Prevalence and Self-regulation of Drivers' Secondary Task Engagement: An Investigation of Behaviour at Intersections Based on Naturalistic Driving Data

by

Rashed Abdulrahman Yusuf Abdulrahim Ismaeel

Submitted in accordance with the requirements for the degree of
Doctor of Philosophy

The University of Leeds

Institute for Transport Studies

April 2021

The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

Acknowledgments

This thesis would not have been accomplished without the support of many people. I would like to express my deepest appreciation to my supervisors, Professor Oliver Carsten and Professor Samantha Jamson, for their guidance, reassurance and continuous encouragement throughout my years of study. This gratitude extends to my former supervisor, Dr. Daryl Hibberd, for his motivation and insightful vision. I would also like to dedicate my thesis to the memory of my former supervisor, Dr. Frank Lai, who supported me at the beginning of my PhD journey. Special thanks go as well to all the members of the Human Factors and Safety Group at the Institute for Transport Studies whom I have had the pleasure to work with.

In addition, I wish to acknowledge colleagues who contributed to this research. I am much grateful to Ahmed Abdulbaki for his help with the data annotation required in the reliability testing and Zhizhou Su for assisting me with MATLAB script formulation. Tremendous thanks likewise to the UDRIVE project team for granting me access to the UDRIVE dataset and for their efforts in collecting and storing the data.

To the completion of this research, the generous financial support from my sponsor, the University of Bahrain (Kingdom of Bahrain), in the last four years was instrumental. A very special gratitude goes to my wife, Noora, for her love, for her patience and for being a steadfast champion along this journey. Finally, I cannot thank my father, mother, sister and all my family members and friends enough for their support throughout my PhD years. They were indispensable to my achievements during my post-graduate journey.

Abstract

Using data from the large-scale European Naturalistic Driving project (UDRIVE), this thesis explored the prevalence of engagement in secondary tasks whilst driving through intersections and investigated whether drivers self-regulate such behaviour in response to variations in roadway and environmental conditions. The thesis also examined the possible influence of secondary task engagement on turn signal usage at intersections. To these ends, 1630 intersection cases were randomly sampled from the UDRIVE dataset for coding and in-depth analysis. In-vehicle video recordings and recordings of external scenes in the selected sample were coded for precisely defined categories of secondary tasks and related contextual variables.

The findings indicated that nearly one-quarter of the total driving time at intersections was spent on secondary activities and that such engagement decreased with increasing age. The drivers were less likely to occupy themselves with secondary tasks as they passed through an intersection itself, as opposed to the approach (upstream) and exit (downstream) phases. The drivers also tended to perform secondary tasks less frequently when their vehicles were moving than whilst they were stationary, when they did not have priority to pass through intersections compared with when they had priority and in bad weather conditions than in fine weather situations. Lastly, the drivers showed less inclination to use turn signals when they were engaged in secondary tasks than when they were driving under normal baseline conditions. In conclusion, the drivers appeared to self-regulate secondary task engagement according to road and driving situations, specifically when the primary task of driving becomes progressively challenging. This self-regulation behaviour was particularly strong for more complex and, therefore, more demanding secondary activities. The outcomes provide initial evidence that can serve as reference in targeting countermeasures and policies related to safe driving and managing distractions.

List of Publications

The following publications and conference presentations have been prepared as a result of this PhD work:

Journal Articles

Ismaeel, R., Hibberd, D., Carsten, O. and Jamson, S. 2020. Do drivers self-regulate their engagement in secondary tasks at intersections? An examination based on naturalistic driving data. Accident Analysis & Prevention. 137, 105464.

Conference Papers and Presentations

Ismaeel, R., Hibberd, D. and Carsten, O. 2018. Prevalence and self-regulation of drivers' secondary task engagement at intersections: An evaluation using naturalistic driving data. In: Proceedings of the Sixth International Conference on Driver Distraction and Inattention (DDI), 15-17 October 2018, Gothenburg, Sweden: MEETX AB, pp.48-57.

Ismaeel, R., Carsten, O., Jamson, S. and Hibberd, D. 2022. Do drivers self-regulate their mobile phone use? Findings from naturalistic driving data. The Seventh International Conference on Traffic and Transport Psychology (ICTTP), 23-25 August 2022, Gothenburg, Sweden (Abstract accepted).

Reports

Ismaeel, R., Carsten, O. and Hibberd, D. 2020. Spotlight on mobile phone use at intersections. In: A naturalistic study of mobile phone distraction during driving: An analysis of the UDRIVE project database (Final report). Leeds: Institute of Transport Studies, University of Leeds.

