of Driver Behavior Using Temporal and Spatial Factors', *Transportation Research Record: Journal of the Transportation Research Board*, vol.2386, pp. 158-167

Ellison AB, Greaves SP and Daniels R (2013) ‘Capturing Speeding Behaviour in School Zones Using GPS Technology’, *Road and Transport Research*, vol.22:4, pp. 30-42

Conference Proceeding/s

Ellison AB, Greaves SP and Bliemer MCJ (2013) 'Examining Heterogeneity of Driver Behavior Using Temporal and Spatial Factors', *Proceedings of the 92nd Annual Meeting of the Transportation Research Board - "Deploying Transportation Research - Doing Things Smarter, Better, Faster"*, Washington D.C., United States, 17th January 2013

Ellison AB, Greaves SP and Daniels R (2013) 'Capturing Speeding Behavior in School Zones Using GPS Technology', *Proceedings of the 92nd Annual Meeting of the Transportation Research Board - "Deploying Transportation Research - Doing Things Smarter, Better, Faster"*, Washington D.C., United States, 17th January 2013

2012

Conference Paper/s

Ellison AB, Greaves SP and Daniels R (2012) 'Profiling Drivers’ Risky Behaviour Towards All Road Users, *Australasian College of Road Safety National Conference ACRS 2012 - "Expanding the Reach"*, Sydney, Australia, 10th August 2012

Ellison AB, Greaves SP and Daniels R (2012) 'Modelling Driver Heterogeneity of Risk Using Attitudinal and Observed Driving Information, *13th International Conference of the International Association for Travel Behaviour Research IATBR*, Toronto, Canada, 19th July 2012

2011

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Greaves SP and Ellison AB (2011) 'Personality, Risk Aversion and Speeding: An Empirical Investigation', *Accident Analysis and Prevention*, vol.43:5, pp. 1828-36

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2010

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Conference Proceeding/s

Ellison AB and Greaves SP (2010) 'Driver Characteristics and Speeding Behaviour', *Proceedings of the 33rd Australasian Transport Research Forum ATRF 2010*, Canberra, Australia, 1st October 2010

Glossary and Abbreviations

α	Cronbach Alpha; Measure of internal consistency
$	Australian Dollar unless otherwise specified
ABS	Australian Bureau of Statistics
ADR	Australian Design Rules; Australian standards
AIC	Akaike Information Criterion; used to compare the quality of models from the same dataset
ANOVA	Analysis of Variance
API	Application Programming Interface
ATSB	Australian Transport Safety Bureau
BAC	Blood Alcohol Concentration; a measure of the proportion of alcohol in a person's blood
BIC	Bayesian Information Criterion; used similarly to AIC
BITRE	Bureau of Infrastructure, Transport and Regional Economics (Australia)
BOM	Bureau of Meteorology (Australia)
BTS	Bureau of Transport Statistics (NSW, Australia)
C4 GPS	GPS device manufactured by Mobile Devices Ingenierie
CART	Classification and Regression Tree
Casualties	Injuries and fatalities
CBD	Central business district or city centre
CHAID	Chi-squared Automatic Interaction Detector
CSV	Comma Separated Values (file type)
DBI	Driver Behaviour Inventory, a survey for assessing aggressive disposition/personality
DBP	Driver Behaviour Profile; composite profile of driver behaviour
DBQ	Driver Behaviour Questionnaire
DVP	Driver and Vehicle Profile; composite profile of driver and vehicle characteristics
g/100ml	Grams per 100 millilitres; equivalent to g/dL

g/dL	Grams per decilitre; unit of measuring blood alcohol concentration (see BAC)
GB	Gigabyte(s)
GIS	Geographic Information System
GISDK	Geographic Information System Developer's Kit, a programming environment for TransCAD
GPRS	General Packet Radio Service
GPS	Global Positioning System
Great Circle Distance	Shortest distance between any two points on Earth
IAT	Implicit Association Test
ISA	Intelligent Speed Adaptation
KAP model	Knowledge, Attitudes and Practices model
Km	Kilometres
Km/h	Kilometres per hour
Latitude	North-south coordinate (90º to −90º)
Longitude	East-west coordinate (180º to −180º)
LOT	Loss of Traction
m	Metres
m/s^2	Metres per second squared, metric unit of acceleration
m/s^3	Metres per second cubed, rate of change of acceleration (in metres per second)
mm	Millimetres
MANOVA	Multivariate Analysis of Variance and Covariance
Miles/h	Miles per hour. Miles is not abbreviated to avoid confusion with metres.
mph/s	Miles per hour per second, unit of acceleration used in United States customary units
MVMT	Million Vehicle Miles Travelled
MySQL	Relational database software
Naturalistic data	Data collected from vehicles using one or more sensors
NHTSA	National Highway Traffic Safety Administration (US)
NMEA	National Marine Electronics Association
NMEA-0183	Data standard used for transmission of GPS

	observations
NSW	New South Wales (Australia)
OBD	On-Board Diagnostics
OCR	Optical Character Recognition
PAYD	Pay as you Drive
Primary key	Variable(s) which (together) uniquely identify a record in a table of a relational database
R	R-project for statistical computing; an open source language and development environment for statistical computing
RFT	Regulatory Focus Theory, a goal pursuit psychology theory developed by Higgins (1997)
RMS	Roads and Maritime Services, previously RTA
RSI	Road Segment Identifier, unique identifier for each road segment
RTA	Roads and Traffic Authority (NSW, Australia)
SAS	Speeding Attitude Scale
SCATS	Sydney Coordinated Adaptive Traffic System
SCT	Smart Car Technologies
SD	Standard Deviation
SE	Standard Error
SEK	Swedish Krona
Sig.	Statistical significance
SOI	Sequential Observation Identifier, a unique sequential identifier assigned to each observation (used as a primary key)
SPSS	Statistical Package for the Social Sciences (statistical analysis software)
SQL	Structured Query Language, used to query relational databases
SQRS	Speeding Risk Belief Scale
Stata	Data analysis and statistical software
TSI	Temporal and Spatial Identifier, an identifier for the

	classification of temporal and spatial environments
TSINTP	Temporal and Spatial Identifier – No Trip Purpose, the same as TSI without trip purpose
TADS	Traffic Accident Database System
TPB	Theory of planned behaviour
TRA	Theory of reasoned action
TransCAD	Geographic Information System software
URL	Uniform Resource Locator
USD	United States Dollar
VKT	Vehicle Kilometres Travelled
VMS	Variable Message Sign
VMT	Vehicle Miles Travelled
Vulnerable Road Users	Pedestrians, cyclists and motorcyclists
WHO	World Health Organisation

Thesis Specific Definitions

As with any field, transport has a number of terms whose exact use differs slightly depending on the context and users. These ambiguous terms are defined here. Unless otherwise stated, the following definitions are used within this thesis.

Acceleration	Positive change in velocity over a time period of one second
Celeration	Any change in speed (lateral and longitudinal)
Accident	A crash/collision regardless of cause or fault; only used when it is necessary to be consistent with referenced sources otherwise crash is used
Active school zone	A designated school zone during its hours of operation
Aggressive acceleration	Acceleration in excess of 4 m/s^2
Aggressive braking	Negative acceleration in excess of -4 m/s^2
Braking	See 'Negative Acceleration'
Casualty crash	A crash that results in an injury or fatality
Intra-driver	Difference in behaviour (for example, speeding) of the same driver across time and space (location)
Inter-driver	Difference in behaviour of different drivers
Jerk	Rate of change of acceleration; measured in m/s^3
Negative acceleration	Negative change in velocity over a time period of one second; sometimes referred to as braking
Primary driver	The driver that completed the demographic and psychological surveys
Private transport	Cars, motorcycles, cycling and walking
Rain	Any precipitation within the previous 30 minutes
Risk index	A scale from 0 (lowest risk) to 100 (highest risk) on which drivers are scored
Risk score	A number on the risk index which describes the risk of injury or death a driver imposes on themselves and other road users
Risk margin	A range of the risk index that describes the variation in drivers' behaviour

Road segment	A series of sequential and uninterrupted observations which share common spatial, temporal and trip characteristics
Road speed segment	A series of sequential and uninterrupted observations which share a common speed limit and trip
Speed limit	The legal speed limit as defined by local legislation and typically posted on road signs. Also known as the 'posted speed limit'
Speeding	Driving in excess of the speed limit by any magnitude – for example, 51 km/h in a 50 km/h zone

Temporal and Spatial Identifiers Reference Guide

Temporal and Spatial Identifiers (TSIs) are used throughout this thesis to control for the road environment. They are discussed in detail in Chapter 7. The following can be used for reference as a reminder as to what they represent.

Codes	
40,50,60,70,80,90,100,110	Posted speed limit
D	Primary driver (absence indicates other driver)
I	Within 25 metres of a signalised intersection
N	Within 25 metres of a non-signalised intersection
O	Within 25 metres of a roundabout
P0	Number of passengers (zero)
P1	Number of passengers (one)
P2	Number of passengers (two)
P3	Number of passengers (three or more)
PE	Trip purpose (education)
PH	Trip purpose (returning home)
PO	Trip purpose (other)
PR	Trip purpose (recreation)
PS	Trip purpose (shopping)
PW	Trip purpose (work related)
R	Presence of rain
S	Presence of school zones
TD	Time of day (day – 09:00 to 14:59)
TE	Time of day (afternoon/evening – 15:00 to 19:59)
TM	Time of day (morning – 05:00 to 08:59)
TN	Time of day (night – 20:00 to 04:59)
W	Weekend (absence indicates weekday)

Frequently observed TSIs	
ST{60,TE-D-PH-P0}	60 km/h, evening, returning home, no passengers
ST{60,TM-D-PW-P0}	60 km/h, morning, work related, no passengers
ST{N-60,TE-D-PH-P0}	60 km/h, non-signalised intersection, evening, returning home, no passengers
ST{N-60,TM-D-PW-P0}	60 km/h, non-signalised intersection, morning, work related, no passengers
ST{50,TE-D-PH-P0}	50 km/h, evening, returning home, no passengers
ST{60,TE-D-P0}	60 km/h, evening, no passengers
ST{60,TD-W-D-P0}	60 km/h, day, weekend, no passengers
ST{60,TM-D-P0}	60 km/h, morning, no passengers
ST{50,TE-D-P0}	50 km/h, evening, no passengers

1 INTRODUCTION

This thesis examines how drivers risk perceptions, concern of injuries, confidence and personality relate to their speeding, acceleration and braking behaviour in day-to-day driving before and after the introduction of a pay-as-you-drive (PAYD) scheme. The intervention comprised a financial incentive *and* a mechanism for making drivers aware of their speeding behaviour permitting both aspects to be investigated. This knowledge can be applied to develop more effective road safety interventions resulting in better societal outcomes.

Globally, road crashes have high social costs amounting to $520 billion (USD) (Jacobs et al., 2000), 1.24 million fatalities and 50 million injuries annually (World Health Organisation, 2013). Despite significant efforts by researchers, road safety organisations and government aimed at reducing this road toll, these statistics show that drivers continue to engage in risky driving behaviour and this is reflected in the continuing high number of road crash casualties. Human factors are a causal factor in over 90 percent of these road crashes (Treat et al., 1979; Petridou and Moustaki, 2001) indicating that driver behaviour – not poor infrastructure, mechanical failures or uncontrollable environmental factors – is largely to blame for road casualties. As a consequence, although improvements in vehicle and road technology have provided tangible benefits (Richter et al., 2005), improving driver behaviour can potentially provide significant reductions in injury and fatalities.

This chapter introduces the background to this research, outlines the research gaps and contribution and concludes with an overview of the structure of the thesis.

1.1 Background

The issue of road safety has gained increasing prominence internationally. For instance, the World Health Organisation's *World Report on Road Traffic Injury Prevention* (Pedan et al., 2004) and *Global Status Report on Road Safety* (World Health Organisation, 2013) presents data showing that road traffic is one of the highest causes of fatalities in the world. The authors of the WHO study state that improving road safety requires a comprehensive systems approach but that this is impeded by the lack of reliable data due to widespread underreporting (Pedan et al., 2004). These views are also expressed in the Australian Transport Council's draft *National Road Safety Strategy 2011-2020* (Australian Transport Council, 2010). This strategy advocates a systems approach using the terms "safe roads" and "safe speeds" for infrastructure elements, "safe vehicles" for technology and "safe people" for human factors. This is echoed by the Vision Zero approach which targets zero road fatalities and became Sweden's road safety policy in 1997 (Johansson, 2009; Belin et al., 2012). However, government strategies aimed at improving road safety are not new. Driver education and road safety campaigns have been used to influence motorised vehicle driver behaviour for the purposes of improving road safety since at least 1917 (Royal Society for the Prevention of Accidents, 2010). Legislation has also been a feature of road safety strategies, with the passing of the Road Safety Act of 1930 in the United Kingdom making drink driving a criminal offence (Ross, 1973) but more than 80 years later drink driving (see Section 2.2.4) remains a problem contributing to 21 percent of road crash fatalities in New South Wales, Australia (NSW Centre for Road Safety, 2009). This is an indication that although there have been improvements in road safety in highly motorised countries (Pedan et al., 2004), there remain elements of road safety that have not been solved.

The risks associated with dangerous driving behaviour – particularly speeding and using mobile telephones while driving – are well documented and publicised. What is less well understood is why, despite well funded enforcement and advertising campaigns, a significant proportion of the population still engage in these behaviours. This has a significant impact on fatalities and injuries. One estimate suggests that if all drivers were to comply with *existing* speed limits, fatalities alone would be reduced by 22 percent (Elvik, 2008). Yet evidence shows that many drivers do not consider speeding to be dangerous (Lieb and Wiseman, 2001). This suggests a disconnect between objective risk and drivers' risk perceptions and how this reflects on driving behaviour. This implies that existing methods used to convince drivers to change behaviour are only partially effective.

1.2 Research gaps

While there have been numerous studies attempting to determine the reasons for this disconnect by studying the influencing factors, magnitude and impact of risky driving behaviour, most studies are limited by the reliance on self-reported and police-enforcement data both of which suffer from underreporting (Hatfield et al., 2008; Yamamoto et al., 2008). It has also been identified that crash data represents a very small proportion of all driving activity and this makes them vulnerable to random variability (Wundersitz and Hutchinson, 2012). Since casualty crashes account for a small proportion of vehicle crashes and vehicle crashes are in themselves extremely rare events, it has been argued that studying crashes is not the best way to study driver behaviour (Wundersitz and Hutchinson, 2012). Wundersitz and Hutchinson (2012) suggest that researchers should find proxies of driver behaviour that can be objectively observed and measured which have a direct link to road safety. However, this approach would require researchers to monitor drivers across time during their normal driving routines, a capability that is not possible using many widely used methods (of which self-reported and crash records are two) of studying driver behaviour.

This is reinforced by research which has shown that in addition to individual driver behaviour there is an inherent risk in each vehicle kilometre travelled (VKT) with higher risks of crashes associated with certain temporal (night) and spatial (rural) characteristics (Litman, 2010). Capturing this level of data is a necessary element in developing accurate risk profiles for individual motorists (Jun et al., 2007). Many of these limitations were imposed by limitations of aforementioned measurement techniques. However, wider availability of sensing technologies, primarily Global Positioning System (GPS) technology has improved the ability to relatively unobtrusively collect large amounts of data from individual drivers (albeit at the expense of higher resource requirements and smaller sample sizes) (Greaves et al., 2010).

Possibly as a symptom of these limitations, studies and road safety campaigns have invariably attempted to categorise drivers by common demographics relying on the assumption that drivers of similar age and gender are similar in their perception and attitudes towards risk, and individual behaviour. Evidence – particularly from the literature on speeding – suggests that at least in terms of on-road driving behaviour this is not an entirely accurate assumption (Greaves and Ellison, 2011) and therefore driver risk assessment requires a more robust approach. Although improved road safety campaigns are not an outcome of this thesis, it is expected that the findings and techniques developed will improve the effectiveness of future road safety interventions and provide a means for evaluating the benefits of future campaigns and interventions.

1.3 Contribution

This research focuses on two over-arching themes. The first relates to identifying if drivers' risk perceptions, concerns of injury, confidence in their driving skills and personalities can be used to predict the frequency and magnitude of their speeding, acceleration and braking behaviour within their normal driving routines – that is, outside of the controlled environment of a driving simulator or survey environment. The second theme relates to how driver behaviour can be improved – as defined by reductions in speeding, aggressive acceleration and aggressive braking – by making drivers both aware of what they are doing and providing a financial incentive to change behaviour. In the process of investigating these issues, this thesis makes a number of contributions to research and practice.

1.3.1 Research and methodology

This thesis makes contributions to the road safety literature and methodological techniques, designed to improve understanding of driver behaviour. The research contributions include:

- Introducing processes for integrating naturalistic driving data with related road environment, trip information, driver characteristics, attitudes and personality together with detailed responses to multi-faceted interventions (Chapter 5);
- Designing a methodology for controlling for the influence of the road environment in analyses of naturalistic driving which can also be used as a method of aggregation that retains the same structure as the disaggregate datasets (Chapter 7);
- Developing a framework and methodology for describing drivers' speeding, acceleration and braking behaviour as a function of the risk of a fatality crash at any level of aggregation incorporating different magnitudes, frequencies and

VKT, which provides an effective method of measuring changes in behaviour across time and space (Chapter 8);

- Developing a driver behaviour profiling/scoring approach, that incorporates several behavioural measures into a single composite driver behaviour profile that can be used to describe an entirety of driver's behaviour (Chapter 8);
- Employing multilevel/hierarchical modelling to identify variables that (in combination) predict drivers' speeding, acceleration and braking behaviour (Chapter 9);
- Employing multilevel/hierarchical modelling to identify changes in driving behaviour that occur as a result of informing drivers of their speeding behaviour and providing a financial incentive to reduce their speeding behaviour (Chapter 10); and
- Identifying a number of implications for research on driver behaviour and before-and-after studies (Chapter 11).

1.3.2 Practice and policy

In addition to the contributions to research, this thesis also makes a number of contributions to practice and policy. These contributions can be applied towards improving the effectiveness of road safety policies and strategies. These include:

- Identifying the potential to redesign the road environment to limit drivers' ability to drive in excess of the posted speed limit (Chapter 11);
- Introducing a framework and tool for describing driver behaviour as a function of risk that can be applied to measure the effectiveness of road safety strategies (Chapter 8);
- Identifying that risk perceptions and personality are related to speeding behaviour – and that these relationships are stronger than demographics – which can be used to improve the design and targeting of road safety campaigns (Chapter 9);
- Identifying two broad groups of drivers, the largest of which comprising approximately 80 percent of drivers, can be encouraged to reduce their speeding behaviour by making them aware of their speeding behaviour and/or providing a financial incentive (Chapter 10); and

- Recommending a suite of hard and soft policy measures, based on the findings of this research, which could be applied to reduce speeding behaviour among both of the aforementioned groups (Chapter 11).

1.4 Thesis structure

This thesis is comprised of 11 chapters (shown in Figure 1-1) and three appendices.

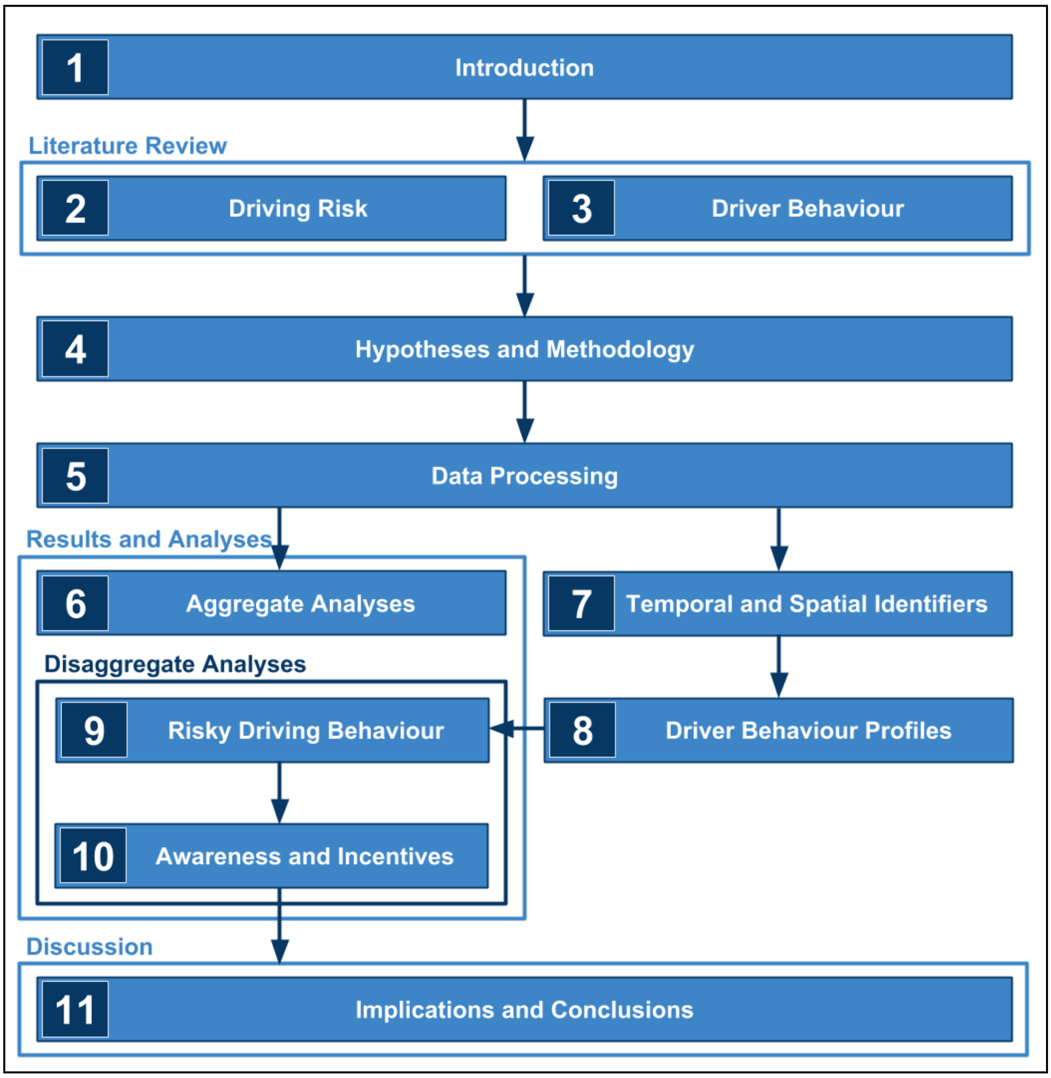

Figure 1-1: Thesis structure

Chapter 2 is a synthesis of the literature on driving risk, risky driving behaviour and research methods for capturing driver behaviour. Section 2.2 examines the literature on the frequency and impact of the most common forms of risky driving behaviour with a particular emphasis on speeding, acceleration and braking as these are the focus of this research. Section 2.3 examines the literature on exposure and other sources of risk that are exogenous to the driver. Section 2.4 reviews the literature on collection of driver behaviour data including surveys, crash data, simulators and naturalistic driving.

Chapter 3 reviews the literature on the factors that influence driver behaviour, methods of categorising drivers and concludes with identifying the research gaps identified from the literature review. Specifically, Section 3.1 reviews the literature on the relationship between driver behaviour and the road environment, demographics, personality, enforcement and risk perception. Section 3.2 summarises the existing literature on behavioural responses to the provision of information. Section 3.3 identifies prior research on categorising drivers on a number of measures including demographics, risk perceptions and observed behaviour.

Chapter 4 describes the study design and methodology that are used in this thesis. The hypotheses that are tested are outlined in detail in Section 4.1. The data that are used to examine the hypotheses are described in Section 4.2. Lastly, an overview of the analysis and methodological approaches are introduced in Section 4.3.

Chapter 5 is a detailed technical discussion of how the datasets employed in this research were stored, cleaned, processed and merged. Section 5.1 describes how the data were stored and queried using relational databases. Section 5.2 deals with the algorithms that were developed to identify the spatial characteristics which were relevant to each GPS observation. Section 5.3 explains how the raw GPS data were used to determine where and when drivers engaged in speeding, aggressive acceleration and aggressive braking behaviour as well as the techniques used to correct and smooth the data. Section 5.4 discusses two methods for aggregating the 80 million GPS observations to a manageable level. Lastly – and distinctly – the demographic, psychological and exit surveys are explained in Section 5.5.

Chapter 6 is the first of three results chapters. It presents a number of analyses selected to illustrate the inherent issues in trying to study driver behaviour with data collected during day-to-day driving outside a controlled environment and the poor model performance that occurs as a consequence. Section 6.1 is an exploratory analysis of (primarily) speeding behaviour at an aggregate level. Section 6.2 contains ANOVA, logistic regression and clustering analyses of driver behaviour using overall speeding for each driver as the dependent variable. Section 6.3 describes the best performing logistic regression models performed using data aggregated to the road segment. Section 6.4 provides some concluding commentary on the results and problems of the models in this section.

Chapter 7 introduces Temporal and Spatial Identifiers (TSI) which is a methodology developed to control for the influence of spatiotemporal factors on driver behaviour and thereby resolve some of the problems identified in Chapter 6. Section 7.1 and Section 7.2 identify the spatial and temporal factors respectively that are accounted for. Sections 7.3 to 7.6 comprise of a technical discussion on how the TSIs are identified, created and subsequently used as the basis for aggregating observations. Section 7.7 and Section 7.8 assess the characteristics and effectiveness of this approach. Lastly, Section 7.9 and Section 7.10 describe how this methodology can be applied in practice.

Chapter 8 describes the development of driver behaviour profiles (DBP) which has been developed as a tool for measuring driver behaviour on a consistent scale while accounting for differences in magnitudes and frequencies. Sections 8.1 to 8.3 outline the framework behind this methodology and how the DBPs can be interpreted. Section 8.4 describes – in detail – the algorithm used to calculate the driver behaviour profiles as well as the changeable options and the final output. Section 8.5 explains the rationale behind the (customisable) weights that have been applied in the algorithm for the speeding, acceleration, braking and composite scores. This chapter concludes with Section 8.6 which explains how driver behaviour profiles can be used to compare behaviour between and within drivers.

Chapter 9 is the second of three results chapters and contains the results for the first set of hypotheses which relates to the extent of risky driving behaviour in day-to-day driving. Section 9.1 explains the methodology that is used and provides some explanatory analyses. Hypothesis 1.1 which deals with perceptions of risk is discussed in Section 9.2. The results for Hypothesis 1.2 which relates to drivers' concern of injury while driving are presented in Section 9.3. Hypothesis 1.3, relating to driving confidence, is examined in Section 9.4. Hypothesis 1.4 which examines the relationship between personality and risky driving behaviour is presented in Section 9.5. A summary and discussion of the results of the first set of hypotheses can be found in Section 9.7.

Chapter 10 is the last of three results chapters and contains the results for the second set of hypotheses. These hypotheses relate to how the magnitude of changes in risky driving behaviour that occur after the introduction of financial and speeding awareness interventions relate to risk perceptions (Section 10.2), concern of injury (Section 10.3), driving confidence (Section 10.4) and personality (Section 10.5). The conclusions that can be drawn from these results are discussed in Section 10.7.

Chapter 11 contains the implications of these results for policy and research. Section 11.2 contains the implications for policy, which are comprised of five aspects. These include changing the road environment, changing risk perceptions, improving speeding awareness, introducing financial incentives to reduce speeding and effective targeting of hard and soft measures for different groups of drivers. Section 11.3 contains a discussion on the research implications which include accounting for the road environment, using driver behaviour profiles for research and implications of these findings for before-and-after studies. The limitations of this research are discussed in Section 11.4. A path for future research is outlined in Section 11.5. The chapter (and thesis) concludes with some brief final remarks in Section 11.6.

Appendix A (Chapter 13) breaks each of the sub-hypotheses into its constituent parts and summarises if they could be accepted or not. Appendix B (Chapter 14) provides a discussion on a number of additional models that were run in the process of testing the first set of hypotheses (Chapter 9) but proved to not be beneficial. Nonetheless, they are provided as background as they contain some observations which have been excluded from the remaining models. Appendix C (Chapter 15) presents a number of models that have been reduced using a step-wise procedure. These are included as background material since the results chapters (Chapter 9 and Chapter 10) include only the full models.

2 LITERATURE REVIEW: 'RISKY' DRIVING BEHAVIOUR

This chapter reviews the literature on the extent of the most common forms of risky driving behaviour: speeding, fatigued driving and drink driving which are each contributing factors in between 20 and 34 percent of fatal crashes[4] (Australian Transport Council, 2010), and other forms of risky driving behaviour such as distractions, aggressive acceleration and aggressive braking. The outcome of these behaviours in terms of road injuries and fatalities are discussed here[5]. This chapter also includes a review of the literature in measuring behaviour and exposure. Although fatigue and drink driving are significant contributors to fatalities they are not examined explicitly in this thesis. However, some of the symptoms of fatigued and drink driving are measured by virtue of the effects on drivers' speed, acceleration and braking behaviour. These effects are discussed in this literature review.

2.1 Defining risk

In this thesis, risk is defined as the probability of a particular factor (or combination of factors) resulting in a casualty crash. Risk in the context of transport safety is a multifaceted concept and is affected by numerous factors of which an individual's driving behaviour is one.

Of the three elements of road safety strategies – infrastructure, vehicle technology and people – the human factor is likely the largest contributor (Petridou and Moustaki, 2001). A key component of this is (so-called) 'risky' driving behaviour. For the purposes of this thesis, risky driving behaviour is defined as behaviour by the driver that puts themselves or others at an increased risk of being involved in an incident that could result in damage, injury or death.

It is important to understand that the risk of a casualty crash associated with a given factor is made up of two related elements. The first is the probability of any crash occurring at all. The second element is the severity of a crash when it occurs (Bagdadi, 2012). For example, speeding is a factor that contributes to a higher

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[4] These factors are not necessarily mutually exclusive.

[5] For a review on the literature of the factors which influence drivers to engage in these behaviours, refer to Chapter 3.

probability of a crash but simultaneously the higher the magnitude of speeding the higher the probability of a fatal crash which would be the most severe impact. In contrast, the presence of rain increases the probability of a crash but the probability of the crash resulting in a fatality is dependent on vehicle speed and numerous other factors (Sun et al., 2010).

2.2 Types of risky driving behaviour

Determining what behaviours are risky is outside the scope of this research. However, previous research has identified a number of driving behaviours that increase the risk of a casualty crash occurring. A summary of the most commonly researched factors is shown in Table 2-1. These behaviours include speeding, aggressive acceleration and braking, driving whilst fatigued, drink driving as well as self-assertive driving and other rule-breaking (Machin and Sankey, 2008), distracted driving, and several road user movements. Reducing the frequency and magnitude of these risky driving behaviours is one method of improving road safety.

Table 2-1: Risky driving behaviours

<table>
<tr><th>Behaviour</th><th>Source(s)</th><th>Description</th></tr>
<tr><td rowspan="2">Speeding</td><td>Pedan et al. (2004) , Elvik (2010a)</td><td>Exceeding the posted speed limit and driving at a speed not safe for the conditions.</td></tr>
<tr><td colspan="2">$$Relative\ Risk = \left(\frac{v}{100}\right)^{4.5} + \left(\frac{v}{100}\right)^{3.0} + \left(\frac{v}{100}\right)^{1.5}$$
100 = reference speed (100 km/h)
v = any speed >= 10 and <= 130 km/h
4.5 = exponent for fatalities
3.0 = exponent for serious injuries
1.5 = exponent for slight injuries</td></tr>
<tr><td rowspan="2">Aggressive braking and acceleration</td><td>Musicant et al. (2010), Liu and Lee (2005), Jun et al. (2007)</td><td>Defined based on the time between the first application and the release of the breaks or no acceleration</td></tr>
<tr><td colspan="2">Relative frequency of hard braking (2.68 metres/s^2) by crash involved drivers adapted from Jun et al. (2007):

Road Type | Time of Day | Relative Frequency
Motorways | Morning | 3
Arterials | Morning | 2
Local | Morning | 2
Local | Night | 2</td></tr>
<tr><td rowspan="2">Fatigue</td><td>May and Baldwin (2009), McConnell et al. (2003)</td><td>Includes sleep-related and task-related fatigue</td></tr>
<tr><td colspan="2">Relative risk of fatality from a crash resulting from fatigued driving is three times the average risk of all crashes (McConnell et al., 2003)</td></tr>
<tr><td>Drink driving</td><td>Chen et al. (2010); (Fillmore et al., 2008)</td><td>Associated with higher speeds, higher acceleration, more frequent lane deviation and more frequent red light running.</td></tr>
<tr><td rowspan="2">Distractions</td><td>McEvoy et al.(2007a), McEvoy et al. (2005)</td><td>Includes mobile telephone usage, eating and drinking</td></tr>
<tr><td colspan="2">Mobile telephone usage is associated with four times the risk of an injury resulting in hospital attendance controlling for risk taking and other driver characteristics (McEvoy et al., 2005).</td></tr>
<tr><td rowspan="2">Red light running and failing to stop/give-way at non-signalised intersections.</td><td>Porter and Berry (2001), Campbell et al. (2004)</td><td>Driving through an intersection during a red light phase and failures to obey violations which are violations of the road rules dealing with traffic lights, stop signs and yield signs.</td></tr>
<tr><td colspan="2">Probability of a crash being fatal[6]
Signalised intersection | 3.1% of all crashes
Signalised intersection (failure to obey violations) | 20% of fatal crashes
Non-signalised intersection | 6.1% of all crashes
Non-signalised intersection (failure to obey violations) | 26% of fatal crashes</td></tr>
<tr><td rowspan="2">Other Road User Movements</td><td>Yan et al. (2007), Retting et al. (2003), Liu et al. (2008)</td><td>Includes u-turns and stopping in the middle of an intersection</td></tr>
<tr><td colspan="2">U-turns at signalised intersections result in 71.6 percent greater crashes than when u-turns are not facilitated (Liu et al., 2008).[7]</td></tr>
</table>

[6] Adapted from Campbell et al. (2004)

2.2.1 Speeding

Speeding is typically defined in one of three ways[8]. The first, driving at a speed in excess of the posted speed limit (for example Goldenbeld & van Schagen, 2007), is the simplest and least subjective but in many cases does not match the legal (enforcement) situation. The second, driving at a speed for which a driver can be penalised (Ogle, 2005), accounts for the impact of enforcement tolerances but reduces comparability across studies due to the different tolerances in different jurisdictions. For example, Ogle (2005) used a 5 mile/hour (8 km/h) threshold and Elvik (2012a) indentified enforcement in Norway applied only when drivers were driving at a minimum of 6 km/h in excess of the posted speed limit. In the Australian states of Victoria and New South Wales, Australia[9], there was (officially) no tolerance threshold (Fildes et al., 2005). The third method of defining speeding is driving at a speed that is unsafe for the conditions (McKnight and McKnight, 2003). This third method is likely to be the most important in terms of contributing to crash risk with one study finding driving too fast for the conditions is a factor in 26 percent of novice crash drivers. This compares to 12 percent for exceeding the posted speed limit (Braitman et al., 2008). However, this definition of speeding is also the most difficult to measure empirically as it requires a judgement to be made regarding the conditions and drivers typically overestimate their ability to accurately assess safe speeds (Blincoe et al., 2006).

Speeding is a factor in 33 percent of fatal crashes in Australia (Bureau of Infrastructure Transport and Regional Economics, 2011). Similar findings are seen in the United Kingdom (Bhagat et al., 2010) and in the United States (National Highway Traffic Safety Administration, 2009). In NSW, 40 percent of fatal crashes and 16 percent of injury crashes are at least partially attributable to speeding (NSW Centre for Road Safety, 2009). This demonstrates that speeding remains a significant safety

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[7] Liu et al. (2008) was conducted in Florida where u-turns at intersections are permitted and in some cases facilitated through left-turn/u-turn lanes. In New South Wales where the data used for this thesis was collected u-turns are not permitted at most signalised intersections thereby potentially increasing the crash risk as a u-turn would not be anticipated by other drivers.

[8] Speeding in this case refers to speeding at any point in time. In some jurisdictions point-to-point speed cameras are used to enforce maximum average speeds (Soole et al., 2012).

[9] This thesis was written using data collected in Sydney, New South Wales.

issue despite recent enforcement and advertising campaigns. The high representation of speeding in the causes of road accident casualties could be misleadingly interpreted as being the result of drivers exceeding the speed limit by significant speeds. Whilst there is a relationship between a vehicle's absolute speed and the risk of a casualty crash (Kloeden et al., 1997) a significant proportion of speeding occurs in lower speed zones (Ellison and Greaves, 2010).

Kloeden et al. (1997) found that the relative risk of being involved in a casualty crash in a 60 km/h zone doubles with only a 5 km/h increase in speed (see Figure 2-1). Travelling at 10 km/h above the speed limit increases the same risk by more than four-fold. Despite the known risk associated with speeding by relatively low magnitudes, both aforementioned speeds are within many jurisdictions' speed enforcement tolerances (Johnston, 2004).

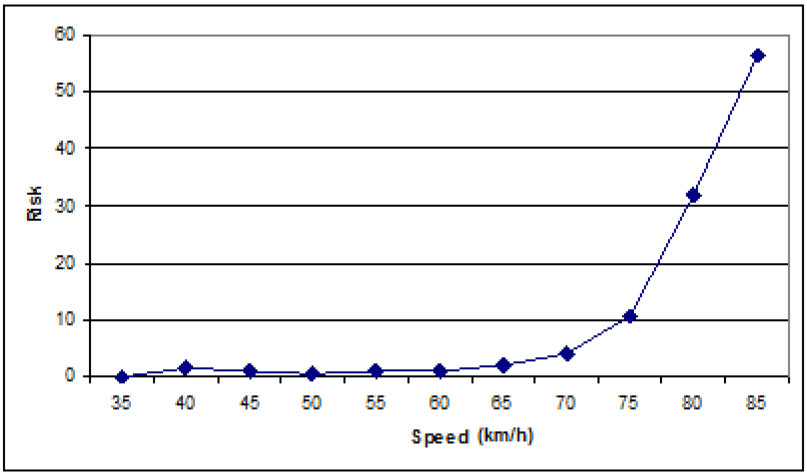

Figure 2-1: Risk of a casualty crash relative to travelling at 60 km/h (Kloeden et al., 1997)

Elvik (2009) determined exponents that apply to a power model of the relationship between vehicle speeds and crashes for rural and urban roads. The findings suggest that for a given reduction in vehicle speed – due to improved enforcement, lower tolerances, lower speed limits or the application of other measures – the exponent applied to the power model for fatal crashes is 4.1 for rural roads and motorways and 2.6 for urban and residential roads. A later analysis of the power model determined that the reduction in fatalities due to a reduction in speed could be better modelled by including the initial speed using an exponential function. The trend demonstrating that reductions in speed result in a corresponding decrease in fatalities is confirmed (Elvik, 2012c).

Also notable is that whilst speeding increases the risk of a crash occurring and the risk of being involved in a casualty crash, it also increases the risk of killing pedestrians and other vulnerable road users. Figure 2-2 illustrates the increasing likelihood of a pedestrian fatality (in the event of a collision) as absolute vehicle speeds increase. Given that speed limits in many urban areas - in Australia and elsewhere – are already higher than 30 km/h (Langford, 2006), exceeding the speed limit only compounds the problem. Of particular concern to pedestrians is that speeding appears to be as prevalent in school zones (Ellison et al., 2011) and 50 km/h zones with high levels of pedestrian activity as it is on motorways with speed limits of 100 and 110 km/h.

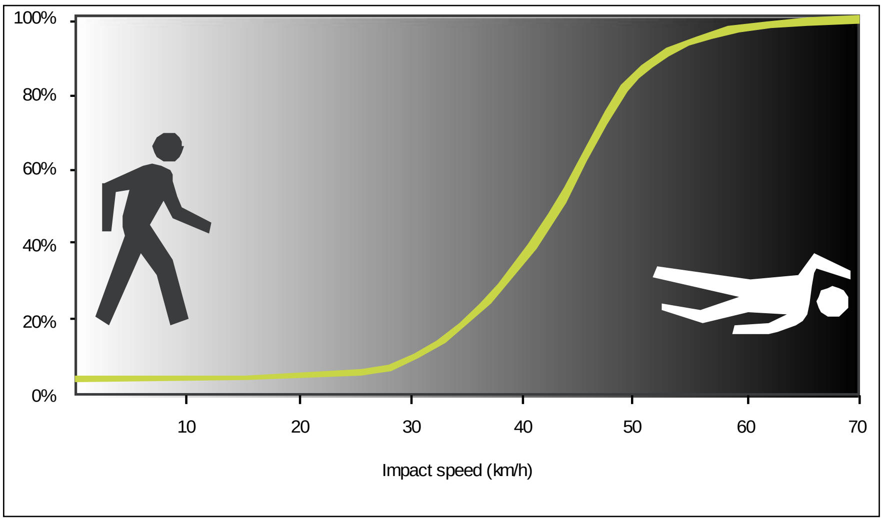

Figure 2-2: Likelihood of Pedestrian Fatality (Pedan et al., 2004)

In addition to absolute speed, the 85th percentile speed for all vehicles on a particular road has been shown to impact the risk of a severe crash occurring (Hewson, 2008). Another study found that the number of crashes on a particular road segment can be predicted using a combination of the speed difference at the start and end of a particular segment and the average speed although the exact relationship varied by crash type (rear-end, sideswipe, others) (Song and Yeo, 2012). Relative differences in speed between vehicles does have an impact on crash risk (Hewson, 2008). Aarts and Van Schagen (2006) reviewed a number of studies examining this aspect of vehicle speeds and its impact on crash risk. They found that there is agreement that driving faster than the average speed of other vehicles is a factor in vehicle crashes however evidence is mixed regarding vehicles that driver slower than the average. They suggest that this may reflect that many crashes occur in the midst of a road user movement – such as turning – which require lower speeds than other vehicles.

Not every incident of speeding results in a crash of any severity and much of the time drivers are able to exceed the speed limit with no consequences. This is observed in the frequency of speeding behaviour but estimates of the exact frequency and magnitude of speeding behaviour vary tremendously. This is partly a function of the different methods of collecting data on speeding behaviour (see Section 2.4 for a discussion of data collection methods) but also reflects the different enforcement regimes used in different jurisdictions. For example, enforcement data in South Australia showed that almost one third of licensed drivers in South Australia were caught exceeding the speed limit (Wundersitz et al., 2009) which is consistent with a study conducted in Australia and China which found that 32.5 and 32 percent of drivers were caught speeding in the preceding three years (Fleiter et al., 2009). This compares to a figure of 39 percent reported in a study conducted in Perth, Western Australia using traffic counters (Radalj, 2000). On the other hand, a national survey in the United States which collected self-reported speeding behaviour found that 73 percent of drivers report exceeding the speed limit on local roads during the previous month and 83 percent report exceeding the speed limit on multiple lane arterials. Speeding on other types of roads (motorways, etc.) also fall within this range. Evidence from the same survey showed that 51 percent of drivers exceed the speed limit on motorways by 10 miles/h (16 km/h) 'sometimes' or 'often' and 12 percent report exceeding the speed limit by 20 miles/h (32 km/h) (Royal, 2003). This appears high but another study of speeding behaviour found that 34.4 percent of drivers preferred to exceed the speed limit in 60 km/h zones and 58.4 percent preferred to exceed the speed limit in 100 km/h zones. The figures for exceeding the speed limit by 10 km/h or more in the same speed zones were 10 and 33.4 percent respectively (Fleiter and Watson, 2006).

The aforementioned studies measured the proportion of drivers speeding (Royal, 2003; Fleiter and Watson, 2006; Fleiter et al., 2009; Wundersitz et al., 2009) or the proportion of vehicles speeding in particular location(s) (Radalj, 2000). Another way to measure speeding behaviour is to look at the proportion of time or distance driven above the speed limit. This requires more advanced methods of measuring speeding and is therefore less common. Speeding by time is computed by calculating the total time spent speeding (however the researchers define speeding) and dividing that by the total driving time. Speeding by distance is similar except the total distance (in kilometres or miles) driven whilst speeding is divided by the vehicle kilometres travelled (VKT) or vehicle miles travelled (VMT). The results of both measures are similar, however speeding by time results in lower proportions of speeding than speeding by distance as driving faster also reduces the time taken (albeit marginally) to travel the same distance.

As part of the Commute Atlanta naturalistic driving study conducted in the United States with 172 vehicles, 40 percent of driving time was found to be in excess of the speed limit and 12 percent of driving time was conducted 10 miles/h (16 km/h) above the posted speed limit (Ogle, 2005). In a study of 85 teenage drivers in the Washington, D.C. area in the United States, speeding by 10 miles/h (16 km/h) or more was observed in the control group[10] for 12 to 15 percent of the distance driven (depending on the study phase) which is comparable to the previous study (Farmer et al., 2010). Speeding behaviour was also measured during a recent trial in New South Wales, Australia of Intelligent Speed Adaptation (ISA) devices. Speed recording devices were successfully installed in 101 private and government vehicles with which speeds were recorded for 1.5 months before the installation of an ISA device. During this period, speeding by less than 10 km/h was observed for an average of 29.1 percent of the time per vehicle across all speed zones. Speeding by 10 to less than 20 km/h and speeding by 20 km/h or more was recorded for 6.2 percent and 0.9 percent of the time respectively. School zones (with a 40 km/h speed limit) had the highest recorded levels

[10] In this case, the control group consisted of drivers that were being monitored using an in-vehicle device which passively recorded their driving behaviour but which provided no information to participants.

of speeding (49.6 percent of the time) whilst 60 km/h roads had the lowest recorded levels of speeding at 30.3 percent of the time (NSW Centre for Road Safety, 2010).

A direct comparison of the extent of speeding behaviour between studies or in different locations is inadvisable. Nonetheless, these studies do provide an indication to how commonly speeding occurs. Given this, it is not surprising that speed related crashes are as prominent in injury and fatality figures. A review of the literature concerning the reasons behind why drivers speed is included in Chapter 3.

2.2.2 Acceleration and braking

Acceleration is defined as the change in velocity over (a period of) time. Acceleration can be positive – when a vehicle's speed is increasing – or negative – when a vehicle's speed is decreasing – which is also known as deceleration or braking. Driving activity therefore always includes a necessary level of positive and negative acceleration. Accordingly, although all behaviours have some element of risk (however small) most acceleration and braking behaviour observed during day to day driving is not considered dangerous. Nonetheless there is increasing evidence that particular patterns of acceleration and braking behaviour are linked to a greater incidence of crashes.

Jun et al. (2007) used GPS data collected for a six month period from 167 drivers in Atlanta (United States) to examine the difference in acceleration behaviour of drivers involved in crashes (26 drivers in the sample) compared to drivers that had not been in crashes. Several measures were used including mean, standard deviation and frequency of hard acceleration events per mile. Frequency of hard (positive and negative) acceleration events were based on several categories with acceleration in excess of 4, 6 and 8 miles per hour/second (mph/s), equivalent to 1.8 m/s^2, 2.7 m/s^2 and 3.6 m/s^2. Using a threshold of 6 mph/s (2.7 m/s^2), the researchers found a statistically significant (positive) difference, at the $\alpha = 0.05$ level, between the frequency of hard acceleration and braking events of the crash-involved and non-crash-involved drivers on freeways, arterials and local roads during the morning (09:00 – 12:00) and on local roads at night (20:00 – 24:00). Differences during other time periods were observed but those are not statistically significant. The authors suggest that the morning and night time periods may be statistically significant because drivers engage in behaviour (for example tailgating or mobile telephone use) that is more difficult during congested conditions that are not typically observed during these time periods.

In a study looking at the effect of mobile telephone use on driving behaviour at intersections, researchers established a base line for braking when approaching a red light at an intersection with no distractions. The total sample was only six drivers which were in turn identified as aggressive or non-aggressive based on the results of a driving behaviour inventory (DBI) survey. Results showed that average negative acceleration when approaching a red light was 1.4 m/s^2 with a standard deviation (SD) of 0.6 m/s^2 for aggressive drivers and 1 m/s^2 with a SD of 0.4 m/s^2 for non-aggressive drivers (Liu and Lee, 2005).

A study of bus driver celeration[11] profiles, which include all lateral and longitudinal changes in speed, conducted in Sweden attempted to test if speed or celeration profiles are the better performing accident[12] predictor. The researchers found celeration profiles to be slightly more correlated with accidents than speed choice (measured using mean speed, maximum speed and standard deviation of speed) but although the effect was statistically significant the difference between the correlations of accidents versus celeration and speed was not (Af Wåhlberg, 2006). Bagdadi and Várhelyi (2011) argue that although most braking during day-to-day driving is (on average) -3.1 m/s^2 and most crashes involve acceleration of between -4 m/s^2 and -7.7 m/s^2 studies have shown that it is not uncommon for braking in a normal (non-conflict) situation to exceed these magnitudes. These magnitudes are higher than those found at intersections by Liu and Lee (2005) which suggests that braking at intersections is at lower magnitudes than elsewhere. Bagdadi and Várhelyi (2011) argue that jerks may be a better way of relating acceleration behaviour to crashes. Jerk refers to the rate of change of acceleration and therefore accounts not for the magnitude of acceleration but also to the change in acceleration during driving activity. Using a sample of 166

[11] Celeration is defined as all changes in speed (lateral and longitudinal) and therefore consists of acceleration, braking and side-to-side movement.

[12] The cited study uses the word accident as opposed to crash. This terminology is maintained here for consistency although 'crash' is the preferred term.

drivers (including 33 crash-involved drivers), a regression model was created to test the relationship between the number of critical – or dangerous – jerks (defined as jerks in excess of -9.9 m/s^3) and self-reported crashes. The results show that each additional critical jerk increases the number of accidents by 1.13 ($p < 0.000$) over a three year period. There is no statistically significant effect with gender although a model stratified by gender shows that the effect of jerks is higher for females (1.42) than for males (1.13).

As part of the "100-Car Naturalistic Driving Study"[13] conducted in Virginia (United States) for the National Highway Traffic Safety Administration (NHTSA) and the Virginia Department of Transportation (VDOT), 100 cars were equipped with a range of cameras, sensors, data loggers and GPS devices. Driving events were categorised based on five severity levels: crash, near-crash, crash-relevant conflict, proximity conflict and non-conflict event. Near-crashes were defined as:

> "*Any circumstance that requires a rapid, evasive manoeuvre by the subject vehicle (or any other vehicle, pedestrian, cyclist, or animal) to avoid a crash. A rapid, evasive manoeuvre is defined as steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle's capabilities. As a guide, subject vehicle braking greater than 0.5g or steering input that results in a lateral acceleration greater than 0.4g to avoid a crash, constitutes a rapid manoeuvre.*" (Dingus et al., 2006)

Braking that results in 0.5g is equivalent to negative acceleration of 4.9 m/s^2 which is a higher threshold than the threshold used by Jun et al. (2007) but within the range identified by Bagdadi and Várhelyi (2011). The threshold of 4.9 m/s^2 of negative acceleration resulted in the detection of 471 near-crash events which represent 61.9 percent of all near-crash events during the study period. Lateral (side to side) acceleration only triggered 3.2 percent of all near-crash events. In terms of the 69 crashes that occurred during the study, the negative acceleration threshold was triggered for 40 crashes (58 percent) and lateral acceleration was triggered for 13 crashes (18.8 percent) (Dingus et al., 2006).

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[13] This study is discussed in depth in Section 2.4.3.

Taken together these studies show that drivers with aggressive acceleration and braking behaviour do tend to be involved in more crashes. The exact threshold of aggressive or critical acceleration behaviour has not yet been established and this will have an impact on results. It is also evident that it may be necessary to use more than one measure to more effectively differentiate between behaviours that are frequently observed (and generally safe) and those that are related to a crash or near-crash incident.

2.2.3 Fatigue

Thiffault and Bergeron (2003) define fatigue as "a general psychophysiological state that diminishes the ability of the individual to perform the driving task by altering alertness and vigilance." McConnell et al. (2003) in their review of the fatigued driving literature identified many different definitions of fatigue and other terms that are sometimes used interchangeably such as sleepiness. Due to the complexity of defining and measuring fatigue (Lal and Craig, 2001) and the relative scarcity of legal penalties (Fletcher et al., 2005) for fatigued driving of cars, the definition of fatigue changes from study to study. This makes comparing results across studies more difficult than for other forms of risky driving behaviour. Nonetheless, numerous studies have found driver fatigue to be correlated with longer reaction times, more erratic driving and generally reduced driving ability (May and Baldwin, 2009). This is reflected in the high number of fatal crashes in Australia (Australian Transport Safety Bureau, 2004), NSW (NSW Centre for Road Safety, 2009) and elsewhere (NHTSA, 2010). It is not possible to accurately determine when fatigue is a factor in a crash. Estimates range from as high as 30 percent in Australia (Australian Transport Safety Bureau, 2004), 16 percent of all fatal crashes in New South Wales, Australia (NSW Centre for Road Safety, 2009) and between zero and 9 percent of fatalities in the United States (National Highway Traffic Safety Administration, 2011) are (at least partially) caused by driver fatigue. Previous research (Hatfield et al., 2006; Chen et al., 2010) has found young drivers to be particularly likely to be involved in crashes due to fatigue. Controlling for differences in age, gender, risk perceptions and other driver characteristics, the relative risk of a fatigue-related crash involving a young driver in rural areas is almost double the risk for young drivers in urban areas (Chen et al., 2009) who are themselves of higher risk than drivers in other age groups. This is in spite of efforts at raising awareness of the dangers of driving when fatigued through advertising campaigns and the introduction of roadside rest areas (NSW Centre for Road Safety, 2008). It appears that although young drivers are knowledgeable about the symptoms of fatigue (Cortes-Simonet et al., 2010), that knowledge does not always translate into appropriate decisions. Currently, fatigue is as significant an issue (in terms of fatalities, injuries and other crashes) as drink driving. Fletcher *et al.* (2005) in their review of fatigue awareness campaigns and legislation point out that unlike drink driving, there is little legislation to combat fatigued driving. Given that the threat of a penalty appears to be a significant factor in the effectiveness of road safety campaigns (Fletcher et al., 2005), development of adequate legislation and subsequent enforcement appears to be a necessity.

Despite the evidence that fatigue is a problem, the complex causes of fatigue make it particularly difficult to develop effective minimisation strategies. May and Baldwin (2009) suggest that driver fatigue should be categorised as sleep-related (SR) or task-related (TR) fatigue – which includes factors such as task demand and duration – and separate techniques that should be used to reduce incidences of each. Another study (Nirupama et al., 2006) employed a driving simulator to determine factors which contribute to fatigue such that countermeasures can be developed to target them. The authors measured fatigue in three ways consisting of physiological measures, psychological measures and a combined physiological/psychological outcome and found different factors to be influential. Using a physiological measure, the researchers found warmer temperatures, extraverted personality and cerebral-electrical activity associated with sleep are factors related to fatigue. In terms of psychological factors, the researchers found trait anxiety, extraverted personalities, negative moods and less healthy lifestyles to be factors related to fatigue. Simulator studies have also shown fatigue to be related to (less) visual stimulation of the road environment and therefore more monotonous driving activity (Thiffault and Bergeron, 2003) which lends credence to the assertion by May and Baldwin (2009) that task-related fatigue is a problem related to the design of the road environment. Task related fatigue includes (in effect) boredom from insufficient cognitive load from the road environment (Barr et al., 2011).

2.2.4 Drink driving

Drink driving has been the subject of extensive research showing that it is dangerous. It has also benefited from legislation, stringent enforcement and education campaigns. This is reflected in research which has found 98 percent of drivers consider drink driving dangerous (Young and Lenné, 2010). Despite this, crash fatality data around the world continues to have a high representation of drunk driving. In the United States in 2010, there were 10,228 fatalities in crashes involving at least one driver with a Blood Alcohol Concentration (BAC) of 0.08 g/dL or more which represent 31 percent of total fatalities. Of the 10,228 fatalities, 17 percent were passengers in a car with a drunk driver and 18 percent were occupants of other vehicles or vulnerable road users. The states of North Dakota and South Carolina recorded the highest proportion of fatalities in the United States with 44 percent of crash fatalities involving a drunk driver (National Highway Traffic Safety Administration, 2012). In NSW – where the legal limit is somewhat lower at 0.05 g/dL – alcohol-related crashes now account for only four percent of crashes yet comprise 21 percent of fatal crashes (NSW Centre for Road Safety, 2009). This means that alcohol-related crashes tend to be more serious than other types of crashes and tend to exacerbate the impacts of other forms of risky behaviour. There are also significant differences in the incidence of alcohol related casualties in different demographics and locations. For example, young drivers, particularly in rural areas, have much higher rates of fatalities due to alcohol than any other age group (Chen et al., 2010). This is also true in the United States which has a legal drinking age of 21 where 18 percent of fatal crash involved drivers age 16 to 20 have a BAC of 0.08 g/dL or more.

In terms of the observable impacts on driver behaviour, alcohol is known to increase steering wheel variability and cause speed to increase significantly compared to the same drivers before alcohol was consumed (Ronen et al., 2010) but the magnitude of the effect varies depending on the BAC and the complexity of the driving task (Lenné et al., 2010). Drivers' acceleration patterns are also influenced by alcohol consumption. Drivers that have not consumed alcohol exhibit higher acceleration in conflict situations than in non-conflict situations. In contrast, alcohol-impaired drivers exhibit acceleration in both conflict and non-conflict situations similar in magnitude to non-impaired drivers in conflict situations (Fillmore et al., 2008).

2.2.5 Other risky driving behaviour

Although speeding, fatigue and drink driving together contribute to over 70 percent of road accident fatalities and a significant number of injury and non-casualty accidents (NSW Centre for Road Safety, 2009), the remainder are caused by other factors which include road user movements – for instance, u-turns and running red lights – and driver distractions. These additional factors are also more common and more dangerous when the driver is speeding, fatigued or drink driving. Wundersitz and Baldock (2011) estimate that 43.4 percent of fatal crashes are the result of 'extreme' behaviour which includes speeding by at least 50 percent of the speed limit or a BAC of 0.150 g/100ml (three times the legal limit in Australia). Illegal but not 'extreme' behaviours[14] are estimated to account for 22.9 percent of fatal crashes whilst general system failures, which are the result of driver errors when using the road network such as drifting out of a lane, account for 33.7 of fatal crashes. The respective proportions of non-fatal crashes in metropolitan and rural (in brackets) areas are 3.3 (9.4) percent for extreme behaviour, 9.9 (16.6) percent for illegal behaviour and 86.8 (74) percent for system failures[15].

Road user (or vehicle) movements refer to actions taken by road users. This includes left turns, right turns, crossing an intersection, reversing, changing lanes and many others. There are some road user movements which are known to be dangerous. This includes right turns (left turns in countries that drive on the right) (Yan et al., 2007), failing to stop at a non-signalised intersection (Retting et al., 2003) and red light running (Porter and Berry, 2001) as well as extreme breaking and acceleration (Liu and Lee, 2005). Some effort has also been made at investigating the types of risky behaviour associated with fatal crashes between cars and heavy vehicles (Kostyniuk et al., 2002). However, not all road user movements are dangerous. To calculate the risk of a crash or fatality occurring due to a particular road user movement, a measure

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[14] These include lower magnitudes of speeding, lower magnitudes of BAC and not wearing a seat belt.

[15] System failures are defined as situations in which a fatal crash occurred after a driver made an unintended error, absent of any illegal behaviours, that the road network should have been able to reduce the severity (through, for example, barriers separating vehicles travelling in different directions).

of exposure – the total number of individual road user movements – is required. Due to the expense of collecting transport exposure data it is often not available or is not suited to the research topic (Wundersitz and Hutchinson, 2008).

Assessing the risk of specific road user movements can be problematic since crashes occur as a result of a number of contributing factors. The risk of a crash when conducting even relatively safe movements can be increased through other factors. Given the high level of cognitive effort involved in the driving task (Elvik, 2006), distractions which force drivers to take their attention away from driving would appear to have an impact on the likelihood of a crash. In fact, evidence shows that one third of all crashes and 42 percent of single vehicle crashes involve some form of driver distraction including passengers, mobile telephone usage, eating or drinking (McEvoy et al., 2007a). Unsurprisingly given these results, many researchers have studied the impact of distracted driving on driving performance and crash risk. Much of this research is focused on mobile telephone usage (Dula et al., 2011; Backer-Grøndahl and Sagberg, 2011) but also includes eating and drinking (Young et al., 2008), distractions outside the vehicle, adjusting the radio and other passengers (Stutts et al., 2005). Cameras installed in instrumented vehicles have also been used to study distracted driving (Stutts et al., 2005; Dingus et al., 2006).

2.3 Other sources of risk from driving

Section 2.2 discusses the impact on the risk of a crash occurring that stems from particular driving behaviours. In addition to those behaviours, there are a number of environmental factors that contribute to the probability of a crash occurring at all or increase the likely impact of a crash if one does occur. This section deals with these additional sources of risk which include distance travelled and night time driving among others.

It has been established that there is a positive relationship (shown in Figure 2-3) between the distance travelled and the probability that a driver will be involved in a crash[16] (Litman, 2010). This means that a safer driver travelling longer distances may have a higher probability of a crash than an unsafe driver travelling short distances,

[16] A crash in which an insurance claim was made.

depending on the relative risks. The risk associated with a particular kilometre varies by numerous factors. Controlling for the influence of speed on travel time on higher speed roads, it has been shown that there is a positive relationship between (higher) crash risk and (higher) speeds (Pei et al., 2012). This per-kilometre risk functions as a proxy for factors or events that are not directly controlled by the driver of a vehicle. This includes other drivers that are driving on the same road at the same time and (potentially) the effect of animals (Sullivan, 2011) or other unexpected obstructions on the road. Ultimately, the probability of one person being involved in a crash (fatal or otherwise) is dependent on their presence in a particular location. For example, it is not possible for a person that is never on a road with a 100 km/h speed limit – as a driver, passenger or other road user – to be exposed to the risk of being in a crash occurring on a 100 km/h road. This characteristic – termed "exposure" – is controlled for in studies of driving risk by dividing total crashes (or fatal crashes) by the total distance travelled where the risk factor being studied applies.

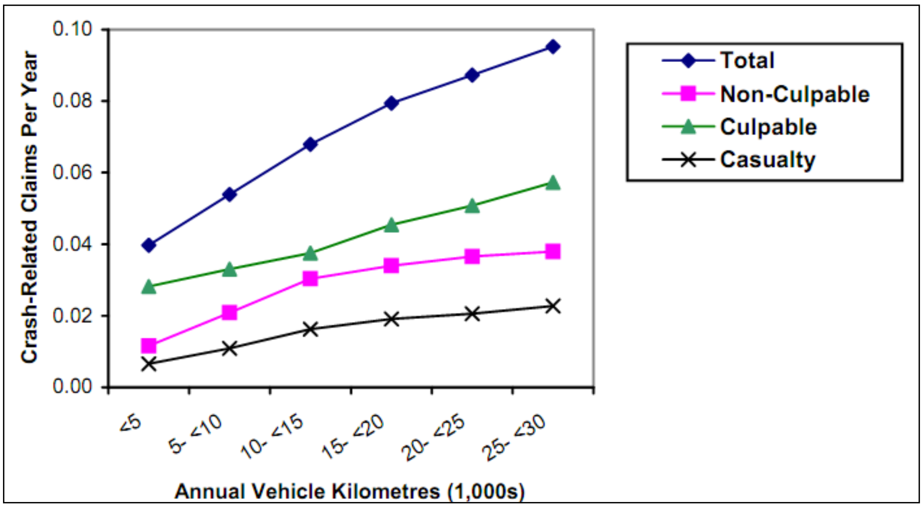

Figure 2-3: Insurance claim crash rate by annual VKT (Litman, 2010)

Furthermore, there is an increased risk for each additional kilometre travelled at night (Johansson et al., 2009) and in rural areas (Chen et al., 2009) relative to the risk associated with travel during the day and in urban areas (Jun, 2006; Fifer, 2008). These factors affect the exposure of drivers to potential crashes by virtue of driving on the road but the complexity, controllability and predictability of the events which are encountered whilst driving can also increase or decrease the risk relative to an average kilometre of travel (Elvik, 2010b). These factors must be included in any comprehensive method of driver risk assessment.

Lastly, if a crash does occur, the ability for those involved in the crash to escape without serious injury is impacted by a number of factors. For car drivers and passengers in particular, the vehicle they are driving has a direct and important influence on the survivability of a crash. Due to the advent of new vehicle safety technologies, all else equal, a driver and car passenger are safer (at lower risk) if they are in a newer vehicle (Anderson et al., 2009). This is not necessarily the case for other road users.

2.4 Capturing driver behaviour

To study the relationship between risk understanding and perception, and its impact on risky driving behaviour it is necessary to acquire data on the exposure, frequency, time and location of different behaviours and influencing factors. This section discusses the most common methods and their respective advantages and disadvantages. These methods are not necessarily mutually exclusive and many studies use more than one method.

2.4.1 Traditional methods and sources

The most common sources of data on driver behaviour and exposure are self-reported information collected from surveys, police enforcement records, driver and vehicle license records and hospital records. Data derived from insurance claims has also been used but is less common due to commercial sensitivity. Together these are sometimes referred to as traditional methods and sources. They continue to be used extensively and have many benefits.

Self-reported speeding behaviour is the most common method of collecting information about the extent of risky driving behaviour. Its primary advantage is that it is relatively inexpensive, especially as part of a larger study where participants already complete a questionnaire or interview, and includes incidences of risky driving behaviour that may not be recorded using other traditional methods. The recruitment process for self-reported surveys also allows researchers to ensure that the sample is representative of the driving population which may not be possible with other methods. However, although there is evidence that self-reported driving behaviour is a valid predictor of actual behaviour (Hatakka et al., 1997) it suffers from extensive under (and in some cases over) reporting of risky driving behaviour (Corbett, 2001; Hatfield et al., 2008). Given that risk perception[17] – defined in this thesis as a person's subjective estimate of the likelihood of an event occurring (Ulleberg and Rundmo, 2003)[18] – appears linked to experience (Rosenbloom et al., 2008) the validity of self-reported driving behaviour is open to question. Furthermore, evidence suggests that there is a limit to the quantity and complexity of the information that can be collected using this method (Goldenbeld and Van Schagen, 2007). Nonetheless, self-reported survey data forms the basis of much of the road safety literature. Provided that results are interpreted with its constraints in mind, they continue to be a source of important contributions to road safety. The number of surveys employing this method makes it impossible to discuss all of them. A selection of studies using a self-report methodology is shown in Table 2-2. This list is not exhaustive but is meant to illustrate the large number of uses of this methodology. These studies were selected on the basis of similarity to the methods employed for the research described in this thesis.

Alternatives (or in some cases complements) to self-reported driving behaviour are police enforcement and licensing records. These records are collected by the police and licensing authorities in the course of enforcing road rules and attending to road crashes. This method allows for analyses using large samples or cross-validating self-reported measures of behaviour. Speeding and red light running benefit from the use of speed and red light cameras (Wundersitz et al., 2009) which can provide more detailed information about behaviour in the locations where they are installed. Drink driving is revealed in these records from on-road enforcement and from crash records. Other forms of risky driving behaviour, for example illegal u-turns, are recorded only when a citation is issued. The disadvantage of these records is they only include incidences where the road rules have been broken and enforced or where a serious

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[17] Risk perception is explored in Section 3.1.5.

[18] Although risk (and risk perception) has been widely studied (Naiitiinen and Summala, 1976; Fuller, 1984; Wilde, 1994) in the traffic psychology literature, there is no single definition.

crash[19] has occurred meaning that as with self-reported driving behaviour this method suffers from under-reporting (Schafer and Mastrofski, 2005; Wilson et al., 2006). It is also likely that police enforcement records tend to overstate more extreme behaviours whilst understating the extent of less extreme (but more common) behaviours or magnitudes of behaviours. This can be particularly problematic when attempting to calculate crash risk because an accurate crash risk calculation requires an accurate record of frequency or exposure. Since not all forms of risky driving behaviour are illegal, this method is not useable for research on risky but legal driving behaviour.

Table 2-2: Selection of studies employing a self-report methodology

Citation	Self-Reported Behaviours and Factors Studied	Country	Sample Size	Self-Report Only?
(Delhomme et al., 2009b)	Speeding; Risk judgements; Personality	France	3,002	Y
(Iversen and Rundmo, 2002)	Speeding; Risky driving (general); Crash involvement; Personality	Norway	2,605	Y
(Wood et al., 2009)	Driver-Cyclist conflicts, Cyclist visibility; Cyclist safety	Australia	1460	Y
(Horwood and Fergusson, 2000)	Drink driving; Distance travelled	New Zealand	1011	N
(Donovan et al., 1999)	Road safety advertising; Fatigue; Speeding; Inattention; Drink driving	Australia	1000	Y
(Porter and Berry, 2001)	Red light running; Risk perceptions	United States	880	Y
(Soole et al., 2009)	Police enforcement; Speeding	Australia	852	Y
(Beck et al., 2012)	Risky behaviour; Enforcement perceptions; seat-belt usage; Hurried drivers	United States	796	Y
(Fleiter et al., 2006)	Speeding; Influence of passengers; Social influence	Australia	320	Y
(Young and Lenné, 2010)	Distractions; Risk assessment; Crash involvement	Australia	287	Y
(Hatfield et al., 2006)	Fatigue; Road safety campaigns	Australia	230 to 259	Y
(Warner and Aberg, 2006)	Speeding	Sweden	250	N
(Warn et al., 2004)	Street racing; Motor sport; Risky driving	New Zealand	180	Y
(Bagdadi and Várhelyi, 2011)	Crash involvement	Sweden	166	N

Police-reported crashes (Wang et al., 2002; McEvoy et al., 2007a) – as distinct from enforcement records – and hospital records (McEvoy et al., 2005, 2007b) are two other

[19] Many crashes are not reported to police if there is little/no damage and/or no injuries (Shinar et al., 1983).

sources of risky driving behaviour. Police crash records are likely accurate for crashes resulting in fatalities but as many as 30 percent of injury crashes are not reported to police (Shinar et al., 1983). In addition, since these databases only capture behaviour when it has resulted in a crash they ignore the (likely) many instances where the same behaviour has not resulted in an injury. Since every time a driver engages in risky behaviour with no consequences (either injury or penalty) reinforces perceptions of safety (Falk and Montgomery, 2007; Mannering, 2009) this is a potential issue. Hospital records face a similar problem but can be used in conjunction with police records to reduce under reporting of crashes (Shinar et al., 1983). However the process of matching hospital records to their related police crash records (if there is one) is not simple. When possible, researchers face the complication of conflicting records since medical practitioners will likely make a different assessment of sustained injuries than police (Tarko and Azam, 2011). In addition, police and hospital/medical records provide an indication as to the frequency of serious crashes but they do not adequately represent the frequency of behaviour since most driving behaviour goes unrecorded. Therefore it is not possible to determine, for example, the frequency of speeding behaviour by examining licensing/enforcement records which shows that 30 percent of drivers were fined for speeding in the preceding three years (Fleiter et al., 2009). Similarly, looking at crash records will reveal the proportion of crashes where a certain behaviour (speeding, fatigue, etc.) was a factor but not the frequency (or magnitude) to which a behaviour occurs on the road.

Keeping in mind the previously stated caveats about the comparability of different data sources, police enforcement, driver licensing, police crash and medical records can all be used in conjunction with self-reported behaviour. By combining more than one of these methods it is possible to gain a more detailed picture of a driver's history including fines or medical issues that have been the result of a crash or which may increase the risk of a crash occurring. In one study, police crash records from fatal crashes were combined with police enforcement records and driving licence records to examine the effect of fines and demerit points on crash risk (Redelmeier et al., 2003). Table 2-3 contains a selection of studies which employed more than one data source including self-reports, police enforcement, crash records and medical records.

The primary disadvantage of all of these methods is the limited ability to monitor the same drivers across time and location. Although some time series data can be collected by administering multiple surveys to the same drivers or using licensing records to retrieve a history of driving convictions, the majority of driving activity is not accounted for in these datasets. This makes it impossible to determine the frequency and magnitudes of some key measures of driver behaviour including speeding, acceleration and braking.

Table 2-3: Selection of studies employing multiple traditional data sources

Citation	Behaviours and Factors Studied	Police Enforce-ment	Police Crash	Medical	Self-Report
(Cooper, 1997)	Speeding and crash involvement	Y	Y	—	—
(Redelmeier et al., 2003)	Traffic law enforcement and its effect on fatal vehicle crashes	Y	Y	—	—
(McEvoy et al., 2005)	Drivers' use of mobile telephones	— [b]	—	Y	Y
(Patil et al., 2006)	Driver behaviour and personality	Y	Y	—	Y
(Williams et al., 2006)	Speeding	Y	—	—	— [c]
(McEvoy et al., 2007a)	Driver distractions	—	—	Y	Y
(Vassallo et al., 2007)	Risky driving behaviour among young drivers	Y[a]	—	—	Y
(Chen et al., 2009)	Road crashes in rural areas by young drivers	Y	Y	—	Y
(Ivers et al., 2009)	Novice drivers' risky behaviour, perceptions and crash risk	Y	Y	—	Y
(Tarko and Azam, 2011)	Pedestrian injuries	—	Y	Y	—
(Wundersitz and Baldock, 2011)	Road system failures, illegal driving behaviour, extreme driving behaviour	Y	Y	Y	Y

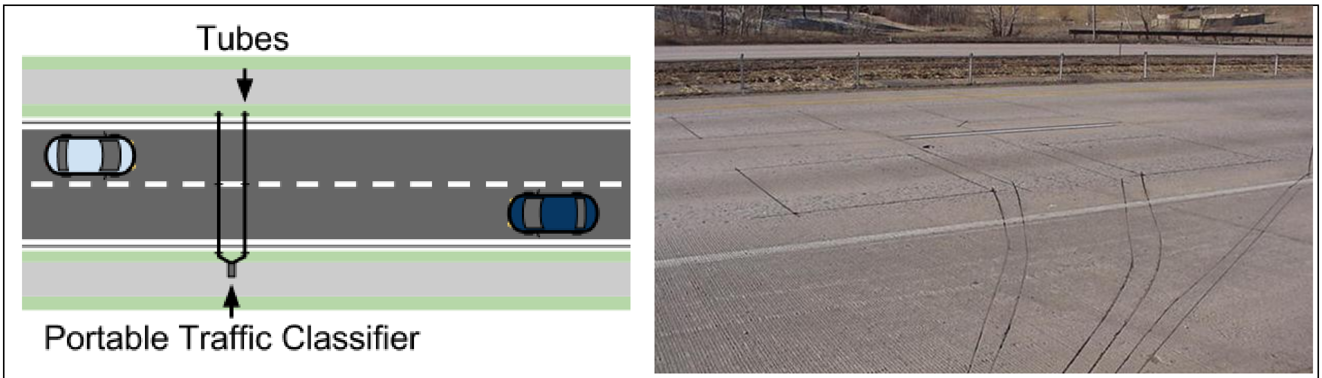
— Indicates data source was not used.
[a] Police enforcement data was not used but telephone records were obtained from the telecommunications providers.
[b] Vehicle speeds were measured from the road side and matched to licence data using the licence plate number.
[c] Only used to assess validity of self-reported data.

2.4.2 Simulators and traffic counters

Technology has been playing an increasingly important role not only in enforcement through the use of red light cameras and speed cameras but also in transport planning and research. They help reduce some of the disadvantages of the traditional measures of driver behaviour discussed in Section 2.4.2 although they also introduce a number of their own disadvantages.

Traffic counters/classifiers and inductive loop detectors are primarily used for monitoring congestion and providing vehicle counts in particular locations to road departments. They work by detecting when a vehicle passes over it and can be configured as one or more loops (Soriguera and Robusté, 2011). The installation can be either permanently installed (Soriguera and Robusté, 2011) – as is frequently the case on motorways – or installed temporarily (Radalj, 2000). These devices can collect and/or calculate a number of different measures[20] including number of vehicles, date, time, vehicle speed, vehicle type and number of axles (Radalj, 2000). A diagram of a portable traffic classifier and a photograph of a loop detector are shown in Figure 2-4.

Although these devices can collect a lot of data for the location where one is installed, they are incapable of uniquely identifying each vehicle and therefore they cannot track the same vehicle across time. This means that although these devices can determine the average speed of vehicles on a particular stretch of road during different time periods of the day, researchers are unable to examine the influence of driver and most vehicle characteristics on speed. On the other hand, since the locations are known by researchers detailed spatial information can be employed if multiple locations are measured.



Loop Detector
(Colorado Department of Transportation, 2005)

Figure 2-4: Portable traffic classifier and loop detector

Due to the nature of the data collected using traffic classifiers and loop detectors, most studies of driver behaviour using these sources focus on drivers' speed or speeding

[20] Exactly which measures can be recorded differs from device to device.

behaviour. They are particularly suited for before and after studies of infrastructure or speed limit changes. For example, Kweon and Kockelman (2005) used crash data and data collected from loop detectors installed on high speed roads in Washington State (United States) to study the effect of speed limit changes on the numbers of fatal and non-fatal crashes. The results show that for roads with speed limits up to 55 miles/h (88 km/h) non-fatal crash rates are reduced, but fatal crash rates remain unchanged while the findings are sensitive to differences in traffic levels. In Finland, the impact of variable message signs (VMS) on vehicle speed and headways on 80 km/h roads was investigated by collecting data from three locations with traffic counters along the same stretches of road. Traffic counters were located 536 to 1,800 metres before the VMS, 360 to 1,100 m after the VMS and lastly 7,670 to 13,000 metres after the VMS. In general the researchers found vehicle speeds are reduced by 1 to 2 km/h for distances up to approximately 1 km from the VMS but changes after a longer distance are not statistically significant (Rämä and Kulmala, 2000). The effect of a change in the default speed limit[21] in Western Australia from 60 km/h to 50 km/h was studied using traffic classifiers installed in 138 locations of which 23 roads maintained a 60 km/h speed limit after the change. On average, after 12 months the 85th percentile speed[22] was reduced by 2 km/h from 64.4 km/h to 62.4 km/h on the roads where a 50 km/h speed limit was now in effect. In comparison, the roads which remained at 60 km/h (but were now signposted to this effect) experienced a reduction in 85th percentile speed of 1.2 km/h after 12 months from 69 km/h to 67.8 km/h (Kidd and Radalj, 2003).

Overall these devices are useful for collecting large amounts of data from a given set of locations over a period of time. The conclusions that can be drawn from the collected data however are based on the behaviour of the population of drivers rather than the behaviour of individual drivers. This needs to be considered when determining if this is the optimal source of data to answer a particular research question. In comparison, simulators allow researchers to examine detailed aspects of driver behaviour in a controlled environment. Since study participants need to be present in-person to

[21] The default speed limit is the speed limit that applies when there is no posted speed limit.

[22] 85th percentile speed refers to the speed at which 85 percent of vehicles are travelling at or below. It is frequently used as the basis for setting speed limits (Rawson, 2012).

complete simulator experiments these studies are also frequently able to make use of some of the traditional sources of driver behaviour data discussed in Section 2.4.1.

Simulator experiments use virtual reality to create a simulated vehicle environment. The characteristics change from simulator to simulator but the most advanced simulators, such as the simulator shown in Figure 2-5 from The University of Leeds, include movement, sound and genuine vehicle controls. The primary benefit of simulator experiments is that while they recreate the experience of driving on the road (albeit imperfectly) researchers are able to control all aspects of the road environment.

Figure 2-5: Inside and outside the University of Leeds driving simulator (Jamson et al., 2010)

Simulator studies have been used to study the impact of road treatments on driver speed choice (Jamson et al., 2010), eating and drinking on driver performance (Young et al., 2008) and road width on vehicle speed and lateral displacement (Lewis-Evans and Charlton, 2006). They have also been used to test the application of psychological theories such as the theory of planned behaviour (TPB) to predict driver behaviour (Elliott et al., 2007) and to determine the speed differential before drivers pass another vehicle (Bar-Gera and Shinar, 2005). The range of driver behaviour studies using simulators is shown in Table 2-4.

Simulator studies have been shown to have relative validity for the purposes of examining crash risk (Yan et al., 2008) but an individual's behaviour in a simulator may not be reflective of their behaviour on a real road. Tests of differences in intra-driver variability of reaction time between simulator driving and on-road driving have shown that variability is higher in on-road experiments than in a simulator (Riener, 2010). In addition, it is not feasible to monitor drivers for weeks or months using a simulator environment and as such although the data may be valid it does not necessarily reflect the same individual's driving across time and space.

Table 2-4: Selection of simulator studies of driver behaviour

Citation	Behaviours and Factors Studied	Sample Size
(De Winter and Happee, 2011)	Motivational models of driver behaviour	10 to 804
(Conner et al., 2007)	Testing theory of planned behaviour on intention to speed	83 to 303
(Elliott et al., 2007)	Testing theory of planned behaviour on speeding behaviour	150
(Farah et al., 2009)	Risk associated with passing behaviour	100
(Yan et al., 2007)	Left-turn gap acceptance	63
(Thiffault and Bergeron, 2003)	Impact on driving performance of monotony-induced fatigue	56
(Lewis-Evans et al., 2011)	Impact of cognitive load on speed maintenance	53
(Lewis-Evans and Charlton, 2006)	Impact of road width on speed and lateral displacement	49
(Stephens and Groeger, 2009)	Impact of anger and anxiety traits on driver behaviour	48
(Lenné et al., 2010)	Driving on arterial roads under the influence of alcohol and cannabis	47
(Hatfield et al., 2008)	Reliability of implicit association test (IAT) in predicting speeding behaviour	45
(Mesken et al., 2007)	Impact of emotions on speeding behaviour	44
(Jamson et al., 2010)	Impact of road treatments on speed	40
(Strayer et al., 2006)	Comparison of driver performance between drink driving and mobile telephone usage	40
(Donmez et al., 2007)	Driver distraction from in-vehicle information systems	29
(Riener, 2010)	Reaction time in simulator versus on-road experiments	18
(Lenné et al., 1997)	Time of day variation in driving performance	11
(Jamson, 2006)	Impact of ISA on speeding behaviour	10

2.4.3 Naturalistic / on-road monitoring

The main disadvantages of the methods of determining the extent of risky driving behaviour discussed in Sections 2.4.1 and 2.4.2 are the significant under-reporting of incidences of risky driving behaviour and the limited availability and usefulness of time series data. The advent of Global Positioning System (GPS) devices and other in-vehicle sensors for the study of driving behaviour (Ogle, 2005; Greaves et al., 2010) has – at a cost of smaller sample sizes – reduced these problems. Studies have employed GPS, accelerometers[23], video cameras, distance sensors and on-board diagnostics (OBD)[24]. Although this technology has its own limitations it has the potential to provide a more complete record of the extent of risky driving behaviour in day-to-day driving.

The number of studies employing this type of technology is more limited than other types due primarily to the cost and resources involved, but they are becoming increasingly common. Table 2-5 summarises a number of naturalistic driving studies. The monitoring period ranges from as little as one day to two years. Similarly, the sample size ranges from a minimum of 17 to a maximum of 1,950. At a minimum GPS or an accelerometer is used with some studies including video and audio recording. The research questions of each study influence the choice of technology but for all studies one of the underlying aims is to ensure that the research reflects real-world driving.

Of the studies using GPS, the studies that share the greatest similarity in the data collection methodology are NSW Centre for Road Safety (2010), Musicant et al. (2010), Jun et al. (2007), Dingus et al. (2006) and Biding and Lind (2002). All five studies used GPS data – Dingus et al. (2006) also had additional sensors – to determine the extent of risky driving behaviour during drivers' normal routines.

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[23] Accelerometers measure acceleration in three axes: longitudinal (X), lateral (Y) and yaw (Z).

[24] On-board diagnostics link into vehicles' on-board computers which are capable of reporting details of vehicle inputs (acceleration, braking and sometimes steering), engine status and speedometer speed among other measures.

Table 2-5: Selection of naturalistic studies of driving behaviour

Citation[25]	In-Vehicle Technology Used	Location	Monitoring Period	Sample Size[26]
(Biding and Lind, 2002)	GPS, ISA, street-level speed sensors, compass	Sweden (four locations)	1 to 2 years	4,840[27]
(Antin et al., 2011)[28]	GPS, video, alcohol monitor, illuminance sensor, accelerometer, OBD	United States (six locations)	1 to 2 years	1,950
(Keay et al., 2012)	GPS, two-axis accelerometer, compass, video	Maryland (US)	5 days	1,242
(Ogle, 2005)	GPS	Georgia (US)	1 year[29]	487
(Hultkrantz and Lindberg, 2009)	GPS, ISA	Borlänge, Sweden	3 and 12 months	250 to 114
(Bagdadi and Várhelyi, 2011)	GPS, ISA	Lund, Sweden	Not Specified	166
(Greaves et al., 2010)[30]	GPS	Sydney, NSW, Australia	> 10 weeks	148
(NSW Centre for Road Safety, 2010)	GPS, ISA	NSW, Australia	6.5 months	114
(Dingus et al., 2006)	GPS, accelerometer, video, radar, lane tracker	Washington, D.C. area	13 months	109
(Musicant et al., 2010)	GPS, accelerometer	Not Specified	6 months	109
(Farmer et al., 2010)	GPS, OBD	Washington D.C. area	24 weeks	85
(Paris and Van Den Broucke, 2008)	GPS	Flanders, Belgium	3 weeks	55
(Mesken et al., 2007)	GPS, Heart rate monitor	Delft and Den Haag, The Netherlands	1 day[31]	44
(Lee et al., 2011)	GPS, accelerometer, video, radar, lane tracker	Virginia (US)	18 months	42
(Barr et al., 2011)	Accelerometer, steering position, brake pedal activation, video	United States	2 weeks	42[32]
(Toledo and Lotan, 2006)	GPS, accelerometer	Israel	7 months	33

[25] Most naturalistic studies have more than one paper published from the same dataset. One citation is shown here for reference purposes but in most cases there are others.

[26] Sample size refers to the number of vehicles unless otherwise stated

[27] Of the 4,840 vehicles in the study, 4,000 used street-level sensors installed on lampposts to detect position while the remainder were equipped with GPS.

[28] This study – Strategic Highway Research Program (SHRP) 2 Naturalistic Driving Study – is currently in the data collection phase.

[29] The entire study takes place over three years.

[30] The dataset used for this thesis was collected for this study.

[31] In this study a driving instructor was in the car at all times and therefore although it is an on-road study is not considered 'naturalistic'.

[32] This study was conducted on 42 long and short-haul freight drivers.

Citation[25]	In-Vehicle Technology Used	Location	Monitoring Period	Sample Size[26]
(Ericsson, 2001)	GPS, OBD	Sweden	2 weeks	30
(Eby et al., 2011)	GPS, video, microphone, OBD, accelerometer, infra-red	Michigan (US)	4 to 9 weeks	17
(Van Schagen et al., 2011)	Various (accelerometer at minimum)	Europe (five countries)	Various	Various

The first study (NSW Centre for Road Safety, 2010) was conducted as part of a trial by the New South Wales Roads and Traffic Authority (now known as Roads and Maritime Services – RMS) into the effectiveness of Intelligent Speed Adaptation (ISA) in reducing speeding behaviour. In this trial, a speed data recorder device designed to collect speed, heading and position every second was installed in participants' vehicles for the full 6.5 month trial. During the first month and a half, the speed data recorder was the only device installed in the vehicle. After 1.5 months, an ISA device was installed for a three month period. After the ISA device was removed from the vehicle, vehicle speeds continued to be monitored for a further two months. The speed data recorder remained in the vehicle for the duration of the study. The study initially commenced with 114 participants although a number dropped out of the study before it finished. The drivers were the primary drivers of the vehicles which were a mix of private and company-owned vehicles. As with most studies of this type, younger drivers (younger than 25 years old) were particularly hard to recruit and were therefore underrepresented in the study.

In terms of the data collected, drivers completed a number of surveys addressing participants' attitudes towards speeding and their self-reported speeding behaviour. They also agreed for the release of their driver licence records and a subset of the sample participated in individual interviews and focus groups. In total, 7.5 million seconds of driving behaviour were collected during the trial. Of the 114 drivers that started the study, 106 drivers had sufficient data for a before-and-after analysis which in total represented 1.91 million km of driving. Although all driving activity was recorded to isolate driving activity where drivers had a choice of travel speed, only driving where the speed exceeded 75 percent of the speed limit was included in the reported results.

Musicant et al. (2010) conducted an exploratory analysis of data collected from 109 drivers over 117,195 trips using a GPS device (Green-Box) designed to identify unsafe driving behaviour. The purpose of the analysis was to determine if there was a relationship between the frequency of unsafe driving events, when and where they occurred, the gender of the driver and (ultimately) if these trends were similar to the trends for vehicle crashes. The data consisted of speed and location collected from a GPS device every second. An accelerometer recorded lateral and longitudinal acceleration 40 times every second. Only the gender of the primary driver was known to the researchers. The GPS and accelerometer data were processed by pattern recognition algorithms capable of detecting 20 road user movements including cornering, lane changes, extreme braking and acceleration. These movements (or events) were analysed on the basis of the frequency measured by the number of recorded events per minute. Data were analysed by gender, time of day, day of the week and trip portion (first and last five minute periods of each trip and the rest of the trip) and combinations thereof. Whilst limited to an exploratory analysis at this point, the authors found that there were inter-trip as well as intra-trip differences in behaviour. They also found that although there was a relationship between the frequency of events and the time of day and driver's gender, there was (surprisingly) no relationship by day of the week.

Jun et al. (2007) used data from the 12-month Commute Atlanta study of over 400 vehicles. In this study, GPS devices were installed in participants' vehicles to record position, speed and speeding behaviour. The purpose of this aspect of the study was to determine the behavioural differences between those drivers who were involved in crashes during a six month period whilst the device was installed in each car and those who were not involved in crashes during the same period. Since the Commute Atlanta study used a number of waves, this particular analysis included 167 drivers for the period of January to June 2004. Of these drivers, 26 drivers – 13 male and 13 female – were involved in a (self-reported) crash during the study period and no additional information (other than that a crash had occurred) was collected. Drivers younger than 35 were considerably under-represented in this study accounting for only 15 percent of the sample compared to 35 percent of the population.

In terms of the analysis, seven measures of speeding behaviour were calculated. These were mean speed, mean running speed[33], difference between speed and posted speed limit, difference between speeds above the posted speed limit and the posted speed limit and the frequency (in seconds) of speeding by 10 miles/h (16 km/h), 15 miles/h (24 km/h) and 20 miles/h (32 km/h). Data were analysed by crash-involvement, time of day and road type (freeway, arterial and local). As with Musicant et al. (2010), Jun et al. (2007) found significant differences in driver behaviour at different times of the day. Specifically, drivers who were involved in crashes drove significantly more and at higher speeds during peak times and during the night than drivers who were not involved in crashes. The frequency of aggressive deceleration also appeared as a significant factor.

The fourth notable study – known as the 100-Car Naturalistic Driving Study – included a large number of devices to measure the driver, the vehicle and other vehicles (Dingus et al., 2006). The primary purpose of the study was to gain a better understanding of pre-crash behaviours and to serve as a pilot for a planned national US naturalistic driving study to include almost 2,000 vehicles (Antin et al., 2011). Each vehicle was equipped with the following instruments:

a) Accelerometer;
b) Radar to measure distances to vehicles in front and behind the vehicle;
c) GPS to measure speed and position (latitude and longitude);
d) Video-based lane tracking system; and
e) Five video cameras monitoring inside and outside the vehicle.

The data was used to detect a number of risky driving behaviour including fatigue, violation of road rules and aggressive driving. Self-reported behaviour (violations, crashes and driving) and some demographics were also collected. Of particular interest in this study was the behaviour immediately before crashes, near-crashes and incidents. In this study, crashes were defined as any contact with an object, near-crashes as an event that required a sudden evasive manoeuvre that approached the operational limits of the vehicle and incidents as events where the vehicle was within

[33] Running speed was defined as any driving with a speed of at least 5 miles/h (8 km/h).

close proximity to another object. In total there were 82 crashes[34] of which 15 were reported to or by police, 761 near-crashes and 8,295 incidents. The most frequent conflict type associated with these events was a single vehicle crash, a lead vehicle[35] near-crash and a lead-vehicle incident. The final dataset contained data recorded from 100 vehicles and 241 drivers over a period of 12 to 13 months. In total there was 43,000 hours of data and 2 million VMT (3.2 million VKT). To-date this is the most comprehensive naturalistic study and has produced a wealth of information on driver distraction in particular.

Lastly, the largest ISA trial was conducted in Sweden between 1999 and 2002 involving almost 5,000 vehicles (Biding and Lind, 2002). Unlike the aforementioned studies, 4,000 of the vehicles in this study used street-level reference transmitters to determine the position, providing data less prone to the issues commonly found with GPS data such as cold start problems and urban canyons.[36] The overall purpose of the study was to identify the road safety impacts of implementing ISA and to gain an understanding of driver attitudes towards ISA. Various forms of ISA were tested during the study, not all at the same time, including visual (real-time) speed limit display, visual and audible speeding indicators, and active accelerator pedals that provide physical feedback when speeding.

The devices were installed in the vehicles prior to the system being activated which permitted a baseline (before) speeding behaviour to be recorded and compared to speeding behaviour after the device was activated. The results show reductions in speeding in the short term of between 14 and 18 percent with an active accelerator pedal and between 10 and 17 percent with an information-only ISA.[37] In the longer term, modest increases in speeding were observed with both ISA technologies relative to the short term but remained substantially below speeding in the baseline period.

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[34] Of the 82 crashes, 13 had to be excluded from the analysis due to incomplete data.

[35] A lead vehicle event is an event involving a vehicle in front of the instrumented vehicle.

[36] The cost of installing the necessary infrastructure means it is only financially feasible in dense environments. Differential GPS has similar advantages (and disadvantages) but can fall back on standard GPS when it is unavailable.

[37] The two ISA types were trialled in different cities and some of the differences may be partially attributable to environmental differences.

There were, however, substantial differences in speeding behaviour and differences in the magnitude of changes depending on the speed limit of the road. For example, with the information-only ISA devices, speeding on 30 km/h roads reduced by 9.6 percent (from 33.8 percent in the baseline period) compared to a reduction of 16.4 percent from 31.1 percent in the baseline period on 50 km/h roads. The researchers also noted significant reductions in the speeds of vehicles approaching intersections but not in turning speeds. Conflict studies, examining conflicts between different road users, were performed in one of the study locations (with 4,000 participating vehicles) and noted a reduction in conflicts of 68 percent overall. Conflicts with vulnerable/unprotected road users fell by 54 percent suggesting that ISA was beneficial to all road users.

GPS data provides a more complete picture of drivers' behaviour than can be achieved from traditional methods but it does have a number of disadvantages. For example, the data collection process is more expensive and resource intensive and once collected requires extensive processing. The large amount of data requires researchers to either aggregate data at some level or to isolate small segments of the data to make it manageable. Some researchers have suggested that pattern matching algorithms are used to identify patterns that are of interest to researchers and to focus analysis on these portions of the data (Musicant et al., 2010). Others have developed software applications to identify particular events and use video footage to determine if they are valid and to determine who is driving the car since this cannot be determined from GPS (Dingus et al., 2006).

The other main drawback of naturalistic studies is that they are susceptible to noise from exogenous factors which may not be measured by any of the sensors in the vehicle. These include factors in the road environment such as congestion, construction, traffic light timings and other vehicles. It also potentially includes factors which are not related to the driving task itself but influence the drivers' behaviour. For example, if the driver is late for an important event, had been drinking, was fatigued or was worrying about something else they needed to do. The use of video cameras goes some way towards reducing (but not eliminating) this problem but requires a degree of manual processing that is very labour intensive.

Accelerometers which have been employed in several studies (for example, Barr et al., 2011; Lee et al., 2011) provide detailed information on lateral and longitudinal acceleration which provides additional data on cornering, lane changes and other more precise movements which are not easily detectable with GPS and cameras. The data is, however, more difficult to analyse given the high sampling rate which can be over 30 observations per second compared to every second with GPS.

2.5 Summary

This chapter commenced (Section 2.1) by identifying the three primary sources of driving risk: infrastructure, vehicle technology and human factors. Of these, human factors are the largest contributors (Petridou and Moustaki, 2001) and are the focus of this thesis. Specifically, risky driving behaviour, which is defined as behaviour that puts the driver or others at an increased risk of being involved in a crash forms the basis of this research and underpins this literature review chapter.

Subsequently, the chapter reviews the literature on the types of risky driving behaviour that are most closely associated with crashes. These include speeding, aggressive acceleration and braking, fatigue and boredom, drink driving and driver distractions. It has been well established that these behaviours are associated with higher crash risk and the review of the literature quantifies the extent to which each of these factors contribute to crash risk and to what extent they may vary by frequency and magnitude.

Lastly, the different methods of capturing driver behaviour are identified from the literature with a view to identifying the advantages and disadvantages of each. Surveys, police records and hospital records have been used extensively to study a large number of factors. Although they are the oldest forms of data collection, they continue to be an important source of information. Improvements in technology have allowed for studies to be conducted on virtual reality simulators allowing a much greater level of detail to be collected and analysed in a controlled laboratory environment. More recent technology has allowed for drivers to be monitored across time and space as they go about their day-to-day driving. These create the richest datasets while also creating challenges for analysis due to the volume and detail of data collected.