Table of Contents

Acknowledgments iii

Abstract iv

List of Publications v

Table of Contents vi

List of Tables xiii

List of Figures xvi

Abbreviations xviii

Chapter One: Introduction 1

1.1 Rationale and research problem 1

1.2 Thesis outline 5

Chapter Two: Background on the Distracted Driving Problem 8

2.1 Statement of the problem 8

2.1.1 Road safety challenge 8

2.1.2 The distracted driving problem 9

2.1.3 Why does distraction occur? 10

2.1.4 Upward trend 11

2.2 Defining driver distraction 11

2.2.1 What are the activities critical for safe driving? 15

2.2.2 Distinguishing between driver distraction and driver inattention 15

2.3 Theoretical approaches to dual-task interference 16

2.3.1 Capacity sharing theories 18

2.3.2 Bottleneck theories 19

2.4 Sources of driver distraction 20

2.5 Types of driver distraction 21

2.5.1 Visual distraction 22

2.5.2 Auditory distraction 22

2.5.3 Physical distraction 22

2.5.4 Cognitive distraction 22

2.6 A review of driver distraction studies 23

2.6.1 Prevalence of driver distraction 23

2.6.2 Self-regulation behaviour 37

Chapter Three: Background on Intersection Research 44

3.1 What is an intersection? 44

3.2 Statistics on intersection crashes 45

3.3 Intersection crashes: Types and contributory factors 47

3.4 Physical and functional areas of intersections 50

3.5 General driver behaviours at intersections 52

3.6 Studies regarding driver distraction at intersections 54

3.6.1 Huisingh et al. (2015) 54

3.6.2 Charlton et al. (2013) 56

3.6.3 Xiong et al. (2015) 57

3.7 Summary 58

Chapter Four: Tools and Research Questions 60

4.1 The ND approach 60

4.1.1 ND study in relation to field operational test (FOT)..62

4.1.2 Added value of the ND approach...63

4.1.3 Limitations of the ND approach...64

4.1.4 Previous ND studies...65

4.2 Research questions 67

Chapter Five: General Methodology 69

5.1 UDRIVE project 69

5.1.1 UDRIVE dataset 70

5.1.2 Data acquisition system (DAS)..71

5.1.3 Additional data sources...73

5.1.4 Data management and protection in UDRIVE 74

5.1.5 Data visualisation and processing tool (SALSA) 75

5.2 UDRIVE data limitations and issues, as determined from the perspective of the current thesis 76

5.3 Data access and ethical approval for this thesis 77

5.4 Training on the use of UDRIVE data...78

5.5 Identification of intersection segments 79

5.6 Sampling choices 81

5.7 Final sample 82

5.7.1 Participants 82

5.7.2 Intersection cases 82

5.8 Coding procedure 84

5.8.1 Pass A: General secondary task annotation 84

5.8.2 Pass B: Detailed coding of sub-categories of mobile phone interactions 87

5.8.3 Pass C: Secondary task in relation to VM complexity and technological aspects 88

5.8.4 Pass D: Contextual variable coding 88

5.9 Inter-rater reliability 92

5.9.1 Cohen's kappa coefficient 92

5.9.2 Intraclass correlation coefficient (ICC) 93

5.9.3 Reliability testing outcomes 94

5.10 Selection and coding for non-intersection segments 96

Chapter Six: Prevalence and Main Self-regulatory Strategies of Drivers' Secondary task Engagement 97

6.1 Aims and hypotheses 97

6.2 Methods 98

6.3 Results 100

6.3.1 How prevalent is secondary task engagement at intersections? 100

6.3.2 Did drivers regulate their secondary activities across intersection phases? 110

6.3.3 Did drivers regulate their secondary activities across motion conditions? 115

6.3.4 Does being stationary influence self-regulation behaviour? 120

6.3.5 How do changes in speed influence secondary task engagement? 121

6.3.6 Are there differences in the willingness to engage in secondary tasks between intersection and non-intersection segments? 122

6.4 Discussion 125

6.4.1 Prevalence of secondary task engagement at intersections..125

6.4.2 Secondary task engagement across intersection phases..129

6.4.3 Secondary task engagement across motion conditions..130

6.4.4 The influence of speed on the willingness to engage in secondary tasks 131

6.4.5 Secondary task engagement in intersections and non-intersection segments 132

6.5 Summary and conclusion..133

Chapter Seven: What Driver-related and Contextual Factors Predict the Willingness of Drivers to Engage in Secondary Tasks? 135

7.1 Aims and hypotheses 135

7.2 Methods..139

7.2.1 Binary logistic regression..139

7.2.2 Multiple linear regression 142

7.2.3 Multicollinearity..144

7.3 Results..146

7.3.1 Binary logistic regression results..146

7.3.2 Multiple linear regression results..158

7.4 Discussion 169

7.5 Summary and conclusion..176

Chapter Eight: Exploring the Relationship Between Secondary Task Types and Driver-related and Contextual Factors 178

8.1 Aims and hypotheses 178

8.2 Methods 179

8.3 Results 180

8.3.1 Driver-related factors 180

8.3.2 Contextual factors 187

8.4 Discussion 200

8.4.1 Driver-related factors 200

8.4.2 Contextual factors 203

8.5 Summary and conclusion 205

Chapter Nine: The Influence of Secondary Task Engagement on Turn Signal Usage at Intersections 207

9.1 Introduction 207

9.2 Aims and hypotheses 209

9.3 Methods 209

9.4 Results 211

9.4.1 What are the typical rates of turn signal use that indicate drivers' intention to turn at intersections, and does signalling rate for left and right turns differ? 212

9.4.2 Does engagement in secondary tasks whilst approaching intersections influence rates of turn signal use? 212

9.4.3 How do changes in the complexity of secondary activities influence rates of turn signal use? 213

9.5 Discussion 214

9.6 Summary and conclusion 216

Chapter Ten: Conclusions and Recommendations 218

10.1 Overview 218

10.2 Methodological reflections 223

10.3 Implication of the research findings 225

10.4 Limitations 227

10.5 Future work 228

10.6 Thesis summary 230

References 232

List of Tables

Table 2-1. Prevalence estimates of various secondary tasks 35

Table 2-2. Breakdown of multilevel driving control process 38

Table 4-1. Small-scale European projects (using the ND methodologies) 66

Table 5-1. Size of the UDRIVE dataset 71

Table 5-2. Length-based values of the intersection functional area 80

Table 5-3. Gender and age and distributions of drivers across countries 82

Table 5-4. Coded intersection cases per country 83

Table 5-5. Secondary task categories for annotation (Pass A) 85

Table 5-6. Sub-categories for mobile phone interactions for annotation (Pass B) 87

Table 5-7. Key contextual variables for coding (Pass D) 90

Table 5-8. Contextual factors acquired from coding 91

Table 5-9. Inter-rater agreement between the two coders for the categorical variables 95

Table 5-10. Intraclass correlation between the two coders for the continuous variables 95

Table 6-1. Secondary task engagement by category, as determined from data coding 102

Table 6-2. Mobile phone use by sub-task, as determined from data coding 105

Table 6-3. Secondary tasks by VM complexity level 106

Table 6-4. Secondary tasks by the existence of technological aspects 107

Table 6-5. Driver performance of multiple tasks 108

Table 6-6. Multiple task events by task category 109

Table 6-7. Multiple task events by VM complexity 109

Table 6-8. Comparison of secondary task engagement in non-intersection and intersection segments 123

Table 6-9. Non-intersection vs. intersection segments by secondary task type 124

Table 7-1. Binary dependent variables used to address Research Question A 137

Table 7-2. Continuous dependent variables used to address Research Question B.............. 137

Table 7-3. Predictor variables (driver-related factors) used to address RQs A and B 138

Table 7-4. Predictor variables (contextual factors) used to address RQs A and B 138

Table 7-5. VIF statistics for testing multicollinearity 145

Table 7-6. Model for predicting task engagement along the total intersection segment 148

Table 7-7. Model for predicting task engagement in the upstream intersection phase.......... 149