Having established the types of behaviour that are substantial contributors to crash risk and identified the methods with which they can be studied, the next objective is to reduce the frequencies and magnitudes with which they occur. To accomplish this, it is necessary to understand the factors that influence drivers to engage in these behaviours and how this can, in turn, be used to encourage drivers to change their behaviour. Prior research on these factors is reviewed in Chapter 3.

3 LITERATURE REVIEW: EXPLAINING DRIVER BEHAVIOUR

Measuring drivers' behaviour provides insight into the extent of risky driving behaviour but does not explain why drivers engage in these behaviours. This is necessary to develop interventions for changing behaviour. This chapter examines the literature in three ways. First, Section 3.1 reviews the literature on the factors which influence how drivers behave. This is related but distinct from the factors associated with higher casualty rates in that this deals with *why* drivers drive how they drive. Section 3.2 explains the potential for information and financial incentives to be used to change drivers' behaviour including feedback and audible warnings. Lastly, Section 3.3 examines the literature on methods to group and classify drivers to enable better targeting of legislation, enforcement and education policies and strategies.

3.1 Influential factors in driver behaviour

There are a number of factors which have been shown in the literature to influence drivers' behaviour. These can be broadly classified into two groups:

1) Factors which restrict drivers' ability to choose whether or not to engage in a behaviour or the magnitude of a behaviour (hard measures); and
2) Factors which influence a drivers' choice of behaviour (and magnitude) when they have the opportunity to make that choice (soft measures).

The first set of factors consists of constraints imposed on the driver including congestion and some physical road treatments such as road humps. In these cases the driver is physically unable to engage in speeding even if they otherwise would do so. The second set of factors includes personal, societal and environmental influencers of behaviour. For instance, personality (personal), enforcement (societal) and environmental (road width) all fall into this category. Unlike in the first group, in this case drivers are physically able to engage in risky driving behaviour but for one or more reasons choose not to. The emphasis of this literature review is on this second category. However, one of the challenges in studying travel or driving behaviour is the heterogeneity or variability of intra and inter-driver behaviour.

Longitudinal variability refers to differences in the frequency or magnitude of the same behaviour (speeding, aggressive acceleration, etc.) exhibited over a period of time by the same driver. Cross-sectional variability refers to differences in the frequency or magnitude of the same behaviour exhibited by different (or between) drivers. In the context of risky driver behaviour, this heterogeneity reflects a distribution of behaviours – from the lowest risk to the highest risk – for the same driver across time and space – and for different drivers.

At its simplest level, the effect of cross-sectional heterogeneity on speeding behaviour can be illustrated by plotting the proportion of the distance speeding for each driver as shown in Figure 3-1. The differences in speeding behaviour between drivers at the aggregate level show that heterogeneity of speeding behaviour between drivers is considerable (Familar et al., 2011) with the most frequent speeding occurring for over 60 percent of the distance driven and the least frequent speeding occurring for one to three percent of VKT.

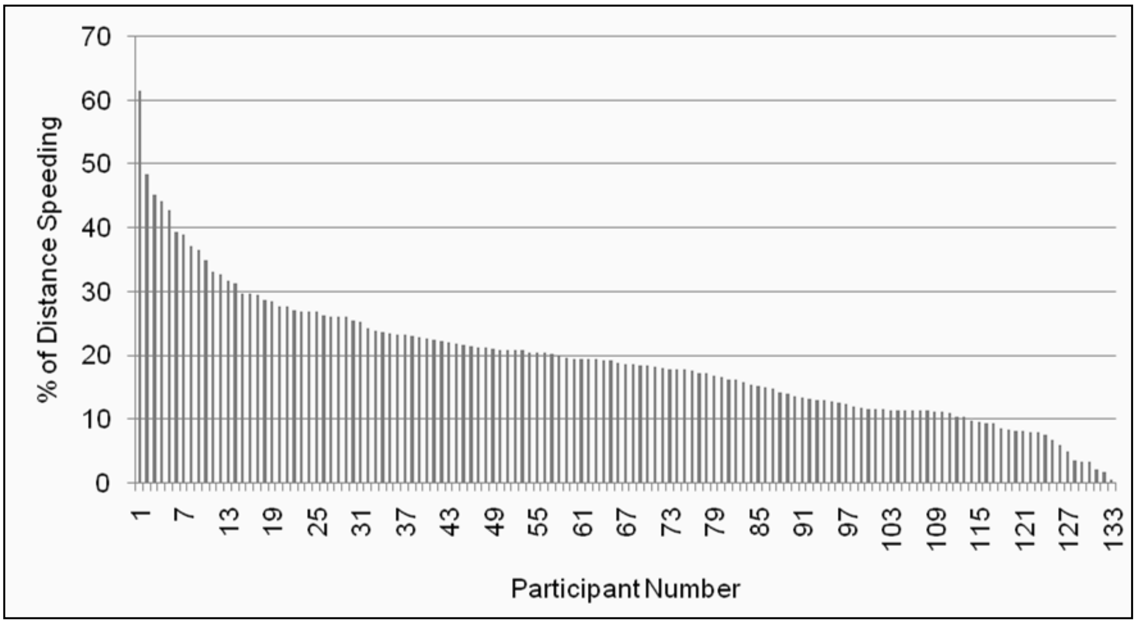

Figure 3-1: Proportion of distance speeding by driver (Greaves and Ellison, 2011)

These results are consistent with a recent naturalistic driving study conducted in the United States which looked at driving behaviour more broadly including driver inattention and fatigue. The study found that the frequency of events[38] per million vehicle miles travelled (MVMT) was extremely heterogeneous and the authors advised that this should be considered when interpreting the analyses (Dingus et al., 2006).

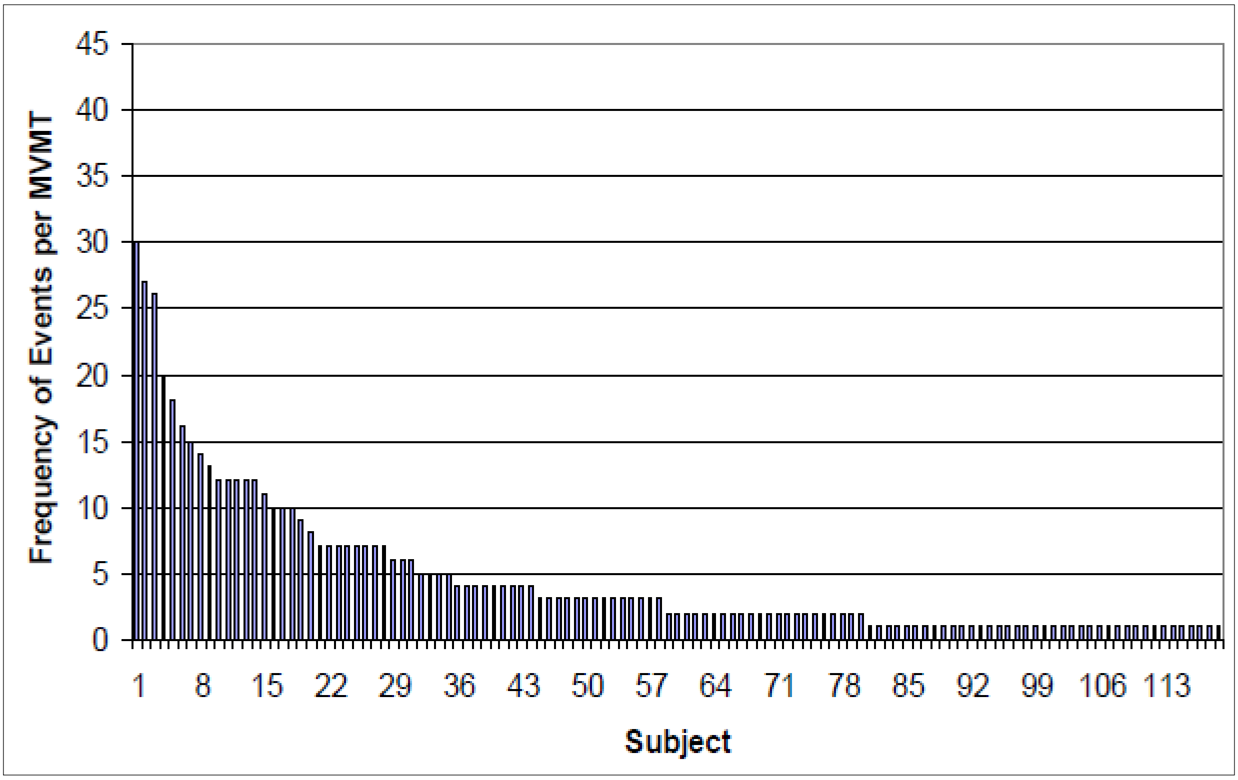

Figure 3-2: Number of events per million vehicle miles travelled (Dingus et al., 2006)

These high levels of heterogeneity are also apparent within drivers (De Winter and Happee, 2011). Figure 3-3 is a graphic representation of this intra-driver variability. It shows the proportion of distance driven in excess of the speed limit by a single, typical, driver for each day during a 35 day period and ranges from five percent to over 30 percent.

[38] Defined as incidents, near-crashes and crashes.

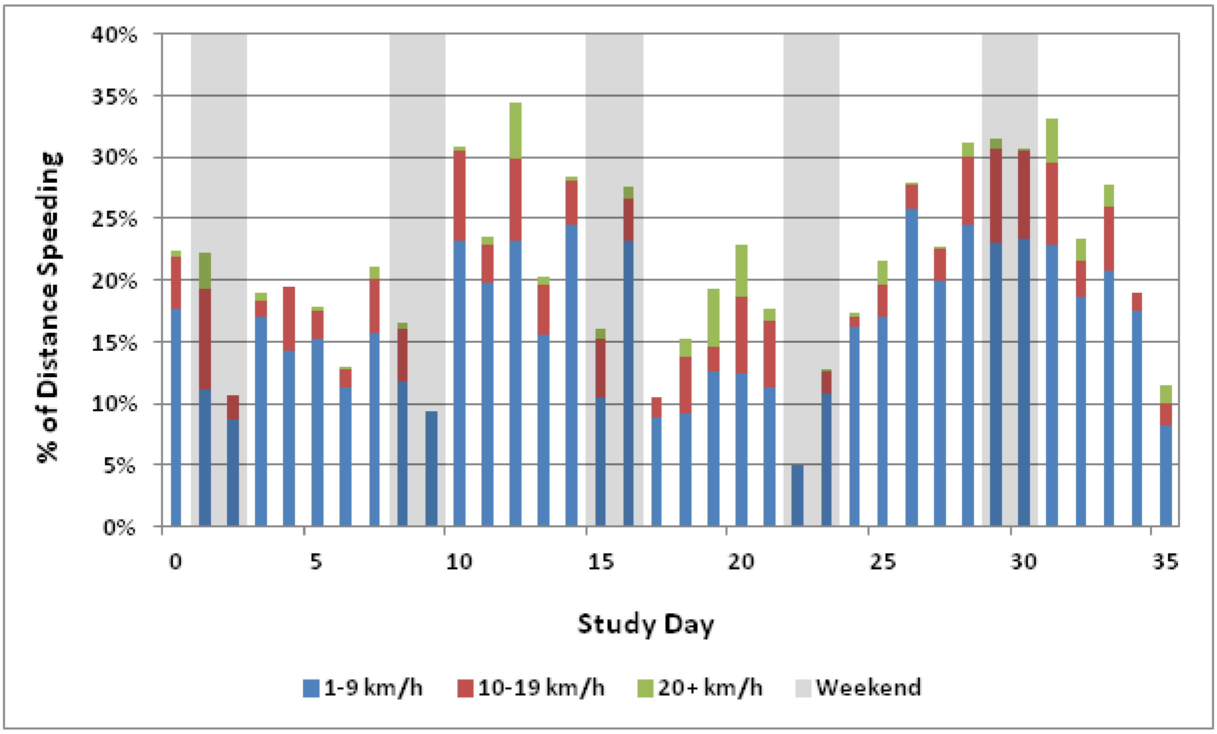

Figure 3-3: Proportion distance speeding by study day for a single driver[39]

Figure 3-1, Figure 3-2 and Figure 3-3 are examples of how heterogeneity is reflected in naturalistic driving behaviour data. There are a number of reasons for this heterogeneity which can be classified into four categories:

1) External factors which change across time including congestion, weather, visibility, presence of pedestrians and the behaviour of other drivers;
2) External factors which change across space but remain the same through time for the same locations. These include road width, lane width, fencing and road markings;
3) Factors related to the driver that change across time, for example, urgency of trip, presence of passengers, non-trip related events that impact on drivers' mood and temperament; and
4) Unobserved variability in human behaviour.

The observed variability is due to a combination of these factors. In addition, some observable factors, the road environment in particular, may be proxies for unobserved

[39] Graph created from GPS data used in this thesis (see Section 4.2.3)

effects such as individuals' risk choices which would be consistent with research on risk decision making (Ball et al., 2010). Ericsson (2000) developed a conceptual cause effect model of variability in driving patterns. This model (shown in Figure 3-4) includes six categories of factors which influence speed and acceleration profiles (or, collectively, driving patterns). A simpler model using five street types, gender and on-peak/off-peak times were tested in relation to 26 measures of speeding and acceleration. The results showed significant variation for all measures across drivers and street types. Some measures exhibited differences due to gender and on-peak/off-peak status. Interactions between the different factors were also observed for some measures.

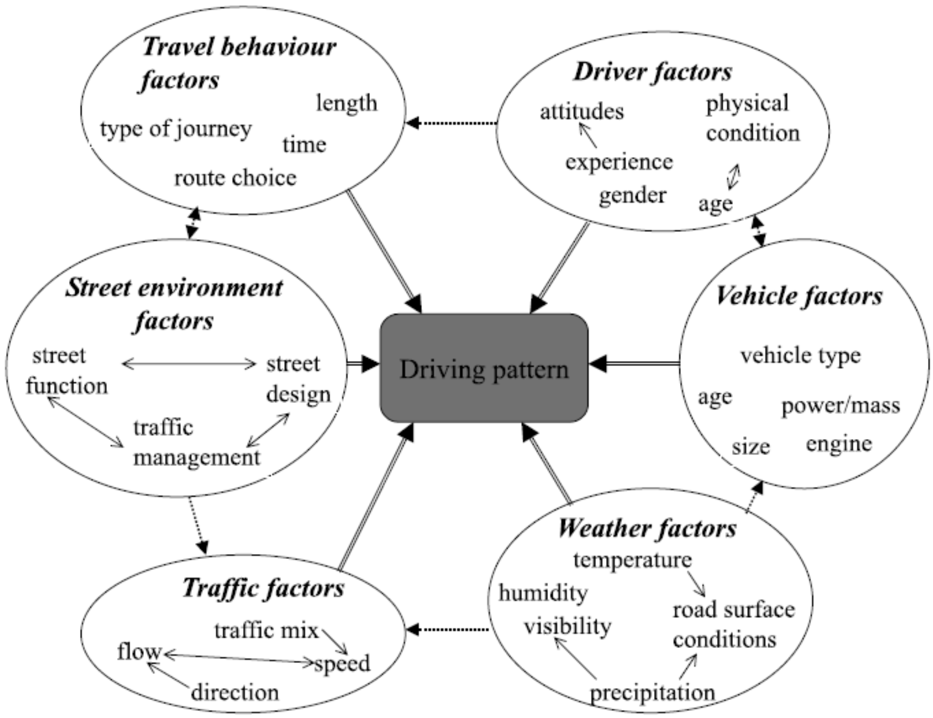

Figure 3-4: Cause effect model of variability in driving patterns (Ericsson, 2000)

Controlling for these factors allows for a more effective understanding of drivers' choices by isolating drivers' intrinsic characteristics. That is not to say that the road environment, weather and congestion are not important but that these factors have a sufficiently large impact on behaviour that the influence of the driver may be missed.

In addition to this, evidence suggests that there is extensive heterogeneity in risk factors which contribute to crashes. For instance, the quantity of supervised driving, drug and alcohol use, mental health and road risk behaviour in the population (Ivers et al., 2006). As identified by Schönfelder et al. (2002), much of the existing literature has not properly accounted for this variability and this has impaired transport policies' effectiveness. De Winter and Happee (2011) go further and state that even without the effect of the road environment drivers exhibit large (and seemingly random) variability in longitudinal and cross-sectional behaviour. Simulator studies have confirmed this to be the case (Hoogendoorn et al., 2011). Therefore, it is important when interpreting results of driver behaviour studies to acknowledge that although a driver may engage in risky driving behaviour more or less frequently or at a greater or lesser magnitude than other drivers, this behaviour is not uniform.

Some researchers have accounted for this phenomenon by including fixed and random effect parameters in their models (Kweon and Kockelman, 2005). Tarko (2009) introduced multipliers into a model of speed choice to account for the heterogeneity of disutility[40] from driver, road, trip and weather characteristics.

3.1.1 Impact of the road environment

The road environment was identified by Ericsson (2000) as one of the sources of variability in driver behaviour but has also been shown to be influential in the frequency and magnitude of speeding, acceleration and braking (Brundell-Freij and Ericsson, 2005). This is confirmed by more recent research (see Figure 3-5) which found network effects to be a contributor to as much as 70 percent of the variation in driver behaviour on urban roads (Familar et al., 2011). A national survey of speeding behaviour in the United States found significant differences in self-reported speeding behaviour on different classes of roads. For instance, 78 percent of drivers reported speeding on multi-lane interstate motorways in the previous month compared to 73 percent for city, town and local (neighbourhood) roads (Royal, 2003). The influences of these factors are clearly important but the impact varies considerably from one situation to another. The road environment functions as a constraint on driver

[40] Disutility refers to the perceived costs associated with a particular activity. In Tarko (2009) disutility is defined as the sum of the subjective cost of travel time, perceived risk of a crash and its consequences and the perceived enforcement of the speed limit.

behaviour preventing drivers from (for example) speeding when given the choice they would speed.

Even controlling for some aspects of the road environment by only studying one type of road, studies on speeding in school zones have found differences in behaviour depending on the design of the school zone (Roper et al., 2006; Kattan et al., 2011). This indicates that although drivers are responsible for a majority of road crashes, network effects – including road design and characteristics of the street environment – are significant influencers of behaviour. Therefore, studying driver behaviour requires controlling for road environment (network) effects. Not doing so risks finding statistically significant factors to be non-significant.

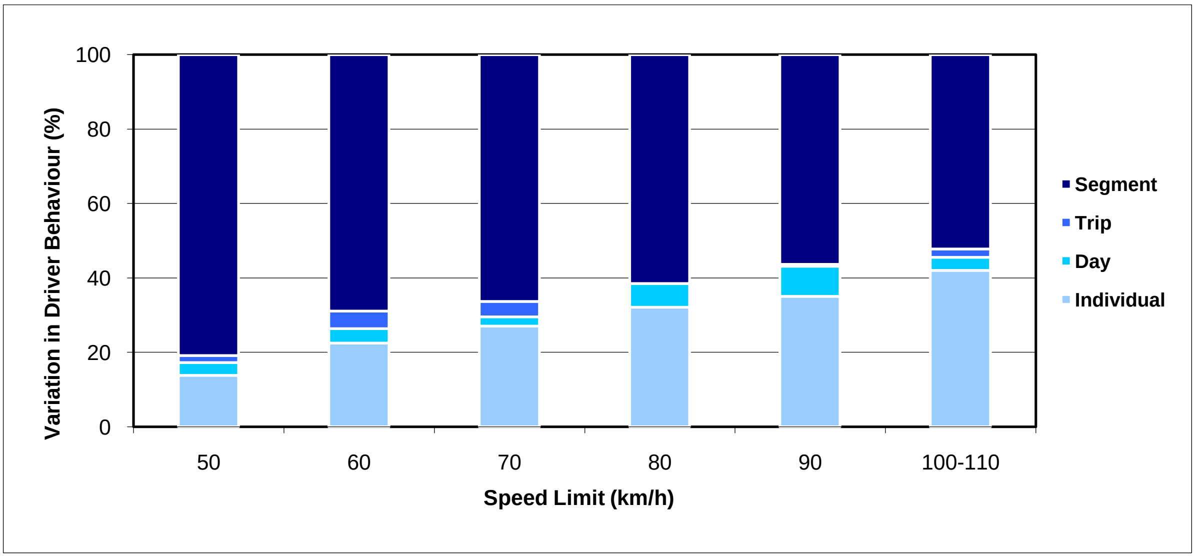

Figure 3-5: Variation in driver behaviour attributable to different factors on Sydney urban roads (Familar et al., 2011)

Although the road environment is frequently referred to as if it is a single concept it encompasses many different factors. The road environment includes 'hard' road infrastructure such as road width, fencing, roundabouts and many other elements built as part of (or in conjunction) with the road. These are typically the factors associated with the term. However, other permanent[41] infrastructure is also included

[41] Permanent infrastructure is infrastructure which once installed is not removed (or changed) more than once every one or two years. This is to say that a red light camera or road sign will be installed

in the road environment, such as the proximity of buildings to the road, red light cameras and road markings. Also shown to be a significant contributor to driver behaviour are non-infrastructure elements such as the presence of pedestrians and cyclists, visible police presence and congestion.

The majority of the literature on the influence of the road environment on driver behaviour is focused on speed and speeding. Analyses of acceleration and braking behaviour in relation to the road environment are sparse with the exception of intersections. In addition, due to the complexity in creating adequate controls many studies of the influence of the road environment employ simulators of varying complexity.

It has been well established that wider road and lane widths are correlated with higher travel speeds (Lewis-Evans and Charlton, 2006) although the relationship is non-linear (Odhams and Cole, 2004). However, the magnitude of the effect appears to be influenced by other characteristics of the road environment such as the type of road (Fitzpatrick et al., 2003). Lane width and road width are slightly different concepts (shown in Figure 3-6) but the effects are similar. Lane and road width are a factor in driver speed choice on both straight road segments (Lewis-Evans and Charlton, 2006) and curves (Odhams and Cole, 2004; Lewis-Evans and Charlton, 2006).

and kept at the same location over a period of several years. This is contrary to (for example) mobile speed cameras or signage relating to road construction which may be temporary.

Road width:	Width of entire road include all lanes and verges
Lane width:	Width of a single vehicle lane between lane markings
Building distance:	Distance from closest building to the side of the road

Figure 3-6: Road, lane and street distances

Using an instrumented vehicle, De Waard et al. (1995) showed that if the width of the lane is reduced there is a modest (3 km/h) reduction in average driving speed despite the width of the road itself having not been changed. They also found that lateral movements were reduced on the same road. An increase in drivers' heart rates appears to indicate a corresponding increase in cognitive load as a result of the reduced width and this was reflected in participating drivers' appraisals of the road. A simulator study had similar findings with narrow lanes (2.5 m) exhibiting mean speeds 2.23 km/h lower than the medium lanes (3 m) although speeds on the wide road (3.6 m) were not significantly different (Godley et al., 2004). A more recent simulator study confirms this effect but also found that the distance from the start of the road segments (where the reduction in road and lane width began) has a U-shaped effect on speed (Lewis-Evans and Charlton, 2006). The presence of a shoulder (and therefore a wider road) appears to influence drivers to increase their speed. This is true on straight roads and corners albeit at different magnitudes (Abele and Møller, 2011). Interestingly, it appears that both road markings and physical (raised) medians have the same effect on reducing vehicle speeds (Jamson et al., 2010). Goldenbeld and Van Schagen (2007) support the findings of other studies by asking respondents to identify their preferred speed and a perceived safe speed limit for different types of road environments. Road width was a significant characteristic in preferred speed for older respondents (40 and older), low sensation seeking drivers and drivers with one speeding ticket in the past three years. Road width is also a significant factor in perceived safe speed limits for all driver age groups except for drivers age 26 to 39 and drivers with one or two speeding fines. However, these results are not confirmed by all studies which suggest that there may be either an interaction effect with other factors or a minimum reduction in road width for an effect to be observable. For example, Rosey et al. (2009) found that reducing lane width from 3.30 metres (without a shoulder/verge) to 3 metres (with a 30 cm paved shoulder) did not result in a reduction in speed but did influence drivers to drive closer to the centre of the lane.

Another aspect that has been extensively studied in the literature is the impact of non-road objects and buildings which are visible to drivers from their cars but which – with the exception of pedestrians – do not move. For example, the presence of buildings adjacent to the road has been shown to be a significant factor in speed choice. Goldenbeld and Van Schagen (2007) conducted an ANOVA analysis which found that the presence of buildings alongside a road with an 80 km/h speed limit were a statistically significant factor in both preferred speed (83.5 km/h with buildings compared to 89.2 km/h without buildings) and perceived safe speed limit (79.3 km/h compared to 84.9 km/h without buildings). Osmers (2001) found that in the case of schools, the visibility of the school from the road has a significant impact not only on (lower) speeds but also on the effectiveness of speed warning signs. On the other hand, the evidence that trees planted alongside the road reduce vehicle speeds is mixed. One study found that the presence of trees did not significantly influence speeds (Abele and Møller, 2011). On the other hand Van der Horst and De Ridder (2007) found that trees were correlated with lower speeds but only when the trees were located 2 metres from the road. They found no effect when the trees were positioned 4 metres from the road.

The presence of pedestrians, parked cars and road-side infrastructure to support them has also been studied in the context of choice of speed. Edquist et al. (2012) looked at four parking scenarios on 60 km/h simulated roads: arterial no parking, urban no parking, urban empty parking and urban full parking. Unsurprisingly, the findings suggest that mean and maximum speeds are significantly lower for an urban full parking scenario than in an urban no parking and urban empty parking[42] (which were not significantly different from each other). The arterial no parking scenario exhibited significantly higher mean and maximum speeds than the urban no parking scenario. The researchers also examined drivers' response time to the presence of pedestrians in the same four scenarios and found that response time, braking pressure and collision measures were significantly worse for the full parking scenario than the no parking or empty parking scenarios. Other studies have shown that both mean and 85th percentile speeds are lower when there are children present (Kattan et al., 2011) which is consistent with beliefs that the perceived risks associated with speeding are higher when pedestrians are present (Tarko, 2009).

At a less detailed level of the road environment, researchers have studied the impact of network density and design which includes the distances between intersections, the type of intersections[43] used and the use of traffic signals. Ewing and Dumbaugh (2009) conducted a comprehensive review of the literature of the impact of the road environment on driving behaviour and crashes. Marshall and Garrick (2011) investigated the impact of street network design on vehicle crashes and severity particularly in relation to vehicle speeds. They found that higher intersection densities were correlated with fewer crashes and suggest this is due to lower vehicle speeds. In addition, they suggest that the behaviour (and safety) effects of the design of a particular road segment are related not only to street-level factors but also to how those road segments are connected to neighbouring segments and to the broader road network. Some times of day and locations have higher than average speed related crashes. This may be because many drivers consider that driving on deserted rural roads and at night is low risk and therefore it is acceptable to speed (Falk and Montgomery, 2007).

Table 3-1 summarises the key aspects of the road environment that have been shown in the literature to be important in influencing driver behaviour (including but not limited to speeding behaviour).

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[42] Urban no parking scenarios have no permitted parking while urban empty parking scenarios have parking permitted (and the appropriate line markings) but no parked cars.

[43] Types of intersections include roundabouts, three-way intersections and four-way intersections.

Table 3-1: Road environment characteristics related to driver behaviour

Spatial element	Key citations
Number of lanes / Road type / Road width	(Goldenbeld and Van Schagen, 2007; Jun et al., 2007; Abdel-Aty et al., 2007; Kattan et al., 2011)
Proximity of buildings to road; visibility of buildings from road	(Osmers, 2001; Goldenbeld and Van Schagen, 2007; Kattan et al., 2011)
School zone signage type	(Osmers, 2001; Roper et al., 2006)
Traffic control (lights) / Signalised intersections	(Campbell et al., 2004; Abdel-Aty et al., 2007; Kattan et al., 2011)
Median type	(Abdel-Aty et al., 2007; Jamson et al., 2010)
Pedestrian refuge	(Jamson et al., 2010)
Dragon's teeth / road markings	(Goldenbeld and Van Schagen, 2007; Jamson et al., 2010)
Pedestrian crossings	(Pyta and McTiernan, 2010)
Rural / Urban	(Falk and Montgomery, 2007; Fuller et al., 2008)
Residential / Business	(Fuller et al., 2008)
Roundabout	(Møller and Hels, 2008)
Network density	(Ewing and Dumbaugh, 2009; Marshall and Garrick, 2011)
Fencing	(Kattan et al., 2011)
Trees	(Van der Horst and De Ridder, 2007; Abele and Møller, 2011)
Speed ratio	(Abdel-Aty et al., 2007)
Curves / Road geometry	(Odhams and Cole, 2004; Goldenbeld and Van Schagen, 2007)
Parking spaces / cars	(Edquist et al., 2012)

3.1.2 Demographics

Driver demographics are the most frequently used factors in studies of driving behaviour. Many researchers have found correlations between behaviour and demographic factors such as age and gender – note that in reading this review of the literature caution should be taken to avoid confusing significant correlations with causal relationships.

Ogle (2005) used speeding data collected using GPS devices to examine the speeding behaviour of drivers. Age was a significant factor in speeding behaviour but gender was only significantly different for some older age groups. In the 45 to 54 age group an interesting finding was that females exceed the speed limit more frequently than males which is the reverse of most research. In contrast a study of crash-involved young drivers found that male drivers were more likely (48 percent of male drivers) than females (26 percent) to have speeding as a causal factor in a crash (Braitman et al., 2008). Royal (2003) found that drivers of all age groups and gender speed but male drivers are 50 percent more likely to report speeding than female drivers and younger drivers report speeding more frequently and on more road types than older drivers. In terms of social acceptability of speeding behaviour, male drivers had higher acceptance rates of speeding than female drivers particularly in the higher/faster speed zones (Walker et al., 2009) and this may be reflected in higher self-reported frequency of speeding by male drivers.

Dingus et al. (2006) examined the relationship between age, gender and lane change incidents and found significant differences between combined age-gender groups. For example, females had almost double the rate of events per MVMT compared to male drivers across all age groups. For near-crash events – the most serious incidents that do not actually result in a crash – the 18 to 24 age group exhibited very similar rates for male and female drivers.

In terms of other unsafe behaviours such as red light running and failing to stop at stop signs, male drivers are more likely to self-report engaging in these behaviours than female drivers. In one study, six percent of male drivers report having driven through a red light compared to two percent of female drivers. In the same study 37 percent of male drivers report having failed to stop at a stop sign compared to 24 percent of female drivers. Significant differences by age were also found with drivers older than 45 significantly less likely to report engaging in these behaviours (Royal, 2003). Crash-involved young drivers that had failed to detect another vehicle were significantly more likely to be female (48 percent of female drivers) than male (32 percent) (Braitman et al., 2008). Another study of young crash-involved drivers in Norway examined the relationship between crash-involvement, gender and personality (further explored in Section 3.1.3). The researchers found that gender (male) and lack of adherence to social norms[44] were strong predictors of crash involvement (Oltedal and Rundmo, 2006).

3.1.3 Personality

Personality has also been identified in the literature as an influencing measure of driver behaviour. Despite this there is no universal definition of personality. In this thesis the following definition proposed by McCrae and Costa (1995) is used: "common dimensions of individual differences that transcend situational constraints". Personality is studied through surveys that ask participants to respond to behaviours

[44] Drivers that did not conform to social norms of behaviour were termed "normless" by the authors.

that are associated with particular personality traits. The results of these surveys are then compared to the same drivers' demographics, self-reported behaviour, crash history, licensing records and observed driving behaviour depending on the study and its objectives. The Driver Behaviour Questionnaire (DBQ) (Reason et al., 2011) also applied by Lucidi et al. (2010), Driver Behaviour Inventory (DBI) (Gulian et al., 1989) later used by Liu and Lee (2005) and the Speeding Attitude Scale (SAS) (Whissell and Bigelow, 2003) are some of the surveys that have been used in road safety studies.

The Driver Behaviour Questionnaire is used for many studies (for example Grayson and Elliott, 2004; Yasar and Jameel, 2007; Falk, 2010) and there are several versions. A modified version that has been used in several studies was developed by Lawton et al. (1997) and consists of 12 violation questions such as "How often do you race away from traffic lights with the intention of beating the driver next to you?" and eight error questions including "manoeuvre without checking mirror". Some researchers have suggested that personality studies can predict risky driving behaviour as early as mid childhood (Vassallo et al., 2007).

The results of the first study using the modified DBQ (Lawton et al., 1997) found that some (typically male) drivers drive faster than they should or in an aggressive manner do so for their own enjoyment rather than due to an aggressive personality. On the other hand, there are drivers whose driving behaviour was described by the researchers as focused on "maintaining progress", which means that they wanted to keep on moving, tend to impatience, intolerance and uncontrolled anger which on the road is borne by other road users (Lawton et al., 1997). Gulliver and Begg (2007) conducted a study of young drivers looking at the relationship between personality and persistent risky behaviour which was defined as incidents of drunk driving, drug driving, driving fast for the thrill and driving faster than 120 km/h[45]. The results indicate that no personality factors were significantly related to drink driving. On the other hand, higher levels of aggression were related to drug driving, driving fast for the thrill and driving faster than 120 km/h. Lower levels of control and traditionalism were related to driving fast for the thrill of it and driving faster than 120 km/h respectively.

[45] The study was conducted in New Zealand where the highest speed limit on any road is 100 km/h.

A study that combined appraisal theory (Lazrus, 1991) based surveys with an on-road study was also conducted. While a small sample was used it mirrored the characteristics of Dutch driving licence holders. Researchers found that anger was associated with higher speeds on roads with a 100 km/h speed limit but anxiety and happiness were not significant (Mesken et al., 2007).

The psychological survey used in this thesis was adapted from the Road Safety Behaviour (RSB) survey developed by Machin and Sankey (2008). It combines the NEO-Personality Inventory (Costa and McCrae, 1992) and Normlessness scale (Kohn and Schooler, 1983) as applied by Ulleberg and Rundmo (2003) with risk perception scales (Rundmo and Iversen, 2004) and cognition-based scales from the Learner Driving Experience Questionnaire (Dorn and Machin, 2004).

There is some discussion as to which risk perception (discussed in Section 3.1.5) and personality variables are correlates and/or contributors to risky driving behaviour. However, there is sufficient evidence to suggest that there are direct and indirect effects of personality on driving behaviour (for example Iversen and Rundmo, 2002, 2004; Rundmo and Iversen, 2004; Machin and Sankey, 2008). In particular, Ulleberg and Rundmo (2003) identified in their literature review, and subsequent research, five personality known in the literature to be predictors of (different) driving behaviours related to involvement in crashes (including Hilakivi et al., 1989; Booth-Kewley and Vichers Jr., 1994; Caspi et al., 1997; West and Hall, 1997; Jonah, 1997; Cellar et al., 2000). Four of these personality factors (anxiety, anger, excitement, altruism) were personality measures from the NEO-Personality Inventory (Costa and McCrae, 1992) and had later been converted into facet scales by Goldberg (1999). These scales exhibited good internal consistency as measured by Cronbach alpha's calculated by Goldberg (1999). These were altruism ($\alpha = 0.73$), anger ($\alpha = 0.88$), anxiety ($\alpha = 0.83$) and excitement-seeking ($\alpha = 0.78$). Similarly, the normlessness scale (derived from Kohn and Schooler (1983)) exhibited an internal consistency of $\alpha = 0.71$. Affect-based and cognition-based scales developed by Rundmo and Iversen (2004) and Machin and Sankey (2008) respectively also exhibited good internal consistency that has subsequently been confirmed by research using the same dataset employed in this thesis (Greaves and Ellison, 2011). In their own research, Machin and Sankey (2008) found the likelihood of an accident, efficacy, less risk aversion, excitement seeking and less altruism were significant predictors of speeding behaviour of young drivers.

Since demographics and personality are some of the most frequently studied factors influencing driving behaviour there are a very large number of studies. Table 3-2 lists a selection of these studies with particular emphasis on those incorporating multiple aspects.

Table 3-2: Selection of studies of demographics and personality impacts on driving behaviour

Citation	Behaviour(s) studied	Age significant	Gender significant	Personality significant	Sample size
(Grayson and Elliott, 2004)	Driving offences	Y	Y	Y	8,000
(Patil et al., 2006)	Various risky driving measures			Y	5,362
(Royal, 2003)	Red-light running, failing to stop and other unsafe behaviours	Y	Y		4,010
(Iversen and Rundmo, 2004)	Speeding, driving offences	Y	Y	Y	2,614
(Iversen and Rundmo, 2002)	Speeding			Y	2,605
(Walker et al., 2009)	Speeding acceptability	Y	Y		1,500
(Oltedal and Rundmo, 2006)	Crash-involvement factors		Y	Y	1,356
(Vassallo et al., 2007)	Speeding, drink driving, fatigued driving, non-seatbelt usage		Y	Y	1,135
(Gulliver and Begg, 2007)	Speeding, drink driving, drug driving		Y	Y	1,037
(Lucidi et al., 2010)	Driving offences	—	Y	Y	1008
(Ogle, 2005)	Speeding	Y	I		487
(Thake et al., 2011)	Loss of traction events[46]	Y	Y	Y	422
(Machin and Plint, 2010)	Speeding	Y	Y	Y	400
(Constantinou et al., 2011)	Crash-involvement factors and traffic offences	Y	Y	Y	352
(Braitman et al., 2008)	Crash-involvement factors		Y		260
(Whissell and Bigelow, 2003)	Speeding		Y	Y	257
(Lawton et al., 1997)	Driving offences	I	I	Y	211
(Falk, 2010)	Various measures of risky driving behaviour			Y	193 to 149
(Machin and Sankey, 2008)	Speeding		—	Y	155
(Dingus et al., 2006)	Lane change incidents	I	I		100
(Mesken et al., 2007)	Speeding			Y	44

Y: Factor statistically significant; I: Significant interaction with other factor(s);
—: Not significant; Blank: Not studied.

[46] Loss of traction events include skids, donuts, 'burn outs' and 'fishtailing' which are behaviours engaged in with the intention of causing a vehicle to lose traction.

3.1.4 Enforcement

Enforcement of road legislation – particularly in terms of speeding and red light running – is known to be one of the most effective methods of reducing risky driving behaviour. Enforcement of other illegal behaviours such as mobile telephone use has proven to be more difficult and this is reflected in (self-reported) violations (McCartt and Geary, 2004; McEvoy et al., 2007a). Studies have examined the influence of different methods of enforcement including hand-held radar (Soole et al., 2009), speed cameras (Kattan et al., 2011), average or point-to-point speed cameras (Soole et al., 2012), red light cameras (Kloeden et al., 2009) and visible enforcement by police (Walker et al., 2009). There is debate whether overt (visible) or covert (hidden) enforcement is more effective (Keall et al., 2001, 2002) but the studies in the literature support both to varying degrees.

A recent study of drivers' perceptions of speeding enforcement in Norway found that drivers over-estimated the probability of being caught speeding. The extent to which this occurs was correlated with the distance driven each year with those driving more being more accurate in their assessment. In terms of behaviour, it was revealed that drivers do slow down for sign posted speed cameras but only for a few hundred metres (Elvik, 2012a). There does not appear to be the 'halo' effect that research on hidden speed cameras have found to be the case where the frequency of speeding is reduced beyond the immediate vicinity of the camera (Keall et al., 2001, 2002).

Fleiter and Watson (2006) determined that the perceived certainty of punishment and direct punishment avoidance were both significant predictors of the variance in frequency of speeding behaviour albeit by relatively small proportions, one and two percent of the variance respectively. This appears consistent with the results of a survey on drivers' attitudes to speeding and speeding enforcement (Walker et al., 2009) whose results show that 61 percent of drivers were discouraged from speeding by the presence of police with hand-held radar and 56 percent in the presence of fixed speed cameras. The same study found that demerit points were a greater disincentive for speeding than fines for 42 percent of respondents. This proportion was higher for males, higher income earners and those with weekly driving times of more than 12 hours. In comparison 33 percent of respondents stated that fines were a greater disincentive. A qualitative study also identified that drivers employ various strategies to avoid being caught speeding, such as identifying speed camera locations and looking for police cars. Strategies to avoid the fines and/or demerit points if they are caught speeding were also mentioned by participants. These include demerit point sharing or driving without a licence (Fleiter et al., 2007).

Although the literature shows that enforcement is a significant factor in speeding behaviour, the evidence for red light running is mixed. A review of the effectiveness of (signposted) red light cameras in reducing crashes at intersections produced inconclusive results (Kloeden et al., 2009). On the other hand, a survey conducted in the United States found that 38.8 percent of drivers believe that increasing the legal consequences for red light running would change the red light running behaviour of other drivers (Porter and Berry, 2001).

A selection of studies on the impact of enforcement on speeding and red light running behaviour is shown in Table 3-3. These have been selected to provide an overview of the different enforcement methods previously studied in the literature.

Table 3-3: Selection of studies of enforcement impacts on speeding and red light running

Citation	Speeding	Red light running	Enforcement method	Visible or hidden	Country
(Elvik, 2012a)	Y		Speed cameras, police	Visible	Norway
(Elvik, 2012b)	Y		Various	Not specified	Various
(Soole et al., 2012)	Y		Average speed cameras	Both	Various
(Kattan et al., 2011)	Y		Speed cameras	Visible	Canada
(Fleiter et al., 2009)	Y		Speed cameras, police	Both	Australia, China
(Kloeden et al., 2009)		—	Red light cameras	Hidden	Australia
(Soole et al., 2009)	Y		Speed cameras, hand-held radar, police, police vehicle	Both	Australia
(Tarko, 2009)	Y		Hand-held radar	Visible	United States
(Walker et al., 2009)	Y		Speed cameras, average speed cameras, hand-held radar, police vehicle radar, police	Both	Australia
(Damsere-Derry et al., 2008)	—		Police	Visible	Ghana
(Hatfield et al., 2008)	Y		Not specified	Not specified	Australia
(Fleiter et al., 2007)	Qualitative		Speed cameras, police	Both	Australia
(Blincoe et al., 2006)	Y		Speed cameras	Visible	United Kingdom
(Fleiter and Watson, 2006)	Y		Speed cameras, police	Not specified	Australia
(Keall et al., 2002)	Y		Speed cameras	Both	New Zealand
(Keall et al., 2001)	Y		Speed cameras	Both	New Zealand
(Porter and Berry, 2001)		Y	Red light cameras	Not specified	United States

Y: Enforcement statistically significant;
—: Enforcement not significant;
Blank: Not studied.

3.1.5 Perceptions and attitudes of crash risk

Perceived risk is what an individual believes is the risk of a particular event occurring to themselves – or those they are concerned about. This may or may not be an accurate representation of risk and it may be higher or lower than the objective risk. If the perceived risk is lower than the objective risk then a driver may be a more careful driver. Objective risk is the actual probability of a particular event occurring. A discrepancy between the actual and perceived risks is one possible reason for behaviour that would appear – given an objective risk – to be contrary to expectations. A distinction also needs to be made between an individual's understanding of risk and an individual's perception of risk. The former refers to how well somebody understands the concept of risk and probabilities while the latter refers to what a person believes is the likelihood that a particular event will occur. Mathematical ability has been used as a control proxy in studies about risk perception to ensure that differences in risk perception were not the result of a better understanding of risk (Svenson, 2009). The focus in this literature review and research is on perceptions of risk.

Attitudes towards risk are a slightly different concept to risk perception and relate to drivers' tendencies to evaluate the merits of a particular behaviour more or less favourably on the basis of *perceived* risk (Iversen, 2004). Much of the research on attitudes towards risk is based on the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975) and the theory of planned behaviour (TPB) (Ajzen, 1991). Warner (2006) explains this as follows:

> *According to Ajzen's* (2006) *theory of planned behaviour people's attitude towards the behaviour, their subjective norm and their perceived behavioural control determine their behaviour (a defined action) indirectly via their intention (a willingness to try to perform the behaviour).* (Warner, 2006)

Since its introduction, TRA and TPB have been used extensively in the literature. Warner (2006), Brown and Cotton (2003), Iversen (2004) and Falk and Montgomery (2007) are some examples of researchers that have applied these theories to investigate speeding behaviour.

The relationship between risk perception and driving behaviour – particularly speeding – has been investigated by researchers for many decades (for example, Colbourn, 1978). In the study described by Colbourn (1978), drivers were shown videos of real road scenes as seen from the inside of a car to mimic what the participants would see if they were driving the car. For each video, participants (12 male drivers 18 to 24 years old) were asked to rate the perceived risk of each situation relative to a "safe" situation recorded on an empty dual carriageway. The results showed that less experienced drivers tend to provide higher risk estimates for interactions with other road users. The risk estimate was higher as the conflict became closer. In contrast, more experienced (albeit still young) drivers exhibited very similar risk perceptions for all situations suggesting that young experienced drivers can become over confident. However, the author does caution that studying perceived risk is complicated as different participants interpret the same task differently.

More recently, the literature on risk perception and driving behaviour has examined a number of different aspects of risk perception and its influence on driver behaviour. Elvik (2010a) and Titchener and Wong (2010) examined how accurately drivers perceive risk. Other studies attempt to see how risk perception relates to – typically self-reported or licensing data – driving behaviour (for example, Musselwhite, 2006; Ivers et al., 2009). A number of studies attempt to do both (Delhomme et al., 2009b). Young drivers in particular have been the focus of many studies on risk perception and driving behaviour (including Falk and Montgomery, 2007; Machin and Sankey, 2008; Ivers et al., 2009).

Generally, studies have found that drivers' perceptions of driving risks are not accurate and in many cases significantly lower than the objective risks. However, although there does appear to be a relationship between drivers' perceptions of risks and their driving behaviour, this effect is tempered by other factors including the perceived benefits (Fleiter et al., 2007; Walsh et al., 2008), risk of penalty and perceived enforcement of illegal behaviour (see Fleiter et al., 2009; Soole et al., 2009; Constant et al., 2009) and personality (Vassallo et al., 2007; Gulliver and Begg, 2007; Machin and Sankey, 2008; Delhomme et al., 2009b). There is also evidence that how drivers react to perceived risks is not consistent from driver to driver (Musselwhite, 2006). Risk perception has also been used to study drivers' inclination to speak on a mobile telephone whilst driving but with mixed results. Nelson et al. (2009) found that perceived risk was a significant negative predictor of initiating and answering telephone calls but interestingly was not a predictor of frequency. A study by Atchley et al. (2011) attempted to determine if the findings of Nelson et al. (2009) could be replicated for text messaging while driving. Although the effect of risk perception on initiating a text message (as opposed to reading or replying) was significant, risk perception only accounted for one percent of the variance in behaviour.

In regards to speeding in particular, despite the evidence that speeding is indeed dangerous, only 22 percent of drivers perceive speeding to be a threat to the safety of themselves or their families at 5 miles/h (8 km/h) above the posted speed limit and worse, two percent of drivers do not think speeding is dangerous at any speed (Mannering, 2009). This already low figure of 22 percent is even more of a concern considering evidence that shows drivers may not realise how frequently they speed (Greaves and Ellison, 2011). These findings add to a growing body of literature (for example Svenson, 2009; Delhomme et al., 2009; Elvik, 2010a) showing that drivers frequently underestimate the risks of travelling at a given speed. Although there is recognition by drivers that the risks of injury (and therefore crashes) increase with higher speeds (Delhomme et al., 2009b), Elvik (2010a) demonstrated in Figure 3-7 that this gap between reality and perception increases as the relative speed increases. The same is true for fatigued driving (Hatfield et al., 2006; Cortes-Simonet et al., 2010) and driver distractions (Nelson et al., 2009).

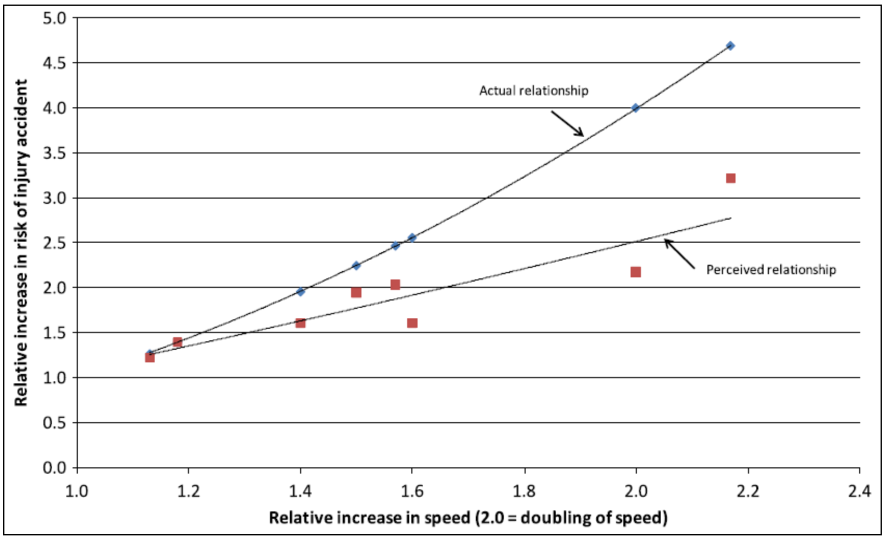

Figure 3-7: Difference between actual and perceived risk of injury (Elvik, 2010a)

More broadly, Rosenbloom et al. (2008) looked at drivers' risk perceptions of 34 driving behaviours including speeding, drink driving, eating, driving on wet roads and reversing before and after undergoing driver training. The authors found that the perceived risk increased significantly for all but six of the behaviours studied. The exceptions were behaviours – driving after two alcoholic drinks for example – which were perceived to be high risk before the training and had high legal penalties. In terms of demographic differences, females and older drivers had higher perceptions of risks than males and young drivers respectively with age accounting for nine percent of the variance in perceptions and gender accounting for six percent of the variance.

Regardless of the accuracy of drivers' risk perceptions, another strand of research attempts to examine how drivers' risk perceptions relate to their driving behaviour. Lucidi et al. (2010) conducted a cluster analysis to identify three types of driver: risky drivers, worried drivers and careful drivers. Risky drivers had received more fines and been involved in more crashes than the other two groups. Careful drivers had received the lowest number of fines and had been involved in the fewest number of accidents. Despite the very different behaviours, both groups had similar risk perceptions[47]. The worried drivers cluster had the highest risk perception but the behaviour of drivers in this group fell between the risky and careful driver clusters. One possible reason for this is the presence of a threshold effect which results in stable risk perceptions until a critical point (or threshold) is reached at which point the risk perceptions increase substantially (Lewis-Evans et al., 2010).

Braking behaviour has also been shown to be influenced by risk perceptions. In one study Regulatory Focus Theory (RFT) was used to explain differences in the delay before braking is initiated when confronted with a dangerous traffic situation. The researchers hypothesised that drivers with a prevention focus, who have a tendency to minimise losses and therefore high risk perceptions, will brake earlier than drivers with a promotion focus, which have an inclination to maximise gains and lower risk perceptions. The results show that in an unambiguous situation prevention focused and promotion focused drivers behave similarly. However, in an ambiguous situation where the outcome (a crash) is less certain, prevention focused drivers braked significantly earlier (Werth and Förster, 2007). A similar effect for speeding was found by Brown and Cotton (2003) in a study employing the Speeding Risk Belief Scale (SRBS). They determined that risk perception was related to self-reported speeding behaviour across all age groups and genders. However, the authors also

[47] The risk perception variable was a composite variable measuring the participants' perceived risk of being involved in a crash relative to other drivers and how worried they were about the possibility of being in a crash.

suggest that drivers' risk-mitigating beliefs, which were also found to be correlated with speeding behaviour in the same study, are used by drivers to rationalise speeding by reducing the perceived risk and thereby rationalising their own (higher) speeding behaviour. In effect, drivers' risk perceptions are based not on (incorrect) knowledge of the risk of speeding but on beliefs about the dangers of speeding – such as "I can drive safely at high speeds" – that are formed to rationalise their behaviour. This is consistent with research by Mannering (2009) which found that drivers' perceptions of the risk associated with speeding are significantly related to how likely they think they will be fined for speeding. The author also observed a positive relationship between how many times a driver had been stopped for speeding and what they considered to be a safe speed.

The theory of planned behaviour (TPB) (Ajzen, 1991) has also been applied to look at the influence of drivers' attitudes to their behavioural intentions to speed and their observed speeding behaviour. The findings of one study using the TPB by Paris and Van den Broucke (2008) show that a driver's attitude to speeding is a significant predictor of the intention to not speed but this does not translate into a significant predictor of observed behaviour as measured by in-vehicle GPS units. A simulator study confirms these findings with attitudes being predictors of intention to speed but not a significant predictor of observed speeding. Intention to speed was a predictor of observed speeding behaviour (Conner et al., 2007). Hatfield et al. (2008) also conducted a simulator study which found that higher negative attitudes to speeding was related to lower self-reported likelihood to speed as well as less observed simulator speeding behaviour and lower mean speed speeds. A qualitative study based on the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975) finds that when drivers are in situations which they subjectively consider being low risk they consider it to be permission to speed. In addition, the researchers found that drivers did not consider the possibility that their speeding behaviour could result in a fatality or serious injury (Falk and Montgomery, 2007). Many other models of driver behaviour have also been tested in the literature. Lewis-Evans (2012) provides a comprehensive literature review of these other models.

Rundmo and Iversen (2004) segmented risk perception into four different elements, namely, probability judgements, concern, worry and insecurity and emotional reactions. They found that neither concern about the risks nor probability judgements, which relate to young drivers' estimates of risk, are related to self-reported risky driving behaviour. In contrast, emotional reactions to traffic hazards are a significant (negative) predictor of self-reported risky driving behaviour. This was true for male and female drivers. Research on young drivers in other countries appears to support these results (Ivers et al., 2009).

Given the evidence it appears reasonable to conclude that existing methods of communicating the impact of risky driving behaviour to drivers and others could be improved. However, the literature is mixed on if there is a causal relationship between risk perception and drivers' on-road behaviour. It suggests that improving the accuracy of drivers' judgement of risks may not result in changes to drivers' observed behaviour. On the other hand there appears to be a link between how drivers rationalise risk and their behaviour suggesting that strategies designed to change how drivers think about risk may be effective.

3.2 Behavioural responses to information and incentives

Chapter 2 and Section 3.1 outlined the extent to which risky driving behaviour occurs and the factors which influence drivers' behaviour. This section covers the methods of influencing behaviour for individual and societal benefits using information. This information is used to try to change personality, attitudes, perceptions and knowledge of risk and road safety to influence behaviour.

3.2.1 Information

Communication of risk using information – through education campaigns – is one strategy used by governments to reduce the frequency of risky driving behaviour. Other strategies include appeals to emotions or fear, increased (or more visible) enforcement, more stringent penalties, changes to legislation and graduated licence schemes.

The majority of the literature on methods of reducing risky driving behaviour focuses on the impacts of advertising campaigns. As such, this research is overwhelmingly about speeding, drink driving and to a lesser extent fatigue and mobile telephone usage. Research on other types of risky driving behaviour is largely limited to the types discussed in previous sections.

Communicating risk (and therefore safety) information tends to take one of two forms. The first focuses on communicating the risk of an event occurring using statistics. The second focuses on the outcome of risky driving behaviour. Within these two categories are different strategic methods of which the most prominent normally uses fear, shock or shame tactics to induce behaviour change. A multi-platform media campaign developed by the Roads and Traffic Authority (RTA), New South Wales (NSW), Australia used shame tactics to target speeding behaviour and is arguably the most successful single road safety campaign (Watsford, 2008; Faulks, 2011).

A literature review by Lewis et al. (2007) examined theoretical and empirical studies on the effectiveness of fear-arousing road safety advertising. The main finding of these studies is that although fear campaigns can be successful, the key component is the ability to communicate the relevance of the risk to the target audience. Since drivers have a tendency to show optimism bias where they perceive themselves to be better drivers than others (Tarko, 2009) this appears to be a logical conclusion. The need to effectively target road safety messages at particular groups (Tay, 2002) is consistent with the findings in other fields (Kahn et al., 2002) where tailoring information was found to be a necessary component to produce behavioural change. However, there is evidence that education strategies and enforcement (and therefore legislation) are both necessary to induce behaviour change (Tay, 2005). As some forms of risky driving behaviour – such as driving whilst fatigued – are currently not legislated against for non-commercial drivers (Hatfield et al., 2006) this is a limitation in changing behaviour. These characteristics of a successful road safety education campaign are summarised and documented in a manual for developing road safety campaigns by Delhomme et al. (2009a). In addition to a thorough review of the literature, the manual outlines the importance of targeting the information appropriately, deciding on what needs to be said/written and how it is to be communicated. It also discussed the merits of different methods of communicating the information and how to evaluate the success of a campaign.

Some studies have examined the best way to communicate risk information to drivers. Hatfield et al. (2006) tested different methods (and combination of methods) of providing information on the risk of fatigued driving to young drivers. Two examples are shown in Figure 3-8. All four groups received basic information about fatigued driving. Drivers in two groups were also presented with information refuting incorrect but commonly believed myths about strategies to reduce fatigue. An additional control group was surveyed but no information was provided to them. The findings were that the information was a factor in eight significant beneficial changes relative to the control, including:

- The perceived likelihood of having a crash when fatigued increased for all groups but particularly for the groups that were not shown the myth information;
- The group shown the risk ladder (Figure 3-8, right) but not the myths exhibited reduced optimism bias when not fatigued with the two myth groups exhibiting a smaller effect;
- Reduced intention of attempting false methods of reducing fatigue was seen in all four groups but particularly in the two groups that received information specifically targeted at these myths; and
- All groups exhibited a reduction in the intended frequency of fatigued driving but the group that received the myths information but not the risk ladder had the highest reduction.

The authors suggest that overall the group that received both the myth information and the risk ladder showed the best improvement but that there may be some secondary effect of the myth information on perceived crash risk if drivers interpreted the information to mean that they could reduce their crash risk by behaving correctly.

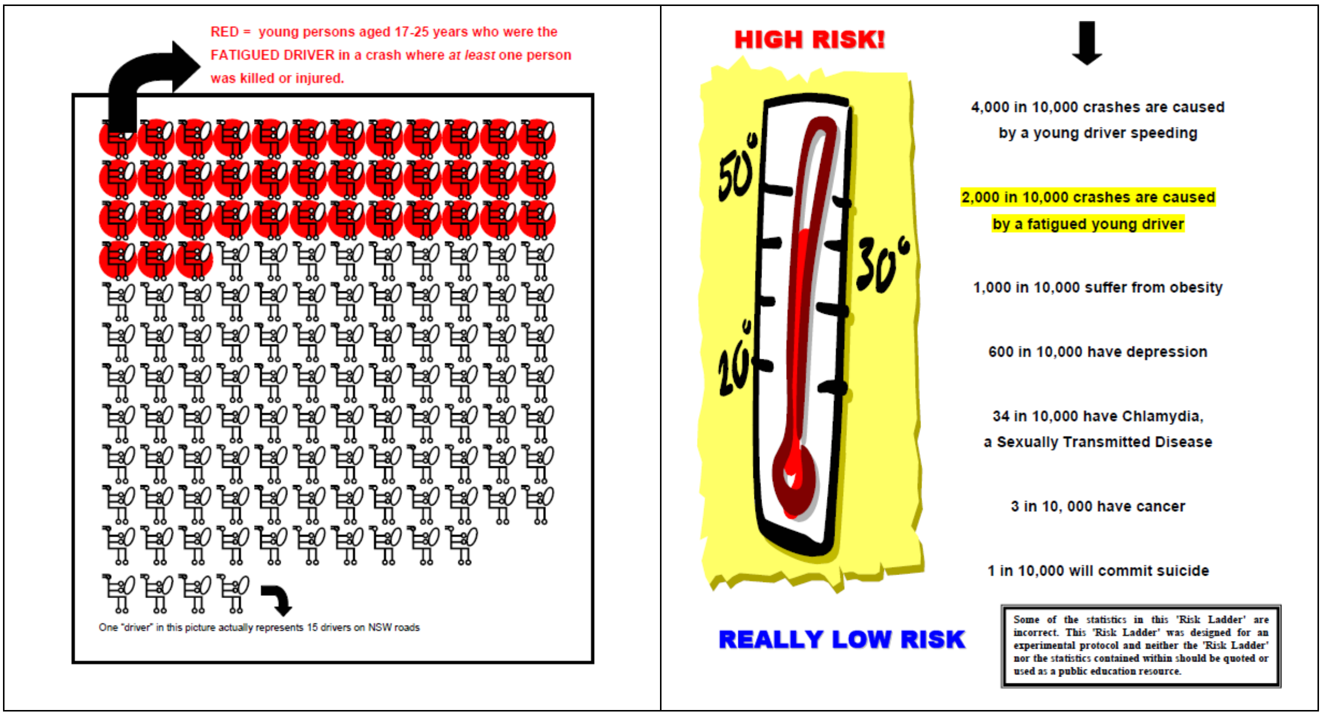

Figure 3-8: Diagrams depicting fatigue-driving related statistics (Hatfield et al., 2006)

Lund and Aaro (2004) also conducted an extensive review of the literature to determine if there was any evidence to support the Knowledge, Attitudes and Practices (KAP) model, which suggests that attitude modification leads to a change in attitudes and beliefs which in turn leads to a change in behaviour which ultimately reduces accidents and injuries, but only found a weak relationship. However they did identify promising trends which are consistent with other studies (Tay, 2002; Lewis et al., 2007). Specifically, information that has been tailored to specific individuals or groups is effective at changing behaviour as is combining education campaigns with legislation and enforcement. There is also some evidence that there is an interaction effect on drivers' ability to recall information between the types of information presented (neutral as opposed to risk information) and a drivers' inherent optimism[48] (Pedruzzi and Swinbourne, 2009).

Research focusing on the use of information about the impacts of risky driving behaviour on family and friends is surprisingly limited. Despite this, the studies that do exist (Stead et al., 2005; Mannering, 2009) show that communicating the impact on

[48] Optimism in this case refers to a personality characteristics and not optimism bias which is individuals' tendency to think that negative events are more likely to occur for others.

drivers' families is among the most effective strategies. This is consistent with the finding of studies that have found that social (or family) perceptions have an impact on drivers' own perceptions of the safety of risky driving behaviour (Elliott et al., 2004; Fleiter et al., 2006). Similarly, some studies have shown that presenting information about social norms is more effective at changing behaviour than information about crashes or fines but this relies on the social norm representing the desired behaviour which in some cases it may not (Gaker et al., 2010).

3.2.2 Feedback and warnings

Changing behaviour through information can be approached from two directions. On one hand information can be used to educate drivers about the consequences associated with engaging in particular behaviours in the hope that changes in knowledge, attitude or perceptions will create a beneficial change in behaviour as discussed in Section 3.2.1. On the other hand, for behaviours that drivers already know are dangerous and/or are illegal and have legal penalties providing real time or retrospective feedback on what they are doing may change behaviours by making drivers more conscious of what they are doing.

Intelligent Speed Adaptation (ISA) trials which alert drivers in a number of ways – including audible warnings and visual warnings on a screen – to their speeding behaviour in real time allude to the possibility that advising drivers in real-time of what they are doing may be sufficient to encourage a change in behaviour. For example, drivers in an ISA trial conducted in NSW, Australia revealed that being advised that they were speeding (using an audible warning) increased their awareness of their frequency of speeding behaviour and made them aware they were speeding when they inadvertently drove in excess of the posted speed limit. Overall, 89 percent of vehicles recorded lower proportions of time speeding with an ISA device installed than before it was installed (NSW Centre for Road Safety, 2010). These results are consistent with other ISA trials (for example Jamson, 2006) although a study of young drivers has found that monitoring and alerts by themselves are not sufficient to change risky driving behaviour in the long term (Farmer et al., 2010). Another study incorporated a real-time feedback and reward scheme[49] for participants to reduce speeding. Although only 37 drivers participated the results suggest speeding was reduced during the feedback phase. After the completion of the feedback phase drivers' speeding increased but remained lower than the baseline phase for higher speed limits[50]. The authors note that the speed limit was a significant factor in explaining behaviour (Merrikhpour et al., 2012; Merrikhpour, 2013).

Similar studies have been conducted on distracted driving with some promising results from in-vehicle feedback, retrospective feedback and combined feedback using both real-time and retrospective methods (Donmez et al., 2007, 2008; Toledo et al., 2008). Donmez et al. (2008) used driving simulators to test the effect on braking behaviour of real-time and retrospective feedback presented at the end of each trip. The authors found that the results were similar for both combined feedback[51] and retrospective feedback with both showing significant improvement compared to drivers that received no feedback. Moreover, there appeared to be a learning effect whereby braking behaviour (for both feedback types) improved over the four simulated driving sessions. In another study of retrospective feedback – this time using an in-vehicle device installed in a fleet of company vehicles – the authors found a significant reduction in crash rates (38 percent) after the feedback was introduced compared to the control group which received no feedback (19 percent reduction). This improvement was sustained over the seven months of the analysis although the authors note that a longer analysis appeared to indicate a slight increase in crash risk in the longer term (Toledo et al., 2008).

Two studies of young drivers examined the effect of feedback on driver behaviour. This is of interest given evidence from other research that young drivers respond differently to feedback (Farmer et al., 2010). Musicant and Lampel (2010) studied the effect of feedback on unsafe driving events (including sharp turns, aggressive braking and aggressive acceleration) for 32 vehicles and found that the frequency of these

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[49] The reward scheme consisted of points accumulated for compliance which could be redeemed for gift cards at the completion of the study.

[50] The authors defined higher speed limits as 70, 80, 90 and 100 km/h speed limits.

[51] Combined feedback incorporated both real-time feedback and retrospective feedback.

events reduced by 50 percent in the feedback phase. These results were not related to the day of the week, time of day or the gender of the participants. The feedback was accessed through a website with weekly e-mail reports provided to participants and their parents. Importantly, participants and their parents were trained on how to interpret the feedback in an in-person session. Simons-Morton et al. (2013) examined the effect of feedback on braking behaviour for 90 teenage drivers using accelerometers[52]. The participants were provided with real-time feedback using lights which indicated if an event had been recorded. The parents of half the sample received e-mailed reports and access to videos of events. The authors found that participants whose parents did not receive reports exhibited no effect from the feedback. In contrast, parental participation was related to significant reductions in heavy braking. There was no relationship between changes in behaviour and demographic characteristics.

3.2.3 Financial incentives

Financial incentives (and disincentives) have been used to encourage drivers to comply with speed limits and other road rules with legislated fines for speeding infringement being the most common form. Some insurance companies have trialled pay-as-you-drive (PAYD) insurance schemes typically targeted at young drivers that pay the highest premiums (The Co-Operative Insurance, 2012; Desyllas and Sako, 2012). Unfortunately the methodologies are confidential but Co-Operative Insurance claims that 51 percent of drivers under 25 would save money under their insurance plan (The Co-Operative Insurance, 2012). The benefit of this compared to fines is that the monetary component is linked to all driving behaviour and not only the (rare) occasions when a driver is caught speeding by police or speed cameras.

Hultkrantz and Lindberg (2009) conducted an on-road experiment with 114 cars with ISA devices installed[53]. Drivers were provided with a monthly monetary incentive (250 SEK or 500 SEK)[54] for each of the two months of the study with this incentive

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[52] GPS was not used and exposure data was recorded using odometer readings.

[53] These participants had already been using the ISA devices with feedback provided but no monetary incentive.

[54] At the time the study was conducted these values were equivalent to $20 and $40 respectively.

being reduced by 0.10 SEK to 1 SEK (approximately 20 cents) or by 0.10 SEK to 2 SEK (depending on the magnitude and the group) for each minute driven over the speed limit for some of the participants. Drivers were informed of their remaining incentive at the end of each month. The findings were that there was no significant difference in changes in speeding behaviour in the first month between those with a variable and fixed incentive. However, in the second month drivers that received a variable incentive reduced their speeding behaviour by 64 percent compared to 15 percent for those receiving a fixed incentive. There was also no difference in behaviour for the drivers with higher penalty rates compared to drivers with lower penalty rates. The authors suggest that drivers decide to reduce their speeding behaviour or not and this appears to be unrelated to the amount of the incentive.

In a somewhat different study, Muermann and Straka (2012) used data from an insurance company's PAYD customers to determine if there was a relationship between driver behaviour and choices in the level of first-party and third-party liability insurance. The findings were that speeding is negatively related to the level of third-party liability while the number of trips and proportion of night-time driving is positively related to first-party insurance coverage. The authors explain that drivers who are less risk-averse buy lower third-party coverage, exceed the speed limit more frequently and have more frequent shorter trips.

3.3 Driver risk profiling

Driver risk profiling is a method of representing driver characteristics. It can include one or more elements including driver trait characteristics such as personality and task characteristics which are comprised of mechanistic models (De Winter and Happee, 2011). Risk profiles have been developed for drivers (Toledo and Lotan, 2006) and for locations in the road network (Pyta and McTiernan, 2010). The insurance industry has long used methodologies for assessing the risks associated with insuring particular cars and drivers (Litman, 2011) using police and crash records, information about prior claims, place of residence and driver demographics (Ong and Stoll, 2008).

The development of risk profiles is important as road safety measures influence behaviour to varying extents in different people (Lewis et al., 2010). Most studies looking at the risk profiles of drivers categorise risk groups by demographics (primarily age and gender but sometimes location[55]) (Wundersitz and Hutchinson, 2008). This method is consistent with how crash statistics are reported (NSW Centre for Road Safety, 2009) and is useful for studying the differences between demographic groups that are over/under represented in crash statistics but ignores the heterogeneity of driver behaviour discussed in Section 3.1.

There have been a number of attempts to categorise risk groups based on self-reported behaviour and risk preferences. For instance, Goldenbeld and Van Schagen (2007) categorised drivers based on low, average or high sensation seeking in addition to demographics, number of speeding fines and location of residence. Machin and Plint (2010) used a questionnaire of self-reported speeding, personality and perceptions to determine the factors that influence speeding behaviour. The final model explained 50 percent of the variance identifying three risk perception variables, one personality variable and one coping strategy as statistically significant contributors to speeding behaviour. Arguably the more interesting conclusion is that at least five predictors are needed for the model and these predictors are of varying types. In another study, hierarchical cluster analysis was performed to dynamically categorise drivers into four risk groups comprising of a calculated risk taking group, unintentional risk taking group, continuous risk taking and a reactive drivers group (Musselwhite, 2006). The development of risk profiles based on behaviour and risk preferences – and the assessment of risk itself – is complicated by the interdependencies of different risky behaviour (Musselwhite, 2006). Lucidi (2010) used cluster analysis to classify young drivers based on three risk profiles comprising 34.3 percent of the sample (risky drivers), 27.9 percent (worried drivers) and 37.8 percent (careful drivers) respectively. These profiles were comprised of drivers' personality characteristics and the membership of each cluster was analysed based on drivers' risk perceptions, attitudes, past road rule violations and speeding behaviour, past drink driving, driver errors and involvement in crashes in a number of severity categories. The clusters were significant predictors of driving violations, lapses and errors.

[55] The risk of crashes can vary by location but this is a factor that is exogenous to the driver.

Boyce (1999) used an instrumented vehicle driven by study participants for a one hour period to develop clusters of driving behaviours. A profile (termed Global Percent Safe Score) was calculated incorporating speeding, speed variation, off-task behaviours, turn-signal use and following distance. This score was then compared to the same drivers' personality and demographic characteristics. No effect was found for any of the personality characteristics but there was a statistically significant relationship with the age of the driver. The average score of young drivers was 73 percent compared to 78 percent for middle aged drivers[56] and 83 percent for older drivers. Some researchers have also applied risk profiling to assess the safety of professional drivers using in-vehicle data recorders. For example, Toledo et al. (2008) developed a system for installation in a fleet of commercial vehicles to monitor and provide feedback to drivers to improve their driving on a range of measures. In the process of doing this they created a risk index (from 0, lowest risk, to 1, highest risk) which was a numerical representation of each individual driver's risk of being involved in a car crash. The risk index was defined in Equation 1. Speed was an integral component of the risk index but due to its importance, a separate speed index was also created.

Equation 1: Calculation of risk index developed by Toledo et al. (2008)

$R_{it} = \frac{\Sigma_j \Sigma_s \beta_{js} N_{ijst}}{DT_{it}}$	R_{it} is the risk index for driver i during time period t DT_{it} is the driving time for driver i during period t N_{ijst} represents the number of events[57] of type j and severity s β_{js} represents the weights given to each event and severity

To simplify reporting to drivers, the output of the risk index was classified into one of three categories: moderate behaviour (green), intermediate behaviour (yellow) and risky behaviour (red). Indices were reported for each driver as well as for each trip. There was a positive relationship between drivers' risk index and the expected crash rate and at-fault crash rates. The same approach was later adapted for modelling the behaviour of newly licensed young drivers. In the young driver study, the risk indices for each driver were compared during the first year that they held a licence. The risk

[56] Not statistically significant

[57] Events include lane changes, speeding and sudden braking.

index was used to compare the same driver across time to determine if increased experience would result in a reduction in the index and therefore indicate that the driver is becoming safer. The results show that driving experience alone does not – at least in the first year – reduce drivers' risk indices but that additional supervised driving does (Prato et al., 2010).

Ericsson (2000) studied the impact of driving patterns on emissions. Although this study does not create a single composite measure of driver behaviour, as was done in the previously mentioned studies, it does examine a number of measures of speed, acceleration and braking that would be included in a composite measure of behaviour (and, ultimately, risk). Higgs (2011) also developed speed profiles – in this case for heavy vehicles – and found there to be significant variation across drivers and locations and suggested a composite measure for drivers' speed behaviour. A similar speed profile was developed for specific corridors in a road network using data collected from GPS units by Boonsiripant (2009) and the results compared to the history of crashes along the same corridors. There appears to be some merit to this approach particularly when detailed road geometry and usage data is not available. Using the same data used by Boonsiripant (2009), Jun (2006) examined speed, acceleration and braking profiles for crash-involved and non-crash involved drivers. Although a composite measure of risky driving behaviour was not created, a model containing the various behavioural measures did correctly predict 68 percent of crash-involved drivers and 87 percent of non-crash-involved drivers.

Another form of profiling uses drivers' acceleration and braking behaviour to classify drivers. Bagdadi and Várhelyi (2011), for example, used acceleration and braking behaviour collected during an ISA trial in Sweden. This was used to calculate the rate of change of acceleration (jerks) which were analysed over the period of the study to attempt to predict crash involvement. These driver 'jerk' profiles were determined to be a statistically significant predictor of crash involvement and therefore appear to have merit as at least one of a number of behavioural measures to be included in a driver risk profile.

3.4 Summary and research gaps

There have been many studies which aim to gain a better understanding of drivers and driver behaviour to improve the effectiveness of road safety strategies. The majority focus on the three most common factors in fatal crashes: speeding, drink driving and fatigue. Within this body of literature demographics, social norms, personality, legislation, enforcement and some spatial factors have all been identified as possible influencers of risky – and safe – self-reported driving behaviour. The accuracy of an individual's risk perceptions has also been studied determining that people do not accurately perceive the risk of different driving behaviours. In addition, a small but growing number of studies using instrumented vehicles have helped reduce the reliance on self-reported, police and hospital data in determining the frequency of risky driving behaviour. The findings of these studies have been used to improve the effectiveness of road safety campaigns primarily for speeding, drink driving and fatigue. Nonetheless there are aspects of risky driving behaviour that remain inadequately explored. Although it is known that the perceived risks of different forms of risky driving behaviour are inaccurate it is unclear if the reasons for this are due to a lack of understanding of the concept of risk or if the methods used to provide risk information are not effectively reaching all drivers that engage in this behaviour. Furthermore, there have been few studies which relate drivers' risk perceptions to how they behave on the road through time. However, given the evidence that all the aforementioned factors are linked, perhaps the largest gap is not in the focus of the studies themselves but in the lack of any studies that bring together different forms of risky driving behaviour in day-to-day driving with individuals' demographics, psychological profiles, perceptions of various risks and how to best classify drivers to adequately target and customise road safety messages.

The disconnected nature of previous studies is evident in current road safety campaigns which assume that all drivers in the target demographic are homogenous and therefore the same factors influence their behaviour. Previous research suggests that this assumption may not be valid and this reduces the effectiveness of road safety campaigns. If, as seems evident from the literature, tailoring information consistently produces the best results, there appears to be a significant need to improve our understanding of how best to classify drivers into targetable groups.

Based on the review of the literature in Chapter 2 and Chapter 3 and the identification of the research gaps, in Chapter 4 two sets of hypotheses are developed and suitable data sources are identified to test these hypotheses.

4 STUDY DESIGN AND METHODOLOGY

Chapter 2 and Chapter 3 reviewed the literature on risky driving behaviour and the factors that influence behaviour. This chapter describes the study hypotheses, design and methodology. The study tests two sets of hypotheses which are specified in Section 4.1. Section 4.2 outlines the data sources that are used for this research and the methodological approach is described in Section 4.3.

4.1 Hypotheses

A review of the literature highlighted that although there have been many studies into the factors that influence driver behaviour, none combine observed naturalistic driving data with drivers' personality, demographics and risk perceptions. Furthermore, many of the studies rely on sources of data that suffer from a lack of spatiotemporal coverage of the same drivers' driving behaviour. Therefore, the purpose of this research is to identify the extent of risky driving behaviour, specifically speeding and aggressive acceleration/braking behaviour, in day-to-day driving and identify the demographic, attitudinal, psychological and risk perception influencers of driving behaviour. It is expected that drivers' attitudes, experiences and psychological characteristics influence their perceptions which in turn influences their driving behaviour. These findings will provide information that will help to improve the targeting of road safety campaigns.

To accomplish this, two sets of hypotheses are formulated and tested. The first of these is aimed at gaining a better understanding of the extent of risky driving behaviour in day to day driving and how this is influenced by drivers' personality, attitudes and perceptions. The second set of hypotheses deals with changes in the frequency and magnitude of risky driving behaviour as a result of an increase in drivers' awareness of their own behaviour.

4.1.1 Hypotheses set 1: Influences on extent of risky driving behaviour

Most previous research that has attempted to determine the frequency and magnitude of risky driving behaviour and its influencing factors has relied on sources of data (see Section 2.4.1) which are likely to understate the extent of risky driving behaviour. Furthermore, attempts at studying the influence of attitudes and psychological factors in risky driving behaviour rely heavily on self reported measures of behaviour – speeding in particular – and therefore may reflect the influence of psychological factors on self-reported as opposed to observed driving behaviour. This first set of hypotheses determines and tests the frequency and magnitude of risky driving behaviour within a driver's normal driving routine and then identifies the psychological, attitudinal and risk perception factors that are associated with risky driving behaviour.

H 1. The frequency and magnitude of risky driving behaviour is influenced by a driver's attitudes, beliefs and experience.

- H1.1 Drivers with lower perceptions of the danger of risky behaviour engage in risky driving behaviour more frequently as measured by objective data.
- H1.2 Drivers with more concern about passenger safety engage in risky driving behaviour less frequently as measured by objective data than drivers with similar concerns for themselves and other drivers.
- H1.3 Drivers with more confidence in their own driving abilities engage in risky driving behaviour more frequently as measured by objective data.
- H1.4 Drivers with more aggressive, excitable and car-dependent personalities engage in risky driving behaviour more frequently as measured by objective data. Conversely more altruistic drivers engage in risky driving behaviour less frequently as measured by objective data.

These hypotheses constitute multiple aspects. They are restated with their constituent parts in Appendix A (Section 13.1) along with a summary of the hypothesis testing outcome.

4.1.2 Hypotheses set 2: Driver risk perceptions and behaviour recognition and their link to risky driving behaviour

The first set of hypotheses attempts to better understand the psychological and attitudinal influencers of risky driving behaviour and determine a method of categorising drivers by these determinants in addition to demographics. However, the literature has identified that not only are drivers poor judges of the risks they face but they also frequently fail to acknowledge their own behaviour. Therefore although drivers may be similar in terms of psychology and attitudes to risk, their actual behaviour is likely influenced by how they perceive and recognise the risks of their own driving behaviour. The purpose of this set of hypotheses is to determine if making drivers aware of how they drive results in less risky driving and, if so, how the magnitude of the change is influenced by drivers' perception of the risks driving.

H 2. Drivers engage in risky driving behaviour less frequently once they are made aware of their actual speeding behaviour and provided with a financial incentive; however the magnitude of the change varies depending on the individual driver's attitudes, beliefs and experience.

- H2.1 Drivers with lower perceptions of the danger of risky behaviour have a lower magnitude change in risky behaviour than drivers with similar demographic characteristics but higher perceptions of danger (whether accurate or not) once they are made aware of their speeding behaviour.
- H2.2 Drivers with more concern about passenger safety have a higher magnitude change in risky driving behaviour than drivers with less concern once they are made aware of their speeding behaviour.
- H2.3 Drivers with more confidence in their own driving abilities exhibit a lower magnitude change in risky driving behaviour compared to drivers with less confidence in their own driving abilities once they are made aware of their speeding behaviour.
- H2.4 Drivers with more aggressive, excitable and car-dependent personalities have a lower magnitude change in risky driving behaviour compared to drivers with less aggressive, excitable and car-dependent personalities once they are made aware of their speeding behaviour. Altruistic drivers have the opposite (higher) magnitude change in behaviour.

These hypotheses constitute multiple aspects. They are restated with their constituent parts in Appendix A (Section 13.2) along with a summary of the hypothesis testing outcomes.

4.2 Data and data collection[58]

This study uses three types of data: observed driving behaviour, driver surveys and supplementary spatial and driving risk information. All data are stored in a single relational database. With the exception of the supplementary spatial and driving risk information (discussed in Section 4.2.9), the remainder of the data were sourced from a broader study of driver behaviour (Greaves et al., 2010). The design of this broader study is summarised in Section 4.2.1. Recruitment and retention of participants is discussed in Section 4.2.2. The observed driving behaviour (GPS) data are described in Section 4.2.3. Details on how trip information was collected are provided in Section 4.2.4. The intervention is described in detail in Section 4.2.5. The driver surveys are explained in Section 4.2.6. Lastly, the supplementary sources of spatial and driving risk data are described in Section 4.2.9.

With the exception of the supplementary spatial and driving risk information (discussed in Section 4.2.9), the remainder of the data were sourced from a broader study of driver behaviour (Greaves et al., 2010).

4.2.1 Study design

Observed driving behaviour data were collected from 148 drivers in Sydney, Australia, as part of a broader study of driver behaviour (see Greaves et al., 2010 for more information). The overall study consisted of five distinct phases as shown in Figure 4-1 incorporating survey and GPS phases.

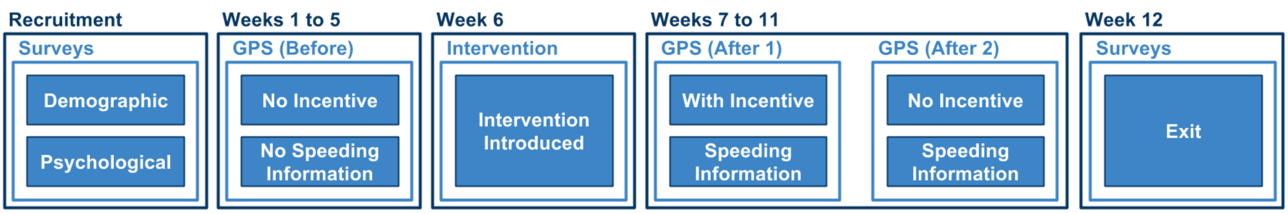

Figure 4-1: Study phases

[58] The content in this section dealing with study recruitment, design and data collection is derived from several papers (Greaves et al., 2010; Greaves and Fifer, 2010) written by the original researchers on the project from which most of the data are sourced.

Briefly, the study consisted of demographic and psychological surveys followed by a five week GPS *before* phase during which time the purpose of the study was unknown to participants. At this stage study participants were not informed that their speed was being monitored. To avoid any potential effect on behaviour resulting merely from the installation of the GPS device, data from the first week after installation was collected but excluded from the analysis leaving a 35 day (five week) period of usable data.

Subsequently, participants were introduced to the intervention (discussed in Section 4.2.5) comprising a charging regime and the display of speeding information for each trip. A further five week 'after' GPS period was then undertaken followed by exit surveys at the completion of the study.

4.2.2 Recruitment and retention

Drivers were recruited from an online research panel comprised of individuals who had previously expressed interest in participating in surveys/research. A sample size of 148 was selected on the basis of the number of available GPS devices of which 29 were assigned to a control group. Initially, the aim was to recruit an equal numbers of male and female drivers in two broad age groups (17 – 30 and 31 – 65). However, young drivers, particularly males, proved to be more difficult than expected to recruit. In contrast, older females proved easier to recruit.

Of the 148 drivers originally recruited into the study, 125 completed all phases. Unfortunately, the control group suffered from a particularly high drop-out rate due (primarily) to loss of interest as well as recruitment delays. This made the control group (effectively) unusable for its intended purpose due to the small number of remaining control participants. Due to the reduction in useable sample, a number of previously ineligible participants were invited to complete a further five week charging phase bringing the total number of completed participants to 133.

Data cleaning and quality control were performed on the data of the 133 participants. This included ensuring that the vehicle odometer readings were consistent with those calculating using the GPS and checking for long holidays in the after period[59] or other lifestyle changes such as a new job, move or children that could impact comparability between study phases. Following these checks, 106 drivers remained with eligible before-and-after data and, therefore, are included in the analyses presented in this thesis. The number and demographic characteristics of these drivers are shown in Table 4-1.

Table 4-1: Demographic characteristics of final sample (Greaves et al., 2013)

		Age Group		
	Num. Drivers	**17-30**	**31-45**	**46-65**
Gender	**Male**	5	19	20
	Female	21	24	17

4.2.3 Observed driving behaviour (GPS) data

Mobile Devices Ingenierie C4 GPS devices (shown in Figure 4-2) equipped with an external antenna were installed in participants' vehicles for the duration of the study by a trained research company and powered using the vehicle's cigarette lighter. These devices recorded a National Marine Electronics Association (NMEA) 0183 standard-observation every second whilst the car's engine was turned on and data were transmitted to a processing server using General Packet Radio Service (GPRS) every 20 seconds. Turning the vehicle's ignition on and off were configured as triggers for turning the GPS device on and off respectively. These events were also used to delineate trips (Greaves et al., 2010).

[59] Participants with holidays in the before period had already been excluded by this stage.

Figure 4-2: Mobile Devices Ingenierie C4 GPS (Greaves et al., 2010)

For each observation, the GPS device recorded the vehicle's Doppler speed, latitude, longitude, altitude, date, time and the number of satellites in view. These data were used in conjunction with a GIS-based database of speed limits to infer speeding[60]. Figure 4-3 illustrates second-by-second GPS observations layered on top of the Sydney street network.

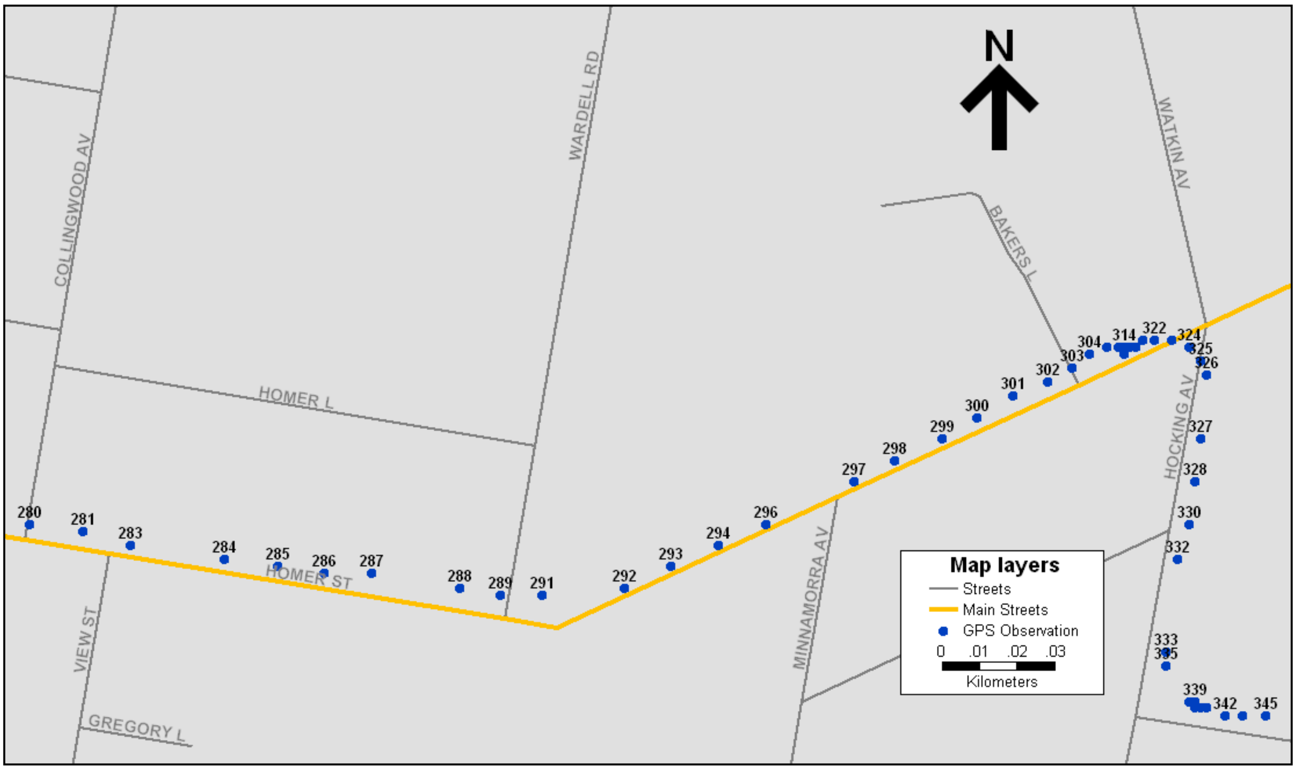

Figure 4-3: Example of GPS observations

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[60] The speed limit database was developed by Smart Car Technologies (a project partner on the original data collection) by driving all the streets in Sydney.

During the full study over 80 million observations were recorded from 148 vehicles representing more than 22,000 hours of driving. The GPS devices were installed in the participant's own vehicles, some of which were driven by more than one person. For the purposes of this study, the person that completed the surveys was considered as the primary driver irrespective of how frequently they drove the car. Since it is not possible to determine which additional drivers were able to see their speeding behaviour and not all data are available for these drivers only data from the primary driver of each vehicle was used.

These data were used to determine the frequency and magnitude of speeding behaviour and determine acceleration and braking patterns in day-to-day driving. This is discussed in greater depth in Section 5.3.

4.2.4 Trip information

Throughout the study, participants were aware that where they drove was being monitored. To collect information about each trip that was not available from the GPS data, participants were asked to access a web-based prompted recall interface shown in Figure 4-4 (Greaves et al., 2010). This prompted recall survey displayed every trip recorded by the GPS devices including known information such as the date, departure time, arrival time, distance travelled in addition to a map illustrating the origin, destination and route taken. Using the interface, participants indentified the driver of the vehicle, number of passengers, trip purpose (from a predefined list) and the number of intermediate stops. This information was subsequently used to differentiate between trips driven by the participants and those trips made by other drivers.

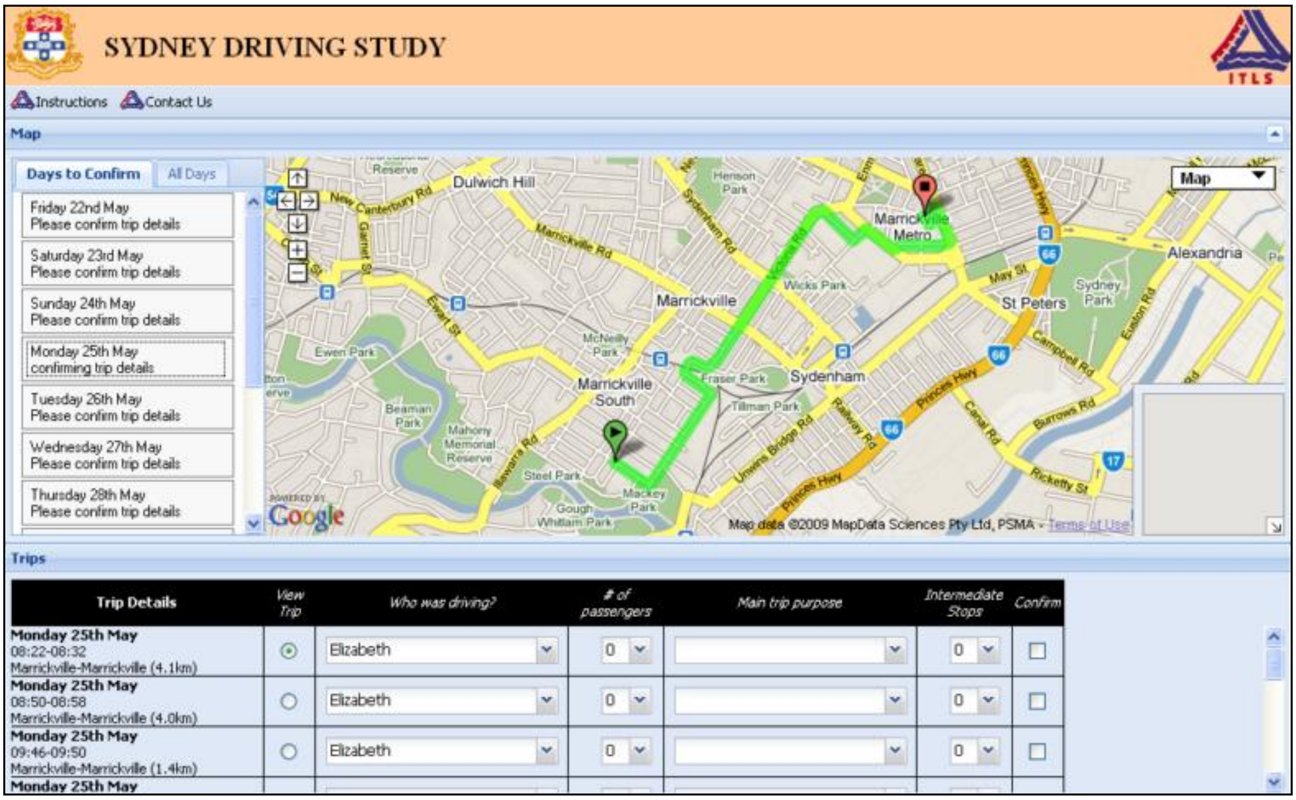

Figure 4-4: Screenshot of participant website interface (Greaves et al., 2010)

4.2.5 Intervention

Prior to the start of the 35 day (five week) *after* phase, drivers were informed that their speeding behaviour was being monitored and were invited to participate in a pay as you drive (PAYD) charging experiment. This scheme allocated each participant a starting incentive[61] based on their driving in the *before* phase. Money was deducted from the incentive for each kilometre driven (VKT) with additional amounts for each kilometre driven above the posted speed limit (speeding VKT) and for each kilometre driven at night (night-timer VKT) as shown in Table 4-2[62]. Distances of less than 1 km were charged a prorated amount. For example, a driver speeding during the day over a distance of 500 metres was charged 30 cents (drivers 17 – 30) or 22.5 cents (drivers 31 – 65). At the completion of the study drivers were paid any remaining incentive. Under this scheme a driver that drove identically – in terms of VKT, speeding and night VKT – in the *before* and *after* phases would complete the *after*

[61] This incentive was in addition to a fixed $30 incentive given to all participants. See Fifer et al. (2011) for more details on the financial components of the study.

[62] Night time driving was defined as driving from 20:00 to 04:59

phase with $0.00 remaining (shown in yellow in Figure 4-5). A driver with less (combined) VKT, speeding and night VKT would complete the *after* phase with an incentive greater than $0.00 – represented in green. In contrast a driver with (combined) higher VKT, more speeding and more night VKT in the *after* phase – shown in red – would end the study with no incentive[63]. Changes in driver behaviour were measured against the same driver's before period and therefore a driver that drove and sped a lot in the before period could improve in the after period but still be a bad driver. Note that a driver could reduce VKT and night-time VKT but increase speeding relative to their own before period and still end the study with some remaining incentive.

Table 4-2: Per kilometre rates used in the after phase (Greaves and Fifer, 2010)

		Time of Day and Speeding Status			
		Day (Non-Speeding)	**Day (Speeding)**	**Night (Non-Speeding)**	**Night (Speeding)**
Age	**17-30**	$0.20	$0.60	$0.80	$2.40
	31-65	$0.15	$0.45	$0.60	$1.20

In this phase, participants were made aware of the proportion of the distance driven above the posted speed limit for each trip using the prompted recall interface. Drivers with an incentive greater than $0.00 were therefore able to see how frequently they exceed the speed limit and were rewarded financially for reducing this frequency. Once drivers depleted their incentive (shaded pink in Figure 4-5) they continued to be informed of their speeding behaviour but the financial incentive no longer applied. At no stage during the study were drivers presented with information on their acceleration or braking behaviour.

[63] Drivers with a negative incentive did not receive an incentive but also did not pay any amount.