Table 7-8. Model for predicting task engagement in the within-intersection phase............. 150

Table 7-9. Model for predicting task engagement in the downstream intersection phase..... 151

Table 7-10. Model for predicting task engagement in the moving intersection status 152

Table 7-11. Model for predicting task engagement in the stationary intersection status 153

Table 7-12. Model for predicting task engagement along the non-intersection segment...... 154

Table 7-13. Summary of ORs and fractional odds (%) of predictors in parsimonious logistic regression models[a] 155

Table 7-14. Model for predicting the percentage of time allocated to secondary tasks along the total intersection segment 159

Table 7-15. Model for predicting the percentage of time allocated to secondary tasks in the upstream phase... 160

Table 7-16. Model for predicting the percentage of time allocated to secondary tasks in the within-intersection phase 161

Table 7-17. Model for predicting the percentage of time allocated to secondary tasks in the downstream phase.. 162

Table 7-18. Model for predicting the percentage of time allocated to secondary tasks in the moving intersection status... 163

Table 7-19. Model for predicting the percentage of time allocated to secondary tasks in the stationary intersection status 164

Table 7-20. Model for predicting the percentage of time allocated to secondary tasks along the total non-intersection segment 165

Table 7-21. β and *b* coefficients in parsimonious multiple regression models 167

Table 8-1. Engagement in each secondary task type by gender 181

Table 8-2. Engagement in each secondary task type by age... 184

Table 8-3. Engagement in each secondary task type by country 186

Table 8-4. Engagement in each secondary task type by trip length...................................... 188

Table 8-5. Engagement in each secondary task type by intersection control 190

Table 8-6. Engagement in each secondary task type by intersection priority 192

Table 8-7. Engagement in each secondary task type by lighting conditions 193

Table 8-8. Engagement in each secondary task type by weather conditions......................... 195

Table 8-9. Engagement in each secondary task type by passenger presence 197

Table 8-10. Engagement in each secondary task type by seat belt usage 199

List of Figures

Figure 3-1. Injury crashes in the UK and their relationship with intersections (2019) 46

Figure 3-2. Fatal crashes in the UK and their relationship with intersections (2019) 47

Figure 3-3. Physical and functional areas of an intersection 50

Figure 5-1. UDRIVE car camera views. 72

Figure 5-2. Google Earth views of a four-way intersection in the UK....................................74

Figure 5-3. SALSA user interface 76

Figure 5-4. Distribution of intersection cases by travel time 83

Figure 5-5. Coding of secondary tasks by intersection phases 86

Figure 6-1. Percentages of intersection cases with secondary task engagement by number of drivers 100

Figure 6-2. Distribution of annotated intersection cases by number of secondary tasks.......101

Figure 6-3. Percentages of total intersection time devoted to secondary task events............101

Figure 6-4. Percentage of total intersection time by category of secondary task 103

Figure 6-5. Mean duration vs. frequency by task category...104

Figure 6-6. Mean duration vs. frequency by mobile phone sub-task.....................................105

Figure 6-7. Secondary task mean duration by VM complexity level 107

Figure 6-8. Secondary task engagement by intersection phase 110

Figure 6-9. Secondary task engagement by intersection phase and gender...........................111

Figure 6-10. Secondary task engagement by intersection phase and age group....................112

Figure 6-11. Secondary task engagement by intersection phase and country 112

Figure 6-12. Percentage of time allocated to each secondary task category across intersection phases..113

Figure 6-13. Percentage of time allocated to each mobile phone sub-task across intersection phases 114

Figure 6-14. Percentage of time associated with each task complexity group across intersection phases 114

Figure 6-15. Percentage of time allocated to technology- vs. non-technology-based tasks across intersection phases 115

Figure 6-16. Secondary task engagement by motion status 116

Figure 6-17. Secondary task engagement by motion status and gender 116

Figure 6-18. Secondary task engagement by motion status and age group 117

Figure 6-19. Secondary task engagement by motion status and country 117

Figure 6-20. Percentage of time allocated to each task category across motion status 118

Figure 6-21. Percentage of time allocated to each phone sub-task across motion status 119

Figure 6-22. Percentage of time associated with each task complexity group across motion status 119

Figure 6-23. Percentage of time allocated to technology- vs. non-technology-based tasks across motion status 120

Figure 6-24. Secondary task engagement on the basis of stationary presence 121

Figure 6-25. Secondary task engagement by speed group 121

Figure 9-1. UDRIVE over-the-shoulder camera view 210

Figure 9-2. Turn signal use by turning direction 212

Figure 9-3. Turn signal use by secondary task engagement 213

Figure 9-4. Turn signal use by secondary task complexity 214

Abbreviations

CAN	Internal controller area network
CDC	Central data centre
DAS	Data acquisition system
DMRB	Design Manual for Road and Bridges
FOT	Field operational test
LDC	Local data centre
ND	Naturalistic driving
OS	Operational site
SALSA	Smart Application for Large-Scale Analysis
SPSS	Statistical Package for the Social Sciences
SV	Subject vehicle
TTC	Time to collision
VM	Visual manual

Chapter One

Introduction

1.1 Rationale and research problem

Driving is a complex multitasking activity that necessitates a substantial degree of continuous attention to road and traffic situations as well as vehicle control. It involves the simultaneous execution of several physical, cognitive and sensory skills on the part of a driver (Young et al., 2007). Despite the complexity of the driving task, however, drivers commonly engage, willingly or involuntarily, in various distracting activities (secondary tasks) whilst driving (Dingus et al., 2016; Regan et al., 2009). Driver distraction can be defined as 'the diversion of attention away from activities critical for safe driving toward a competing activity' (Lee et al., 2009b, p.34). Any secondary activity that diverts attention from the driving task or competes for the limited cognitive resources of drivers can potentially diminish driving performance and may thereby result in a range of consequences, from minor errors to more serious safety outcomes (i.e. serious or fatal crashes). The risk that such horrifying possibilities will occur is particularly dangerous if attention is misdirected at some critical period during driving (Young et al., 2019; Victor et al., 2015).