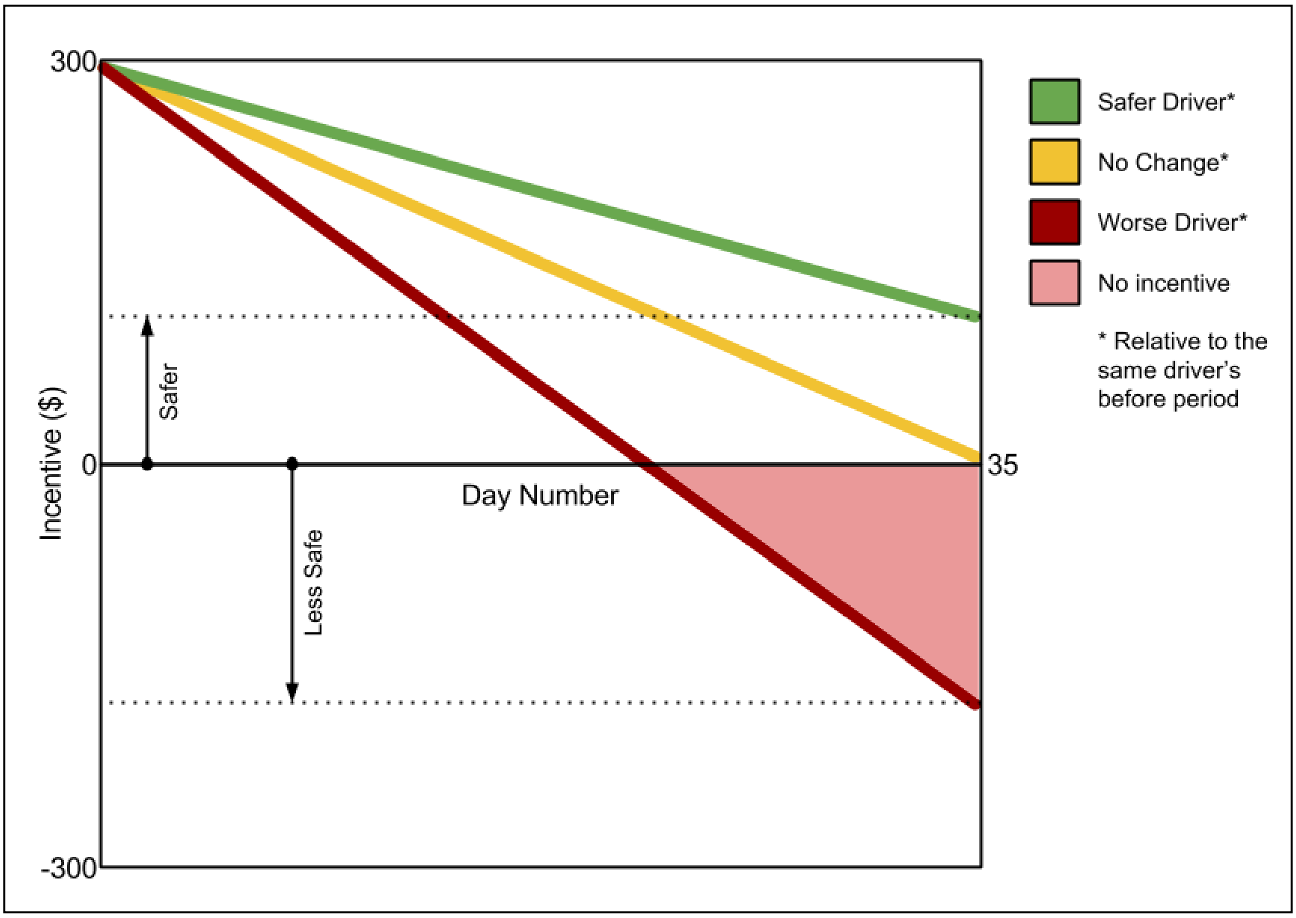

Figure 4-5: Pay-as-you-drive incentive scheme

4.2.6 Demographic and vehicle survey

Three surveys were conducted as part of the same study from which the driver behaviour data (see Section 4.2.3) were collected. The surveys were completed online by the primary drivers in whose vehicles the GPS device was installed. Each survey response was uniquely identified such that responses could be linked to their observed behaviour data.

At the recruitment stage, participants completed a demographic and vehicle information survey. The information collected is summarised in Table 4-3. Age and gender were collected for the most frequent secondary driver of the vehicle and for other household members.

Table 4-3: Summary of demographic and vehicle information survey variables

Variable	Primary Driver	Other Driver	House-hold	Vehicle
Demographics				
Age	Y	Y	Y	
Gender	Y	Y	Y	
Relationship to participant			Y	
Postcode			Y	
Licence type	Y			
Number of licensed drivers			Y	
Employment status	Y			
Income	Y		Y	
Household size			Y	
Home ownership			Y	
Vehicle				
Number of cars			Y	
Number of other drivers		Y		
Make				Y
Model				Y
Transmission type				Y
Year of manufacture				Y
Engine capacity (litres)				Y
Fuel type				Y
Body type				Y
Vehicle owner				Y
Frequency of refuelling				Y
Frequency of use	Y	Y		
Accidents in past 5 years	Y			
Typical parking location				Y

4.2.7 Psychological survey

Once a participant was selected for inclusion in the study a fifty question psychological online survey was administered. The survey used was the Road Safety Behaviour (RSB) survey developed by Machin and Sankey (2008) and was intended to capture aspects of personality, risk perception and self-reported driving behaviour summarised in Table 4-4. A review of the theoretical background of the survey can be found in Section 3.1.3. This survey was only completed by the primary driver/participant and therefore these data are not available for the secondary driver(s) of the vehicles in the study.

The complete survey consisted of 50 questions, of which a subset of these was used in this thesis. In Table 4-4, factors used in the analyses presented in this thesis are indicated with an asterisk. The objective was to select variables that have been identified by other researchers (see Section 3.1.3 and Section 3.1.5) to be predictors of driver behaviour.

Table 4-4: Summary of psychological survey (Greaves and Ellison, 2011)

Variable Categories	Scale	Items	Citation	Cronbach alpha[64]
Personality				
Aggression*	Ten point scale Not at all to Very much	9	(Costa and McCrae, 1992)	0.857
Excitement-seeking*		6		0.765
Altruism*		5		0.643
Risk perception				
Worry and concern*	Five point scale	3	(Rundmo and Iversen, 2004)	0.893
Likelihood of accident (self)*	Ten point scale	2	(Machin and Sankey, 2008)	N/A
Likelihood of accident (other)*				
Efficacy*	Five point scale	5		0.890
Aversion to risk*		9		0.639
Self-reported driver behaviour				
Speeding ≥ 10 km/h[a]*	Five point scale Never to Very Often	6	b	0.857
Speeding ≥ 20 km/h[a]*				
Overtaking other cars[c]			(Machin and Sankey, 2008)	0.860
Following too closely				
Bend traffic rules				
Ignore traffic rules				
General lifestyle, travel and personality attitudes				
Lifestyle attitudes[d]	Seven point scale Strongly disagree to Strongly agree	18	(Goldberg, 1999)	N/A
Travel attitudes[e]		18		
Personality attitudes[f]	Seven point scale Not at all to Almost completely	18		

[a] Individual questions for 50 km/h, 60-80 km/h and 100-110 km/h zones
[b] Categories reflect enforcement thresholds in study area
[c] Applies to overtaking cars travelling at the speed limit
[d] Consists of 18 statements relating to lifestyle
[e] Consists of 18 statements relating to attitudes to travel
[f] Consists of 18 statements relating to general personality characteristics
* Indicates that the variable/scale is used in this thesis.

The personality scales are derived from the NEO-Personality Inventory (Costa and McCrae, 1992). They comprise of a number of statements to which respondents are asked to indicate the extent to which they agree or disagree or indicate the frequency with which they engage in a particular behaviour. Examples of these questions

[64] Cronbach alpha (α) is a measure of internal consistency.

include “I lose my temper when another driver does something I think is wrong”, “I make a point of checking every side road I pass for emergency vehicles” and “I get a real thrill out of driving fast”. These questions were measured on a ten-point scale from “not at all” to “very much”. The full list of questions for each of these scales used in this thesis can be found in Section 9.5.

The risk perception scales were cognition-based scales developed by Rundmo and Iversen (2004) and Machin and Sankey (2008). They consist of both five point and ten-point scale questions (see Table 4-4) and include questions such as “To what extent are you worried that you yourself could be injured in a traffic accident while driving” and “Please rate your chances of having an accident within the next 12 months”.

In addition, six measures of self-reported risky driving behaviour were included in the survey (from Machin and Sankey (2008). These questions measured the frequency of (self-reported) behaviour on a five point scale from “never” to “very often”.

4.2.8 Exit survey

After the completion of the ‘after’ phase, an online exit survey was completed by each participant. The exit survey consisted of 10 questions and a mixture of open response and multiple choice questions. The purpose of the survey was to receive feedback on the different components of the study and the GPS device and to help identify if participants made a conscious decision to change their behaviour on the basis of the charging scheme. Although there were no questions that explicitly addressed the issue of awareness of speeding, many participants nonetheless mentioned various aspects relating to awareness of speeding behaviour. Questions included “What was your reaction when you first learnt about the charging phase” and “Do you have any other comments about the charging phase of the study that you would like to share with us?” Similarly to the other data sources, acceleration and braking behaviour were not mentioned.

An explanation of how the exit survey was coded can be found in Section 5.5.3.

4.2.9 Supplementary spatial data

The data described in Section 4.2.3 and Section 4.2.6 were augmented with additional spatial data from other sources. This supplementary data was matched to each individual observation based on the time, latitude and longitude of the vehicle. As the data were not in the same format as the existing dataset, tools were developed to clean, convert and merge these supplementary data with the existing dataset. Data processing is discussed in Chapter 5.

Supplementary data sources used were:

- School zone location information;
- Rainfall data;
- Sydney GIS street network; and
- Location of signalised intersections.

School zone location data were used to identify observations recorded in school zones. A school zone is a unique spatiotemporal environment in the study area for several reasons. First, a speed limit of 40 km/h applies during operating hours which is slower than the default (residential) speed limit of 50 km/h[65]. Second, school zones exhibit particularly unique drop-off and pick-up behaviour by drivers. Lastly, school zones have particularly high concentrations of vulnerable road users relative to other areas. Refer to Section 5.2.3 for details on school zone data processing.

Rainfall is known to influence driver behaviour (see Section 3.1) and therefore was included as an additional spatiotemporal variable. The rainfall data was provided by the Australian Bureau of Meteorology (BOM) on a half-hourly frequency[66] for 15 observation stations across the study area. These data were used to determine the presence of rain at a particular time, data and location. See Section 5.2.4 for an in-depth discussion on the data processing required and how these data were used.

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[65] School zones typically operate from 08:00 to 09:30 and from 14:30 to 16:00 in Sydney during which time the speed limit is reduced to 40 km/h.

[66] The frequency of data varied up to a maximum of 30 minutes but occasionally more frequently, depending on the observation station and if the station was manned or fully automated at the time the observation was made.

The Sydney GIS street network is a digital representation of the road network in Sydney. It is used to identify the locations of intersections and some road characteristics associated with a particular location in which GPS observations were recorded. In addition to the street network, a separate table containing the locations of signalised intersections in Sydney is also used since the street network does not differentiate between signalised and non-signalised intersections. Section 5.2 contains an explanation of how these data are processed and used in this study.

Each of these data sources contained over 10,000 records. Due to the large volume of spatial data and the uniqueness of the dataset it was necessary to develop custom processing algorithms. Software to process spatial data used for previous work (Ellison and Greaves, 2010) was developed further to make use of the additional data sources used for this research. This software also formed the basis of the development of algorithms to identify risky driving behaviour (see Section 5.3).

No data for traffic conditions (such as congestion and traffic light timings) were available. Road environment variables such as the width of the road and the distance between the road and the buildings were also not available.

4.3 Analysis and methodological approach

To test the hypotheses (Section 4.1), the datasets introduced in Section 4.2 are linked on the basis of common driver, vehicle, trip and road characteristics. Measures of driver behaviour are the core units of analysis. Specifically, these are the frequencies and magnitudes of speeding, aggressive acceleration and aggressive braking. In this research, driving 1 km/h or more above the posted speed limit is considered to be speeding. This reflected the enforcement regime in place at the time the data were collected and that odometers are designed to overstate the actual speed (Australian Commonwealth Government, 2004) and therefore there is a built-in tolerance of (approximately) 3 km/h between the GPS speed and the speed indicated on the speedometer. Acceleration of 4 m/s^2 or more and braking of -4 m/s^2 or more was considered to be aggressive. The rationale for these thresholds is discussed in Section 8.4.2. This is based on previous studies (discussed in Section 2.2.2) which found that behaviour in excess of these levels is commonly observed immediately before crashes.[67] Figure 4-6 illustrates the different components that fit into the study and which ones are used to test each of the hypotheses. Hypotheses 1 use only data from the 'before' phase whilst hypotheses 2 uses data from both the before and the after phases.

Regardless of the original source of each variable, the final dataset groups variables into four categories: driver and vehicle, trip (temporal), road segment (spatial) and behavioural. The driver and vehicle variables remain unchanged for the duration of the study whilst the other variables change at various frequencies. Factors exogenous to the driver and vehicle that potentially influence behavioural outcomes are controlled by a Temporal and Spatial Identifier (TSI) which uniquely describes the environment in which an observation occurs. These are created by combining the temporal and spatial variables from which each unique combination forms a single TSI. The behavioural measures are analysed within these unique environments. For hypotheses 2, changes in the behavioural measures before and after drivers are made aware of their behaviour are compared between phases within each TSI. The construction of TSIs are further discussed in Chapter 7.

[67] More details on the rationale behind the speeding, acceleration and braking measures can be found in Section 8.4.2.

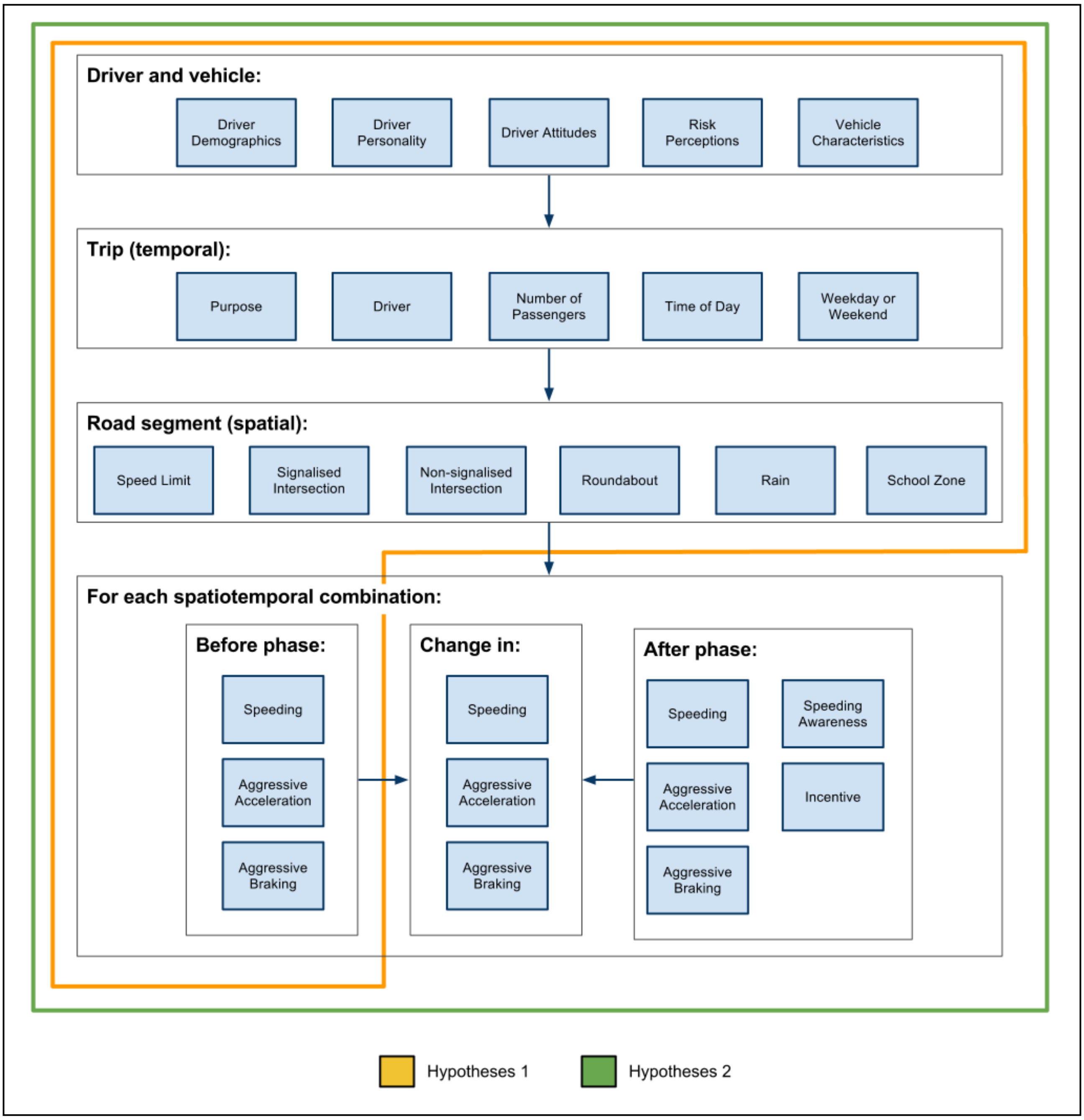

Figure 4-6: Methodological framework

To account for the hierarchical relationships between the variables included in this study, composite profiles are built to describe drivers' behaviour as shown in Figure 4-7. The driver behaviour profile (DBP) is comprised of the summation of the frequency of each behaviour multiplied by the magnitude and by the weight associated with each behaviour (speeding, aggressive acceleration and aggressive braking)[68].

[68] These weights are derived from the literature. The rationale for these weights is discussed in Section 8.5.

This is done for each TSI and weighted by the distance travelled such that (for example) a TSI comprising 100 km of driving has twice the weight of a TSI with 50 km of driving. The driver and vehicle variables – including a driver's risk perceptions and personality characteristics – are also linked to each DBP. Factors associated only with the 'after' period are also included as additional elements. The *a priori* expectation is that the driver and vehicle characteristics influence the driver behaviour profile.

By creating composite profiles that describe the driver, vehicle and behaviour it is possible to model and compare driver behaviour across time, within the same environment or between drivers. The composition, calculation and use of these profiles are explained in detail in Chapter 8.

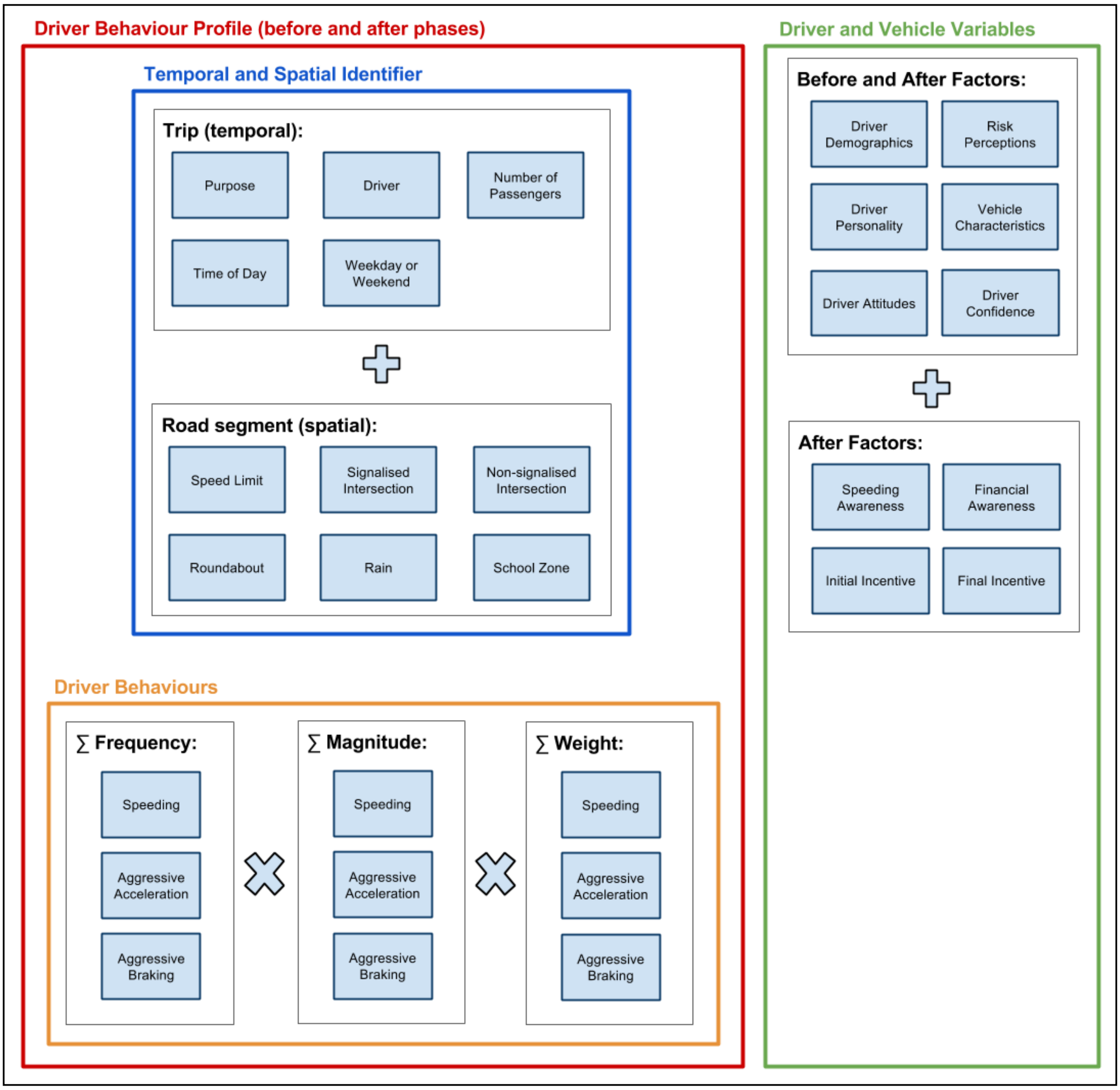

Figure 4-7: Driver profiles

4.3.1 Levels of aggregation of GPS data

The large volume of data – in terms of the number of records and the number of individual and composite variables – necessitates analyses to be conducted at various levels of aggregation. Although information is lost when aggregating, many types of analyses would be too time computationally intensive, if not impossible, to conduct using fully disaggregate data. Therefore, the process of aggregating and analysing the aggregate data by driver or space, allows for a gradual refinement in the selection of variables, which are required to be included in the more disaggregate analyses.

The results and analysis section is organised in order of aggregation, from the most aggregate to the most disaggregate. Figure 4-8 summarises the different levels used. The same variable(s) may be used in more than one level of aggregation. Each level is differentiated by the temporal or spatial coverage or how much time or distance is covered by each aggregated observation.

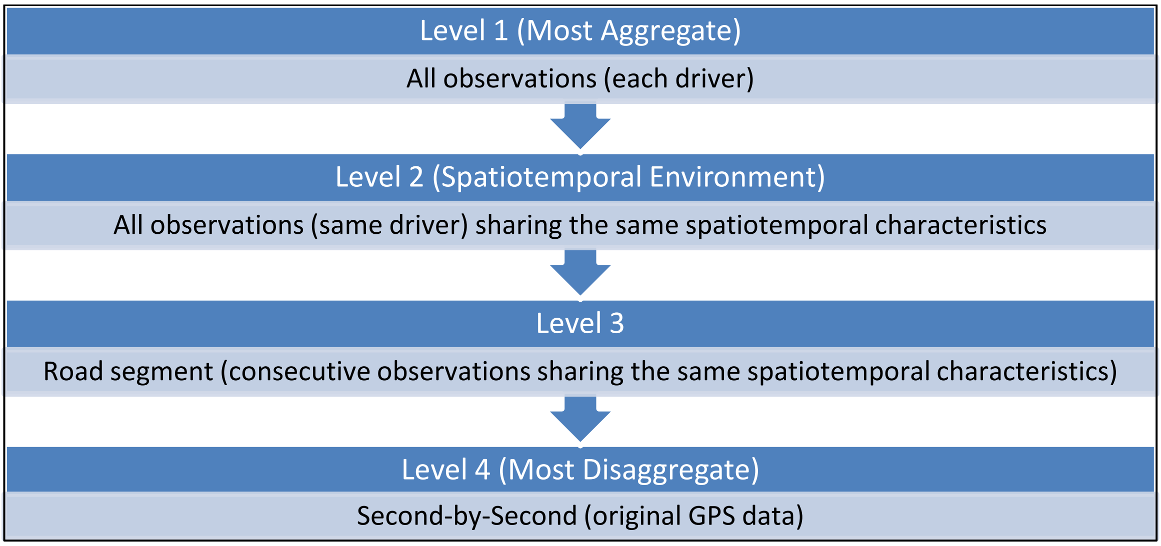

Figure 4-8: Summary of levels of aggregation

Data processing is conducted at the most disaggregate level (second-by-second) where each observation represents one second of driving behaviour. Modelling is conducted primarily at the spatiotemporal and road segment levels and to a lesser extent at the most aggregate level where one observation represents one driver.

4.3.2 Data processing and analytical techniques

This section summarises the data processing and analytical techniques that are applied in this research. Table 4-5 outlines the research process. The individual steps are discussed in detail in the indicated chapters.

Table 4-5: Summary of data processing and analysis steps

	Description	Category	Section(s)
1	Identify spatial characteristics relevant to each observation of driving behaviour	Data	5.2
2	Smooth second-by-second observations	Data	5.3.3
3	Detect speeding, acceleration and braking behaviours at the second-by-second level of aggregation	Data	5.3
4	Identify road segments based on speed limit	Data	5.4
5	Re-categorise demographic and psychological survey variables where necessary	Data	5.5.1, 5.5.2
6	Code open responses to exit survey	Data	5.5.3
7	Analyse speeding behaviour across all drivers using descriptive measures	Analysis	6.1
8	Aggregate speeding, acceleration and braking behaviour for each driver	Data	6.2
9	Conduct ANOVA, logistic regression and clustering analyses at the driver-level of aggregation.	Analysis	6.2
10	Conduct logistic regression using road segments defined by speed limits	Analysis	6.3
11	Identify road segments using spatiotemporal variables	Data	7.5
12	Create aggregate measures of speeding, acceleration and braking at the road segment level	Data	7.6
13	Create composite driver behaviour profiles ('before' and 'after' phases)	Data	8
14	Perform ANOVA analyses using driver behaviour profiles and 'before' data	Analysis	9.1.1
15	Perform a multilevel regression model using the driver behaviour profiles for the before period as the dependent variable and the driver characteristics and spatiotemporal variables as the independent variable to test Hypothesis 1.1	Analysis	9.2
16	Repeat step 15 for Hypothesis 1.2, 1.3 and 1.4	Analysis	9.3, 9.4, 9.5
17	Repeat step 15 for the after period to test Hypothesis 2.1, 2.2, 2.3 and 2.4	Analysis	10.2, 10.3, 10.4, 10.5

Prior to any aggregation or additional data processing being conducted, all observations are matched to their relevant spatial characteristics using the supplementary spatial data sources described in Section 4.2.9. These are used as the basis for any data cleaning or smoothing that is required prior to the calculation of the frequency and magnitudes of the three behaviours of interest at the second-by-second level of aggregation.

Aggregation is conducted at the road segment level after identifying the temporal and spatial identifier (TSI) associated with each observation. Aggregate measures of behaviour are then calculated for each road segment from the frequency and magnitudes calculated at the second-by-second level.

Driver and vehicle characteristics can then be associated with the observations from each driver which are then used – in conjunction with the aforementioned aggregated data – to create composite profiles or indices of driver behaviour. These indices are created from each driver's GPS behaviour data for speeding, acceleration and braking[69]. The measures are combined into several indices reflecting the types and magnitudes of risks incurred as a result of these behaviours (see Table 2-1). The purpose is to allow for comparison between drivers of a number of related and/or correlated measures of behaviour. Many previous studies (Iversen and Rundmo, 2004; Warner and Aberg, 2008) have used composite indices created from survey responses. Profiles based on drivers' characteristics and responses to the psychological, attitude, perception and risk understanding survey responses are also used in this study to complement the risk indices created using objective behavioural data. A detailed discussion on the driver behaviour profiles can be found in Chapter 8.

Due to the inherently hierarchical nature of the data being studied, multilevel regression models are developed as opposed to (single-level) regression models. The dependent variable in these models is the driver behaviour profiles (DBP) of each driver. Since the results of multilevel models can be sensitive to the levels chosen by the analyst, a number of different levels are used. The main objective in this case is to identify the interactions between the dependent variables and determine to what extent the driver, vehicle and road characteristics influence behaviour.

The multilevel models are conducted initially using only data collected during the *before* phase prior to the introduction of the intervention. Subsequently, the same process is done using the *after* phase data and adding the additional after period variables to the models. The second set of hypotheses are tested by comparing the results between the before and after phases. Separate models, analyses and results are run for all situations and separately for the most frequently observed spatiotemporal environments. This is consistent with preliminary findings (Ellison et

[69] Acceleration and braking are not provided explicitly by the GPS data. Instead, approximations are calculated using the change in speed over time. An accelerometer would provide more detailed acceleration and braking information but was not available in this case.

al., 2013a) which conclude that different spatiotemporal environments produce very different results.

4.4 Summary

This chapter introduced two overall research questions and a number of sub-hypotheses for each. The first of these addresses the driver characteristics that influence the extent (frequency and magnitude) of risky driving behaviour in day-to-day driving before the introduction of the charging regime intervention. These results are presented and discussed in Chapter 9. The second research question deals with changes in risky driving behaviour that occur after the introduction of the intervention and how the magnitudes of the changes (if any) are related to the same driver characteristics tested in the first research question. These results are presented and discussed in Chapter 10.

As stated in Section 4.2, the primary source of data for this thesis was sourced from a broader study on driver behaviour. The observed behaviour (GPS) and survey instruments are described here as are the study design, recruitment, participant retention and, importantly, the mechanics of the intervention. Briefly, the study was a multi-phase study comprising survey phases at the beginning and end of the study and two five-week GPS phases separated by a one week period in which the intervention was introduced. Prior to the introduction of the intervention, the true purpose of the study was masked to inhibit contamination of the GPS data in the before phase – which functioned as the baseline for the intervention and the before-and-after comparisons studied as part of the second research question.

An overview of the analysis and methodological approach was presented in Section 4.3. The methodological process commences with data processing procedures that were devised and run on the source datasets. These are discussed in Chapter 5. The processed dataset is then examined in an aggregate analysis in Chapter 6 with a view towards identifying the characteristics of the dataset and identifying some preliminary indication as to the outcome of the hypothesis testing. This section also introduces – for the first time – temporal and spatial identifiers (TSI) and driver behaviour profiling (DBP) methodologies. These methodologies have been developed in this thesis to control for the influence of spatiotemporal characteristics and the uneven risks associated with different behaviours and magnitudes of behaviour. The development, use and rationale behind these methodologies are discussed in Chapter 7 (TSI) and Chapter 8 (DBP).

5 DATA PROCESSING

This study uses a number of large datasets which must be processed prior to analysis. This chapter discusses the processing done for each of the datasets used for this research.

5.1 Data storage and management

As described in Section 4.2, the data employed in this research are comprised of a number of very large datasets, which total in excess of 30 Gigabytes (GB) in storage size. Each dataset is related to others in a number of ways; by time, location and driver. These characteristics mean that common statistical or analytical software such as SPSS and Stata are not useable as a means of data storage. Instead, the data are stored in a relational database using MySQL. This approach allows for the data to be queried using Structured Query Language (SQL) such that portions of the data can be sorted, filtered and aggregated prior to being exported for analysis in statistical software. Although the filtered and aggregated datasets are still large at almost 500,000 records and over 300 variables they are manageable in most statistical packages.

5.2 Spatial data

The largest dataset used for this research is the GPS data collected from study participants' in-vehicle driving. However, as identified in Section 3.1.1, the road environment is a known factor in driver behaviour and therefore although it is not the focus of this research its impact must be controlled for. Therefore, a number of spatial (geographic) data sources have been acquired for this purpose. As these data are not all in the same format, they have been processed and merged.

5.2.1 Sydney street network

The basis for incorporating the road environment into the analysis is a Sydney street network available as a GIS geographic layer. At its simplest level, the network is a series of links and nodes (see Figure 5-1). A node represents an intersection[70], corner or a dead-end. A link represents the road segment between nodes.

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[70] Each exit in a roundabout is a separate node as is the middle of the roundabout.

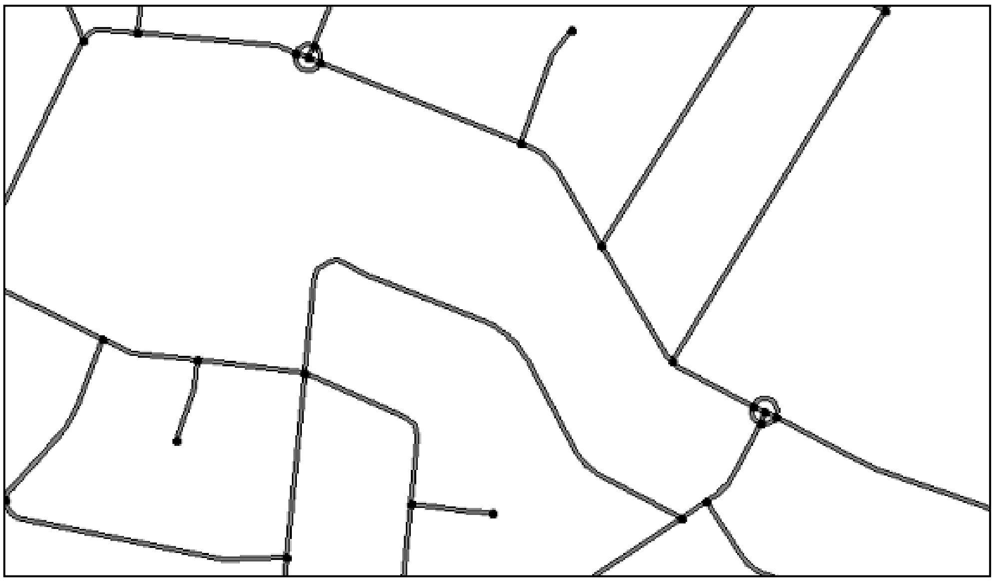

Figure 5-1: Example of links and nodes in street network

In addition to the location data (latitude and longitude) each road segment contains a number of additional attributes. The attributes relevant to this study are listed in Table 5-1. These attributes provide additional information about the road environment, which are possible methods of accounting for differences in behaviour during portions of the same trip or different trips on the same type of road. Although not complete, it provides a form of differentiation between two roads that otherwise would appear similar from the speed limit data (see Chapter 7). The attribute data for each road segment and node is also used as the basis for merging the other spatial datasets.

Table 5-1: Street network attributes

Name	Description
Road Type	A numerical road classification code which allows for the differentiation of road segments by type, for example, main road, roundabout, local road, bridge, highway, freeway)
Length	The length of the road segment in kilometres; Useful for identifying stretches of road with few intersections
Street	The street name; Useful for manually checking that data sources have been merged correctly
From Left	Address numbers; Useful for merging multiple sources of data which may not have latitude and longitude positions
To Left	
From Right	
ToRight	

This spatial data is added to a GIS (Geographic Information System) street network for Sydney, which incorporates spatial elements of the road environment for each road segment. This network can be queried for a number of analyses and latitude/longitude points collected using GPS technology can be matched to the road network to enable observations of driving behaviour to be linked to the spatial characteristics associated with the location of each observation.

5.2.2 Intersection characteristics

The characteristics of intersections have been shown in prior research to be a significant factor in driver behaviour (see literature review in Section 3.1.1). For this study, the focus is on non-signalised intersections which are over represented in crash statistics (Retting et al., 2003).

Although the Sydney street network described in Section 5.2.1 identifies the location of intersections, it does not differentiate between signalised and non-signalised intersections. For this reason, a geographic layer containing the location of SCATS[71] (Sydney Coordinated Adaptive Traffic System) intersections is used to identify intersections where traffic signals are installed. This data does not identify the status of the traffic signals at any particular time and therefore it is not possible to study driver behaviour during different signal phases.

A custom TransCAD[72] GISDK (Geographic Information System Developer's Kit) program was written to combine the Sydney street network and the SCATS database to identify five distinct types of intersections:

1. Signalised t-intersection
2. Non-signalised t-intersection
3. Roundabout
4. Other signalised intersection
5. Other non-signalised intersections

[71] SCATS is a system used to manage traffic signals in Sydney.

[72] Geographic Information System (GIS) software

For the purposes of analysis, signalised t-intersections and other signalised intersections are grouped together. Similarly non-signalised t-intersections are grouped with other non-signalised intersections.

5.2.3 School zones

In New South Wales there are over 10,000 school zones for 3,200 schools (Roads and Traffic Authority, 2009a) within which the speed limit is lowered to 40 km/h during operating hours (08:00 – 09:30 and 14:30 – 16:00 on school days). In the study area, there is no reliable source of latitude-longitude (coordinate) data indicating the start and end points of school zones. This information is necessary to differentiate between school zones and other areas with 40 km/h speed limits. Therefore, a method was developed to determine all driving activity recorded during the study in an active school zone.[73] Since school zones are irregular in length and are placed on more than one road adjoining or in proximity to a school, determining the locations of school zones is not a straight forward problem.

The Google Maps Application Programming Interface (API)[74] was used to find the street names adjoining each of the school entrances in a database containing the latitude and longitude of school entrances. The road name was then extracted from the street address before being placed into a new database table containing the latitude, longitude, school name and entrance road name. For schools with multiple entrances, a different record for each entrance is used. Once this was done, any latitude-longitude pair could be tested to determine if it occurred inside a school zone.

For 40 km/h zones, speed zoning guidelines specify a *minimum* recommended zone length of 200 metres (NSW Centre for Road Safety, 2009) although on roads with school entrances, school zones are longer than the minimum 200 metres. As exact start and end points are not available a conservative estimate of 150 metres of a school

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[73] A school zone is active on weekdays during school terms from 8:00 to 9:30 and from 14:30 to 16:00. The speed limit is reduced to 40 km/h and penalties are increased during these times.

[74] The Google Maps Web Services API allows for the querying of Google Maps data (including elevation, directions and place information) from custom application. More details can be found on http://code.google.com/apis/maps/documentation/webservices/index.html

entrance is used if a point is on the same road. If the point is not on the same road (as determined by the name of the road) a distance of 50 metres is used to determine a school zone. Since the speed limit database used for the study included some but not all temporal school zones, any activity within 150 metres of a school zone entrance with a speed limit of 40 km/h is also deemed a school zone even if it is not on the same road. In cases where a point is within 150 metres of multiple school entrances, the procedure is completed for all school entrances until a school zone is found or there are no more entrances. A graphical depiction of the algorithm is shown in Figure 5-2.

This method of detecting school zones is designed to be conservative, opting for false negatives rather than false positives. Therefore although some school zones are reduced in length or missed entirely, drivers are not incorrectly determined to be driving in a school zone. This is important because as school zones use the lowest standard speed limit (of 40 km/h) false positives would overstate speeding. To further ensure accuracy, (successful) spot checks were conducted on the results of the school zone detection algorithm.

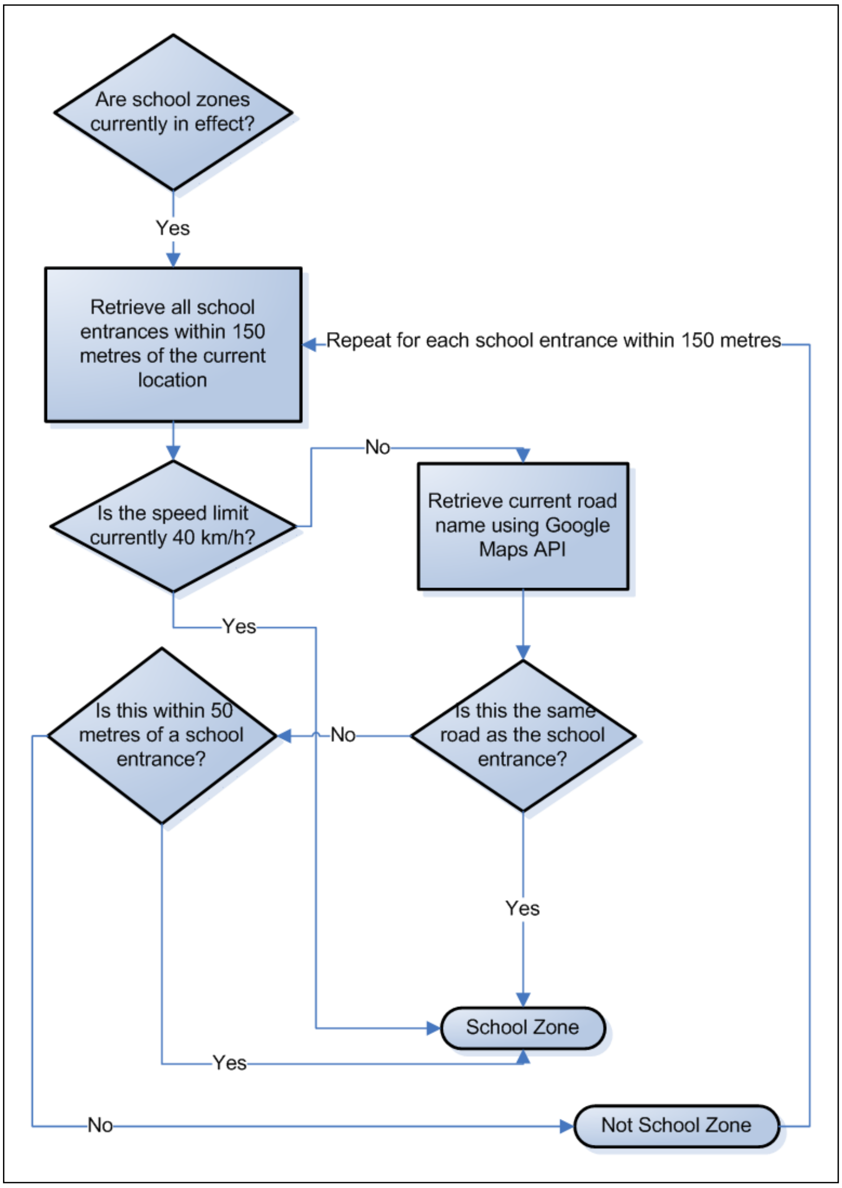


Figure 5-2: School zone detection algorithm

5.2.4 Rainfall / weather

The presence of rain was obtained for each driving observation by determining if rainfall had been observed within the previous 30 minutes at the closest of 15 weather observation stations within the study area. The weather data was provided by the Australian Bureau of Meteorology at a 30 minute frequency. The location of the weather stations relative to the recruitment suburbs is shown in Figure 5-3.

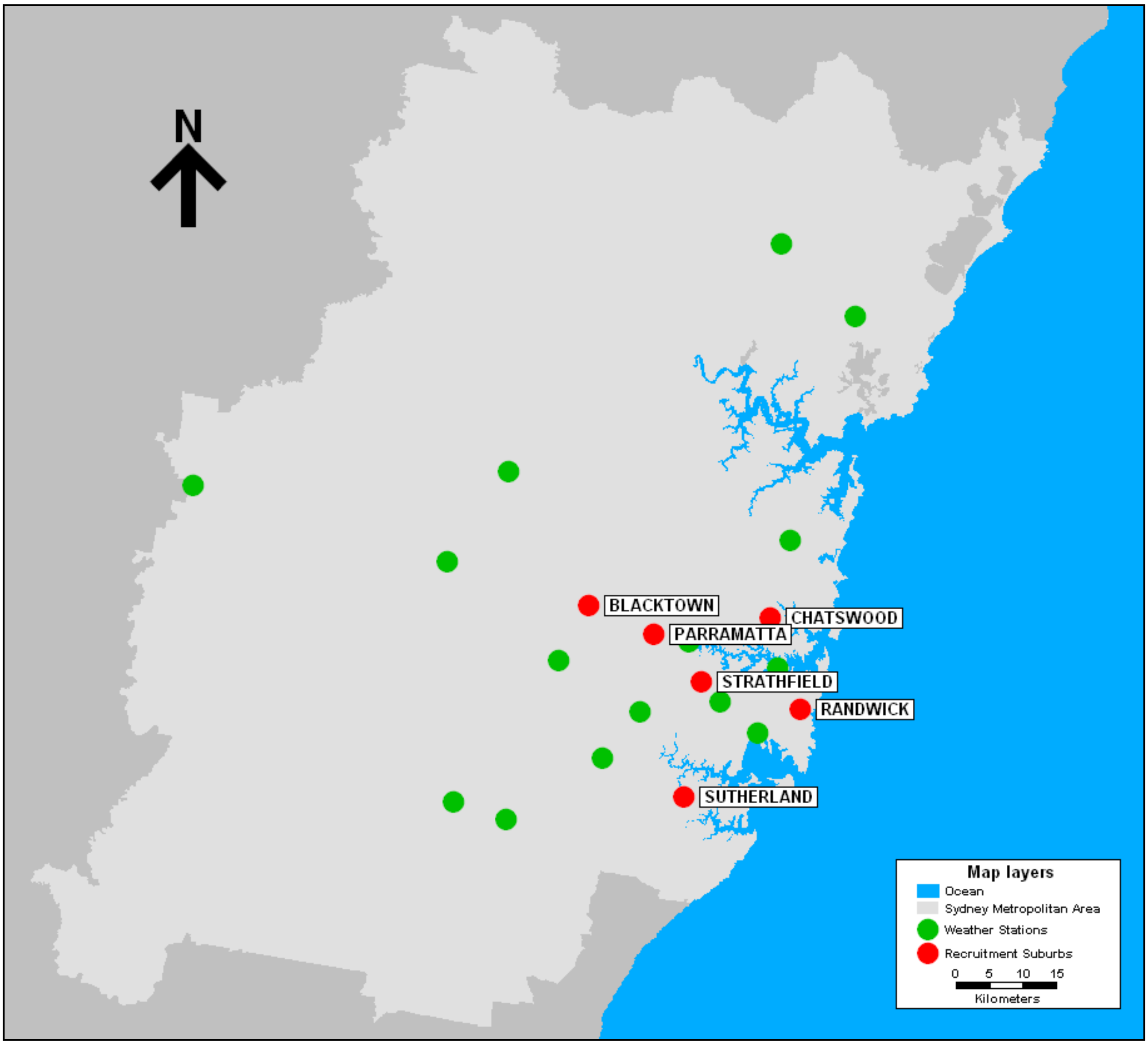


Figure 5-3: Recruitment suburbs and weather station locations

The observations were obtained in CSV (comma separated values) format with data from each weather observation station in a separate file. Each record contains the unique observation station number, the date and time the observation was taken and the total precipitation since 09:00 in millimetres (mm). The precipitation is reset after 09:00 each day. As such, the amount of precipitation in the previous 30 minutes needs to be calculated from the provided data. To simplify analysis, a binary indicator is used to identify the presence of rain based on precipitation greater than zero mm recorded within each 30 minute period as shown in Table 5-2. Using a categorical variable or a higher threshold was considered but proved to create too many small categories and required a subjective decision on the composition of the categories. The final data containing the additional derived columns was added to a relational database together with each observation station's latitude and longitude.

For each vehicle GPS observation, the closest weather observation station was identified by calculating the great circle distance[75] between the location of the vehicle and the location of each of the weather observation stations. The closest weather observation station was used as the basis for determining if rain was present for that particular GPS observation. If the binary rain indicator value (1 : rain, 0 : no rain) for the first precipitation observation after the date and time of the GPS observation had a value of one, then the presence of rain was assumed for that GPS observation. Note that this is an indicator of a wet road as opposed to rainfall or reduced visibility since it is only possible to determine if there has been precipitation in the 30 minute period in which the GPS observation was made.

If the closest weather observation station was greater than 50 km from the vehicle then the rain value was set to -1 (data not available) and it was assumed no rain was present. This was only the case for a very small proportion of observations.

[75] The great circle distance is the shortest distance between any two points on earth.

Table 5-2: Example of rainfall data

Station Number	Date and Time	Rain since 09:00 (mm)	Rain in previous 30 min (mm)	Binary rain indicator
61087	19/06/2009 20:30	0.0	0.0	0
61087	19/06/2009 21:00	1.8	1.8	1
61087	19/06/2009 21:30	3.0	1.2	1
61087	19/06/2009 22:00	3.6	0.6	1
61087	19/06/2009 22:30	3.6	0	0
61087	19/06/2009 23:00	3.8	0.2	1
61087	19/06/2009 23:30	3.8	0	0
61087	20/06/2009 00:00	3.8	0	0
61087	20/06/2009 00:30	4.6	0.8	1
61087	20/06/2009 01:00	4.6	0	0
61087	20/06/2009 01:30	7.6	3	1
61087	20/06/2009 02:00	7.6	0	0
61087	20/06/2009 02:30	7.6	0	0
61087	20/06/2009 03:00	7.6	0	0
61087	20/06/2009 03:30	7.6	0	0
61087	20/06/2009 04:00	7.6	0	0
61087	20/06/2009 04:30	7.6	0	0
61087	20/06/2009 05:00	7.6	0	0
61087	20/06/2009 05:30	7.6	0	0
61087	20/06/2009 06:00	8.2	0.6	1
61087	20/06/2009 06:30	8.2	0	0
61087	20/06/2009 07:00	8.2	0	0
61087	20/06/2009 07:30	8.4	0.2	1
61087	20/06/2009 08:00	8.4	0	0
61087	20/06/2009 08:30	10.0	1.6	1
61087	20/06/2009 09:00	10.0	0	0
61087	20/06/2009 09:30	0.0	0	0
61087	20/06/2009 10:00	0.0	0	0
61087	20/06/2009 10:30	0.4	0.4	1
61087	20/06/2009 11:00	0.4	0	0
61087	20/06/2009 11:30	0.8	0.4	1
☐ Column included in file				
■ Value derived from provided data				

5.2.5 Additional road characteristics

Section 3.1.1 included a review of research on the influence of road characteristics on driver behaviour. Although some of the factors identified are included in this study, some data is not available or is not available at sufficiently high quality to be included. The methodology used in this research can accommodate these variables but for this study they are not included. Information on the number of lanes, the distance to adjoining buildings and additional land use data are examples of variables that could be included.

5.3 Detection of driving behaviours from GPS data

In its raw form, a single observation in the GPS dataset used in this study represents one second of driving behaviour. This characteristic makes it possible to detect some forms of risky driving behaviour (see Section 2.4.3). The GPS data provides time, latitude, longitude and speed (km/h) at one second intervals. Speeding, acceleration and braking can be extracted or derived from this information.

The raw data is (effectively) recorded on a time basis. That is, each observation represents one second of driving behaviour but each observation also represents a variable distance travelled during that one second period. In this study, distance is used as the primary basis of measurement – not time – since using time would understate behaviour that occurs primarily at higher speeds. It is therefore necessary to associate each observation with the distance travelled in the time period since the previous observation was made. This is done by using the great circle distance shown in Equation 2 for each observation in turn and its previous observation. The distance associated with the first observation of each trip is assumed to be 0 km.

Equation 2: Great Circle Distance

$$VKT = \frac{\sqrt{\left(69.1 \times (Latitude_1 - Latitude_0)^2 + \left(69.1 \times (Longitude_0 - Longitude_1) \times \cos\left(\frac{Latitude_1}{57.3}\right)\right)^2\right)}}{0.621}$$

In Equation 2 and in Figure 5-4, $latitude_1$ and $longitude_1$ are the latitude and longitude of the current observation. Similarly, $latitude_0$ and $longitude_0$ are the latitude and longitude of the previous observation. As can be seen in Figure 5-4, although the time period between each observation is the same (1 second), the distance changes. Calculating the distance between observations in this way allows for the frequency of behaviours to be expressed as a proportion of the distance travelled (VKT).

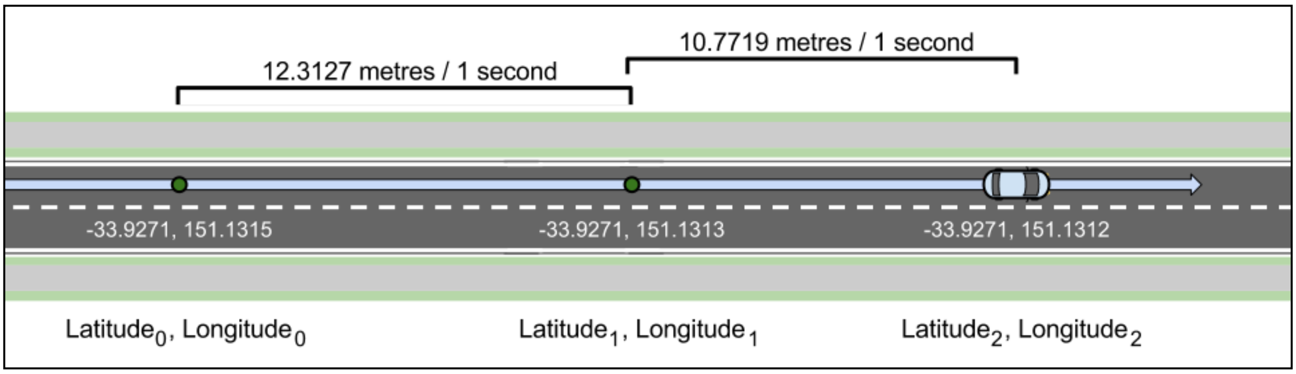


Figure 5-4: Distance calculation from GPS observations

5.3.1 Speed and speeding

The GPS devices used in this study provide the speed of the vehicle using a GPS-Doppler speed measurement technique. This method of calculating speeds relies on the Doppler effect whereby the phase difference in the signals received by three or more satellites is used to determine the speed of the device and therefore the vehicle (Torres-Guijarro et al., 2010). Using this technique it is possible to measure vehicle speeds with an accuracy of 0.1 km/h (Torres-Guijarro et al., 2010) to 0.1 m/s (Greaves et al., 2010) depending on the device used. The raw GPS speed and location data were processed by Smart Car Technologies (SCT) to overcome the issues associated with lag and to determine the appropriate speed limit for each observation. See Greaves et al. (2010) for more details on this process.

Once the speed limit is determined it is possible to determine if a driver is exceeding the speed limit and, if so, by what magnitude. In this study speeding is considered to be driving at any speed 1 km/h or more above the posted speed limit (see Section 8.4.2 for more details). Therefore a driver recorded at a speed of 51 km/h in a 50 km/h zone is considered to be speeding.

At the second-by-second level, binary variables are used to classify speeding behaviour at various magnitudes, namely 1+ km/h, 5+ km/h, 10+ km/h, 15+ km/h and 20+ km/h. These are inclusive categories such that driving at 10 or more km/h above the posted speed limit also results in the 1+ and 5+ km/h categories having a value of 1 (speeding) as opposed to 0 (not speeding). A separate set of distinct binary speeding categories are also created (1-4 km/h, 5-9 km/h, 10-14 km/h, 15-19 km/h and 20+ km/h above the posted speed limit) for use in models where the speeding variables need to be independent. Speeding is converted from an interval to an ordinal measure to allow for aggregation at a later stage. If this were not done, aggregation would require the use of a mean or median value of speeding, which does not sufficiently account for the variation in speeding behaviour that occurs over a distance with several observations. The same applies to acceleration and braking behaviour discussed in Section 5.3.2. Although speeding fines in the study area are defined in 10 km/h bands, in this case bands of 5 km/h are used to allow for greater differentiation of speeding 1 to 9 km/h, which accounts for the majority of speeding behaviour.

5.3.2 Acceleration and braking

Acceleration is the rate of change of velocity[76] over a period of time and is typically measured in metres per second squared (m/s^2). Negative acceleration is commonly known as braking speed and applies when acceleration is negative. In this research unless otherwise stated acceleration is deemed to be positive acceleration and braking is considered negative acceleration. If the speed remains unchanged then there is no acceleration.

For the purposes of this study acceleration for a particular observation is calculated using the Doppler-GPS speed converted from km/h to m/s for that same observation and the previous observation. Where there is no previous observation[77] for the same trip, acceleration is assumed to be zero. This process is illustrated in Figure 5-5.

[76] Velocity is speed in a given direction. We only consider one-dimensional acceleration and therefore, in this case, velocity is equal to speed.

[77] In theory every trip should start with an observation where speed is zero km/h. However due to 'cold start' problems and signal loss in tunnels this is not always the case.

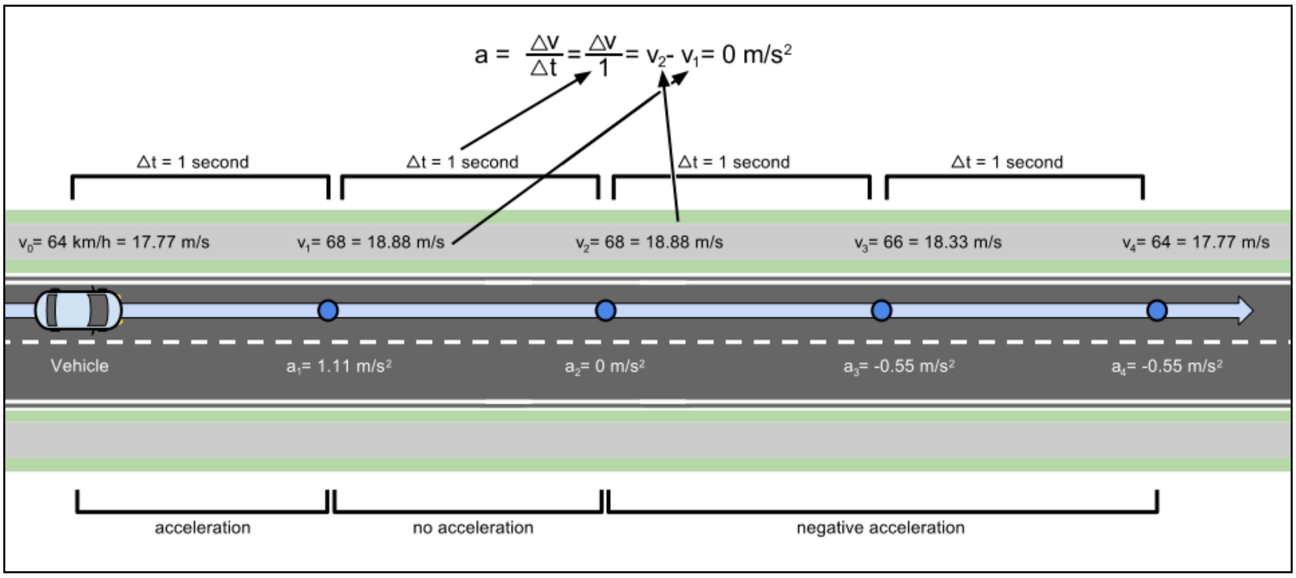


Figure 5-5: Calculation of acceleration using GPS observations

After calculating the absolute magnitude of acceleration, each observation is classified using a series of binary variables similar to the speeding variables described in Section 5.3.1. A distinct binary variable is created for each 1 m/s^2 range of acceleration from 1 to less than 2 m/s^2 to 9+ m/s^2. Braking variables are the same. These variables represent acceleration and braking in absolute magnitudes which are the same for every driver. However, since different vehicles have different capabilities, a second set of acceleration and braking variables is created where the maximum acceleration of the vehicle for the duration of the study is considered to be the maximum the vehicle is capable of doing. Thereafter binary categories for each 10 percent range from 1-10 percent to 91-100 percent are created.

For both sets of variables, only one category has a value other than zero and this may be the zero/null category, which indicates that although the vehicle may be moving it has not increased nor decreased in speed since the last observation was made.

5.3.3 Smoothing and data correction

Doppler-GPS speeds are reliable even under less than ideal conditions (Torres-Guijarro et al., 2010). Nonetheless, periodic issues do occur particularly in locations without direct line of sight to satellites. This is known as the 'urban canyon' problem and can produce anomalies in the speed data. It is particularly common in central business districts (CBDs) and requires some form of correction.

Since the processing algorithms that are applied to the raw GPS data (see Section 5.3.1) correct many of these issues, the speeds are considered accurate unless the acceleration for a particular observation is ±10 m/s^2 or more. This threshold is considered the extreme limit of possible acceleration and is considerably higher than typical driving conditions (Bagdadi and Várhelyi, 2011). If this threshold is reached, the speed is adjusted by using the exponential moving average of the previous four observations. This process is repeated by increasing the number of observations used to calculate the exponential moving average until acceleration falls within feasible thresholds. This algorithm is illustrated in Figure 5-6.

The adjusted speeds are used to calculate the acceleration and (if applicable) the exponential moving average of all subsequent points in the same trip. A single anomaly will therefore be smoothed out as will a series of consecutive observations that exhibit implausible acceleration.

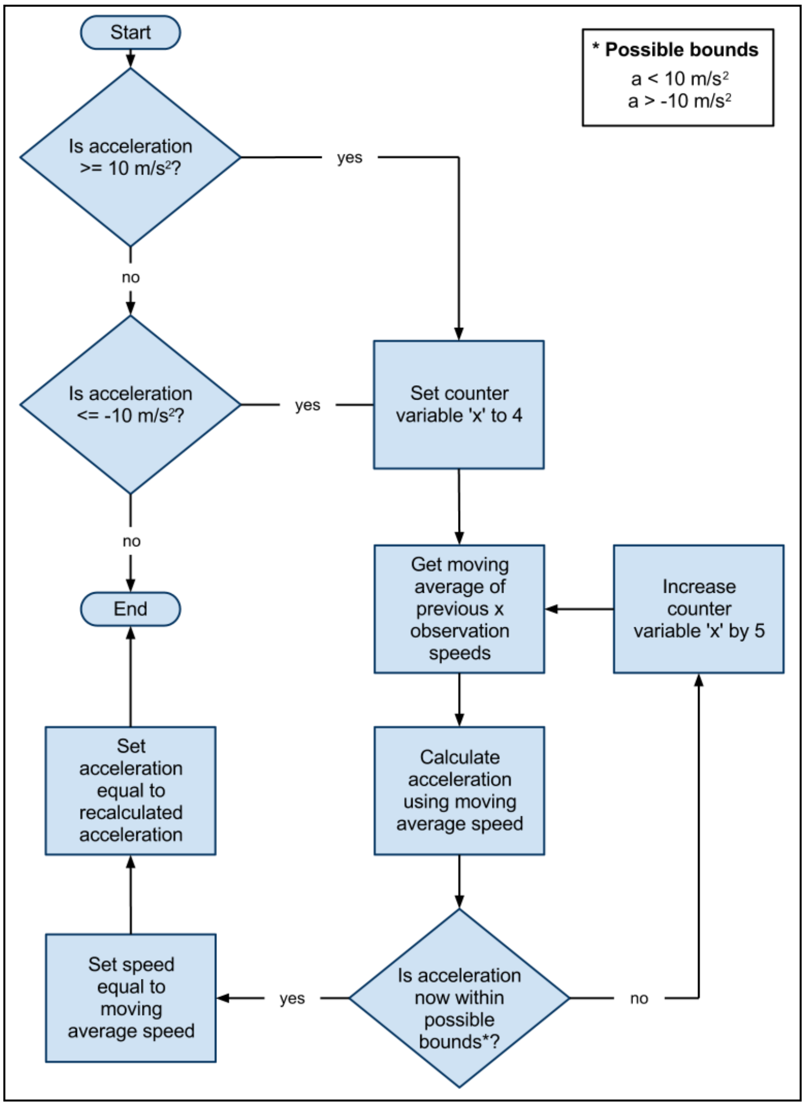


Figure 5-6: Speed smoothing algorithm

5.4 Road speed segments

At the second-by-second (disaggregate) level, GPS data – despite cleaning and smoothing) can contain noise which is an impediment in modelling. To deal with this, data is aggregated to the road segment level (see Section 4.3.1). For the purposes of this research, two forms of road segment aggregation are used:

1. Road speed segments; and
2. Road segments.

A road speed segment is comprised of a series of sequential and uninterrupted second-by-second observations which share a common speed limit, school zone status and trip. For example, they share the same speed limit and are all in a school zone or none are in a school zone. Figure 5-7 is an illustrative example of road segments based on the speed limit of the road. Importantly, a road speed segment may include observations from more than one physical road but may not include driving by more than one driver. In addition, the start and end of trips are always the start and end of a road speed segment.

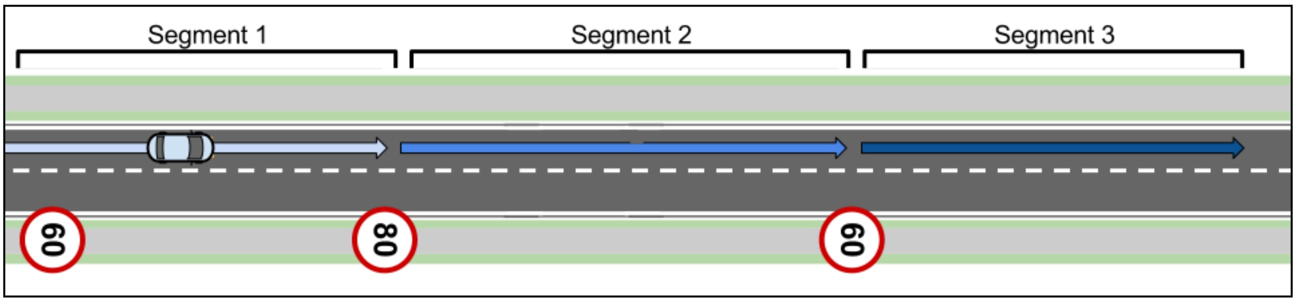


Figure 5-7: Illustration of road speed segments

Common driver, vehicle, trip and speed limit characteristics are kept unchanged in the aggregated dataset. However due to the aggregation a number of aggregate variables are required to account for variables that change *within* a road speed segment. Most of these relate to acceleration, braking and speeding behaviour as the acceleration during a segment may change and a driver could exceed the speed limit for none, some or all of a particular segment and do so at various magnitudes. A summary of these additional variables is shown in Table 5-3. For most analyses, the distance (as a proportion of the total segment distance) is used as the measure of speeding. This reduces the loss of information that occurs as a result of using categorical variables.

Table 5-3: Road segment aggregated variables

Variable	Description
NumObs	Number of second-by-second observations included in the road speed segment
TotSegDist	Total segment distance
Rain	Binary variable indicating if there was rainfall recorded for at least 50 percent of observations included in the segment (1) or not (0).
AvgSpeed	Average speed recorded within the segment where speed > 0 km/h
Speeding Variables	
Speed1S	Binary variable indicating if the driver exceeded the speed limit by 1 km/h or more for at least 20 percent of observations included in the segment
DistSpeed75P	Total distance driven at a speed exceeding 75 percent of the speed limit
DistSpeed01 **DistSpeed05** **DistSpeed10** **DistSpeed15** **DistSpeed20**	Total distance driven at or above 1 km/h, 5 km/h, 10 km/h, 15 km/h or 20 km/h above the speed limit
Speed75Pp	Proportion of observations recorded in excess of 75 percent of the speed limit
SpeedO1p **SpeedO5p** **SpeedO10p** **SpeedO15p** **SpeedO20p**	Proportion of observations recorded at or above 1 km/h, 10 km/h or 20 km/h above the posted speed limit
SpeedD75Pp	Proportion of distance recorded in excess of 75 percent of the speed limit
SpeedD1p **SpeedD5p** **SpeedD10p** **SpeedD15p** **SpeedD20p**	Proportion of distance recorded at or above 1 km/h, 5 km/h, 15 km/h or 20 km/h above the posted speed limit
Acceleration and Braking Variables	
Accel0P **Accel1P** **Accel2P** **…** **Accel9P**	Proportion of acceleration events where acceleration is ≤ 1 m/s², ≤ 2 m/s², ≤3, ≤4, ≤5, ≤6, ≤7, ≤8, ≤9 and >9 m/s²
Brake0P **Brake1P** **Brake2P** **…** **Brake9P**	Proportion of braking events where acceleration is ≤ 1 m/s², ≤ 2 m/s², ≤3, ≤4, ≤5, ≤6, ≤7, ≤8, ≤9 and >9 m/s²
Accel0Pd **Accel1Pd** **Accel2Pd** **…** **Accel9Pd**	Proportion of acceleration events where acceleration is ≤ 10%, ≤20%, ≤30≤, ≤40%, ≤50%, ≤60%, ≤70%, ≤80%, ≤90% and ≤100% of the maximum acceleration recorded for that driver.

Variable	Description
Brake0Pd **Brake1Pd** **Brake2Pd** **…** **Brake9Pd**	Proportion of braking events where negative acceleration is ≤ 10%, ≤20%, ≤30≤, ≤40%, ≤50%, ≤60%, ≤70%, ≤80%, ≤90% and ≤100% of the maximum acceleration recorded for that driver.

Road speed segment aggregation is used for analyses where the speed limit of the road is considered to be the main unit of analysis. Where more detailed temporal and spatial data is necessary, road segments (see Section 7.5) are used instead.

5.5 Survey results

A number of surveys were conducted during different phases of the study (recruitment, completion, etc.). These surveys contain quantitative and qualitative data. Qualitative data requires coding and some quantitative data was recalculated and or reclassified. This is done to combine similar responses and reduce the complexity of the data.

5.5.1 Demographics

Driver demographics were collected during recruitment. This includes age, gender, occupation, number of crashes, licence type as well as some basic vehicle information (make, model, year of manufacture and transmission type). In addition, age, gender and relationship data was collected for all household members. Information about the household location was requested but can also be derived from analysing the GPS data (Ellison et al., 2010).

The processing conducted on the demographic data was limited to categorising or re-categorising demographics to create variables with fewer but larger numbers of drivers in each category. This was predominantly used for age, gender and vehicle year of manufacture. Table 5-4 covers the most commonly used categories but other configurations have also been used for specific analyses. If this is the case, it is mentioned in the section covering that particular part of the analysis.

Table 5-4: Common categorisation of demographic variables

Variable	Categories
Age (2 categories)	18-30, 31-65
Age (3 categories)	18-30, 31-45, 46-65
Age (4 categories)	18-25, 26-30, 31-45, 46-65
Licence Type	Learner/Provisional, Full
Vehicle Model Year	<= 1999, 2000 to 2004, >= 2005
Vehicle Type	Sedan, Hatchback, Other

5.5.2 Psychological survey

After recruitment, drivers completed a five section, fifty question psychological survey adapted from a previous study by Machin and Sankey (2008). The survey was conducted online and covered a range of factors including personality, risk perception and self-reported driving behaviour. See Greaves and Ellison (2011) for more details on the background of the psychological survey.

The responses to the survey are all nominal variables. Depending on the specific analysis they are used either as standalone variables or as part of the following eight composite personality scales:

- Speeding;
- Aggression;
- Altruism;
- Excitement;
- Worry and Concern;
- Likelihood of Accident;
- Efficacy; and
- Aversion to Risk.

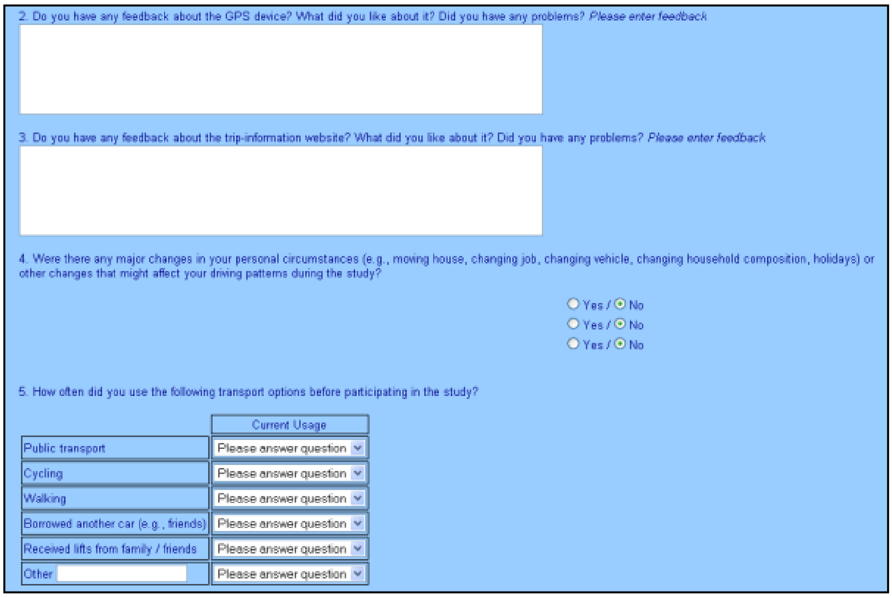
These composite scales are the average responses to the questions which make up each of these scales.

The data collected in this survey is used to incorporate drivers' inherent personality characteristics into their driver and vehicle profile. This also includes drivers' perceptions of the risk associated with a number of driving behaviours. This includes speeding (by 10 and 20 km/h), using a mobile telephone and running red lights.

5.5.3 Exit survey

After the completion of the GPS data collection period, study participants completed an exit survey. The purpose of this survey was to understand (generally) how participants felt about the study and its components. It also served to assist in determining if changes detected in behaviour by the GPS device were changes drivers were cognisant that they were making. In all, of the 106 drivers determined to have valid 'before' and 'after' data, 103 drivers completed the exit survey.

The exit survey was conducted online (see Figure 5-8) and consisted of a number of multiple choice and open-ended questions. Each participant in the study was provided with a unique URL with which to access the survey to ensure that responses could be accurately matched with the participant's other study data.


2. Do you have any feedback about the GPS device? What did you like about it? Did you have any problems? *Please enter feedback*

3. Do you have any feedback about the trip-information website? What did you like about it? Did you have any problems? *Please enter feedback*

4. Were there any major changes in your personal circumstances (e.g., moving house, changing job, changing vehicle, changing household composition, holidays) or other changes that might affect your driving patterns during the study?

Yes / No
Yes / No
Yes / No

5. How often did you use the following transport options before participating in the study?

	Current Usage
Public transport	Please answer question
Cycling	Please answer question
Walking	Please answer question
Borrowed another car (e.g., friends)	Please answer question
Received lifts from family / friends	Please answer question
Other	Please answer question

Figure 5-8: Screenshot of exit survey

The primary use of the exit survey in this research is to account for the influence of the financial incentive on changes in behaviour and to identify those drivers that were more aware of their speeding behaviour. This assists in answering the second set of hypotheses which aims to determine if making drivers more aware of their driving behaviour makes them safer drivers (see Section 4.1.2). With this aim in mind a set of indicator variables, shown in Table 5-5, were developed. Afterwards, each survey response was manually coded into the indicator variables. Each Boolean variable indicates if that particular aspect was mentioned (Y) or not (N). It did not matter where in the survey it was mentioned. In some cases the same aspect was mentioned in responses to more than one question but these were not codified differently. Each record in the codified dataset contains a user ID, a unique variable, which functions as the primary key. This is the same variable used to identify the vehicle in the other datasets and therefore simplifies aggregation and analysis.

Table 5-5: Variables created for use in exit survey analysis

Variable Name	Description
Financial aspects	
Incentive (as motivator)	Was the financial incentive mentioned as a motivator for participating in the study?
Incentive (charge phase)	Was the ability to earn money mentioned in the context of the introduction of the charging phase?
Incentive (post-survey)	Was the remaining financial incentive at the end of the study mentioned?
Made money[78]	Did the driver make money / Was the remaining incentive greater than $0.00?
Speeding	
Speeding (any mention)	Was speeding mentioned in response to any open-ended question in any context?
Speeding (in denial)	Was there an indication that the driver was sceptical/disbelieving of the speeding behaviour they were shown during the study?
Speeding (awareness)	Was there an indication that the driver became more aware of their speeding behaviour than they had been before the charging phase?
Speeding (self-reported)	Did the driver indicate that they had reduced speeding in the charging phase 'sometimes', 'often' or 'always'? 'Not at all' and 'Occasionally' responses were treated as no.
Speeding (reduce > incentive)	Did the driver indicate that they *would have* reduced their speeding in the charging phase if the incentive had been doubled or tripled? 'Sometimes', 'often' and 'always' responses for double and/or triple incentives were treated as yes.
Speeding (any reduce)	Did the driver indicate they did or would have reduced their speeding in the charging phase for the current incentive and/or double incentive and/or triple incentive.
Speeding (GPS)[79]	Did the GPS device record a reduction in speeding as a proportion of total distance in the charging phase compared to the 'before' phase?

5.6 Summary

The data used in this thesis are comprised of a number of disparate but related datasets. In order to allow for statistical analyses to be conducted these individual datasets needed to be cleaned, restructured and combined. This chapter described the processes involved in accomplishing this such that an observation in one dataset can be directly related to the relevant observations in the other datasets.

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78 Derived from GPS data

79 Derived from GPS data

The spatial datasets (Section 5.2) represented the road environment in the study area. These include the location of intersections, school zones, rainfall and other characteristics. These were matched to each second-by-second GPS observation based on the position (latitude and longitude) of each. The GPS data itself was in turn used to detect the driving behaviours of interest (speeding, acceleration and braking) using the methods described in Section 5.3. Subsequently, it became possible to aggregate the GPS observations – over 80 million in total – to road speed segments whereby a new road speed segment started every time the speed limit changed. These aggregated segments – together with the coded survey results completed by each driver – are in turn used as the unit of analysis and independent variables in the aggregate analyses presented in Chapter 6.

6 RESULTS AND DISCUSSION: AGGREGATE ANALYSES

This chapter provides an aggregate analysis of speeding behaviour. The aim is two-fold. First, the analysis allows for a better understanding of the characteristics of the dataset and thereby aid in determining the best methods of studying a change in a driver's behaviour that occurs after drivers are made aware of their speeding behaviour. Secondly, this chapter demonstrates – through a series of models – that due to the high degree of noise in this dataset, a disaggregate analysis is necessary to isolate the inherent driver characteristics that are of interest. These analyses were conducted in an aggregate form using the road speed segments discussed in 5.4 and the aggregate behavioural variables created for each of these segments. Similar analyses were conducted for acceleration and braking behaviour but those performed worse than the already poor models of speeding and are therefore not presented here. In this chapter only data from the 'before' phase are used.

6.1 Exploratory driver-level analyses[80]

The simplest and most aggregate level at which these data can be analysed is by pooling all data from all drivers. At this level, behavioural data for all drivers are aggregated into one dataset and analysed simultaneously. The analyses in this section are not weighted and therefore drivers with higher vehicle kilometres travelled (VKT) contribute more to the total figures than drivers with lower VKT. However, at this level of aggregation, weighting only reduces the percentage of distance speeding by one to three percent in each category, such that the distribution remains unchanged.

The proportion of speeding is significantly different between speed limits (p = .000)[81] for speeding overall (1 or more km/h above the speed limit) and for all speed magnitudes (Figure 6-1). This ranges from a low of 14 percent of the distance travelled on roads with a 70 km/h speed limit to a high of 28 percent of distance on roads with a 110 km/h speed limit. VKT (at all speeds) – marked in green in Figure

[80] Parts of the analysis in this section were conducted using a slightly larger sample and presented in Ellison and Greaves (2010).

[81] Unless otherwise specified, significance values in this section are calculated using ANOVA.

6-1 – also varies greatly by speed limit zone with 60 km/h zones being the most common covering almost 40,000 km.

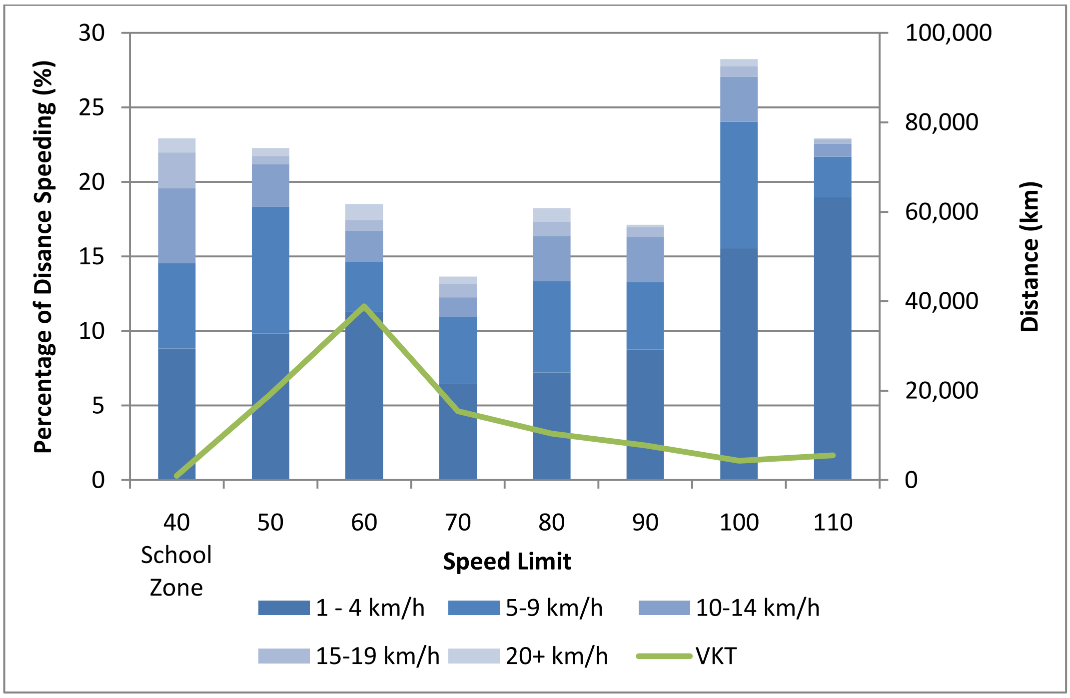

Figure 6-1: Proportion speeding by speed limit

The frequency of braking events (Figure 6-2) and acceleration events (Figure 6-3) per kilometre also vary significantly (p = .000) by speed limit. In this case, the higher the speed limit, the fewer total acceleration and braking events and the fewer higher magnitude events are observed per kilometre of driving.

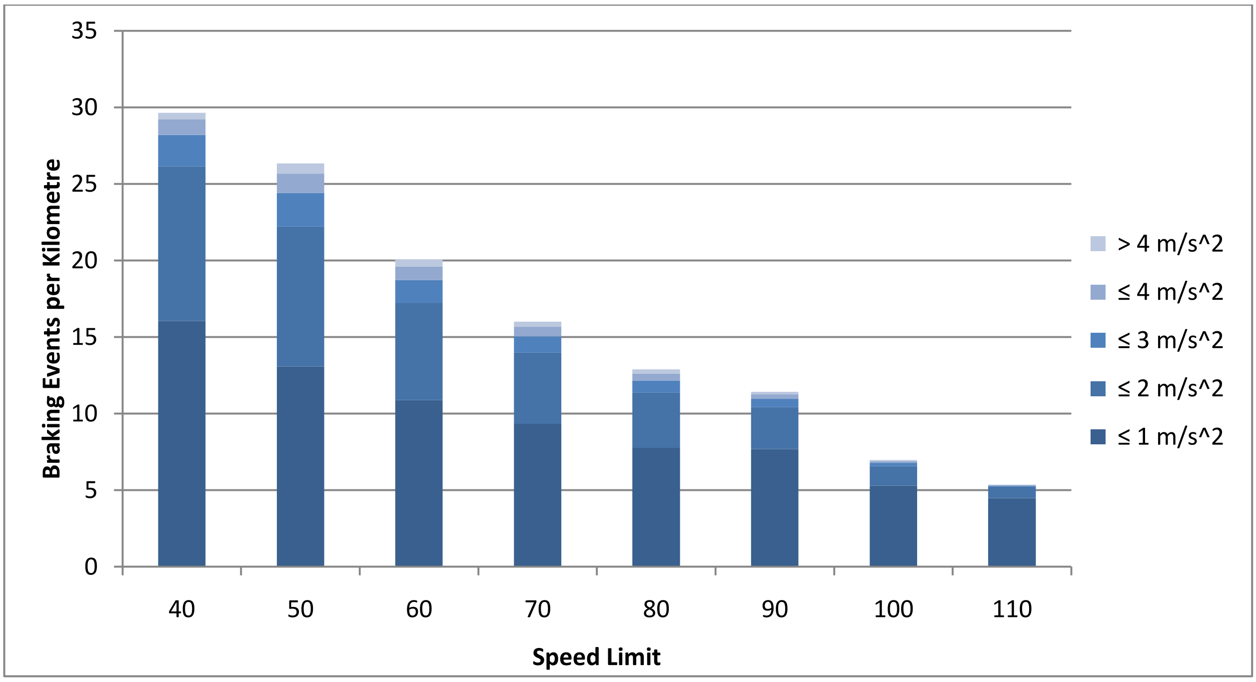

Figure 6-2: Number of braking events per kilometre by speed limit

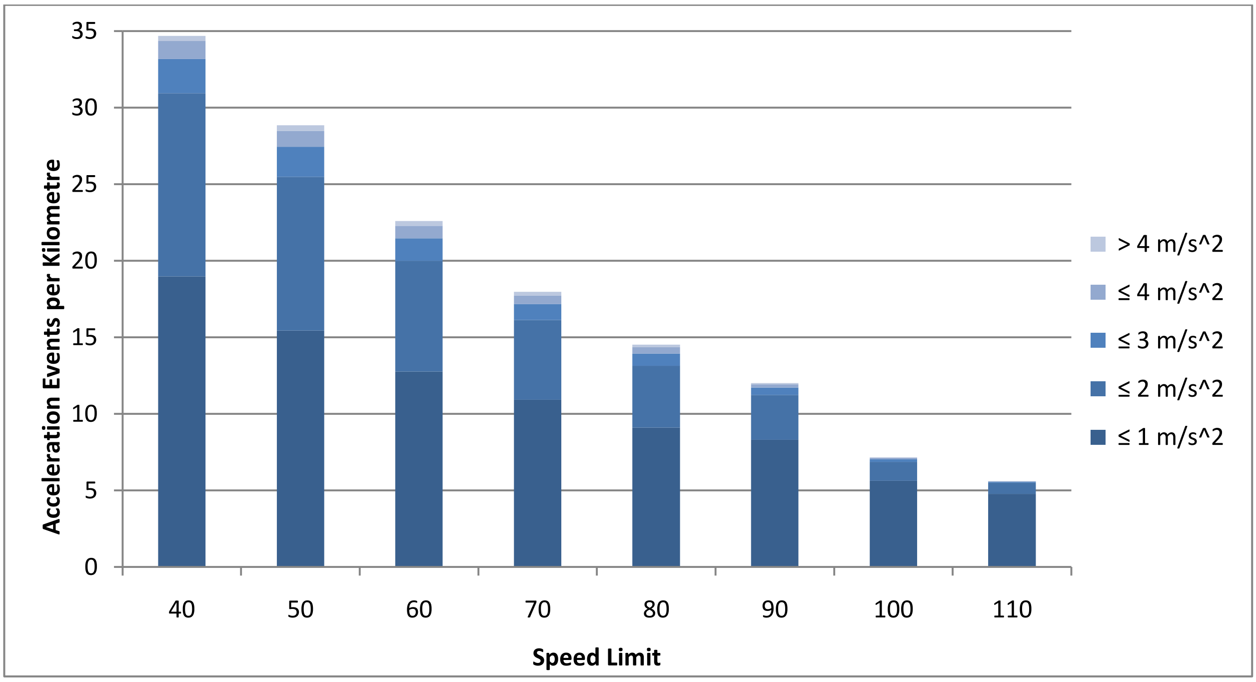

Figure 6-3: Number of acceleration events per kilometre by speed limit

Speeding by time of day (Figure 6-4) is significantly different (p = .000) overall and across all speeding magnitudes. The morning (05:00 – 08:59) exhibits the highest proportions of speeding at 23 percent of the distance driven, while the night (20:00 – 04:59) exhibits the lowest (17 percent). Although this appears counter-intuitive and contrary to established research (Giles, 2004), given that the morning period includes the morning peak which is more congested, VKT in the morning period is far lower than VKT in the night period which covers a greater span of time. This means that whilst in percentage terms speeding in the morning exceeds speeding at night, in absolute terms the distance travelled in excess of the speed limit is more than double at night (6,681 km) than in the morning (2,559 km). The time periods used here were selected to match the time periods used for the charging regime described in Section 4.2.3 to provide a time variable across analyses. Similarly, differences in speeding behaviour between weekdays and weekends (Figure 6-5) are also statistically significant (p = .000) except for speeding by 10-14 km/h (p = .077). Speeding on weekends is higher than on weekdays.

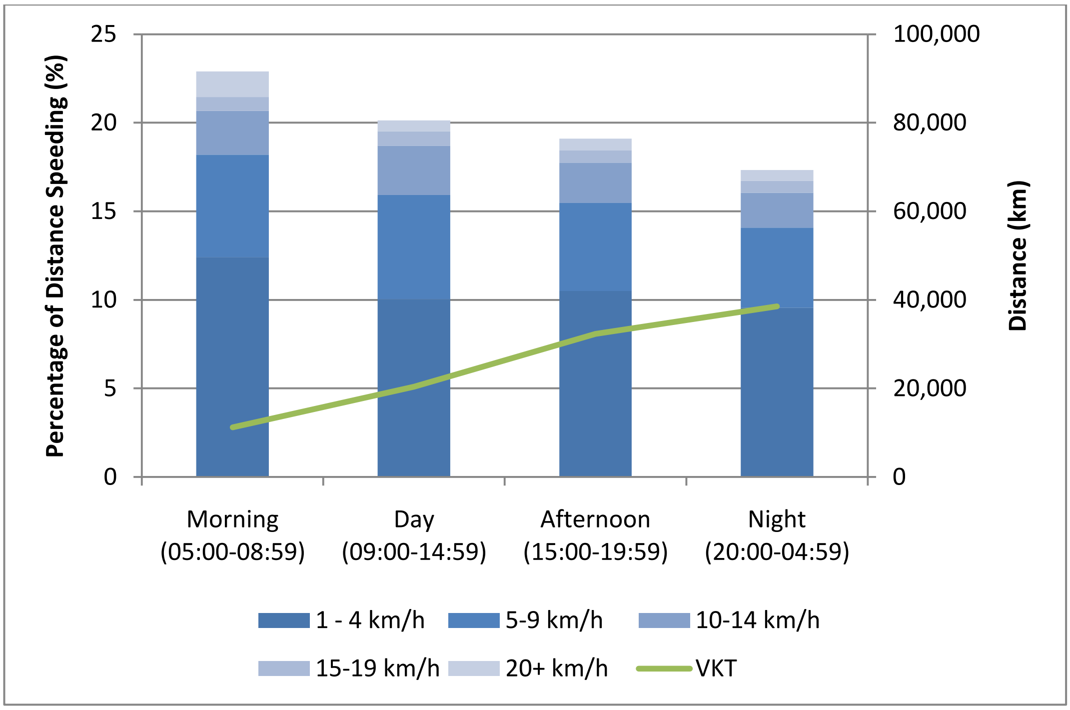

Figure 6-4: Proportion speeding by time of day

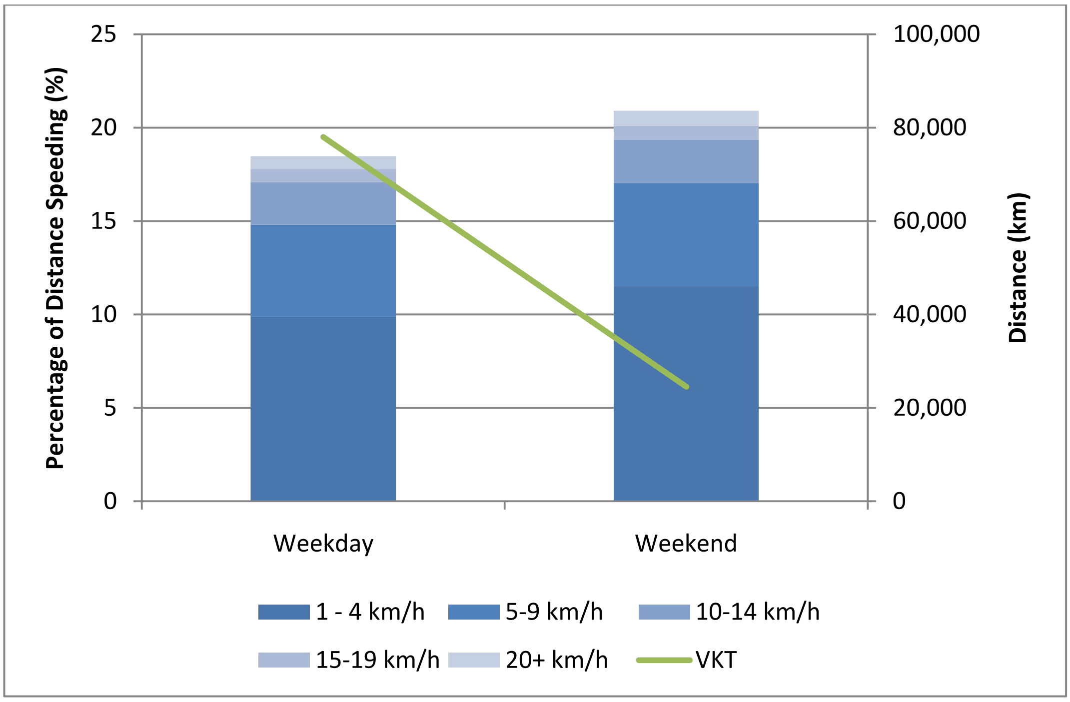

Figure 6-5: Proportion speeding by day of the week

Speeding also varies significantly (p = .000) by the number of passengers (Figure 6-6) and trip purpose (p = .000) with education exhibiting the lowest proportions of speeding and commuting and work related travel exhibiting the highest proportions of speeding behaviour (Figure 6-7). Some studies have shown higher rates of speeding with higher numbers of passengers but this effect appears to be limited to certain groups (Whissell and Bigelow, 2003). The presence of passengers has also been shown to be related to lower incidences of forms of risky driving behaviour other than speeding such as alcohol and seat belt use (Lee and Abdel-Aty, 2008). This also coincides with the driving behaviour by trip purpose which finds that speeding behaviour is lower during trips where the number of child passengers are likely to be higher (education trips) than on trips with a trip purpose where there are likely to be no or few passengers (work related trips). Given the composition of the sample in this study, these results appear consistent with that of prior research.

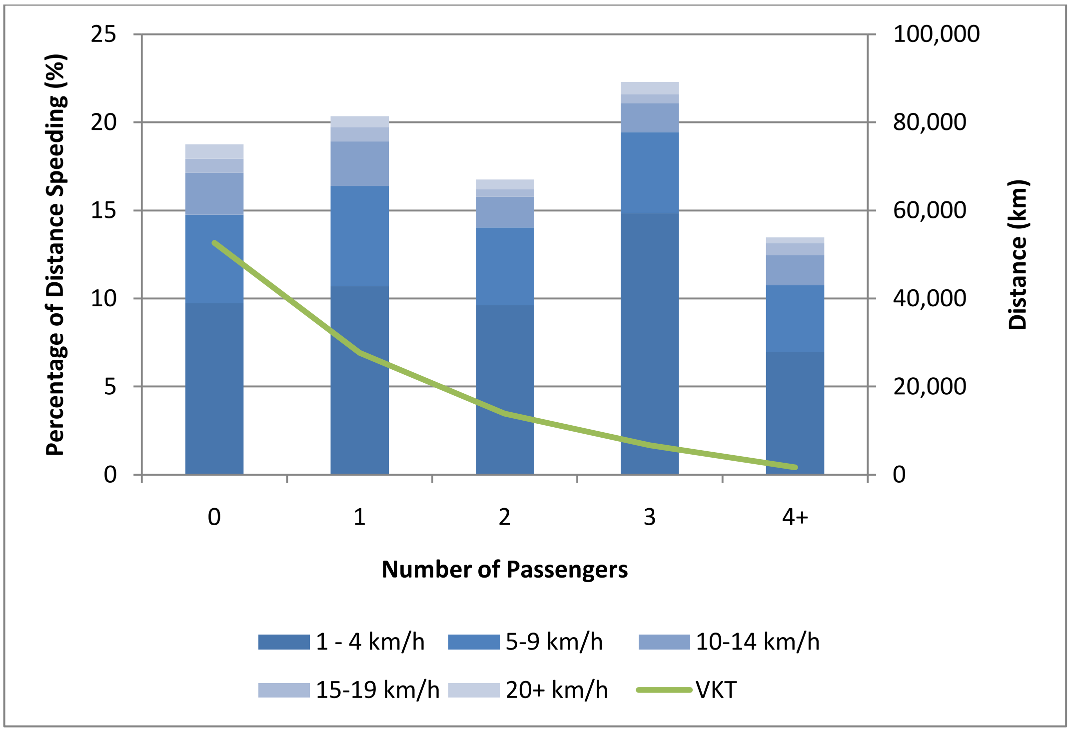

Figure 6-6: Proportion speeding by number of passengers

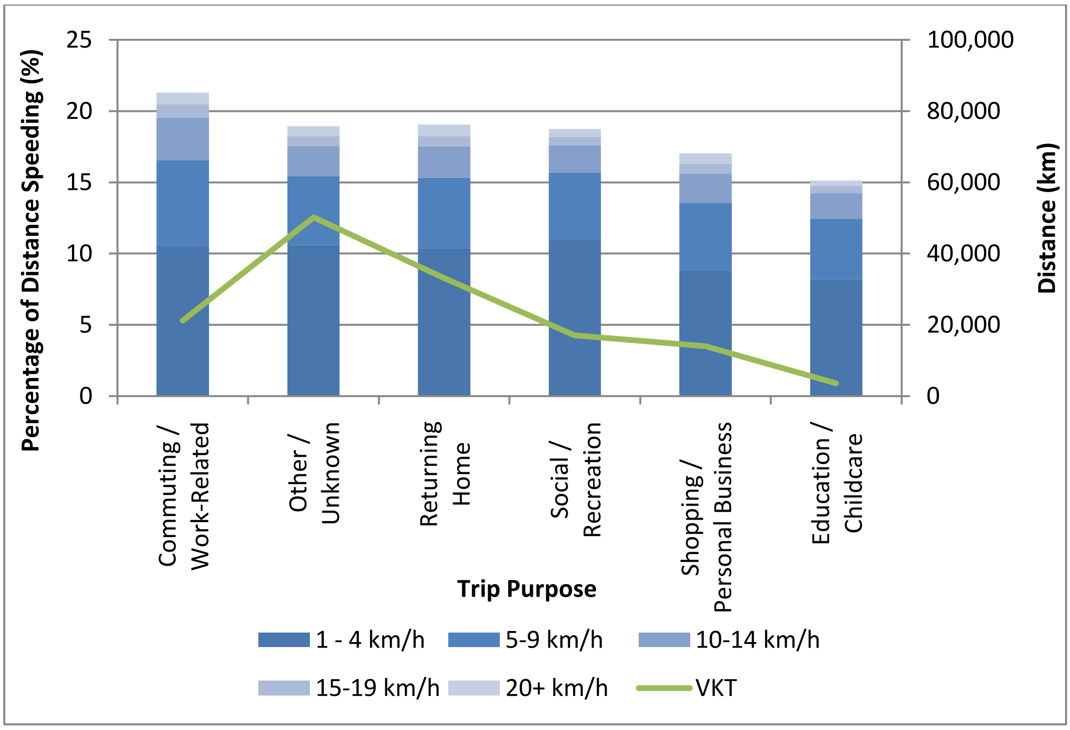

Figure 6-7: Proportion speeding by trip purpose

An exploratory analysis using the psychological survey conducted at recruitment and described in detail in Section 4.2.6 was also performed. This survey included questions regarding participants' attitudes, beliefs and preferences towards risk (driving and generally).

There is some evidence in the literature (see Section 3.1.5) that drivers are less concerned about the risks to themselves of being injured than they are for their passengers. In addition, there is ample evidence to show that speeding, distracted driving and u-turns are perceived as risky driving behaviours (see Chapter 3) although there is considerable heterogeneity in how risky these behaviours are viewed. The results of the exploratory analysis are consistent with this prior research.

Figure 6-8 shows – in green – the proportion of drivers that are not at all to extremely concerned about injuries to themselves, passengers and other drivers. A greater proportion of drivers are very or extremely concerned about their passengers being injured than are very or extremely concerned about themselves or other drivers being injured. This difference is important in understanding the contextual differences in behaviour and in effectively targeting road safety messages. This is not reflected in differences in speeding behaviour which is shown in Figure 6-8 as bar charts. Observed speeding behaviour is not significantly different ($p = .119$) for injuries to themselves[82], or injuries to passengers ($p = .447$)[83] or injuries to other drivers ($p = .640$)[84]. An analysis using a somewhat larger sample sourced from the same study did find some correlations between speeding and some of the psychological variables as well as with speeding and self-reported speeding (Greaves and Ellison, 2011).

The difference in perceived danger between the study participants and other drivers is not replicated in their assessment of the likelihood themselves or another driver would be involved in a crash as shown in Figure 6-9. Consistent with prior research (White et al., 2011), which has found drivers to consider themselves to be above average drivers, drivers in this study believe other drivers are more likely to be involved in a traffic accident than they are themselves. However, there are no statistically

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[82] Speeding was also not statistically different for any individual magnitude. $p = .071$ (1-4 km/h), .333 (5-9 km/h), .168 (10-14 km/h), .195 (15-19 km/h) and .353 (20+ km/h).

[83] Speeding was also not statistically different for any individual magnitude. $p = .555$ (1-4 km/h), .297 (5-9 km/h), .112 (10-14 km/h), .129 (15-19 km/h) and .638 (20+ km/h).

[84] Speeding was also not statistically different for any individual magnitude. $p = .383$ (1-4 km/h), .912 (5-9 km/h), .518 (10-14 km/h), .180 (15-19 km/h) and .195 (20+ km/h).

significant differences in speeding behaviour based on the driver's perceived probability of a crash (p = .791)[85] or based on the perceived probability of another driving being involved in a crash (p = .702)[86].

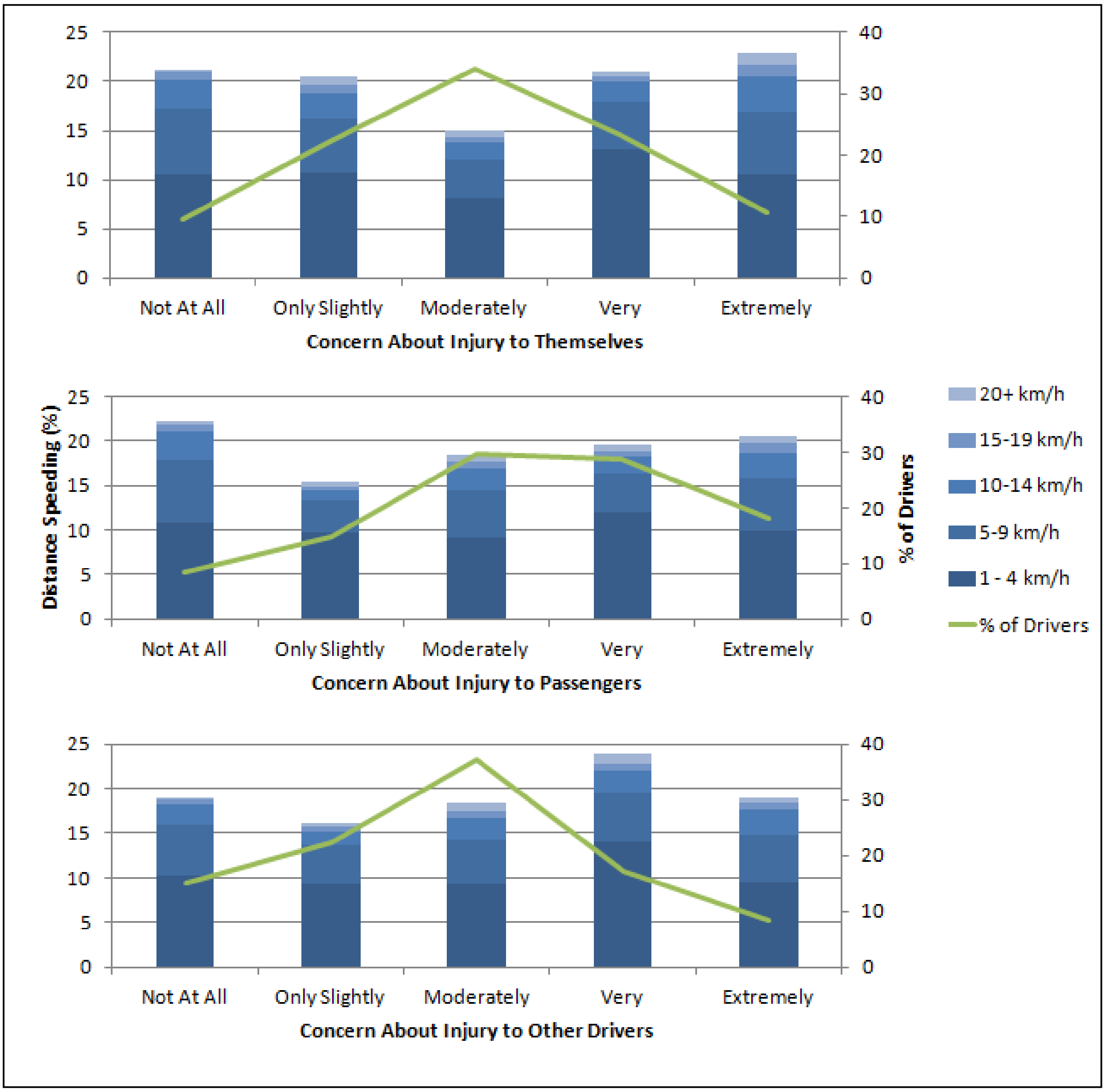

Figure 6-8: Drivers' concern about injury to themselves, passengers and other drivers

[85] Speeding was also not statistically different for any individual magnitude. p = .310 (1-4 km/h), .967 (5-9 km/h), .930 (10-14 km/h), .713 (15-19 km/h) and .880 (20+ km/h).

[86] Speeding was also not statistically different for any individual magnitude. P = .560 (1-4 km/h), .438 (5-9 km/h), .871 (10-14 km/h), .972 (15-19 km/h) and .416 (20+ km/h).

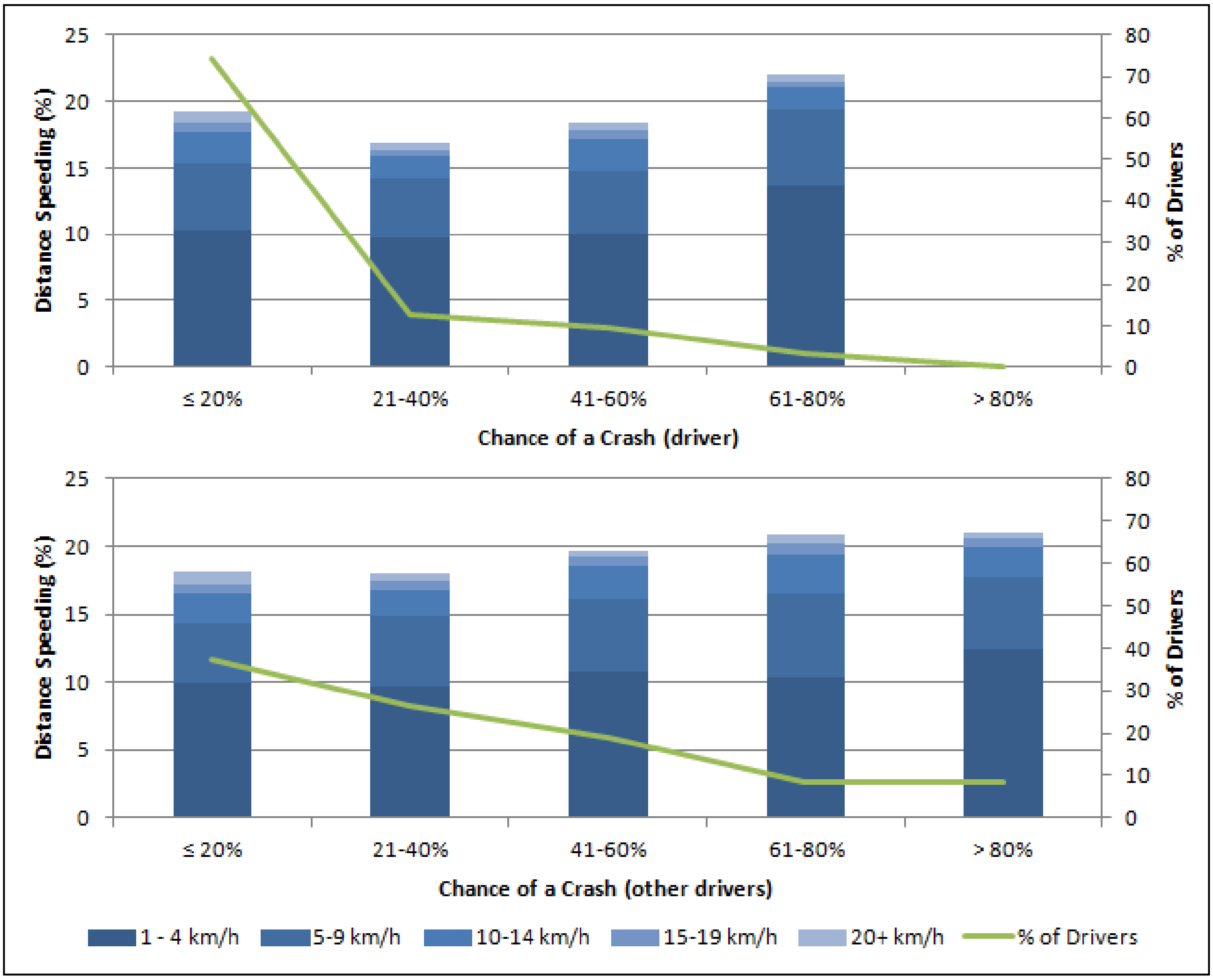

Figure 6-9: Drivers' perceived chance of a crash

Drivers' confidence in their own driving abilities has been found by other researchers to contribute to a driver's perceptions of the risks associated with speeding and other on-road behaviour (Chung and Wong, 2012; Knight et al., 2013). An analysis was conducted at an aggregate level to determine if speeding behaviour by drivers varies with the confidence in their own driving abilities. The 'not at all confident' category and, to a lesser extent, the 'extremely confident' categories were only selected by a small proportion of drivers which is consistent with responses to other surveys (Weijters et al., 2009). In addition, the aggregate measures of speeding used here are for all situations and not the situation (high traffic, unfamiliar roads, etc.) indicated in each question. The results should be interpreted with this in mind.

Speeding behaviour of any magnitude was not significantly different for any of the situations as illustrated in Figure 6-10. Confidence in heavy traffic was the most significantly different between categories ($p = .085$) whilst driving on unfamiliar roads exhibited the lowest significant difference ($p = .831$). In terms of the individual magnitudes only confidence in poor driving conditions at 1 to 4 km/h ($p = .048$) and confidence in heavy traffic at 5 to 9 km/h ($p = .038$) had one speeding magnitude that was significantly different between driving confidence categories.

The results at this level of aggregation appear to show that most apparent differences in speeding behaviour between drivers with different levels of confidence are not statistically significant. However, given that the results of other research have found significant differences, it is possible that examining these relationships in situations closer to those addressed in the question would yield different results.

It can be concluded from this exploratory analysis that at an aggregate level there are statistically significant differences in speeding behaviour between different trip and road characteristics but the same is not true for most of the driver psychological variables. The usual caveats in regard to self-reported data (as discussed in Section 2.4.1) and varying interpretations by different participants (Richardson et al., 1995) apply and should be considered in interpreting these results.

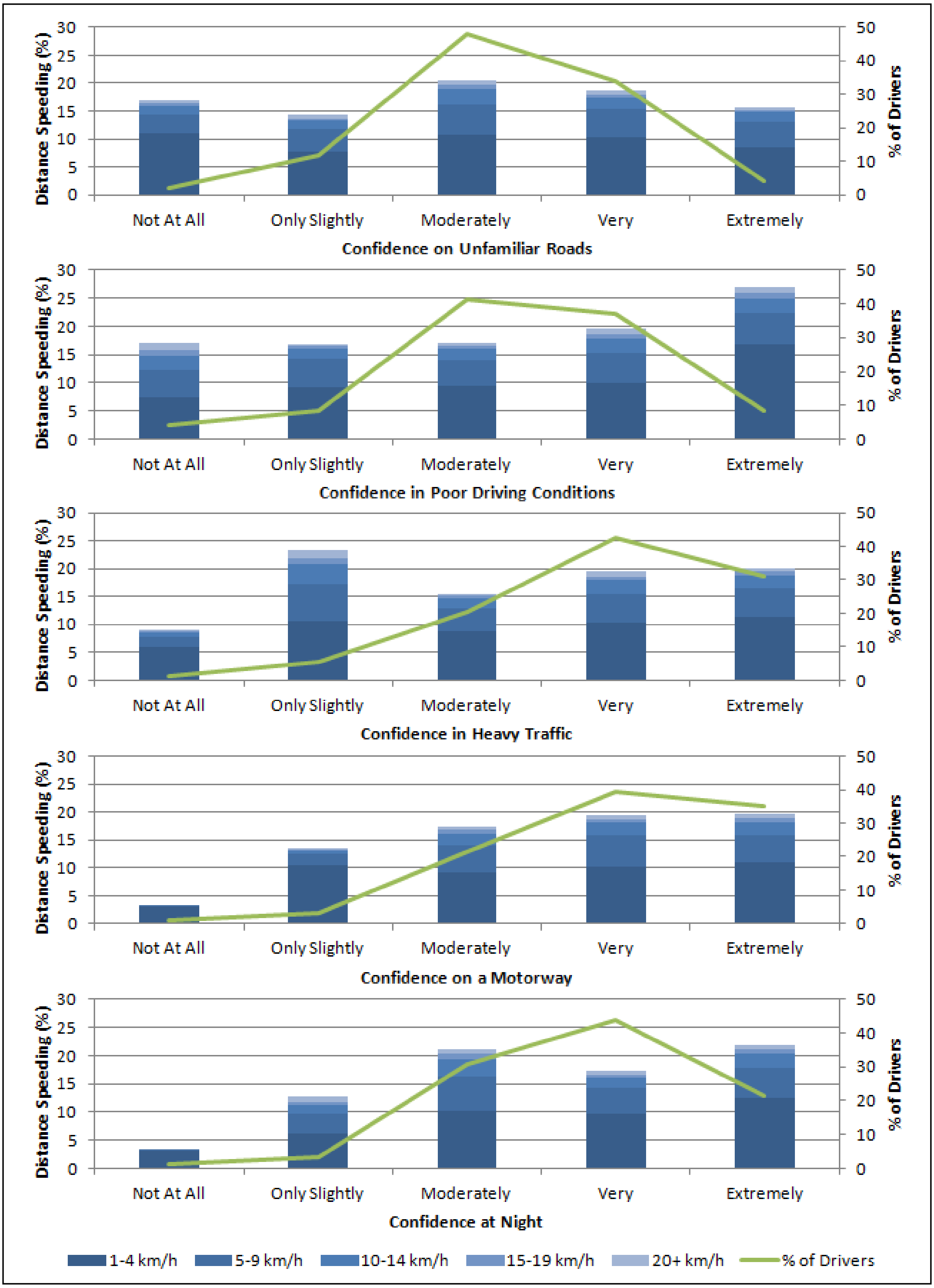

Figure 6-10: Drivers' driving confidence in various situations

6.2 Driver profiling using aggregated data

Another approach to examining driver behaviour is to pool all data collected from a single driver. Analyses using this approach are presented here and in Section 6.3. The purpose of these analyses is to test a number of methods of categorising or describing drivers based on their observed behaviour, demographics, vehicle characteristics and psychological variables. Of particular interest in this section are the variables associated with prolific rule breakers. Due to the level of noise in the dataset it is necessary to apply two methods of grouping drivers into categories and a number of statistical techniques are applied. This ensures that the results are robust and not (solely) a function of the methods or techniques employed. The first of these methods groups drivers on the basis of the proportion of their driving over the speed limit. The second groups drivers using their psychological attributes. In both methods, drivers' total speeding is used as either a dependent or independent variable and therefore this does not take into account variability and spatial or temporal context in behaviour. In addition, some of the independent variables are measured on an ordinal scale and therefore both parametric and non-parametric methods were applied but the results proved to be similar. Parametric methods were, therefore, applied as these are simpler to interpret.

6.2.1 One-way ANOVA tests

To determine if the averages of drivers' personality were statistically significantly different between more frequent speeders and less frequent speeders, one-way ANOVA (analysis of variance) tests were conducted with the factor representing the proportion of speeding for each driver in equally sized four, three and two ordered categories such that the same number of drivers are assigned to each of the categories. That is, in the four category variable, 25 percent of the sample is assigned to each group on the basis of their speeding behaviour by 1 km/h or more above the speed limit as a proportion of their total distance (spd1P). Of the drivers in the lowest category, the highest proportion of speeding is 10.176 percent. Alternatively a proportion of the total distance driven at speeds of at least 75 percent of the speed limit (spd1P75) is used as a proxy for congested conditions. The upper bounds of each category are summarised in Table 6-1.

ANOVA is used to determine if the means of a dependent variable are significantly different between groups. In this case, ANOVA is applied by comparing the means of a number of driver characteristics between drivers with different proportions of overall speeding. In effect, the question that is being asked is: is the mean (for example) aggression of the 50 percent of drivers with the highest overall speeding significantly different from the 50 percent of drivers with the lowest overall speeding? With two groups of drivers (as in the aforementioned example), ANOVA is equivalent to a two-sample t-test however it is particularly useful in comparing three or more groups. The objective here is not to determine the direction or magnitude of the differences but merely to identify if a potential difference exists and is worthy of further examination.

Table 6-1: Observed speeding categories for ANOVA

Variable	Upper Bound of Speeding Categories (%)			
	1	2	3	4
Four categories				
% of Drivers	25%	25%	25%	25%
Spd1P	10	17	23	100
Spd1P75	17	25	34	100
Three categories				
% of Drivers	33%	34%	33%	
Spd1P	12	20	100	-
Spd1P75	19	31	100	-
Two categories				
% of drivers	50	50		
Spd1P	17	100	-	-
Spd1P75	25	100	-	-

The results – presented in Table 6-2 – show that the means for most variables do not differ significantly between the different groups of drivers. The distance travelled at 75 percent of the speed limit is the only variable that is significantly different for all six speeding categories. The total distance travelled is significantly different for all but two of the tests. Of the personality and vehicle variables, significant differences are only observed for efficacy, aversion to risk, self-reported speeding (all except for Spd1P with two categories) and the vehicle type (vehicle body).

Table 6-2: ANOVA F-test and significance for speeding categories

Variable	Four Categories				Three Categories				Two Categories			
	Spd1P		Spd1P75		Spd1P		Spd1P75		Spd1P		Spd1P75	
	F	Sig.	F	Sig.	F	Sig.	F	Sig.	F	Sig.	F	Sig.
Aggression	.454	.715	.400	.754	.285	.753	.606	.548	.211	.647	.353	.554
Altruism	1.409	.245	.928	.431	2.065	.133	1.395	.253	1.171	.282	.474	.493
Excitement	1.871	.140	2.305	.082	2.511	.087	1.450	.240	.054	.816	.027	.869
Worry & Concern	.731	.536	2.079	.109	1.068	.348	2.684	.074	.000	.989	.800	.373
Likelihood of a Crash	1.784	.156	1.797	.153	2.703	.072	2.315	.105	.453	.502	.008	.928
Efficacy	.789	.503	.427	.734	.814	.446	.640	.530	3.968	.049	.698	.405
Aversion to risk	1.086	.359	3.527	.018	1.032	.361	2.577	.082	.610	.437	.818	.368
Self-reported Speeding	6.648	.000	6.524	.000	9.079	.000	6.861	.002	3.152	.079	4.654	.034
Vehicle Body	1.845	.144	3.190	.027	2.290	.106	4.772	.010	.337	.563	3.144	.079
Year Of Manufacture	.267	.849	.090	.966	.200	.819	.108	.898	.146	.704	.003	.957
Age (three categories)	.476	.700	.895	.447	.272	.762	.552	.578	1.938	.167	.333	.565
Vehicle Transmission	1.336	.268	1.594	.196	.1259	.289	2.392	.097	.152	.698	.666	.416
Gender	.292	.831	.159	.923	.392	.677	.241	.786	3.489	.065	.867	.354
Total distance	3.843	.012	2.944	.037	4.716	.011	.2939	.057	9.439	.003	2.981	.087
Distance at 75% of speed limit	6.670	.000	4.841	.003	8.393	.000	5.054	.008	16.940	.000	5.276	.024

These results suggest that driver demographics, psychological and vehicle categories are not predictors of speeding behaviour when aggregated by driver. To confirm that these results are not due to the magnitude of speeding, additional ANOVA analyses using exactly the same procedure were performed for speeding behaviour 5 km/h or more above the speed limit and for speeding behaviour 10 km/h or more above the speed limit with largely similar results. This is contrary to established research (discussed in 3.1.2) which has found that driver characteristics appear to influence speeding behaviour. This may be because most research on drivers' speeding behaviour relies on either self-reported speeding behaviour, which can be unreliable (Greaves and Ellison, 2011), or uses speed camera or crash data both of which significantly under report the frequency of speeding (see Section 2.4.1) which can lead to only the most egregious infractions being included.

6.2.2 Multinominal logistic regression

Multinominal logistic regression allows two or more categories to be used in the dependent variable and determines the factors that are related to a single reference category. Logistic regression models determine the probability of a particular (categorical) outcome given a set of independent variable values. Logistic regression is used instead of the (more common) linear regression because the dependent variable is categorical and linear regression assumes a continuous variable linearly related to the independent variables, neither of which is satisfied in this particular case.

In total, six models were developed; one for each of the categories used for the ANOVA tests in Section 6.2.1 for both all speeding and for speeding for distances with speeds above 75 percent of the speed limit (spd75p). In all cases the reference category is the category containing drivers with the highest proportions of speeding behaviour at an aggregate (driver) level.

The best model has a dependent variable with 4 categories and speeding as proportion of total distance at speeds of at least 75 percent of the speed limit. In terms of model fit, the likelihood ratio significance is 0.015 and the model correctly predicts 53.8 percent of drivers and 52.4 percent of the most prolific speeders[87]. Nonetheless, the confidence intervals (shown in Table 6-3) for the small number of significant variables[88] are very close to 1 which represents the odds ratio for no significant effect. The only exception is self-reported speeding.

[87] An R^2 value cannot be computed for logistic regression. A number of pseudo-R^2 measures have been created but have been largely dismissed as unreliable.

[88] A reduced model was also run but with very similar results. The full model is shown here (including insignificant variables) to provide detail on the insignificant variables and to maintain consistency between the models presented in this chapter.

Table 6-3: Parameter estimates of multinomial logistic regression model (driver aggregate)[89]

		B	Std. Error	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
						Lower Bound	Upper Bound
1	Intercept	-6.251	6.509	.337			
	Gender	.279	.967	.773	1.322	.199	8.794
	Vehicle Body	-.587	.523	.262	.556	.199	1.551
	Age	.309	.597	.605	1.362	.423	4.388
	Transmission Type	1.759	.904	.052	5.804	.988	34.110
	Model Year	.195	.514	.704	1.215	.444	3.326
	Aggression	.263	.313	.401	1.301	.704	2.402
	Altruism	.417	.315	.186	1.518	.818	2.815
	Excitement	.022	.303	.941	1.023	.564	1.854
	Worry and Concern	-.843	.420	.045	.430	.189	.981
	Efficacy	.202	.614	.743	1.223	.367	4.076
	Aversion to Risk	1.578	1.245	.205	4.845	.422	55.582
	Self-Reported Speeding	-2.656	1.002	.008	.070	.010	.501
2	Intercept	-1.009	5.765	.861			
	Gender	.746	.881	.397	2.108	.375	11.844
	Vehicle Body	-1.124	.485	.020	.325	.126	.840
	Age	.082	.511	.872	1.086	.399	2.959
	Transmission Type	.440	.880	.617	1.553	.277	8.707
	Model Year	.009	.470	.985	1.009	.402	2.535
	Aggression	.316	.297	.288	1.372	.766	2.457
	Altruism	.236	.275	.389	1.267	.739	2.170
	Excitement	.017	.279	.950	1.017	.589	1.757
	Worry and Concern	-.630	.380	.097	.532	.253	1.122
	Efficacy	.271	.543	.618	1.311	.452	3.803
	Aversion to Risk	.804	1.144	.482	2.235	.237	21.044
	Self-Reported Speeding	-2.035	.865	.019	.131	.024	.712
3	Intercept	4.991	5.491	.363			
	Gender	.975	.857	.255	2.651	.494	14.224
	Vehicle Body	-1.131	.490	.021	.323	.123	.844
	Age	-.478	.516	.354	.620	.225	1.706
	Transmission Type	-.187	.896	.834	.829	.143	4.797
	Model Year	-.634	.500	.204	.530	.199	1.412

[89] The leftmost column represents the speeding category (from Table 6-1) with four categories where the fourth category is the reference category.

	B	Std. Error	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
					Lower Bound	Upper Bound
Aggression	-.001	.296	.998	.999	.560	1.784
Altruism	.591	.285	.038	1.806	1.032	3.159
Excitement	.268	.263	.310	1.307	.780	2.190
Worry and Concern	-.757	.370	.041	.469	.227	.969
Efficacy	.024	.519	.963	1.024	.371	2.831
Aversion to Risk	-.856	1.123	.446	.425	.047	3.839
Self-Reported Speeding	-.454	.782	.562	.635	.137	2.941

Looking more closely at the estimated response probabilities for each driver, there appears to be little to differentiate the probabilities where the correct prediction was made from the probabilities where an incorrect prediction was made. The mean probability where the predicted category was correct was 0.56. This compares to a mean probability of 0.48 where the predicted category was incorrect. However, the difference in probabilities between the correctly and incorrectly classified drivers is statistically significant (p = .004). In combination, these characteristics lead to the conclusion that these models do not reliably predict individual speeding behaviour – at an aggregate level – on the basis of these driver and vehicle variables.

6.2.3 Driver profiling using psychological clustering

The psychological variables (aggression, altruism, excitement, worry and concern, likelihood of a crash, efficacy, aversion to risk and self-reported speeding behaviour) were used as inputs into a hierarchical cluster model with three case groupings. Hierarchical clustering attempts to group observations (in this case drivers) who have similar scores across the explanatory variables (Ulleberg, 2001). Although the variables to be used to cluster observations are defined by the analyst, the values of the variables in each cluster are not. In this case, the cluster analysis did not include driver's observed behaviour as one of the independent variables but is instead used as a basis for comparison between clusters. The purpose of clustering is to group observations (in this case, drivers) such that those within a cluster exhibit more similarity in the values of the input variables than observations in other clusters. Hierarchical clustering has the same objective but performs better for complex datasets.

Since the clustering procedure does not identify the characteristics which apply to each cluster, the first step after the hierarchical cluster algorithm has assigned one of three clusters to each driver is to look at the properties of each cluster in terms of the psychological and demographic characteristics of drivers. The age and gender distributions are shown in Figure 6-11. The youngest participants are distributed approximately equally among the three clusters but older drivers are more polarised in the first and third categories. Male and female participants have the opposite trends with more male participants being assigned to the third cluster compared to the first and second clusters. In contrast, a higher proportion of female participants are assigned to the first cluster and smaller proportions in the other two categories.

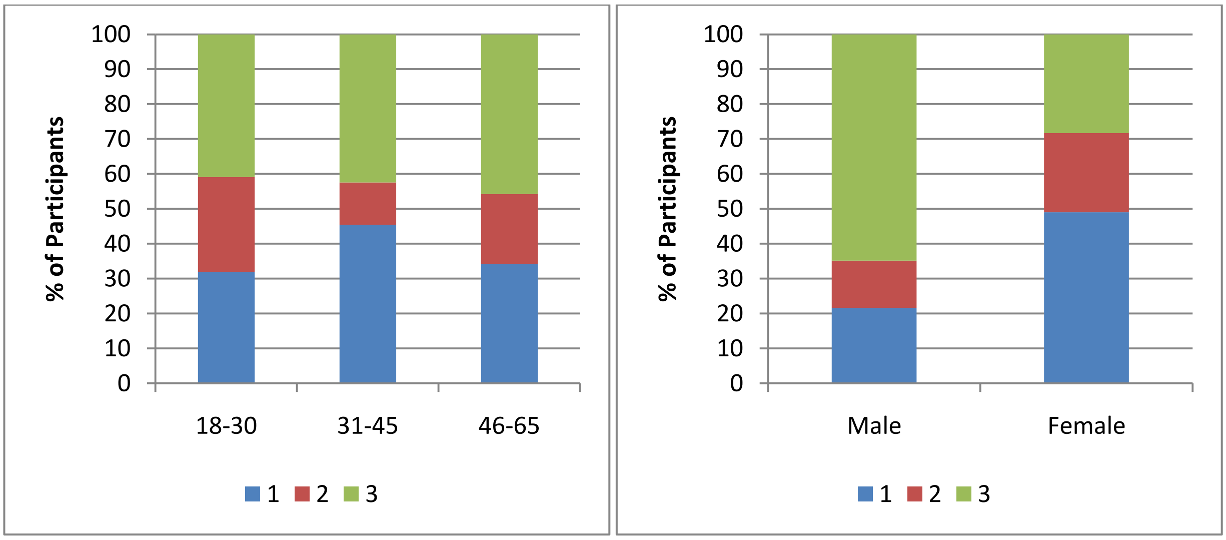

Figure 6-11: Proportion of male and female participants in each cluster group

Looking at the average scores of the three clusters (Figure 6-12) for each of the personality scales used, it is clear that cluster 1 tends to be more altruistic, risk averse, worry and is less easily excited. Cluster 2 and 3 are fairly similar to each other except that drivers assigned to cluster 2 have higher perceptions of the likelihood of a crash and exhibit more worry and concern. Consequently, the three clusters can be seen as careful (1), excitable-and-aware (2) and excitable-and-unaware (3).

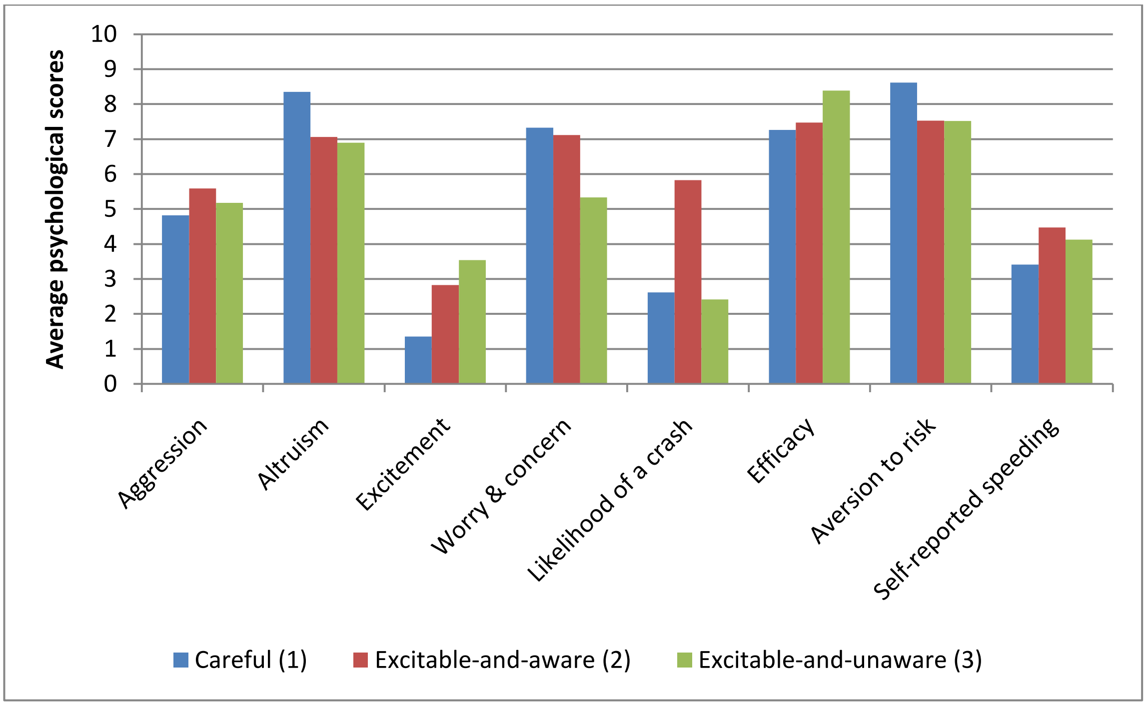

Figure 6-12: Psychological attributes by cluster group

An independent-samples t-test was performed to determine if the clustering procedure was able to create clusters with statistically significant differences between clusters 1 and 2, between clusters 1 and 3 and between clusters 2 and 3 for each of the psychological variables in addition to observed speeding behaviour. A summary of the results is shown in Table 6-4 with statistically significant differences shaded in grey.

Table 6-4: Summary of t-tests of psychological variables between clusters

Variable	Careful vs. Excitable-and-aware		Careful vs. Excitable-and-unaware		Excitable-and-aware vs. Excitable-and-unaware	
	Cluster 1 vs. 2		Cluster 1 vs. 3		Cluster 2 vs. 3	
	t	Sig. (2-tailed)	t	Sig. (2-tailed)	t	Sig. (2-tailed)
Speeding (% of distance)	-1.762	.084	-2.212	.030	-.148	.883
Speeding (75% proxy)	-1.818	.075	-2.501	.015	-.334	.740
Aggression	-1.848	.071	-1.110	.271	1.067	.291
Altruism	3.914	.000	5.092	.000	.420	.676
Excitement	-3.918	.000	-6.257	.000	-1.485	.143

Worry and concern	.395	.695	4.365	.000	3.219	.002
Likelihood of a crash	-7.123	.000	.690	.493	9.422	.000
Efficacy	-.453	.653	-3.323	.002	-2.626	.011
Aversion to risk	4.824	.000	6.634	.000	.074	.941
Self-reported speeding	-3.660	.001	-3.252	.002	1.242	.220

The results of the t-tests show that there is only a statistically significant difference in the observed speeding behaviour of the careful drivers compared to the excitable-and-unaware drivers. In terms of the psychological variables, aggression is not statistically different between any of the clusters whilst the remaining variables are statistically different for two of the three comparisons.

Overall this appears to show that the psychological characteristics of drivers are a suitable method of differentiation between drivers as a function of their speeding behaviour when the driver has the psychological characteristics associated with the careful and excitable-and-unaware cluster categories. However, a closer examination of individual drivers' behaviour in relation to their assigned cluster group (Figure 6-13) shows that drivers from all three cluster groups appear to speed for considerable proportion of distances and there is no discernable pattern. This indicates that personality does not – on its own – adequately explain drivers' speeding behaviour.

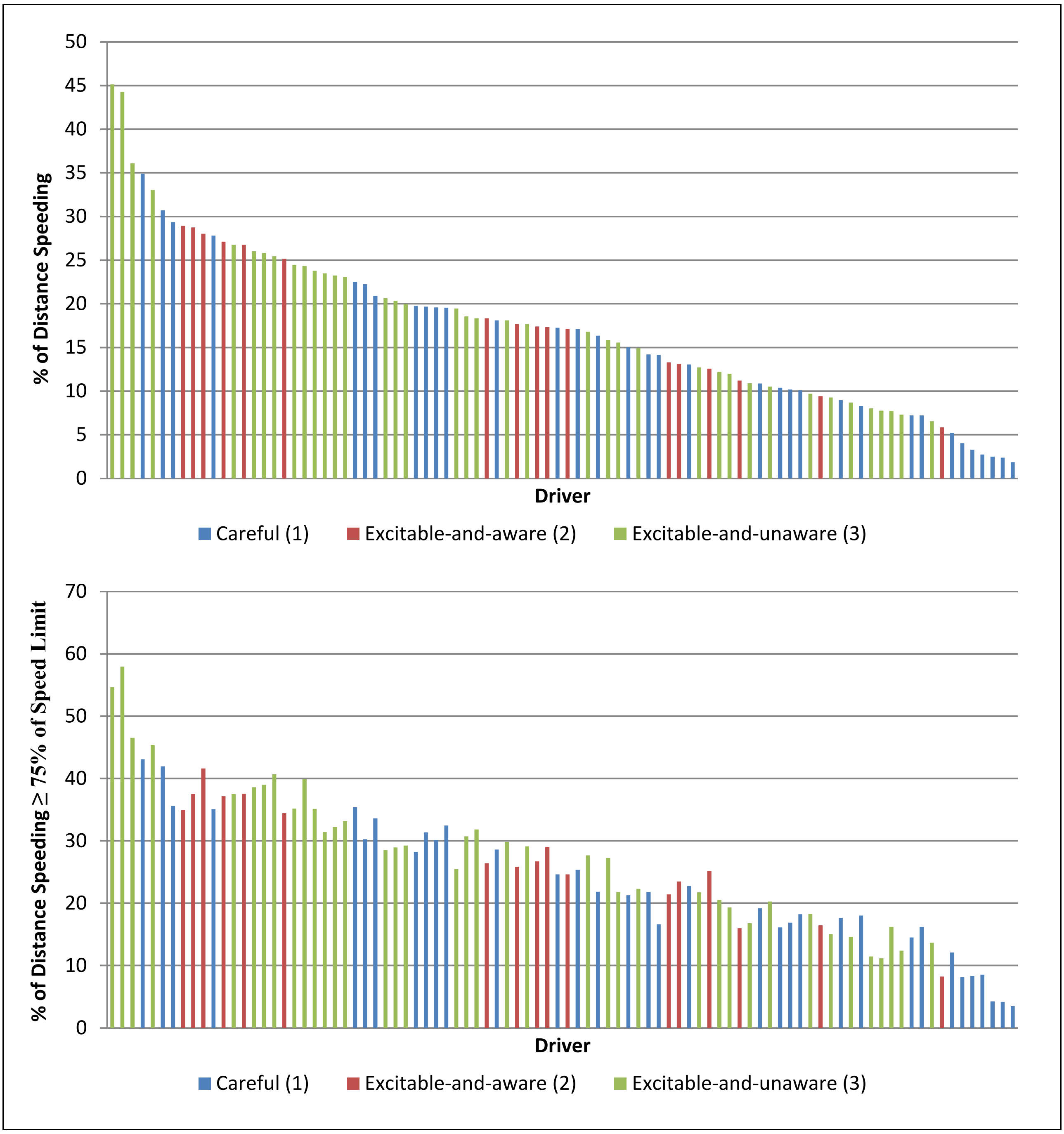

Figure 6-13: Percent of distance speeding by driver by cluster group

6.3 Speed limit zone analyses

Previous analyses on a larger sample of this dataset (Ellison and Greaves, 2010; Familar et al., 2011) have found that speeding behaviour and predictor variables vary by the speed limit of the road. As a consequence, it was hypothesised that separate models for each speed limit would provide more meaningful results than the model discussed in Section 6.2.2 which incorporates data from roads of all speed limits.

As a first step, speeding behaviour as a proportion of all distance and as a proportion of distance travelled at speeds in excess of 75 percent of the speed limit was converted into four categories. These categories are based on the proportion of speeding such that an equal number of driver-speed limit combinations are in each category. This created the categories shown in Table 6-5. The categories have a different composition from those used at the driver-level of aggregation because the lower the VKT included at a particular level of aggregation, the more spread out the distribution of speeding behaviour.

Table 6-5: Speeding categories for aggregate multinomial regression

Variable	Upper Bound of Speeding Categories (%)			
	1	2	3	4
Driver-level aggregation				
% of drivers	25	25	25	25
Spd1P	10	17	23	100
Spd1P75	17	25	34	100
Speed-limit level aggregation				
% of drivers	25	25	25	25
Spd1P	6	16	28	100
Spd1P75	12	27	40	100

Using the same procedure as for the driver-level models (Section 6.2.2), models were created for each speed limit with a dependent variable with four categories and a binary dependent variable with 50 percent of the sample in each group. Although these models have slightly better model fit than the driver-level model they exhibit the same problematic confidence intervals and few (if any) statistically significant variables. The best model is for 100 km/h roads and uses speeding as a proportion of distance travelled in excess of 75 percent of the speed limit as the (binary) dependent variable. Since all models performed poorly, only this model is presented here. Caution should be used in the interpretation of the results due to the poor model fit.

6.3.1 100 km/h speed limit

Of the drivers in the study, only half (53) had observations in 100 km/h speed zones and had completed the psychological survey. As a result of this, the 100 km/h aggregate model only contains this limited sample and this should be kept in mind when interpreting the results. As a further consequence, the number of drivers with frequencies of speeding in each of the four categories defined in Table 6-5 is relatively smaller than for the 50 km/h and 60 km/h models (the most frequently observed speed limits) and, therefore, a model with four categories of speeding behaviour could not be computed. A binary logistic regression model was created instead.

In this model, the correct category of speeding was predicted for 84.9 percent of all drivers and 75 percent of higher frequency speeders. Despite these relatively good numbers, the probabilities were not significantly different between correctly and incorrectly predicted drivers (p = .162). In terms of the significant variables, only gender (p = .047) and having an older car (p = .035) were statistically significant (Table 6-6) in explaining the differences in speeding behaviour between low (reference) and high frequency speeders. High frequency speeders in 100 km/h speed zones were more likely to be female and be driving a car manufactured before 2000. However, the confidence intervals for these variables exhibit the same problems as in the driver-level model and the models for the other speed limits (not shown).

Table 6-6: Parameter estimates for 100 km/h binary logistic regression model

		B	Std. Error	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
						Lower Bound	Upper Bound
3+	Intercept	-2.593	6.520	.691			
	Aggression	.071	.392	.856	1.074	.498	2.318
	Altruism	.433	.404	.284	1.541	.698	3.403
	Excitement	.109	.277	.693	1.115	.649	1.918
	Worry and Concern	.296	.443	.505	1.344	.564	3.202
	Perceived Risk of a Crash	-.022	.229	.925	.979	.625	1.532
	Efficacy	1.025	.755	.175	2.788	.634	12.251
	Aversion to Risk	-1.754	1.312	.181	.173	.013	2.265
	Self-Reported Speeding	1.506	1.234	.223	4.507	.401	50.635
	Gender	-3.051	1.371	.026	.047	.003	.695
	Vehicle Transmission	-2.449	1.389	.078	.086	.006	1.314
	Age (31-45)	.528	1.162	.649	1.696	.174	16.548
	Age (46-65)	-2.131	1.396	.127	.119	.008	1.830
	Year of Manufacture (2000 to 2004)	3.548	1.679	.035	34.731	1.293	932.610
	Year of Manufacture (≥ 2005)	1.537	1.278	.229	4.652	.380	56.922
	Vehicle Body (Hatchback)	-.244	1.293	.851	.784	.062	9.876
	Vehicle Body (Other)	-2.861	1.607	.075	.057	.002	1.336

6.3.2 School zones[90]

Although the speed limit specific models performed slightly better than the driver-level model the results remain unreliable. This may be due to the large number of possible situations in which data at each speed limit was collected. For example, 50 km/h roads include narrow local roads and multiple lane arterials. They are also recorded during the morning peak and on weekend nights among other spatiotemporal differences which may contribute to confounding or insignificant results. In contrast, school zones are school zones share a number of characteristics, namely:

[90] Parts of this section were presented at the Transportation Research Board Annual Meeting, 2013 in Washington D.C. (Ellison et al., 2013c)

- A common speed limit of 40 km/h;
- Occurs in a limited period of time (Monday – Friday, 08:00-09:30 and 14:30-16:00);
- High pedestrian activity; and
- Presence of signage and road markings (exact configuration varies).

Whilst all school zones are not identical they are more similar than roads with a common speed limit and therefore are well suited for examining driver behaviour because many external spatiotemporal factors are held constant (or near constant). This section describes an analysis of speeding in school zones at the highest aggregate level using primarily the proportion of distance in school zones driven in excess of 40 km/h as the key measure. Of the drivers in the study, 84 had at least 1 km of driving in school zones and therefore this analysis uses this reduced sample. The results are consistent with a similar analysis conducted using a sample of 119 drivers (Ellison et al., 2013c)[91].

At an overall level drivers exceed the speed limit in school zones for 23 percent of the distance driven in school zones. This is a larger proportion than any other speed zone other than 100 and 110 km/h zones. This also holds true for speeding by 10 km/h or more which equates to driving 50 km/h in a 40 km/h zone. This is despite the increased signage and penalties. However, this number (23 percent) masks the heterogeneity of this behaviour which is shown in Figure 6-14. To better understand the reasons for these differences further analyses were conducted using vehicle, demographic and psychological variables.

[91] In this thesis, the drivers included require valid data in the before and after period of the study. Although this particular analysis does not use data from the after period, the sample is kept the same for consistency. The cited paper does not have this requirement and therefore can include drivers which are not qualified for the before-and-after analysis which allows for a slightly larger sample.

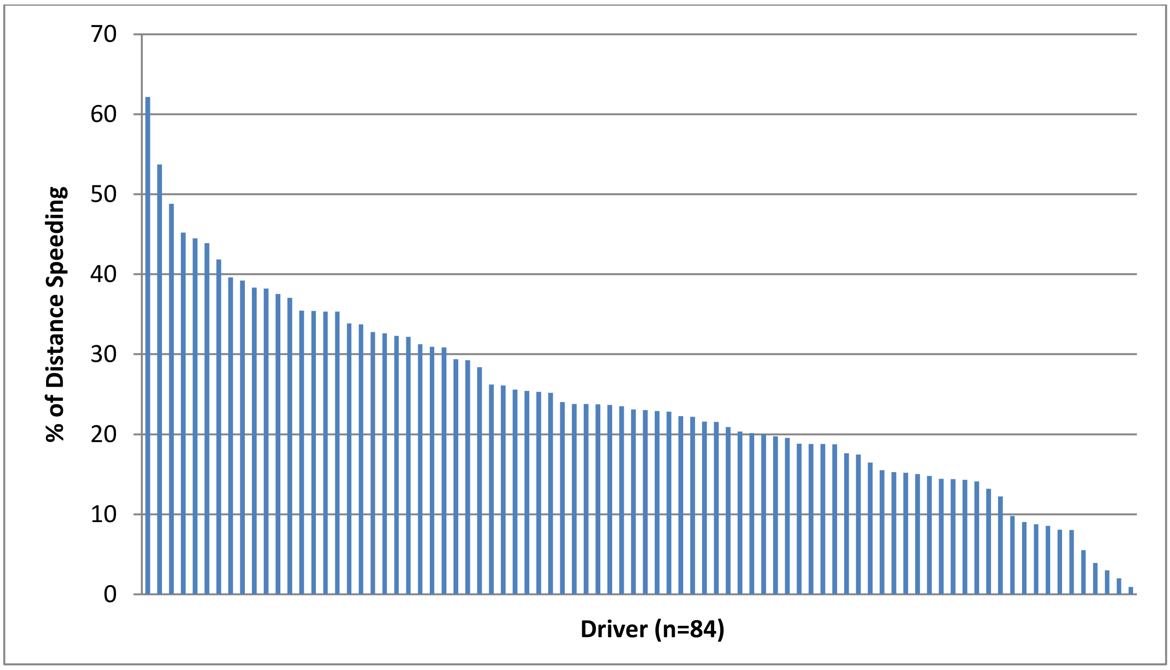

Figure 6-14: Proportion of distance speeding in school zones by driver

Since speeding behaviour in school zones is higher than in most other speed zones, different categories of speeding behaviour are used here. The upper bound of each of the categories is shown in Table 6-7 alongside the upper bounds of the categories used for the 50, 60 and 110 km/h speed zone analyses. Otherwise, the process is the same.

Table 6-7: Speeding categories for aggregate school zone regression analysis

Variable	Upper Bound of Speeding Categories (%)			
	1	2	3	4
Speed-limit level aggregation				
% of drivers	25	25	25	25
Spd1P	6	16	28	100
Spd1P75	12	27	40	100
School zones only				
% of drivers	25	25	25	25
Spd1P	15	23	33	100
Spd1P75	26	35	44	100

Due to the smaller sample, using a dependent variable consisting of four categories proved problematic and resulted in insignificant models. Instead, binary logistic regression was performed by combining category 1 with 2 and category 3 with 4.

This model appears to perform reasonably well, correctly predicting the speeding behaviour in school zones of 69.9 percent of all drivers and 70.3 percent of the more frequent speeders which is better than most other speed limit models. The difference in the probabilities between the correctly predicted and incorrectly predicted drivers was also significant (p = .000). The parameter estimates (Table 6-8) reveal a potential problem with the model as only one variable (self-reported speeding) is significantly different between the two groups of drivers and the 95 percent confidence intervals for this variable remains quite large.

Table 6-8: Parameter estimates for school zone binary logistic regression model

		B	Std. Error	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
						Lower Bound	Upper Bound
3+	Intercept	-7.165	5.269	.174			
	Aggression	-.156	.268	.561	.856	.507	1.446
	Altruism	-.083	.258	.748	.920	.555	1.526
	Excitement	.208	.205	.312	1.231	.823	1.841
	Worry and Concern	.439	.338	.194	1.551	.800	3.007
	Perceived risk of a crash	.073	.176	.677	1.076	.762	1.520
	Efficacy	-.836	.528	.113	.433	.154	1.220
	Aversion to Risk	1.529	.981	.119	4.614	.674	31.569
	Self-Reported Speeding	1.708	.734	.020	5.518	1.309	23.263
	Gender (Male)	.704	.726	.332	2.023	.488	8.385
	Vehicle Body (Hatchback)	.805	.794	.311	2.236	.472	10.598
	Vehicle Body (Other)	1.016	.966	.293	2.763	.416	18.354
	Year of Manufacture (2000 to 2004)	-.665	.881	.450	.514	.091	2.889
	Year of Manufacture (≥ 2005)	-.663	.683	.332	.515	.135	1.967
	Age (31-45)	.365	.921	.692	1.440	.237	8.759
	Age (46-65)	1.135	.774	.143	3.110	.682	14.191
	Vehicle Transmission	-.590	.805	.463	.554	.114	2.684

Although this model only includes school zones, the dependent variable is an aggregated variable including all driving behaviour in all school zones. As a result of this, there is a loss of variables which may differ across time or space. To test if a less disaggregate model would be better, a similar procedure to that used in the previous model was employed except for the application of a step-wise methodology and the addition of three variables: time of day, number of passengers and if the observation occurred within 25 metres of a roundabout, signalised intersection or non-signalised intersection. For this model, each observation represents a driver's speeding behaviour in school zones for a particular time of day, number of passengers and presence (or lack) of nearby intersections. The dependent variable is a binary variable consisting of any amount of speeding behaviour (51 percent of observations) or no speeding behaviour (49 percent of observations). The critical difference between this model and the previous model is that the previous model contains one observation per driver while this model contains a separate observation for each school zone segment[92].

The results of this model are in line with the previously discussed models. The model is statistically significant overall (p = .000) but correctly predicts the speeding behaviour of only 58.6 percent of all observations and 61.2 percent of observations with speeding behaviour. The differences in probabilities between correctly predicted and incorrectly predicted observations are statistically significant (p = .000) and the confidence intervals for the significant variables are improved from the original school zone model. Furthermore, whilst a single model is described and shown below, the parameter estimates proved to be more consistent between different models with slightly different categories employed for some of the variables.

The results show that the higher the number of passengers, the less likely the driver is to be speeding. In addition, the proximity to intersections has a negative association with speeding behaviour whereby people are less likely to be speeding if they are in close proximity to an intersection. Speeding observations are also more likely to be observed by male drivers, younger drivers, less altruistic drivers, and drivers with more self-reported speeding, higher aversion to risk, (slightly) higher

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[92] The creation of segments is discussion in Section 5.4.

likelihood of a crash. With the exception of aversion to risk these results are in line with *a priori* expectations.

Table 6-9: Parameter estimates for expanded school zone binary logistic regression model

		B	Std. Error	Sig.	Exp(B)	95% C.I.for EXP(B)	
						Lower	Upper
1	Time of Day	-.073	.044	.094	.929	.853	1.013
	Number of Passengers	-.091	.035	.010	.913	.853	.978
	Near Intersection(s)	-.488	.072	.000	.614	.533	.707
	Gender (Female)	-.353	.086	.000	.703	.594	.831
	Age	-.238	.059	.000	.788	.702	.885
	Altruism	-.143	.035	.000	.867	.810	.928
	Worry and Concern	.081	.039	.039	1.084	1.004	1.171
	Perceived Risk of a Crash	.049	.021	.019	1.050	1.008	1.094
	Aversion to Risk	.626	.118	.000	1.870	1.482	2.358
	Self-Reported Speeding	.234	.081	.004	1.264	1.079	1.481
	Constant	-.887	.527	.093	.412		

Note: Vehicle Body, Year of Manufacture, Vehicle Transmission, Aggression, Excitement and Efficacy were removed in previous iterations as they were not statistically significant.

This expanded model continues to explain only a subset of observations but the introduction of the three additional variables has improved the robustness of the results and points to the need to include additional variables that could account for some of the variability observed in each driver's behaviour. This is consistent with prior research discussed in Section 3.1.1 which has found the road environment to be a significant unexplained factor in drivers' speeding behaviour.

6.4 Conclusions

The majority of the models and analyses presented in this chapter were not statistically different from their respective null models meaning that they have no predictive power and, therefore, are of no use for policy making. At such a highly aggregate level it appears that driver and vehicle characteristics are poor predictors of speeding behaviour. Nonetheless, there are a number of conclusions that can be drawn from this process. The first of these confirms previous findings that the characteristics of the road environment are important influencers of speeding behaviour, and in different ways, of acceleration and braking behaviours (see Section

3.1.1). It appears, based on the speed limit models and the school zone models, that the more disaggregate the analysis and the more road environment variables that are included, the more significant the model and the difference in behaviour between groups. The predictive accuracy of even the most disaggregate model (Table 6-9) is still relatively poor but the differences in probabilities are significant as are the predictor variables themselves. What should be drawn from this is that in order to isolate the impact, if one exists, of the drivers' characteristics, it is necessary to somehow control for the road environment and trip factors. Secondly, the results were sensitive to the way in which the dependent variable was converted into a categorical variable and the significant factors appear to vary (to some extent) by the various magnitudes of speeding. Similar analyses of acceleration and braking behaviour were affected to an even greater extent.

Given these conclusion, it would appear to be inappropriate to create a single model that uses a dependent variable that does not account for the different magnitudes of speeding. In the same vein, since the behavioural variables collected from the same driver are correlated it is not possible to create a model that considers each of these as separate variables. Therefore, it would appear prudent to combine the behavioural variables into a single composite measure that appropriately accounts for the varying importance associated with individual behaviours and magnitudes.

To address these issues, a method for controlling for the spatiotemporal elements is created and discussed in Chapter 7 and a composite measure of driver behaviour is developed in Chapter 8. They are then employed in disaggregate analyses presented in Chapter 9 and Chapter 10.

7 TEMPORAL AND SPATIAL IDENTIFIERS

The dataset used for this research provides a very detailed and rich source of information on driver behaviour. However, with this level of detail the variability inherent in any behaviour – particularly one as complex as driving – can present challenges when conducting statistical analyses. The results presented in Chapter 6, demonstrate the strong influence of spatiotemporal characteristics on driver behaviour. It is therefore necessary to control for spatiotemporal factors when analysing driver behaviour so as to isolate the driver and vehicle characteristics, which are the primary objective of this research. To achieve this, a method was devised to control for spatial and temporal factors by assigning a unique temporal and spatial identifier (TSI) to each GPS observation. This chapter discusses the composition of these TSIs, explains how they are determined and demonstrates its practical application.

It is recognised that classifying factors as spatial or temporal is subjective and that many factors are a function of both spatial and temporal environments. Although the construction of TSIs treats these as separate components, TSIs have been designed to be treated as a single unified entity and therefore the exact division between a temporal and spatial variable is not critical. The methodology can be applied without needing to make this distinction and is included primarily to make the TSIs easier to identify at a glance. Nonetheless, it is important to understand that all the factors (regardless of classification) are related directly or indirectly to each other and to factors that have not been included.

Figure 7-1 is a simplified illustration of the complexity involved in determining the relationships and interactions that exist between the different factors in driver behaviour. There is significant interaction between temporal and spatial characteristics and it might be anticipated that each driver's response to particular factors would also differ based on their personality and the vehicle. In fact, many of the factors shown in Figure 7-1 – which are not exhaustive – could be considered both spatial and temporal. For example, congestion is known to occur more frequently during peak hours but is also observed to a greater extent on the same roads, which may have a number of common characteristics. Although the factors that have been included are limited due to the availability of data, the TSI methodology is flexible enough to incorporate as many additional factors as required provided the data and computing resources are adequate.

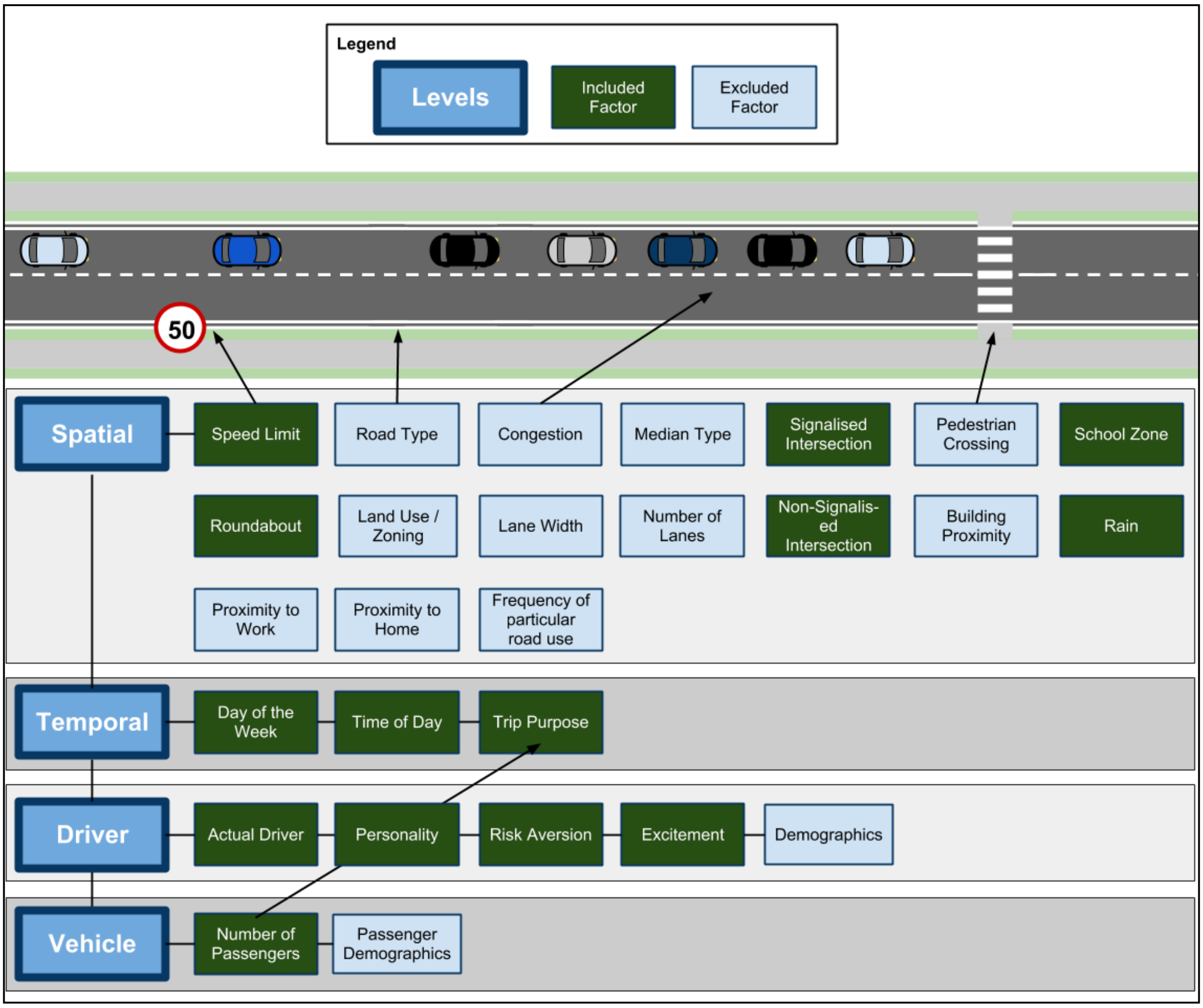

Figure 7-1: Relationships between temporal and spatial factors

7.1 Spatial factors

Spatial factors represent the variables that change based on the location of a vehicle. There are many spatial factors that could be included but comprehensive and detailed data is not available for every factor. Factors for which there is no data or for which there is only incomplete date have not been included Figure 7-1. For the spatial factors for which data is available, a selection of the most pertinent factors has been selected although the algorithm has been developed such that additional variables can be included at a later date. Table 7-1 lists the spatial factors considered for inclusion in this research. Factors with a light grey background are included; those with a white background are excluded.

Table 7-1: Spatial factor data availability

Data Available	Incomplete Data Available	No Data
Signalised intersection	Road geometry	Fencing
Non-signalised intersection	Road type	Pedestrian crossing
Four-way intersection	Proximity to work location	Pedestrian refuge
T-intersection	Speed camera (approximate)	Road marking
Roundabout	Urban / rural classification	Median type
Speed limit	Residential / business classification	Building proximity
Rain		Lane width
School zone		
Proximity to home location		

Four-way intersections and t-intersections are subsets of signalised and non-signalised intersections. They are not included in the TSI in order to keep the number of unique TSIs to a manageable level (see Section 7.7). Proximity to the home location is not included in the TSI for the same reason. However, in this case this variable can be included as an additional variable within each road segment and used as an independent variable in any analyses.

Each spatial factor is assigned one or more unique codes – depending on the number of categorical values – which represent the characteristics that apply to that TSI. Table 7-2 lists the codes for each spatial factor that is included in TSIs. If a factor is not present it is not used – for instance the code for a school zone is "S" and the code for no school zone is null.

Table 7-2: Spatial factor identifier codes

Variable	Code	Description
School Zone	S	Active school zone
Rain	R	Rain detected (any amount)
Signalised intersection	I	Presence of signalised intersection within 25m on-road (any direction)
Non-signalised intersections	N	Presence of non-signalised intersection within 25m on-road (any direction)
Speed limit	40,50,60,70,80,90,100,110	Speed limit of the road
Roundabout	O	Presence of roundabout within 25m on-road (any direction)

7.2 Temporal factors

Temporal factors represent the variables that change through time without reference to location. Table 7-3 lists the temporal factors considered for inclusion in generating TSIs. As with the spatial factors, they do not represent all the factors that are included in this research.

Some temporal factors (trip purpose, number of passengers) do not change within a trip. Other temporal factors (time of day, day of the week) may or may not change during a trip.

Table 7-3: Temporal factor data availability

Data Available	Incomplete Data Available	No Data
Time of day		Speed ratio
Day of the week		Congestion
Driver[93]		Demographics of Passengers
Trip purpose		
Number of passengers		

As with the spatial factors, each included temporal factor is assigned one or more unique codes depending on the number of category values. The absence of a binary variable (weekend and primary driver) indicates that it does not apply. The one exception to this rule is trip purpose. Although there is always a trip purpose relating to a particular observation, in some cases it is desired to exclude trip purpose from the TSI to both reduce the number of unique TSIs and to increase the number of segments associated with some of the less frequently occurring TSIs. In these cases, trip purpose may still be included as an independent variable in road segment level analyses since the trip purpose does not change within a trip or road segment.

[93] In this study the driver of each trip is identified and only driving by the primary driver is included. The primary driver is the driver who completed the demographic and psychological surveys.

Table 7-4: Temporal factor identifier codes

Variable	Code	Description
Time of Day	TM,TD,TE,TN	Morning (05-08:59), Day (09-14:59), Afternoon/Evening (15-19:59) and Night (20-04:59)
Weekend	W	Indicates if trip occurs on the weekend
Primary Driver	D	Indicates if driven by the primary driver
Trip Purpose	PH, PW, PE, PR, PS, PO	PH (returning home), PW (work related), PE (education), PR (recreation), PS (shopping) and PO (other)
Passengers	P0,P1,P2,P3	Number of passengers: 0, 1, 2, 3+

7.3 Composition of temporal and spatial identifiers

A TSI takes the form of a string (text), which includes a number of binary and categorical characteristics of a particular road environment at a particular point in time from the spatial and temporal characteristics listed in Table 7-2 and Table 7-4. Binary characteristics such as the proximity of a non-signalised intersection are only included if they apply. The TSI is bounded by curly brackets with a comma separating spatial and temporal factors. Each factor is delineated by a hyphen. Although the order of the factors does not matter as each code uniquely represents a single factor or factor value, maintaining the same order allows for less computationally intensive TSI matching. An example is shown in Figure 7-2.

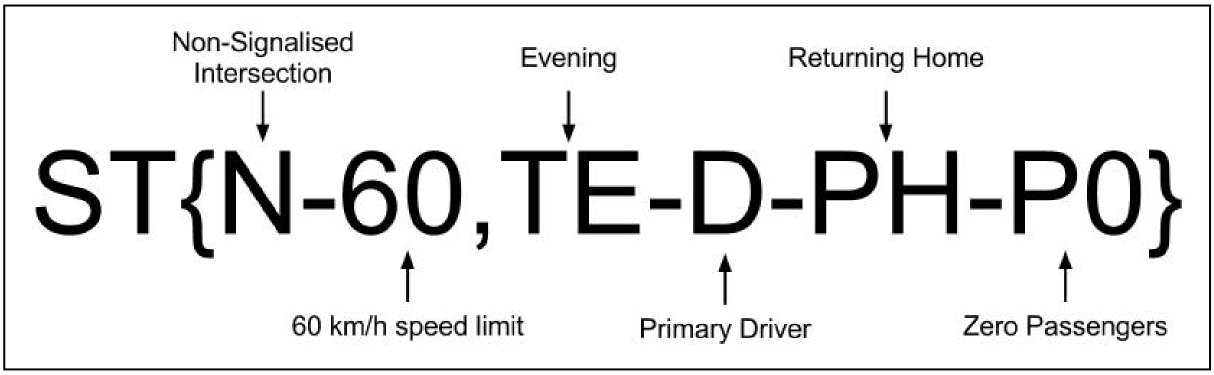

Figure 7-2: Example of temporal and spatial identifier (TSI)

Each second-by-second observation of GPS data is assigned a TSI based on the characteristics associated with that latitude and longitude and that particular date and time. For example, the TSI in Figure 7-2 is assigned to an observation with the following spatial characteristics:

- Within 25 metres of a non-signalised intersection (N);
- In a 60 km/h speed limit (60);
- Not in a school zone (absence of S);
- Not within 25 metres of a signalised intersection (absence of I) or roundabout (absence of O); and
- Not raining at that time (absence of R).

Similarly, the same observation has the following temporal characteristics:

- In the afternoon or evening from 15:00 to 19:59 (TE);
- Not on the weekend (absence of W);
- Driven by the primary driver in the study (D);
- Trip purpose is returning home (PH); and
- With zero passengers (P0).

Observations with exactly the same TSI are considered to be spatially and temporally similar to each other. It is important to note that although a one character difference in the TSI may at first appear to be a small difference it can represent a very different temporal or spatial environment. Using the example in Figure 7-2 again, ST{N-60,TE-D-PH-P0} appears very similar to ST{60,TE-D-PH-PO} but the latter is not within close proximity to a non-signalised intersection and therefore one could reasonably expect quite different driving behaviour.

7.4 Observation and road segment identifiers

At this stage the dataset remains as one observation per second. A unique second-by-second observation identifier is assigned to every observation. This includes observations that are subsequently excluded from the analysis. The purpose of this identifier is to uniquely identify each observation within the dataset so that any analyses or aggregation performed later can be linked back to the original observations. The identifier is assigned sequentially by the database when the TSI is assigned to the observation. This identifier is not used for analysis.

In addition, each observation is related to other observations by the driver, trip and the road environment. The road segment is one unit of analysis and represents a particular stretch of road and forms the relationship between sequential observations. Each segment is a series of uninterrupted observations that share the same spatial and temporal characteristics and therefore share the same TSI. Unlike the TSI, the road segment identifier (RSI) is unique to a particular segment at a specific time and for a specific driver. In the same manner as the observation identifier, the RSI is assigned sequentially by the database when a road segment is created. This should not be interpreted as meaning that sequential RSIs relate to temporally sequential road segments since they may have been observed on different days or involve different drivers. The purpose here is to enable individual road segments to be identified when used for an aggregate analysis. These identifiers do not have any meaning or impact on the analyses themselves.

7.5 Creating road segments using temporal and spatial identifiers

The second-by-second dataset contains over 80 million observations and can be difficult to analyse due to the computational resources required to manage such a large dataset. Road segments are a method of aggregating these individual observations such that the dataset is more easily analysed yet retains the spatiotemporal variables which previous research has shown to be important. Note that the road segments described in this section use more variables as delimiters of road segments and therefore create more road segments with shorter distances than the speed limit road speed segments described in Section 5.4.

In this case, road segments are generated from sequential second-by-second GPS observations and are not directly related to the physical road. A new road segment starts at the beginning of each trip and every time the TSI changes. This means that turning onto a different road does not create a new road segment unless the TSI also changes. An illustration is shown in Figure 7-3.

In the example shown in Figure 7-3, the vehicle is shown in a 60 km/h zone without any school zones or nearby intersections in Segment 1. When the vehicle reaches 25 metres from a signalised intersection, a new road segment starts (Segment 2). The vehicle then turns left onto another road but the road segment remains the same as the spatial characteristics are still the same. Specifically these are a 60 km/h speed limit, a signalised intersection within 25 metres and not a school zone. After travelling for 25 metres on this road, the vehicle enters an active school zone[94] with a 40 km/h speed limit and no intersection within 25 metres. At this point Segment 2 ends and Segment 3 starts.

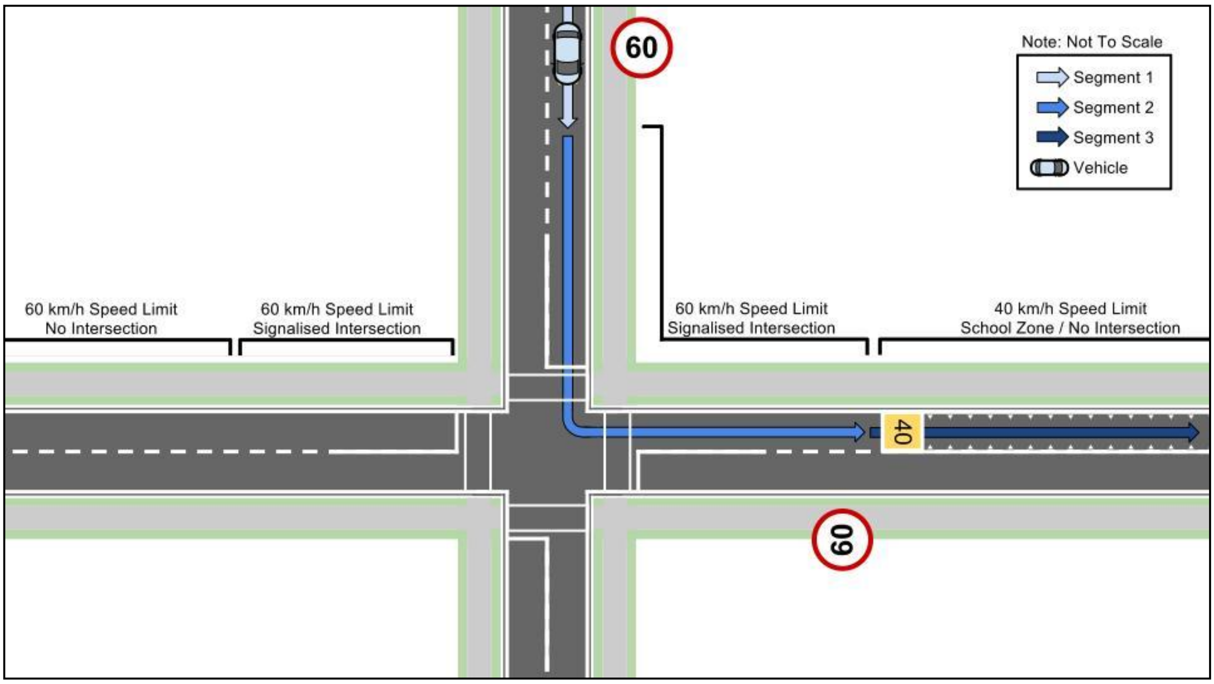

Figure 7-3: Road segments

The same example used in Figure 7-3 can be shown using the TSI coding described in Section 7.3. In this way it is possible to see how the TSI changes from one segment to another. In this case, illustrated in Figure 7-4, the temporal component does not change from one segment to the next since all occur on a weekday in the morning time category from 05:00 to 08:59. In contrast, the spatial component which is represented by the codes before the comma delimiter does change from one segment to another. In Segment 1 the speed limit is 60 km/h with no nearby intersections, school zones or rain. In Segment 2, although the speed limit remains 60 km/h, the vehicle is now within close proximity to a signalised intersection and therefore the code for a signalised intersection ('I') has been added. In Segment 3 there are three spatial differences from the previous segment. The vehicle is now in a school zone (indicated by 'S') and the speed limit is now 40 km/h (indicated by '40'). In addition, since the

[94] An active school zone is a school zone within its operating hours.

vehicle is no longer in close proximity to a signalised intersection the code that represents a signalised intersection ('I') is dropped from the TSI.

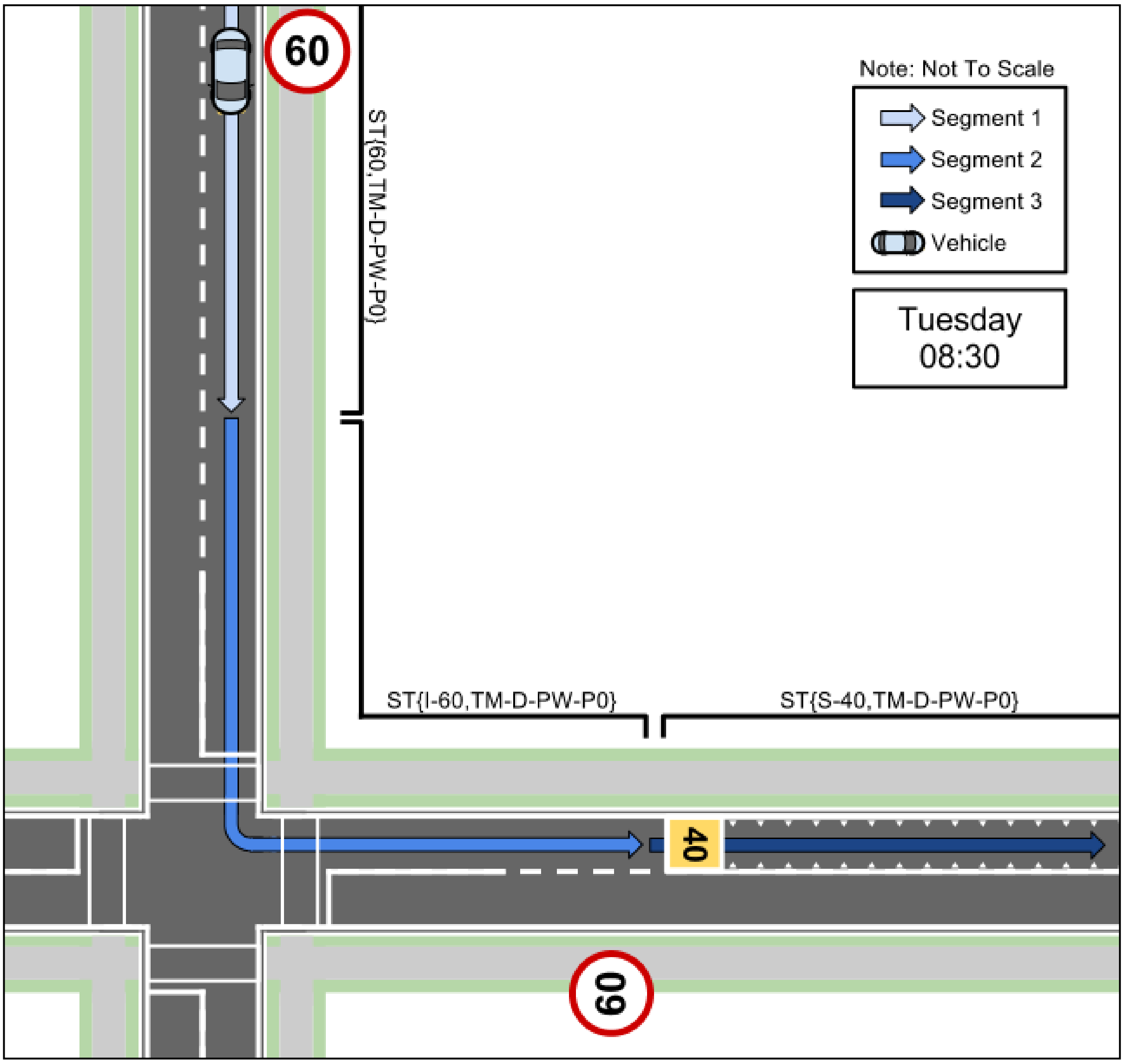

Figure 7-4: Road segment temporal and spatial identifier (TSI)

The components of a TSI which are derived from trip-level variables – such as the driver, the trip purpose and the number of passengers – never change within a trip. Therefore, all the road segments in the same trip share some common elements in each segment's TSI. Using Figure 7-4 again, the primary driver (D), the trip purpose (PW) and the number of passengers (P0) do not change. The time of day element (TM) may or may not change during a trip.

7.6 Aggregated variables for road segments

Aggregate variables are created for speeding, acceleration and braking (negative acceleration) behaviour for each road segment. Speeding behaviour is measured by the distance driven over the speed limit (at various magnitudes) as opposed to by time. Acceleration and braking behaviour is measured by the number of events (or observations). The aggregate behavioural measures created for each road segment are summarised in Table 7-5 based on the behavioural measures discussed in Section 5.3.

Table 7-5: Summary of aggregate road segment behavioural measures

Speed (km/h)	Acceleration (m/s^2)[95]	Deceleration (m/s^2)[96]
Maximum	Maximum	Maximum
Average[97]	Average	Average
Minimum	Standard deviation	Standard deviation
Standard deviation	Absolute number of events where acceleration is ≤ 1, ≤ 2, ≤ 3, ≤ 4, ≤ 5, ≤ 6, ≤ 7, ≤ 8, ≤ 9 and > 9 m/s^2	Absolute number of events where negative acceleration is ≥ -1, ≥ -2, ≥ -3, ≥ -4, ≥ -5, ≥ -6, ≥ -7, ≥ -8, ≥ -9 and < -9 m/s^2
Total distance at any speed		
Distance at 75% of speed limit	Absolute number of events where acceleration[b] is ≤ 10%, ≤ 20%, ≤ 30%, ≤ 40%, ≤ 50%, ≤ 60%, ≤ 70%, ≤ 80%, ≤ 90% and > 90% of the maximum acceleration by that driver.	Absolute number of events where negative acceleration[c] is ≤ 10%, ≤ 20%, ≤ 30%, ≤ 40%, ≤ 50%, ≤ 60%, ≤ 70%, ≤ 80%, ≤ 90% and > 90% of the maximum negative acceleration by that driver.
Distance at ≥ 1 km/h over speed limit[a], ≥ 5 km/h, ≥ 10 km/h, ≥ 15 km/h and ≥ 20 km/h		

[a] Speed categories overlap (i.e. 1+, 5+, 10+, etc.)
[b] Acceleration categories are distinct (i.e. ≤ 1 consists of acceleration events > 0 m/s^2 and ≤ 1 m/s^2)
[c] Deceleration categories are distinct in the same manner as acceleration events.

Speeding behaviour is aggregated by summing the VKT within a segment driven at speeds in excess of the speed limit in various cumulative categories[98]. In contrast, acceleration and deceleration is aggregated by counting the number of observations within distinct categories 1 m/s^2 in size and (as an alternative measure) as a

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[95] No minimum acceleration is recorded because when the speed (velocity) remains the same, acceleration is zero.

[96] Negative acceleration and braking are equivalent.

[97] Each observation is weighted by distance travelled (VKT) to ensure that observations at lower speeds are not overrepresented.

[98] Although the speeding categories are cumulative such that driving at >= 1 km/h includes all driving at >= 5 km/h, 10 km/h, 15 km/h and 20 km/h, these categories can be disaggregated to create distinct categories when necessary for a particular analysis.

proportion of the maximum acceleration observed by that driver for the duration of the study period. This alternative measure corrects for the differences in vehicle capabilities and allows for a more equal comparison between drivers. An example of this is shown in Figure 7-5 where in a 10 second/observation, 204 metre segment speeding by 1 km/h or more is 168 metres (82 percent), speeding by 5 km/h or more is 60 metres (29 percent) and speeding by 10 km/h or more is 0 metres (zero percent).

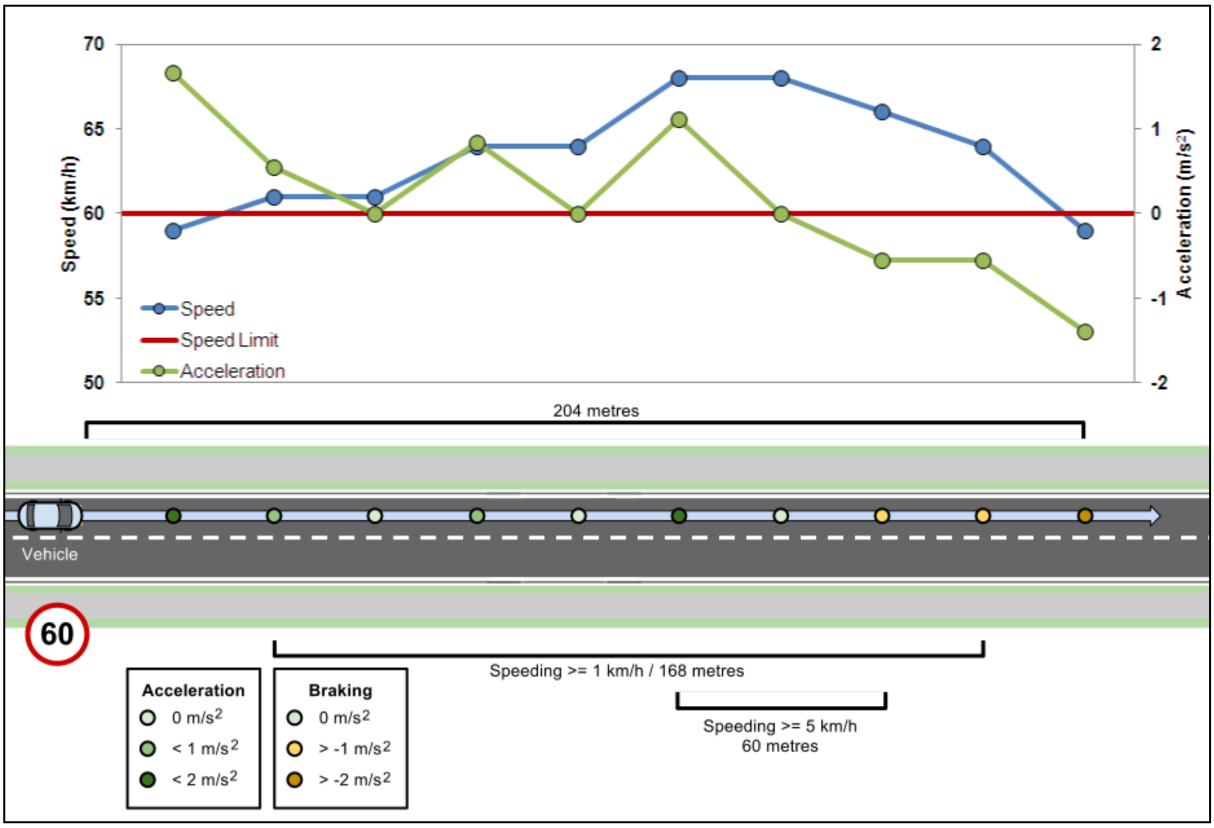

Figure 7-5: Example of aggregation of speeding and braking variables for road segments

To account for differences in the number of observations and the distance driven in different road segments, the proportion of distance (for speeding) and observations (for acceleration and braking) is taken for each road segment. In both cases, observations where the speed is zero km/h are excluded. When conducting analyses using the aggregated dataset, each road segment is weighted by total distance such that a 1 km (1000 m) segment has twice the weight of a 500 m segment.

7.7 Characteristics of aggregated dataset

The aggregated dataset (for primary driver data) contains 1.98 million road segments for the before and after period covering over 199,904 km of driving. In total there are 6,233 unique TSIs across the dataset across all drivers. The most common TSI, ST{60,TE-D-PH-P0}, is associated with 35,448 road segments which is equivalent to 1.8 percent of all road segments. At the other extreme, 525 TSIs are only associated with a single road segment. Figure 7-6 and Figure 7-7 show the distribution of TSIs by frequency and VKT on logarithmic scales. In both cases, there are a small number of very high frequency (or high distance) TSIs and a very long tail.

For the purposes of analyses, TSIs with frequencies of less than 20 road segments per driver are excluded. This threshold is considered on a driver-by-driver basis and therefore a TSI which is excluded for one driver may not be excluded for another. Examples of TSIs which are excluded on this basis include TSIs with a speed limit that is unknown or below 40 km/h – which in the study area are limited to parks and private roads – and weekend education trips with no passengers.

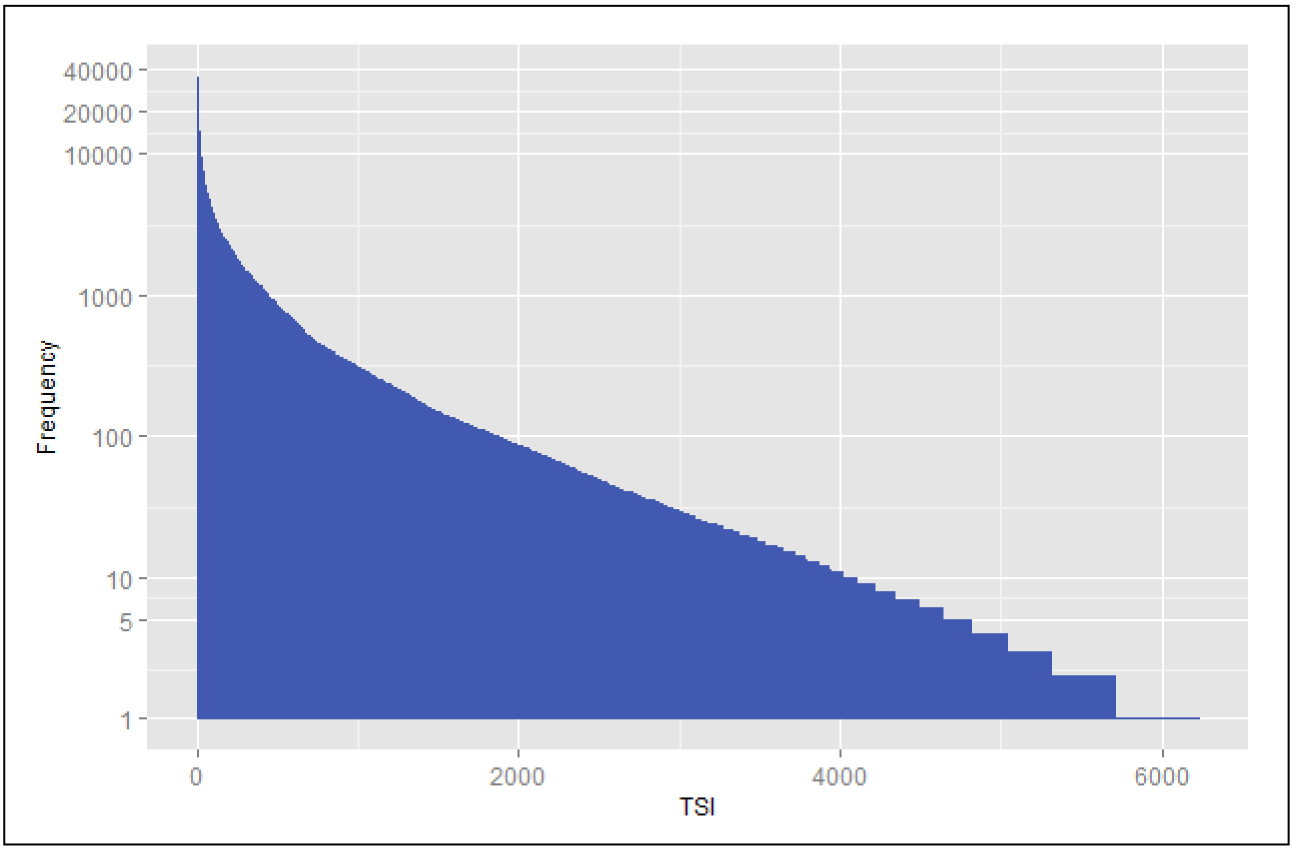

Figure 7-6: Unweighted temporal and spatial identifier road segment frequency

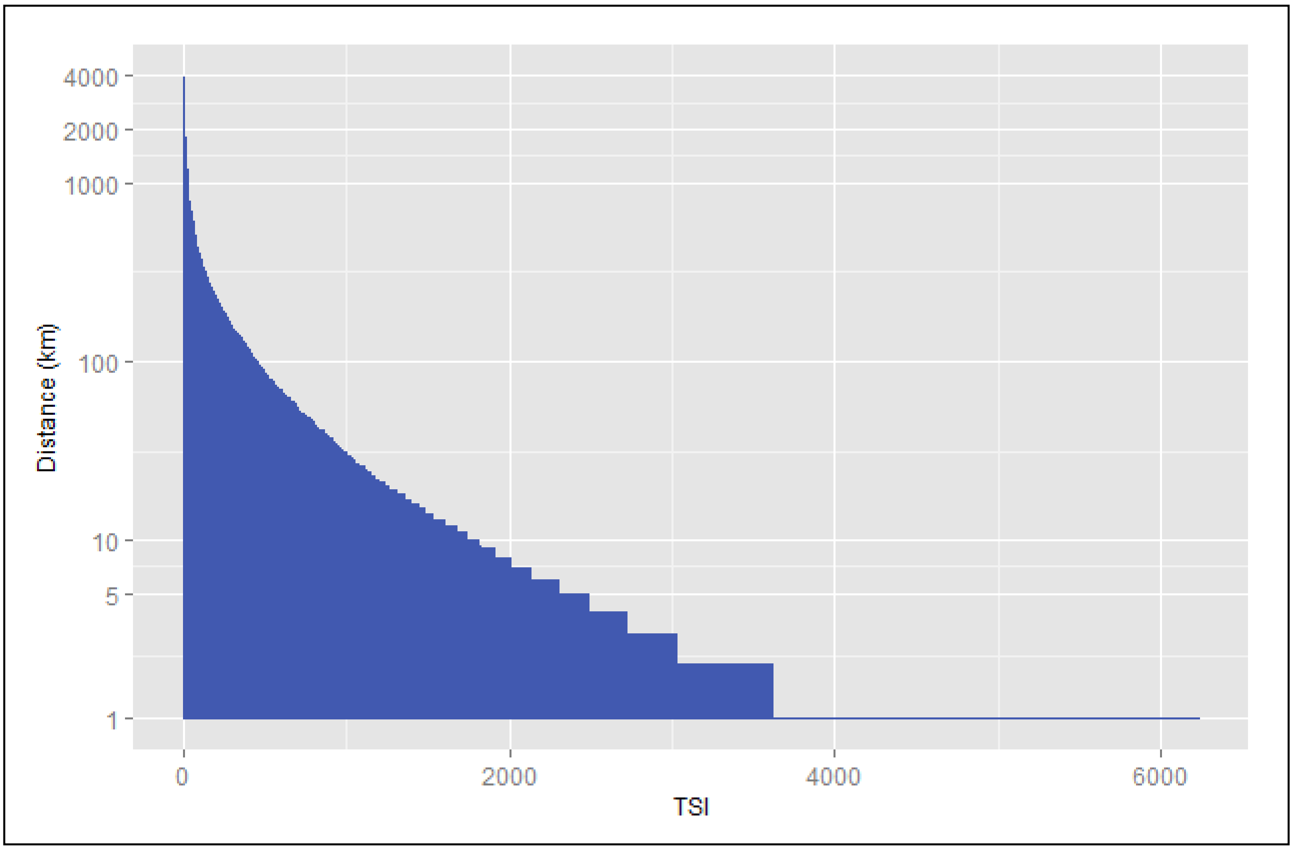

Figure 7-7: VKT by temporal and spatial identifier

When trip purpose is excluded from the construction of TSIs, the number of road segments remains the same at 1.98 million but the number of unique TSINTPs is reduced to 1,671. The most common TSINTP is ST{60,TE-D-P0} which is associated with 67,456 road segments covering a distance of 7,513 km. In comparison, 121 TSINTPs are associated with a single road segment. The distributions of both the frequency (Figure 7-8) and VKT (Figure 7-9) for TSINTPs are similar to those of TSIs which include trip purpose shown in Figure 7-6 and Figure 7-7.