The problem of driver distraction is a long-standing issue in relation to road safety, with occurrence dating back to the point at which people first started to drive (Caird and Dewar, 2007), but the last two decades has seen the spotlight being directed towards this issue (see e.g. the reviews of Kircher et al., 2011; TRL et al., 2015; Ranney, 2008). Governments, policy makers, the media and the public have become progressively interested in distraction problems after the increased use of portable devices (e.g. mobile phones) during driving (Kircher, 2007) and the proliferation of on-board technology. Distraction has been especially prevalent after the introduction and widespread adoption of the aforementioned sources (Damiani et al., 2009), and it is likely to escalate as more technologies find their way into vehicles (Regan et al., 2011; Brace et al., 2007). This problem, however, is not restricted to technological sources but can originate from many other sources occurring within everyday activities, such as smoking, eating, grooming and interacting with passengers (Young et al., 2019; Carsten et al., 2017; Stutts et al., 2003a). This proliferation of potentially distracting activities motivated researchers to develop approaches to estimate the magnitude of distraction.

Although various methods are characterised by some disparity in estimations of the magnitude at which distraction occurs, the problem is widely classified as a significant road safety concern and a leading contributor to road crashes (Dingus et al., 2016; Beanland et al., 2013; Olson et al., 2009; Wang et al., 1996; Stutts et al., 2001) along with fatigue, drunk driving and speeding (Trezise et al., 2006). A large body of research, particularly experimental studies (e.g. those using simulators and test tracks), consistently demonstrated that driver distraction adversely affects many aspects of driving performance, such as the longitudinal and lateral control of a vehicle and situational awareness (e.g. Jamson and Merat, 2005; Engström et al., 2005; Hancock et al., 2003). Overall, this kind of research has reinforced our understanding of the negative effects of secondary task engagement on driving performance. Nevertheless, the impact of such an engagement on safety level and crash risk remains unclear because not all effects on facets of driving performance are indications of higher crash risk and poorer safety.

In response to the above-mentioned challenge, researchers have examined driving behaviour in the real world using a relatively new observational method known as Naturalistic Driving (ND) study, which involves collecting data through unobtrusive equipment installed in vehicles, with no experimental intervention applied (van Schagen et al., 2011). With the advent of the ND approach, the safety impacts of driver distraction, became a major, if not the major, area of research addressed in the field (Carsten et al., 2017). Many ND studies were carried out to estimate the crash risk associated with engagement in certain secondary behaviours. For example, data from the 100-car study found that complex visual and/or manual secondary tasks are associated with triple the risk of crashing than normal baseline driving (Klauer et al., 2006a). An important consideration, however, is that determining the relative likelihood of a crash whilst drivers perform secondary tasks without considering both the prevalence of these tasks and how drivers manage or self-regulate their engagement addresses only part of the safety problem.

This thesis contrasts itself from previous studies in terms of focus on obtaining a deeper understanding of how drivers self-regulate secondary behaviours, with attention paid particularly to when they choose to perform secondary tasks, what categories of tasks they execute, which drivers engage in these activities and whether they make adjustments in response to variations in the demands imposed by the driving task. Self-regulation encompasses the intention to refrain altogether from secondary task engagement whilst driving or abstaining from specific tasks under certain demanding conditions. Acquiring a better understanding of this self-regulatory behaviour can improve crash risk estimation and augment knowledge regarding the safety effects of driver distraction (Dingus et al., 2011)—a knowledge that is essential in developing effective and targeted countermeasures (Young et al., 2009).

Several studies have been conducted to elucidate whether and how drivers self-regulate secondary task engagement. Some found inconclusive results relating to the self-regulatory tendency (e.g. Teh et al., 2018), but the overall consensus has been that engagement in secondary tasks is not arbitrary, at least to a certain extent, with drivers exercising a variety of strategies or tactics in deciding on when and whether to engage or not (e.g. Risteska et al., 2021; Tivesten and Dozza, 2015; Young and Regan, 2013; Young and Lenné, 2010). This observation aligns with a previously proffered explanation, wherein drivers are regarded as active receivers and processors of distraction-related information. They are seen as capable of effectively managing their behaviours in accordance with changes in demand situations, thereby mitigating the consequences of distraction on driving performance and safety (Fitch et al., 2014; Young et al., 2009; Lee and Strayer, 2004). Notwithstanding the insights provided by such initiatives, the self-regulatory behaviours of drivers, particularly for secondary tasks other than mobile phone use, remain inadequately understood. There is also a lack of studies that deal with these behaviours at intersections and areas near these intersections.

Exploring behavioural aspects at intersections is a relevant component of inquiries into self-regulation because driving through these locations imposes additional demands on drivers who are accordingly required to appropriately assess numerous visual stimuli, including several diverse moving objects (e.g. other vehicles and pedestrians) (Tawari et al., 2016). Intersections also feature remarkably in crash statistics, with crashes at these locations representing 45% to 60% of the total number of injury crashes in the US, Australia, Europe and the UK (National Highway Traffic Safety Administration [NHTSA], 2009; Young et al., 2011; Simon et al., 2014). Disturbingly, however, the prominent occurrence of intersection-related crashes has thus far rarely motivated direct investigations of real-world driving behaviours at these sites. This thesis addresses the prevalence and self-regulation of distraction at these safety-critical locations to illuminate part of the background that could inform future attempts to improve intersection safety.

ND studies are particularly suitable for this kind of investigation as experimental research typically suffers from the instruction effect (i.e. participants are normally instructed to perform a specific secondary task at a specific point in time). For this reason, in spite of improved comprehension owing to experiments, these explorations are less appropriate for research that centres on drivers' management of secondary behaviours. This thesis used ND data from the large-scale European project known as UDRIVE (eUropean naturalistic Driving and Riding for Infrastructure & Vehicle safety and Environment), which provided a unique opportunity to gain insights into the prevalence and self-regulation of a wide range of secondary activities across a diverse sample of drivers from several countries.

The current thesis also intends to examine the possible association between the use of turn signals (as a positive and potentially valuable means by which drivers can communicate) and secondary task engagement on approach to intersections. This examination aims to extend the current state of knowledge about rates of turn signal use by illuminating the influencing role of secondary tasks in these rates. This analysis will provide insight into how performing these concurrent tasks influence the performance of one or both tasks.

The UDRIVE data were put to advantage in answering the following and other related questions: How prevalent is secondary task engagement at intersections? What specific categories of secondary tasks do drivers typically engage in? Which driver populations are most willing to perform secondary tasks? Do drivers self-regulate secondary task engagement at intersections, and what strategies and tactics (if any) do they adopt in this respect? Are there certain groups of drivers who do not self-regulate? Is there a disparity in self-regulation across secondary tasks types? Does engagement in secondary tasks influence rates of turn signal use?