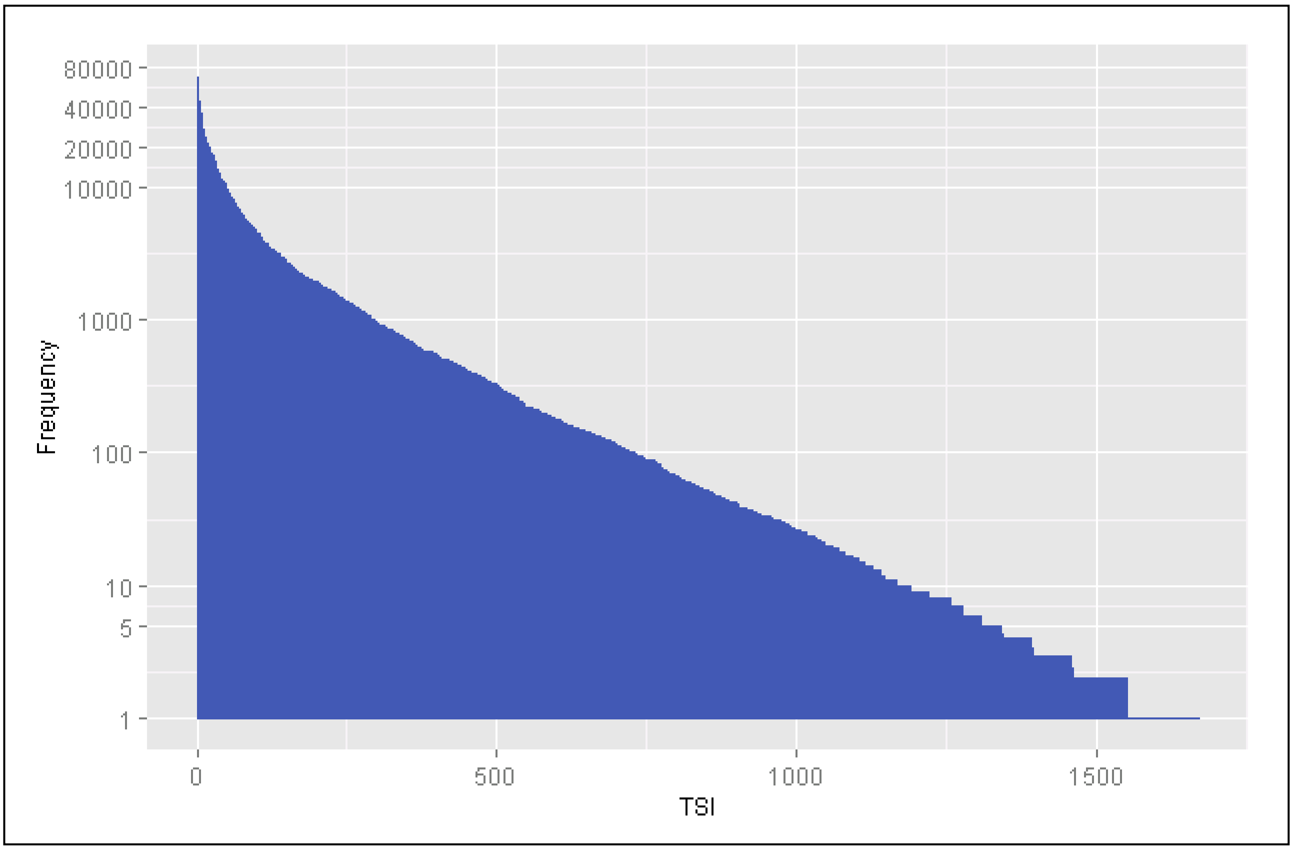

Figure 7-8: Temporal and spatial identifier (excluding trip purpose) frequency distribution

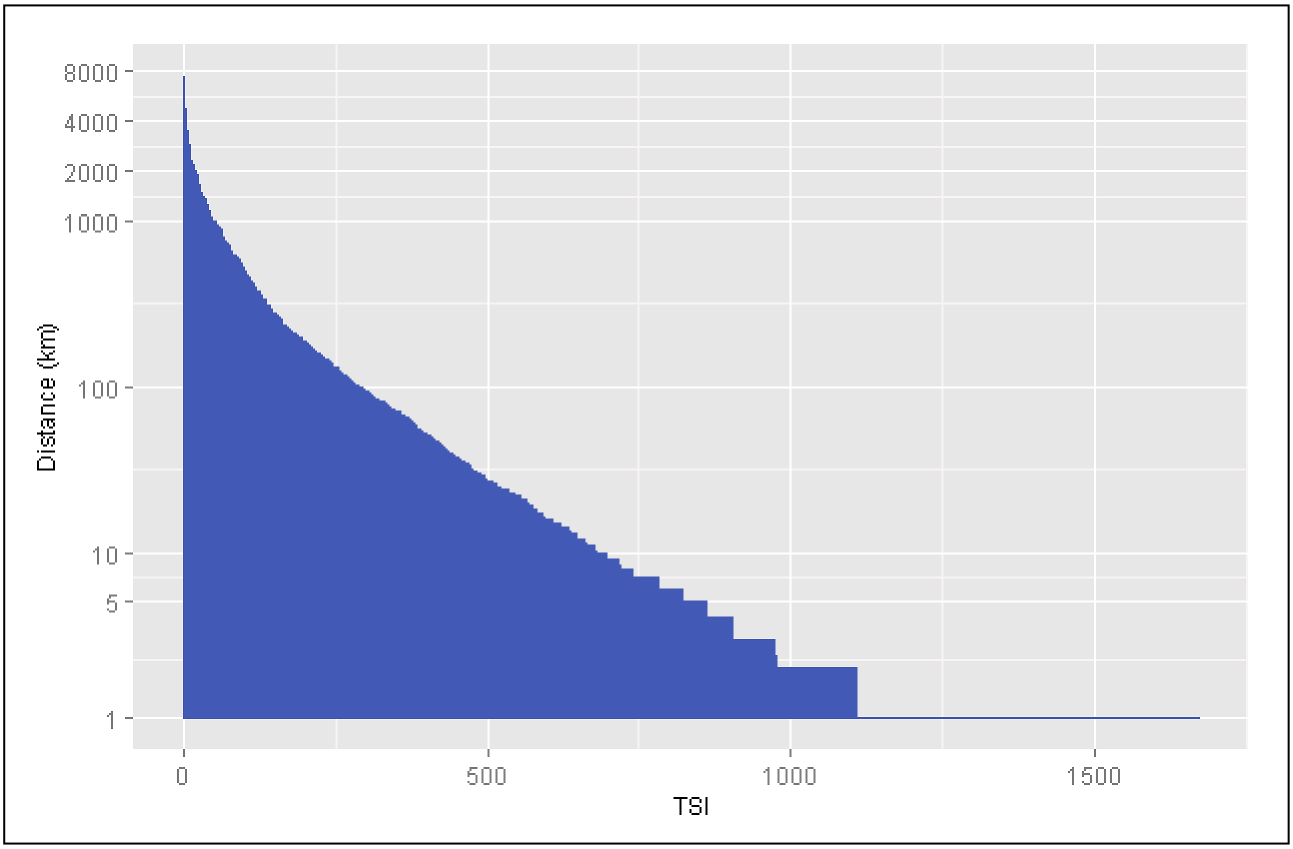

Figure 7-9: VKT by temporal and spatial identifier (excluding trip purpose)

7.8 Verifying validity of TSI approach[99]

To recap, the purpose of the TSI approach is to control for the influence of spatial and temporal characteristics on driver behaviour such that the unexplained longitudinal and cross-sectional heterogeneity of driver behaviour would be reduced between and within TSIs. The issue here is not the frequencies or magnitudes of behaviours – which were not analysed in this process – but the variability of behaviour for the same driver and road environment.

To test this, the standard deviation (SD) for the aggregate measures of driver behaviour (speeding, acceleration and braking) described in Section 7.6 were calculated for three sets of road segments:

a) All road segments by the same driver;
b) All road segments with the same TSI by all drivers; and
c) All road segments with the same TSI by the same driver.

The base case is the SD for all road segments by the same driver (a) that represents variability without consideration of the spatiotemporal characteristics. Subsequently, the difference between the SD for each TSI-driver combination (c) and the SD for the same driver across all road segments (a) was taken. The SD for each driver (a) was compared to the SD for each individual driver in the same TSI (c). If for a given driver the SD across all road segments (a) is more than the SD for the same driver in each TSI (c) then that driver exhibits greater between-environment variability than within-environment variability in (for example) speeding behaviour and vice versa. The results, shown in Figure 7-10, indicate that for all behavioural measures, most drivers exhibit more variability between TSIs (environments) than variability within TSIs (environments). This appears to reflect the fact that drivers are more consistent in their behaviour – particularly in speeding behaviour – than may have been previously assumed. However, this consistency is confined to the same TSI which represent particular spatiotemporal environments and therefore goes some way to explaining

[99] Parts of Section 7.8 and Section 7.9 were accepted for publication as Ellison et al. (2013b) in Transportation Research Record.

why attempts at explaining behaviour at an aggregated driver level (as was done in Chapter 6) have proven problematic.[100]

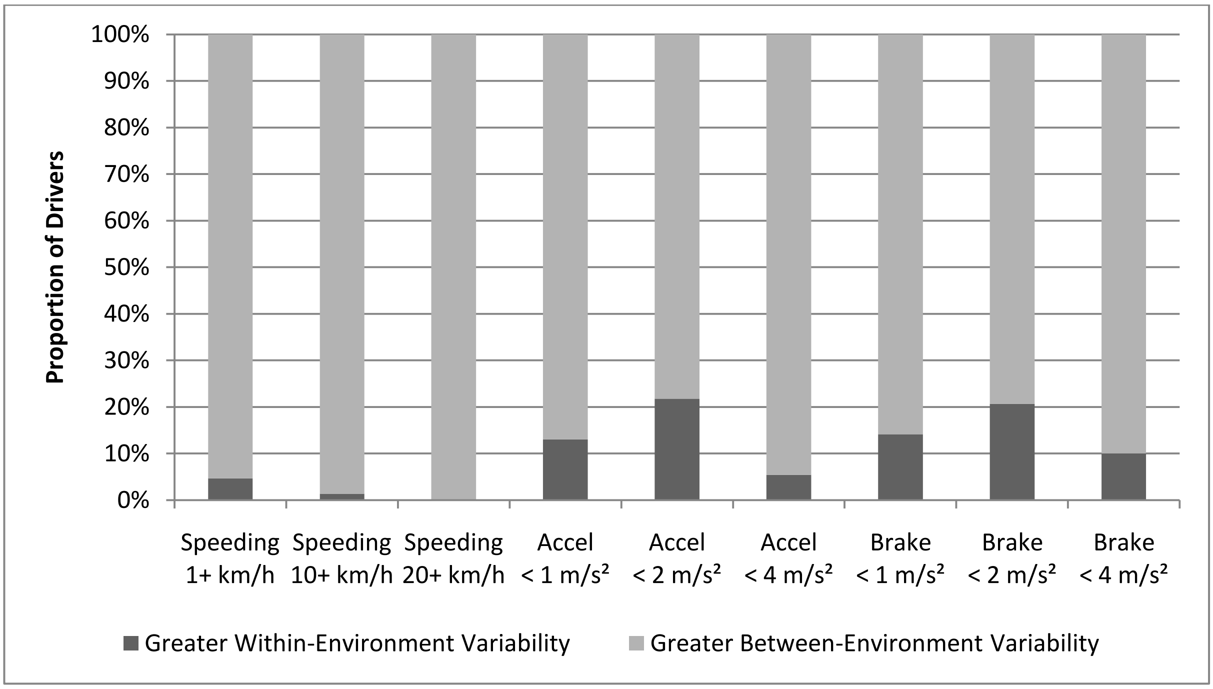

Figure 7-10: Within-temporal and spatial identifier vs. between-temporal and spatial identifier variability by driver[101]

The same procedure was then repeated using the SD for a particular TSI (b) and the SD for each driver for that same TSI (c). The results, shown in Figure 7-11, illustrate that 80 percent of TSIs have more cross-sectional variability in speeding than longitudinal variability. This means that in 80 percent of spatiotemporal environments, each individual's speeding behaviour is less variable than the overall behaviour of the sample. Therefore, holding the spatiotemporal factors equal isolates the influence of the driver allowing for greater differentiation between drivers.

In Figure 7-11, measures of speeding behaviour are speeding by 1 km/h or more, 10 km/h or more and 20 km/h or more – note these are overlapping categories in that

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[100] Some of this variability may be captured by the speed limit, however, the aggregate analyses discussed in Section 6.3.2 show that there is a measurable improvement in model performance once more detailed spatiotemporal elements are incorporated.

[101] Speeding by 5+ km/h, acceleration 2-3 m/s^2 and braking 2-3 m/s^2 are not shown to improve clarity. The results follow the same patterns as the other behavioural categories.

speeding by 1+ km/h includes speeding by 10+ km/h and speeding by 20+ km/h. The measures of acceleration (accel) represent acceleration by < 1 m/s², 1 to 2 m/s² and 3 to 4 m/s². The three braking measures (brake) are measures of negative acceleration in the same 1 m/s² categories. Acceleration and braking observations ≥ 4 m/s² account for only one and two percent respectively of all observations and are therefore not shown here.

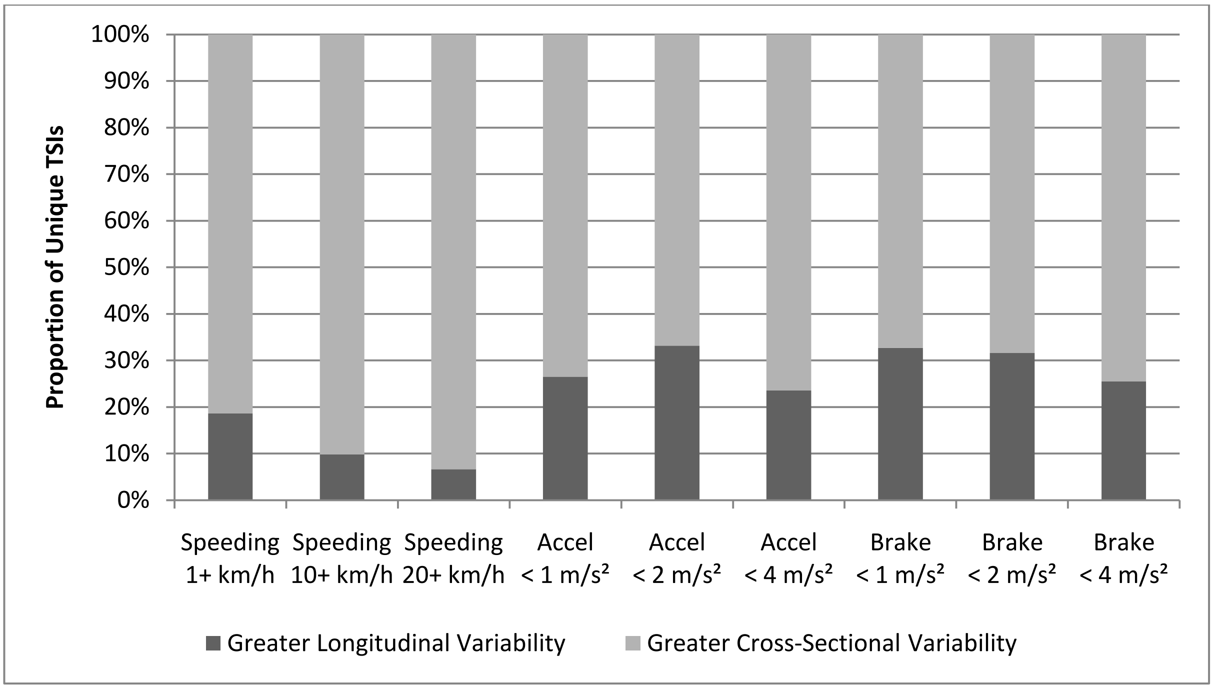

Figure 7-11: Longitudinal vs. cross-sectional variability by temporal and spatial identifier[102]

What is seen here is that by controlling for at least some aspects of the spatiotemporal environment both directly and indirectly through proxies – for example congestion by time of day, weekday or weekend and proximity to intersections – it is possible to reduce the unexplained heterogeneity in behaviour being observed for a particular driver and across all drivers. There remains some degree of heterogeneity across all measures which result from factors that have not been included or from inherent variability in human behaviour.

[102] Speeding by 5+ km/h, acceleration 2-3 m/s² and braking 2-3 m/s² are not shown to improve clarity. The results follow the same patterns as the other behavioural categories.

It is important to clarify these results explain differences in the range of behaviour exhibited by a particular driver or in a particular road environment. They do not say anything about the *magnitude* of behaviour. The same driver may therefore speed considerably more in one road environment than another but within a similar range. For example, they may exceed the speed limit by 1 km/h for 5 to 10 percent of the distance in one road environment whilst exceeding the speed limit by 1 km/h for 70 to 75 percent of the distance in another. In both cases, the range of behaviour is within a band of 5 percent.

7.9 Applying the TSI method

The TSI method successfully controls for the influence of spatiotemporal characteristics on driver behaviour. Applying this approach to data modelling and analysis is done primarily in two ways which are described in this section.

7.9.1 Individual TSI models

The first – and simplest – application involves developing separate models of behaviour for each TSI as opposed to a single comprehensive model encompassing behaviour from all spatiotemporal environments. This can be beneficial in that different spatiotemporal environments exhibit a large range of variation of behaviour. Figure 7-12 demonstrates this by plotting the standard deviation of acceleration, braking and speeding behaviours (plotted on 100-point scales) identifying the extent to which this variability differs between TSIs. In some cases this can lead to (for example) regression models identifying no statistically significant variables where as individual models can identify significant variables for particular TSIs.

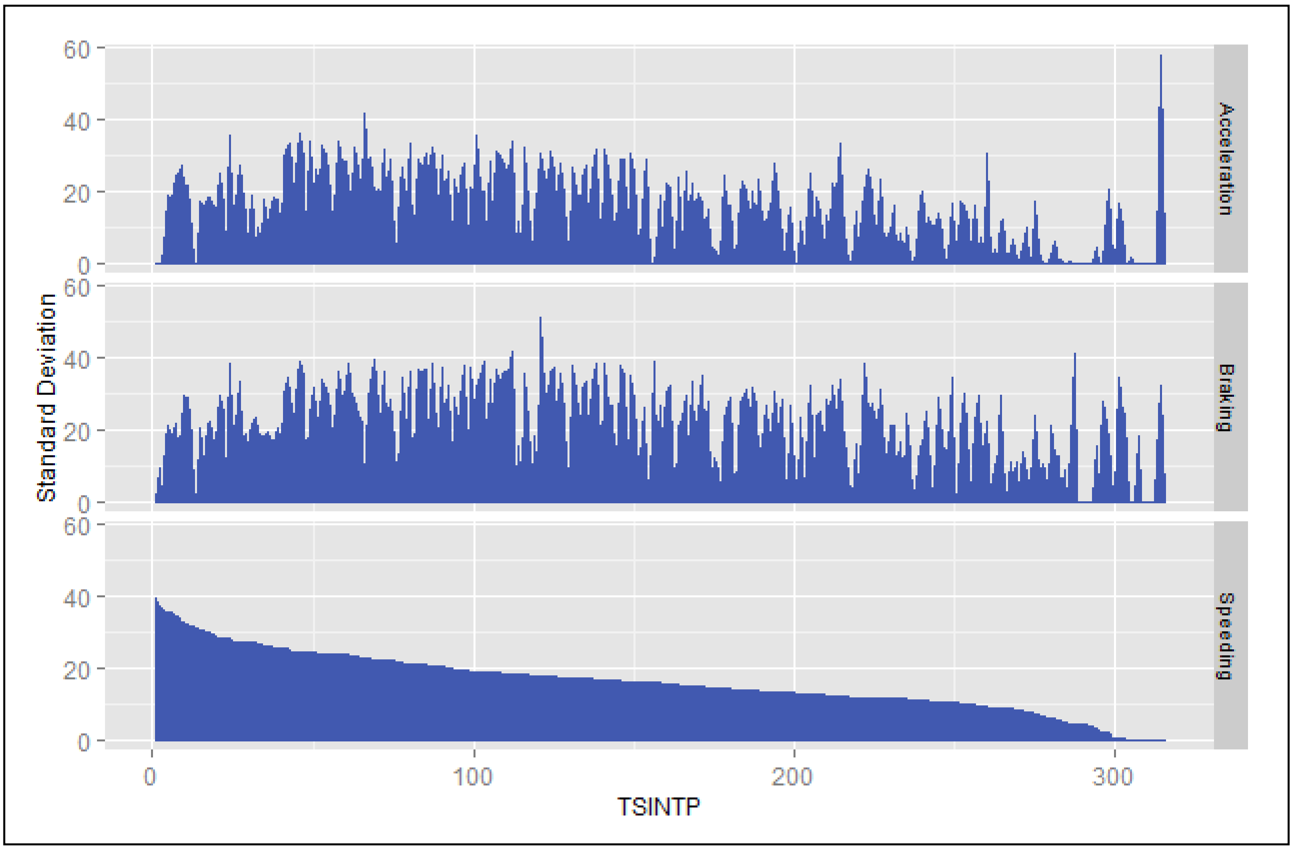

Figure 7-12: Standard deviation of driving behaviours by temporal and spatial identifier (excluding trip purpose)[103]

As a case study, individual cluster and binary logistic regression analyses were conducted for five of the most frequently observed TSIs during a 25-day consecutive period[104] during the 'before' phase of the study which account for 10 percent of VKT. To ensure consistency across TSIs, identical procedures and model parameters were used for all TSIs. Better models could be developed for individual TSIs by adjusting the specifications to better account for the unique characteristics of each TSI. The models make use of the variables summarised in Table 7-6 which consist of aggregate road segment behavioural measures (described in detail in Table 7-5) and a selection of driver demographics, driver personality and vehicle characteristics described in detail in Chapter 5. The purpose of this analysis is to demonstrate the benefits of developing separate models for each TSI. However, the obvious drawback of this approach is the need to model and interpret (potentially) hundreds of individual

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[103] To simplify readability, this figure only includes TSINTPs covering distances greater than 5 km.

[104] Since different drivers commenced the study on slightly different days, a 25 consecutive period was selected such that all drivers started on the same day of the week.

models. As such, this approach is likely more appropriate when the properties of the dataset contain a relatively small number of TSIs or when a small sub-sample of TSIs is of greater interest.

Table 7-6: Additional clustering and regression variables

Variable	Name	Description
≤ 1 m/s²	Accel0P	Proportion of acceleration events within 1 m/s² distinct categories. For example, Accel0P consists of acceleration events > 0 m/s² and ≤ 1 m/s²
≤ 2 m/s²	Accel1P	
≤ 3 m/s²	Accel2P	
≤ 4 m/s²	Accel3P	
≤ 5 m/s²	Accel4P	
≤ 1 m/s²	Brake0P	Proportion of braking events within 1 m/s² distinct categories. For example, Brake0P consists of braking events > 0 m/s² and ≤ 1 m/s²
≤ 2 m/s²	Brake1P	
≤ 3 m/s²	Brake2P	
≤ 4 m/s²	Brake3P	
≤ 5 m/s²	Brake4P	
Gender	QGender	1: Male, **0: Female**
Age	Age3cat	1: 18-30, 2: 31-45, **0: 46-65** (years)
Aggression	AggrAve	Scale from 0 to 100
Altruism	AltruAve	Scale from 0 to 100
Excitement	ExcitAve	Scale from 0 to 100
Worry and concern	WorryAve	Scale from 0 to 100
Self-reported probability of having an accident in the next 12 months	ChanceOfAcc	1: ≤ 10%, 2: 11-20%, 3: 21-30%, 4: 31-40%, 5: 41-50%, 6: 51-60%, 7: 61-70%, 8: 71-80%, 9: 81-90%, **0: > 90%**
Vehicle Transmission	VehTrans	1: Automatic, **0: Manual**
Vehicle Body	VehBody	1: Sedan, 2: Hatchback, **0: Other**
Vehicle Model Year	YearOfMan	1: ≤ 1999, 2: 2000 to 2004, 0: **2005 or newer** (year)

Note: Bolded values refer to the regression reference categories and units are shown in brackets.

Each cluster analysis was limited to two clusters plus an outlier category, which was excluded from the regression analysis. A summary of the frequencies of each TSI and cluster membership is shown in Table 7-7. It is clear from examining the frequency of cluster membership in the different models that despite identical variables and cluster parameters, the resulting clusters for each model are very different. This adds credence to the need to create separate models for each TSI but says nothing about the factors associated with cluster membership. Due to this the regression results should not be compared between TSIs since they predict membership of cluster 1 and the composition of cluster 1 for each model is different.

Table 7-7: Summary of temporal and spatial identifiers frequency and cluster analysis

ST{60,TE-D-PH-P0}	**60 km/h Zone, Evening, Returning Home, No Passengers**	***(1)***
Frequency	11,555 road segments	
Cluster membership	Cluster 1 = 30%, Cluster 2 = 68.9%, Outliers = 1%	
ST{60,TM-D-PW-P0}	**60 km/h Zone, Morning, Commuting to Work, No Passengers**	***(2)***
Frequency	11,012 road segments	
Cluster membership	Cluster 1 = 42.5%, Cluster 2 = 56.5%, Outliers = 1%	
ST{N-60,TE-D-PH-P0}	**Non-signalised intersection, 60 km/h Zone, Evening, Returning Home, No Passengers**	***(3)***
Frequency	10,668 road segments	
Cluster membership	Cluster 1 = 15.6%, Cluster 2 = 83.7%, Outliers = 0.7%	
ST{N-60,TM-D-PW-P0}	**Non-signalised intersection, 60 km/h Zone, Morning, Commuting to Work, No Passengers**	***(4)***
Frequency	10,396 road segments	
Cluster membership	Cluster 1 = 95.8%, Cluster 2 = 3.1%, Outliers = 1.1%	
ST{50,TE-D-PH-P0}	**50 km/h Zone, Evening, Returning Home, No Passengers**	***(5)***
Frequency	3,503 road segments	
Cluster membership	Cluster 1 = 45.4%, Cluster 2 = 54%, Outliers = 0.7%	

Each road segment was assigned one of three possible cluster values (cluster 1, cluster 2 and outlier). Outliers were excluded leaving a dichotomous variable representing cluster membership. To identify the factors that are significant in cluster membership, a binary logistic regression procedure was run using the same variables used for the cluster analysis. The same binary logistic regression was run for each TSI. As expected, since the same variables were used to create the clusters which form the dependent variable of these regression models the model fit was very high with a pseudo-R^2 greater than 90 percent and correct classification exceeding 95 percent across cluster memberships.

To maintain consistency across models the reference dependent category was always cluster 1 even if this represented the minority cluster in terms of frequency.

Similarly, the reference categories for the dependent variables described in Table 7-6 were also maintained between models.

No statistically significant variables were found for models 2 and 3. The full results of the binary logistic regression models for the other three TSIs are presented in Table 7-8. Variable codes and descriptions are the same as shown in Table 7-6.

The most prominent result is that two of the models have no significant explanatory variables despite the excellent model fit. In fact, their presence in the model appears to be completely unnecessary and this is confirmed by running an additional step-wise binary logistic regression. It would appear that for these two models (2 and 3) in particular, despite holding the spatiotemporal variables constant there appears to be an almost random or, alternatively, an unexplained effect which is influencing drivers' behaviour in these two situations. The most logical explanation for this is congestion in the case of the second model (ST{60,TM-D-PW-P0}) as it occurs in the morning peak during the commute to work. Similarly, the third model (ST{N-60,TE-D-PH-P0}), which represents driving in the evening within close proximity to a non-signalised intersection is being influenced by potential delays in crossing or joining the connecting road. The fourth model (ST{N-60,TM-D-PW-P0}) is largely similar but has two significant variables (altruism and vehicle type) with a strong negative effect which may reflect the tendency for some drivers to behave particularly aggressively at non-signalised intersections on the way to work although caution is advised given the distorted cluster membership and the unknown state of the traffic signals at the time of each observation.

The remaining first and fifth models presented here are the only ones to show a significant effect for acceleration and braking behaviour (albeit notably with opposite signs). The fifth model is the only model presented here with a significant effect for the various speeding measures as well as a number of vehicle and driver characteristics. This is likely to reflect fewer 'hard' limits on drivers' opportunity to speed or drive aggressively on residential roads. The results indicate that on 50 km/h roads during the evening on the way home (model 5) road segments with more frequent speeding of less than 10 km/h also exhibit more aggressive acceleration and braking. The drivers also tend to prefer excitement and drive older vehicles with manual transmission. For road segments on 60 km/h roads (model 1) acceleration and braking is less aggressive for one group of road segments than the other but there is no statistical difference in speeding behaviour or in any of the driver and vehicle characteristics which suggests that there is a significant variable that has not been included in the model.

Another important finding is that gender and age variables were not significant for any model. This was true even when interactions between gender and age were accounted for.

Table 7-8: Binary logistic regression coefficients and standard errors by temporal and spatial identifier

Variable	ST{60,TE-D-PH-P0} (1)			ST{N-60,TM-D-PW-P0} (4)			ST{50,TE-D-PH-P0} (5)		
	ß	(SE)	Sig.	ß	(SE)	Sig.	ß	(SE)	Sig.
Intercept	-25.687	3937.367	.995	.697	29.741	.981	468.573	199.515	.019
Acceptable acceleration and braking									
accel0P	.007	.004	.099	.000	.020	.996	**-.002**	**.001**	**.000**
accel1P	**.151**	**.006**	**.000**	.002	.031	.941	**.043**	**.001**	**.000**
accel2P	**-.413**	**.016**	**.000**	.004	.075	.961	**-.212**	**.002**	**.000**
brake0P	**.076**	**.005**	**.000**	.001	.021	.956	**-.024**	**.001**	**.000**
brake1P	**-.258**	**.011**	**.000**	.001	.035	.978	**-.378**	**.003**	**.000**
brake2P	**.562**	**.026**	**.000**	.001	.070	.991	**.036**	**.001**	**.000**
Aggressive acceleration and braking									
accel3P	**-.256**	**.015**	**.000**	.000	.075	.996	**.196**	**.002**	**.000**
accel4P	1.541	437.236	.997	-.004	.241	.986	**.413**	**.010**	**.000**
brake3P	-.028	.034	.402	.002	.086	.983	**.093**	**.002**	**.000**
brake4P	**-.488**	**.026**	**.000**	-.003	.188	.986	**.555**	**.004**	**.000**
Speeding									
spd1P	.443	1.223	.717	-.006	.030	.834	**.050**	**.001**	**.000**
spd5P	.309	6.486	.962	-.001	.069	.986	**.052**	**.001**	**.000**
spd10P	-.025	13.719	.999	.004	.101	.972	**-.141**	**.002**	**.000**
Personality variables									
AggrAve	-23.133	140.600	.869	-1.298	2.248	.564	**-45.433**	**19.285**	**.018**
AltruNAve	13.594	113.059	.904	**-3.361**	**1.619**	**.038**	**-22.025**	**7.326**	**.003**
ExcitNAve	-2.922	84.135	.972	1.199	1.360	.378	**60.234**	**24.177**	**.013**
WorryAve	10.241	330.392	.975	2.525	2.145	.239	**23.534**	**6.192**	**.000**
ChanceOfAcc	-	-	1.000	-	-	.522	**-**	**-**	**.000**
ChanceOfAcc(1)	229.463	3529.746	.948	-2.803	8.447	.740	**75.727**	**36.864**	**.040**
ChanceOfAcc(2)	106.062	3465.110	.976	-.877	17.794	.961	**267.247**	**109.564**	**.015**
ChanceOfAcc(3)	189.962	3662.123	.959	4.610	10.839	.671	335.497	202.192	.097
ChanceOfAcc(4)	46.478	4598.694	.992	4.773	10.393	.646	250.888	118.770	.035
ChanceOfAcc(5)	156.015	3295.536	.962	1.326	11.094	.905	**17.792**	**4.587**	**.000**
ChanceOfAcc(6)	32.090	5468.383	.995	NE	NE	NE	-4.179	2437.998	.999
ChanceOfAcc(7)	49.812	3676.684	.989	NE	NE	NE	NE	NE	NE
Vehicle characteristics									
VehBody	-	-	.996	**-**	**-**	**.034**	**-**	**-**	**.017**
VehBody(1)	-53.855	1103.420	.961	-11.206	7.053	.112	**-103.254**	**36.639**	**.005**
VehBody(2)	-78.142	992.179	.937	**-9.734**	**3.753**	**.009**	**-684.121**	**308.420**	**.027**
VehTrans(1)	119.092	687.710	.863	8.237	8.719	.345	**-255.465**	**114.286**	**.025**
YearOfMan	-	-	.998	-	-	.996	**-**	**-**	**.000**
YearOfMan(1)	65.114	999.948	.948	-.333	10.169	.974	**287.189**	**122.612**	**.019**
YearOfMan(2)	-7.607	1027.086	.994	-.346	5.092	.946	**12.380**	**4.602**	**.007**

SE : standard error; - : not applicable; NE : not in equation; bold text signifies statistical significance ≤ 0.05
Non-significant variables: spd20P, Age3Cat, QGender

Although these models are merely case studies using a subsection of the data collected for this study, they demonstrate that the determinant factors in driver behaviour – for the same drivers – change from one spatiotemporal environment to another. Due to this, it would appear unwise to generalise drivers' behaviour in a particular spatiotemporal environment to disparate environments. Furthermore, in regard to modelling of behaviour in particular, it may sometimes be best to develop separate models for individual TSIs.

7.9.2 Composite models and profiling

The second approach to employing TSIs is to incorporate the TSI into a composite model – which encompasses data from multiple spatiotemporal environments – or driver profile. This is the methodology applied for the majority of the analyses presented in Chapter 9 and Chapter 10. It is introduced here but makes extensive use of the driver risk profiling methodology discussed in-depth in Chapter 8.

At its simplest level, a TSI can be included in composite models as an independent variable. This can be done as an alternative to employing interaction effects between several combinations of spatiotemporal variables. Since the TSI is a single variable, the interpretation of the models is likely to be simplified compared to an otherwise similar model which employs interaction effects for the variables that comprise a TSI. However, given the number of TSIs it is likely that attempts at modelling behaviour in this way would be impaired by outliers and, therefore, it is recommended that prior to employing this approach each TSI is weighted by a measure indicative of its importance to the factor(s) being studied such as the VKT associated with that particular TSI. Alternatively where weighting is either not desirable or a suitable weighting variable cannot be identified, TSIs which represent spatiotemporal variables with unusual or likely significant exogenous factors are excluded from the composite model and instead modelled in isolation using individual models as described in Section 7.9.1.

A more advanced composite profile (see Chapter 9) can also apply TSIs to control for spatiotemporal characteristics. Profiles allow individual scores to be calculated for individual behaviours within each TSI before combining the results of all behavioural measures in one or several scores that balance the contribution of individual TSIs against the distribution of behaviours across all TSIs. In so doing it mitigates some of the inherent problems created by outlier TSIs and provides an indication as to the range of behaviour between different spatiotemporal environments.

7.10 Excluded road segments

It is recognised that there are a large number of spatial and temporal factors that could have an impact on drivers' behaviour but are not included here. This approach can be extended to accommodate additional variables if the data are available. However, in this case some road segments must be excluded from any analysis since these segments occur in areas with substantial exogenous variability.

Intersections – and signalised intersections in particular – are locations where driving behaviour is particularly influenced by the behaviour of other changing factors for which data are not available. For example, it is not possible to determine the status of traffic lights at a particular point in time for each individual road segment nor is it possible to determine the presence (or lack thereof) of stopped or slowing vehicles at or near signalised intersections. As the focus of this research is on speeding, acceleration and braking behaviour and these measures are likely to be influenced by these unknown variables and including these segments can lead to incorrect or inconclusive results. Therefore any road segments with a TSI or TSI (excluding trip purpose) indicating the presence of a signalised, non-signalised or roundabout intersection are excluded from these analyses. After excluding these road segments and road segments associated with low-frequency TSIs (see Section 7.7) 385 unique TSIs (excluding trip purpose) remain. These comprise of 344,264 road segments driven over 107,701 km. Analyses and results presented in Chapter 9 and Chapter 10 include only these road segments.

7.11 Summary

The aggregate analyses presented in Chapter 6 identified that spatiotemporal characteristics have a considerable impact on drivers' speeding behaviour. Consistently, in integrated models, these factors were found to be significant while, in contrast, the driver characteristics – which, are of most interest in this thesis – were not. As such, to effectively study the influence of driver characteristics on driving behaviour it was deemed necessary to, somehow, control for these factors. To accomplish this, temporal and spatial identifiers (TSI) were devised to uniquely identify the spatiotemporal characteristics associated with each GPS observation or road segment. In so doing it became possible to control for the influence of spatiotemporal characteristics by holding these constant. This chapter (7) describes the development, structure and processes for applying this methodology to this, and other, datasets.

The next chapter, Chapter 8, applies this approach to creating composite measures of driver behaviour that account for the variation in risks associated with different behaviours and magnitudes of behaviour. These driver behaviour profiles (DBP) address the other main conclusion identified in Chapter 6, namely, that using a measure of (for example) speeding behaviour that does not account for differences in magnitude risk leading to incorrect conclusions.

8 DEVELOPMENT OF DRIVER BEHAVIOUR PROFILES

The hierarchical structure and very large number of observations and variables that make up the multi-source dataset, which forms the basis of this research, is appealing for several reasons. This includes less reliance on self-reported behaviour and the ability to monitor drivers for longer periods. The creation of a composite measure of drivers' speeding, aggressive acceleration and aggressive braking behaviour is designed to allow driver behaviour to be described using a single measure whilst accounting for the variability and multitude of aspects embedded within the driving task. This measure allows drivers to be compared to each other and for the same driver to be compared across time and space facilitating empirical testing of the effects of interventions in a before and after study. The driver behaviour profile is calculated from the speeding, acceleration and braking behaviour and controls for the spatiotemporal environment through the application of TSIs (see Chapter 7).

These behavioural profiles are used as the primary dependent variable in the analyses presented in Chapter 9 and Chapter 10. This chapter describes the composition, calculation and output of these profiles.

8.1 Framework

The driver behaviour profile framework shown in Figure 8-1 illustrates the different components that are included in the driver behaviour profile and how they fit together. It incorporates three types of data, namely:

- An individual driver's observed behaviour, demographics, personality and perceptions;
- Spatial and temporal data to account for the road environment such as speed limits, road types, school zones, intersections, number of passengers, time of day and day of the week; and
- Relative risk factors for behaviours derived from the literature and applied as weights depending on the magnitude of the observed behaviours.

These inputs are combined into a driver behaviour profile, which includes individual speeding, acceleration and braking scores and a composite total score on a zero to 100 point driver risk index. These scores are accompanied by risk margins, which represent the upper and lower bounds of an individual driver's typical speeding, acceleration, braking or total (composite) behaviour. Standard deviation is provided as a measure of variability within a particular measure.

The framework is designed such that each magnitude of each of the included behaviours is assigned a weight on the basis of the risk (in this case) of a casualty crash[105]. However, the origin of these weights – and the behaviours which are included – should be adjusted, added or removed as necessary depending on the behaviours of interest.

[105] A casualty crash, in this case, is defined as a crash that results in an injury or fatality consistent with its use in Kloeden et al. (1997).

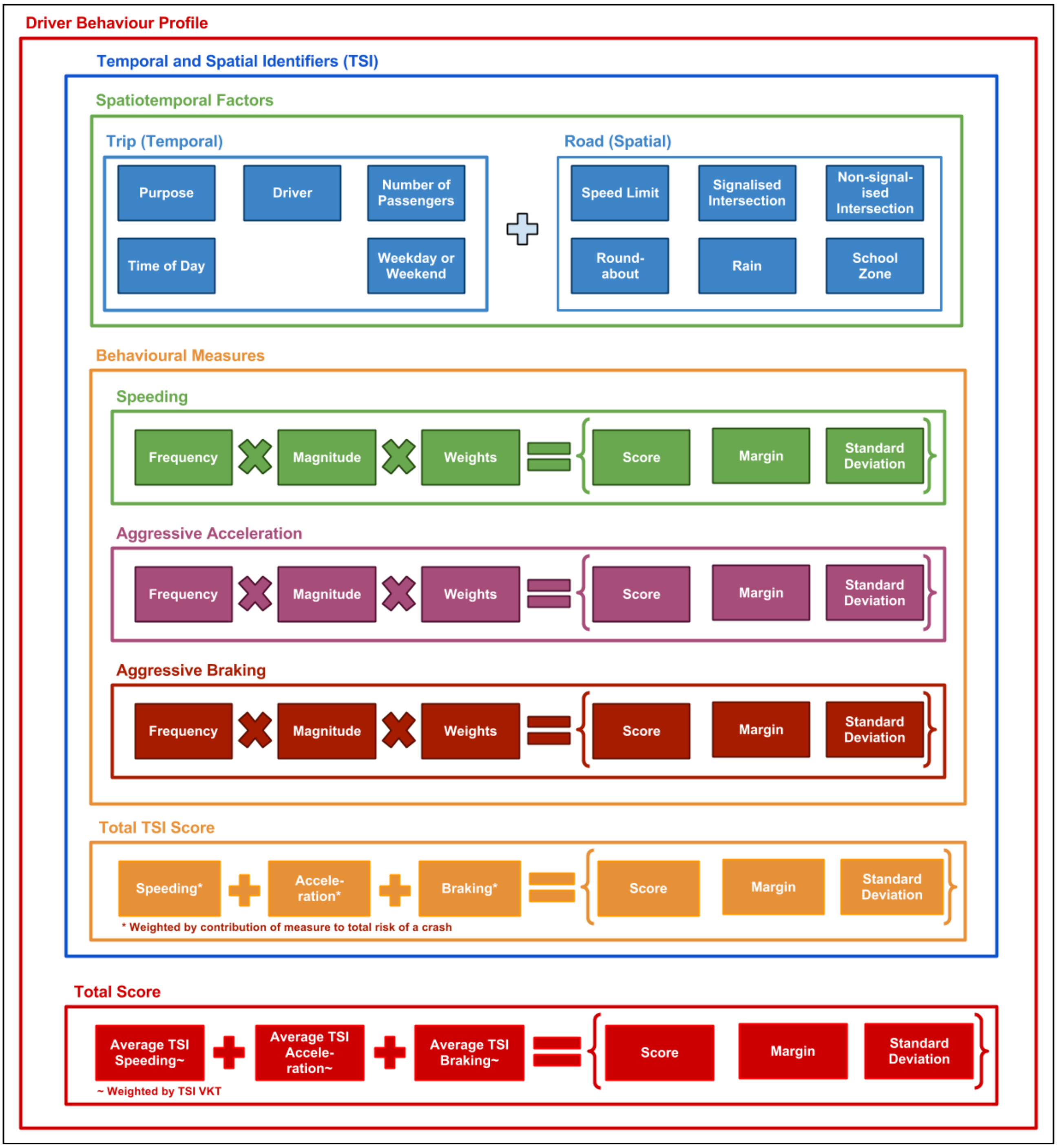

Figure 8-1: Driver Behaviour Profile Framework

The driver risk index is a normalised scale from 0 (low risk) to 100 (high risk). The score is a unit-less measure that represents how risky a particular driver is relative to other drivers. The risk margin represents the range of behaviours of the same driver. Conceptually, a low risk driver would have a low risk score and a small risk margin. Note that the scores may not be at the midpoint of the margins. An example is shown in Figure 8-2 where the low risk, medium risk and high risk drivers represent the average total scores for the lowest, middle and highest thirds of the sample.

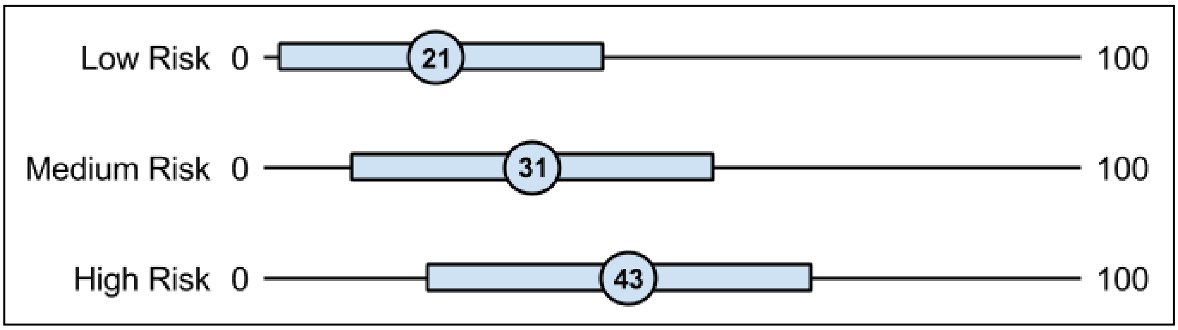

Figure 8-2: Illustration of risk index, risk score and risk margin

Each individual behaviour score is normalised to fit on a common scale which fits the 90th percentile of each of the behaviours. The composite (or total) score is calculated by applying a weight to each of the included behaviour scores such that the sum of the weights is equal to 1 thereby ensuring that the total score is on the same scale as the individual behaviours. This process is repeated for each individual TSI whose individual scores can then be used to calculate a composite score for an individual driver as a whole and scores for the entirety of the same driver's different behavioural measures. In this case these are speeding, aggressive acceleration and aggressive braking. An implementation of this framework is discussed in detail in Section 8.4.

As this is a framework, it has been designed to be flexible, and, therefore the behaviours that are included and the weights that are applied as well as the spatiotemporal factors included in the TSI can all be changed whilst maintaining the same conceptual framework. In this way it is possible to continually expand the scope of the driver behaviour profile as more data becomes available or if the outcome of interest changes. For example, it would be possible to calculate a driver environment score by applying weights to the behaviours based on the environmental emissions associated with a particular measure. Section 8.5 describes the derivation of the weights based on the risk of a casualty crash as they are applied in this research.

8.2 Profile score interpretation

Previous sections have discussed the composition and calculations involved in generating the driver behaviour profiles and its constituent scores. Interpreting these scores allows for the correct application of these profiles in analyses. All the scores included in the output are on a common 0 to 100 point scale where zero represents the lowest risk of involvement in a casualty crash and 100 represents the highest risk of involvement in a casualty crash. Crucially, a score of zero does not imply that there is no risk but instead represents the risk associated with driving according to recommended and legislative practices. If the weights used here are adjusted to include behaviour below the speed limit and/or to include acceleration and braking behaviour within normal limits a score of zero would represent the behaviour at the lowest magnitude with a non-zero weight. Similarly, a score of 100 represents the risk associated with behaviours that are unusual but have been observed[106]. Since the scale is restricted to these two points, two drivers with a score of 100 could have different behaviours, albeit both of whom at levels only observed infrequently. Adjusting the minimum and maximum points on the scale is possible but has the effect of reducing the numeric differences between drivers with more common frequencies and magnitudes of speeding, aggressive acceleration and aggressive braking behaviour. The scale limits applied in this research have been selected to maximise the numeric differences between drivers whilst maintaining the differences between TSIs. This is reflected in the distribution of risk scores and margins shown in Figure 8-10. To provide a few points of reference, in the before period, a synthetic driver created by treating the entire sample as a single driver has a total score of 34 with an upper margin of 57 and a lower margin of 11. The driver with the highest (riskiest) score has a total score of 58 and upper and lower margins of 72 and 43 respectively. In contrast, the driver with the lowest (least risky) score has a total score of 10, an upper margin of 30 and a lower margin of 0 which is the lowest possible score. Put another way, the synthetic driver's total score is at the lower margin of the risky (or 'extreme') driver and at the upper margin of the least risky (or 'safest') driver.

[106] As a consequence some drivers have TSIs with scores of 100. In addition, drivers that are not in this sample could exhibit scores of 100 representing behaviour that exceeds the 90th percentile of the behaviour in this sample.

Although the scale itself is bounded by the points set out above, any score more than zero and any score less than 100 reflects the differences in the relative risk associated with the behaviours of each driver, TSI or time period (as appropriate). A driver with a total score of 50 has a relative risk of being involved in a casualty crash twice that of a driver with a total score of 25. To use the selected drivers above, the synthetic driver has (on average) a relative risk of being involved in a casualty crash 3.4 times that of the safest driver in the sample. However, the safest driver has 3 times the risk of being involved in a casualty crash in the TSIs for which we observe the highest risk driving by that same driver compared to the average across TSIs.

8.3 Perspectives of risk

Each behaviour, spatiotemporal environment, demographic and personality trait has its own relative risk factors. These risk factors are different for the driver themselves and for other road users. At its simplest example, two drivers both exceeding the speed limit by 10 km/h – one in a school zone and one on a motorway with a 100 km/h speed limit – have different risk factors. Furthermore, although the driver in the 100 km/h speed zone has a higher risk of crashing due to their speed alone, the driver in the school zone has a higher risk of injuring or killing another road user. These risks can be broken down further by examining the relationship between a particular behaviour and:

a) The risk to the individual driver from their own behaviour;
b) The risk imposed on the driver's passenger(s) as a result of the driver's behaviour;
c) The risk imposed on other road users – pedestrians, cyclists, motorcyclists and users (drivers and passengers) of other vehicles – by the driver's behaviour; and
d) The risk imposed on the driver by other road users.

It is possible to incorporate the demographic, personality, spatial, temporal or behavioural elements by employing the relevant risk factors for each of these four perspectives. Individual risk scores could be calculated for each of these perspectives, as shown in Figure 8-3, in the same way that individual scores can be calculated for each TSI and behaviour. The sum of the relevant risk factors would represent the total risk to society imposed by that driver.

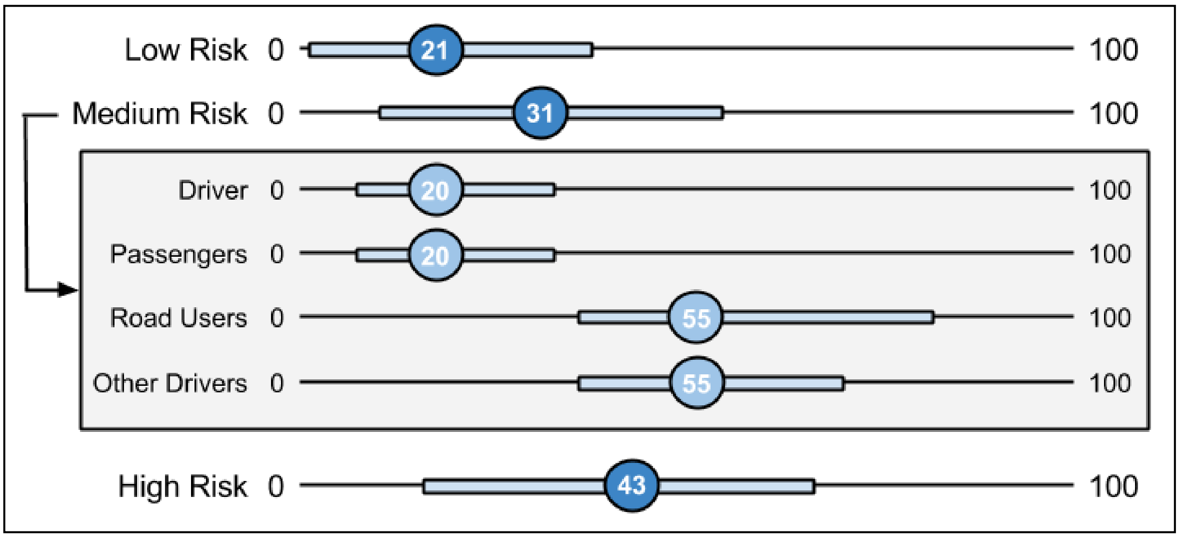

Figure 8-3: Illustrative example of risk score and margins by risk perspective

In this research, sufficient data was not available to calculate the risks to this level of detail and therefore a simplified approach has been taken which uses the risk of a driver being involved in a casualty crash as the basis for the risk calculations and, in effect, is an aggregate of the individual risk perspectives.

8.4 Driver behaviour profile algorithm

The driver behaviour profile algorithm is an implementation of the framework described in Section 8.1. The algorithm calculates the score, margin and standard deviation for each of the behaviours and the total score for each TSI. After calculating the scores for the TSI-level scores it then calculates the driver-level score, margin and standard deviation. Figure 8-4 diagrammatically illustrates the algorithm's work process. The algorithm works through each driver, TSI and segment in sequence – ignoring segments associated with excluded TSIs – before storing the results in the database.

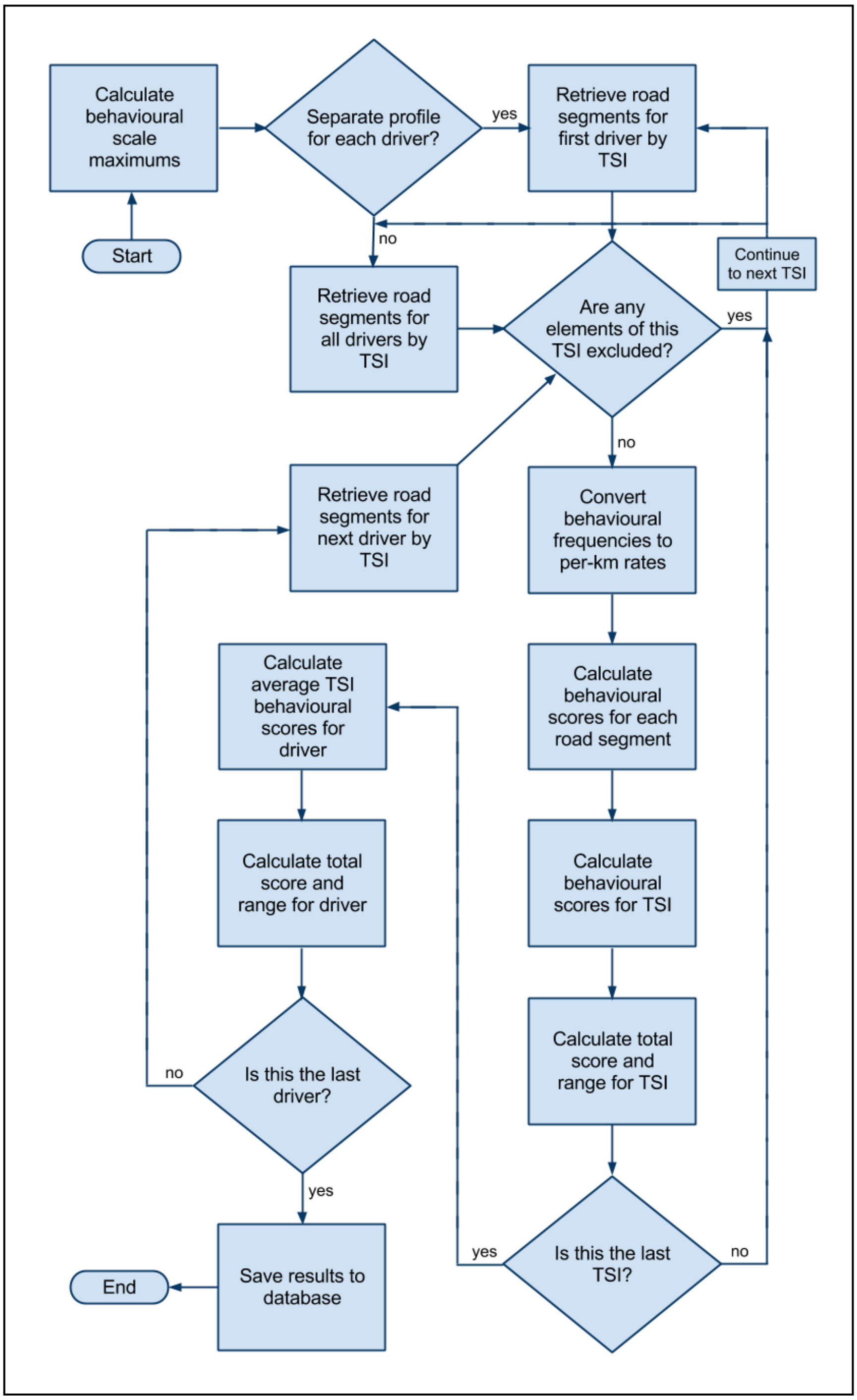

Figure 8-4: Driver behaviour profile algorithm flowchart

The basic element of the risk score calculations is the frequency of the behaviours of interest. In the case of this research these are speeding, acceleration and braking events. These are derived from the second-by-second GPS observations described in Section 4.2.3.

For each driver d, $d = 1,\dots,D$, we have $I_d + 1$ GPS observations denoted by (x_i, t_i), for $i = 0,\dots,I_d$, spanning the entire observation period, comprising multiple trips over multiple days, where x_i is the location of observation i observed at time instant t_i. For notational convenience, index d is omitted for the moment. We let the total time travelled by driver d be defined by T_d and let the total distance travelled be L_d.

We also define each time interval by $\Delta t_i \equiv (t_{i-1}, t_i)$, $i = 1,\dots,I_d$. For each GPS observation we have an observed speed, denoted by $v(x_i, t_i)$, which we assume is stationary over interval Δt_i. The distance travelled during time interval $\Delta t_i \equiv (t_{i-1}, t_i)$ – which is typically one second – is given by $l_i = \Delta x_i \equiv \|x_i - x_{i-1}\|$, where $\|\cdot\|$ is the Euclidian norm. The change in speed during time interval Δt_i (i.e., acceleration or deceleration) can be computed as $\Delta v(x_i, t_i) = \dfrac{v(x_i, t_i) - v(x_{i-1}, t_{i-1})}{\Delta t_i}$. This may yield a positive value (accelerating), negative value (decelerating), or zero meaning the speed is the same as for the previous observation.

Each observation of (x_i, t_i) can be mapped to a road segment (described in Section 7.5) comprised of sequential GPS observations with the same spatiotemporal characteristics. We let each segment be denoted by index g, $g = 1,\dots,G$. Then we define a segment mapping indicator $\delta_g(x_i, t_i)$, which equals one if (x_i, t_i) is of segment g, and zero otherwise.

Similarly, each observation of (x_i, t_i) can be mapped to a unique temporal spatial identifier (TSI) described in Chapter 7 to control for the influence of the road environment which accounts for a large proportion of the variability in driver behaviour (Familar et al., 2011). This can represent, for example, a school zone with a maximum speed of 40 km/h on a Thursday afternoon with no passengers. We let each TSI be denoted by index m, $m = 1,\dots,M$. Then we define a TSI mapping indicator $\delta_m(x_i, t_i)$, which equals one if (x_i, t_i) is of TSI m, and zero otherwise.

We can in turn map segment g to TSI m. We let δ_{gm} equal 1 if segment g is of TSI m, and zero otherwise. This is used later to determine the risk margin and standard deviations for each TSI.

We further define a number of indicators to represent the magnitudes of behaviour of speeding, acceleration and braking. Let $\delta_{mc}^{\text{speed}}(x_i,t_i)$ be an indicator that equals one if the speed $v(x_i,t_i)$ falls in speeding category $c \in C_s$, where this set of categories is defined as ranges of speeds in excess of the speed limit of TSI m, namely 1-4 km/h, 5-9 km/h, 10-14 km/h, 15-19 km/h, and 20 km/h or more. In a similar manner, we let $\delta_c^{\text{acc}}(x_i,t_i)$ be an indicator that equals one if the change of speed $\Delta v(x_i,t_i)$ falls in acceleration category $c \in C_a$, where the categories are defined as ranges of (positive) acceleration of 1 m/s^2 each, namely 0-1 m/s^2, 1-2 m/s^2 to 9 m/s^2 or more. Finally, we define $\delta_c^{\text{brake}}(x_i,t_i)$ as the indicator that equals one if the change in speed $\Delta v(x_i,t_i)$ falls in braking category $c \in C_b$, where the categories are defined as ranges of (negative) acceleration of 1 m/s^2 from 0 to 1 m/s^2, 1 to 2 m/s^2 until 9 m/s^2 or greater.

From the previously defined indicators, we can then calculate speeding, acceleration and braking scores for each segment in each TSI for each driver (adding driver index d again at this point) using a per-km rate such that:

Total speeding score for segment g, TSI m and for driver d is defined as:

$$s_{gmd} = \frac{1}{L_{gmd}} \sum_i \sum_{c \in C_s} \delta_g(x_i,t_i)\delta_m(x_i,t_i)\delta_c^{\text{speed}}(x_i,t_i) l_i w_c^{\text{speed}}$$

Total acceleration score for segment g, TSI m and for driver d is defined as:

$$a_{gmd} = \frac{1}{L_{gmd}} \sum_i \sum_{c \in C_a} \delta_g(x_i,t_i)\delta_m(x_i,t_i)\delta_c^{\text{acc}}(x_i,t_i) l_i w_c^{\text{acc}}$$

Total braking score for segment g, TSI m and for driver d is defined as:

$$b_{gmd} = \frac{1}{L_{gmd}} \sum_i \sum_{c \in C_b} \delta_g(x_i,t_i)\delta_m(x_i,t_i)\delta_c^{\text{brake}}(x_i,t_i) l_i w_c^{\text{brake}}$$

Where w_c^{speed}, w_c^{acc}, and w_c^{brake} are exogenous weights which relate to the contribution to casualty crash risk of a particular behaviour at a particular magnitude. The derivation of these weights is further defined in Section 8.5.

In the same way we can calculate speeding, acceleration, and breaking indicators for each driver in each of the TSIs as follows:

Total speeding score for TSI m for driver d: $$s_{md} = \frac{1}{L_{md}} \sum_i \sum_{c \in C_s} \delta_m(x_i, t_i) \delta_c^{\text{speed}}(x_i, t_i) l_i w_c^{\text{speed}}$$

Total acceleration score for TSI m for driver d: $$a_{md} = \frac{1}{L_{md}} \sum_i \sum_{c \in C_a} \delta_m(x_i, t_i) \delta_c^{\text{acc}}(x_i, t_i) l_i w_c^{\text{acc}}$$

Total braking score for TSI m for driver d: $$b_{md} = \frac{1}{L_{md}} \sum_i \sum_{c \in C_b} \delta_m(x_i, t_i) \delta_c^{\text{brake}}(x_i, t_i) l_i w_c^{\text{brake}}$$

Where w_c^{speed}, w_c^{acc}, and w_c^{brake} are the same exogenous weights used to calculate the segment-level scores.

We now normalise the scores to the ninetieth percentile[107] of each of the behaviours at the segment level which we define as s_m^{max}. Subsequently, the speeding scores s_{md} are normalised as follows: $\bar{s}_{md} = \left(\frac{100}{s_m^{\max}} \right) s_{md}, \quad \forall m, d$. Similarly, the acceleration scores are normalised as $\bar{a}_{md} = \left(\frac{100}{a_m^{\max}} \right) a_{md}$, and the braking scores as $\bar{b}_{md} = \left(\frac{100}{b_m^{\max}} \right) b_{md}$. This normalisation ensures that all scores have a range from 0 to 100 and are on the same scale regardless of if it is a segment-level, TSI-level or driver-level score.

Using these normalised scores we can then compute the average score for each driver and for each TSI:

$$\mu_d = \frac{1}{M} \sum_m \bar{s}_{md}, \quad \forall d$$

$$\mu_m = \frac{1}{D} \sum_d \bar{s}_{md}, \quad \forall m$$

Furthermore, the standard deviations can be calculated. The purpose of providing a measure of variability using the standard deviation statistic is to describe the

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[107] The ninetieth percentile is used to constraint the scale because the highest scores are very unusual and setting the scale to account for these reduces the magnitude of the differences of the majority of the scores.

variability within and between drivers and to adjust drivers' risk margins to account for this. The standard deviations within drivers can be computed as:

$$\sigma_d = \sqrt{\frac{1}{M-1}\sum_m \left(\bar{s}_{md} - \mu_d\right)^2}, \quad \forall d$$

The standard deviation within a TSI is derived from the segment-level scores s_{gmd}, a_{gmd} *and* b_{gmd} for segments g (1 to G) of TSI m which were defined earlier and can be shown as:

$$\sigma_m = \sqrt{\frac{1}{D-1}\sum_d \sum_g \left(\bar{s}_{gmd} - \mu_m\right)^2}, \quad \forall m$$

In order to calculate the speeding, acceleration, and braking scores for each individual driver, we compute the average normalised scores over all TSIs: $\bar{s}_d = \frac{1}{M}\sum_m \bar{s}_{md}$, $\bar{a}_d = \frac{1}{M}\sum_m \bar{a}_{md}$, and $\bar{b}_d = \frac{1}{M}\sum_m \bar{b}_{md}$, respectively. Alternatively a weighted average can be used such that the contribution of each TSI to the driver score is equivalent to the proportion of total distance covered by that TSI such that, for example, speeding can be described as $\bar{s}_d = \frac{1}{M}\sum_m \bar{s}_{md}\frac{L_{md}}{L_d}$.

The speeding risk margin for driver d is comprised of an upper bound which can be defined as $\bar{s}_d^u = \min\left\{\bar{s}_d + \sigma_d, \max_{md}\{s_{md}\}\right\}$ and a lower bound that can be defined as $\bar{s}_d^l = \max\left\{\bar{s}_d - \sigma_d, \min_{md}\{s_{md}\}\right\}$. The risk margins for acceleration and braking are calculated in the same manner.

The final score for a driver d then becomes $\lambda_d = \omega_s\bar{s}_d + \omega_d\bar{a}_d + \omega_b\bar{b}_d$, where $\omega_s \in [0,1]$ is the weight attached to speeding, $\omega_a \in [0,1]$ is the weight attached to acceleration, and $\omega_b \in [0,1]$ is the weight attached to braking, respectively, where $\omega_s + \omega_a + \omega_b = 1$. Each weight represents the contribution of each behaviour to risk. Derivation of these weights is discussed in Section 8.5.3.

8.4.1 Options

The algorithm that has been developed to implement the framework provides a number of different options which can be adjusted depending on the characteristics of the dataset and the behaviour(s) of interest. In addition to the options described in this section, the weights applied to the magnitudes of behaviours and the weights applied to the behavioural scores in calculating the total score can also be changed. These are discussed in Section 8.5.

The algorithm options can be categorised into four sets of options. The first set deals with which TSIs to include in the calculation of the score. The second set is used to determine which road segments to include depending on the size, length or number of events associated with each individual road segment. The third set is used to specify how speeding, acceleration and braking behaviour is defined. The fourth set is used to specify the time period for which a score is being calculated. In a before and after study, there are multiple periods that need to be defined if separate scores are required for each period. A summary of the options available is shown in Table 8-1. The settings applied for the analyses presented in this research are shown in bold and the rationale for this is discussed in Section 8.4.2.

Not all options are mutually exclusive. For example, a TSI may include one or more of the TSI option elements. If a particular TSI contains any element which is excluded then it will be excluded from the score calculations even if it contains other elements which have been specified to include them in the analysis.

Table 8-1: Driver behaviour profile algorithm options[108]

Name	Description
TSI elements	
Signalised Intersections	Include (1) or **exclude (0)** TSIs with signalised intersections
Non-signalised Intersections	Include (1) or **exclude (0)** TSIs with non-signalised intersections
Roundabout	Include (1) or **exclude (0)** TSIs with roundabouts
Rain	**Include (1)** or exclude (0) TSIs with the presence of rain
School Zone	**Include (1)** or exclude (0) school zone TSIs

[108] This table excludes behavioural weights which are discussed in detail in Section 8.5.

Name	Description
Trip Purpose	Indicates if TSIs should be used that incorporate purpose (1) or **not (0)**. If this is set to zero then TSINTP is used instead of TSI to control for spatiotemporal factors.
Minimum road segment characteristics	
TSI Minimum	The minimum number of road segments associated with a particular TSI (**default = 3**) for the TSI to be included
Minimum Observations	The minimum number of observations within an individual road segment for it to be included (**default = 5**). If this threshold is not met then the road segment also does not count towards the *TSI minimum* threshold.
Minimum brake events[109]	The minimum number of braking events for the segment to be included in the calculation of the braking scores (**default = 5**)
Minimum acceleration events[110]	The minimum number of acceleration events for the segment to be included in the calculation of the acceleration scores (**default = 5**)
Behavioural definitions	
Speeding type	Indicates if speeding should be defined as driving at any speed in excess of the posted speed limit **(0)** (i.e. 51 km/h in a 50 km/h zone) or speeding by a minimum of 5 km/h (5) (i.e. 56 km/h in a 50 km/h zone).
Distance base	Indicates if VKT should be based on 100 percent of the distance driven (=100) or distance driven at least 75 percent of the speed limit **(75)**
Acceleration/ Braking Type	Indicates if acceleration and braking should be based on 1 m/s^2 categories **(1)** or categories in bands of 10 percent of the maximum for that driver (0)
Total Scores	Indicates if the driver-level total scores should be based on the average TSI-level scores **(1)**, the median TSI-level scores (2) or calculated in the same way as TSI-level scores but with no differentiation by TSI (0).
Time periods	
After Period	Indicates if the scores should be calculated for the before period **(0)** or the after period **(1)**
Split After	Indicates if the after phase should be split based on the remaining monetary incentive **(1)** or not (0)
Remaining Incentive	Indicates the remaining monetary incentive at the point where the after period is split **(default = 5)**
Absolute or Percentage	Indicates if the remaining incentive option is an absolute value in a currency unit (for example the Australian Dollar) (a) or a percentage of the original monetary incentive **(p)**
After Set	Indicates if the scores should be calculated for when the remaining incentive was greater than the threshold **(1)** or at or below the threshold **(2)**
Profile Type[111]	Indicates if scores should be generated per driver **(1)** or for all drivers as if they were a single driver (3)

The options dealing with the after period(s) only apply if the after period option is set to 1 (after period). These are discussed in more detail in Chapter 10. In addition, to

[109] This includes braking events where the magnitude is < 1 m/s^2

[110] This includes accelerations events where the magnitude is < 1 m/s^2

[111] Initial iterations provided two additional options. One option (per-driver, per-TSI) produced individual scores for each TSI for each driver. Similarly, the second removed option (all drivers, per-TSI) produced individual scores for each TSI across all drivers. These options were removed because they were combined with the remaining options which now output scores for each TSI in addition to the total scores across TSIs.

ensure that it is possible to identify the value of the options associated with a particular score, each driver behaviour profile contains a variable which contains the options applied when generating that particular profile.

8.4.2 Rationale for default TSI, segment and behavioural settings

The default settings shown in Table 8-1 are the settings that applied for the analyses presented in this thesis. They may not be the ideal settings for other datasets. This section explains the rationale behind these choices.

The purpose of the driver behaviour profile is to provide a composite measure of drivers' behaviour in situations where they have the opportunity to engage in risky driving behaviour. As discussed in depth in Section 7.10, driver behaviour at intersections – although important – is restricted by a large number of variables, exogenous factors for which this dataset contains no information. This applies to signalised intersections, non-signalised intersections and roundabouts. Consequently, it is prudent to exclude intersection TSIs from the composite score. In contrast, although rain and the presence of school zones are known to influence driver behaviour, drivers are still able to engage in these environments albeit at the risk of more stringent penalties or a higher crash risk. DBPs are generated using TSINTPs – which do not include trip purpose – as opposed to TSIs to control for spatiotemporal factors. The reason for this is that doing so substantially reduces the number of unique TSIs and preliminary analyses demonstrate that models applying TSINTP better explain driver behaviour than when using TSIs. However, in some spatiotemporal situations – of which school zones is one – trip purpose can be a significant factor and therefore when examining behaviour in particular spatiotemporal environments this may not be the best option to use.

The minimum thresholds for the inclusion of road segments and TSIs ensure that road segments and TSIs contain sufficient observations that they can be said to accurately reflect the behaviour of that particular driver in that particular spatiotemporal environment. A score calculated using a road segment with only one observation or a TSI with only one road segment would be describing the behaviour of that driver in a single point in time. This may indeed be useful in some circumstances but for the purposes of these analyses – where the objective is to relate observed behaviour to driver's inherent characteristics – this may lead to misleading results.

Speeding is defined as any driving in excess of the posted speed limit. That means that an observation recorded at 1 km/h above the speed limit is considered to be speeding for the purposes of this study. There were several reasons for this. First, the enforcement regime in place in the study area at the time of the study included fines for exceeding the speed limit by 1 km/h and therefore choosing the same threshold ensured consistency between the legislation, enforcement and study measures of speeding behaviour. In addition, Australian Design Rule (ADR) 18/03 which specifies the standards vehicles sold in Australia must meet states that the relationship between the speed displayed on the speedometer (designated as V_1) and the true speed of the vehicle (V_2) must be $0 \leq (V_1 - V_2) \leq 0.1\ V_2 + 4$ km/h (Australian Commonwealth Government, 2004). In practice this results in vehicle manufacturers designing their vehicle speedometers to ensure that the displayed speed is at least two to four km/h faster than the true speed. Therefore, if the vehicle speed as measured by the in-vehicle GPS device used in this study records a speed of 1 km/h above the speed limit, the vehicle speedometer is likely to be showing speeds of 3 to 5 km/h above the posted speed limit.

Acceleration and braking magnitudes are based on contiguous 1 m/s^2 bands. An alternative option was investigated which uses categories on the basis of the maximum observed acceleration for that vehicle. This controls for differences in vehicle performance. However, the performance range of the vehicles in the study were similar and, as a result, using contiguous 10 percent of the maximum acceleration categories did not produce any significant changes to the aggregate distributions of behaviour. Therefore, since 1 m/s^2 are easier to interpret, 1 m/s^2 bands are used in this research.

8.4.3 Output

The DBP algorithm outputs 37 variables for every driver and every driver-TSI combination. These contain variables to identify the options used to generate these scores, measures of VKT, the number of elements (road segments or TSIs) included when calculating the scores and the scores themselves. These variables are summarised in Table 8-2. Variables in italics are used for reference purposes and are not used for analysis.

Table 8-2: Driver behaviour profile algorithm output variables

Variable	Possible Values	Description
recordID	1+	Unique database identifier
runID	Any	Summary of algorithm options applied
userID	Any	Unique driver identifier, 0 if all drivers
TSI	Any	TSI for TSI-level scores and null for driver-level
Sumelems	1+	The number of road segments (TSI-level) or TSIs (driver-level) included in the calculations
Speeding	0 – 100	Speeding score
Speeding_stdev	0 – 100	Standard deviation, maximum and minimum speeding scores by segment (TSI-level) or TSI (driver-level)
Speeding_min	0 – 100	
Speeding_max	0 – 100	
Speeding_upper	0 – 100	Upper and lower bounds of speeding behaviour
Speeding_lower	0 – 100	
Accel	0 – 100	Acceleration score
Accel_stdev	0 – 100	Standard deviation, maximum and minimum acceleration scores by segment (TSI-level) or TSI (driver-level)
Accel_min	0 – 100	
Accel_max	0 – 100	
Accel_upper	0 – 100	Upper and lower bounds of acceleration behaviour
Accel_lower	0 – 100	
Brake	0 – 100	Braking score
Brake_stdev	0 – 100	Standard deviation, maximum and minimum braking scores by segment (TSI-level) or TSI (driver-level)
Brake_min	0 – 100	
Brake_max	0 – 100	
Brake_upper	0 – 100	Upper and lower bounds of braking behaviour
Brake_lower	0 – 100	
Total	0 – 100	Total score across all behaviours
Total_stdev	0 – 100	Standard deviation, maximum and minimum total scores by segment (TSI-level) or TSI (driver-level)
Total_min	0 – 100	
Total_max	0 – 100	
Total_upper	0 – 100	Upper and lower bounds of total behaviour
Total_lower	0 – 100	
After	0 – 3	Indicates if the score was generated for the before period (0), after period (1), after period with an incentive (2) or after period with no incentive (3)
Totdist	0+	VKT (km) of included road segments
Dist75p	0+	VKT (km) above 75% of speed limit in included road segments
Totdist_a	0+	VKT (km) of road segments with some acceleration behaviour
Dist75p_a	0+	VKT (km) above 75% of speed limit in road segments with some acceleration behaviour
Totdist_b	0+	VKT (km) of road segments with some braking behaviour
Dist75p_b	0+	VKT (km) above 75% of speed limit in road segments with some braking behaviour
rundt	Any	Date and time of profile calculation; used to identify when a profile was generated. This is not related to when the data was collected.

8.5 Behavioural measure weights

The DBP framework requires that for every behaviour that is measured that a varying weight is applied depending on the magnitude of the behaviour. These weights are used as multipliers for the per-km frequency of each of the behaviours. This section describes the derivation of these weights for the analyses in this research.

8.5.1 Speeding magnitude weights

The speeding magnitudes weights are based on the risk curve identified by Kloeden (1997) which represent the risk of a casualty crash associated with exceeding the speed limit in a 60 km/h zone which is the most frequent speed limit in this dataset in terms of distance and road segments. The literature behind this and other risk curves is discussed in detail in Section 2.2.1.

Kloeden (1997) identified the relative risk of being involved in a casualty crash and upper and lower bounds (based on a 95 percent confidence interval) associated with driving at different speeds in a 60 km/h zone. Table 8-3 lists the relative risk, lower bound of the relative risk and upper bound of the relative risk.

Table 8-3: Risk of involvement in a casualty crash relative to travelling at 60 km/h in a 60 km/h speed zone (Kloeden et al., 1997)

Speed Range (km/h)	Relative Risk	Lower Bound	Upper Bound
58 – 62	1.00	1.00	1.00
63 – 67	2.00	1.17	3.43
68 – 72	4.16	2.12	8.17
73 – 77	10.60	3.52	31.98
78 – 82	31.81	6.55	154.56
83 – 87	56.55	6.82	468.77
88+	Infinite	N/A	N/A

There are three main simplifications to the original curve for this particular implementation. The main simplification is done to reduce the curve to the five speeding magnitudes: 1 – 4, 5 – 9, 10 – 14, 15 – 19 and ≥ 20 km/h. The second simplification is to assume that the same relative risks apply to speeding behaviour in all speed zones. This is done to simplify comparisons in the resulting scores between TSIs with different speed limits. Lastly, the original risk curve included the relative risks for driving at speeds below the speed limit. In this case, driving at speeds at or below the speed limit has an (effective) weight of zero since the intention is to identify drivers which regularly exceed the posted speed limit.

An alternative source for speeding weights is the risk curves developed by Elvik (2012b) – shown in Figure 8-5 – which are derived from changes in the relative number of fatal crashes due to a 10 km/h reduction in speed. The change in the relative number of crashes is used for the speeding score weights.

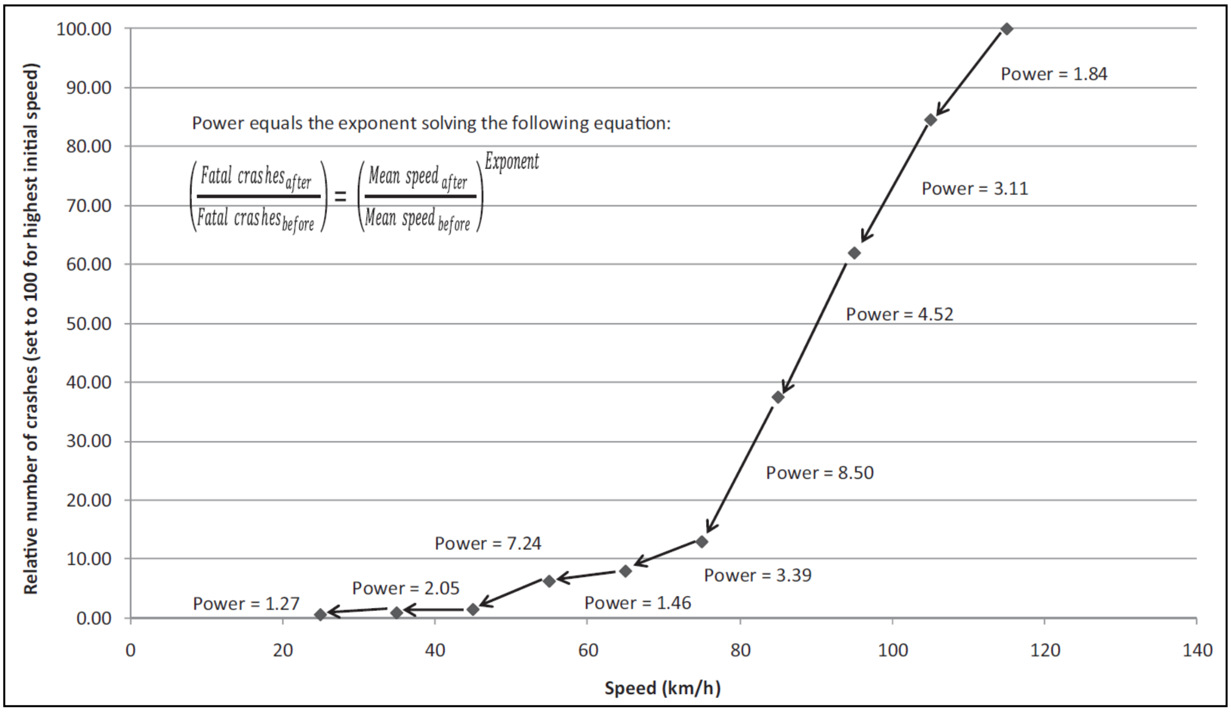

Figure 8-5: Power exponents for 10 km/h changes in speed – effect on fatal crashes (Elvik, 2012b)

To accommodate the 5 km/h speeding categories and reflect the use of a single set of weights for all speed limits, four different sets of weights were applied. These are based on an initial speed of 55 km/h, 65 km/h and 75 km/h and the average of all three. Since the exponents calculated by Elvik (2012b) are based on 10 km/h increments, it is assumed that the midpoint (5 km/h) exhibits the same exponent. The relative change in crashes (crash ratio) from the initial speed can then be calculated for each point using the equation $\left(\frac{Crashes_{after}}{Crashes_{before}}\right) = \left(\frac{Speed_{after}}{Speed_{before}}\right)^{Exponent}$ where the crash ratio is the left side of the equation. The resulting crash ratios (shown in Table 8-4) are used for the speeding weights and an average crash ratio is calculated from the three sets of crash ratios. As with the weights derived from Kloeden et al. (1997), driving below the speed limit is given a weight of zero.

Table 8-4: Crash ratios derived from Elvik (2012b)

Initial Speed (km/h)	Final Speed (km/h)	Exponent	Initial Crashes	Final Crashes	Crash Ratio
55 km/h Base Speed					
55	85	4.12	6	37	6.01
55	80	4.12	6	29	4.68
55	75	2.35	6	13	2.07
55	70	2.35	6	11	1.76
55	65	1.46	6	8	1.28
55	60	1.46	6	7	1.14
55	55	—	6	6	1.00
65 km/h Base Speed					
65	95	5.41	8	62	7.78
65	90	5.41	8	46	5.81
65	85	5.77	8	37	4.71
65	80	5.77	8	26	3.32
65	75	3.39	8	13	1.62
65	70	3.39	8	10	1.29
65	65	—	8	8	1.00
75 km/h Base Speed					
75	105	5.58	13	85	6.54
75	100	5.58	13	64	4.98
75	95	6.63	13	62	4.79
75	90	6.63	13	43	3.35
75	85	8.50	13	37	2.90
75	80	8.50	13	22	1.73
75	75	—	13	13	1.00
Average					
Speed Limit	≥ 20	—	—	—	5.16
Speed Limit	15 – 19	—	—	—	3.86
Speed Limit	10 – 14	—	—	—	2.81
Speed Limit	5 – 9	—	—	—	1.93
Speed Limit	1 – 4	—	—	—	1.38

A sensitivity analysis was conducted using the three Kloeden-derived weights, the four Elvik-derived weights and using a uniform weight – with a value of one – for all speeding categories to determine the sensitivity of the overall speeding score (across all TSIs) to the different weights using the lower bound of the Kloeden (1997) curve as the base case. The distributions are shown in Figure 8-6 maintaining the same driver-order for all the distributions.

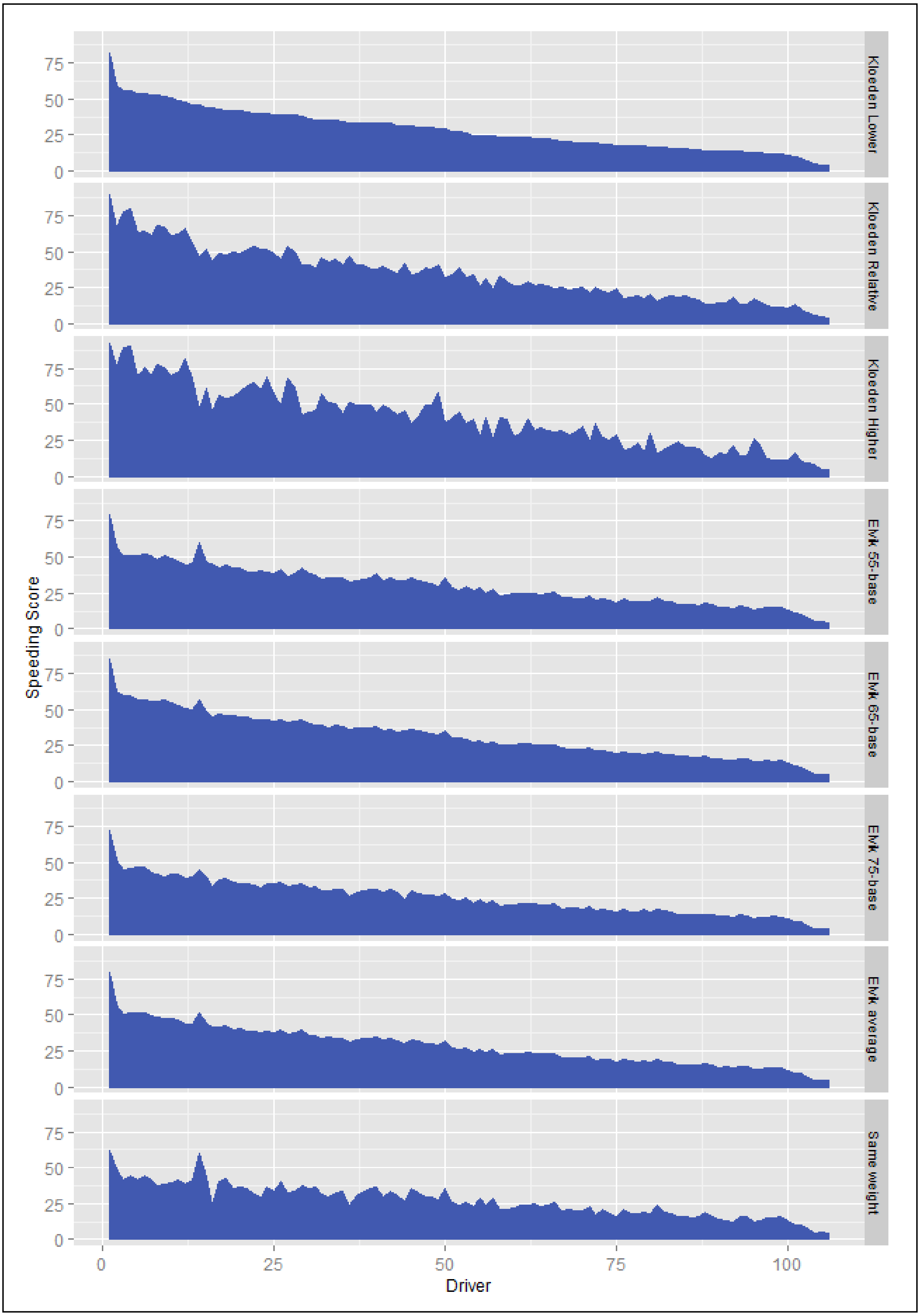

Figure 8-6: Speeding scores (before phase) using different weights

Compared to using the lower bound of Kloeden's curve, using a uniform weight resulted in a maximum (negative) movement along the distribution of 41 and a maximum (positive) movement along the distribution of 23. Put another way, the driver whose score, relative to other drivers in the sample, changed the most when there was no differentiation between the different speeding categories moved from having the 15^{th} highest score to the 57^{th} highest score. The average decrease in position was 6.8 (51 drivers) and the average increase in position was 7.3 (48 drivers). Among the remaining sets of weights, the average decrease in position from the base case (lower bound of Kloeden's curve) was -1.9 (46 drivers) and the average increase was 1.6 (52 drivers). The smallest differences were observed between the lower bound of Kloeden's curve and the weights derived from Elvik's curve using an initial speed of 65 km/h. This was expected since Kloeden's curve was developed for roads with a 60 km/h speed limit. The largest average changes in position were observed between Kloeden's lower bound and upper bounds with an average reduction of 7.6 (44 drivers) and an average increase of 7.1 (47 drivers). However, the maximum positive and negative changes were 27 and 29 respectively which is a slightly smaller range than that observed between Kloeden's lower bound and uniform weights. The scores themselves changed an average of 3.02 (median of 1.72) but this figure is largely meaningless since the scale of the speeding score was adjusted to fit 90 percent of the behaviours using the same weights that are used to calculate the individual driver scores and, therefore, the different scales are not directly comparable to each other. What can be concluded here is that provided the weights change in the same way as the magnitude increases (i.e. that higher magnitudes have higher weights) the results do not differ substantially. In general terms, a driver that has a speeding score in the first (highest) quartile of drivers retains a score in the highest quartile when the weights are adjusted.

The weights applied to the DBP are based on the lower bound shown in Table 8-3. The reason for this is that although speeding by the higher magnitudes is of significantly higher risk, these higher speeds are uncommon in many road environments and therefore the large separation at the lower magnitudes relative to the higher magnitudes creates greater differences in speeding scores between drivers. The final weights that are used are shown in Table 8-5.

Table 8-5: Final speeding behaviour weights by speeding category

Speeding Category (km/h)	Weight
1 – 4	1.17
5 – 9	2.12
10 – 14	3.52
15 – 19	6.55
20 +	6.82

It should be noted that both the framework and the algorithm that have been developed can accept weights for any number of speed and speeding categories in addition to different weights for different magnitudes. This has not been done in this case because study participants were only informed about their overall speeding behaviour for each trip which in many cases included driving on roads of more than one speed limit. In some cases it may be desirable to make use of this functionality. However, in this case, common weights across speed zones reflects the reality that most speeding behaviour occurs at lower magnitudes and therefore devising weights that help to differentiate between drivers that frequently exceed the speed limit by 1 to 4 km/h from those that do so by 5 to 9 km/h and 10 to 14 km/h is more important than differentiating between the (relatively) far fewer drivers that occasionally exceed the speed limit by more than 15 km/h.

8.5.2 Acceleration and braking magnitude weights

In comparison to speeding behaviour, prior research into the relative risks of involvement in a casualty crash associated with particular magnitudes of breaking are rare, and, even more so in regards to acceleration. A detailed review of the literature is included in Section 2.2.2.

Prior research (see Section 2.2.2) has identified a number of braking magnitude thresholds relating to increased incidences of crashes and near-crashes. In general, it appears that drivers with higher frequencies of acceleration and braking events greater than approximately 3 m/s^2 are involved in statistically significantly higher rates of crash involvement (Jun et al., 2007). Other researchers (Bagdadi and Várhelyi, 2011) have identified that most crashes involve braking magnitudes of between 4 and 8 m/s^2. Naturalistic driving studies (Dingus et al., 2006) have also found approximately 5 m/s^2 accelerations to be a good threshold for identifying both near-crashes and crashes. Based on these thresholds, the weights in Table 8-7 were devised with three aims in mind. The first is to exclude lower magnitude acceleration and braking behaviour which are extremely common in day-to-day driving since at some point in any trip there will always be some acceleration and braking events. The second aim is to increase the weights associated with events of higher magnitudes that are known to be associated with more frequent crashes and near-crashes such that they reflect their closer correlation with near-crashes and crashes. This is somewhat different than the approach to speeding behaviour because while lower magnitude acceleration and braking behaviour can occur during typical (safe) driving, lower magnitudes speeding behaviour is considered to be speeding and of a higher relative risk than driving at or below the speed limit. The third aim is to create the maximum separation between the acceleration and braking scores of the aggressive drivers and the less aggressive drivers. The weights shown in Table 8-7 reflect these objectives, and, therefore may not be appropriate for analyses that have different objectives.

It is also important to note that the acceleration and braking weights should not be compared to each other. The acceleration and braking scales are normalised to fit 90 percent of all acceleration behaviour and 90 percent of all braking behaviour respectively. As such, acceleration behaviour at or above the ninetieth percentile of acceleration behaviour has a score of 100 and the same applies to braking behaviour at or above the ninetieth percentile of braking behaviour. This is because the weights reflect the relative impact of higher magnitudes of the same behaviour, not the relative impact of higher magnitudes of different behaviours.

A number of different sets of weights (Table 8-6) were applied and a sensitivity analysis was conducted to examine the influence on drivers' relative positions along the distribution. The four weights that are tested are equal/uniform weights which apply the same weight for all magnitudes above the minimum aggressive threshold along with linear and exponential increases in weights as the magnitude increases. Lastly, a set of weights based on thresholds identified by other researchers (discussed in detail in Section 2.2.2) was also tested.

Table 8-6: Acceleration and braking behaviour weights

Magnitude (m/s²)	Acceleration				Braking			
	Equal	Linear	Expon-ential	Thres-hold	Equal	Linear	Expon-ential	Thres-hold
≤ 1	0	0	0	0	0	0	0	0
≤ 2	0	0	0	0	0	0	0	0
≤ 3	0	0	0	0	1	1	1	3
≤ 4	1	1	1	3	1	2	2	6
≤ 5	1	2	2	5	1	3	4	12
≤ 6	1	3	4	7	1	4	8	24
≤ 7	1	4	8	9	1	5	16	48
≤ 8	1	5	16	9	1	6	32	48
≤ 9	1	6	32	9	1	7	64	48
> 9	1	7	64	9	1	8	128	48

Figure 8-7 illustrates the distribution of acceleration scores for each driver using the four sets of weights. The distribution is ordered by the acceleration scores calculated using the threshold weights. Relative to the equal weights scores, the average increased in position was 6.5 (44 drivers) for linear weights, 10.6 (49 drivers) for exponential weights and 5.1 (43 drivers) for threshold weights. Similarly, the average decrease in position was 5.8 (49 drivers) for linear weights, 10.1 (51 drivers) for exponential weights and 4.3 (51 drivers) for threshold weights. The maximum position changes were 21 for linear weights, 61 for exponential weights and 19 for threshold weights. What this illustrates is that with the exception of the exponential weights – which produce quite different results – the other alternatives do not have a substantial effect on the relative order of drivers' in relation to the overall sample.

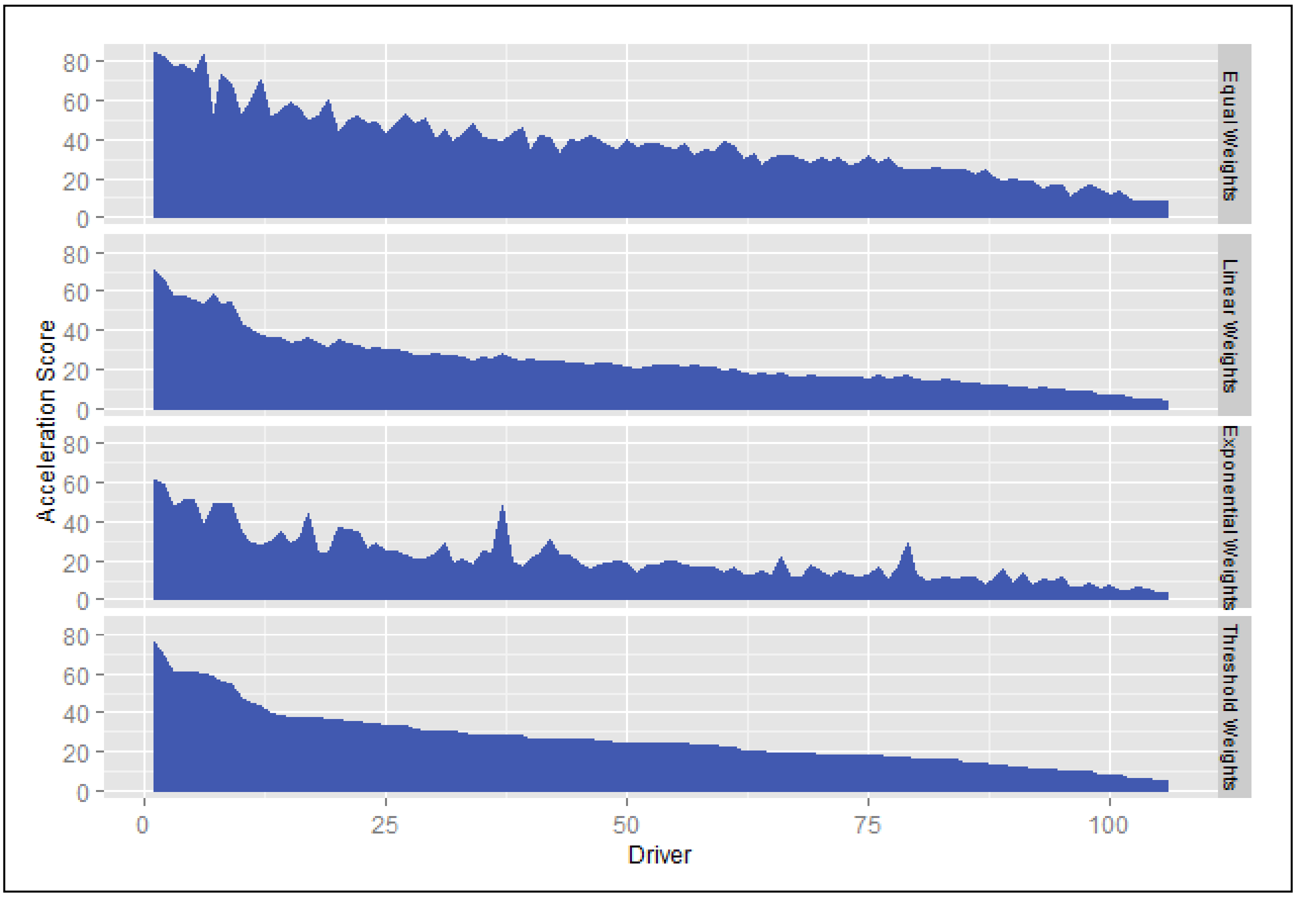

Figure 8-7: Acceleration scores (before phase) using different weights

Larger differences between the different sets of weights are observed for braking behaviour. The distributions, shown in Figure 8-8, still maintain a largely similar trend in that more aggressive drivers have higher scores in all four cases. Similarly, less aggressive drivers have lower scores in all four cases. There are, however, larger differences in average changes in position and the maximum changes. The average reductions from the equal weights are 7.7, 11.3 and 11.4 for the linear, exponential and threshold weights respectively. The average increases in positions are 7.2, 14.4 and 12.4 for the same weights. The maximum changes in position are 41 (linear), 67 (exponential) and 65 (threshold) relative to the positions calculated using equal weights. These larger differences compared to the position changes for the acceleration scores is largely due to the higher frequency of higher magnitude braking compared to the frequency of higher magnitude acceleration.

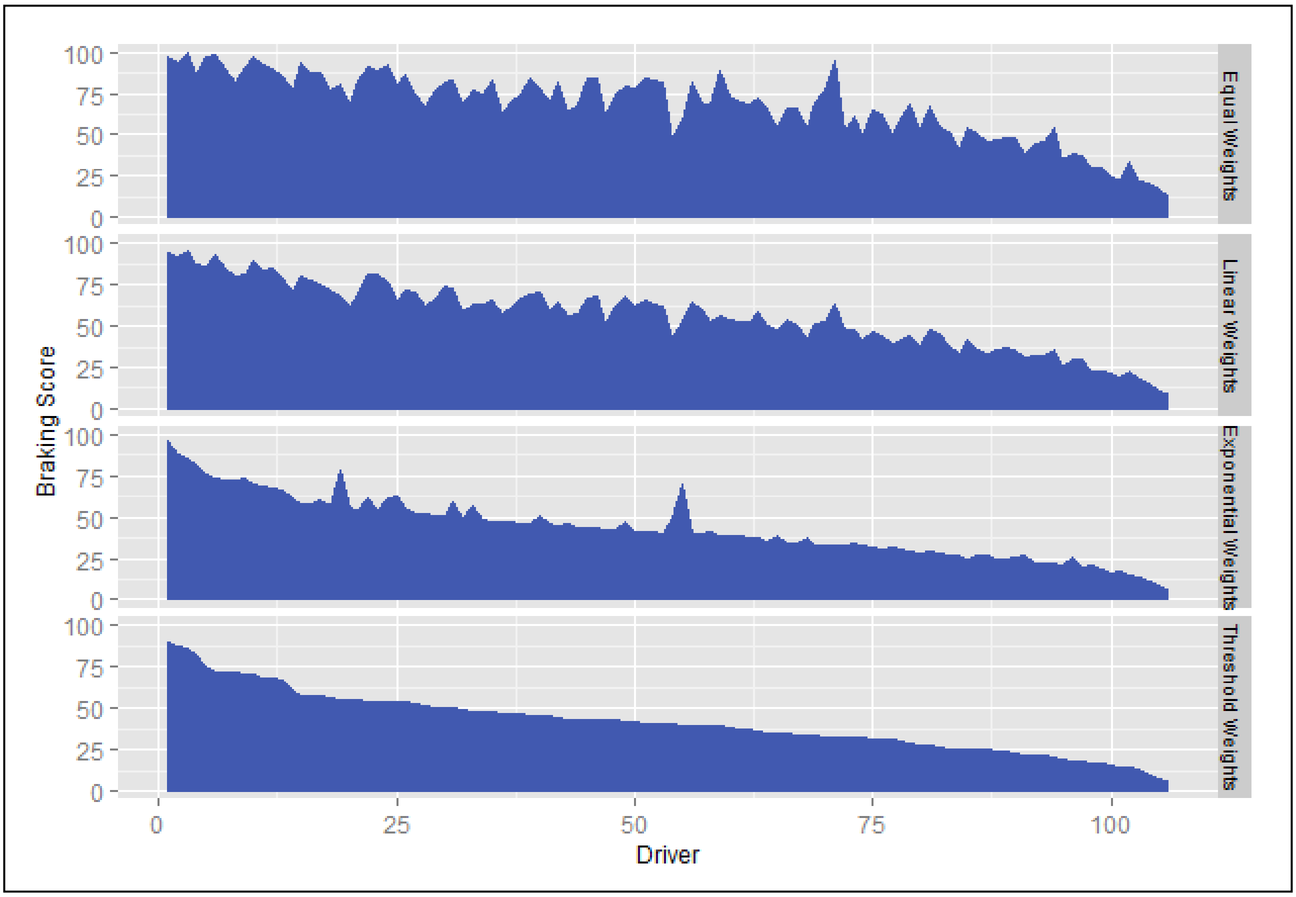

Figure 8-8: Braking scores (before phase) using different weights

The final weights that are used for the acceleration and braking behaviour are shown in Table 8-7. Although there is little difference in the relative positions of drivers relative to the rest of the sample between the linear, exponential and threshold weights, the threshold weights have been selected because they reflect the consensus of researchers as to the magnitudes of braking and acceleration behaviours that are correlated with crashes and near crashes.

Table 8-7: Final acceleration and braking behaviour weights

Acceleration Categories (m/s²)	Acceleration Weight	Braking Categories (m/s²)	Braking Weight
≤ 1	0	**≤ 1**	0
≤ 2	0	**≤ 2**	0
≤ 3	0	**≤ 3**	3
≤ 4	3	**≤ 4**	6
≤ 5	5	**≤ 5**	12
≤ 6	7	**≤ 6**	24
≤ 7	9	**≤ 7**	48
≤ 8	9	**≤ 8**	48
≤ 9	9	**≤ 9**	48
> 9	9	**> 9**	48

As with speeding, this implementation of the DBP framework applies the same weights to acceleration and braking behaviour in all speed limit zones. However, this can be changed at the cost of reduced comparability between drivers or environments with different distributions of road speed limits.

8.5.3 Composite weighting

The different behaviour scores are themselves weighted to create a composite (total) score that reflects all speeding, acceleration and braking behaviour by a particular driver or in a particular road environment. It is important to recognise that speeding and braking behaviour are more closely aligned with crashes and near-crashes whilst acceleration behaviour is more closely aligned with a driver's overall attitude and aggression towards the driving task and this is reflected in the weights that are applied in computing the composite score. Kaplan and Prato (2012) examined the relationship between crash avoidance manoeuvres – including acceleration, braking and speeding – and crash severity. Using an ordered logit model with data from the crash database of the National Highway Traffic Safety Administration (NHTSA) in the United States, the authors determined the probability of a number of behavioural and driver variables associated with higher severity. Separate models were run for different types of crashes. Crashes involving non-motorists had the highest proportion of fatal crashes (4.4 percent) and the highest proportion of incapacitating injuries (20.9 percent). The relative differences in the probabilities for non-motorist crashes for speeding, acceleration and the average of the braking factors from Kaplan and Prato (2012) were used to determine the weights for speeding, acceleration and braking to create the composite score. Using this method, speeding scores are weighted by 0.42, braking scores use a weight of 0.36 and the acceleration score uses a weight of 0.22. Figure 8-9 illustrates the distribution of the scores by driver sorted from the highest to the lowest total score.

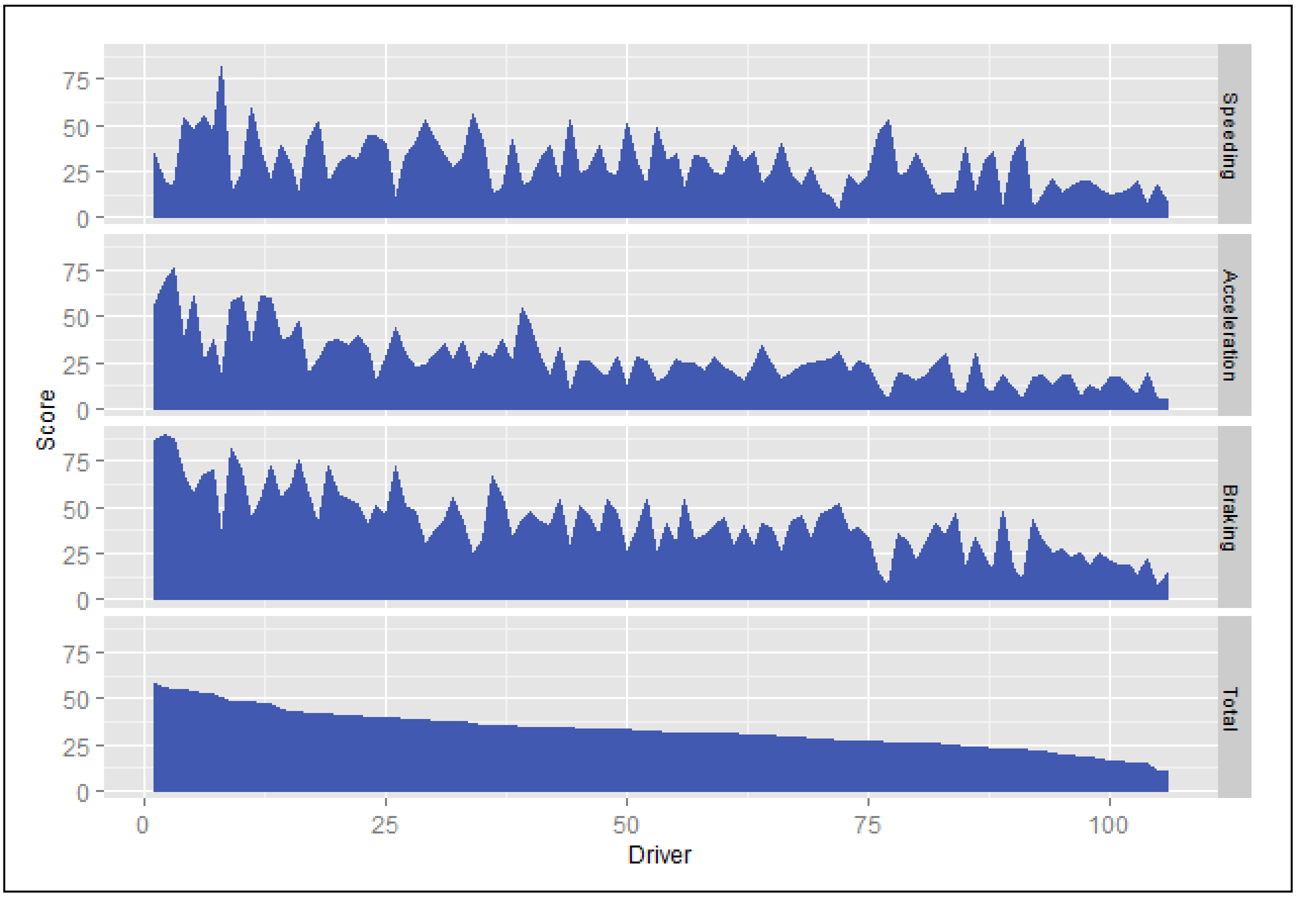

Figure 8-9: Behaviour and composite scores (before phase) by driver

At first glance it appears that no drivers are observed behaving at magnitudes that result in a total score over 60. This needs to be interpreted in light of the fact that although driver's total scores across all TSIs are between 10 and 60, the same drivers exhibit scores across the entire scale (from 0 to 100) in particular TSIs. This can be observed in Figure 8-10 which plots the maximum and minimum TSI-level scores for each driver as well as the upper and lower risk margins for each driver. In addition, even for drivers with a maximum TSI-level score below 100, these drivers may exhibit segment-level behaviour consistent with behaviour of drivers with higher scores albeit at lower frequencies. The ability to drill down to more disaggregate levels requires a common scale to enable comparisons to be made between levels as well as between different elements within the same level.

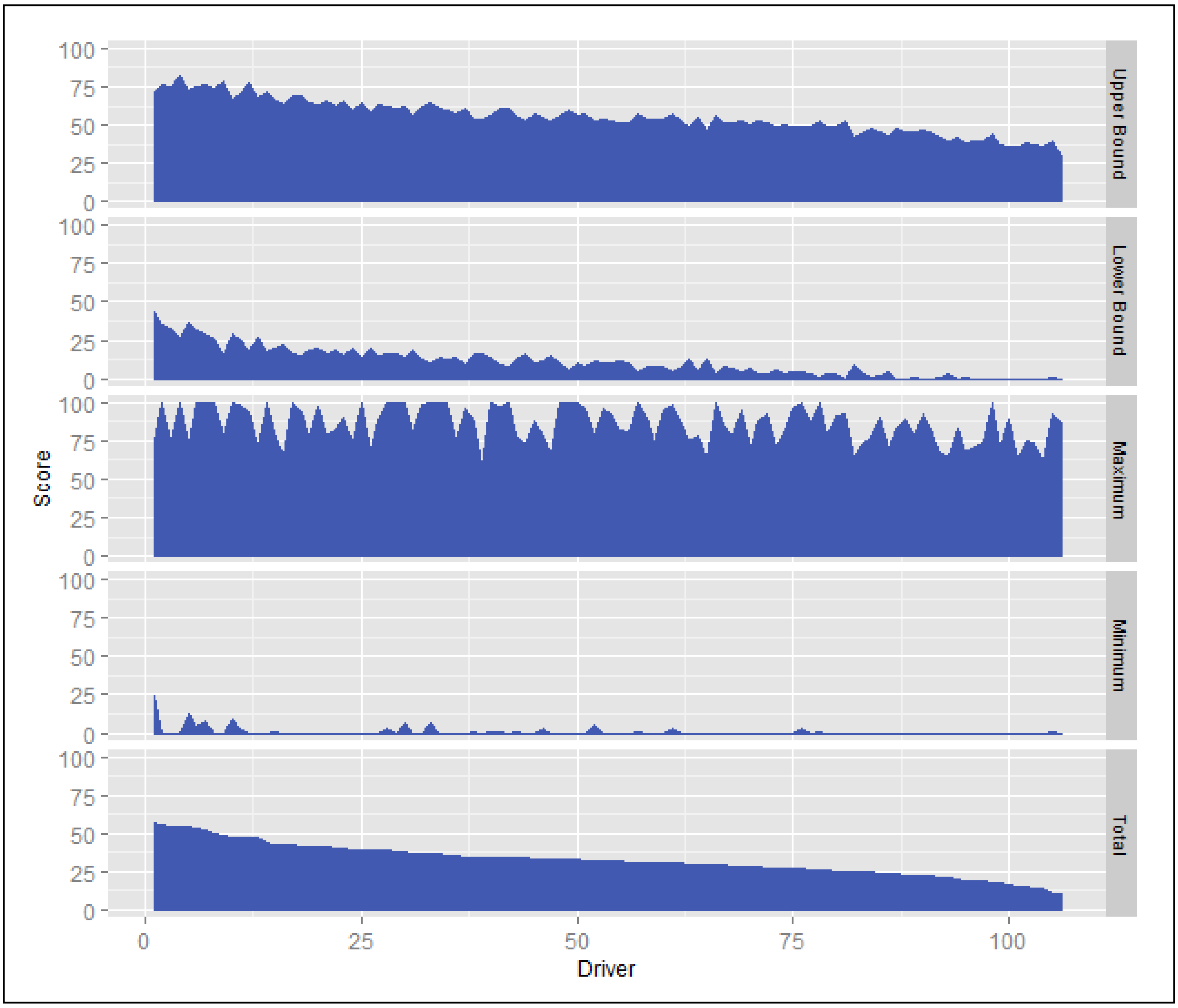

Figure 8-10: Total score ranges (before phase) by driver

8.6 Comparisons using driver behaviour profiles

The primary contribution of driver behaviour profiles is the ability to provide a common unit of behaviour that enables comparisons between different drivers, between the same drivers across time, between the same drivers across spatiotemporal environments and any other combinations of driver, time and space. These comparisons can be further refined to comparisons of individual behaviours as opposed to the total composite scores or to the risk margins to determine, for example, if drivers are becoming more consistent in their behaviour through time. Since the profiling controls for spatiotemporal factors and VKT and the algorithm automatically eliminates infrequent situations it is possible to compare scores (and thereby behaviours) when the data in the comparison subsets have different characteristics. The most suitable application for this is when testing road safety interventions in a before and after study. This is how these scores are used in this thesis and to conduct the before and after analyses in Chapter 10.

Changes in behaviour between any two subsets of observed driving data can be interpreted in the same way as those discussed in Section 8.2. With the same caveat about the scores at the extreme ends of the scale, it can be said that a driver that has a score 10 percent lower in the after period compared to the before period has reduced their relative risk of being in a casualty crash by 10 percent.

8.7 Summary

It was identified in Chapter 6, that models of driver behaviour were sensitive to the composition of the behavioural variable. In particular, the factors that affect lower magnitude speeding were markedly different than factors associated with higher magnitude speeding. In addition, a single measure ignored the differences in (crash) risk associated with varying magnitudes and – by extension – masked considerable variation within a single driver's behaviour. Furthermore, given the heterogeneity in VKT and exposure to different spatiotemporal environments both within a single driver (before and after) but also between drivers, a simplistic measure of speeding (for instance, proportion of distance speeding by 1 km/h or more) would be problematic for comparison purposes. To address these issues, driver behaviour profiles (DBP) were developed and discussed in this chapter (8). DBPs are a flexible framework, which can be used to create composite measures of behaviour that account for the aforementioned issues including the road environment by applying TSIs (Chapter 7). The subsequent results chapters (Chapter 9 and Chapter 10) employ DBPs as the dependent variable.

9 RESULTS AND DISCUSSION: EXTENT OF RISKY DRIVING BEHAVIOUR

This chapter examines the relationship between the frequency and magnitude of risky driving behaviour during day-to-day driving with drivers' attitudes and personality characteristics. In so doing, it addresses and answers the first set of hypotheses – described in detail in Section 4.1.1 – using the DBPs calculated using the GPS data from the before period.

This analysis uses the TSI-level and driver-level aggregated datasets described in Chapter 7 and the behavioural scores described in Chapter 8. In contrast to the segment-level aggregated datasets used for the aggregate analyses in Chapter 6, these datasets exclude road segments (and thereby TSIs) as discussed in Section 7.10. Briefly, TSIs with very low frequencies are excluded as are TSIs which represent road environments in close proximity to intersections (of any type) due to the potential for unmeasurable exogenous factors, such as traffic light timings, to influence results.

A restatement of the hypotheses and a summary of if each sub-hypothesis was accepted can be found in Appendix A (Section 13.1).

9.1 Methodology

ANOVA, multilevel regression and single-level regression analyses were run to test the first set of hypotheses. This section outlines the methodology used for the analyses. For consistency the same process was run for each Hypothesis although only the most important models are shown.

9.1.1 Aggregate ANOVA analyses

As a starting point, a one-way ANOVA was conducted to determine if there were statistically significant differences in the means between participants with different perceptions of risk and their speeding, acceleration, braking and total scores and standard deviations. To reduce the influence of TSIs with low VKT, only TSIs covering a distance of at least one kilometre are included. In addition, due to very low frequencies of 'not at all dangerous', these responses were grouped with the next highest magnitude category. Once the data were transformed in this way, the dataset was successfully tested to ensure it met the assumptions of ANOVA. The ANOVA tests were conducted for a driver's aggregate score, across all TSIs, and for a subset of TSIs.

The results of the ANOVA tests – summarised in Table 9-1 – lead to some interesting conclusions. Firstly, at an aggregate level (i.e., all TSIs), there are no statistically significant differences in the scores between drivers with higher perceived risks and drivers with (relatively) lower perceived risks for speeding by 10 km/h and speeding by 20 km/h. At a more disaggregate level, this is no longer the case, and statistically significant differences begin to emerge. Specifically, in TSIs which (arguably) represent uncongested conditions, there are statistically significant differences in observed speeding behaviour between groups of drivers with lower perceptions of the risks of speeding exhibiting higher speeding scores than drivers with higher perceptions of risks. The same is true to a lesser extent for acceleration behaviour but the opposite is observed for braking behaviour with drivers that perceive higher risks engaging in more frequent and heavier braking. In TSIs which are more likely to represent predominantly non-arterial roads with 40 and 50 km/h speed limits[112], speeding is not significantly different between groups, although the average speeding score remains over 40. In some TSIs with 50 km/h speed limits braking and acceleration exhibit significant differences between drivers with different perceptions of the risk of speeding by 10 km/h. Similar to higher speed roads, opposite trends are observed for acceleration and braking behaviour. In terms of differences in the standard deviations, very few TSIs exhibit statistically significant differences in behaviour indicating that once spatiotemporal characteristics are controlled for the variability between drivers is largely consistent.

It is not possible to make any definitive statements about the relationship between drivers' observed behaviour and their perceptions of the risks of speeding from the results of the ANOVA tests. However, these results do confirm that there is – at a minimum – an interaction between drivers' behaviour and the road environment, as represented here by the different TSIs and, therefore, there remains a possibility that

[112] In the study area, 50 km/h is the default speed limit and – at the time the data were collected – 40 km/h speed zones were largely confined to school zones.

there exists a relationship between drivers' risk perceptions and behaviours in particular TSIs. These results also add to the evidence, discussed previously in Chapter 6, that driver-level aggregate measures of behaviour tend not to be related directly to measures of driver attitudes and personality.

Table 9-1: Significance of differences in behavioural scores by perceived risk

	All TSIs		60,TE-D-P0		60,TD-W-D-P0		60,TM-D-P0		50,TE-D-P0		S-40,TM-D-P0	
	≥ 10[a]	≥ 20[b]	≥ 10	≥ 20	≥ 10	≥ 20	≥ 10	≥ 20	≥ 10	≥ 20	≥ 10	≥ 20
Score (0 – 100)												
Speeding	.249	.098	.969	.104	.026	.011	.352	.979	.400	.987	.331	.994
Acceleration	.192	.812	.068	.022	.171	.039	.941	.038	.074	.108	.636	.188
Braking	.242	.891	.309	.082	.891	.042	.286	.780	.046	.840	.519	.590
Total	.471	.290	.972	.160	.061	.133	.447	.377	.025	.767	.321	.906
Standard Deviation of score												
Speeding	.680	.857	.699	.189	.089	.123	.742	.633	.290	.582	.586	.856
Acceleration	.118	.361	.162	.117	.497	.270	.533	.086	.008	.194	.806	.081
Braking	.315	.255	.267	.609	.855	.343	.885	.800	.091	.492	.754	.617
Total	.392	.447	.292	.303	.140	.372	.816	.434	.162	.412	.205	.530

■ Significant at $p \leq .05$ level
■ Significant at $p \leq .10$ level
a : ≥ 10 km/h over the speed limit
b : ≥ 20 km/h over the speed limit

9.1.2 TSI-level multilevel regression analyses

The interaction that exists between drivers' behaviour and TSI requires a modelling approach that accounts for this. Multilevel regression modelling is one method that can be used to perform regression analyses on data with these properties (Familar et al., 2011). This approach can be used in conjunction with individual models for the most frequent TSIs to gain an understanding of the overall effect of independent variables in addition to the effect of the independent variables in particular TSIs determined by performing regression analyses on individual TSIs.

In a multilevel model, independent variables are assigned to levels in a hierarchical structure such that all the independent variables within a particular level have the same value for all the observations with the same level grouping value. Figure 9-1 illustrates two examples for this dataset. On the left, the driver is level one and therefore all driver-level independent variables – such as vehicle, demographics and personality characteristics – are the same for all observations by the same driver. Similarly, with the second example, where TSI is level one, the TSI-level independent variables – such as the speed limit, time of day and day of the week – are the same for all observations with the same TSI. In this particular dataset, there is one observation for each combination of driver and TSI.[113] Conceivably both of the illustrated structures would be appropriate in this particular case since each driver has multiple TSIs and, likewise, each TSI has multiple drivers. As such, models with both structures are discussed here. Additionally, a cross-effects model where a single level is created employing the interaction between the driver and TSI is described.

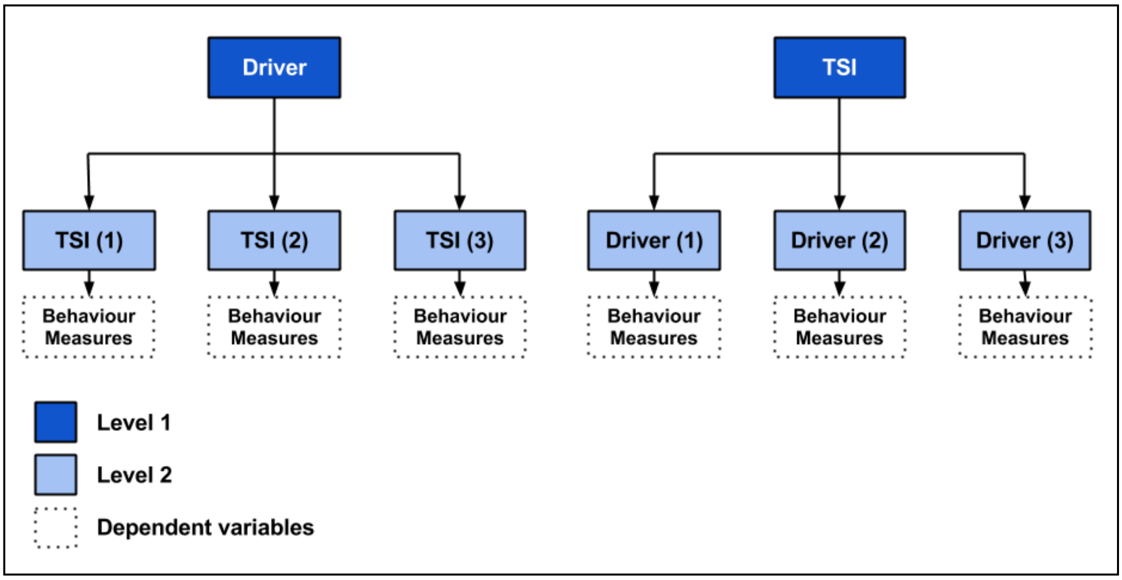

Figure 9-1: Multilevel model structures

Before a regression model can be run, there are a number of characteristics of this dataset at the TSI-level of aggregation that need to be dealt with. The first of these is that despite the minimum requirements imposed by the risk profiling algorithm (see Section 8.4.2) there are observations where a TSI represents very small distances and are, therefore, potentially not representative of a driver's behaviour. To account for this, only observations with a minimum VKT of 1 km are included. The second characteristic is a large number of observations with behavioural scores (the dependent variables) with values of zero or 100 (the extreme ends of the scale). This is atypical and therefore regression models are unable to account for this. To deal with

[113] In some multilevel models there are multiple observations at the lowest level. In this case, the model could be extended to the segment level by using a three-level model with driver as the highest level, TSI as the second level and segment as the third level.

this aspect, three separate models are developed. Two binary logistic regression models are used to describe the difference between the extreme ends of the scales (scores of zero and 100 respectively) and the remaining observations (with scores from one to 99). These models proved to be of no statistical value and are therefore summarised in Appendix B (Section 14.1). The third model is used to describe the remaining observations (with scores from one to 99).

A final characteristic of this dataset is that the distribution of the behavioural scores (from one to 99) does not follow the common distributions (Gaussian, Poisson, etc.) that are employed in regression modelling and therefore for a suitable model to be used the data must be transformed to fit one of these distributions. In this case, a rank transformation is employed to fit the data to a Poisson distribution. This is permissible because the behavioural scores are on a common relative scale and, as such, an observation with a score of 20 represents safer driving than an observation with a score of 30 which in turn represents safer driving than an observation with a score of 50 and so on. As a result, performing a transformation of this sort does not change the underlying differences between observations.

Separate models are developed for speeding, acceleration, braking and total behavioural measures using the same methodology. The independent variables are the same in all cases and are shown in Table 9-2. The driver demographics and vehicle characteristics are the same as those used for the aggregate regression analyses in Chapter 6. To ensure consistency, the same methodology was applied for testing all the hypotheses.

Table 9-2: Multilevel regression model independent variables

Variable	Level	Description
Gender	Driver	**1: Male**, 2: Female
Age	Driver	**1: 18-30**, 2: 31-45, 3: 46-65 (years)
Vehicle Transmission	Driver	**1: Automatic**, 2: Manual
Vehicle Body	Driver	**1: Sedan**, 2: Hatchback, 3: Other
Vehicle Model Year	Driver	**1: ≤ 1999**, 2: 2000 to 2004, 3: 2005 or newer (year)
Speed Limit	TSI	**40**, 50, 60, 70, 80, 90, 100, 110 (km/h)
School Zone	TSI	**0: No**, 1: Yes
Rain	TSI	**0: No**, 1: Yes
Time of Day	TSI	**1: Morning**, 2: Day, 3: Afternoon, 4: Night
Weekend	TSI	**0: No**, 1: Yes
Number of Passengers	TSI	**0: None**, 1: 1, 2: 2, 3: 3+

Note: Bolded values refer to the regression reference categories and units are shown in brackets.

9.1.3 TSI-level and driver-level single level regression analyses

In addition to the multilevel regression analyses described in Section 9.1.2, single-level models were run for observations at the TSI-level. These models use the same variables as the multilevel models except only include observations from a single TSI (for all drivers). As the TSI is constant for all observations in each model, the variables at the TSI level (shown in Table 9-2) are not explicitly included. The multilevel structure is also not explicitly retained but the road environment is nonetheless held constant. In these models there is only observation for each driver. The dependent variables and model specifications are otherwise the same as for the multilevel models.

The outputs of the driver risk profiling described in Chapter 7 include driver-level total, speeding, acceleration and braking scores. These driver-level scores are used as the dependent variable in single-level models at the driver-level. In these models, the TSI-level variables are not included because the driver-level scores are computed across all TSIs with each TSI weighted by its contribution to VKT. In these models, there is also one observation per driver.

9.2 Hypothesis 1.1: Lower perceptions of risk

Hypothesis 1.1 examines the relationship between drivers' risk perceptions and their speeding, braking and acceleration behaviour. At issue here is whether there is any relationship between perceptions of danger and observed driving behaviour. Put another way, drivers that indicate they consider a particular behaviour to be not at all dangerous (1) or slightly dangerous (2) have lower perceptions of risk – and therefore higher behavioural risk scores – than a driver that considers the same behaviour to be very dangerous (4) or extremely dangerous (5) which would have lower behavioural risk scores. Study participants were asked to identify how dangerous nine driving behaviours/manoeuvres were on a five point (subjective) scale from not at all dangerous (1) to extremely dangerous (5). Of these nine behaviours, two addressed speeding directly – by 10 km/h and 20 km/h over the speed limit – while none dealt directly with acceleration and braking behaviour.

9.2.1 Main findings and discussion

Statistically significant effects (to the $p = .05$ level) between at least one of the risk perception variables and the dependent variables were observed in 25 of the 30 models presented here (see summary in Section 9.2.4). The effects were negative in 44 cases and positive in 19 cases. Of the eight risk perception variables, four were predominantly or exclusively negative effects (illegal u-turn, turning right across a busy road, changing lanes without checking and speeding). These are behaviours that are relatively common and can conceivably occur in any TSI. Two of the variables (red light running and talking to passengers) exhibited an equal mix of positive and negative effects. Red light running is a behaviour that would only occur at intersections (which are excluded from this analysis) and is also a behaviour that all participants perceived to be very or extremely dangerous. Talking to passengers was only statistically significant for particular TSIs, none of which include a passenger which may explain the mixed results. Lastly, the remaining two variables (fatigue and mobile usage) were predominantly positive effects. Fatigue was statistically significant (in the positive direction) for all four driver-level models but is also a behaviour that is mostly relevant in particular TSIs. Most participants also consider fatigue driving to be very or extremely dangerous and therefore a higher perceived risk for this variable may be a function of differences in how participants interpreted the scale (Richardson et al., 1995). The perceived risk of using a mobile has a mostly positive effect which suggests that drivers that perceive using a mobile to be more dangerous have a higher score (i.e. worse driving) relative to a driver that perceives a lower risk. As discussed previously, one possible explanation for this is that these drivers perceive a greater danger because they typically engage in more high risk driving behaviours. However, the broader results suggest that the relationship between drivers' risk perceptions and behaviour are context-specific and since this dataset contains no data on drivers' mobile telephone use this needs to be kept in mind when interpreting this measure of risk perception.

In terms of acceleration and braking behaviour in particular, the multilevel models exhibit a small number of statistically significant risk perception variables. The parameter estimates are in the expected, negative, direction and the individual TSI models also exhibit statistically significant negative estimates. The remaining risk perception variables are not statistically significant in the multilevel models and in the individual TSI models the parameter estimates, where they are statistically significant, have different signs for different TSIs.

In general, the evidence from these results suggest that risk perceptions associated with some of the most common driving manoeuvres are negatively related to the frequency and magnitude of drivers' observed risky driving behaviour. Drivers who perceive these behaviours to be of higher risk exhibit lower scores than drivers with lower perceptions of risk and therefore pose a lower risk of a casualty to themselves and other road users. In addition, it appears that measures of risk perception which incorporate spatiotemporal elements would likely perform better as predictors of a drivers' behaviour in related spatiotemporal environments and future research in this area would be beneficial. Lastly, risk perceptions were most strongly associated with the total risk scores which are composite scores incorporating speeding, acceleration and braking behaviour.

Taking all the results together suggests that – in general – higher perceptions of risk are related to less frequent and lower magnitude speeding and total behaviour which allows the hypothesis to be accepted for speeding and total behaviour. Although there is some evidence that perceptions of risk are related to acceleration and braking scores, the evidence is not sufficiently conclusive to accept the hypothesis as-is for these behaviours without further research.

9.2.2 TSI-level models

Separate multilevel regression models are developed for speeding, acceleration, braking and total behavioural risk scores as described in Section 9.1.2. For Hypothesis 1.1, measures of drivers' risk perceptions – shown in Table 14-2 – are included as independent variables in these models.

Table 9-3: Hypothesis 1.1 regression model independent variables

Variable	Description
Running Red Light Fatigued Driving Illegal U-Turn Turning across busy road Changing lane without checking Driving 10 km/h or more over the posted speed limit Driving 20 km/h or more over the posted speed limit[a] Speaking on a mobile telephone Speaking to a passenger	These variables originate in the psychological survey described in Section 5.5.2 and represent drivers' perceived danger of engaging in various driving behaviours on a scale from 1 (not at all dangerous) to 5 (extremely dangerous). Some variables exhibit very low frequencies in some categories and therefore some consecutive categories have been merged.

[a] This variable is highly correlated with speeding by 10 km/h. Models were attempted using speeding by 20 km/h and speeding by 10 km/h with the latter models exhibiting better model fit. Therefore speeding by 20 km/h is not included in the regression models presented in this chapter.

A number of different specifications of models were attempted. The best performing model was the multilevel model with the TSI as level one. The multilevel model with the driver as level one exhibited similar model fit but poorer performance in the parameter estimates. Cross-effects and single-level models performed substantially worse. As such, further discussion in this chapter is confined to multilevel models with TSI as level one. Further details on the other models and a performance comparison are available in Appendix B (Section 14.2).

In this chapter and Chapter 10, the models presented include insignificant variables. This is done for two reasons. Firstly, many variables that were predicted *a priori* to be significant turned out not to be. Secondly, given the large number of models tested and presented in this thesis, the full models simplify comparison for the reader. Although it is acknowledged that this can sometimes incorrectly identify a variable as insignificant, in general, this has not been the case. A number of the reduced models are available in Appendix C (Chapter 15) for further reference.

The model fit of the four behavioural models is shown in Table 9-4 and Figure 9-2. What can be seen is that the predicted values closely resemble the observed values. Unlike the models from the aggregate analyses (Section 6.2 and Section 6.3), the standard errors for the parameter estimates were small and largely reasonable for the statistically significant variables. For speeding, the differences between the predicted and observed scores from the model with TSI as level one range from -8.28 to +7.02 with an average difference of 0.064 and a median of 0.340. This means that the predicted values, in addition to closely following the observed distribution, are within a small range of the observed value for the same observation.

Table 9-4: Measures of model quality for Hypothesis 1.1 multilevel models[114]

	Speeding	Acceleration	Braking	Total
AIC	9152	6004	6461	9718
BIC	9338	6179	6644	9915
Log Likelihood	-4545	-2971	-3198	-4827

[114] The AIC, BIC and Log Likelihood values are used as a measure of model fit for the same dataset and dependent variable. Therefore, these values should be compared to the other comparison models in Appendix A and not to the models for the other behavioural risk scores.

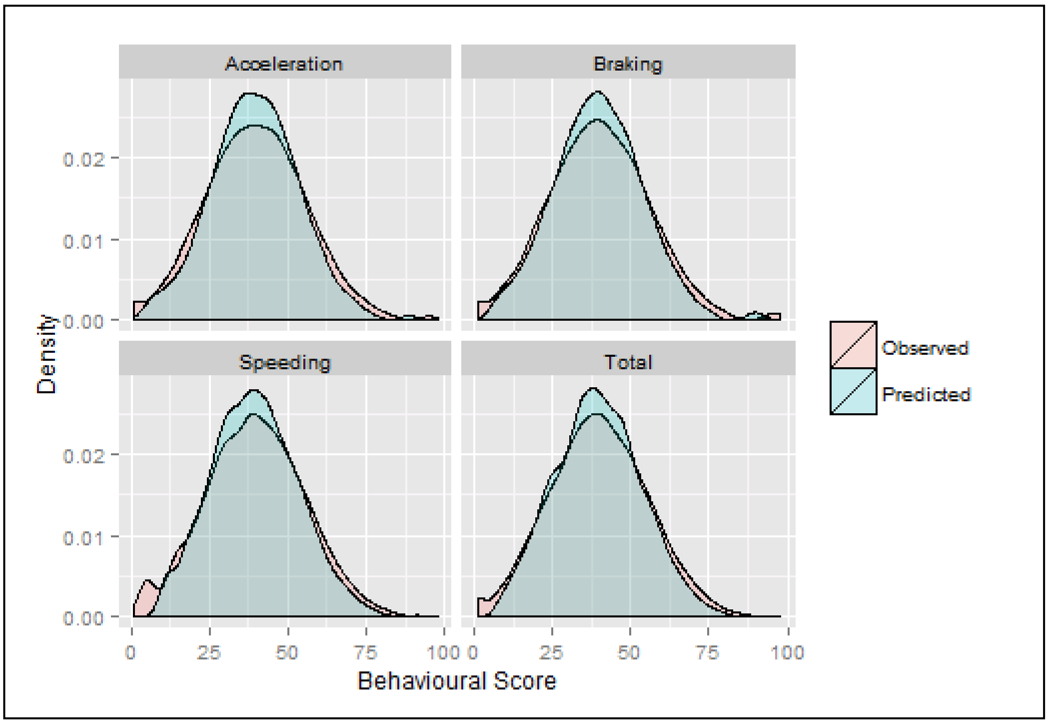

Figure 9-2: Density plot of observed vs. predicted values of Hypothesis 1.1 models

Overall, the models of speeding behaviour show that most of the TSI-level variables are statistically significant predictors of speeding behaviour in the expected direction. In contrast only a small number of the driver-level variables are statistically significant predictors of speeding behaviour. The parameter estimates (shown in Table 9-5) show that drivers exhibit lower speeding scores in school zones, when it is raining, with an increasing number of passengers, when driving a car with a manual transmission relative to a car with an automatic transmission, when driving on weekdays relative to weekends, when driving in the afternoon and, in general, when driving on roads with higher speed limits. For the most part the parameter estimates of the TSI-level variables in the acceleration, braking and total models are consistent with the speeding model albeit with slightly fewer significant variables.

In terms of risk perceptions, the higher a driver's perceived danger associated with speeding and changing lanes without checking, the lower speeding score they exhibited. Of these, higher perceptions of the risk of an illegal u-turn[115] (p = .016) and higher perceptions of the risk of turning right across a busy road were associated with

[115] In the study area, u-turns are illegal at signalised intersections unless otherwise sign posted, at non-signalised intersections when there is a 'no u-turn' sign and across single and double continuous lines.

lower acceleration scores (p = .042). Higher perceptions of the risk of using a mobile telephone while driving were positively related to braking scores (p = .005). The other variables describing perceptions of risk were not significant in any model. The interaction term between gender and age was also significant in all except for the acceleration model with older drivers (of both genders) being related to lower speeding scores. The total risk score model exhibited the most statistically significant risk perception variables and the lowest standard errors. Of the risk perception variables, higher perceived danger of an illegal u-turn, changing lanes without checking and speeding by 10 km/h or more are significantly related to lower total scores. Using a mobile telephone has the opposite effect but may be an anomaly as there is no data indicating when a driver in the study was using a mobile telephone.

Table 9-5: Parameter estimates of multilevel models for Hypothesis 1.1[116]

	Speeding			Acceleration			Braking			Total		
	B	Std. Error	Sig.	B	Std. Error	Sig.	B	Std. Error	Sig.	B	Std. Error	Sig.
Intercept	**4.382**	**0.089**	**0.000**	**3.770**	**0.087**	**0.000**	3.368	0.406	0.000	4.124	0.351	0.000
Speed limit (50)	**-0.227**	**0.057**	**0.000**	-0.025	0.050	0.615	0.465	0.397	0.242	0.012	0.345	0.972
Speed Limit (60)	**-0.429**	**0.057**	**0.000**	*-0.112*	*0.050*	*0.025*	0.457	0.397	0.250	-0.099	0.345	0.774
Speed Limit (70)	**-0.519**	**0.058**	**0.000**	**-0.331**	**0.052**	**0.000**	0.270	0.397	0.496	-0.323	0.345	0.349
Speed Limit (80)	**-0.489**	**0.060**	**0.000**	**-0.484**	**0.054**	**0.000**	0.086	0.398	0.829	-0.449	0.345	0.193
Speed Limit (90)	**-0.594**	**0.063**	**0.000**	**-1.115**	**0.069**	**0.000**	-0.278	0.398	0.486	*-0.850*	*0.346*	*0.014*
Speed Limit (100)	**-0.459**	**0.070**	**0.000**	**-1.546**	**0.109**	**0.000**	*-0.876*	*0.404*	*0.030*	**-0.912**	**0.347**	**0.008**
Speed Limit (110)	**-0.628**	**0.079**	**0.000**	**-2.116**	**0.153**	**0.000**	*-0.860*	*0.405*	*0.033*	**-1.045**	**0.348**	**0.003**
School Zone	**-0.287**	**0.077**	**0.000**	-0.024	0.092	0.799	0.041	0.079	0.602	**-0.166**	**0.050**	**0.001**
Rain	**-0.145**	**0.045**	**0.001**	0.059	0.056	0.292	**-0.141**	**0.046**	**0.002**	**-0.222**	**0.033**	**0.000**
Time (Day)	-0.014	0.025	0.584	0.039	0.027	0.155	0.007	0.028	0.795	0.023	0.019	0.229
Time (Afternoon)	**-0.068**	**0.025**	**0.006**	0.035	0.027	0.192	0.013	0.027	0.625	-0.018	0.019	0.350
Time (Night)	-0.044	0.029	0.128	0.016	0.033	0.613	**-0.154**	**0.032**	**0.000**	**-0.142**	**0.022**	**0.000**
Weekend	**0.076**	**0.017**	**0.000**	-0.018	0.018	0.332	**-0.081**	**0.018**	**0.000**	-0.007	0.013	0.600
Num. Passengers	**-0.022**	**0.008**	**0.009**	0.012	0.009	0.180	-0.011	0.009	0.247	**-0.020**	**0.006**	**0.002**
Type (Hatchback)	0.000	0.021	0.993	-0.021	0.022	0.347	0.014	0.021	0.518	-0.028	0.016	0.076
Type (Other)	0.006	0.022	0.770	-0.035	0.023	0.134	-0.008	0.023	0.717	-0.027	0.016	0.096
Model Year	0.015	0.012	0.196	0.012	0.013	0.363	-0.011	0.012	0.367	-0.008	0.009	0.382
Transmission (Manual)	**-0.112**	**0.022**	**0.000**	0.029	0.023	0.196	0.014	0.022	0.526	**-0.064**	**0.016**	**0.000**
Red Light	-0.021	0.018	0.240	0.020	0.019	0.295	0.032	0.019	0.087	0.003	0.014	0.837
Fatigue	0.032	0.019	0.095	0.001	0.020	0.961	-0.003	0.020	0.895	0.012	0.014	0.382
Illegal U-Turn	-0.015	0.009	0.093	*-0.024*	*0.010*	*0.016*	0.008	0.010	0.402	*-0.014*	*0.007*	*0.049*
Turning Right	-0.015	0.009	0.096	*-0.018*	*0.009*	*0.042*	-0.003	0.009	0.748	-0.011	0.007	0.080
Change Lanes	**-0.082**	**0.019**	**0.000**	0.036	0.020	0.070	-0.036	0.019	0.057	**-0.044**	**0.014**	**0.002**
Speeding	**-0.047**	**0.012**	**0.000**	-0.005	0.012	0.665	0.000	0.012	0.988	**-0.032**	**0.009**	**0.000**
Mobile Usage	0.016	0.012	0.171	0.011	0.012	0.375	**0.035**	**0.012**	**0.005**	**0.040**	**0.009**	**0.000**
Talking to Pass.	0.009	0.013	0.482	0.021	0.014	0.127	0.005	0.014	0.700	0.015	0.010	0.132
Male : Age	**-0.055**	**0.012**	**0.000**	-0.001	0.013	0.960	**-0.032**	**0.012**	**0.009**	**-0.056**	**0.009**	**0.000**
Female : Age	**-0.048**	**0.014**	**0.001**	0.004	0.015	0.798	*-0.032*	*0.015*	*0.030*	**-0.057**	**0.011**	**0.000**

Note (1): Cells in bold are significant at the p = .01 level
Note (2): Cells in italics are significant at the p = .05 level

In addition, a number of individual models were run for the most frequent TSIs. Since these models only contain one observation per driver and the TSI is the same for all

[116] The B values need to be interpreted on the basis of the transformed values.

observations these models do not retain an explicit multilevel structure. The parameter estimates for these models are available in Appendix B (Chapter 14).

Overall, more variables are statistically significant in the TSI which (arguably) provides less congested conditions – ST{60,TD-W-D-P0} – which is consistent with the results of the ANOVA analyses (see Table 9-1). Interestingly higher perceived danger of speeding by 10 km/h is a statistically significant determinant of less frequent speeding in the 60 km/h morning period but not the other TSIs. For most of the statistically significant risk perception variables, higher perceived risk was associated with lower speeding scores. The exceptions to this were speaking to passengers and using a mobile telephone. The former may be an anomaly as the most frequent TSIs did not have any passengers and therefore how dangerous (or not) these drivers perceived speaking to a passenger would have been irrelevant for these particular situations. The latter case may be similar as the data does not indicate if or when a driver was using a mobile telephone. It is likely that the perceived danger of using a mobile while driving would have a stronger relationship with the frequency of mobile use than speeding behaviour. In terms of driver demographics and vehicle characteristics, these results were largely consistent with the multilevel models. The interaction between age and gender were statistically significant but caution is urged in interpretation due to the relatively small sample sizes involved. Manual vehicle transmission is statistically significant negative effect on speeding scores observed except in the TSI representing the morning period on a 60 km/h road. It is unknown why this was the case although the standard error is relatively larger in that model than for the same variable in the other TSI models. The acceleration, braking and total models exhibited relatively fewer statistically significant variables than the speeding models for the same TSI but more than the multilevel models that incorporate all the TSIs. These are summarised in Section 9.2.4 with parameter estimates available in Section 14.2.

9.2.3 Driver-level regression analyses

Using a similar process to the single level model at the TSI-level, Poisson regression models were run using these as the dependent variable to determine the effects, or lack thereof, of each driver's risk perceptions at the driver-level of aggregation. The performance of these models proved to be lower than the multilevel models as illustrated in Figure 9-3.

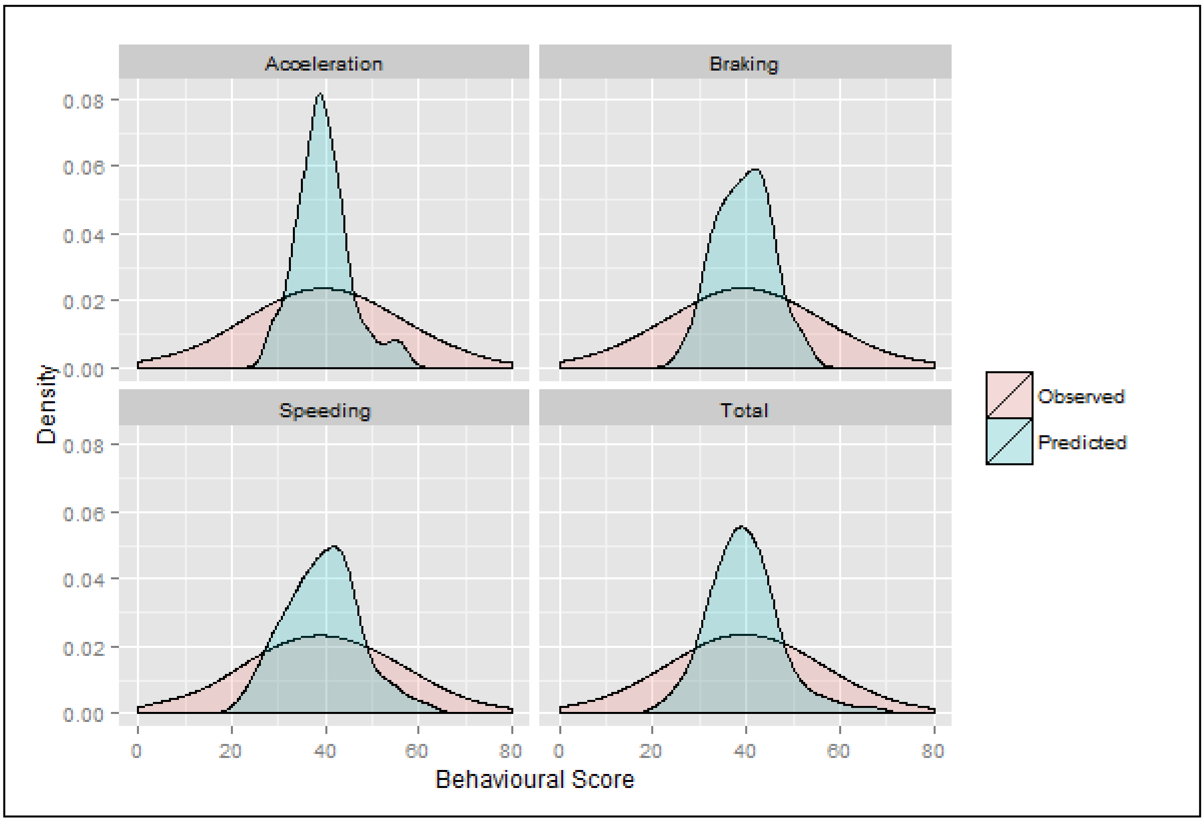

Figure 9-3: Density plot of observed and fitted driver-level speeding scores

Despite the relatively poor model fit, there were a number of statistically significant variables which are shown in Table 9-6. In the highly significant variables (shown in bold), the standard errors are within an acceptable range. At the driver-level, the statistically significant risk perception variables are negatively related to the speeding, acceleration, braking and total scores with the exception of driving whilst fatigued which has the opposite effect. This may be because driving whilst fatigued is a behaviour that is time dependent which is a factor that is not explicitly accounted for in the driver-level scores.

Table 9-6: Parameter estimates for driver-level models

	Speeding			Acceleration			Braking			Total		
	B	Std. Error	Sig.	B	Std. Error	Sig.	B	Std. Error	Sig.	B	Std. Error	Sig.
Intercept	**4.446**	**0.132**	**0.000**	**4.018**	**0.134**	**0.000**	**3.982**	**0.134**	**0.000**	**4.332**	**0.133**	**0.000**
Type (Hatchback)	0.001	0.044	0.976	**-0.126**	**0.043**	**0.004**	**-0.153**	**0.044**	**0.000**	**-0.164**	**0.044**	**0.000**
Type (Other)	0.022	0.043	0.615	*-0.107*	*0.044*	*0.015*	*-0.109*	*0.044*	*0.013*	*-0.098*	*0.044*	*0.024*
Model Year	-0.037	0.024	0.128	-0.006	0.024	0.796	-0.026	0.024	0.293	-0.033	0.024	0.174
Transmission (Manual)	**-0.330**	**0.044**	**0.000**	0.006	0.041	0.887	-0.057	0.041	0.165	**-0.216**	**0.042**	**0.000**
Red Light	*-0.083*	*0.039*	*0.031*	-0.013	0.039	0.734	-0.028	0.039	0.470	-0.053	0.039	0.172
Fatigue	*0.090*	*0.039*	*0.020*	**0.172**	**0.039**	**0.000**	**0.139**	**0.039**	**0.000**	**0.197**	**0.038**	**0.000**
Illegal U-Turn	-0.032	0.019	0.098	-0.006	0.019	0.742	-0.035	0.020	0.077	-0.031	0.019	0.115
Turning Right	*-0.057*	*0.018*	*0.002*	**-0.066**	**0.018**	**0.000**	-0.011	0.019	0.570	*-0.045*	*0.018*	*0.014*
Change Lanes	-0.061	0.039	0.118	*0.076*	*0.039*	*0.048*	0.059	0.039	0.126	0.033	0.039	0.398
Speeding	*-0.063*	*0.025*	*0.012*	*-0.057*	*0.025*	*0.024*	0.000	0.025	0.994	*-0.050*	*0.025*	*0.047*
Mobile Usage	0.040	0.024	0.093	**-0.067**	**0.024**	**0.005**	-0.038	0.024	0.114	-0.024	0.024	0.321
Talking to Pass.	-0.008	0.027	0.763	0.022	0.027	0.404	0.025	0.027	0.350	-0.014	0.027	0.594
Male : Age	*-0.049*	*0.024*	*0.040*	*-0.057*	*0.024*	*0.019*	**-0.120**	**0.024**	**0.000**	**-0.115**	**0.024**	**0.000**
Female : Age	**-0.082**	**0.029**	**0.004**	*-0.056*	*0.029*	*0.050*	**-0.086**	**0.028**	**0.002**	**-0.108**	**0.028**	**0.000**

Note (1): Cells in bold are significant at the p = .01 level
Note (2): Cells in italics are significant at the p = .05 level

9.2.4 Summary of statistical significance

Over 30 models were presented in Section 9.2.2 and 9.2.3. The statistically significant effects for the 30 best models are summarised in Table 9-7. A blank cell indicates no statistically significant effect was observed (but it was tested), a positive sign indicates that higher perceptions of risk are associated with higher risk scores and a negative sign indicates that higher perceptions of risk are associated with lower risk scores.

Table 9-7: Summary of statistical significance of risk perception variables

	Red Light	Fatigue	Illegal U—Turn	Turning Right	Change Lanes	Speeding	Mobile Usage	Talking to Pass.
Speeding								
Multilevel Driver								
Multilevel TSI					—	—		
ST{60,TE-D-P0}				—				
ST{60,TD-W-D-P0}	—	—	—	—			+	—
ST{60,TM-D-P0}		+				—		+
ST{50,TE-D-P0}								
Binary 0 & 1-99				—		—		
Binary 50-99 & 100							+	
Acceleration								
Multilevel Driver								
Multilevel TSI			—	—				
ST{60,TE-D-P0}			—					
ST{60,TD-W-D-P0}	—					—		
ST{60,TM-D-P0}	—				+	—		
ST{50,TE-D-P0}	+		—	—				—
Braking								
Multilevel Driver								
Multilevel TSI							+	
ST{60,TE-D-P0}	+				—		—	+
ST{60,TD-W-D-P0}			—					
ST{60,TM-D-P0}			+					+
ST{50,TE-D-P0}			—	—	—			
Total								
Multilevel Driver						—		
Multilevel TSI			—		—	—	+	
ST{60,TE-D-P0}					—			+
ST{60,TD-W-D-P0}			—			—	+	—
ST{60,TM-D-P0}								
ST{50,TE-D-P0}								—
Driver-Level[117]								
Speeding	—	+		—		—		
Acceleration		+		—	+	—	—	
Braking		+						
Total		+		—		—		
Total Negative (44)	4	1	8	9	5	11	2	4
Total Positive (19)	2	5	1	0	2	0	5	4

Note: + indicates a positive effect, — indicates a negative effect and a blank cell indicates no statistically significant effect

9.3 Hypothesis 1.2: Worry and concern

Prior research has found that passengers have an effect on drivers' speeding behaviour (Fleiter et al., 2006). It was postulated that drivers that are more concerned about injuring passengers engage in risky driving behaviour less frequently and at lower magnitudes than drivers that are less concerned about their passengers being injured.

[117] The model fit of these models was considerably poorer than the multilevel and single level models performed at the TSI level and, therefore, less weight should be given to these results when interpreting the summary table. For details see Section 9.2.3.

This hypothesis is tested using the risk profile measures as the dependent variable and five questions from the psychological survey. The five questions include three dealing with drivers' worry of themselves, their passengers and other drivers being injured while driving[118]. The additional two questions are drivers' self-assessed likelihood of themselves and other drivers being involved in a crash within 12 months[119]. The independent spatiotemporal, driver and vehicle variables are the same as those used for Hypothesis 1.1 (Section 9.2).

Following the results of the Hypothesis 1.1 models, this (and subsequent hypotheses) were tested using the multilevel models with the TSI as level one. In addition individual TSI models were also tested. Since the model specifications for this hypothesis were the same as for Hypothesis 1.1 the spatiotemporal, vehicle and driver demographic variables exhibited the same statistically significant effects as the models presented in Section 9.2.2 to Section 9.2.3. For purposes of conciseness, these parameters are not shown in the modelling results in this section.

9.3.1 Main findings and discussion

Examining the results of all the models (statistically significant effects summarised in Section 9.3.4), the most consistent predictors of drivers' behaviour were their own perceptions of the likelihood of being involved in a crash – related to higher scores – and their concerns of being injured while driving which was related to lower scores. Drivers' concern about other drivers being injured and higher perceived likelihood of other drivers being involved in a crash were both positively related to their behavioural risk scores. Drivers' concerns about their passengers' safety was statistically significant in eight models but in both directions. Furthermore, additional models which included interactions between the number of passengers and concern about injury to passengers exhibited a (positive) statistically significant effect with speeding behaviour as the number of passengers increased. Although drivers are less likely to speed the more passengers there are, this is not related to more concern about passenger safety. It is recognised, however, that there may be a distinction between a driver's concern for a passenger and the same driver's feeling of

[118] These questions were asked on a five point subjective scale from 'not at all' to 'extremely' worried.
[119] These questions were asked on a ten point percentage scale from ≤ 10% to > 90%.

responsibility for a passenger. This may be observable in differences in driver behaviour when the passenger(s) are adults or when the passenger(s) include children.

These results suggest that drivers who engage in more risky driving behaviour self-report a higher likelihood of crash involvement relative to drivers who engage in less risky driving behaviour. This is not altogether surprising considering that perceptions of crash risk are influenced by previous driving experience and drivers who engage in more frequent speeding are more likely to be involved in crashes or near crashes. This may have had an impact on the modelling results with an over-estimation of the importance of this variable. However, even if this is true, one may expect that a crash or near crash experience would result in more cautious driving and, yet, that appears not to be the case. Simultaneously, it appears that drivers that express greater concern about being injured whilst driving exhibit lower behavioural risk scores than drivers that are less concerned. Consequently, it seems that more risky drivers may be aware that they are at greater risk of being involved in a crash but this does not extend to greater awareness of the risk of injury reflecting a possible lack of awareness as to the serious implications of car crashes.

Overall, it cannot be concluded from this data that drivers' concern for passenger safety is related to less risky driving. Instead, it appears that drivers' concern of their own safety is a stronger predictor of behaviour. In addition, there is strong evidence that drivers are largely aware of their own crash risk with drivers with higher self-reported crash risks exhibiting statistically significantly higher speeding, acceleration, braking and total scores once spatiotemporal factors have been taken into account.

9.3.2 TSI-level models

Multilevel models were tested with each of the speeding, acceleration, braking and total scores as the dependent variable. The model fit as defined by the AIC, BIC and log-likelihood values was similar to the respective models used for testing Hypothesis 1.1. This is not surprising since the spatiotemporal variables were the strongest predictors and these remain unchanged. The model fit parameters for all four multilevel models are shown in Table 9-8 and the distribution of predictions is plotted against the observed values in Figure 9-4.

Table 9-8: Measures of model quality for Hypothesis 1.2 multilevel models[120]

	Speeding	Acceleration	Braking	Total
AIC	9173	5995	6462	9729
BIC	9341	6153	6628	9908
Log Likelihood	-4559	-2970	-3202	-4836

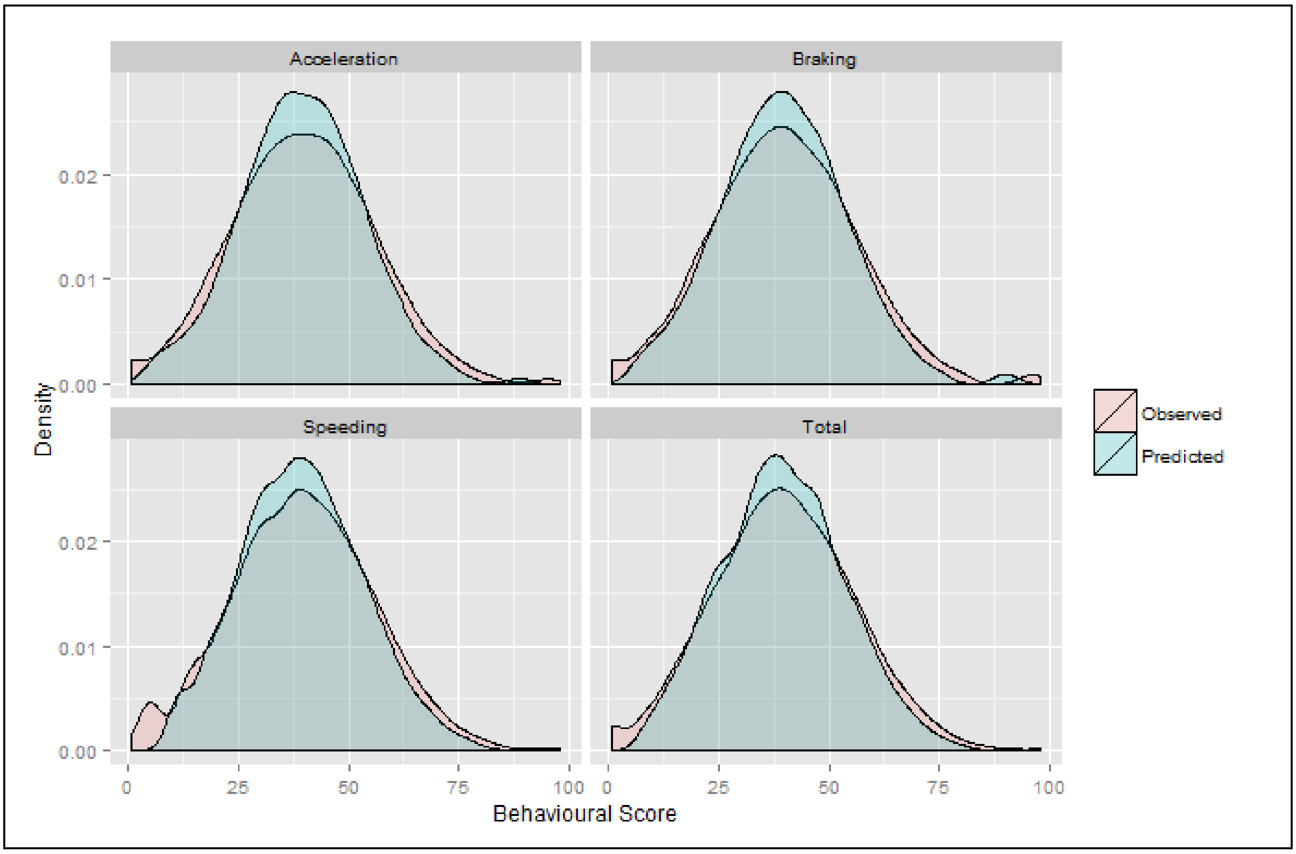

Figure 9-4: Density plot of observed and predicted values for Hypothesis 1.2

In terms of the statistically significant variables (shown in Table 9-9), more concern about a drivers' own risk of an injury was related to lower speeding and braking scores whilst concern about other drivers exhibited an opposite relationship with higher speeding and total scores. Injury to passengers was only statistically significant – in the negative direction – in respect to acceleration behaviour in the multilevel models. It was also statistically significant for some TSIs but in both directions. Higher scores for all four behavioural measures were significantly related to increased (self-reported) likelihood of a crash within the next 12 months. The perceived likelihood of other

[120] These AIC, BIC and Log Likelihood values can be compared to the speeding, acceleration, braking and total models for Hypothesis 1.1 (Section 9.2) but should not be compared between themselves since the samples are slightly different.

drivers being involved in a crash was negatively related only to acceleration scores in the multilevel models but was positively related for a number of TSIs. The other statistically significant effects in individual TSIs were largely consistent with the results of the multilevel models.

Table 9-9: Parameter estimates for Hypothesis 1.2 multilevel models

	B	Std. Error	Sig.
Speeding			
Injury (Self)	**-0.048**	**0.016**	**0.003**
Injury (Passengers)	0.021	0.013	0.101
Injury (Other Drivers)	**0.044**	**0.011**	**0.000**
Crash Likelihood (Self)	*0.012*	*0.006*	*0.041*
Crash Likelihood (Others)	-0.006	0.004	0.138
Acceleration			
Injury (Self)	0.033	0.017	0.051
Injury (Passengers)	*-0.029*	*0.014*	*0.040*
Injury (Other Drivers)	-0.022	0.011	0.056
Crash Likelihood (Self)	*0.016*	*0.006*	*0.011*
Crash Likelihood (Others)	*-0.009*	*0.005*	*0.043*
Braking			
Injury (Self)	*-0.032*	*0.016*	*0.047*
Injury (Passengers)	0.013	0.013	0.337
Injury (Other Drivers)	0.013	0.011	0.255
Crash Likelihood (Self)	**0.017**	**0.006**	**0.008**
Crash Likelihood (Others)	-0.004	0.004	0.339
Total			
Injury (Self)	-0.021	0.012	0.078
Injury (Passengers)	0.004	0.010	0.660
Injury (Other Drivers)	**0.032**	**0.008**	**0.000**
Crash Likelihood (Self)	**0.018**	**0.004**	**0.000**
Crash Likelihood (Others)	-0.006	0.003	0.063

An additional four multilevel models were used which employed an interaction term between the number of passengers and the injury to passenger variable from the survey. The remaining four worry and concern variables were not included but otherwise the model specifications were the same as for the other multilevel models. This was done on the premise that any relationship between drivers' concern for their passengers may only be reflected in situations in which a passenger was present. This interaction term was only statistically significant for speeding with no passengers (positive effect, p = .018) indicating that although the number of passengers was itself a statistically significant predictor of driver behaviour this appears unrelated to the extent of drivers' concern for their passengers' safety.

9.3.3 Driver-level models

Following the same procedure that was conducted for Hypothesis 1.1 (see Section 9.2.3), driver level models were created using the driver-level total, speeding, acceleration and braking scores. Consistent with those results, although the statistically significant variables and the standard errors were in line with the other models, the model fit and the predictive ability of the models proved to be substantially poorer than the multilevel models as illustrated in Figure 9-5. Across the four models, injury to themselves was statistically significant factor in (negatively) predicting speeding (p = .021) and total (p = .024) scores. Conversely injury to other drivers was a statistically significant (positive) predictor of speeding (p = .000) and total (p = .000) scores. Lastly, the risk of other drivers being involved in a crash was a significant positive predictor of speeding behaviour (p = .033).

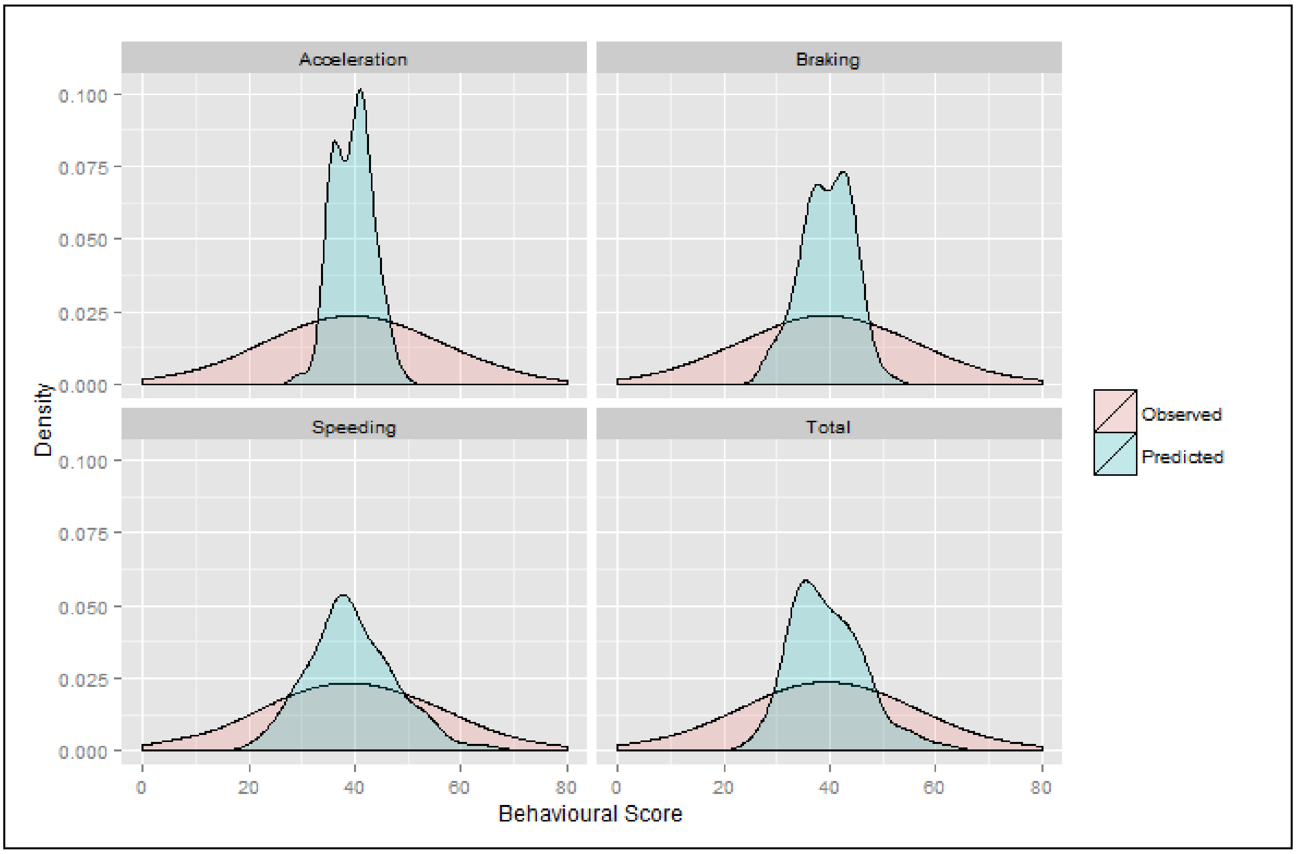

Figure 9-5: Density plot of observed and predicted driver-level values for Hypothesis 1.2

9.3.4 Summary of statistical significance

Table 9-10 summarises the statistically significant effects of the 28 models used to test Hypothesis 1.2. Injury to themselves exhibited the highest number of (mostly negative) statistically significant effects across all behaviours. The speeding models exhibited the largest number of statistically significant effects compared to the acceleration, braking and total models.

Table 9-10: Summary of statistical significance of worry and concern variables

	Injury (self)	Injury (Pass.)	Injury (Other)	Crash (Self)	Crash (Other)
Speeding					
Multilevel TSI	—		+	+	
ST{60,TE-D-P0}		—			
ST{60,TD-W-D-P0}	—	+			+
ST{60,TM-D-P0}	—	+		+	
ST{50,TE-D-P0}				+	
Acceleration					
Multilevel TSI		—		+	—
ST{60,TE-D-P0}					+
ST{60,TD-W-D-P0}			—		—
ST{60,TM-D-P0}					
ST{50,TE-D-P0}	—	+			
Braking					
Multilevel TSI	—			+	
ST{60,TE-D-P0}	+	—			
ST{60,TD-W-D-P0}					
ST{60,TM-D-P0}			+		
ST{50,TE-D-P0}	+	—			+
Total					
Multilevel TSI			+	+	
ST{60,TE-D-P0}					
ST{60,TD-W-D-P0}				+	
ST{60,TM-D-P0}			+		
ST{50,TE-D-P0}					+
Number of Passengers and Passenger Injury Interaction (Multilevel)					
Speeding		+			
Acceleration					
Braking					
Total					
Driver-Level[121]					
Speeding	—		+		+
Acceleration					
Braking					
Total	—		+		
Total Negative (14)	**7**	**4**	**1**	**0**	**2**
Total Positive (24)	**2**	**4**	**6**	**7**	**5**

Note: + indicates a positive effect;
— indicates a negative effect; and
A blank cell indicates no statistically significant effect.

9.4 Hypothesis 1.3: Confidence

Previous studies have found that demographics with higher crash rates are more self-confident in their driving skills (Musselwhite, 2006; Rosenbloom et al., 2007; Lucidi et al., 2010). It was hypothesised that drivers who self-reported greater confidence in their driving skills engage in more risky driving behaviour. The psychological survey

[121] The model fit for the driver-level models was significantly poorer than for the equivalent multilevel models.

conducted during recruitment included five questions regarding drivers' confidence driving on unfamiliar roads, in poor weather conditions, in heavy traffic, on motorways and at night. Drivers were asked to rate their confidence on a five-point subjective scale from 'not at all' confident to 'extremely' confident for each of these situations. Using the driver behaviour profile scores as the dependent variables and the self-reported confidence measures as the independent variables, the process used for Hypothesis 1.1 (Section 9.2) and Hypothesis 1.2 (Section 9.3) was repeated. As in those cases, the spatiotemporal, driver and vehicle characteristics remain unchanged and are therefore not shown here.

9.4.1 Main findings and discussion

A number of conclusions can be drawn from the modelling results. First, drivers' confidence in heavy traffic does not appear to be an important factor in drivers' behaviour, being only statistically significant in two (TSI-specific) models. Second, the driver-level and TSI-specific single level models produced markedly different results with poorer model fit than the equivalent multilevel models. This suggests that driver characteristics with spatiotemporal elements derived from self-reported surveys need to be examined in light of the spatiotemporal characteristics for which they apply. For example, the relationship between driver confidence on unfamiliar roads and their risky driving behaviour needs to be tested using naturalistic data collected while the participant was driving on unfamiliar roads. In the case of the TSI-specific models – and by extension the driver-level models by virtue of the higher VKT – the driver confidence variables derived from the survey were not likely to be relevant. When this occurs it is possible that the statistically significant effects are functioning as proxies for another (unmeasured) variable. Lastly, looking at the 16 multilevel models alone, confidence in heavy traffic was not statistically significant in any model, confidence on unfamiliar roads and on motorways were statistically significant negative and positive effects respectively but in only a small proportion of the models. Drivers' confidence in poor weather was the strongest (positive) predictor being statistically significant in 50 percent of the models across all behavioural measures and multilevel models. The opposite (negative) effect was observed for confidence in night driving which was statistically significant in six models across all behaviours. A summary of the statistically significant effects of driver confidence from the 36 models used to test Hypothesis 1.3 is shown in Section 9.4.4.

Although there is some evidence from these models that driver confidence has some relationship to the extent of drivers' risky driving behaviour, in particular for speeding and total behaviour, the effect is not always in the positive direction. Therefore, it is not possible to accept the hypothesis that a driver with more confidence in their own driving ability is related to more risky driving behaviour.

9.4.2 TSI-level models

Initially four multilevel models were run – one each for speeding, acceleration, braking and total behaviour – using the same procedure as for the other hypotheses. The model quality measures (summarised in Table 9-11) are consistent with that of previous models. The results, however, were not as expected. Higher confidence in night time driving was negatively related to speeding (p = .020), braking (p = .014) and total (p = .000) scores. Higher confidence on unfamiliar roads was also negatively related to speeding (p = .031) and total (p = .000) scores. It had been expected that if these measures were statistically significant that greater confidence would be related to higher scores but this was not the case. In contrast, confidence in poor weather and on motorways was positively related to higher speeding (p = .047 and .000 respectively) and total (p = .003 and .000) scores. No confidence variables were statistically significant for acceleration.

Table 9-11: Measures of model quality for Hypothesis 1.3 multilevel models[122]

	Speeding	Acceleration	Braking	Total
AIC	9172	6009	6463	9717
BIC	9340	6167	6629	9896
Log Likelihood	-4558	-2977	-3202	-4830

Although the results were consistent across the multilevel models, the unexpected relationship prompted further testing to confirm these results. Since the survey

[122] These AIC, BIC and Log Likelihood values can be compared to the speeding, acceleration, braking and total models for Hypothesis 1.1 (Section 9.2) but should not be compared between themselves since the samples are slightly different.

questions referred to specific spatiotemporal situations three additional multilevel models for each of the behaviour measures were created. These models employed the same specifications as the other multilevel models but only included TSIs at night, on motorways and with rain which was used as a proxy for poor weather conditions. The statistically significant variables (shown in Table 9-12) are consistent with that of the multilevel models containing all TSIs. Therefore, these effects do not appear to be confounding effects from differences in where and when individuals with different confidence levels drive. Despite this it is notable that in many cases the statistically significant variables are not the same as the relevant spatiotemporal variable. For example in motorway driving, poor weather is a statistically significant positive predictor of speeding and total scores. Furthermore, across all the multilevel models confidence in poor weather is a statistically significant (positive) predictor in 50 percent of the models, the most frequent of all the confidence measures.

Table 9-12: Parameter estimates for multi-level spatiotemporal-specific models

	Speeding			Acceleration			Braking			Total		
	B	Std. Error	Sig.	B	Std. Error	Sig.	B	Std. Error	Sig.	B	Std. Error	Sig.
Night												
Unfamiliar Roads	-0.023	0.046	0.627	-0.098	0.055	0.074	-0.091	0.052	0.079	-0.055	0.040	0.161
Poor Weather	**0.104**	**0.038**	**0.007**	*0.099*	*0.044*	*0.024*	0.010	0.043	0.822	**0.116**	**0.034**	**0.001**
Heavy Traffic	-0.085	0.050	0.093	0.008	0.054	0.883	0.109	0.056	0.052	-0.071	0.043	0.095
Motorways	0.083	0.055	0.133	0.054	0.065	0.410	0.022	0.063	0.727	**0.162**	**0.047**	**0.001**
Night	-0.073	0.048	0.125	-0.055	0.051	0.286	-0.049	0.051	0.337	**-0.144**	**0.040**	**0.000**
Motorway												
Unfamiliar Roads	0.044	0.112	0.694	0.553	1.166	0.635	-0.248	0.301	0.410	0.015	0.125	0.904
Poor Weather	**0.218**	**0.065**	**0.001**	-0.310	0.414	0.453	0.097	0.181	0.592	*0.173*	*0.073*	*0.017*
Heavy Traffic	-0.103	0.130	0.427	-0.815	1.358	0.549	-0.048	0.379	0.900	0.140	0.145	0.334
Motorways	0.082	0.133	0.539	0.124	0.756	0.870	0.323	0.436	0.459	-0.136	0.154	0.376
Night	0.003	0.102	0.977	0.680	1.104	0.538	-0.051	0.284	0.858	0.040	0.118	0.737
Poor Weather												
Unfamiliar Roads	0.117	0.113	0.301	-0.070	0.087	0.421	-0.116	0.077	0.131	-0.016	0.086	0.853
Poor Weather	0.122	0.103	0.236	0.077	0.080	0.333	**0.217**	**0.072**	**0.003**	0.137	0.079	0.083
Heavy Traffic	-0.163	0.148	0.272	0.060	0.104	0.564	0.101	0.108	0.348	-0.105	0.111	0.346
Motorways	0.038	0.157	0.810	0.134	0.114	0.237	0.033	0.105	0.758	0.030	0.116	0.794
Night	-0.180	0.119	0.132	**-0.288**	**0.096**	**0.003**	**-0.304**	**0.088**	**0.001**	-0.156	0.092	0.089

Note (1): Cells in bold are significant at the p = .01 level
Note (2): Cells in italics are significant at the p = .05 level

Individual models for the most frequent TSIs were also tested to ensure consistency with the other hypotheses with inconclusive results. All five of the measures were statistically significant for at least one TSI but with inconsistent signs. This is likely to be due to the lack of relevance of the confidence measures to any of these TSIs –

none of which included rain, motorway driving or night time driving – and therefore the scores reflect exposure rather than any meaningful differences in behaviour.

9.4.3 Driver-level models

Driver-level models were created using the driver level speeding, acceleration, braking and total scores as the dependent variable. Adding further weight for the argument that a multilevel structure is necessary in studying driver behaviour, the model fit of these models (illustrated in Figure 9-6) was significantly poorer than the equivalent multilevel models. Although the driver-level measures control for the spatiotemporal characteristics using TSIs, it is evident that many of the driver characteristics have different effects in different spatiotemporal environments and it is not possible to model these effectively using these aggregate scores. Nonetheless, in this case all the confidence measures except for drivers' confidence in heavy traffic were statistically significant in predicting the behavioural scores. Drivers' confidence in unfamiliar roads and confidence in poor weather were statistically significant predictors of speeding in the same direction as the multilevel models. In all other cases the statistically significant effects exhibited the opposite direction than the multilevel models. It is unclear why this is but is likely to be a function of differences in exposure in different TSIs which is controlled for in the multilevel models but not in the driver-level scores since the TSI-level scores are weighted by VKT[123].

[123] See Section 8.4 for detail on how the driver-level scores are computed.

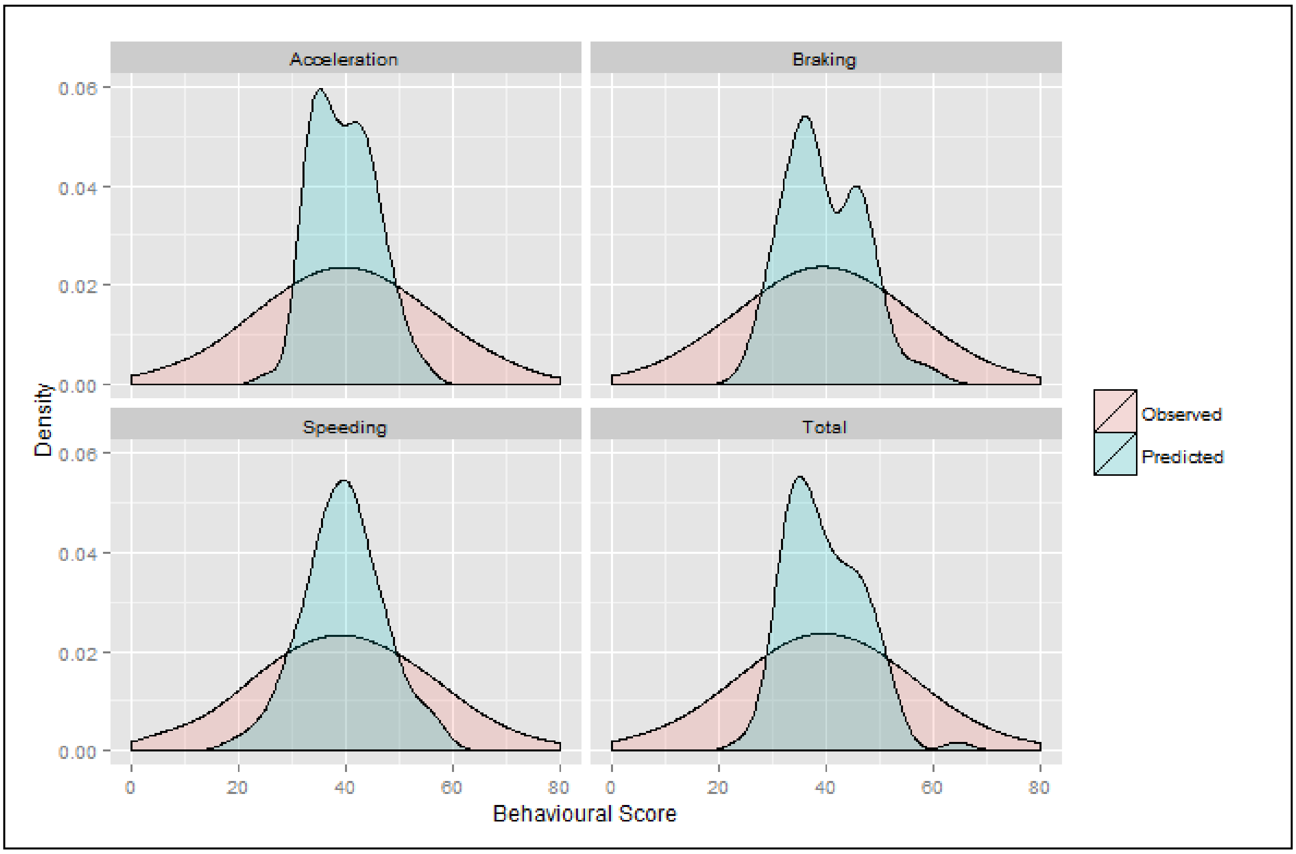

Figure 9-6: Density plot of observed and predicted driver-level values for Hypothesis 1.3

9.4.4 Summary of statistical significance

Statistically significant effects were observed for the five measures of driving confidence in 64 percent (23 of the 36) models run. A summary of the positive and negative effects are shown in Table 9-13.

Table 9-13: Summary of statistical significance of driving confidence measures

	Unfamiliar Roads	Poor Weather	Heavy Traffic	Motorways	Night
Speeding					
Multilevel TSI	—	+		+	—
Night TSIs		+			
Motorway TSIs		+			
Rain TSIs					
ST{60,TE-D-P0}				+	
ST{60,TD-W-D-P0}	—			—	+
ST{60,TM-D-P0}		—		—	+
ST{50,TE-D-P0}					
Acceleration					
Multilevel TSI					
Night TSIs		+			
Motorway TSIs					
Rain TSIs					—
ST{60,TE-D-P0}		—			
ST{60,TD-W-D-P0}	+	—		—	
ST{60,TM-D-P0}	+				
ST{50,TE-D-P0}			—		
Braking					
Multilevel TSI					—
Night TSIs					

	Unfamiliar Roads	Poor Weather	Heavy Traffic	Motorways	Night
Motorway TSIs					
Rain TSIs		+			—
ST{60,TE-D-P0}	+				
ST{60,TD-W-D-P0}					
ST{60,TM-D-P0}			—		
ST{50,TE-D-P0}	+	—			+
Total					
Multilevel TSI	—	+		+	—
Night TSIs		+		+	—
Motorway TSIs		+			
Rain TSIs					
ST{60,TE-D-P0}					
ST{60,TD-W-D-P0}					
ST{60,TM-D-P0}					
ST{50,TE-D-P0}					
Driver-Level[124]					
Speeding	—	+			
Acceleration	+	—		—	+
Braking	+	—		—	+
Total				—	+
Total Negative (24)	**4**	**6**	**2**	**6**	**6**
Total Positive (24)	**6**	**8**	**0**	**4**	**6**
Multilevel Total Negative (8)	**2**	**0**	**0**	**0**	**6**
Multilevel Total Positive (11)	**0**	**8**	**0**	**3**	**0**

Note: + indicates a positive effect; — indicates a negative effect; A blank cell indicates no statistically significant effect; and Light grey cells indicate multilevel models

9.5 Hypothesis 1.4: Personality

As discussed in Section 3.1.2, previous research has found some evidence that drivers' personality characteristics are related to their speeding behaviour. However, most of the existing literature relies on self-reported driving behaviour as a means of comparison. With this in mind, it was hypothesised that drivers with more aggressive, excitable and car-dependent personalities would exhibit more risky driving behaviour than drivers with less aggressive, excitable and car-dependent personalities. Conversely it was thought that more altruistic drivers would exhibit less risky driving behaviour than less altruistic drivers.

To test this hypothesis, questions from the psychological survey conducted as part of the recruitment process (see Section 4.2.6) were used as the basis of several psychological scales – one each for aggression, altruism, excitement and car-dependence. These scales are comprised of the average responses to the questions relating to each of the personality attributes which are shown in Table 9-14. These

[124] The model fit for the driver-level models was significantly poorer than for the equivalent multilevel models.

questions and scales have been used in previous studies (see Section 4.2.6) and Cronbach alphas have previously been used to test their appropriateness for this specific dataset (Greaves and Ellison, 2011).

The specifications of the models in this section including the dependent variables and the other independent variables are the same as those used to test the other hypotheses.

Table 9-14: Personality scale composition[125]

Question	Scale	
Aggression: Please answer the following questions on the basis of your usual or typical feelings about driving.		
I lose my temper when another driver does something wrong	10 point scale Not at all to Very much	**Aggression**
Driving brings out the worst in people		
It is important to show other drivers that they can't take advantage of you		
Other drivers are generally to blame for any difficulties I have on the road		
I find it difficult to control my temper when driving		
I become annoyed if another car follows very close behind mine for some distance		
I am usually impatient in congested traffic		
It annoys me to drive behind a slow moving vehicle		
I get annoyed when the traffic lights change to red when I approach them.		
Altruism: Please answer the following questions on the basis of your usual or typical feelings about driving.		
I make a point of carefully checking every side road I pass for emerging vehicles	10 point scale Not at all to Very much	**Altruism**
I am courteous to other road users		
I make a special effort to be alert even on roads I know well		
I always keep an eye on parked cars in case somebody gets out of them, or there are pedestrians behind them		
I make an effort to see what's happening on the road a long way ahead of me		
Excitement: Please answer the following questions on the basis of your usual or typical feelings about driving.		
I get a real thrill out of driving fast	10 point scale Not at all to Very much	**Excitement**
I think it is worthwhile taking risks on the road		
I like to raise my adrenaline levels while driving		
I would enjoy driving a sports car on a road with no speed limit		
I enjoy the sensation of accelerating rapidly		
I enjoy cornering at high speed		
Car-dependence: Please indicate whether you agree or disagree with the following statements		
I could not survive without access to a car	7 point scale Strongly Disagree To Strongly Agree	**Car-Dependence**
I limit my car travel to help improve congestion and air quality*		
I'd rather have someone else do than driving*		
I prefer to use my car rather than public transport		
To me, the car is a status symbol		
To me, the car is nothing more than a convenient way to get around*		
I view my car as having a personality		

* Indicates that the question response scale is reversed prior to inclusion in composite measure. For example, a score of 6 would be transformed to a score of 1 and a score of 3 would be transformed into a score of 4.

[125] The question text is the same as in the survey.

9.5.1 *Main findings and discussion*

The influence of personality characteristics on speeding behaviour has been previously investigated largely using self-reported speeding data. The models presented in this section have tested the hypothesis that more aggressive, excitable and car-reliant drivers exhibit more (observed) risky driving behaviour and conversely that more altruistic drivers exhibit less risky driving behaviour.[126]

In all, 40 models – including 20 multilevel models – were used to test this hypothesis. The results, summarised in Section 9.5.4, show that aggression only appears to be a significant predictor of acceleration and braking behaviour in a limited number of spatiotemporal situations and not at all a predictor of speeding behaviour. This result was surprising given previous evidence which suggests that aggression, although not the strongest predictor, is a significant factor in risky driving behaviour (Oltedal and Rundmo, 2006). One explanation for this is that previous research on aggression examines the relationship between aggression and either self-reported behaviour or crash and citation data which account for only a small proportion of all driving behaviour.[127]

On the other hand, the modelling results for the relationship between altruism, excitement and speeding are consistent with prior research. There is much less evidence in regards to acceleration and braking behaviour due to much fewer studies on this topic. Overall the multilevel models show that the personality characteristics (when significant) have the opposite effects on speeding behaviour than on acceleration and braking (and by consequence, total) behaviour. This would be consistent with more altruistic drivers being more conscientious about their speed and (simultaneously) also being more prone to heavy braking and acceleration to avoid potential close calls. Further evidence of this can be gained by looking at the multilevel models using the spatiotemporal subsets where higher breaking and total scores are observed by the more altruistic drivers in school zones and in the presence of rain. The opposite effect is seen in relation to the excitement variable which is

[126] Although drivers' driving behaviour is empirically measured using GPS data, drivers' personality characteristics are self-reported. More discussion on this can be found in Section 11.4.1.

[127] See Section 2.4.1 for a detailed discussion on the characteristics of these types of data.

significantly associated with higher speeding scores and higher total scores on motorways and (worryingly) in school zones. Both of these conclusions seem plausible as there is a known link between excitement and speeding behaviour as well as altruism and (less frequent) speeding behaviour (Machin and Sankey, 2008).

The effect of drivers with excitable and car-dependent personalities on speeding and acceleration behaviour is more mixed. At this stage it would be premature to state that these personality characteristics are related to particular acceleration and braking patterns although the driver-level models imply that some effect on braking behaviour does exist.

Overall, the hypothesis that less altruistic drivers and more excitable drivers are associated with more risky driving behaviour can only be accepted for speeding behaviour.

9.5.2 TSI-level models

Initial multilevel models were created for each of speeding, acceleration, braking and total scores. The model quality measures (Table 9-15) are better than the multilevel models of the other hypotheses indicating that of the driver characteristics, personality is the strongest predictor of risky driving behaviour. The predictions are also similar both to previous models and the observed values (Figure 9-7). In addition to confirming the robustness of the model it also confirms that the main factors behind drivers' behavioural scores are the spatiotemporal variables, and to a lesser extent, the vehicle characteristics. Whilst the personality variables are statistically significant, and are stronger predictors than the other driver characteristics, they appear to play a minor role in influencing driver behaviour relative to the spatiotemporal environment.

Table 9-15: Measures of model quality for Hypothesis 1.4 multilevel models[128]

	Speeding	Acceleration	Braking	Total
AIC	9108	5969	6374	9660
BIC	9270	6121	6534	9833
Log Likelihood	-4527	-2957	-3159	-4802

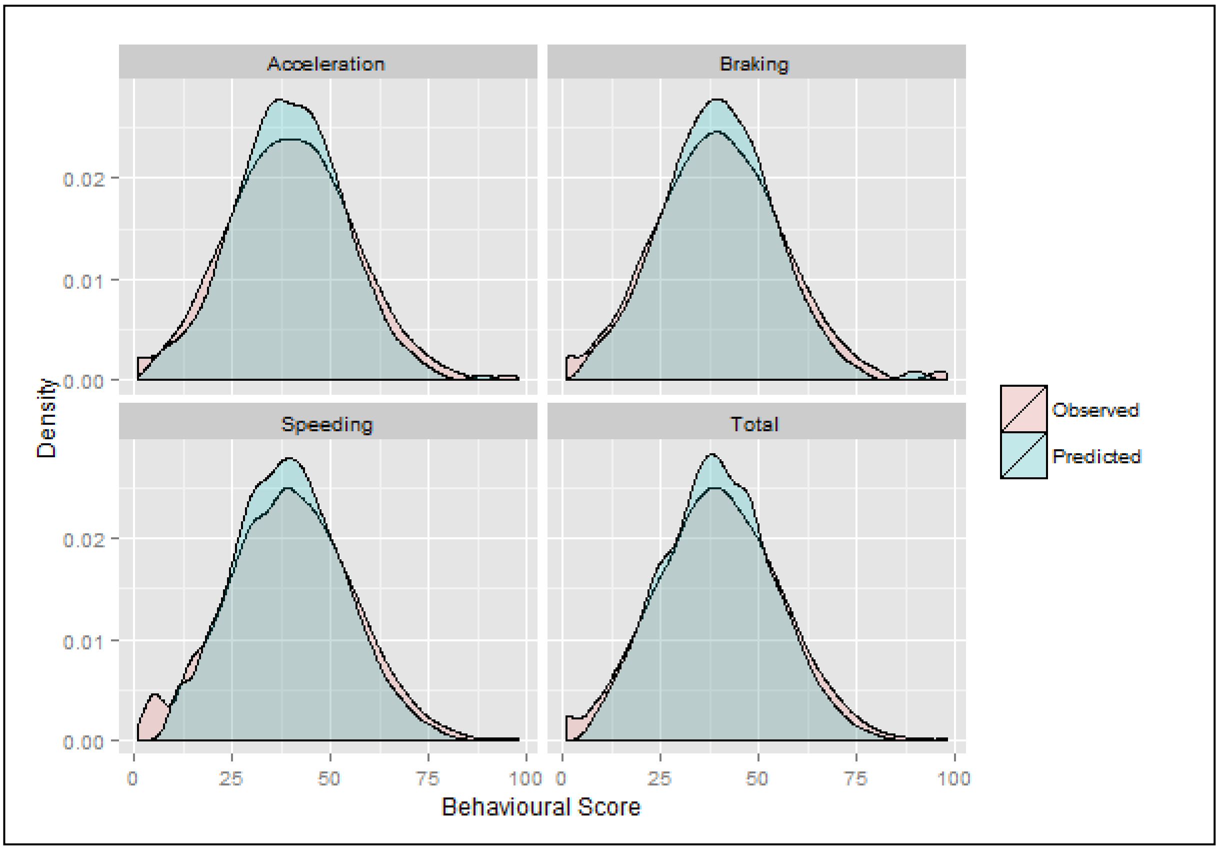

Figure 9-7: Density plot of observed and predicted values for Hypothesis 1.4

Of the four personality scales, altruism is the only factor that is statistically significant for all four behavioural measures being a negative predictor of speeding scores (p = .000) and a positive predictor of acceleration (p = .008), braking (p = .000) and total scores (p = .001). In addition, excitement (p = .036) and car-dependence (p = .008) are positive predictors of speeding behaviour. To investigate if this remains the case in TSIs with particular spatiotemporal characteristics, following the same process

[128] These AIC, BIC and Log Likelihood values can be compared to the speeding, acceleration, braking and total models for Hypothesis 1.1, Hypothesis 1.2 and Hypothesis 1.3 but should not be compared between themselves since the samples are slightly different.

that was used in testing Hypothesis 1.3 (Section 9.4.2), additional multilevel models were run for night, motorway, rain and school zone TSIs. In these more limited subsets none of the personality scales were statistically significant predictors of speeding behaviour and car-dependence was not statistically significant for any behavioural measure. Aggression was a significant negative predictor of acceleration behaviour on motorways (p = .011) and a positive predictor (p = .000) of braking behaviour in rain TSIs. In situations where altruism is statistically significant, it was in the same direction as the overall multilevel models. Excitement was a positive predictor of drivers' total scores on motorways (p = .045) and school zones (p = .010) and a negative predictor of braking (p = .005) and total behaviour (p = .013) in the rain.