1.2 Thesis outline

This section summarises the content of the thesis, which is divided into ten chapters.

Chapter One provides a brief introduction to the topic and highlights the overall importance and goals of the thesis.

Chapter Two introduces the distracted driving problem, its origins and its anticipated trends in the future. The chapter also addresses the issues surrounding the definition of driver distraction and outlines the various sources and forms of distraction. A summary of dual-task interference theories and their link to driver distraction is presented, followed by a thematic literature review of key driver distraction issues that are most strongly related to the current work.

Chapter Three summarises the intersection-related literature relevant to this thesis. A definition of an intersection is first provided, followed by a description of statistics on crashes occurring at intersections. The chapter then describes matters relevant to the determination of the physical and functional areas of intersections. Finally, studies associated with general driver behaviours at intersections are discussed, with a particular focus on the limited research that has dealt with driver distraction at these locations.

Chapter Four provides a detailed description of the ND approach, which was the method adopted in the current thesis to address the research questions. The chapter also outlines the overall goals and research questions of the thesis as well as the significance of the work.

Chapter Five features a brief methodological description of the UDRIVE project, which served as the major source of preliminary data in the thesis. The chapter then describes the methodological issues that were central to the entire work undertaken in this thesis. These issues encompassed aspects related to data management and protection, data reduction, data sampling and data coding.

Chapter Six represents the first of four result chapters and is considered the cornerstone of the findings derived in this thesis. It recounts the investigation into the prevalence and patterns of secondary task engagement whilst driving through intersections and what main self-regulatory strategies drivers adopt to manage such an engagement.

Chapter Seven represents the second chapter that discusses the results of the research. It reports on the role played by various driver-related factors (e.g. age and gender) and contextual driving variables (e.g. intersection priority and weather conditions) in influencing the overall willingness of drivers to engage in secondary tasks.

Chapter Eight details how the findings presented in Chapter Seven were extended through an enquiry into whether any of the driver-related and contextual variables were associated with certain types of secondary activity. In other words, this chapter is an account of the investigation of who engaged in which secondary task types and what contextual situations involved specific secondary behaviours.

Chapter Nine is the last of four chapters that expounds on the obtained findings. It concentrates on illuminating how secondary task engagement affects certain non-critical driving tasks, namely, the use of the turn signal. The aim of the analysis in this chapter was to examine turn signal use and its association with driver involvement in secondary tasks upon approach to intersections.

Chapter Ten concludes the thesis with a summary of the answers that this work provided to the key research questions. It ends with a deliberation on the limitations of the work, the implications of the findings and recommendations for future research that can expand the current results.

Chapter Two

Background on the Distracted Driving Problem

This chapter introduces the distracted driving problem, its origins and the future trends anticipated to characterise it. It also addresses the issues surrounding the definition of driver distraction and outlines the various sources and forms of such a phenomenon. A summary of dual-task interference theories and their link to driver distraction is presented, followed by a thematic review of the literature on key driver distraction issues that are most strongly related to the current thesis.

2.1 Statement of the problem

2.1.1 Road safety challenge

> Deaths and injuries resulting from road traffic crashes remain a serious problem globally and current trends suggest that this will continue to be the case in the foreseeable future (Wold Health Organisation [WHO], 2018, p.1).

The above-mentioned statement is a worrying summary of the road safety problem that plagues the world. Statistics from the WHO showed that 1.35 million people die and 50 million people are injured annually as a result of traffic crashes. In 2016, traffic crashes were the eighth leading cause of death globally, contributing 2.5% to all fatalities. Projections for 2030 indicated that traffic crashes will rise to a rank as the seventh leading cause of global mortality. The consequences of traffic crashes affect people of all age groups, but their effects are particularly remarkable for children and young adults. For example, traffic crashes are the leading cause of death amongst people aged between 5 and 29 years (WHO, 2018; WHO, 2013). Additionally, individuals have a nearly 50% chance of being injured in a crash across their average lifetime and an almost 2% chance every year (Evans, 2004). These crashes distinctly impose a heavy burden on global social, human and economic health (Dhondt et al., 2013; WHO, 2011), thus driving the present ambition to effectively and sustainably reduce costs to societies.

2.1.2 The distracted driving problem

Driver distraction is a long-standing problem in relation to road safety, with occurrence initiated from the time people first started to drive (Caird and Dewar, 2007). Crash data analyses and in-depth crash investigation studies revealed that driver distraction is a contributory factor to approximately 10% to 30% of crashes (see the review by TRL et al., 2015), whilst a recent naturalistic driving study uncovered that 68% of crashes involved some kind of observable distraction (Dingus et al., 2016). Despite differences in results amongst various methods, the driver distraction problem continues to be widely recognised as a primary traffic safety concern and a leading contributor to road crashes.

In recent years, the overall number of injury crashes has gradually decreased because of improvements in road and vehicle safety as well as the proliferation of in-vehicle technologies and driver assistance systems. However, the proportion of crashes involving some type of distraction has increased (Department for Transport [DfT], 2019; NHTSA, 2019), indicating that distracted driving has not been as appropriately or effectively addressed as some other road safety concerns. Distraction is a grave safety threat that should be addressed, and its prevalence should not be disguised by the progressive decrement in the overall incidence of road crashes or casualties.

Past research showed that driver distraction adversely affects many aspects of driving task performance. To illustrate, driver distraction impairs longitudinal control of a vehicle, as evidenced by rising variations in and increasingly poor control of driving speed (Engström et al., 2005) and the reduction in time to collision (TTC) as a driver responds to breaking events (Lamble et al., 1999). It likewise unfavourably influences vehicular lateral control, with drivers engaging in more frequent lane position deviations and exceedances (Dingus, 1995; Reed and Green, 1999; Engström et al., 2005). Deficits in situation awareness have also been observed, such as diminished event detection (Harbluk et al., 2002; Klauer et al., 2006b), slower reactions to road events and hazards (Chisholm et al., 2007; Hancock et al., 2003; Östlund et al., 2004) and narrower visual focus that results in missed objects and errors (Regan and Hallett, 2011).