Single-level models of speeding, acceleration, braking and total scores for the most frequent TSIs were also run with the same results as the multilevel models for all but one case[129] when a variable was significant.

9.5.3 Driver-level models

The single-level driver level models, once again, exhibited relatively poor predictive performance and model fit compared to the multilevel models. Nonetheless, the statistically significant results were consistent with the multilevel models with altruism being a negative predictor of speeding behaviour and a positive predictor of acceleration, braking and total behaviour. Excitement was a negative significant predictor of braking – again consistent with the multilevel models – and car-dependence was a significant positive predictor of speeding behaviour and a negative predictor of braking behaviour. Although the model fit for these driver-level models were lower than desired this is largely due to the lack of specific spatiotemporal variables in these models. The driver behaviour profile's method of controlling for variability due to spatiotemporal differences does appear to have some merit, however, as the personality variable signs are consistent between the multilevel TSI-level models and the driver-level models.

[129] A negative effect of altruism was observed for total behaviour in the TSI with 60 km/h, evening with no passengers.

9.5.4 *Summary of statistical significance*

In total, 40 models were tested for Hypothesis 1.4. The statistically significant positive and negative effects are shown in Table 9-16.

Table 9-16: Summary of statistical significance of personality measures

	Aggression	Altruism	Excitement	Car-Dependence
Speeding				
Multilevel TSI		–	+	+
Night TSIs				
Motorway TSIs				
Rain TSIs				
School Zones				
ST{60,TE-D-P0}		–	+	
ST{60,TD-W-D-P0}		–	+	
ST{60,TM-D-P0}		–		–
ST{50,TE-D-P0}			+	
Acceleration				
Multilevel TSI		+		
Night TSIs				
Motorway TSIs	–			
Rain TSIs				
School Zones				
ST{60,TE-D-P0}				
ST{60,TD-W-D-P0}	+			
ST{60,TM-D-P0}				
ST{50,TE-D-P0}	–			
Braking				
Multilevel TSI		+		
Night TSIs				
Motorway TSIs				
Rain TSIs	+		–	
School Zones		+		
ST{60,TE-D-P0}	–	+		
ST{60,TD-W-D-P0}				
ST{60,TM-D-P0}		+		–
ST{50,TE-D-P0}			–	+
Total				
Multilevel TSI		+		
Night TSIs				
Motorway TSIs			+	
Rain TSIs		+	–	
School Zones			+	
ST{60,TE-D-P0}				–
ST{60,TD-W-D-P0}		–		+
ST{60,TM-D-P0}		+		–
ST{50,TE-D-P0}	–			
Driver-Level				
Speeding		–		+
Acceleration		+		
Braking		+	–	–
Total		+		
Total Negative (19)	4	6	4	5
Total Positive (23)	2	11	6	4
Multilevel Total Negative (4)	1	1	2	0
Multilevel Total Positive (10)	1	5	3	1

9.6 Interpretation

The results of the hypothesis testing which is the focus of this chapter are summarised in Table 9-17. Hypothesis 1.1 which proposes that higher perceptions of risk are associated with less frequent and lower magnitude risky driving behaviour can be accepted for speeding and total behaviour. Drivers that self-reported higher perceptions of risk – that is, they thought particular driving manoeuvres were more dangerous – were associated with lower speeding and total scores relative to drivers that perceived them to be of less danger. The same could not be said for acceleration and braking behaviour where significant effects proved to be more spatiotemporally dependent. Hypothesis 1.2, that drivers with greater concerns for their passengers engage in more risky driving behaviour, could not be accepted for any behavioural measure. In fact, the results suggest that a significant relationship exists between drivers concern for their own safety and their driving behaviour. In addition, it appears that drivers who engage in more frequent risky driving behaviour are aware that this results in a higher risk as drivers which self-identified higher crash risks exhibited higher behavioural scores. Hypothesis 1.3 which relates to the relationship between more driving confidence and more risky driving behaviour could also not be accepted for any behaviour. Although there were statistically significant variables, the effects were both positive and negative. This is possibly due to driving confidence measures being strongly linked to particular spatiotemporal environments or may be an interaction with an unmeasured variable such as prior experience with particular situations such as motorway driving and night-time driving. Lastly, Hypothesis 1.4 states that more aggressive, excitable and car-dependent drivers exhibit more risky driving behaviour and more altruistic drivers exhibit less risky driving behaviour. Aggression and car-dependence proved to be unrelated to drivers' behavioural scores. However, the hypothesis can be accepted for the relationship between drivers' altruism and excitement characteristics and their speeding behaviour. In addition, there is strong evidence to suggest that more altruistic drivers engage in more risky braking and acceleration behaviour. Although this is the opposite of the expected effect it does appear logical that more altruistic drivers would engage in more frequent evasive manoeuvres – even if not technically necessary – which could be observed as higher frequencies of braking and acceleration behaviour. More research is needed using more detailed acceleration and braking data to determine if this is indeed the cause.

Table 9-17: Summary of Hypothesis 1 testing

Hypothesis	Speeding	Acceleration	Braking	Total	Comments
H1.1: Risk Perceptions	Y	N	N	Y	
H1.2: Worry and Concern	N	N	N	N	Opposite effect found
H1.3: Driver Confidence	N	N	N	N	
H14: Personality	Y	N	N	N	Altruism and Excitement Only

Y: Hypothesis accepted
N: Cannot reject the null hypothesis

9.7 Conclusions

This chapter has presented the results of an investigation into the relationship between drivers' risk perceptions, attitudes and personality characteristics and the extent of their observed risky driving behaviour. The four sub-hypotheses were tested using the same methodology with the same dependent variables.

Arguably the most significant finding has been that the spatiotemporal and vehicle characteristics are the strongest predictors of risky driving behaviour. The models with these variables consistently outperformed the single-level models that do not include or do not adequately account for the effects of these spatiotemporal situations. They also go some way to confirming that the poor performance of the models in the aggregate analyses (Chapter 6) and the lack of significance of many of the variables was due to interactions between the spatiotemporal variables and drivers' behaviour. In general, school zones, rain and more passengers are statistically significant (negative) predictors of risky driving behaviour as are higher speed zones. Cars with manual transmissions were consistently related to lower incidences of speeding and total risky behaviour which was an unexpected result. Night time driving was a significantly negatively related to braking and total behaviour and afternoon driving was a negative predictor of speeding behaviour. Furthermore, the interaction between age and gender is also significant with both male and female participants exhibiting lower speeding, breaking and total behaviour as they age.[130] In terms of significance

[130] These effects were stronger for male drivers than for female drivers.

and direction, these results are consistent with the literature discussed in Section 3.1.1 and largely confirm *a priori* expectations.

10 RESULTS AND DISCUSSION: RELATIONSHIP BETWEEN AWARENESS AND RISKY DRIVING BEHAVIOUR

The first set of hypotheses (Chapter 9) examined the relationships between drivers' observed behaviour and their attitudes and perceptions of various aspects of driving as well as their personality traits. The second set of hypotheses – presented in this chapter – extend this concept by examining if it is possible to influence driving behaviour through increasing drivers' awareness of the frequency of their own speeding behaviour.

Recalling the design of the broader study from which the data originated (discussed in Section 4.2.3) the observed driving data collection period can be divided into three distinct phases. The first – "before" – phase allowed drivers to see where they went but not any information about their speeding, acceleration and braking behaviour. Additionally, they were not made aware that these aspects were being monitored. Prior to the second – "after" – phase, drivers were both shown their speeding behaviour for each trip as a proportion of the distance travelled and a monetary incentive calculated based on their driving in the before phase. During this phase every kilometre driven reduced the monetary incentive with an additional reduction for speeding and night time driving. Drivers that did not reduce their VKT, speeding and night time driving, compared to their respective before phase, saw their financial incentive gradually reduce to zero. From that point until the completion of the study, these drivers were still made aware of their speeding behaviour but the financial component of the study no longer applied and this formed the basis of the third ("after two") phase.

It was suspected that the threshold at which the financial incentive was no longer a factor in drivers' behaviour was potentially at some value higher than zero. As a consequence, scores were generated using a threshold of 0, 5, 10 and 15 dollars and similarly a threshold of 0, 5, 10 and 15 percent of the original incentive amount. ANOVA analyses were used to test for statistically significant differences in speeding scores for each threshold and through this process a five percent threshold was deemed to be the most appropriate. As such the after phase comprised of driving with a remaining incentive greater than five percent of the starting incentive and the second after phase comprised of driving with a remaining incentive of a maximum of five percent.

Distinct speeding, acceleration, braking and total scores were calculated for each driver for each phase. However, drivers which completed the study with a remaining incentive of more than five percent of their starting incentive did not have any observations in the after two phase. Furthermore, the minimum thresholds for inclusion (see Section 8.4.2) that were used in calculating the behavioural scores applied individually to each phase. This ensured that TSIs which covered only small distances in the after two phase do not unduly influence results.

In this chapter, a multilevel model is first presented which was used to test that statistically significant differences in driver behaviour were observed between the different phases of the study. Subsequently, following similar procedures used to test the first set of hypotheses, each of the four sub-hypotheses are presented in turn. Each of these examines the relationship between the magnitude of changes that occur in drivers' behaviour as a consequence of making drivers aware of their speeding behaviour and their respective risk perceptions, confidence measures and personality characteristics.

A restatement of the hypotheses and a summary of if each sub-hypothesis was accepted can be found in Appendix A (Section 13.2).

10.1 Hypothesis 2: Changes in behaviour due to increased awareness

The sub-hypotheses were predicated on the assumption that providing drivers with information on their speeding behaviour would induce a change in behaviour. Prior to examining each of the sub-hypotheses, it first needed to be determined if the assumption was valid. To accomplish this, a multilevel model was developed to test for statistically significant relationships between the behavioural scores and the study phase. The multilevel models extended the hierarchical structure used for the first set of hypotheses to include separate behavioural scores for each of the study phases as shown in Figure 10-1. In addition, a number of variables were added to account for the speeding awareness and financial aspects of the study that applied in the after phase. These included a variable to indicate if the participant had some remaining incentive at the completion of the study, their starting incentive, the number of days in the before period on which the study website was accessed and the number of days in the after period on which the study website was accessed. The spatiotemporal, driver and vehicle characteristics were kept unchanged. The hierarchical structure of these models ensures that changes in behaviour are compared like-for-like with driving in each phase associated with a particular driver and a particular TSI. This controls for any differences between the different study phases in where and when participants drive.

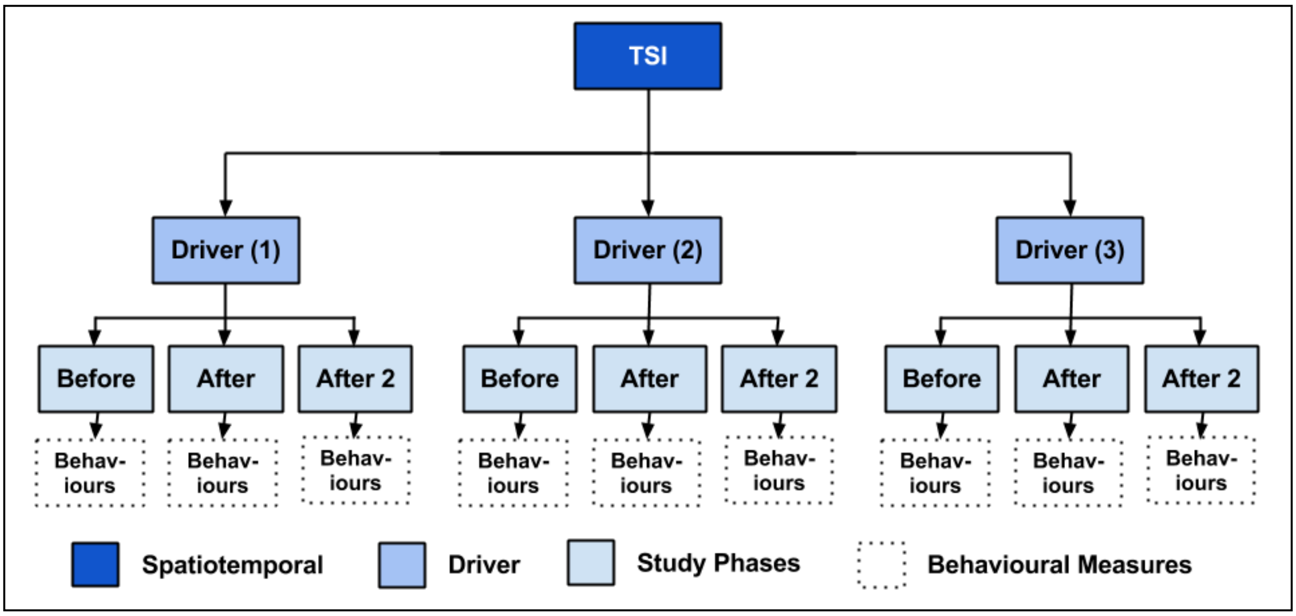

Figure 10-1: Extended multilevel structure incorporating study phases

One multilevel model was developed for each of the four behavioural scores. To ensure comparability between phases and as a result of combining data from the three phases of the study, the raw scores could be used without requiring a rank transformation. Nonetheless scores of 100 were excluded from the multilevel models as these still posed a problem. The distribution included a smaller number of zero scores and – although still skewed – more closely resembled a Poisson distribution which made this possible.

The model fit was good with the predicted values being consistent with the observed values as illustrated in Figure 10-2. There were extended tails which resulted in the maximum predicted score exceeding 100 but this affected only one acceleration observation, four braking observations and six speeding observations. In addition, the standard errors of the parameter estimates were reasonable and the statistically significant spatiotemporal and driver characteristics were consistent with the multilevel models derived using data only from the before phase.[131]

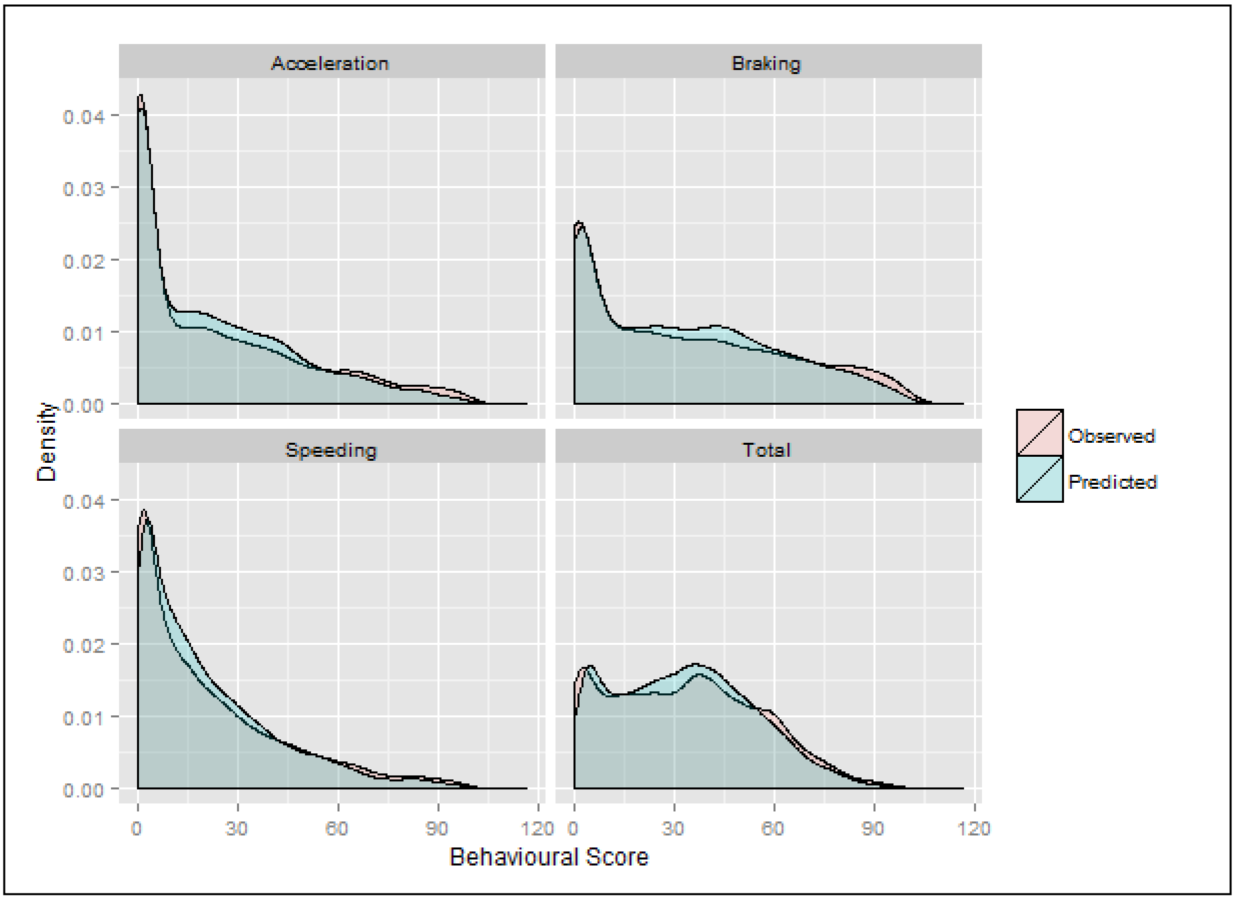

Figure 10-2: Distribution of observed and predicted values for all study phases

The variables accounting for the financial and awareness aspects of the study proved to be highly significant factors in speeding behaviour. Unsurprisingly given that the frequency of speeding was a component of the financial scheme, drivers which earned money at the end of the study exhibited lower speeding scores and drivers with greater starting incentives exhibited higher speeding scores. Arguably of more importance was that those drivers that did not make money exhibited higher speeding scores in the before period (p = .000) the more frequently they logged in to the study

[131] Presented in Chapter 9.

website which was used as a proxy for speeding awareness[132]. In the after one period, these same drivers exhibited lower speeding scores (p = .001) as the frequency of logins increased. Once the financial component was removed, in the after two period, there was no statistically significant relationship between the frequency of logins and the speeding score. For those drivers that did make money, there was a negative relationship between the frequency of logins and the speeding score in the before phase (p = .000) and the after one phase (p = .000). The magnitude of the relationship was three times stronger in the after one phase than in the before phase.[133] Furthermore, the relationship between the study phase and the speeding score was also highly significant (p = .000) with the after one phase exhibiting a negative effect on speeding scores and the after two phase exhibiting a significant negative effect but of a (12 percent) lower magnitude than the after one phase. These results suggest that providing a financial incentive and increasing drivers' awareness of their own speeding behaviour has a measurable effect on reducing speeding behaviour with incremental benefits the more frequently drivers are exposed to information about the frequency of their speeding behaviour. Furthermore, it appears that when the financial incentive is removed (after two) speeding remains substantially reduced from the before period, albeit to a slightly lesser extent than when the financial incentive is in place (after one). Although the last phase of the study only observes drivers over the short term it provides some indication that improving drivers' awareness of their own speeding behaviour can induce beneficial changes in drivers' speeding behaviour independently of a financial incentive. This is illustrated in Figure 10-3 where the majority of observations in both after periods are found in the area shaded in green which represent driver-level speeding risk scores with lower speeding risk scores relative to the before period. Furthermore, drivers with a higher number of website logins in the after period, shown with larger points, generally exhibit smaller differences between the two after periods. This suggests that drivers which are more

[132] It is possible that in addition to speeding awareness it may also reflect the conscientiousness of the participant in completing the prompted recall components of the study and, by extension, their interest in the study.

[133] Additionally, there were four participants that made money but did so below the 5 percent threshold. Although the effect for the after two period was statistically significant (p = .000) this result is reflective of the behaviour of those participants.

influenced by the financial incentive tended to have less exposure to their speeding information.

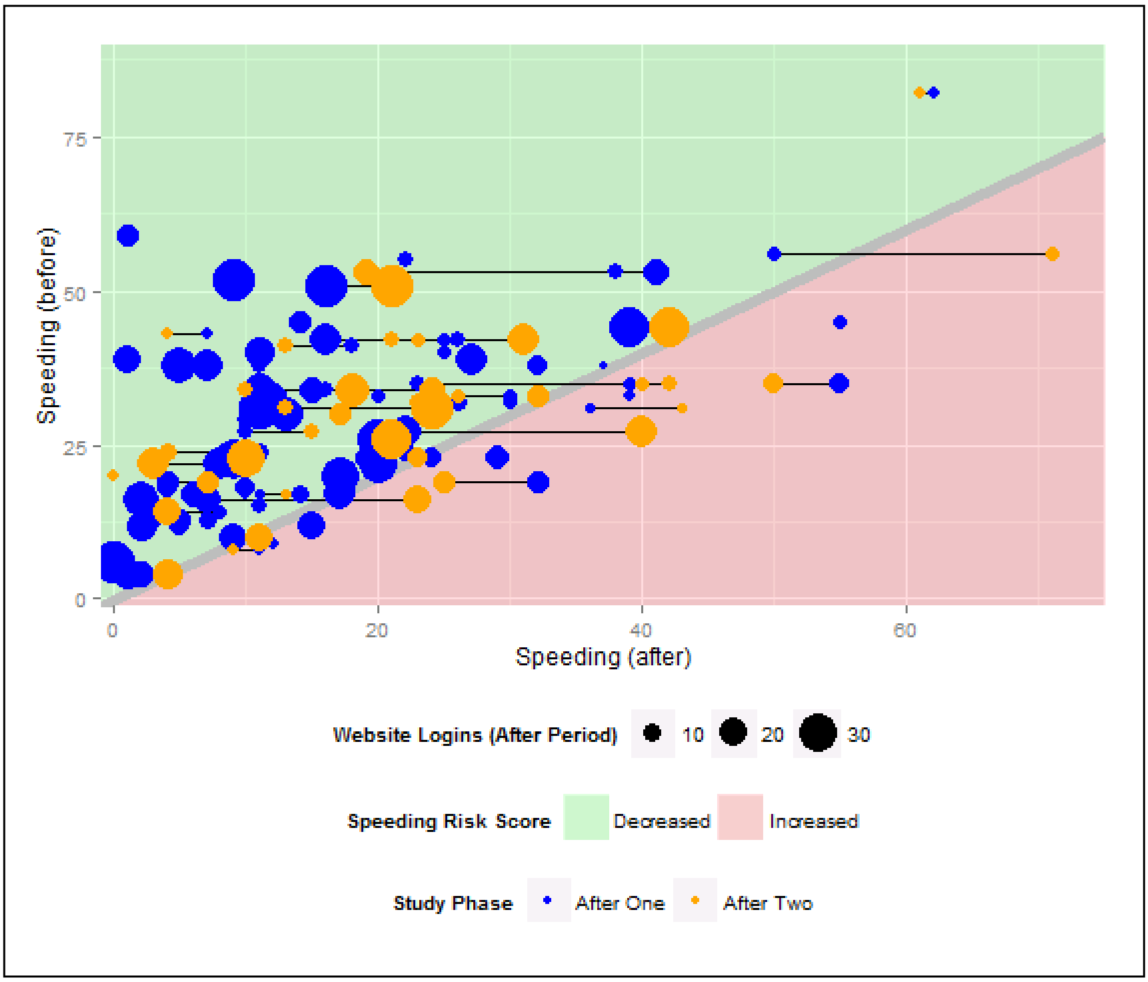

Figure 10-3: Speeding behaviour between before and after periods (driver-level)[134]

Acceleration, braking and (by extension) total scores largely followed a similar pattern to speeding behaviour with the after phases exhibiting significantly lower scores than in the before phase. However, unlike with speeding these effects were stronger in the after two period than in the after one period. It is not clear why this is the case but is a trend that is observed in the acceleration, braking and total models. It is possible, given that similar trends are observed in relation to participants' use of the study website, that these results are reflective of more conscientious driving by participants

[134] After two observations that appear to not be associated with an after one observation are reflective of there being no change in the driver-level scores between the after one and after two periods for that driver.

as a by-product of becoming more self-aware of their behaviour. Since participants were never explicitly shown or told that their acceleration and braking behaviour was monitored it cannot be a direct effect of the financial incentive or the speeding information. This possibility is further enhanced by examining the differences between the statistically significant variables in these models with the equivalent models using only data from the before period. It is notable that in the models using only the 'before' data fewer spatiotemporal variables were statistically significant[135] suggesting that drivers changed their behaviour in particular situations.

Table 10-1: Parameter estimates for before-and-after multilevel models

	Speeding			Acceleration			Braking			Total		
	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.
Intercept	3.457	0.184	0.000	0.805	0.272	0.003	2.687	0.186	0.000	4.058	0.084	0.000
Speed limit (50)	-0.455	0.148	0.002	1.773	0.198	0.000	1.210	0.138	0.000	-0.110	0.059	0.060
Speed Limit (60)	-1.048	0.148	0.000	1.493	0.197	0.000	1.283	0.137	0.000	-0.298	0.058	0.000
Speed Limit (70)	-1.709	0.151	0.000	0.523	0.202	0.009	0.661	0.139	0.000	-0.785	0.060	0.000
Speed Limit (80)	-1.887	0.154	0.000	-0.361	0.208	0.083	-0.119	0.143	0.404	-1.159	0.062	0.000
Speed Limit (90)	-2.255	0.161	0.000	-3.048	0.242	0.000	-1.552	0.152	0.000	-2.122	0.068	0.000
Speed Limit (100)	-1.989	0.176	0.000	-4.078	0.332	0.000	-3.323	0.195	0.000	-2.372	0.082	0.000
Speed Limit (110)	-2.590	0.191	0.000	-4.313	0.401	0.000	-3.137	0.212	0.000	-2.677	0.093	0.000
School Zone	-0.443	0.199	0.026	0.244	0.312	0.434	0.757	0.221	0.001	-0.112	0.090	0.214
Rain	-0.714	0.093	0.000	-1.686	0.159	0.000	-0.899	0.106	0.000	-0.358	0.048	0.000
Time (Day)	0.213	0.065	0.001	0.710	0.109	0.000	0.239	0.075	0.001	0.067	0.034	0.047
Time (Afternoon)	0.040	0.064	0.537	0.659	0.108	0.000	0.292	0.074	0.000	0.017	0.034	0.621
Time (Night)	-0.137	0.073	0.062	-0.357	0.124	0.004	-0.527	0.084	0.000	-0.307	0.039	0.000
Weekend	0.206	0.043	0.000	-0.688	0.072	0.000	-0.347	0.049	0.000	-0.033	0.023	0.144
Num. Passengers	-0.070	0.021	0.001	-0.161	0.035	0.000	-0.083	0.024	0.001	-0.043	0.011	0.000
Type (Hatchback)	-0.340	0.053	0.000	-0.188	0.088	0.033	-0.046	0.060	0.439	-0.171	0.028	0.000
Type (Other)	0.071	0.053	0.180	-0.210	0.089	0.019	-0.148	0.061	0.015	-0.059	0.028	0.035
Model Year	0.179	0.028	0.000	0.044	0.048	0.351	-0.046	0.032	0.151	0.040	0.015	0.007
Transmission (Manual)	-0.299	0.051	0.000	-0.100	0.084	0.231	-0.150	0.057	0.008	-0.119	0.027	0.000
Made Money	-0.162	0.055	0.003	0.156	0.083	0.059	0.160	0.059	0.007	0.000	0.032	0.998
Starting Incentive	0.014	0.001	0.000	0.014	0.002	0.000	0.004	0.001	0.001	0.006	0.001	0.000
Phase (After 1)	-0.346	0.014	0.000	-0.075	0.014	0.000	-0.150	0.013	0.000	-0.133	0.010	0.000
Phase (After 2)	-0.307	0.023	0.000	-0.274	0.025	0.000	-0.247	0.023	0.000	-0.201	0.018	0.000
Male : Age	-0.209	0.029	0.000	-0.128	0.048	0.007	-0.150	0.033	0.000	-0.121	0.015	0.000
Female : Age	-0.153	0.034	0.000	-0.127	0.056	0.024	-0.147	0.038	0.000	-0.101	0.018	0.000
Drivers who did not make money in the study												
Before : Logins	0.007	0.002	0.000	0.013	0.002	0.000	0.004	0.002	0.011	0.005	0.001	0.000
After 1 : Logins	-0.005	0.001	0.001	0.010	0.002	0.000	0.009	0.001	0.000	-0.001	0.001	0.488
After 2 : Logins	0.001	0.002	0.460	0.011	0.002	0.000	0.005	0.002	0.001	0.003	0.001	0.012
Drivers who did make money in the study												
Before : Logins	-0.010	0.002	0.000	-0.015	0.002	0.000	-0.005	0.001	0.001	-0.005	0.001	0.000
After 1 : Logins	-0.029	0.002	0.000	-0.011	0.001	0.000	-0.002	0.001	0.150	-0.012	0.001	0.000
After 2 : Logins	-0.011	0.003	0.000	-0.024	0.003	0.000	-0.024	0.003	0.000	-0.009	0.003	0.000

Statistically significant positive effect at the $p = .05$ level
Statistically significant negative effect at the $p = .05$ level

These models do not provide a definite causal link between the financial and awareness components of the study and drivers' behaviour. However, there is

[135] The variables that were statistically significant in the before period are consistent with these results.

evidently a distinct difference in drivers' behaviour between the different phases of the study which strongly suggest that there is a statistically significant relationship between drivers' awareness of their speeding behaviour and their speeding behaviour. More broadly – although the reasons are unclear – there appears to be a 'halo' effect on other forms of driver behaviour. The following sections explore possible differences in how the magnitude of the changes that were observed can be related to drivers' risk perceptions, concerns, confidence and personality.

10.2 Hypothesis 2.1: Lower perceptions of risk

Hypothesis 2.1 examines the relationship between drivers' self-reported risk perceptions of a number of driving behaviours and the magnitude of the change in observed behaviour that occurs as a result of increasing drivers' awareness of their speeding behaviour. The risk perception variables are the same as those of Hypothesis 1.1 (see Section 9.2) and include running red lights, fatigued driving, illegal u-turns, turning right across a busy road, changing lanes without checking, speeding by 10 km/h, speaking on a mobile telephone and talking to passengers.

In the before period the hypothesis that higher perceptions of risk can be related to less risky driving behaviour was accepted for speeding and total behaviour but not for acceleration and braking behaviour. The focus of this section is on the relationship between the magnitudes of improvements in behaviour (as defined by reductions in the speeding, acceleration, braking and total scores) and drivers' risk perceptions. The magnitude change is defined as the score in the *after one* period as a proportion of the score for the same driver, and if applicable, the same TSI as in the *before* period. For example, if the before score is 40 and the after one score is also 40 then the proportion is 100 percent. If the after one score is 20 then the proportion is 50. Similarly, if the after one score is 60 then the proportion is 150. This measure is used instead of the absolute change in the behavioural scores because the results would otherwise by biased by drivers and TSIs with higher scores in the before period. As such, a driver with a score in the before period of 20 would be unable to exhibit an absolute reduction in the after period of 30 unlike a driver with a score in the before period of 50. The disadvantage of this approach is that the opposite bias may occur where small absolute changes are perceived to have a larger effect because the base (before) score is small. However, given the majority of values fall in the lower range this is deemed appropriate.

For a TSI to be included in these analyses, in addition to the requirements imposed for inclusion in the overall multilevel models presented in Section 10.1, there must be at least one kilometre of data in each of the before and at least one of the after periods. Additionally the score in the before period must be greater than zero as otherwise a percentage change cannot be calculated. In terms of speeding behaviour, 1807 Driver-TSI combinations met these conditions. Of these 1423 exhibited improved behaviour (a proportion of between 0 and 99), three were unchanged and 467 exhibited worse speeding behaviour than in the before period. The distributions of changes in the speeding and other behavioural scores are shown in Figure 10-4. The majority of observations are between zero and 200 – with a majority of these showing improvements – with a long tail largely attributable to observations with large differences in VKT between the before and after period. This is true for changes between the before period and the after one phase as well as (although to a lesser extent) changes between the before period and the after two phase. The distributions in the after 2 period show a shift downwards and towards the right relative to the after 1 period indicating that, as a whole, drivers drove worse in the after 2 period relative to the after 1 period but a majority still exhibited better driving than in the before period.

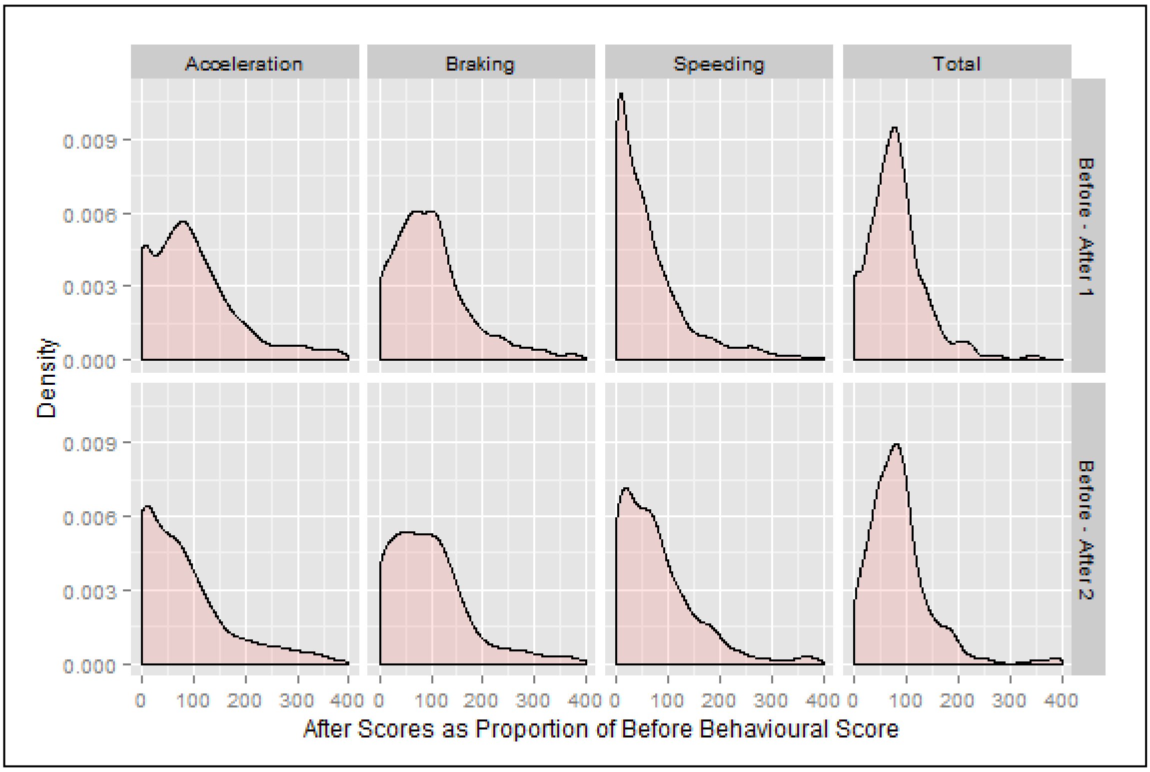

Figure 10-4: Distribution of change in behaviour between before and after periods

Multi-level TSI models driver-level models are used here to identify relationships between drivers' risk perceptions.

10.2.1 Main findings and discussion

The results of these models strongly support the results presented in Section 10.1 which show that making drivers aware of their own speeding behaviour has a strong effect on drivers' observed speeding behaviour over and above the change influenced by the financial component of the study. Although there appears to be some effect from the study design on acceleration and braking behaviour, not unexpectedly, these do not appear to be adequately captured by the number of logins or the financial component. Change in total behaviour falls somewhere between the speeding, acceleration and braking models which is consistent with the computation of the total scores.

These trends are also reflected in the statistically significant risk perception variables as summarised in Section 10.2.4. With the exception of red light running and turning right across a busy road (which only apply at intersections), higher perceptions of the danger of illegal u-turns, changing lanes without checking, speeding, mobile telephone usage and talking to passengers were all associated with speeding scores in the after periods that are smaller proportions of their respective speeding scores in the before period.

Figure 10-5 illustrates the change in participants' speeding risk scores (at the TSI-level) as their perceptions of the risk associated with particular behaviours increase.[136] The density in the green-shaded areas increases as the risk perception increases with this trend particularly noticeable for those with higher perceptions of the risk of speeding.

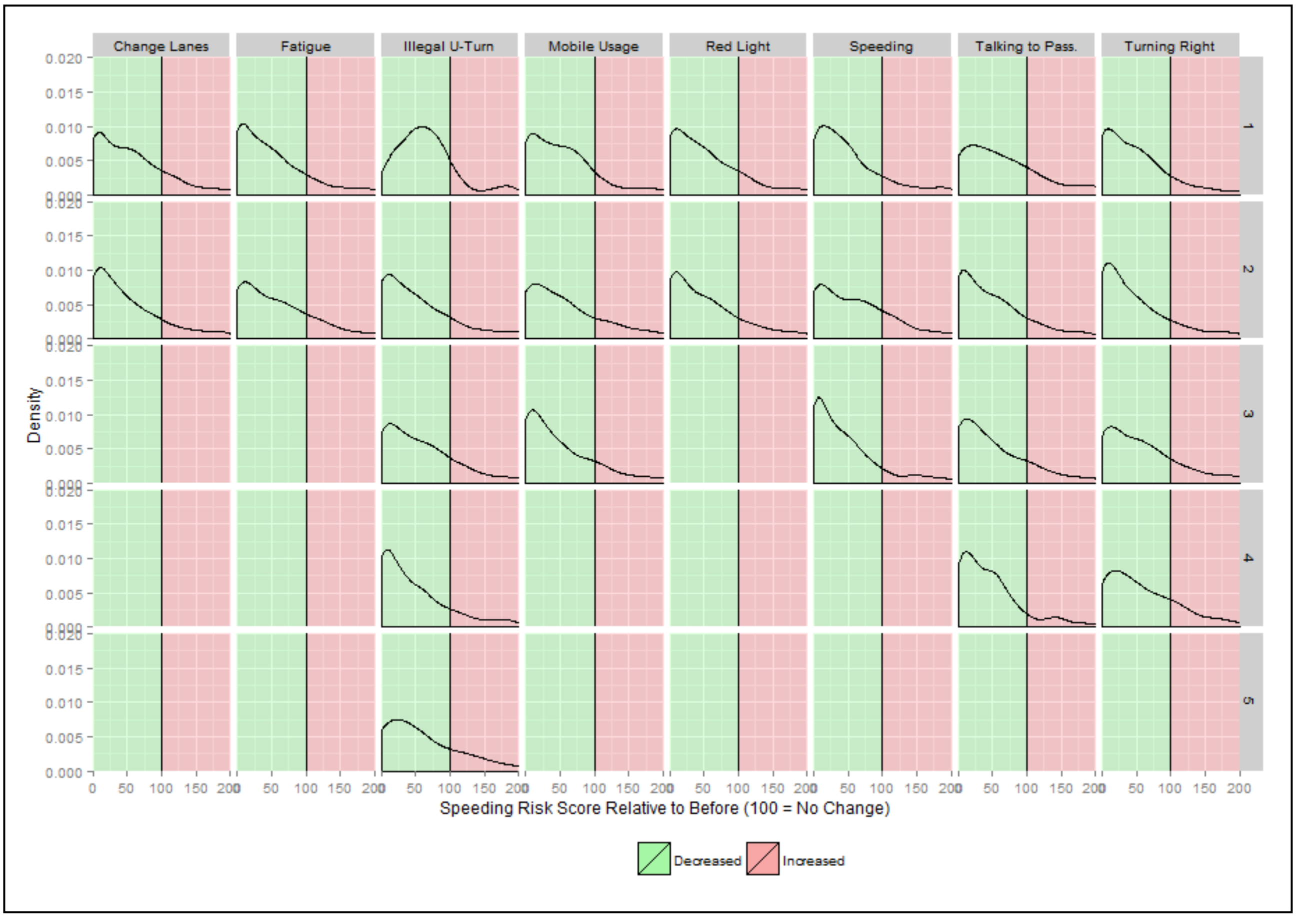

Figure 10-5: Speeding risk score relative to before by risk perception

136 Some categories have been combined due to low sample sizes. The lowest risk perception is category 1.

Total behaviour had fewer statistically significant variables but the statistically significant variables were significant in the same direction as in the speeding model. The driver-level models exhibited few statistically significant risk perception variables with the strongest predictors from these models relating to the number of logins and the financial incentive. It can be concluded from this that spatiotemporal characteristics effect how much drivers change their behaviour although it has not been established to what extent this is due to the underlying characteristics of these spatiotemporal environments.

Comparing these results with those of the models using only the data from the before phase (see Section 9.2) suggests that drivers' risk perceptions have a greater impact on the potential to change their behaviour than these variables do on drivers' existing (pre-intervention) driving – at least as far as speeding behaviour is concerned. The effect on acceleration and braking behaviour is less clear but this must be interpreted in the context of the study which did not address acceleration or braking or, more abstractly, driving style in any way. A study which provided drivers with this information would be needed in order to draw any conclusions as to the potential for using increased awareness to improve behaviour.

Overall, the hypothesis that drivers with higher perceptions of the risk of certain driving behaviours exhibit greater magnitude changes in behaviour once they are made aware of their speeding behaviour can be accepted for speeding behaviour and total behaviour.

10.2.2 TSI-level models

For each of the behaviours, multi-level models were run with the first level as the TSI and the second level defined as the driver. The dependent variable was the after one or after two score (as applicable) as a proportion of the before score for the same driver and TSI. The independent variables were the same in all cases and were the same as those in the multilevel models used to test the equivalent hypothesis using the before period data with the addition of three variables that account for the speeding awareness and financial components of the study (see Section 10.1) and a variable to identify if the observation relates to the change in behaviour in the after one period or the after two period relative to the before period.

The model fit, as shown in Figure 10-6, is very good with the predicted values following the same trend as the observed values for all four behavioural measures albeit slightly less so for acceleration and braking behaviour. This is not unexpected given that acceleration and braking were not explicitly addressed in the awareness and financial components that made up the intervention. The spatiotemporal components remained the strongest predictors of behaviour albeit to a lesser extent than the equivalent models for the before period. Since the dependent variables were computed relative to the before period for the same spatiotemporal environments, statistically significant effects in these models indicate spatiotemporal environments in which greater (or lesser) changes were observed relative to the before period. That is to say that two spatiotemporal variables with the same parameter estimate indicates an equivalent change in behaviour relative to their respective before periods and not equivalent scores in the before period. Specifically, higher speed zones and night time driving were statistically significant predictors of lower proportions (i.e. generally improved scores relative to the before period) whilst afternoon/evening driving was statistically significant predictor of higher proportions.[137] The effect of the after period on night time driving is notable given that the financial component of the study incorporated a higher per-km rate for night time driving.

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[137] It should be noted that a positive effect here does not necessarily indicate that drivers drove worse in the after period (although that is the case for some observations) but that relative to the morning period the proportion of the before score was higher in the afternoon.

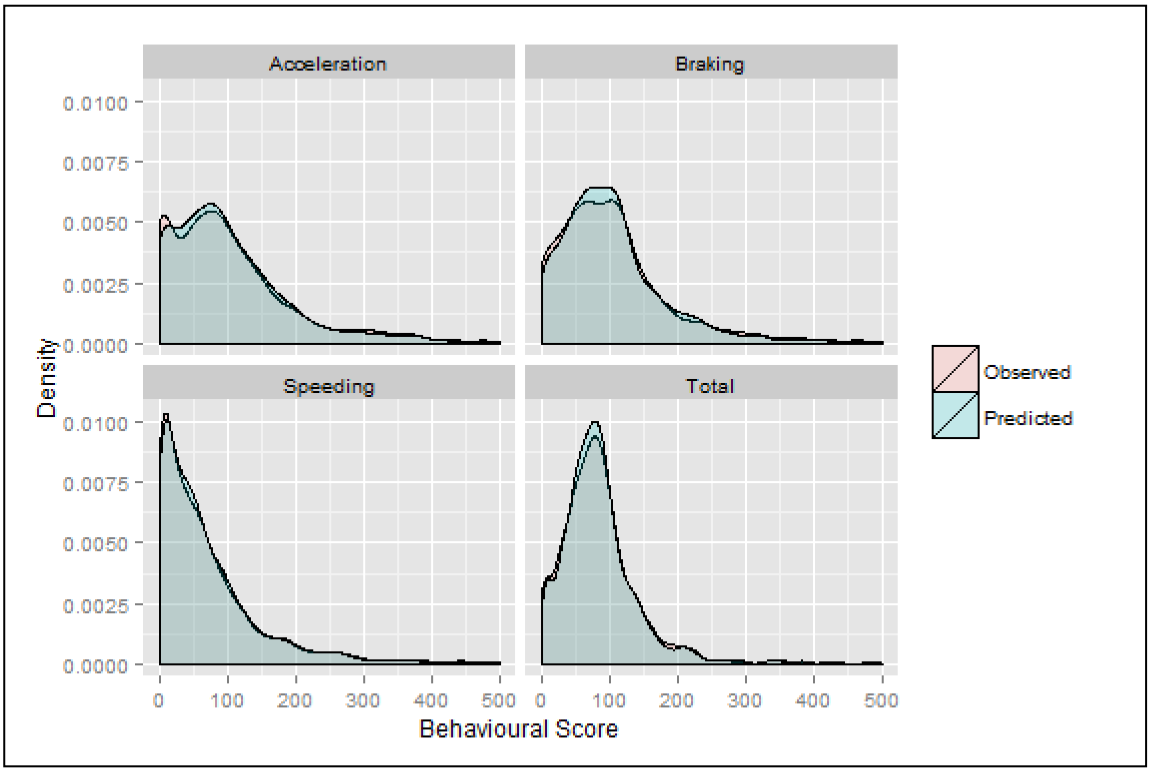

Figure 10-6: Density plot of observed and predicted values of Hypothesis 2.1 models

The intervention variables were also statistically significant predictors of changes in speeding behaviour with a higher starting incentive associated with higher proportions of the before score. Observations in the after two period (once the financial incentive had been depleted) was also statistically significantly related to higher proportions compared to observations from the after one period. Conversely, higher frequency of logins in the after period was associated with lower proportions for drivers that made money in the study[138].

Driver demographics and risk perceptions proved to be significant predictors of changes in speeding behaviour. Male drivers exhibited speeding behaviour in the after periods which were smaller proportions of their behaviour in the equivalent before period as their age increased (p = .040). The same was not true for female drivers. Higher perceptions of the danger of illegal u-turns, changing lanes, speeding, using a mobile telephone and speaking to passengers were all statistically significantly related to lower proportions of speeding relative to the before period.

[138] The effect was negative but only statistically significant at the p = .1 level for drivers that did not make money.

Higher perceptions of the danger of red light running and turning right across busy roads had the opposite effect although both of these measures only apply to intersections which have been explicitly excluded from the data included in this analysis.

The number of statistically significant predictors of acceleration and braking behaviour were fewer than for speeding but where a variable was significant its effect was in the same direction as seen in the speeding model. The same is true for total behaviour which largely mirrored the speeding model. The exception was the relative difference between the after two periods. In this particular case, drivers exhibited lower relative acceleration and braking scores in the after two period compared to the after one period which is the opposite effect observed for the speeding model but is a result that is consistent with the multilevel model of absolute scores presented in Section 10.1.

Of the risk perception variables only mobile telephone use was statistically significant in the braking model and no risk perceptions variables were statistically significant in the acceleration model. The observed differences in acceleration and braking behaviour are best explained by the spatiotemporal characteristics. However, the statistical significance of the phase variable suggests that there may be secondary effects of the study design that is not captured by the financial or speeding awareness components of the study, neither of which were statistically significant for the acceleration and braking models. The parameter estimates for all four models are shown in Table 10-2.

Table 10-2: Parameter estimates for Hypothesis 2.1 multilevel models

	Speeding			Acceleration			Braking			Total		
	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.
Intercept	4.460	0.518	0.000	4.748	0.836	0.000	4.487	0.442	0.000	4.109	0.238	0.000
Speed limit (50)	0.268	0.370	0.469	0.706	0.709	0.319	0.215	0.323	0.506	0.491	0.162	0.002
Speed Limit (60)	0.033	0.371	0.930	0.331	0.708	0.640	0.058	0.322	0.858	0.383	0.162	0.018
Speed Limit (70)	-0.460	0.378	0.224	-0.082	0.713	0.909	-0.215	0.325	0.508	0.303	0.165	0.067
Speed Limit (80)	-0.814	0.388	0.036	-0.350	0.722	0.628	-0.368	0.331	0.267	0.036	0.169	0.832
Speed Limit (90)	-1.637	0.408	0.000	-1.399	0.756	0.064	-1.737	0.342	0.000	-0.820	0.178	0.000
Speed Limit (100)	-1.414	0.453	0.002	-2.142	0.931	0.021	-1.749	0.422	0.000	-1.008	0.208	0.000
Speed Limit (110)	-1.202	0.547	0.028	-4.570	1.303	0.000	-1.513	0.470	0.001	-1.090	0.247	0.000
School Zone	0.767	0.458	0.094	0.189	0.885	0.831	-0.263	0.477	0.582	0.554	0.209	0.008
Rain	-0.712	0.407	0.080	-0.168	0.540	0.756	0.001	0.332	0.998	0.127	0.167	0.448
Time (Day)	0.096	0.137	0.485	-0.189	0.210	0.369	-0.129	0.121	0.285	-0.071	0.065	0.275
Time (Afternoon)	0.338	0.134	0.012	-0.462	0.204	0.023	-0.039	0.116	0.734	0.015	0.063	0.809
Time (Night)	-0.329	0.164	0.045	-0.554	0.257	0.031	-0.368	0.145	0.011	-0.315	0.078	0.000
Weekend	-0.131	0.099	0.184	-0.427	0.154	0.005	-0.137	0.087	0.114	-0.072	0.046	0.118
Num. Passengers	-0.061	0.050	0.223	-0.135	0.077	0.081	0.014	0.046	0.757	-0.028	0.024	0.242
Type (Hatchback)	-0.655	0.106	0.000	-0.081	0.132	0.537	-0.196	0.090	0.029	-0.171	0.052	0.001
Type (Other)	-0.332	0.116	0.004	-0.003	0.147	0.983	-0.104	0.101	0.305	0.011	0.056	0.839
Model Year	0.012	0.061	0.841	0.015	0.076	0.841	0.007	0.052	0.885	0.012	0.029	0.674
Transmission (Manual)	-0.641	0.108	0.000	-0.242	0.133	0.070	-0.116	0.088	0.186	-0.129	0.052	0.013
Made Money	0.237	0.174	0.175	0.298	0.219	0.174	-0.103	0.150	0.491	0.037	0.085	0.662
Starting Incentive	0.009	0.002	0.000	0.004	0.003	0.112	0.003	0.002	0.124	0.002	0.001	0.027
Phase[139]	0.138	0.009	0.000	-0.184	0.010	0.000	-0.092	0.010	0.000	-0.011	0.008	0.182
Red Light	0.273	0.090	0.002	0.060	0.116	0.604	0.109	0.077	0.158	0.131	0.044	0.003
Fatigue	-0.050	0.100	0.617	0.056	0.125	0.654	0.039	0.086	0.651	0.036	0.048	0.457
Illegal U-Turn	-0.094	0.047	0.047	-0.032	0.061	0.602	-0.075	0.043	0.080	-0.038	0.023	0.101
Turning Right	0.352	0.046	0.000	-0.029	0.055	0.595	-0.006	0.038	0.880	0.074	0.022	0.001
Change Lanes	-0.297	0.092	0.001	-0.213	0.117	0.069	-0.145	0.078	0.062	-0.092	0.045	0.041
Speeding	-0.181	0.061	0.003	-0.025	0.076	0.746	0.065	0.053	0.219	0.020	0.030	0.493
Mobile Usage	-0.255	0.056	0.000	-0.096	0.070	0.171	0.103	0.050	0.039	-0.072	0.027	0.008
Talking to Pass.	-0.194	0.068	0.004	-0.022	0.084	0.792	0.044	0.057	0.436	-0.075	0.033	0.022
Male : Age	-0.124	0.060	0.040	-0.084	0.075	0.266	-0.082	0.050	0.104	-0.024	0.029	0.409
Female : Age	0.018	0.074	0.807	-0.135	0.092	0.140	-0.056	0.062	0.363	0.003	0.035	0.937
Made money (no): Logins	-0.012	0.007	0.072	0.014	0.008	0.096	0.002	0.006	0.679	-0.003	0.003	0.344
Made money (yes): Logins	-0.055	0.007	0.000	-0.009	0.009	0.312	0.003	0.006	0.585	-0.012	0.003	0.000

■ Statistically significant positive effect at the p = .05 level ■ Statistically significant negative effect at the p = .05 level

[139] Difference between the before and after two period relative to the difference between the before and after one period

10.2.3 Driver-level models

The driver-level scores computed by the driver behaviour profiles were used to create driver-level models of speeding, acceleration and braking behaviour. These models are similar to the driver-level models used to evaluate the first set of hypotheses (see Section 9.2.3) but are multi-level models which include observations from both after periods and the financial incentive and speeding awareness variables. Nonetheless, since these are driver-level scores they do not explicitly include the spatiotemporal variables. The dependent variables are the driver-level equivalents of the dependent variables used for the TSI-level models (Section 10.2.2) and are computed in the same way.

The model fit, as illustrated in Figure 10-7, of the four models is better than the equivalent models for the before period (Section 9.2.3) although they exhibit few statistically significant variables and the acceleration, braking and total models suffer from high standard errors. Consistent with the TSI-level models, the speeding model has the best model fit with more frequent website logins in the after period being negatively related to the proportion of the before score for drivers that made money in the study ($p = .000$). The after two phase ($p = .000$) and higher perceptions of the danger of turning right across a busy road ($p = .000$) were positively related to the proportion of the before score which is consistent with the significance and direction of these variables in the TSI-level models. The statistically significant variables in the acceleration, braking and total models (despite the high standard errors) are also consistent with the TSI-level models.

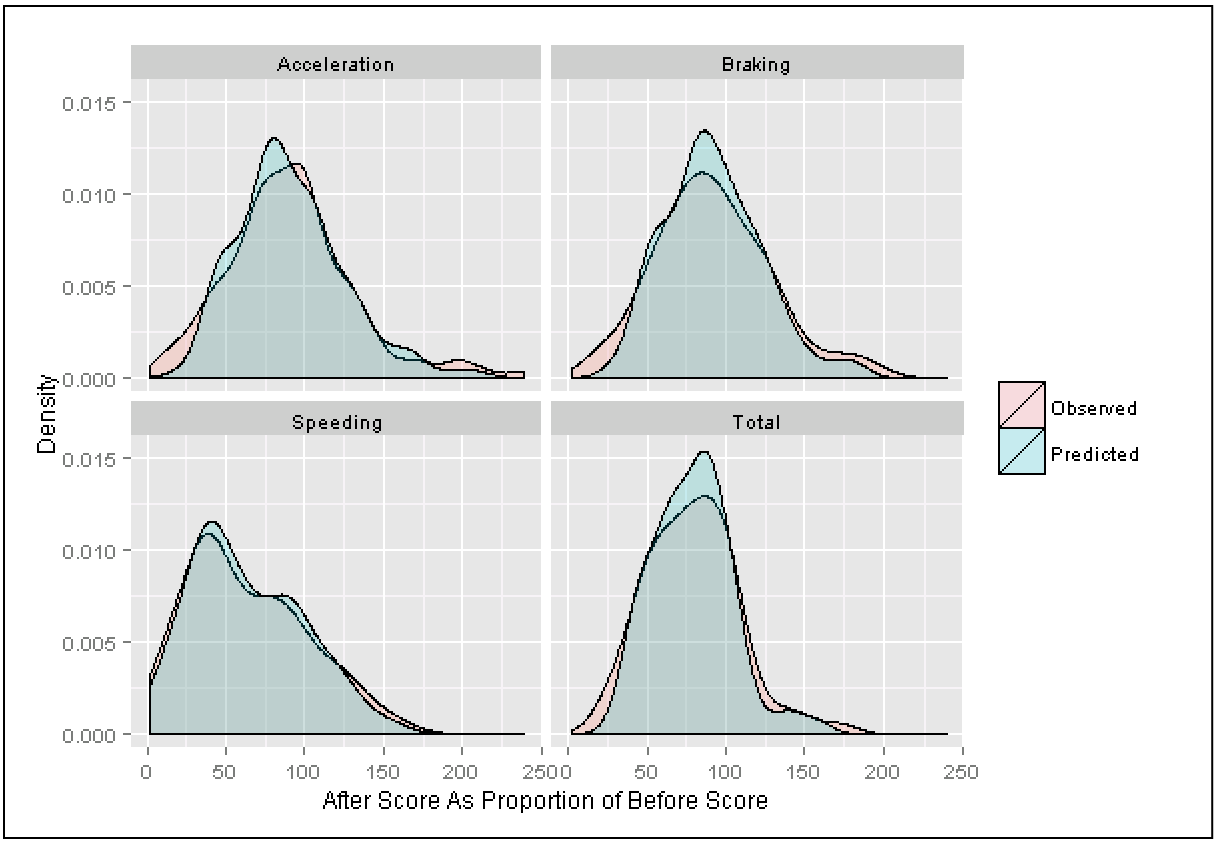

Figure 10-7: Driver-level hypothesis 2.1 observed and predicted density plots

10.2.4 Summary of statistical significance

The speeding and total models exhibited the most statistically significant risk perception variables. In contrast, the acceleration and braking models exhibited very few statistically significant results. A summary of the positive and negative statistically significant effects are shown in Table 10-3.

Table 10-3: Summary of statistical significance of risk perception variables (after)

	Red Light	Fatigue	Illegal U—Turn	Turning Right	Change Lanes	Speeding	Mobile Usage	Talking to Pass.
TSI-Level								
Speeding	+		—	+	—	—	—	—
Acceleration								
Braking							+	
Total	+			+	—		—	—
Driver-Level[140]								
Speeding				+				
Acceleration					—		—	
Braking								
Total							—	
Total Negative (11)	**0**	**0**	**1**	**0**	**3**	**1**	**4**	**2**
Total Positive (6)	**2**	**0**	**0**	**3**	**0**	**0**	**1**	**0**

Note: + indicates a positive effect, — indicates a negative effect and a blank cell indicates no statistically significant effect

10.3 Hypothesis 2.2: Worry and concern

Hypothesis 2.2 is that drivers with more concern about passenger safety have a higher magnitude (negative) change in risky driving behaviour than drivers with less concern about passenger safety once they are made aware of their speeding behaviour. Using the same five questions used to test Hypothesis 1.2 (Section 9.3)[141] and the same methodology applied to examine Hypothesis 2.1 (Section 10.2), models were run for each of the risk scores.

Since the dependent and independent spatiotemporal and after phase variables are the same as for Hypothesis 2.1 the statistical significance of these variables is not discussed here.

10.3.1 Main findings and discussion

Overall, these models (summarised in Section 10.3.4) add more evidence that the study intervention mostly influenced speeding behaviour – as would be expected given that only speeding was addressed in the study. There does appear to be some residual effect on the other behaviours but this is largely captured by the after phase variables and is only influenced by drivers worry and concern measures in a limited number of cases. The hypothesis itself – that higher concern of passenger injuries is related to

[140] The standard errors in these models were relatively high and caution should be used when interpreting these results.

[141] The five questions are drivers concern about injury to themselves, their passengers or other drivers and the self-reported likelihood of a crash within the next 12 months for themselves and for other drivers their age.

higher magnitude changes – cannot be accepted with the results demonstrating the opposite effect. On the other hand, greater concern about injury to the driver and other drivers as well as a higher perceived likelihood of other drivers being involved in a crash were all associated with higher magnitude changes once these drivers were made aware of their speeding behaviour.

These findings suggest that drivers that are more concerned about being injured themselves or other drivers being injured in a crash are likely to make greater changes to their speeding behaviour compared to drivers that are less concerned about injuries. At the same time, it appears that drivers who self-report a higher likelihood of being involved in a crash make smaller changes to their speeding behaviour in response to information on their behaviour and a financial incentive. However, these drivers do also tend to have higher before scores (Section 9.3.2) and, as such, may be aware of the risks they incur as a result of their behaviour and choose to continue speeding despite this knowledge and the intervention.

The financial incentive also clearly had an effect on behaviour in the after period as once the incentive was no longer a factor the speeding risk score increased but not to the same level as the before period.

10.3.2 TSI-level models

Individual multilevel models at the TSI-level of aggregation were run for each of the risk scores. The model fit for these models was almost identical to the TSI-level models used to test Hypothesis 2.1 which further emphasises the contribution of the spatiotemporal and after phase variables to the models. The parameter estimates (shown in Table 10-4) indicate that having controlled for the spatiotemporal environment and the effects of the financial and awareness components of the study, all five worry and concern variables are statistically significant predictors of the change in speeding behaviour. However, contrary to the hypothesis but consistent with the findings of Hypothesis 1.2 (Section 9.3.2), higher concern about passengers was related to higher proportions of the before score. This is to say that the higher a driver's concern about injury to their passengers, the closer to the before score that was observed in the after period. The same was true for drivers with a higher self-reported likelihood of a crash. In contrast, drivers with a higher concern of themselves or other drivers being injured and greater self-perceived likelihood of other similarly aged drivers being involved in a crash were associated with lower proportions of the before score and therefore a larger magnitude change between the before and after periods. To ensure that these results were not partly a function of an interaction between the concern of injury to passengers and the number of passengers in the car, an additional model was attempted with this interaction but with no change to the results.

In the acceleration model none of the worry and concern variables were statistically significant. The braking and total scores exhibited statistically significant effects of the crash likelihood questions in the same direction as for the speeding model (albeit with higher standard errors relative to the estimate).

Table 10-4: Parameter estimates for Hypothesis 2.2 TSI-level models

	B	Std. Error	Sig.
Speeding			
Injury (Self)	*-0.182*	*0.081*	*0.026*
Injury (Passengers)	**0.359**	**0.069**	**0.000**
Injury (Other Drivers)	*-0.124*	*0.060*	*0.039*
Crash Likelihood (Self)	**0.167**	**0.030**	**0.000**
Crash Likelihood (Others)	**-0.148**	**0.022**	**0.000**
Acceleration			
Injury (Self)	-0.013	0.101	0.899
Injury (Passengers)	-0.069	0.084	0.412
Injury (Other Drivers)	0.057	0.076	0.453
Crash Likelihood (Self)	0.034	0.037	0.362
Crash Likelihood (Others)	-0.041	0.027	0.138
Braking			
Injury (Self)	-0.011	0.067	0.864
Injury (Passengers)	0.011	0.056	0.841
Injury (Other Drivers)	-0.042	0.052	0.425
Crash Likelihood (Self)	*0.054*	*0.025*	*0.032*
Crash Likelihood (Others)	**-0.056**	**0.019**	**0.003**
Total			
Injury (Self)	-0.073	0.039	0.064
Injury (Passengers)	0.060	0.033	0.068
Injury (Other Drivers)	-0.017	0.029	0.561
Crash Likelihood (Self)	*0.031*	*0.014*	*0.030*
Crash Likelihood (Others)	**-0.051**	**0.011**	**0.000**

Bold cells indicate significance at the p = .01 level
Italic cells indicate significance at the p = .05 level
Green cells indicate significant negative effect
Red cells indicate significant positive effect
White cells indicate no statistically significant effect

10.3.3 Driver-level models

Following the same procedure used for Hypothesis 2.1 (Section 10.2.3), driver-level multilevel models were run for each of the risk scores. The model fit, illustrated in Figure 10-8, while consistent with the driver-level models for Hypothesis 2.1 were poorer than the TSI-level models.

For the speeding model, the most significant variables relate to the study phase with the after two phase exhibiting higher proportions (lower magnitude change) compared to the before period and drivers with more frequent logins to the study website exhibiting lower proportions (higher magnitude changes). In terms of the worry and concern variables, only the perceived likelihood of other drivers being involved in a crash was (negatively) statistically significant. In the acceleration model – as in the TSI-level acceleration model – no worry and concern variables were statistically significant. The braking and total models only exhibited negative statistically significant concern about other drivers being injured which is the same direction as for the speeding model.

Figure 10-8: Driver-level hypothesis 2.2 observed and predicted density plots

10.3.4 Summary of statistical significance

Consist with the results of Hypothesis 2.1 (Section 10.2), the speeding models exhibited the most statistically significant worry and concern variables. The other models exhibited none, one or two as shown in Table 10-5.

Table 10-5: Summary of statistical significance of worry and concern variables (after)

	Injury (self)	Injury (Pass.)	Injury (Other)	Crash (Self)	Crash (Other)
TSI-Level					
Speeding	–	+	–	+	–
Acceleration					
Braking				+	–
Total				+	–
Driver-Level[142]					
Speeding					–
Acceleration					
Braking			–		
Total			–		
Total Negative (8)	**1**	**0**	**3**	**0**	**4**
Total Positive (4)	**0**	**1**	**0**	**3**	**0**

Note: + indicates a positive effect;
— indicates a negative effect; and
A blank cell indicates no statistically significant effect.

10.4 Hypothesis 2.3: Confidence

It was hypothesised that drivers with more confidence in their driving abilities would exhibit lower magnitude changes in risky driving behaviour once they were made aware of their speeding behaviour. It was speculated that this was the case on the basis that drivers who are more confident in their driving would consider themselves more capable of handling the risks associated with speeding, acceleration and braking behaviour. This hypothesis was tested using the same approach used for Hypotheses 2.1 and 2.2 and the answers to five self-reported confidence measures which were also used to test Hypothesis 1.3 (Section 9.4). These five measures represent drivers' self-reported confidence, on a five-point subjective scale, driving on unfamiliar roads, in poor weather conditions, in heavy traffic, on motorways and at night. TSI-level and driver-level models were run for each of the risk scores.

[142] The model fit for the driver-level models was significantly poorer than for the equivalent multilevel models.

10.4.1 Main findings and discussion

Although there may be a relationship between drivers confidence in various situations on their propensity to engage in risky driving behaviour – not necessarily in the negative direction – they do not appear to have an effect on the magnitude of changes following the provision of information. The few statistically significant effects (summarised in Table 9-13) observed at the TSI-level show positive and negative effects which suggest that they are functioning as proxies for other unexplained factors. Furthermore, the TSI-level speeding models of night-time and motorway TSIs did not exhibit any statistically significant relationship with drivers' confidence in those situations. Taking these results together with the driver-level models (which exhibited no statistically significant effects) it is not possible to accept the hypothesis that drivers with more confidence in their driving skills exhibit lower magnitude changes in risky driving behaviour once they are made aware of their speeding behaviour.

A limitation here is that increasing drivers' awareness of their own speeding behaviour does not alter drivers' perceptions about speeding or any other behaviour. Drivers that are confident in their driving skills are likely already aware of the potential risks they face (as found in Hypotheses 1.2 and 2.2) and therefore making them aware of the extent of their speeding behaviour has no direct impact on their perceptions of speeding. Clearly, future research would benefit from more closely pairing the information provided to participants with the measures of confidence.

10.4.2 TSI-level models

The TSI-level models followed the same specifications as the TSI-level models presented in previous sections. The model fit (Figure 10-9) once again proved to be good – particularly for speeding as would be expected – but the majority of the predictive power was derived from the after period variables and spatiotemporal characteristics.

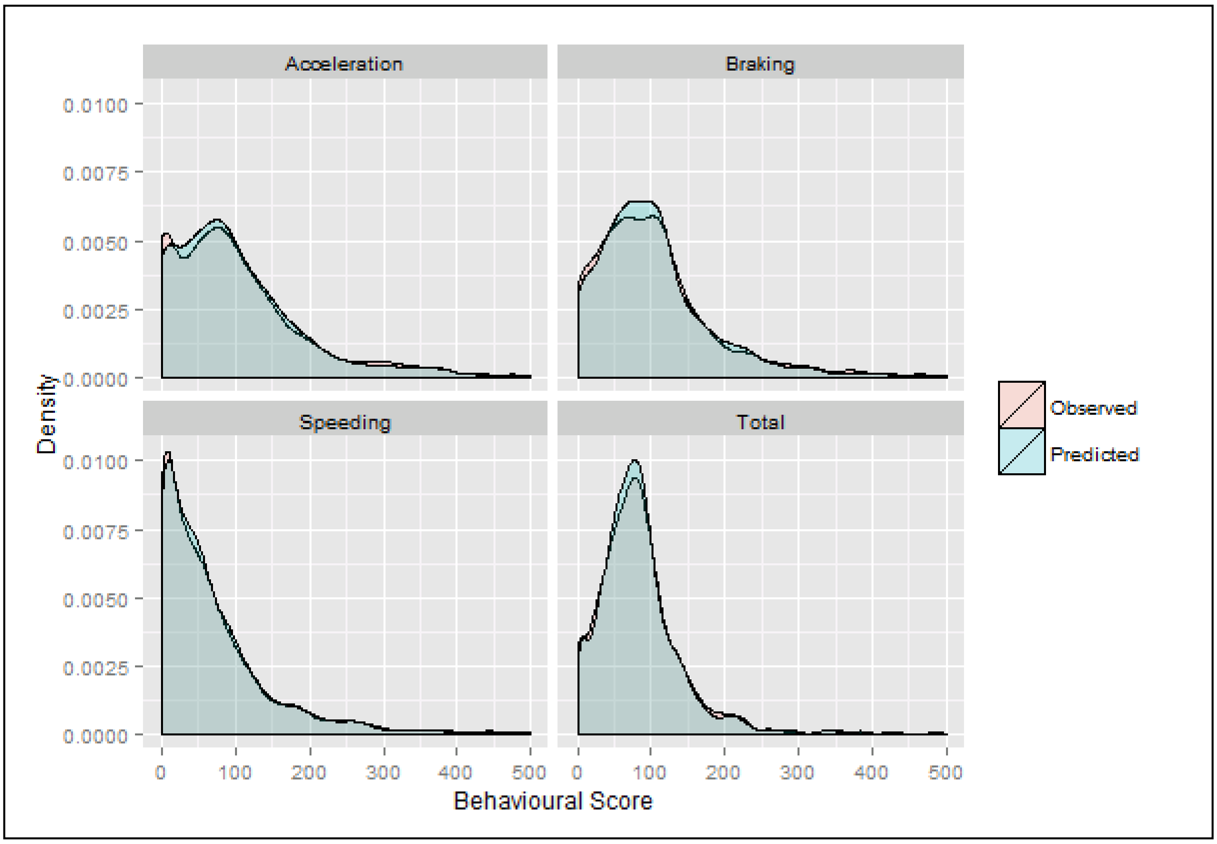

Figure 10-9: Temporal and spatial identifier-level hypothesis 2.3 observed and predicted density plots

The model of changes in speeding behaviour was of most interest but only drivers' confidence on unfamiliar roads was significant and this was significant in the opposite than expected direction with higher confidence being associated with lower proportions of the before score (p = .016). To test that these confidence measures were not applicable only in the specific spatiotemporal context to which they relate, an addition two models were tested using identical specifications but including only night-time and motorway TSIs respectively. These additional models failed to exhibit any statistically significant confidence variables adding further evidence that drivers' confidence in their own driving ability is not a factor in changing speeding behaviour.

Of the other risk scores, acceleration also exhibited no statistically significant confidence variables. The braking model exhibited a positive effect for poor weather (p = .009) and a negative effect for heavy traffic (p = .031) but with relatively high standard errors. The total model exhibited the most statistically significant effects –

with the same direction as the speeding and braking models – although these also suffered from high standard errors.

10.4.3 Driver-level models

Driver-level models were run using the driver confidence measures and otherwise the same specifications as the driver-level model for the other hypotheses. Although the same spatiotemporal and study variables as the driver-level models for Hypothesis 2.1 and Hypothesis 2.2 were statistically significant none of the driver confidence measures were statistically significant for any of the models. This is in contrast to the driver-level models for the before period (discussed in Section 9.4.3) where all four models exhibited statistically significant driver confidence variables (albeit with inconsistent signs).

10.4.4 Summary of statistical significance

The summary of the statistically significant effects of the models presented in this section are shown in Table 10-6. Although several multilevel models of speeding, there was only one significant effect observed. A few more were observed for the braking and total models but with no discernable pattern.

Table 10-6: Summary of statistical significance of driving confidence measures (after)

	Unfamiliar Roads	Poor Weather	Heavy Traffic	Motorways	Night
Speeding TSI-level models					
Multilevel TSI	—				
Night TSIs					
Motorway TSIs					
Other TSI-level models					
Acceleration					
Braking		+	—		
Total	—		—	+	
Driver-Level[143]					
Speeding					
Acceleration					
Braking					
Total					
Total Negative (4)	**2**	**0**	**2**	**0**	**0**
Total Positive (2)	**0**	**1**	**0**	**1**	**0**

Note: + indicates a positive effect;
— indicates a negative effect;
A blank cell indicates no statistically significant effect

[143] The model fit for the driver-level models was significantly poorer than for the equivalent multilevel models.

10.5 Hypothesis 2.4: Personality

There has been extensive research on the relationship between drivers' personality and driving behaviour (summarised in Section 3.1.2). Using data from the before phase, statistically significant relationships were found between drivers' speeding behaviour and altruism and excitement personalities (see Section 9.5). Hypothesis 2.4 postulated that more aggressive, excitable and car-dependent personalities exhibit lower magnitude changes in risky driving behaviour once they are made aware of their speeding behaviour. Conversely, it was predicted that more altruistic drivers would exhibit greater magnitude changes in risky driving behaviour once they are made aware of their speeding behaviour.

Following the same procedure used for the previous hypotheses and the same personality variables used to test Hypothesis 1.4 (Section 9.5), TSI-level and driver-level models were run for each of the risk scores.

10.5.1 Main findings and discussion

The results of the models used to test Hypothesis 2.4 (summarised in Table 10-8) show a strong relationship between drivers' personality characteristics and their propensity to change their speeding behaviour as a result of being made aware of their speeding behaviour. It is clear that this is the case regardless of the imposition of a financial incentive (although that increases the magnitude of the change). Worryingly, however, more excitable drivers - who were found in Hypothesis 1.4 (Section 9.5) to exhibit higher speeding scores in the before period – also exhibit smaller magnitude changes, as do more aggressive and car-dependent drivers. More altruistic drivers were strongly related to after scores that were smaller proportions of the before score and therefore a higher magnitude beneficial change in speeding behaviour. There is also some evidence that more altruistic drivers reduce their acceleration and braking behaviour at an overall driver level although this does not appear to be a direct effect of the increased awareness of speeding behaviour.

Some of these relationships can be observed in Figure 10-10 which plots the changes in the TSI-level speeding risk scores relative to the before period by drivers' personality characteristics. More altruistic drivers as well as less aggressive, car-dependent and excitable drivers show a stronger inclination towards larger (negative) changes relative to more aggressive, car-dependent and excitable drivers together with less altruistic drivers. Interestingly, there appear to be shifts in the distributions from the after one period (shown in blue) to the after two period (shown in yellow) regressing (to some extent) back towards the before period but to varying degrees by personality.[144]

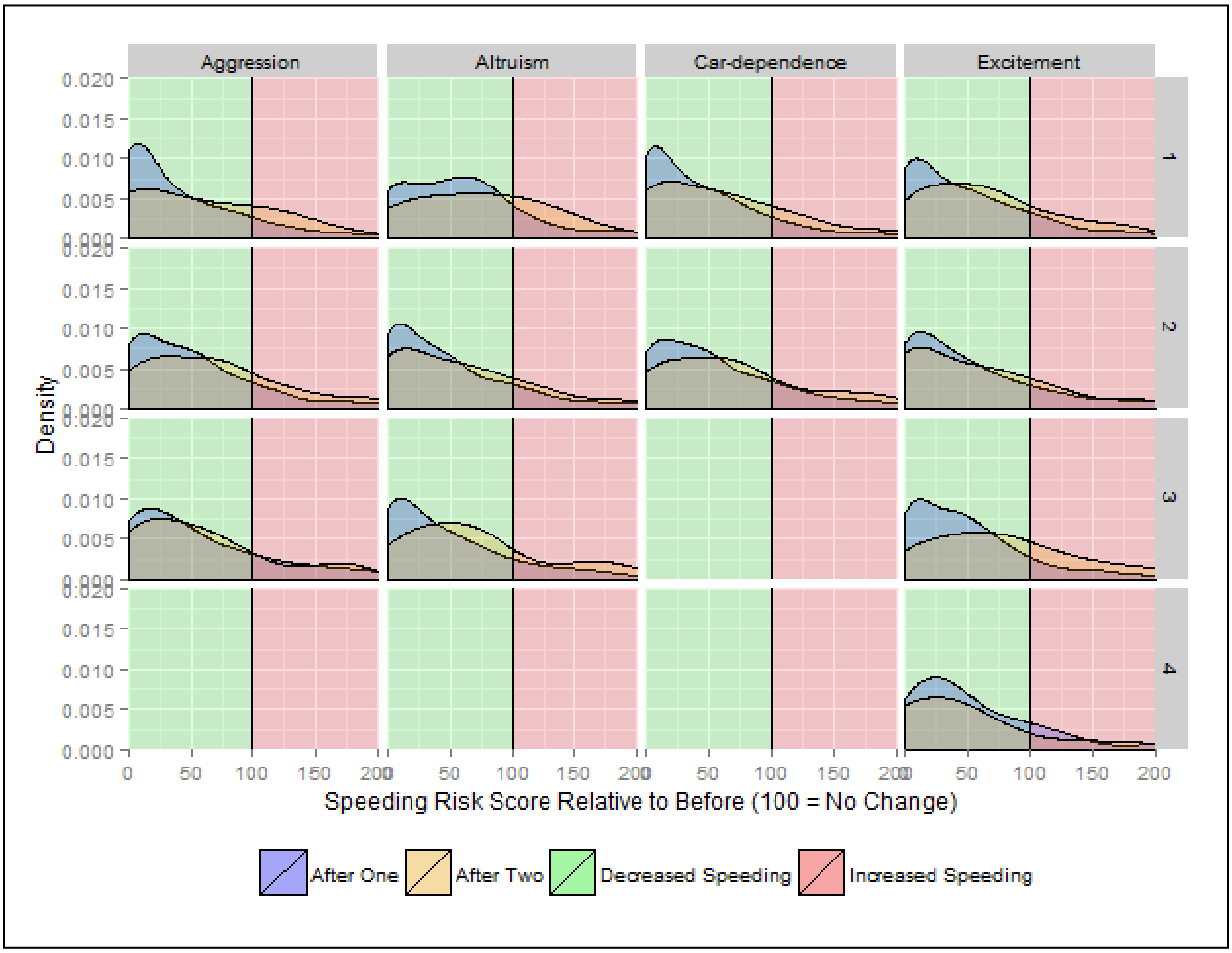

Figure 10-10: Changes in temporal and spatial identifier-level speeding risk scores by personality characteristics[145]

[144] Since the after two period was made up of drivers with a remaining incentive of less than 5 percent of their starting incentive, the drivers included in the after two phase are a subset of those in the after one phase.

[145] Personality scales have been converted into integers and then combined to make the charts easier to interpret. The models presented in Section 10.5.2 and Section 10.5.3 use the original values.

Taking the evidence as a whole, including the importance of the spatiotemporal environment which has clearly been shown to be important, the hypothesis can be accepted in regard to speeding behaviour. The hypothesis cannot be accepted for the other risk scores because there is insufficient evidence to confirm that the observed relationships are not the result of other factors.

10.5.2 TSI-level models

These TSI-level models exhibited the best model fit of all the models tested for the second set of hypotheses. Nonetheless, none of the personality variables were statistically significant in the acceleration, braking and total models. In contrast, all four personality variables were statistically significant in the expected direction in the speeding model. The parameter estimates (shown in Table 10-7) indicate that aggression, excitement and car-dependence were statistically significant positive predictors of the proportion of the speeding score in the before period. This means that the more aggressive, excitable or car-dependent a driver the smaller the magnitude change in speeding behaviour that occurs once drivers are made aware of their speeding behaviour. More altruistic drivers exhibit the opposite trends with more altruism being related to higher magnitudes of (negative) change in speeding behaviour compared to the before period.

Table 10-7: Parameter estimates for Hypothesis 2.4 temporal and spatial identifier-level models

	B	Std. Error	Sig.
Speeding			
Aggression	**0.144**	**0.035**	**0.000**
Altruism	**-0.139**	**0.034**	**0.000**
Excitement	*0.058*	*0.029*	*0.050*
Car-Dependence	**0.211**	**0.055**	**0.000**
Acceleration			
Aggression	-0.040	0.042	0.346
Altruism	-0.051	0.040	0.211
Excitement	0.028	0.037	0.439
Car-Dependence	-0.032	0.068	0.637
Braking			
Aggression	0.041	0.029	0.154
Altruism	-0.014	0.027	0.617
Excitement	-0.032	0.025	0.193
Car-Dependence	0.009	0.045	0.837
Total			
Aggression	0.000	0.017	0.987
Altruism	-0.028	0.016	0.087
Excitement	0.013	0.014	0.364
Car-Dependence	0.017	0.026	0.508

Bold cells indicate significance at the p = .01 level
Italic cells indicate significance at the p = .05 level
Green cells indicate significant negative effect
Red cells indicate significant positive effect
White cells indicate no statistically significant effect

These results show that personality characteristics are factors not only in the extent of drivers' speeding behaviour but that they also relate (indeed, more strongly) to how likely drivers are to reduce their speeding behaviour once they are made aware of their speeding behaviour. A financial incentive is beneficial but awareness on its own appears to be effective. At the TSI-level of aggregation there does not appear to be any indirect effect on acceleration and braking behaviour.

10.5.3 Driver-level models

Although the model fit[146] at the driver-level of aggregation was good, the speeding model exhibited no statistically significant personality variables. This is best illustrated in Figure 10-11 which plots the relationship between drivers' speeding risk scores and their personality characteristics. There is no distinct pattern evident and linear and logarithmic trend lines (not shown) are almost horizontal. The difference

[146] Measured by comparing the predicted and observed values.

between the TSI-level and driver-level speeding models adds further evidence of the interaction between the spatiotemporal environment and changes in speeding behaviour. Altruism was a statistically significant negative predictor of changes in acceleration (p = .001) and braking (p = .011) which is the same direction as the TSI-level speeding model. The standard errors, in these cases, were reasonable.

It is not clear why changes in acceleration and braking behaviour are significant in the driver-level models but not the TSI-level models. It is possible that the driver-level changes reflect shifts in when and where more altruistic drivers drove in the after period compared to the before period. Since these models do not incorporate the spatiotemporal variables, this trend would not be captured by these variables in the model.

Figure 10-11: Changes in driver-level speeding risk scores by personality characteristics

10.5.4 Summary of statistical significance

All four personality measures were statistically significant predictors of changes in speeding behaviour. Although altruism was statistically significant for acceleration and braking at the driver-level no other significant effects were observed for the other models as shown in Table 10-8.

Table 10-8: Summary of statistical significance of personality measures

	Aggression	Altruism	Excitement	Car-Dependence
TSI-Level				
Speeding	+	–	+	+
Acceleration				
Braking				
Total				
Driver-Level				
Speeding				
Acceleration		–		
Braking		–		
Total				
Total Negative (3)	0	3	0	0
Total Positive (3)	1	0	1	1

10.6 Interpretation

This chapter presented the results of models run to test four hypotheses dealing with the relationship between drivers' risk perceptions, worry and concern, driving confidence and personality, and the magnitude of changes in their driving behaviour once they are made aware of their speeding behaviour. In all, the hypotheses (summarised in Table 10-9) could be accepted in three (out of 16) cases. Drivers' with higher perceptions of risk were associated with greater magnitude changes in speeding and total risk scores. In terms of personality, the hypothesis was accepted for speeding alone showing that more aggressive, excitable and car-dependent personalities were associated with lower magnitude changes in their speeding risk scores and more altruistic drivers were associated with higher magnitude changes in their speeding risk scores after they were made aware of their speeding behaviour.

Table 10-9: Summary of Hypothesis 2 testing

Hypothesis	Speeding	Acceleration	Braking	Total	Comments
H2.1: Risk Perceptions	Y	N	N	Y	
H2.2: Worry and Concern	N	N	N	N	Opposite effects observed
H2.3: Driver Confidence	N	N	N	N	
H2.4: Personality	Y	N	N	N	

Y: Hypothesis accepted
N: Cannot reject the null hypothesis

More broadly, although the hypotheses were accepted in only a small number of cases it is evident that the speeding awareness and financial incentive had a statistically significant effect on drivers' behaviour. Keeping in mind that the AIC values can only be compared for the same dependent variable, Figure 10-12 illustrates the improvements compared to the null model in cumulative models.[147] The null multilevel model contains only indicators of the TSI and driver (used to create the individual levels) but none of the constituent variables such as the age or gender.[148] Focusing on the speeding models, the spatiotemporal variables improved the model and to a lesser extent so did the driver and vehicle characteristics. The biggest improvements in the model fit occurred with the addition of the after variables which account for drivers' exposure to their speeding behaviour and the financial incentive. Comparing the hypotheses, Hypothesis 2.3 (driver confidence) exhibited the same model fit as the model containing the after variables. Hypothesis 2.2 (worry and concern) and Hypothesis 2.1 (risk perceptions) demonstrated improved model fit compared to the model with the after phase variables. However, of the four hypotheses, the personality model of speeding (Hypothesis 2.4) had the largest improvement in the model fit exhibiting an almost as large improvement as the additional of the after period variables.

In the other behavioural models Hypotheses 2.1, 2.2 and 2.3 exhibited almost identical model fit to the model containing the after variables while Hypothesis 2.4 exhibited substantially improved model fit. As with the speeding models, the spatiotemporal, driver, vehicle and after phase variables contributed the majority of the improvements over the (multilevel) null model.

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[147] The driver and vehicle model also includes the spatiotemporal variables. The after model contains the spatiotemporal, driver and vehicle variables. The hypotheses contain the after, driver, vehicle and spatiotemporal variables but not the variables from the other hypotheses.

[148] This has the effect of capturing the unexplained variability at each level. Once variables are added to each level the unexplained variability is reduced but any factors that are intrinsically included in these levels remains captured by the level intercept.

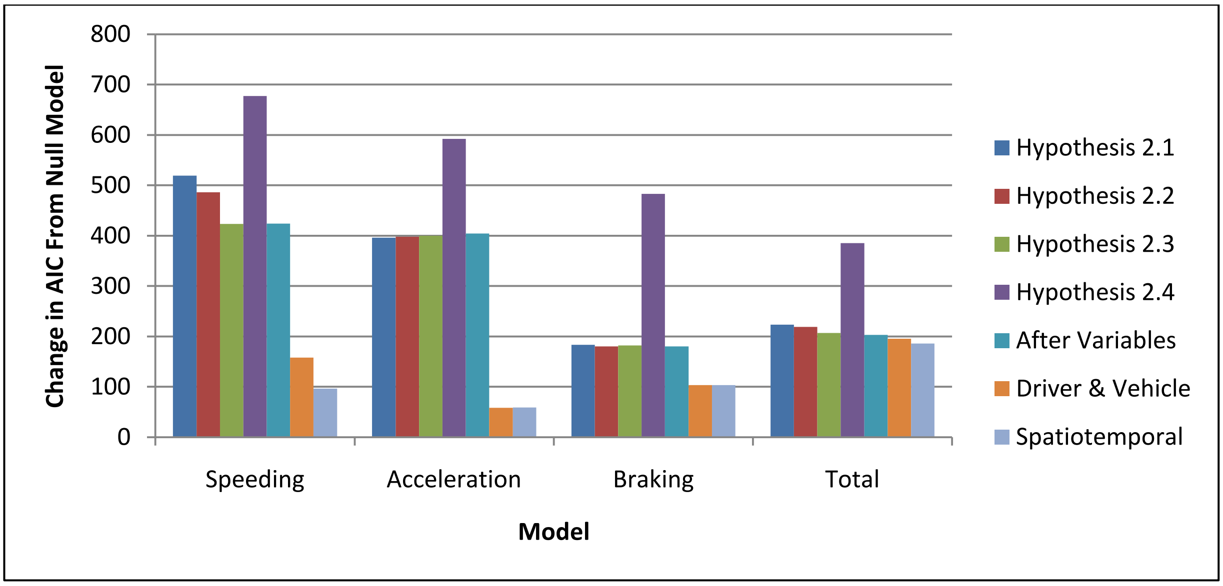

Figure 10-12: Improvement in fit of temporal and spatial identifier-level models from null multilevel model

10.7 Conclusions

In conclusion, drivers' risk perceptions and personality are predictors of speeding behaviour but they are much stronger predictors of drivers' propensity to reduce their speeding behaviour once they are made aware of their speeding behaviour. There is some (limited) evidence that there is an indirect effect on aggressive acceleration and braking behaviour but it is likely that reductions in these behaviours would require targeted interventions. In this study only speeding was an inherent component of the study and this is reflected in these results. Furthermore, these findings show that informing drivers of the frequency of their speeding behaviour and (to a lesser extent) providing a financial incentive to reduce speeding behaviour are effective methods of reducing speeding behaviour. However, as has been apparent throughout this thesis, the spatiotemporal environment has a large impact on drivers' behaviour (speeding, acceleration and braking) and this has a number of implications for studies of speeding behaviour and before-and-after studies in particular.

11 CONTEXT, IMPLICATIONS AND CONCLUSIONS

This thesis examined the relationship between drivers' personal characteristics and their speeding, acceleration and braking behaviour before and after the introduction of an intervention. The intervention comprised a variable financial incentive to reduce VKT, night-time driving and speeding combined with a web-based interface, which informed participants of their remaining incentive and frequency of speeding behaviour for each trip. This research made use of GPS data and survey data collected from the same participants over a 10 week period.

The results of this research provide both an indication as to possible policies and tools for examining driver behaviour so as to isolate the critical factors that influence driver behaviour. This chapter focuses on speeding behaviour since it was not possible to identify relationships between driver characteristics and braking and acceleration behaviour.

This chapter discusses the policy and research implications of this thesis, outlines the limitations of the study, presents a path of future research and concludes with some final remarks.

11.1 Context and interpretation

Chapter 9 and Chapter 10 presented the results of the hypothesis testing. Between them, 16 sub-hypotheses were tested using a combination of single-level and multilevel regression models at various levels of aggregation. This section summarises the findings and puts them within the context of the literature (see the literature review in Chapter 2 and Chapter 3 for a broader review of previous research) in three broad categories: road environment, driver characteristics and the intervention.

For reference, a summary of the individual hypotheses that were tested can be found in Appendix A. This summary includes whether or not each hypothesis has been accepted.

11.1.1 Road environment

Spatiotemporal factors were important in explaining the differences in speeding behaviour that were observed in each phase of this study. During the 'before' phase, road environment factors were significant predictors of speeding behaviour. The speed limit of the road exhibited the largest parameter values with the highest speeding scores observed for the lower speed limits (school zones and 50 km/h zones) consistent with other research (Biding and Lind, 2002)

Larger magnitude changes in speeding were observed on roads with higher speed limits and at night (relative to speeding in the morning) while lower magnitude changes were observed in the afternoon. Speeding behaviour in school zones, during rain, on weekends and on trips with more passengers were not statistically significant predictors of changes in speeding behaviour relative to non-school zones, dry weather, weekdays and trips with no passengers respectively. With the exception of weekends, all of these variables tended to exhibit lower scores in the before period and these results suggest that the interventions did not result in higher (or lower) magnitude changes compared to other spatiotemporal environments. It is notable that night-time driving exhibited statistically significantly larger magnitude improvements in speeding behaviour relative to morning driving. It is possible this was partly a reflection of the intervention, which incorporated night time driving into the financial incentive although this is uncertain as smaller changes in speeding behaviour were observed in the afternoon (again, relative to driving in the morning). Another possibility is that there is an interaction effect between drivers' risk perceptions, personality, speeding awareness and spatiotemporal factors that make drivers more (or less) likely to change their behaviour in particular situations that are accounted for by the road environment. It would be beneficial to pursue further research to clarify some of these issues.

Although there have been a number of studies examining the effects of ISA[149] (such as Swedish National Road Administration, 2002; NSW Centre for Road Safety, 2010; Reagan et al., 2012), the published literature on these studies frequently do not break

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[149] ISA is different to the technology in this study but the objective in both cases is to inform the driver of their speeding behaviour and, therefore, ISA studies are useful for comparison.

down speeding behaviour by road environment, with the exception of speed limits. This makes some comparisons to changes in behaviour difficult. Nonetheless, these (ISA) studies reveal that higher speed limits are associated with proportionally greater changes in speeding behaviour following the introduction of ISA (Biding and Lind, 2002; NSW Centre for Road Safety, 2010) and while speeding in school zones is reduced compared to before the intervention it is not significantly different to non-school zone speeding (NSW Centre for Road Safety, 2010). Both results are consistent with the findings of this research.

11.1.2 Profiling and categorising drivers

The main focus of this thesis was on identifying the driver characteristics associated with speeding, acceleration and braking behaviour. None of the hypotheses could be accepted in terms of acceleration or braking behaviour. In regards to speeding, the results from both the before phase (Chapter 9) and after phase (Chapter 10) show that after controlling for the influence of the road environment (see Section 11.1.1) a number of driver characteristics are significant predictors of speeding behaviour and changes in speeding behaviour.

Eight measures of risk perceptions were tested in this research (Section 9.2 and Section 10.2) of which four (illegal u-turn, turning right across a busy road, changing lanes without checking and speeding) exhibited primarily negative effects – indicating that higher perceptions of risk were associated with lower speeding scores – while the remainder exhibited mixed or context-specific effects. Following the introduction to the intervention, higher perceptions of the danger of illegal u-turns, changing lanes, speeding, mobile telephone use and talking to passengers were all associated with higher relative reductions in speeding behaviour.

Results of prior research (see Section 3.1.5) are more mixed with some studies (for example Lucidi et al., 2010) finding that risk perceptions were not related to speeding and crashes. However, there is some evidence that drivers rationalise their behaviour through (incorrect) risk-mitigating beliefs (Brown and Cotton, 2003) and that these beliefs are, in turn, correlated with speeding behaviour. This would be consistent with the results presented in this thesis as risk perception was measured on the basis of individual behaviours.[150] Findings from Rundmo and Iversen (2004) reinforce this with their finding that probability judgements of risk are not significant determinants of self-reported risky driving behaviour but emotional reactions to traffic hazards (speeding, etc.) are significant.

In addition to perceptions of risk associated with particular driving behaviours, participants were asked to indicate the extent to which they were worried or concerned about themselves, their passengers and other drivers being involved in or injured in a crash (Section 9.3 and Section 10.3). It was expected *a priori* that concern for passenger safety was a determinant of speeding behaviour. This turned out to not be the case. Instead, a driver's concern about injuring themselves was a significant (positive) predictor of speeding behaviour and (similarly) drivers self-reporting a higher likelihood of crash involvement also exhibited significantly higher speeding scores. Once the intervention was implemented higher magnitude changes were observed for those with more concern of injury to themselves while lower magnitude changes were observed for those self-reporting higher probabilities of crash involvement.

These results differ somewhat from the broader literature (see Section 3.1.5). For example, Lucidi et al. (2010) identified three groups of drivers of which those with the least concern of injury (of themselves or others) exhibit the highest number of driving violations and the group with the greatest concern of injury exhibited the lowers. On the other hand, Falk (2010) studied how drivers self-reported probability of a crash and concern of injury changed over time and found that drivers self-reported a higher likelihood of a crash after completing a survey on risky driving behaviour. These same drivers also reported to be more concerned about injuring others (a concern that was not significant in this thesis). One explanation for this is that previous research relied on either self-reported behaviour or enforcement records while this thesis employed GPS to measure speeding behaviour during all driving. It is possible that the more common data collection methods (see Section 2.4.1) predominantly capture only the most extreme behaviours.

[150] Many studies (for example Lucidi et al., 2010) measure risk perception by asking about crash risk instead of behaviours.

Taking this one step further, Section 9.4 and Section 10.4, presented the results of an analysis examining the relationship between driving confidence and speeding behaviour. In general, there appears to be no significant relationship between driving confidence and speeding behaviour before and during the charging phase. It is speculated that this is due to the context-specific nature of confidence measures but even TSI-specific models proved to be of little statistical value. This appears to be at odds with the findings of Falk and Montgomery (2007) which finds that driver's confidence in his/her own driving ability is a common factor in how they drive. However, it appears that most drivers have confidence in their own driving abilities and they use this to rationalise their (different) behaviours.