2.1.3 Why does distraction occur?

When driving, a driver can encounter a wide range of stimuli that can detract from the attention on the primary task of driving (and potentially lead to a distracted driving). These stimuli can occur inside or outside a vehicle, can be driving or non-driving related and can be based on technology or a non-technological source. In itself, driver distraction is not necessarily a safety threat nor are non-distracted situations necessarily safe. On the one hand, the likelihood that a driver involved in a crash was distracted is relatively high; on the other hand, the possibility that a distracted driver will be involved in such a crash is comparatively low. The latter outcome is attributed to the fact that the driving task demand is often low, which permits drivers to divide their attention between driving and distracting activities without it leading to a noticeable degradation in driving performance (Ashley, 2001). This unnoticeable performance degradation, in turn, may encourage the misconception that the behaviour is safe and consequently impair decision making (Hibberd, 2012).

Driver distraction can endanger safety when a driver decides to engage in a complex distracting activity whilst driving in a situation that imposes high demands on driving (i.e. challenging driving scenario). This can impose a high level of workload on the driver’s capabilities and therefore negatively influence driving performance. An essential question to ask here is how much distraction a driver can handle, which is difficult to determine given the presence of many overlapping issues, including driving task demand, secondary task demand and driver characteristics.

2.1.4 Upward trend

Increasing evidence has been derived as to the classification of driver distraction as a major safety threat in modern vehicles, and this problem is likely to increase in the future as more technological developments that have the potential to distract drivers are incorporated into vehicles (Regan et al., 2011; Young et al., 2007; Damiani et al., 2009). Predictions reflect that the use of in-vehicle and portable technologies whilst driving will grow in prevalence as technologies are imbued with functionalities covering communication (e.g. mobile phone), entertainment (e.g. audio systems), information (e.g. navigation system) and driver support (e.g. adaptive cruise control and intelligent speed adaptation) (European Commission, 2018). Consequently, the drivers of modern/future vehicles will be confronted with an increasing array of stimuli that can compete for their limited cognitive resources and draw their attention away from the primary task of driving.

2.2 Defining driver distraction

The term ‘driver distraction’ is extensively used in the transport literature, but no consensus has been reached as regards a single acceptable definition (TRL et al., 2015; NHTSA, 2008; Trezise et al., 2006). Given the absence of a common definition, many researchers developed their own descriptions or have been content to leave the term ambiguous in their research (Kircher, 2007). The use of different definitions, and sometimes inconsistent ones, across studies can generate a number of problems for researchers. First, distraction-related crash data can be interpreted differently and thereby lead to varying evaluations of the role of driver distraction in crashes (TRL et al., 2015). Second, inconsistent definitions can render direct comparisons of research results very difficult because it is unclear whether researchers are examining the same concepts or outcomes (Lee et al., 2009b).

In their review of distraction definitions cited in the literature, Pettitt et al. (2005) stated that the diversity in definitions is understandable because of the different purposes for which such explanations have been established. For scientific purposes, a precise definition that can be used consistently across studies is essential to easing cross-research comparisons. For some specific situations, however, a more operational definition is required. An example is when researchers need to annotate or code driver distractions from video channels in ND studies (e.g. Carsten et al., 2017; Dingus et al., 2006a; Klauer et al., 2006a). A specific and operational definition that can facilitate the annotation of driver distraction is featured in the study carried out by Klauer et al. (2006a), who defined the phenomenon as 'occurring when a driver has chosen to engage in a secondary task that is not necessary to perform the primary driving task' (p.6). Notwithstanding the value presented by this explanation, the main issue remains the importance of establishing a general definition that is acceptable and appropriate for both operational and scientific aims (Regan et al., 2011).

One approach to satisfying this requirement is to identify the features common to the definitions provided in the literature. Such an initiative was carried out by Lee et al. (2009b), who presented, analysed and compared 14 distinct definitions of driver distraction. The authors identified key similarities and minor differences in focus (e.g. effects on driving performance or triggering event) between the reviewed definitions. They then used the findings as basis in formulating the following definition: 'Driver distraction is the diversion of attention away from activities critical for safe driving toward a competing activity' (Lee et al., 2009b, p.34). Using a methodology similar to that of Lee et al. (2009b), Regan et al. (2011) evaluated distraction definitions to develop the following definition (p.1776):

> The diversion of attention away from activities critical for safe driving toward a competing activity, which may result in insufficient or no attention to activities critical for safe driving.

The definitions above are similar in terms of distraction involving a diversion of attention away from activities that are essential to safe driving. Regan et al. (2011) argued, however, that Lee et al.'s (2009b) definition fails to address the fact that not all competing activities cause diversion from critical safe driving tasks. In some situations, drivers are still able to direct sufficient attention to essential safe driving activities even under divided attention. This holds true for a competing but simple activity (i.e. low-demand activity) that is performed in low-demand driving situations (Regan et al., 2011).

An alternative approach is to motivate agreement amongst experts in the field. This strategy was employed in a 2007 workshop organised by the DfT in the UK (Basacik and Stevens, 2008) and in a 2005 international conference on driver distraction in Canada (Hedlund et al., 2006). In these events, the following definitions were agreed upon:

> Diversion of attention away from activities required for safe driving due to some event, activity, object or person, within or outside the vehicle.
>
> - Note 1: safe driving requires monitoring of the road and traffic environment (which includes pedestrians and other road users) and control of the vehicle.
> - Note 2: safe driving also requires an appropriate degree of attention and vehicle control to maintain a reasonable safety margin allowing for unexpected events.
> - Note 3: types of distraction may be visual, auditory, biomechanical or cognitive, or combinations thereof (Basacik and Stevens, 2008, p.44).

> A diversion of attention from driving, because the driver is temporarily focusing on an object, person, task or event not related to driving, which reduces the driver's awareness, decision making ability and/or performance, leading to an increased risk of corrective actions, near-crashes, or crashes (Hedlund et al., 2006, p.2).

These definitions also resemble each other, although that of Basacik and Stevens (2008) provides additional details related to safe driving and distraction types. A problematic issue regarding Hedlund et al.'s (2006) conception is its consideration of the negative consequences of distraction, such as impaired performance, weakened decision making and increased crash risk. These are common outcomes of distraction, but not all distraction cases cause the same adverse effects. This point is crucial because some studies revealed that cognitive distraction generates improved lateral control performance (Engström et al., 2005; Carsten and Brookhuis, 2005). Generalising the definition to cover all types of distractions is therefore difficult.

Another frequently cited definition within the literature is that developed by (Treat, 1980), who formulated his description on the grounds of monitored factors that contribute to crashes. The author stated the following:

> [Driver distraction occurs] when a driver is delayed in the recognition of information needed to safely accomplish the driving task, because some event, activity, object, or person within or outside the vehicle, compelled or tended to induce the driver's shifting of attention away from the driving task (Treat, 1980, p.21).

Although the aforementioned definitions were established using various approaches, they share critical attributes and only slightly differ, suggesting a convergence of interpretations regarding the term. Overall, they tend to manifest the following principal features (which contribute to the understanding of the general meaning of driver distraction):

(1) Attention is diverted away from driving (or activities critical for safe driving).

(2) Attention is directed towards a competing activity (e.g. an event, task, person and object), which can be related or unrelated to driving and can occur inside or outside a vehicle.

(3) Attention to a competing activity can be driven willingly (i.e. driver's choice) or involuntarily (i.e. compelled by a source).

(4) An explicit or implicit assumption is that safe driving is negatively influenced by engagement in a secondary task.

2.2.1 What are the activities critical for safe driving?

An important consideration is that most definitions of driver distraction in the literature are anchored in the phrases 'safe driving' or 'activities critical for safe driving'. According to Hancock et al. (2008), defining the activities that a driver should handle at any given moment whilst driving is exceedingly challenging, thus precluding a single explanation that can appropriately encompass all driving task scenarios. Regan et al. (2011) asserted that the understanding of activities critical for safe driving requires the development of a consistent taxonomy of activities discussed in observational and crash studies. For the purposes of this thesis, the explanation put forward by Engström et al. (2013a) appears to be the most appropriate/sufficient: 'those activities required for the control of safety margins' (p.17).

2.2.2 Distinguishing between driver distraction and driver inattention

Even as the definition of driver distraction has evolved to take on a general meaning, an essential requirement is to consider the relationship between driver distraction and driver inattention. A common feature of most driver distraction definitions, which can distinguish distraction from inattention, is the presence of a competing activity or triggering event (Lee et al., 2009b; WHO, 2011). Two schools of thought regarding the distraction–inattention relationship have emerged. The first maintains that driver distraction is a specific form of driver inattention, whereas the second contends that each term represents a distinct concept (Regan et al., 2011).

Driver inattention applies to any state or situation that directs a driver's attention away from the main driving task without necessarily having been triggered by a competing activity. This can include situations in which inattention occurs as a result of drowsiness and fatigue or wherein drivers look away from the forward roadway even without the presence of a physical triggering event (Lee et al., 2009b). In the literature, controversy surrounds the consideration of a driver's internal thoughts as a trigger and, therefore, whether their occurrence should be taken as a case of inattention (Ranney, 2008) or distraction (Stutts et al., 2001; Lee et al., 2009b).

For the purposes of the current thesis, a rational approach would be to use the definitions put forward by Engström et al. (2013a), Regan et al. (2011) and Pettitt et al. (2005) regarding driver inattention; that is, driver inattention refers to general situations wherein drivers do not pay attention to the main driving task (including instances of being lost in thought), and driver distraction pertains only to one subset of factors that can provoke driver inattention. From these points of view, driver distraction can be recognised as a cause of driver inattention, but the latter is not necessarily the result of the former.

2.3 Theoretical approaches to dual-task interference

For more than 100 years, psychologists have been interested in an individual's ability (or inability) to perform different tasks or activities simultaneously (Pashler, 1998). Researchers suggested that performing two tasks in conjunction is a highly difficult challenge, and people often fail, even for simple tasks, in the outcomes of their performance (Pashler, 1994). This section clarifies the concept of dual-task interference and illustrates the conditions in which such interference diminishes the performance of one or both competing tasks. These situations are directly applicable to the case of driver engagement in secondary tasks whilst driving.

An important scientific purpose for understanding dual-task interference is that overloading a system is regarded as an important means of identifying the components of the system and how these parts function together. For this reason, understanding the failure of an individual to efficiently engage in dual tasks and the conditions conducive to such failure serves as an important window to the functional architecture of the brain and the human information processing system (Pashler, 1994).

Generally, individuals do not realise the difficulty of performing different tasks concurrently, unless the tasks are mentally challenging or physically incompatible. This impression seems to be supported by some casual observations of individual behaviours outside laboratory settings (e.g. drivers engage in conversations whilst driving). With this consideration, researchers may need to look into exceptional tasks to detect interference from dual tasking. This perspective, however, was opposed in experimental studies wherein many tasks significantly interfered with one another even though they were neither physically incompatible nor mentally demanding (Pashler, 1994; Pashler, 1998).

Several competing theories as to why people encounter difficulties in simultaneously performing two tasks have been put forward. These theories offer contradictory predictions about the occurrence and nature of dual-task interference because of variations in task processing mechanisms. Two of the most influential theories and their link to driver distraction are summarised in the succeeding sections.

2.3.1 Capacity sharing theories

Capacity sharing theories assume that people distribute their restricted information processing resources (or mental capacity) across concurrent tasks (Pashler, 1994). The factors that determine the distribution of these resources are currently available resources, task demands and task priority levels (Norman and Bobrow, 1975). Performing two tasks in concert reduces the resources available for each individual task, and the performance of one or both tasks may be degraded when the demands of the tasks exceed available resource supply. Two types of capacity sharing theories were suggested by theorists: single resource theories, which suggest the presence of a single pool of processing resources that can be divided amongst different tasks or processing stages in a graded fashion (Kahneman, 1973), and multiple resource theories, which posit the existence of multiple differentiated resource pools (Wickens, 1984).

The primary weakness of single resource theories that led to their eventual dismissal as valid frameworks of explanation is the fact that dual-task interference is not determined by task characteristics. The upshot of this weakness is that the theories cannot distinguish dual-task performance as a result of changes in task modalities or task stimuli (Hibberd, 2012). The theories were discredited because of their orientation towards demonstrating improved dual-task performance of dissimilar tasks (in term of modalities) instead of similar ones (North, 1977). This issue is treated differently in multiple resource theories, in which dual-task interference depends on task modalities. What makes multiple resource theories stronger than single resource theories is that in the former, human resource capabilities can be modality specific (Navon and Gopher, 1979). Performing auditory and visual stimulus tasks synchronously, for instance, is less challenging than performing two visual stimulus tasks.