Of the driver characteristics tested, personality was the strongest predictor of speeding behaviour by a substantial margin in all phases of the study. In particular, more altruistic drivers exhibited lower speeding scores (Section 9.5) and greater magnitude (beneficial) changes in speeding behaviour in the 'after' phase (Section 10.5). More excitable drivers exhibited the opposite effect (in both study phases). More aggressive drivers exhibited the same effects in the after phase (i.e. smaller changes) but, surprisingly, no significant effects in the before phase. These results are broadly consistent with prior research on driving psychology (see Section 3.1.3 for a review of the literature). For example, Machin and Sankey (2008)[151] identified more excitement seeking and less altruism as predictors of speeding behaviour as did Ulleberg and Rundmo (2003). Other researchers found personality traits to be predictors of crash-involvement (Iversen and Rundmo, 2002; Gulliver and Begg, 2007; Constantinou et al., 2011). There is little research on the effects of personality on changes in behaviour following an intervention similar to the one used in this thesis however given that personality is the strongest predictor of speeding behaviour before an intervention it is likely that it would also be a predictor of the magnitude of responses to an intervention.

[151] Machin and Sankey (2008) used the same personality survey (see Section 4.2.7) used for this thesis.

11.1.3 Speeding awareness and financial incentives

The results that incorporate the speeding awareness and financial components of the study (Chapter 10) show that both strategies are effective at encouraging drivers to reduce their speeding behaviour relative to the before period. Comparing the effect of the study period on changes in the speeding risk score and the after scores as a proportion of the before score reveals that speeding risk scores were measurably lower in the after 1 period (financial and awareness components) compared to the before period. Speeding risk scores in the after 2 period (awareness only) were also lower than in the before period but to a lesser extent than in the after 1 period with (allowing for the error margin) 12 to 14 percent higher speeding scores in the after 2 period relative to the after 1 period. This suggests that making drivers aware of their speeding behaviour – or simply that their speeding behaviour is being monitored – is sufficient to reduce the speeding behaviour of most drivers, at least in the short term, irrespective of a financial incentive.

In addition, the results show that (in general) the higher the starting incentive[152] the higher the speeding score and the smaller the improvement in speeding behaviour in the after periods. Since the starting incentive was partially determined by the frequency of speeding in the before period this suggests that the worst speeders also exhibited the smallest magnitude changes in behaviour relative to their own before period speeding behaviour. Therefore, while the strategies result in significant reductions in speeding behaviour these changes are disproportionately due to improvements in behaviour by drivers that were already (relatively) safer drivers. In effect, the drivers that most need to change – and at which many of the policies against speeding are targeted – are also the drivers that are least inclined to change their behaviour. This is reinforced by looking at the parameter estimates for the interaction between drivers that made money in the study and the number of logins to the study website.

In the before period, during which time the interventions had not been introduced and drivers' had not been told that their speeding behaviour was being monitored, drivers

[152] The starting incentive was different for every driver as it was based on their driving in the before period. A full discussion of how the financial component functioned can be found in Section 4.2.3.

that made money already exhibited a negative trend in speeding behaviour for every additional time they accessed the website. Those drivers that did not make money had the opposite effect. In the after one phase, both groups exhibited negative relationships but the magnitude was almost six times higher for the group that made money in the study. In the after two period there was no statistically significant effect for those drivers who did not make money while the group that did make money exhibited a negative effect of a higher magnitude than the before period. These trends suggest that those drivers that made money in the study were already predisposed to being better drivers as judged by their conscientiousness in accessing the prompted-recall component of the study before the introduction of the intervention. A model similar to the one shown in Table 10-1 was performed to examine the relative difference in absolute scores between drivers that made money and those that did not in each of the study phases. The results confirm that those drivers that made money in the study already exhibited lower speeding scores in the before period with the magnitude difference in speeding scores between the two groups increasing seven-fold in the after one period and three-fold in the after two period (relative to the difference in the before).

What has been observed here is that the combination of a financial incentive and increasing awareness of a driver's own behaviour provides the best results across the sample. Increasing drivers' awareness of their behaviour is effective in reducing speeding behaviour independently, which is consistent with previous research (Merrikhpour et al., 2012). Figure 11-1 and Figure 11-2 illustrate the distribution of speeding scores at the driver and TSI levels respectively for each phase of the study. There is a clear shift to the left (representing lower scores) in the after one phase relative to the before phase and then a shift back to the right in the after two phase. However, there are a core group of drivers – representing approximately 20 percent of the sample – that appear unwilling to change their speeding behaviour as a result of these interventions.

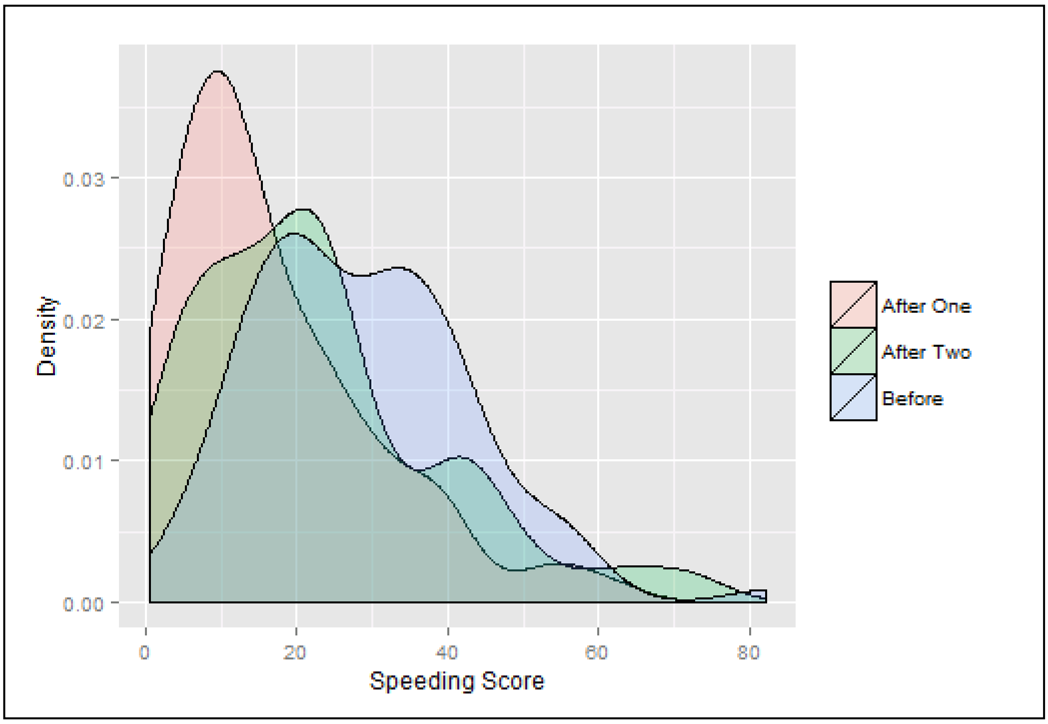

Figure 11-1: Density of driver-level speeding scores in all phases

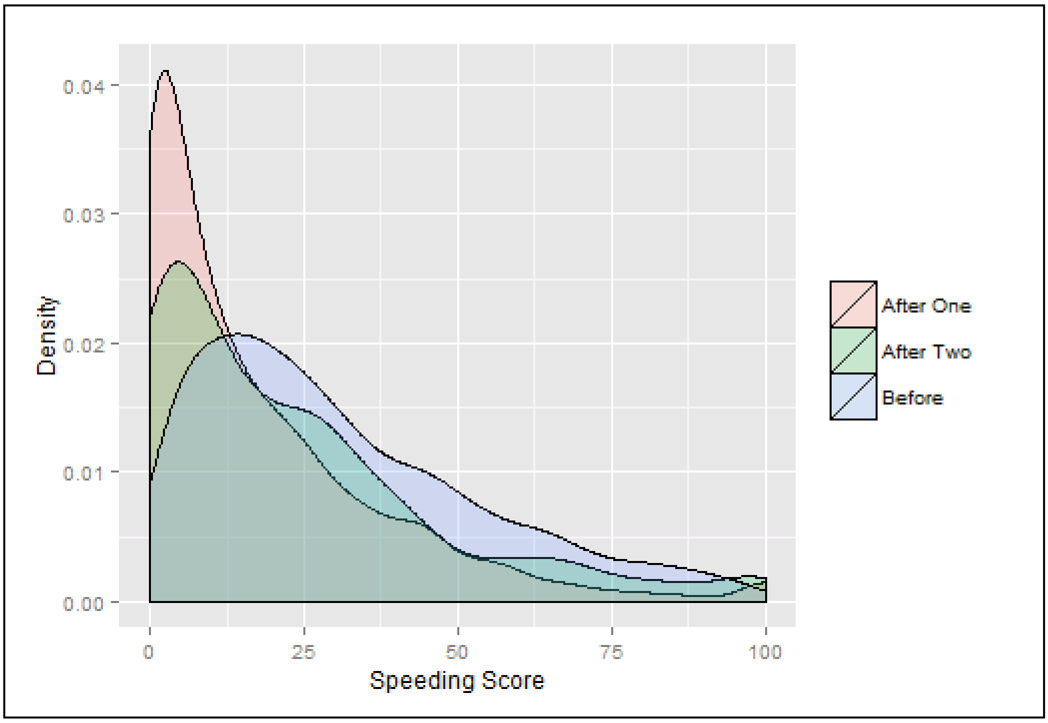

Figure 11-2: Density of temporal and spatial identifier-level speeding scores in all phases

11.1.4 Summary

Overall, the findings presented in this thesis are consistent with the existing literature. However, the findings strongly suggest that many of the facets of driver behaviour are more nuanced than may be elicited through aggregate or self-reported measures. The strong influence of the road environment functions not only as a constraint on driver behaviour but also, indirectly, as a factor in risk perceptions and confidence. Among the driver characteristics tested, personality traits are consistently the strongest predictors of driving behaviour and (perhaps as importantly) propensity to change behaviour suggesting that personality should be integrated into broader studies of behaviour, as was done in this thesis, instead of being treated as a distinct factor for investigation in a separate study.

11.2 Policy implications

There are various implications for policy makers based on the results of this research. These policies include changing the road environment to encourage or force drivers to slow down, improving drivers' awareness of their speeding behaviour, introducing financial incentives and the need to recognise that a substantial minority of drivers require stronger measures to reduce their speeding behaviour.

11.2.1 Changing the road environment

Despite the efforts focused on trying to change drivers' behaviour through 'soft' measures including education, personalised information and monetary incentives (or disincentives), these results (Section 9.6) suggest that making changes to the design of the road infrastructure may prove an effective tool, albeit as a complement to other behavioural change strategies not as a replacement. These changes may include adjusting the width of the lanes, road or verge (Lewis-Evans and Charlton, 2006), installation of speed humps or chicanes to force drivers to slow down, installation of pedestrian refuges, painted hatching or rumble strips (Jamson et al., 2010) or the installation of dynamic speed display signs (Gehlert et al., 2012). However, changes to hard infrastructure with the aim of reducing speeding need to be made within a broader context to avoid unintended increases in crash risk as can occur with on-street parking (Edquist et al., 2012).[153]

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[153] On-street parking has the effect of slowing down vehicles which consequently reduces the risks associated with speeding. However, research (Edquist et al., 2012) has found that in some cases this can increase crash risk due to higher cognitive load.

These findings (Section 9.2.1) also suggest that the driver characteristics that are associated with speeding vary from one road environment to another. This would indicate that existing strategies to reduce speeding have proven more effective in some road environments than in others and that the effects are not homogeneous across the sample. That being the case, in addition to behavioural change programmes needing to be personally relevant to individuals (Lewis et al., 2007), it would appear that they would also benefit from being contextually relevant by targeting behaviour in particular road environments.

While changing the road environment is likely the most expensive strategy for changing driver behaviour it also appears to be the most effective particularly when the road environment is designed such that drivers are physically unable to exceed the speed limit. In locations where speeding is particularly common or concerning, with school zones being a prominent example, this would be especially beneficial.

11.2.2 Changing risk perceptions

These results (Section 9.2 and Section 10.2) have a number of implications for policies aimed at reducing speeding behaviour. It is evident that drivers that perceive higher risks of certain driving behaviours (speeding, changing lanes without checking, etc.) are associated with lower speeding scores. This suggests that changing drivers' perceptions of the risks associated with driving could encourage a reduction in speeding behaviour as has been observed in reducing drunk driving (Tay, 2002). Clearly this should be done with caution to avoid unintended effects such as making drivers believe they are not the intended target of the campaign (Lewis et al., 2007). More generally, it appears that existing strategies to reduce speeding behaviour have been less effective for drivers with lower perceptions of risk. As such, in addition to trying to change risk perceptions it would also be beneficial to devise behaviour change strategies that are targeted at these drivers in particular.

More effective targeting may be achieved by using drivers' personality characteristics. These results[154] (and those of other researchers, see Section 3.1.3) have found that more excitable personalities have higher rates of speeding whilst more altruistic

[154] See Section 9.5 and Section 10.5.

drivers have lower rates of speeding. Furthermore, drivers that are more aggressive or excitable and those with car-dependent personalities[155], exhibit lower magnitude changes in speeding behaviour than altruistic drivers. Clearly, personalities cannot be changed in the way that risk perceptions can. Nonetheless, these results suggest that behavioural change strategies should be targeted based on personality profiles as a supplement or instead of demographics with different strategies used for different personality profiles. Some researchers (for example, Tay et al., 2003) suggest that drivers with personality characteristics associated with more speeding could be managed using strategies designed to shift their risk perceptions. Others suggest that focusing campaigns on changing driver's attitudes towards speeding eventually leads to a change in behaviour but that there are substantial differences between different personality groups (De Pelsmacker and Janssens, 2007), which is consistent with the results presented in this thesis.

Importantly, given the focus on changing behaviour, personality characteristics were even stronger predictors of drivers changing their behaviour following the introduction of the study financial incentive and speeding awareness interventions. The implication of this is that drivers that are likely to make larger magnitude (voluntary) changes to their speeding behaviour are also more likely to be drivers that exhibit lower speeding risk scores to begin with. Those drivers that exhibit larger risk scores made smaller improvements and would appear to require different strategies or stronger measures such as licence demerit points and licence suspension. In effect, these strategies do little to improve the behaviour of the drivers we are most concerned about. This coincides with a growing trend, which replaces fear campaigns (as in Figure 11-3) with campaigns aimed to change attitudes towards speeding (and other forms of risky behaviour) similar to the one shown in Figure 11-4.

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[155] Drivers with car-dependent personalities emotionally identify with their cars. A more detailed discussion on this is available in Section 10.5.

Figure 11-3: Shock road safety poster (Environment Waikato, 2004)

Figure 11-4: Road safety billboard in South Australia (Motor Accident Commission, 2011)

11.2.3 Improve speeding awareness

The study for which the data used here was collected, incorporated an intervention designed to reduce VKT, night time driving and speeding. This was done, as discussed in Section 4.2.3, by providing a variable financial incentive at the time of the intervention, which was depleted for every kilometre driven with higher amounts for night time driving and speeding behaviour. Accessing the study website provided participants with the financial cost and the proportion of distance speeding for every trip.

From a policy perspective, there appears to be potential to improve driver behaviour through the implementation of in-vehicle and road-side systems for making drivers aware of their own behaviour. There are a number of methods for providing this information including dynamic speed display signs shown in Figure 11-5 (Gehlert et al., 2012; Roberts and Smaglik, 2012), passive in-vehicle Intelligent Speed Adaptation (ISA) devices fitted to vehicles, through smart-phone apps such as the one shown in Figure 11-6, using active ISA[156] that physically pushes back on the accelerator when the driver is speeding (Várhelyi et al., 2004), or post-travel through a web-based system similar to the one used in this study which could be provided in conjunction with insurance companies as part of pay-as-you-drive (PAYD) insurance plans. In most cases participation in these schemes would be voluntary but, potentially, legislation could be changed to require repeat speeding offenders to have an ISA device installed or to use a PAYD insurance plan as a condition for avoiding a licence suspension.

[156] Active ISA is also known as Active Accelerator Pedal (AAP)

Figure 11-5: **Speed display sign** (Road Kare International, 2013)

Figure 11-6: Speed alert live (Smart Car Technologies, 2013)

11.2.4 Introduce financial incentives

The largest reductions in speeding behaviour were observed when drivers were provided with a financial incentive to reduce their speeding behaviour. This indicates that financial incentives may be useful in reducing speeding behaviour. For policy makers this suggests that financial incentives could be devised to reduce speeding behaviour among a large proportion of drivers. This could be applied through insurance companies running in-vehicle monitoring devices as part of PAYD insurance plans. An additional option would be for governments to charge higher annual registration fees with either refunds or discounts off the annual renewal cost for drivers or vehicles that have not been recorded or caught speeding. This would need to be done in conjunction with enforcement and a greater number of speed cameras, including point-to-point speed cameras. In jurisdictions with high thresholds for speed fines – such as Norway where fines are not routinely issued for speeding by less than 6 km/h (Elvik, 2012a) – this may be a more politically palatable method than reducing tolerance of speeding to 0 km/h. A variation of this scheme is in place in New South Wales, Australia where a discount in provided on the driver licence renewal fee if there were no driving offences in the previous five years, however this only amounts to $83 every five years, which is arguably too infrequent.

It should, however, be kept in mind that (in general) prior to the intervention, study participants could already be divided into two groups, one of which exhibited lower speeding scores and was noticeably more engaged in the study. Policy makers would, therefore, be advised to keep in mind the characteristics of the drivers that are likely to be predisposed (to some extent) to change their behaviour following an intervention and should ensure that this is consistent with the intended target market for the intervention.

11.2.5 Targeting of hard and soft measures

The policy implications of these findings (Chapter 10) is that substantial shifts in drivers' speeding behaviour could be found by providing drivers with more frequent information about the frequency of their own speeding behaviour, as discussed in Section 11.2.3, combined with financial mechanisms (see Section 11.2.4). However, the societal benefits from this strategy would be derived largely from improvements in the behaviour of the majority of drivers who are not the worst offenders. In effect, drivers can be divided into two groups, those for which 'soft' measures would be beneficial and those drivers which require 'hard' measures as illustrated in Figure 11-7. These hard measures, such as licence suspension, may be more effective than fines or other monetary penalties as it appears that for these drivers a financial mechanism has a relatively minor effect on speeding behaviour. Soft measures have been shown in this thesis and by other researchers (for example, Jamson, 2006) to be of limited use for the worst drivers.

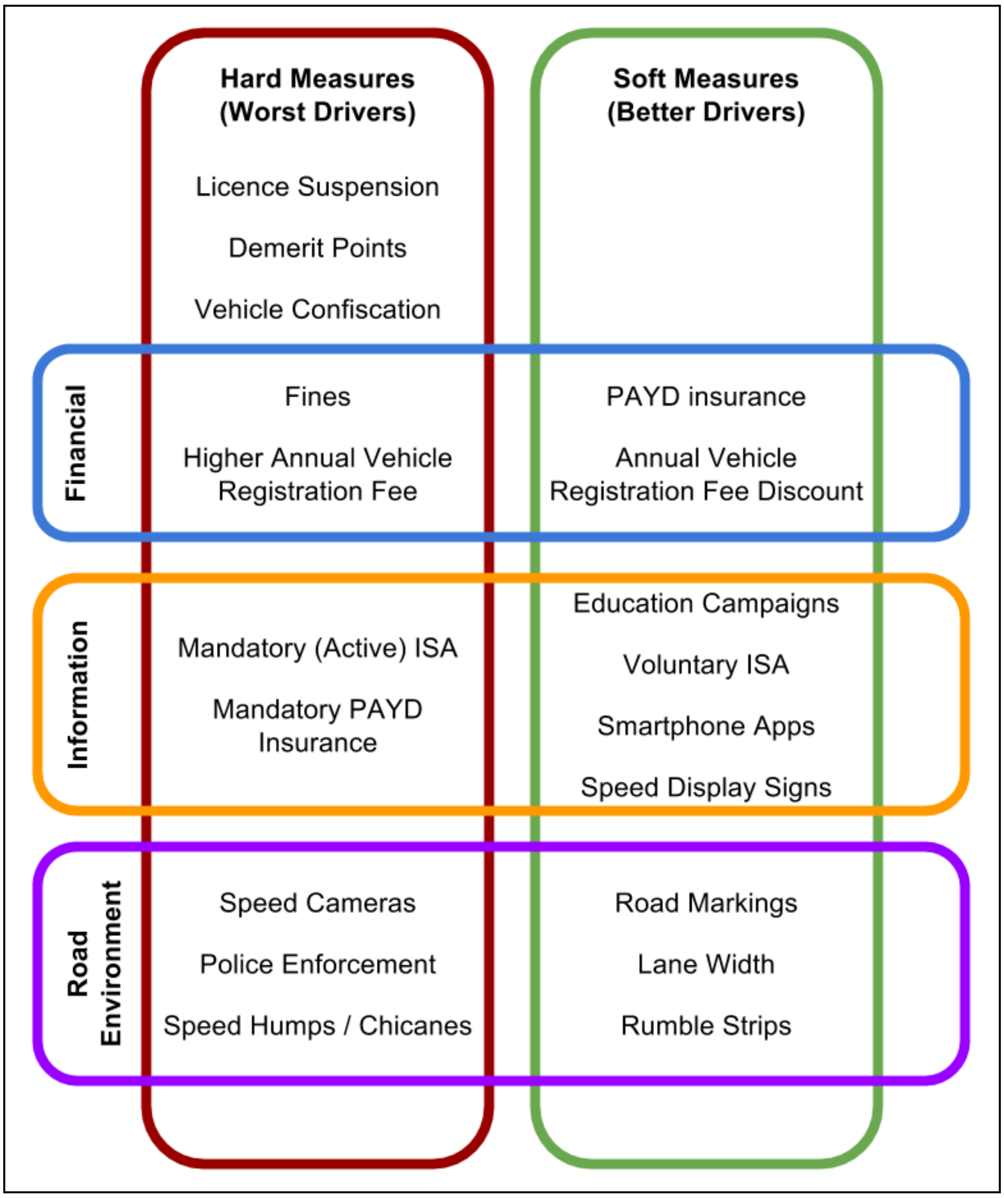

Figure 11-7: Policy measures for speeding behaviour change

The over-riding conclusion that can be drawn from these results is that, for the highest risk drivers, engineering and technology solutions are where the main efforts to reduce the incidence of speeding behaviour should be focused. In the longer term, this would suggest progressively taking control of the vehicles away from drivers towards (eventually) fully autonomous vehicles as technology improvements allow. Ultimately, voluntary changes in driver behaviour are useful strategies for the majority of drivers that are amenable to changing their behaviour, but will never – on their own – reduce road casualties to acceptable (i.e. zero) levels because even the safest drivers will occasionally engage in risky driving behaviour (albeit perhaps inadvertently). Although physically changing the road environment is likely to be the most expensive solution, technology can be used both to warn drivers about what they are doing, providing personalised information on their speeding behaviour through various mechanisms, and to limit the control drivers have over their vehicles. In addition to (likely) being cheaper than changing the entire road network, technological solutions also have the benefit of enabling more targeted interventions. These (technology) solutions could be mandated as part of the design rule standards that vehicles – by legislation – must meet. Once the vehicle fleet has been replaced the necessary technology would be in place in all vehicles reducing the need for retrofitting. In the shorter term, as part of the hard measures targeted at repeat offenders, it should be possible to require the retrofitting of technology – such as active ISA – as is done in some jurisdictions with alcohol-locks, which prevent a vehicle from starting until a breathalyser test is completed.

11.3 Research implications

In addition to the implications for policy makers, these results identify a number of issues of relevance to driver behaviour researchers. In particular, the potential for differences in the road environment to influence results, the need for measures of speeding that account for different magnitudes and issues in comparing behaviour before and after an intervention when collecting data outside a controlled laboratory environment.

11.3.1 Road environment

The literature includes a large body of research on the influence of the road environment on driver behaviour (see Section 3.1.1 for a summary). Despite this, most studies of speeding behaviour – including naturalistic driving studies – have failed to take this fully into account. The results presented in this thesis (see Section 11.1.1) demonstrate – at every stage of the analysis – the need to do so. From the most aggregate to the most disaggregate analysis, the spatiotemporal factors have consistently proven to be the strongest predictors of drivers' speeding behaviour. Given that this is the case, isolating the driver (human) factors requires controlling for the spatiotemporal variables in some way.

Overall, it is evident that spatiotemporal factors are intrinsically linked to drivers' speeding – as well as acceleration and braking – behaviour. In addition, neither speeding behaviour nor changes in speeding behaviour that occur as a result of an intervention are homogenous across all road environments meaning that when evaluating the effectiveness of behavioural change strategies it is necessary to account for spatiotemporal factors. It is likely that this extends to many other elements of the driving task.

The TSI methodology presented here (Chapter 7) is a flexible tool for incorporating the spatiotemporal factors inherent in driver behaviour into an analysis of driver behaviour. Although the relevant variables that comprise the TSI will differ from one study to another the methodology is transferrable. Naturalistic data which in many cases requires some form of aggregation to reduce the number of observations to a manageable level particularly benefits from this approach.

Combining the TSI methodology and a multilevel/hierarchical structure appears to be effective at controlling for these elements. The research implications of this are that interpreting research which assumes homogenous behaviour across different road environments should be done with caution. It would be advisable for researchers who intend to aggregate observations to ensure that there are at least some commonalities in the road environments from which the observations are made. At a minimum this should include the speed limit, school zone and if it is a weekday or weekend.

11.3.2 Driver behaviour profiles

In most studies of driver behaviour (see Chapter 2 and Chapter 3), a single measure is used for each of the behaviours being studied. This provides a simple and easy to interpret dependent variable on which to perform analyses. However, for speeding, acceleration and braking, which are the focus of this research, this does not account for the non-linear impact of different magnitudes. For example, the potential impacts on drivers, other road users and society as a whole of driving at 1 km/h above the posted speed limit is substantially different than a driver exceeding the speed limit by

10 km/h or 20 km/h.[157] To account for this it is necessary to create distinct models for different magnitudes (or categories of magnitudes), or alternatively, some type of composite measure is necessary. In this thesis, driver behaviour profiles (DBP) have been used to create measures of speeding, acceleration, braking and total behaviour which account for the increasing effect of higher magnitude speeding, acceleration and braking behaviour on fatal crash risk (see Chapter 8 for a more detailed discussion).

DBPs describe a driver's behaviour by computing risk scores for each behaviour and a composite score for all behaviours. Individual scores are computed for each driver and for each driver in each TSI. In this thesis the scores are used to compare drivers and compare the same driver in different study phases but there are a number of other potential applications for this approach.

Since the scores are derived from the risk of a fatal crash, and by extension the risk of less severe crashes, monetary (dollar) amounts can be tied to each score. Using the scoring mechanism as a framework, insurance companies could calculate an appropriate premium (or discount) on the basis of observed behaviour over a period of time. The ability to change driver behaviour (to lower risk behaviours) could be enhanced through this mechanism by providing drivers with their scores in addition to the financial advantage in a similar manner to that conducted in this study. Similar schemes have been trialled or launched by a number of insurance companies however since the method of computing the premiums is not publicly available it is not possible to compare those methods with the output of the algorithms applied for this research.

For government, the scores could be used as the basis for measuring a change in behaviour that occurs as a result of an education or enforcement campaign as well as legislative or infrastructure changes. This would (arguably) be a useful complement to the number of fatalities and serious injuries as it would not be as susceptible to very small sample sizes that are common in crash analyses. Furthermore, this could be done at any level of aggregation from a single location to a national level comparison. Once a sufficient quantity of driver scores have been collected from before-and-after

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[157] A full discussion on the varying effects of increasing magnitudes of speeding is included in Section 2.2.1.

studies of this nature, it would be possible to simulate the effect on risk and societal benefits of proposed infrastructure or policy changes at a micro or macro level. At the micro level consisting of a small number of locations this could be done by observing the behaviour of all vehicles in these locations and using optical character recognition (OCR) of licence plates to identify the same vehicle over a period of time. At a macro level this would require the instrumentation of (private) vehicles and could be expensive unless it is done in conjunction with other uses[158].

The DBP methodology – and accompanying algorithms – uses a modular structure and, as such, can be extended to incorporate any number of additional measures of behaviour as long as they can be reliably measured. This includes cornering, lateral acceleration, lane changing and following distance. Therefore, there is the potential to use this methodology for assessing a large number of potential behaviours in addition to those presented in this thesis. Although, the most detailed data requires naturalistic (or simulator) data which is highly disaggregate, it is also possible to use the framework using less detailed data albeit at the cost of not accounting for all behaviour.

11.3.3 Implications for before-and-after studies

Before-and-after studies are used to test the effectiveness of an intervention on driver behaviour. These interventions include education campaigns, changes in enforcement or legislation and the implementation of speed cameras, among others. One of the difficulties in examining changes in behaviour outside a controlled laboratory environment is isolating the effect of the intervention from other changes that may have occurred to the vehicle, driver, family or in broader society.

Using a simulator it is possible to control for many of the environmental factors that influence driver behaviour but this is not possible with naturalistic driving data. As such, comparing a measure such as the proportion of VKT driven above the speed limit in two different phases will provide a measure of the change in speeding behaviour as a result of the combined set of personal, environmental and policy changes that have

[158] For example, some vehicles come equipped with services similar to General Motors' On-Star which includes tracking capability using GPS.

occurred since the base line period. This may produce confounding or contradictory effects if the aggregate effect of all the non-intervention changes is substantial or exceeds the magnitude of the effect of the intervention. Typically, this is dealt with by employing a control sample that is not exposed to the intervention but this methodology assumes a certain level of homogeneity in the sample. By extension, given the strong influence of spatiotemporal characteristics (Section 11.3.1) on driver behaviour this also assumes that both individual drivers and the sample as a whole drive in the same places before and after the introduction of the intervention. This is clearly not the case as illustrated in Figure 11-8 which shows the number of driver-TSI combinations in each phase of the study and combined phases. Only 55 percent of driver-TSI combinations that were observed in the before period were also observed in the after one period. As a consequence of this, comparing driver behaviour in the before period to the after one period would explain differences in where and when participants drove rather than the difference in speeding behaviour itself. This is likely to be one of the reasons for the poor predictive performance of the driver-level models as these compare all included driving regardless of the TSI.

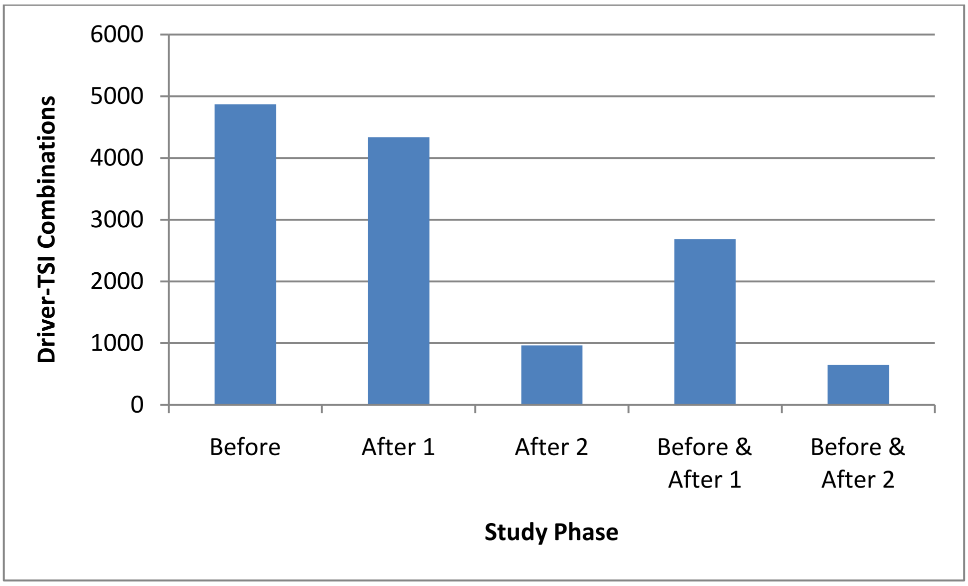

Figure 11-8: Unique driver-temporal and spatial identifier combinations in each study phase

The implication of this phenomenon on before-and-after studies is that comparisons between study phases must be framed within the same spatiotemporal environment to enable a like-for-like comparison. The TSI methodology ensures that before-and-after comparisons are made for the same driver, in the same spatiotemporal environment across any number of time periods. The same methodology could be applied on a week-to-week basis instead of (or in addition to) the phases used in this thesis. The DBP methodology extends this to allow for the same measure of behaviour to be used in each phase, accounting for different magnitudes and distances in each phase.

While isolating the effects of an intervention is (arguably) of most importance in studies using highly disaggregate naturalistic datasets, the same underlying principles apply to before-and-after studies with other types of datasets. The driver-level measures used in this study are an example of measures which describe the aggregate behaviour for a particular driver in a particular time period. Although the aggregation process is likely to mitigate the influence of driver variability on behaviour the relatively poorer performance of these models suggest that it does not do so in its entirety. Self-reported data or data collected at an aggregate level, such as odometer readings and crash data, is similarly affected. In essence, what is needed is to account for changes in exposure between the different phases of the study. For example, a study comparing the number of crashes before and after the launch of an enforcement or education campaign would need to compare the crashes in similar spatiotemporal environments as opposed to an aggregate measure across all spatiotemporal environments. Some studies have controlled for exposure by using fatality ratios which accounts for changes that occur across comparison groups (Fell et al., 2011) but this approach does not account for changes in individual exposure. Other studies have not controlled for individual differences but have controlled for spatiotemporal differences, albeit not in a before-and-after study (Christoforou et al., 2011). Consistent with the results of this research, the authors found that spatiotemporal characteristics had a considerable impact on results compared to a univariate analysis. Their approach could be extended for use in a before-and-after study of crashes in a similar manner to the TSI and risk profiling approach used here.

In summary, this thesis has introduced two complementary methods – TSIs and Driver Behaviour Profiles – that together can be used to more effectively isolate the variables of interest (driver characteristics in this case) in a before-and-after study. This is done by accounting for the differences attributable to spatiotemporal characteristics and exogenous factors that are captured by the driver and TSI levels of the multilevel structure, effectively isolating the relationship between driver characteristics (which are kept unchanged) and the dependent variable.

11.4 Limitations

There were a number of specific limitations of this study, which are discussed in this section. Generally, as the funding and resources available to carry out the data collection were limited this imposed a number of restrictions on the design of the study. Although the speeding behaviour of the participants was largely consistent with those of other studies (such as Dingus et al., 2006; NSW Centre for Road Safety, 2010) it is not possible to confirm the extent to which the driver characteristics (risk perceptions and personality) were consistent with other studies and the driving population as a whole. As a consequence, the generalisability of these results requires further investigation. Nonetheless, the results identified some interesting and important relationships between driver behaviour and risk perceptions, concern of injury and personality. These proved to be robust within the sample and in the different phases of the study. This strongly points to the need for more research to confirm the findings with a larger sample. This is discussed further in Section 11.5.

11.4.1 Driver characteristics and driver behaviour

A limitation with driver characteristics was that although drivers' speeding behaviour was observed empirically, the measures of risk perception, driving confidence, risk of a crash and personality were all self-reported by the participant in a self-administered online questionnaire. The characteristics of self-reported data, discussed in Section 2.4.1, also apply here and can affect the results in two ways. First, each participant could have interpreted the scale differently meaning that two participants who state that a particular behaviour is 'very dangerous' may not consider it to be equally dangerous and, therefore, although the two participants provide the same answer they should be treated as different answers. A possible solution to this is using an anchor or vignette technique (Soest et al., 2011) to put all responses on the same objective scale but this needs to be incorporated into the design of the questionnaire and was not done in this case. However, given that the trends are highly significant for the entire scale, while this likely has an effect on the parameter estimates the significance and the direction of significance are unlikely to be affected. Second, since the response is self-reported it may not always be an accurate reflection of reality. This is particularly true for the driving confidence and personality measures. The personality measures used for the analyses conducted here are averages of the same driver's response to several questions and this will mitigate some of the bias that may exist in participants' response to these questions and since the results are consistent between both sets of hypotheses, the results appear robust. In addition, the before-and-after analysis uses the responses from the same questionnaire for the before and after observations, which ensures that if there are any issues with participants responses to the questions they are kept unchanged for the duration of the study.

Driver behaviour was measured empirically using GPS devices for the duration of the study. While the GPS device was installed in participants' vehicles there was a short delay of up to several minutes while the first position was found every time the vehicle was started.[159] This resulted in not recording the first part of some trips and missing some shorter trips in their entirety. The GPS signal in dense urban areas with tall buildings, typically the city centre, was sometimes unreliable. These were mostly removed through smoothing (see Section 5.3.3) but some instances may remain. Similarly, the GPS devices were powered using the car's cigarette lighter and occasionally would be unplugged inadvertently or to plug in another device. VKT, for calculating the incentive, could be inferred (Greaves et al., 2010) but data on driver behaviour was lost. Since the devices were installed in each vehicle, it was also not known if drivers used another vehicle during the study period. Lastly, GPS does not provide any data on acceleration and braking behaviour. Average acceleration and braking behaviour could be calculated for one-second averages but this is not as accurate as using an accelerometer.

The large number of models tested and presented in Chapter 6, Chapter 9 and Chapter 10 could be affected by mass significance whereby an insignificant variable is incorrectly deemed to be significant (i.e. a type I error). This issue could be addressed using Bonferroni corrections. However, in these analyses, a hypothesis is only accepted if the overwhelming majority of models indicate the same result thereby mitigating the likelihood of a type I error.

[159] This is known as a "cold start" problem.

11.4.2 Interventions

There are a number of important considerations that need to be considered when interpreting the results of this research and comparing the results of this study with other research including pay-as-you-drive (PAYD) and Intelligent Speed Adaptation (ISA) studies. Firstly, the financial component explicitly included speeding as well as VKT and night-time VKT but participants were only shown the total cost per trip and the remaining incentive.[160] The individual elements of the financial component were not broken down for participants. Instead the proportion of VKT driven above the posted speed limit was provided as a distinct piece of information for each trip. Secondly, drivers' GPS data was processed and uploaded to the study website on a nightly basis. For participants to be exposed to the financial and speeding awareness information they had to login to the study website at which point they were able to see their trips, incentive and speeding behaviour for previous days. This is in contrast to ISA studies where drivers are made aware of their speeding behaviour in real-time using audible or visual alerts (see Section 2.4.3). To account for this, the numbers of website logins during each study phase were used as a proxy for exposure to the intervention information. As the study required participants to access the website to provide supplementary information (purpose, driver, number of passengers) and confirm each trip, most participants regularly accessed the website (Greaves and Ellison, 2013). However, it is not possible to determine to what extent participants paid attention to the incentive and speeding information. The number of logins therefore also functions as a proxy, albeit an imperfect proxy, for how conscientious participants were in their participation in the study. Thirdly, some researchers (for example Ettema et al., 2010) suggest that behavioural responses to incentives, such as the one used in this study, may be different than if drivers need to pay a charge through their own earned income. In an academic study such as this one it is not possible to charge participants for their driving but it is acknowledged that this is a potential issue. Lastly, unlike other studies of speeding, the intervention in this case included both a financial incentive and an awareness component. This made it

[160] When the financial component was introduced participants were made aware of the rates for each kilometre, night-time kilometre and speeding kilometre but the per-trip totals and the remaining incentive counters were not broken down for participants.

necessary to devise a method for separating out these two effects. This was done by creating two distinct after periods, the first of which included both components and the latter comprising only speeding awareness information as the financial incentive had been depleted. One consequence of this is that the two after periods differed in length for each driver. This was controlled for in the analysis by using TSIs and DBPs. However, the drivers that finished the study with more than 5 percent of their incentive remaining did not have an after two (after incentive) period and those drivers that did, the observations only reflect short-term change. A distinct 'after incentive' phase for all drivers would have been a more reliable indicator of these longer term trends.

11.4.3 Road environment

Although several data sources were used to incorporate characteristics of the road environment in this research, there are a number of important road environment characteristics that could not be identified due to a lack of data. Of most importance were the lack of access to data on traffic volumes, congestion and traffic light timings. This meant that observations made in close proximity to intersections had to be excluded from the analysis and proxies were needed to account for congestions which was not ideal. Other road environment variables that have been shown in the literature (see Section 3.1.1) such as lane width and the presence of road markings could also not be accounted for due to a lack of data.

Although methodologies were developed to control for the road environment, a limitation of using the TSI and risk profiling methodologies in a before-and-after study is that it requires the same TSI to be observed for a minimum distance and number of observations in at least two phases of the study in order to be included in the analysis. As a consequence of this, analyses which examine the change in behaviour can only consider a subset of observations. In the case of this study, only 55 percent of TSIs and 74 percent of the VKT in the before period as well as 62 percent of TSIs and 80 percent of the VKT in the after one period are able to be included in these analyses. This does not impact analyses that look at absolute numbers, such as the analysis presented in Section 10.1, as the multilevel structure allows for each observation to be treated distinctly while maintaining the interdependence of an observation with those of the same driver and/or TSI. The disadvantage of that approach is that it cannot identify a change in (for example) speeding behaviour in a particular spatiotemporal variable (such as a school zone) across time periods since these changes are instead captured by the phase variable.

11.4.4 Sample

This research was conducted using an extensive amount of data collected from participants over a ten week period. However, due to a number of factors (see Greaves and Fifer, 2011) of the original (already small) sample of 148 only 106 drivers completed all the driving and prompted-recall components of the study. Of these, 14 drivers provided incomplete personality surveys and, therefore, were not included in the analyses which required these data. The small sample size was a function of the funding available for the purchase of GPS devices that needed to be installed in each vehicle and the resources available to manage the data collection process. As a consequence of this and other recruitment problems, young drivers in particular were under-represented in the sample. The lack of a usable control group inhibited comparison between an intervention and non-intervention group although this was partly mitigated by comparing the behaviour of each driver in the after period to their own behaviour during the before period. In addition, it needs to be noted that the participants were recruited from an online panel[161] and voluntarily agreed to participate. It is likely that the worst drivers would not voluntarily agree to participate suggesting that the sample are likely to be (relatively) more legally-compliant drivers than the driving population. Despite these issues, the results proved to be robust across a range of different subsets, analyses and analytical techniques. It is also of note that the distribution of speeding behaviour between drivers was not only consistent across speed zones and time periods but was also largely consistent with a large ISA trial conducted in the study area (NSW Centre for Road Safety, 2010).

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[161] An online panel is a list of individuals that have registered to be invited to complete (unspecified) surveys.

11.5 Future research

The results of this research raise a number of possibilities for future research. As mentioned in the discussion of limitations (Section 11.4), there is some question as to the generalisability of the results and, therefore, a priority would be to re-run the procedures and analyses used in this thesis on another dataset to confirm these results. This could be done by administering the psychological survey to participants of one of the ongoing naturalistic driving studies (for example, Regan et al., 2012). The data processing, TSI and DBP methodologies could be applied to the GPS data with only minor changes to the processing tools.

It was not possible, in this study, to identify the long term effects of the intervention once drivers were no longer actively engaged in the study. Clearly, what happens to driver behaviour over the long term is of interest to identify if these interventions need to be used (essentially) for ever or if they can be applied at intervals. Additionally, the use of a distinct phase in which only information was provided would aid in distinguishing between the effects of money and information. Evidence from eco-driving programmes suggests that recurring training is necessary to maintain the improvements in behaviour (Beusen et al., 2009). A follow up study with the same drivers perhaps a year or so after the completion of the study would be ideal for this but would likely require a larger initial sample. Alternatively, the data could be collected by an insurance company as part of a PAYD insurance scheme. This would permit a longer term monitoring period (perhaps over several years) and would have the additional advantage that participants would pay a higher premium if they drove worse than in the baseline period.

Of the driver characteristics, personality was the strongest predictor of speeding behaviour. This suggests that further research on personality would be beneficial in shaping road safety strategies. In particular, a broader set of personality traits other than the four (aggression, altruism, excitement and car-dependence) applied here should be investigated for association with driver behaviour. Only a subset of the questions in the existing psychological survey has been used and they should be investigated as a first step in identifying other personality traits meriting further research. A number of improvements could also be made to the existing questionnaire. Specifically, the questions would benefit from some contextual aspects relating to the road environment since drivers clearly behave differently in different situations. The survey could also be improved by incorporating an anchoring technique for the scale questions to reduce differences in how drivers interpret the questions.

The technology components of the study worked effectively. Nonetheless, the use of distance sensors to identify congestion would be beneficial in the absence of this information from other sources. Similarly, an accelerometer would provide more detailed information on acceleration (and braking) and side to side movements which could be used to study more driving behaviours particularly in conjunction with interventions that are focused on these behaviours as opposed to on speeding behaviour. These sensors could also be used to measure the reaction times of drivers and – by extension – their driving skills thereby providing another measure of risk since drivers with faster reaction times are more likely to successfully avoid crashes (Anstey et al., 2005).

At a broader level, researchers (such as Wundersitz and Hutchinson, 2012) have identified the difficulties in determining the impact of campaigns and interventions on driver behaviour. The DBP approach could be applied to investigate the effect of many types of interventions on driving behaviour. For example, given the increasing contribution of distracted driving to road crashes it would be intriguing to apply the methodologies developed for this thesis in that context. A number of studies have collected video footage of the driver in conjunction with accelerometer and GPS data (Dingus et al., 2006), which would provide the necessary disaggregate data for creating a distraction risk score for individual drivers and specific distractions. This could also be used to identify the road environments with the highest frequencies of in-vehicle and environmental distractions.

Lastly, this study used speeding, acceleration and braking behaviour to calculate risk scores representing the risk of a driver being involved in a fatal crash. Since (fortunately) none of the drivers were involved in a crash, of any severity, during the study it was not possible to determine if drivers with involvement in crashes (of various severities) have higher risk scores than other drivers. Research performed in conjunction with insurance companies could be used to match scores with claims history.

11.6 Concluding remarks

This thesis applied several unique datasets and a number of new methodologies to investigate two broad themes in the road safety literature. These relate to the frequency and magnitude of risky driving behaviour within day-to-day driving, outside of a controlled laboratory environment, and its association with drivers' risk perceptions, concerns of injury, confidence in their driving skills and personalities. The second theme relates to how the extent of risky driving behaviour can be reduced by making drivers both aware of what they are doing and providing a financial incentive to change behaviour. In the process of investigating these issues, this thesis makes a number of contributions to research and practice which can be applied to evaluate changes in driver behaviour for road safety outcomes.

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13 APPENDIX A: HYPOTHESES ACCEPTANCE SUMMARY

This appendix contains both sets of hypotheses broken down into its constituent parts and a summary of if it was possible to accept the hypothesis. Cross-references are provided to the detailed results within the body of this thesis.

13.1 Extent of risky driving behaviour

This first set of hypotheses determines and tests the frequency and magnitude of risky driving behaviour within a driver's normal driving routine and then identifies the psychological, attitudinal and risk perception factors that are associated with risky driving behaviour. Further background can be found in Section 4.1.1 and detailed results and discussion can be found in Chapter 9.

H 1. The frequency and magnitude of risky driving behaviour is influenced by a driver's attitudes, beliefs and experience.

Speeding:

H1.1 Drivers with lower perceptions of the danger of risky behaviour engage in speeding behaviour more frequently as measured by objective data.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 9.2.1.

H1.2 Drivers with more concern about passenger safety engage in speeding behaviour less frequently as measured by objective data than drivers with similar concerns for themselves and other drivers.

The null hypothesis cannot be rejected. The opposite effect was found. Analysis can be found in Section 9.3.1.

H1.3 Drivers with more confidence in their own driving abilities engage in speeding behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.4.1.

H1.4a Drivers with more aggressive personalities engage in speeding behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4b Drivers with more excitable personalities engage in speeding behaviour more frequently as measured by objective data.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 9.5.1.

H1.4c Drivers with more car-dependent personalities engage in speeding behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4d Drivers with more altruistic personalities engage in speeding behaviour less frequently as measured by objective data.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 9.5.1.

Acceleration:

H1.1 Drivers with lower perceptions of the danger of risky behaviour engage in acceleration behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.2.1.

H1.2 Drivers with more concern about passenger safety engage in acceleration behaviour less frequently as measured by objective data than drivers with similar concerns for themselves and other drivers.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.3.1.

H1.3 Drivers with more confidence in their own driving abilities engage in acceleration behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.4.1.

H1.4a Drivers with more aggressive personalities engage in acceleration behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4b Drivers with more excitable personalities engage in acceleration behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4c Drivers with more car-dependent personalities engage in acceleration behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4d Drivers with more altruistic personalities engage in acceleration behaviour less frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

Braking:

H1.1 Drivers with lower perceptions of the danger of risky behaviour engage in braking behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.2.1.

H1.2 Drivers with more concern about passenger safety engage in braking behaviour less frequently as measured by objective data than drivers with similar concerns for themselves and other drivers.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.3.1.

H1.3 Drivers with more confidence in their own driving abilities engage in braking behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.4.1.

H1.4a Drivers with more aggressive personalities engage in braking behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4b Drivers with more excitable personalities engage in braking behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4c Drivers with more car-dependent personalities engage in braking behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4d Drivers with more altruistic personalities engage in braking behaviour less frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

Composite/total behaviour:

H1.1 Drivers with lower perceptions of the danger of risky behaviour engage in risky driving behaviour more frequently as measured by objective data.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 9.2.1.

H1.2 Drivers with more concern about passenger safety engage in risky driving behaviour less frequently as measured by objective data than drivers with similar concerns for themselves and other drivers.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.3.1.

H1.3 Drivers with more confidence in their own driving abilities engage in risky driving behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.4.1.

H1.4a Drivers with more aggressive personalities engage in risky driving behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4b Drivers with more excitable personalities engage in risky driving behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4c Drivers with more car-dependent personalities engage in risky driving behaviour more frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

H1.4d Drivers with more altruistic personalities engage in risky driving behaviour less frequently as measured by objective data.

The null hypothesis cannot be rejected. Analysis can be found in Section 9.5.1.

13.2 Relationship between awareness and risky driving behaviour

The second set of hypotheses attempts to determine if making drivers aware of how they drive results in less risky driving and, if so, how the magnitude of the change is influenced by drivers' perception of the risks driving. Further background can be found in Section 4.1.2 and detailed results and discussion can be found in Chapter 10.

H 2. Drivers engage in risky driving behaviour less frequently once they are made aware of their actual speeding behaviour and provided with a financial incentive; however the magnitude of the change varies depending on the individual driver's attitudes, beliefs and experience.

Speeding:

H2.1 Drivers with lower perceptions of the danger of risky behaviour have a lower magnitude change in speeding behaviour than drivers with higher perceptions of danger (whether accurate or not) once they are made aware of their speeding behaviour.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 10.2.1.

H2.2 Drivers with more concern about passenger safety have a higher magnitude change in speeding behaviour than drivers with less concern once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.3.1.

H2.3 Drivers with more confidence in their own driving abilities exhibit a lower magnitude change in speeding behaviour compared to drivers with less confidence in their own driving abilities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.4.1.

H2.4a Drivers with more aggressive personalities have a lower magnitude change in speeding behaviour compared to drivers with less aggressive personalities once they are made aware of their speeding behaviour.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 10.5.1.

H2.4b Drivers with more excitable personalities have a lower magnitude change in speeding behaviour compared to drivers with less excitable personalities once they are made aware of their speeding behaviour.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 10.5.1.

H2.4c Drivers with more car-dependent personalities have a lower magnitude change in speeding behaviour compared to drivers with less car-dependent personalities once they are made aware of their speeding behaviour.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 10.5.1.

H2.4d Drivers with more altruistic personalities have a higher magnitude change in speeding behaviour compared to drivers with less altruistic personalities once they are made aware of their speeding behaviour.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 10.5.1.

Acceleration:

H2.1 Drivers with lower perceptions of the danger of risky behaviour have a lower magnitude change in acceleration behaviour than drivers with higher perceptions of danger (whether accurate or not) once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.2.1.

H2.2 Drivers with more concern about passenger safety have a higher magnitude change in acceleration behaviour than drivers with less concern once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.3.1.

H2.3 Drivers with more confidence in their own driving abilities exhibit a lower magnitude change in acceleration behaviour compared to drivers with less confidence in their own driving abilities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.4.1.

H2.4a Drivers with more aggressive personalities have a lower magnitude change in acceleration behaviour compared to drivers with less aggressive personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4b Drivers with more excitable personalities have a lower magnitude change in acceleration behaviour compared to drivers with less excitable personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4c Drivers with more car-dependent personalities have a lower magnitude change in acceleration behaviour compared to drivers with less car-dependent personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4d Drivers with more altruistic personalities have a higher magnitude change in acceleration behaviour compared to drivers with less altruistic personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

Braking:

H2.1 Drivers with lower perceptions of the danger of risky behaviour have a lower magnitude change in braking behaviour than drivers with higher perceptions of danger (whether accurate or not) once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.2.1.

H2.2 Drivers with more concern about passenger safety have a higher magnitude change in braking behaviour than drivers with less concern once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.3.1.

H2.3 Drivers with more confidence in their own driving abilities exhibit a lower magnitude change in braking behaviour compared to drivers with less confidence in their own driving abilities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.4.1.

H2.4a Drivers with more aggressive personalities have a lower magnitude change in braking behaviour compared to drivers with less aggressive personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4b Drivers with more excitable personalities have a lower magnitude change in braking behaviour compared to drivers with less excitable personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4c Drivers with more car-dependent personalities have a lower magnitude change in braking behaviour compared to drivers with less car-dependent personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4d Drivers with more altruistic personalities have a higher magnitude change in braking behaviour compared to drivers with less altruistic personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

Composite/total behaviour:

H2.1 Drivers with lower perceptions of the danger of risky behaviour have a lower magnitude change in risky driving behaviour than drivers with higher perceptions of danger (whether accurate or not) once they are made aware of their speeding behaviour.

This hypothesis can be accepted (null hypothesis rejected). Analysis can be found in Section 10.2.1.

H2.2 Drivers with more concern about passenger safety have a higher magnitude change in risky driving behaviour than drivers with less concern once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. The opposite effect was found. Analysis can be found in Section 10.3.1.

H2.3 Drivers with more confidence in their own driving abilities exhibit a lower magnitude change in risky driving behaviour compared to drivers with less confidence in their own driving abilities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.4.1.

H2.4a Drivers with more aggressive personalities have a lower magnitude change in risky driving behaviour compared to drivers with less aggressive personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4b Drivers with more excitable personalities have a lower magnitude change in risky driving behaviour compared to drivers with less excitable personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4c Drivers with more car-dependent personalities have a lower magnitude change in risky driving behaviour compared to drivers with less car-dependent personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

H2.4d Drivers with more altruistic personalities have a higher magnitude change in risky driving behaviour compared to drivers with less altruistic personalities once they are made aware of their speeding behaviour.

The null hypothesis cannot be rejected. Analysis can be found in Section 10.5.1.

14 APPENDIX B: MODELS USING ALTERNATIVE SPECIFICATIONS

A number of models were run which proved to be of no statistical value. This appendix summarises the results of some of these models.

14.1 Binary logistic regression models of extreme speeding scores

Binary logistic multilevel models were also run to identify the statistically significant predictors of the scores at the extreme ends of the speeding scale (zero and 100) relative to observations with speeding scores from 1 to 99. This was done because the risk scores were constrained between zero and 100 and this caused a large number of observations to exhibit these scores distorting the distributions. Based on the results of the multilevel models described in Chapter 9, two multilevel models were tested. The first sets the driver as the first level and the second sets TSI as the first level. With the exception of the binary composition of the dependent variable, the specifications of the models were otherwise identical to those of the earlier models. Due to the poor performance of the cross-effects multilevel model and the single level model in earlier tests, this process was not repeated for the binary models. The model quality indicators for the four models are shown in Table 14-1.

Table 14-1: Measures of model quality for speeding binary multilevel models[162]

	Zero (0) vs. 1 to 99 (1)		1 to 99 (0) vs. 100 (1)	
	Driver (level one)	TSI (level one)	Driver (level one)	TSI (level one)
AIC	2115	1406	795	798
BIC	2305	1596	1008	1011
Log Likelihood	-1027	-671.8	-362.5	-363.8

Of the two models containing zero scores, the model with TSI as level one was of higher quality but exhibited no statistically significant variables. The model with the driver as level one resulted in a number of statistically significant variables which were consistent with the results of the 1 to 99 model. Specifically, the presence of rain (p = .000), a manual transmission (p = .034), higher perceived danger of turning right across a busy road (p = .038), higher perceived danger of speeding by 10 km/h (p =

[162] These values should not be compared to the AIC, BIC and Log Likelihood values in Table 14-2 because observations with a speeding score of zero were excluded from those models and the type of model was different (Poisson regression).

.009) were associated with an increased probability of a score of zero. In contrast, but consistent with the previous models, weekend driving (p = .009) was significantly associated with a lower probability of a score of zero, or, conversely, a higher probability of a score above zero.

Neither of the two models containing 100 scores resulted in statistically significant variables. This suggests that there do not appear to be statistically significant differences between the independent variables for observations with scores of 1 to 99 and scores of 100. However, this may be a reflection on the heterogeneity in scores of 100 created as a result of the scale normalisation process (see Section 8.4). It was also speculated that this was the result of the comparison category comprising scores from 1 to 99 and therefore alternative models were attempted where the comparison category was 50 to 99 and 75 to 99. The small sample size prevented the use of a two-level model in these cases. Instead cross-effects multilevel models were applied. Of these, the 75 to 99 model also failed to exhibit any statistically significant variables and the 50 to 99 model had four[163] statistically significant variables – with parameter estimate signs consistent with the other multilevel models – but with the exception of the school zone and weekend variables the standard errors were relatively large. As a consequence, all the remaining models presented in this section are limited to observations with scores from 1 to 99.

14.2 Hypothesis 1.1 models

In addition to the multilevel models presented in Section 9.2.2, an additional three model specifications were attempted. These consist of a single level model, a multilevel model with the driver as level one and a cross-effects multilevel model. These are shown in the following sections for speeding, acceleration, braking and total risk scores.

14.2.1 Speeding behaviour

Of the four models of speeding behaviour (single level model, cross-effects multilevel model, TSI as level one and the driver as the level one) for speeding scores from one to

[163] The four statistically significant variables were school zone, time of day (night), weekend and the perceived danger of mobile telephone use.

99 (inclusive), the multilevel model with the driver as level one was the best model as judged by the AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion) and log likelihood values[164]. The multilevel model with the TSI as level one produced similar values but the other two models performed notably worse. As such, further discussion is limited to the first two models. Unlike the models from the aggregate analyses (Section 6.2 and Section 6.3), the standard errors for the parameter estimates were small and largely reasonable for the statistically significant variables.

Table 14-2: Measures of model quality for speeding behaviour multilevel models

	Driver (level one)	TSI (level one)	Cross-effects	Single level
AIC	8867	9152	15191	34610
BIC	9053	9338	15395	N/A
Log Likelihood	-4403	-4545	-7562	N/A

Overall, the models of speeding behaviour show that most of the TSI-level variables are statistically significant predictors of speeding behaviour in the expected direction. In contrast only a small number of the driver-level variables are statistically significant predictors of speeding behaviour. The parameter estimates (shown in Table 14-3) show that drivers exhibit lower speeding scores in school zones, when it is raining, with an increasing number of passengers, when driving a car with a manual transmission relative to a car with an automatic transmission, when driving on weekdays relative to weekends, when driving in the afternoon and, in general, when driving on roads with higher speed limits.

In the model where the TSI is the highest level in the model, the higher a driver's perceived danger associated with speeding and changing lanes without checking, the lower speeding score they exhibited. The other variables describing perceptions of risk were not significant in any model. The interaction term between gender and age was also significant in this model with older drivers (of both genders) being related to lower speeding scores.

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[164] Multilevel and non-linear models do not have an equivalent to the R^2 value observed in linear models. The AIC, BIC and Log Likelihood values are used to compare models from the same dataset. For AIC and BIC a lower value is better. For log likelihood a value closer to zero is better.

Table 14-3: Parameter estimates of multilevel models of speeding behaviour[165]

	Driver (level one)			TSI (level one)		
	B	Std. Error	Sig.	B	Std. Error	Sig.
Intercept	**4.535**	**0.180**	**0.000**	**4.382**	**0.089**	**0.000**
Speed limit (50)	**-0.296**	**0.053**	**0.000**	**-0.227**	**0.057**	**0.000**
Speed Limit (60)	**-0.518**	**0.053**	**0.000**	**-0.429**	**0.057**	**0.000**
Speed Limit (70)	**-0.636**	**0.054**	**0.000**	**-0.519**	**0.058**	**0.000**
Speed Limit (80)	**-0.619**	**0.056**	**0.000**	**-0.489**	**0.060**	**0.000**
Speed Limit (90)	**-0.751**	**0.059**	**0.000**	**-0.594**	**0.063**	**0.000**
Speed Limit (100)	**-0.652**	**0.066**	**0.000**	**-0.459**	**0.070**	**0.000**
Speed Limit (110)	**-0.818**	**0.075**	**0.000**	**-0.628**	**0.079**	**0.000**
School Zone	**-0.360**	**0.072**	**0.000**	**-0.287**	**0.077**	**0.000**
Rain	**-0.173**	**0.043**	**0.000**	**-0.145**	**0.045**	**0.001**
Time (Day)	0.012	0.024	0.615	-0.014	0.025	0.584
Time (Afternoon)	*-0.049*	*0.023*	*0.033*	**-0.068**	**0.025**	**0.006**
Time (Night)	-0.041	0.028	0.134	-0.044	0.029	0.128
Weekend	**0.069**	**0.016**	**0.000**	**0.076**	**0.017**	**0.000**
Num. Passengers	**-0.026**	**0.009**	**0.004**	**-0.022**	**0.008**	**0.009**
Type (Hatchback)	0.015	0.056	0.794	0.000	0.021	0.993
Type (Other)	0.006	0.057	0.922	0.006	0.022	0.770
Model Year	0.024	0.031	0.449	0.015	0.012	0.196
Transmission (Manual)	**-0.169**	**0.055**	**0.002**	**-0.112**	**0.022**	**0.000**
Red Light	-0.048	0.050	0.333	-0.021	0.018	0.240
Fatigue	0.035	0.050	0.491	0.032	0.019	0.095
Illegal U-Turn	-0.031	0.025	0.209	-0.015	0.009	0.093
Turning Right	-0.026	0.023	0.268	-0.015	0.009	0.096
Change Lanes	-0.074	0.050	0.136	**-0.082**	**0.019**	**0.000**
Speeding	-0.041	0.032	0.202	**-0.047**	**0.012**	**0.000**
Mobile Usage	0.016	0.031	0.614	0.016	0.012	0.171
Talking to Pass.	0.018	0.035	0.603	0.009	0.013	0.482
Male : Age	-0.060	0.031	0.053	**-0.055**	**0.012**	**0.000**
Female : Age	-0.054	0.037	0.145	**-0.048**	**0.014**	**0.001**

Note (1): Cells in bold are significant at the $p = .01$ level
Note (2): Cells in italics are significant at the $p = .05$ level

In terms of the models' predictions, the predicted values follow a similar distribution to the observed values as shown in Figure 14-1. In addition, the first quartile, third quartile, median and mean values are within a range of ± 1 between the two models and the predicted values. Lastly, the differences between the predicted scores from the driver as level one model and the observed values are in a range from -10.26 to +7.52 with an average difference of 0.009 and a median of 0.263. The differences between the predicted and observed scores from the model with TSI as level one range

[165] The B values need to be interpreted on the basis of the transformed values.

from -8.28 to +7.02 with an average difference of 0.064 and a median of 0.340. The distribution of the differences can be seen in Figure 14-2.

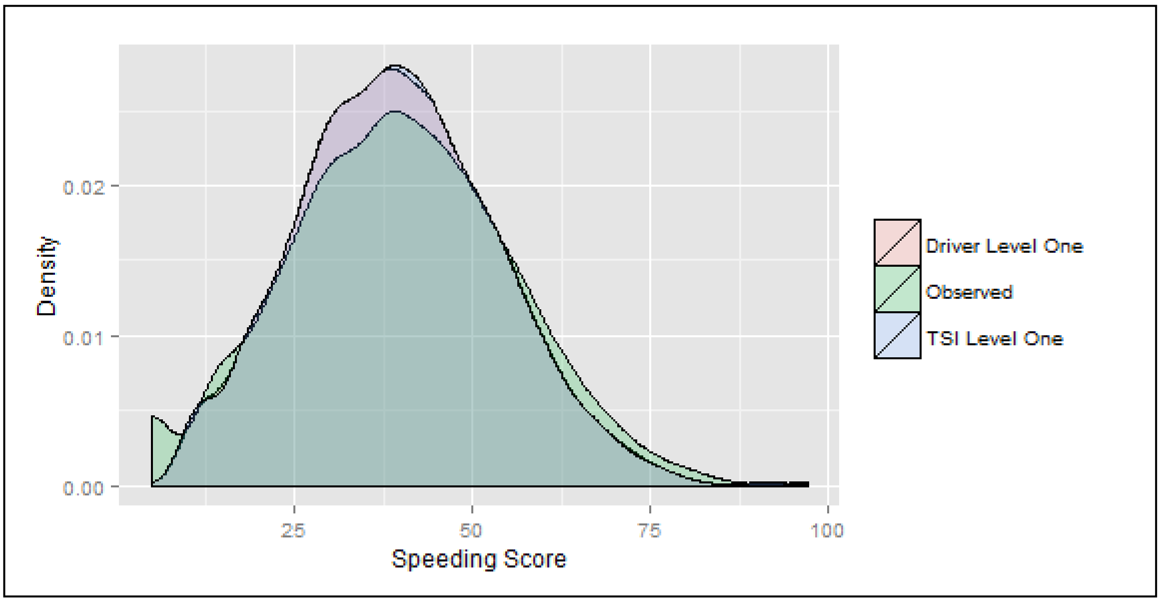

Figure 14-1: Density plot of observed and fitted speeding scores

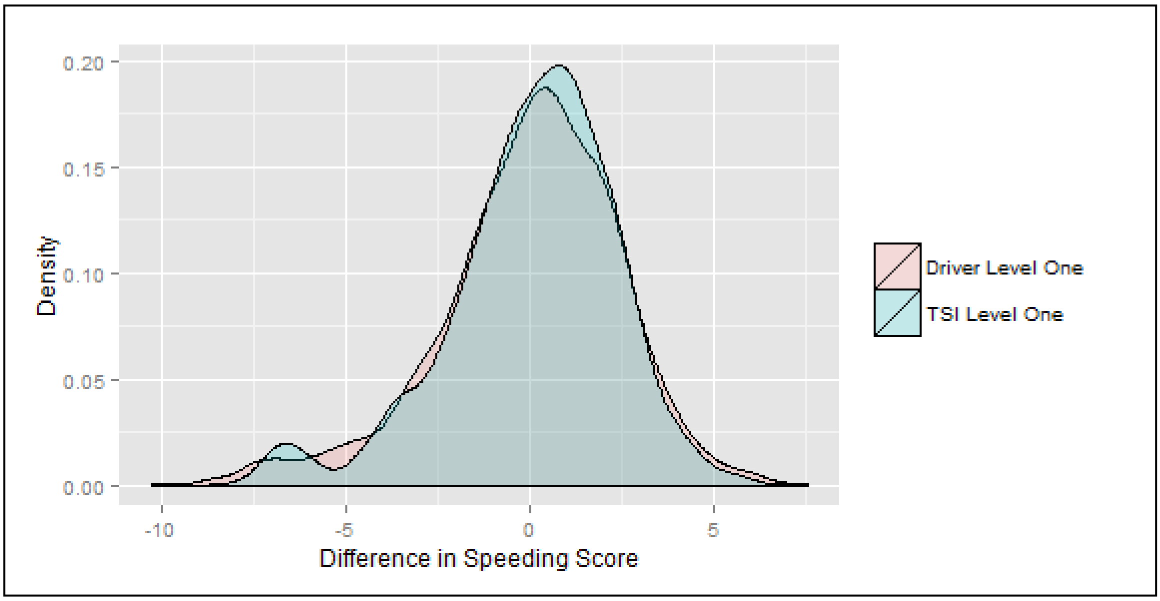

Figure 14-2: Density plot of difference between observed and predicted values

Taken together, the two-level multilevel models appear to have good model fit, good predictive power and the results are in line with the published literature. This is in marked contrast to the single-level aggregate models that are presented in Section 6.2 and Section 6.3.

In addition, a number of individual models were run for the most frequent TSIs. Since these models only contain one observation per driver and the TSI is the same for all observations these models do not retain an explicit multilevel structure. The parameter estimates for these models are shown in Table 14-4.

Overall, more variables are statistically significant in the TSI which (arguably) provides less congested conditions – ST{60,TD-W-D-P0} – which is consistent with the results of the ANOVA analyses (see Table 9-1). Interestingly higher perceived danger of speeding by 10 km/h is a statistically significant determinant of less frequent speeding in the 60 km/h morning period but not the other TSIs. For most of the statistically significant risk perception variables, higher perceived risk was associated with lower speeding scores. The exceptions to this were speaking to passengers and using a mobile telephone. The former may be an anomaly as the most frequent TSIs did not have any passengers and therefore how dangerous (or not) these drivers perceived speaking to a passenger would have been irrelevant for these particular situations. The latter case may be similar as the data does not indicate if or when a driver was using a mobile telephone. It is likely that the perceived danger of using a mobile while driving would have a stronger relationship with the frequency of mobile use than speeding behaviour. In terms of driver demographics and vehicle characteristics, these results were largely consistent with the multilevel models. The interaction between age and gender were statistically significant but caution is urged in interpretation due to the relatively small sample sizes involved. Manual vehicle transmission is statistically significant negative effect on speeding scores observed except in the TSI representing the morning period on a 60 km/h road. It is unknown why this was the case although the standard error is relatively larger in that model than for the same variable in the other TSI models.

Table 14-4: Parameter estimates for individual temporal and spatial identifier speeding models

	ST{60,TE-D-P0}			ST{60,TD-W-D-P0}			ST{60,TM-D-P0}			ST{50,TE-D-P0}		
	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.
Intercept	**4.544**	**0.188**	**0.000**	**5.584**	**0.187**	**0.000**	**3.124**	**0.216**	**0.000**	**4.081**	**0.146**	**0.000**
Type (Hatchback)	0.052	0.058	0.364	0.076	0.059	0.199	**0.266**	**0.083**	**0.001**	0.057	0.050	0.250
Type (Other)	0.091	0.066	0.169	**0.243**	**0.072**	**0.001**	*0.172*	*0.084*	*0.042*	*0.130*	*0.053*	*0.014*
Model Year	0.039	0.036	0.272	*-0.095*	*0.037*	*0.010*	**0.135**	**0.047**	**0.004**	*0.062*	*0.030*	*0.037*
Transmission (Manual)	**-0.305**	**0.062**	**0.000**	**-0.272**	**0.057**	**0.000**	0.187	0.100	0.062	*-0.129*	*0.050*	*0.010*
Red Light	-0.081	0.052	0.118	**-0.272**	**0.052**	**0.000**	-0.118	0.074	0.113	-0.030	0.044	0.496
Fatigue	-0.001	0.052	0.992	**-0.196**	**0.054**	**0.000**	**0.215**	**0.071**	**0.002**	0.020	0.043	0.647
Illegal U-Turn	-0.047	0.025	0.061	**-0.132**	**0.025**	**0.000**	0.025	0.032	0.436	-0.017	0.023	0.464
Turning Right	**-0.071**	**0.025**	**0.005**	**-0.192**	**0.028**	**0.000**	0.013	0.034	0.700	-0.027	0.021	0.209
Change Lanes	-0.016	0.053	0.762	0.022	0.057	0.695	0.003	0.073	0.971	0.007	0.043	0.872
Speeding	-0.062	0.037	0.096	-0.058	0.038	0.126	**-0.134**	**0.051**	**0.008**	-0.054	0.030	0.072
Mobile Usage	-0.060	0.033	0.069	**0.100**	**0.036**	**0.005**	-0.037	0.046	0.427	0.023	0.027	0.401
Talking to Pass.	-0.047	0.038	0.219	**-0.111**	**0.039**	**0.005**	**0.207**	**0.052**	**0.000**	0.035	0.033	0.278
Male : Age	**-0.110**	**0.033**	**0.001**	**0.109**	**0.039**	**0.005**	**-0.113**	**0.039**	**0.004**	**-0.118**	**0.028**	**0.000**
Female : Age	-0.041	0.039	0.290	**0.196**	**0.043**	**0.000**	**-0.236**	**0.044**	**0.000**	**-0.136**	**0.033**	**0.000**

Note (1): Cells in bold are significant at the $p = .01$ level
Note (2): Cells in italics are significant at the $p = .05$ level

Taking all the results together suggests that – in general – higher perceptions of risk are related to less frequent and lower magnitude speeding behaviour which allows the hypothesis to be accepted. What is less clear is to what extent risk perceptions of individual behaviours are related to low frequencies and magnitudes of speeding behaviour. Taking the spatiotemporal environment into account as the primary unit of analysis – either as the first level in a multilevel model or using separate models for each TSI – results in different risk perception variables emerging as statistically significant. This suggests that drivers' risk perceptions are more nuanced and situation-specific than has been elicited in the survey used in this research. As such, although it is not possible to accept the hypothesis for all variables with this data it is possible to do so in particular situations. Clearly, this aspect would benefit from a more detailed survey of drivers' risk perceptions which incorporates spatiotemporal environments.

14.2.2 Acceleration behaviour

The same process that was applied for analysing speeding behaviour was used to develop multilevel models where acceleration is the dependent variable. Otherwise, the model specifications and the variable compositions are the same.

The two multilevel acceleration models proved to have virtually identical model fit (Figure 14-3) and were broadly similar to the observed values. In terms of statistical significance, the speed limit was significant for both models but only the model with TSI as level one exhibited any additional significant variables. Of these, higher perceptions of the risk of an illegal u-turn[166] (p = .016) and higher perceptions of the risk of turning right across a busy road were associated with lower acceleration scores (p = .042). No other variables were statistically significant to the p = .05 level.

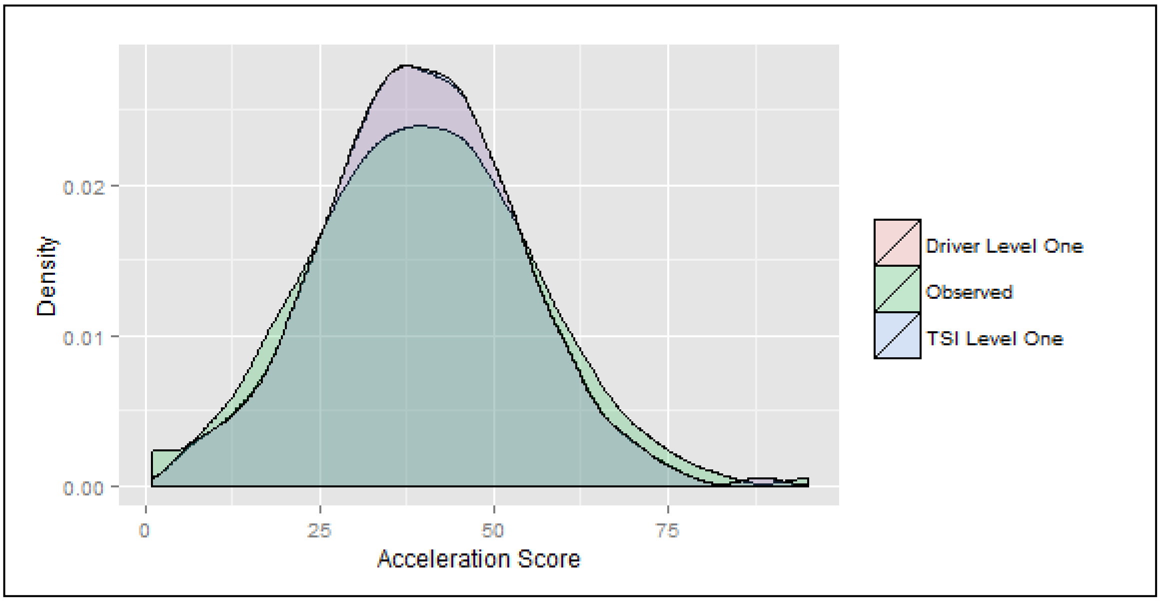

Figure 14-3: Density plot of observed and fitted acceleration scores

To determine if stronger effects are observable in individual TSIs, the procedure for speeding was repeated for acceleration. These results exhibited a greater number of statistically significant variables, albeit fewer than the equivalent speeding models. The parameter estimates for these models are shown in Table 14-5. No variables were statistically significant for all four TSIs. Of the variables that were significant, the

[166] In the study area, u-turns are illegal at signalised intersections unless otherwise sign posted, at non-signalised intersections when there is a 'no u-turn' sign and across single and double continuous lines.

risk perception variables (with the exception of changing lanes) were related to lower acceleration scores as the perceived risk increased. It is interesting to note that in the TSI representing weekend conditions, a higher perception of the risk of speeding is associated with lower acceleration scores whilst the same variable is not significant in the equivalent speeding model. The statistically significant driver and vehicle characteristics tended to be associated with higher acceleration scores. Given that these scores are calculated from driving behaviour away from intersections, and therefore should exclude most acceleration related to intersections, it is likely that the acceleration scores are largely reflective of overtaking manoeuvres.

Table 14-5: Parameter estimates for individual temporal and spatial identifier acceleration models

	ST{60,TE-D-P0}			ST{60,TD-W-D-P0}			ST{60,TM-D-P0}			ST{50,TE-D-P0}		
	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.
Intercept	**4.160**	**0.160**	**0.000**	**4.063**	**0.195**	**0.000**	**3.767**	**0.219**	**0.000**	**4.375**	**0.197**	**0.000**
Type (Hatchback)	-0.006	0.052	0.910	-0.011	0.060	0.852	0.082	0.074	0.271	*-0.113*	*0.057*	*0.047*
Type (Other)	*0.129*	*0.062*	*0.037*	-0.038	0.081	0.641	0.022	0.083	0.796	**0.155**	**0.060**	**0.010**
Model Year	*-0.062*	*0.031*	*0.048*	0.041	0.036	0.248	-0.073	0.044	0.098	-0.043	0.040	0.283
Transmission (Manual)	-0.067	0.064	0.293	0.011	0.064	0.860	-0.134	0.106	0.206	*-0.140*	*0.058*	*0.016*
Red Light	0.017	0.048	0.725	*-0.146*	*0.060*	*0.015*	-0.076	0.070	0.280	*0.106*	*0.051*	*0.038*
Fatigue	0.049	0.048	0.313	0.059	0.058	0.309	0.010	0.070	0.885	-0.014	0.050	0.775
Illegal U-Turn	*-0.053*	*0.025*	*0.034*	-0.053	0.027	0.051	-0.002	0.034	0.943	**-0.074**	**0.027**	**0.007**
Turning Right	-0.019	0.024	0.414	0.035	0.030	0.239	0.045	0.035	0.197	**-0.076**	**0.023**	**0.001**
Change Lanes	-0.092	0.048	0.054	-0.017	0.058	0.764	**0.259**	**0.068**	**0.000**	0.032	0.050	0.524
Speeding	-0.062	0.034	0.065	**-0.110**	**0.039**	**0.005**	*-0.106*	*0.047*	*0.023*	-0.012	0.035	0.739
Mobile Usage	-0.007	0.031	0.810	0.017	0.040	0.681	-0.071	0.043	0.096	0.057	0.031	0.063
Talking to Pass.	0.009	0.038	0.816	-0.069	0.044	0.120	0.034	0.048	0.476	**-0.150**	**0.038**	**0.000**
Male : Age	**0.090**	**0.028**	**0.001**	0.024	0.036	0.492	0.012	0.038	0.742	0.042	0.033	0.196
Female : Age	0.062	0.033	0.063	**0.155**	**0.040**	**0.000**	0.005	0.039	0.906	*0.085*	*0.035*	*0.016*

Note (1): Cells in bold are significant at the p = .01 level
Note (2): Cells in italics are significant at the p = .05 level

The multilevel models exhibit two statistically significant risk perception variables. The parameter estimates are in the expected, negative, direction and the individual TSI models also exhibit statistically significant negative estimates. The remaining risk perception variables are not statistically significant in the multilevel models and in the individual TSI models the parameter estimates, where they are statistically significant, have different signs for different TSIs. As a result, it is not possible to accept the hypothesis that higher perceptions of risk are related to less risky acceleration behaviour.

14.2.3 Braking behaviour

Repeating the same procedure using the braking score as the dependent variable, the multilevel model exhibited good model fit as shown in Figure 14-4. In terms of statistically significant variables, driving in speed zones of 100 (p = .030) and 110 km/h (p = .033), rain (p = .002), night (p = .000), weekend (p = .000), older male drivers (p = .009) and older female drivers (p = .030), were negatively related to braking scores. These results are consistent with *a priori* expectations in that they relate to situations in which drivers would either be more careful (as in rain) and in which there would be less variation in speed (as in high speed roads). Higher perceptions of the risk of using a mobile telephone while driving were positively related to braking scores (p = .005). No other risk perception variables were statistically significant to the p = .05 level suggesting that drivers' braking behaviour is predominantly influenced by factors external to the driver.

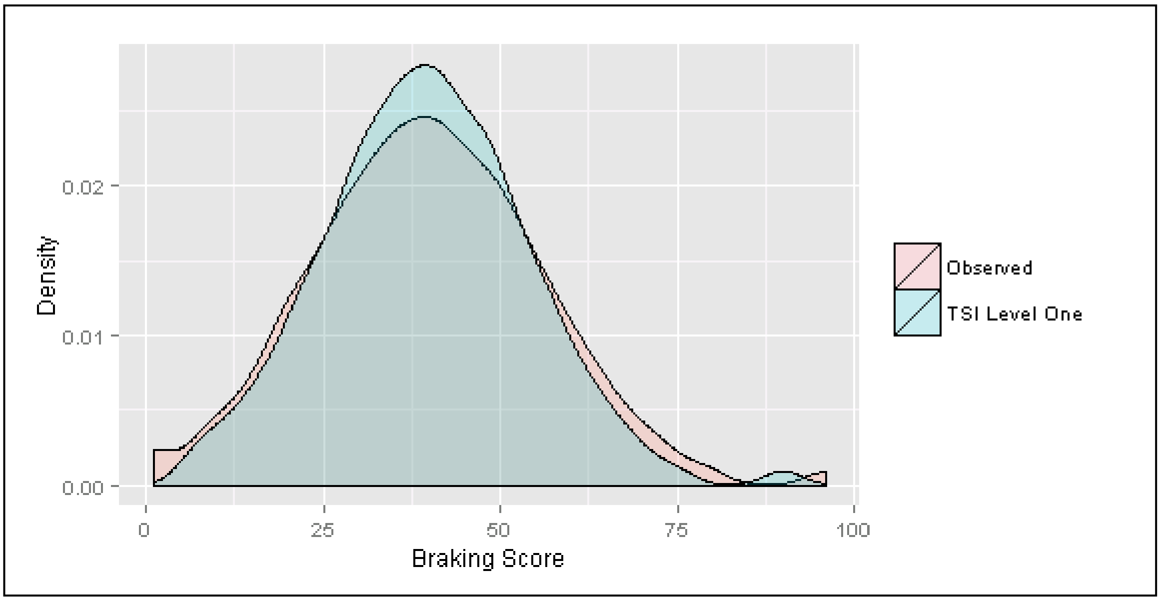

Figure 14-4: Density plot of observed and fitted braking scores

Further exploring these factors, individual models were run for some of the most frequent TSIs. In contrast to the multilevel models, the perceived danger of using a mobile telephone was only statistically significant for the 60 km/h evening TSI. A number of other risk perception variables were statistically significant for one to three TSIs (see Table 14-6) but with no consistent pattern.

Table 14-6: Parameter estimates for individual temporal and spatial identifier braking models

	ST{60,TE-D-P0}			ST{60,TD-W-D-P0}			ST{60,TM-D-P0}			ST{50,TE-D-P0}		
	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.	B	Std. Err.	Sig.
Intercept	**3.937**	**0.143**	**0.000**	**3.620**	**0.208**	**0.000**	**2.953**	**0.278**	**0.000**	**4.716**	**0.244**	**0.000**
Type (Hatchback)	-0.023	0.055	0.674	*0.175*	*0.089*	*0.049*	**-0.284**	**0.080**	**0.000**	**0.167**	**0.063**	**0.008**
Type (Other)	*-0.124*	*0.060*	*0.038*	0.052	0.080	0.521	**-0.265**	**0.095**	**0.005**	-0.078	0.078	0.315
Model Year	-0.059	0.033	0.071	-0.075	0.040	0.063	-0.012	0.065	0.859	**-0.129**	**0.045**	**0.004**
Transmission (Manual)	0.010	0.058	0.858	*0.174*	*0.082*	*0.034*	**0.516**	**0.128**	**0.000**	-0.118	0.072	0.103
Red Light	*0.127*	*0.054*	*0.018*	0.101	0.069	0.147	0.134	0.088	0.127	0.008	0.061	0.891
Fatigue	-0.077	0.056	0.168	0.054	0.079	0.491	0.023	0.074	0.750	-0.027	0.064	0.675
Illegal U-Turn	0.003	0.024	0.911	*-0.083*	*0.038*	*0.028*	**0.139**	**0.041**	**0.001**	*-0.072*	*0.030*	*0.019*
Turning Right	0.003	0.024	0.892	0.008	0.039	0.832	-0.023	0.035	0.507	*-0.062*	*0.030*	*0.039*
Change Lanes	*-0.117*	*0.050*	*0.020*	0.115	0.075	0.125	-0.120	0.071	0.090	*-0.156*	*0.061*	*0.011*
Speeding	0.017	0.035	0.624	0.007	0.044	0.867	-0.055	0.047	0.249	0.010	0.037	0.776
Mobile Usage	*-0.072*	*0.032*	*0.023*	0.080	0.051	0.118	-0.118	0.066	0.072	0.010	0.044	0.817
Talking to Pass.	**0.116**	**0.038**	**0.002**	0.093	0.066	0.157	**0.291**	**0.061**	**0.000**	-0.050	0.043	0.252
Male : Age	*0.061*	*0.028*	*0.030*	-0.080	0.042	0.055	**0.158**	**0.046**	**0.001**	*0.101*	*0.040*	*0.011*
Female : Age	0.002	0.033	0.945	*-0.112*	*0.053*	*0.034*	0.087	0.055	0.113	**0.121**	**0.046**	**0.008**

Note (1): Cells in bold are significant at the $p = .01$ level
Note (2): Cells in italics are significant at the $p = .05$ level

As with the acceleration scores, braking scores are predominantly influenced by the spatiotemporal environment. Perceptions of danger do not appear to be related to braking scores in any discernable way. As such, the hypothesis that higher perceptions of risk relate to lower braking scores cannot be accepted.

14.2.4 Total behaviour

In addition to the individual speeding, acceleration and braking behaviours, a composite measure of driver behaviour as described in Section 8.1 was also computed. This was used as the dependent variable following the same procedure used for the speeding, acceleration and braking models. Of all the models, the composite score exhibited the highest number of statistically significant variables and the lowest standard errors. The model's predictive ability – illustrated in Figure 14-5 – was in line with the other models and with the observed values.

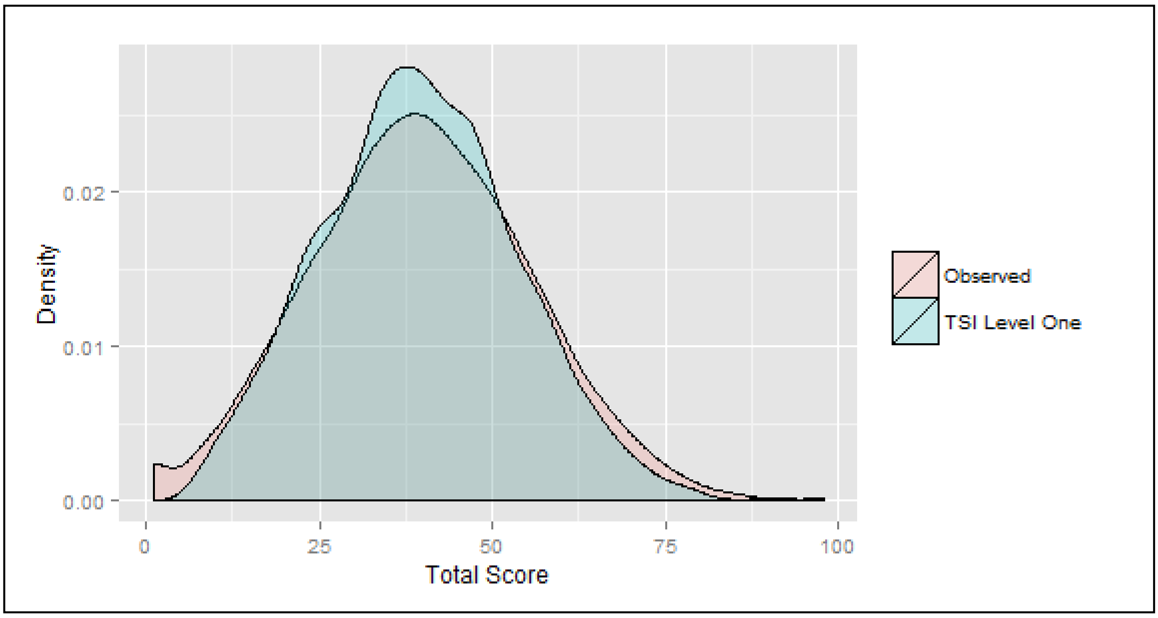

Figure 14-5: Density plot of observed and fitted total scores

The parameter estimates (shown in Table 14-7) show that the higher speed zones are significantly related to lower total scores which is consistent with speeding. The same is true of school zones, the presence of rain, night and the number of passengers. All of this is consistent with *a priori* expectations and the results of the speeding, acceleration and braking models. In terms of driver and vehicle characteristics, a manual transmission is significantly related to lower total scores as is the interaction between gender and age. Of the risk perception variables, higher perceived danger of an illegal u-turn, changing lanes without checking and speeding by 10 km/h or more are significantly related to lower total scores. Using a mobile telephone has the opposite effect possibly for the same reasons as the individual TSI speeding models (Table 14-4).

Table 14-7: Parameter estimates of multilevel model of total behaviour

	TSI (level one)		
	B	Std. Error	Sig.
Intercept	**4.124**	**0.351**	**0.000**
Speed limit (50)	0.012	0.345	0.972
Speed Limit (60)	-0.099	0.345	0.774
Speed Limit (70)	-0.323	0.345	0.349
Speed Limit (80)	-0.449	0.345	0.193
Speed Limit (90)	*-0.850*	*0.346*	*0.014*
Speed Limit (100)	**-0.912**	**0.347**	**0.008**
Speed Limit (110)	**-1.045**	**0.348**	**0.003**
School Zone	**-0.166**	**0.050**	**0.001**

	TSI (level one)		
	B	Std. Error	Sig.
Rain	**-0.222**	**0.033**	**0.000**
Time (Day)	0.023	0.019	0.229
Time (Afternoon)	-0.018	0.019	0.350
Time (Night)	**-0.142**	**0.022**	**0.000**
Weekend	-0.007	0.013	0.600
Num. Passengers	**-0.020**	**0.006**	**0.002**
Type (Hatchback)	-0.028	0.016	0.076
Type (Other)	-0.027	0.016	0.096
Model Year	-0.008	0.009	0.382
Transmission (Manual)	**-0.064**	**0.016**	**0.000**
Red Light	0.003	0.014	0.837
Fatigue	0.012	0.014	0.382
Illegal U-Turn	*-0.014*	*0.007*	*0.049*
Turning Right	-0.011	0.007	0.080
Change Lanes	**-0.044**	**0.014**	**0.002**
Speeding	**-0.032**	**0.009**	**0.000**
Mobile Usage	**0.040**	**0.009**	**0.000**
Talking to Pass.	0.015	0.010	0.132
Male : Age	**-0.056**	**0.009**	**0.000**
Female : Age	**-0.057**	**0.011**	**0.000**

The same risk perception variables are statistically significant for many of the individual TSI models and, where this is the case, the effects are the same. Speaking to passengers is statistically significant for three of the TSI models, 60 km/h evening with no passengers (p = .019), 60 km/h day weekend (p = .049) and 50 km/h evening with no passengers (p = .048), with opposite signs. This is likely to be an anomaly as neither of these TSIs includes passengers.

It appears from these results that whilst general risk perception measures such as those used in this study are predictors of speeding, acceleration and braking behaviour in particular spatiotemporal environments, they are better predictors of the total score that comprises the combination of these three behaviours. Based on this, **the hypothesis that drivers with lower perceptions of risk engage in risky driving behaviour more frequently, and at higher magnitudes, than drivers with lower perceptions of risk can be accepted.**

15 APPENDIX C: REDUCED MODELS

The models presented in Chapter 9 and Chapter 10 are the full models include both significant and insignificant variables. It is acknowledged that this sometimes results in biased parameter estimates such that it may (incorrectly) exclude significant variables. This appendix contains reduced models for Hypothesis 1.1 and Hypothesis 2.1. These are equivalent to those presented in the aforementioned chapters with the exception that insignificant variables have been excluded in a step-wise manner. For details and discussion on each of the models, refer to the cross-referenced section in Chapter 9 or Chapter 10.

The reduced models for the other hypotheses are also similar to their respective full models but are not included here. The reduced models for Hypothesis 1.1 and Hypothesis 2.1 are provided as examples.

15.1 Hypothesis 1.1 reduced speeding models

Table 15-1 displays the parameter estimates for reduced speeding models for Hypothesis 1.1, at the TSI and driver levels. These models are the result of excluding insignificant variables from the full model (see Table 9-5 and Table 9-6) in a step-wise procedure. For a full discussion of this hypotheses and results refer to Section 9.2. The significant variables in these reduced models are the same as in the full model but have been included here for completeness.

In Table 15-1, cells with diagonal lines drawn across are not significant or not applicable. The driver-level model does not include spatiotemporal variables.

Table 15-1: Parameter estimates of reduced H1.1 speeding models

	TSI-level			Driver-level		
	B	Std. Error	Sig.	B	Std. Error	Sig.
Intercept	4.381	0.071	0.000	4.295	0.102	0.000
Speed limit (50)	-0.231	0.057	0.000			
Speed Limit (60)	-0.432	0.057	0.000			
Speed Limit (70)	-0.521	0.058	0.000			
Speed Limit (80)	-0.494	0.060	0.000			
Speed Limit (90)	-0.600	0.063	0.000			
Speed Limit (100)	-0.468	0.070	0.000			
Speed Limit (110)	-0.636	0.079	0.000			
School Zone	-0.286	0.077	0.000			
Rain	-0.142	0.045	0.002			
Time (Day)	-0.011	0.025	0.656			
Time (Afternoon)	-0.066	0.025	0.007			
Time (Night)	-0.045	0.029	0.121			
Weekend	0.075	0.017	0.000			
Num. Passengers	-0.023	0.008	0.004			
Transmission (Manual)	-0.104	0.019	0.000	-0.320	0.041	0.000
Red Light				-0.093	0.037	0.011
Fatigue				0.105	0.038	0.005
Turning Right				-0.062	0.018	0.000
Change Lanes	-0.093	0.017	0.000			
Speeding	-0.046	0.011	0.000	-0.060	0.024	0.013
Male : Age	-0.051	0.011	0.000	-0.067	0.022	0.002
Female : Age	-0.042	0.013	0.001	-0.104	0.025	0.000

15.2 Hypothesis 2.1 reduced speeding models

Table 15-2 displays the parameter estimates for reduced speeding models for Hypothesis 2.1, at the TSI and driver levels. These models are the result of excluding insignificant variables from the full model (see Table 10-2) in a step-wise procedure. For a full discussion of this hypotheses and results refer to Section 10.2. The significant variables in these reduced models are the same as in the full model but have been included here for completeness.

Table 15-2: Parameter estimates of reduced H2.1 speeding models

	TSI-level			Driver-level		
	B	Std. Error	Sig.	B	Std. Error	Sig.
Intercept	4.949	0.405	0.000	3.454	0.293	0.000
Speed limit (50)	-0.244	0.245	0.320			
Speed Limit (60)	-0.509	0.245	0.038			
Speed Limit (70)	-1.001	0.256	0.000			
Speed Limit (80)	-1.339	0.270	0.000			
Speed Limit (90)	-2.179	0.299	0.000			
Speed Limit (100)	-1.953	0.356	0.000			
Speed Limit (110)	-1.774	0.468	0.000			
Time (Day)	0.055	0.139	0.692			
Time (Afternoon)	0.290	0.137	0.034			
Time (Night)	-0.363	0.169	0.032			
Transmission (Manual)	-0.620	0.102	0.000			
Starting Incentive	-0.295	0.112	0.008			
Phase	-0.627	0.105	0.000	0.115	0.027	0.000
Red Light	0.009	0.002	0.000			
Turning Right	0.138	0.009	0.000	0.195	0.076	0.010
Change Lanes	0.282	0.089	0.001			
Speeding	-0.076	0.046	0.095			
Mobile Usage	0.345	0.044	0.000			
Talking to Pass.	-0.318	0.087	0.000			
Male : Age	-0.188	0.060	0.002			
Female : Age	-0.245	0.054	0.000			
Made money (no): Logins	-0.217	0.066	0.001	-0.011	0.010	0.260
Made money (yes): Logins	-0.120	0.059	0.041	-0.026	0.009	0.005