Wickens' theory, which is one of the most popular multiple resource theories, suggests the presence of four pools of processing resources that can be divided amongst different tasks;

these resource pools are share stages (perceptual/cognitive or response), sensory modalities (visual or auditory), processing codes (spatial or verbal) and visual channels (focal or ambient) (Wickens, 2002). Within each pool, different resources can be assigned to the performance of competing tasks, thereby permitting parallel task performance. For example, auditory and visual stimulus tasks can be performed at the same time without interference because of the distinct resources available for the tasks within the sensory modality pool. Dual-task interference can occur in any of the four processing pools, degrading the performance of one or both tasks, when the capacity resources for any separate pool are insufficient to enable the handling of task demands (Wickens, 2008).

Multiple resource theories are more pertinent to driver engagement in secondary tasks than are single resource theories. A noteworthy point is that the primary driving task, which involves mainly visual stimulus and manual response, can possibly interfere more strongly in a secondary task that requires visual stimulus and manual response than in a secondary task that necessitates different competing resources. This point suggests that secondary tasks that differ from the primary driving task in term of modalities can decrease the potential for distracted driving, whereas secondary tasks that have modalities similar to those of the primary driving task can increase the potential for distracted driving.

2.3.2 Bottleneck theories

Similar to capacity sharing theories, bottleneck theories suggest a restricted resource capacity in information processing mechanisms. The idea that distinguishes the latter is its contention that parallel task processing may not be possible for certain mental operations because some of these operations can simply demand the use of a single mechanism for a specific period. The bottleneck processing stage forms when competing tasks require a single mechanism within the same period. Accordingly, one of the tasks is postponed; otherwise, performance is impaired (Pashler, 1994). During the non-bottleneck processing stage, competing tasks can be performed in parallel, but at the bottleneck processing stage, processing resources can be assigned only to a single task (Hibberd, 2012). As with the case of capacity sharing, multiple bottlenecks or a single bottleneck can be associated with different task processing stages or different mental operation mechanisms (Pashler, 1994).

Bottleneck theories appear to be pertinent to driver engagement in secondary tasks, during which drivers exhibit performance degradation in the timely overlapping of dual-task conditions. As suggested by these theories, improved management of intervals between competing tasks (the driving task and a secondary task) can potentially decrease the negative driving performance effects of engagement in secondary tasks.

2.4 Sources of driver distraction

As mentioned earlier, driver distraction may derive from competing tasks and objects that are inside or outside a vehicle, with in-vehicle distraction subcategorised extensively (Dingus et al., 2016; Stutts et al., 2003a; Regan et al., 2009).

In-vehicle (internal) distraction can originate from various sources within a vehicle, including reading, eating or drinking and smoking, as well as from the use of factory-fitted entertainment systems (e.g. media devices) and interaction with passengers (Stutts et al., 2003a). In-vehicle distraction sources also encompass the increasing number of electronic devices brought into a vehicle; these can be referred to as nomadic or portable devices, such as mobile phones, iPods and non-vehicular integrated navigation systems. Distraction from within a vehicle likewise includes the growing number of advanced driver assistance systems (e.g. adaptive cruise control and lane departure warning), in-vehicle information systems and communication technologies (e.g. Bluetooth technologies) that are integrated into vehicles (WHO, 2011; Young et al., 2007). It can also be generated by some driving-related tasks, both critical or non-critical ones, covering changing gears, checking the speedometer, using indicators and adjusting windows, mirrors, seat belts and sun visors. On the basis of these enumerated items, in-vehicle sources of distraction can be classified as technology- or non-technology-based distraction (Young et al., 2003), driving- or non-driving-related distraction (Regan et al., 2011) and self-initiated or non-self-initiated distraction (European Commission, 2018).

Conversely, external distraction can arise when driver attention is diverted towards external stimuli, such as road signs, surrounding buildings and environmental features, people outside a vehicle (e.g. pedestrians) and roadside advertisements. This thesis centred on internal distraction sources, specifically non-driving-related activities. Correspondingly, the extensive research on driver distraction from external stimuli and driving-related activities will not be discussed further.

2.5 Types of driver distraction

Driver distraction can be categorised into four distinct types, namely, visual, auditory, biomechanical (physical) and cognitive distraction (European Commission, 2015; Young et al., 2003; Pettitt et al., 2005). This categorisation is related to the composition (or modality) of secondary tasks instead of the influence of such activities on the primary driving task. However, Wickens's (1984) multiple resource theory elucidates that similar competing tasks requiring similar processing resources can more strongly interfere with one another than can dissimilar tasks. Consequently, the type of secondary task may indicate which components of the driving task are affected. For instance, a visual distraction may diminish the perception of events within the forward view of a driver, whereas a physical distraction may degrade steering control and thereby impair the lateral control of a vehicle.

2.5.1 Visual distraction

Visual distraction occurs when drivers avert visual attention away from the roadway towards a competing visual target (e.g. looking away from the road to look at a mobile phone).

2.5.2 Auditory distraction

Auditory distraction transpires when a driver focuses attention towards auditory stimuli (e.g. responding to a ringing mobile phone or to notifications from an in-vehicle navigation system). This type of distraction rarely occurs in isolation without the need for a response (Young et al., 2003). Therefore, the distraction tasks involved here are also categorised mostly as cognitive distraction tasks.

2.5.3 Physical distraction

Physical distraction develops when drivers perform a manual physical movement inside a vehicle that is not a part of the primary driving task. The manual movement involves hand removal (one or both hands) from the steering wheel to physically manipulate an object—a task that takes away from concentration on the physical tasks required for safe driving (e.g. grooming or eating and drinking).

2.5.4 Cognitive distraction

Cognitive distraction includes deviation induced by tasks that do not necessarily impose a visual processing load on drivers (e.g. talking to a passenger or engaging in mobile phone conversations). This type of distraction generally belongs to the response selection process component and decision-making component of tasks; thus, all distraction tasks can constitute cognitive distraction (WHO, 2011).

The four forms of distraction refer to distinct stages of a secondary task. In more detail, visual and auditory secondary tasks operate at the perceptual stage, physical secondary tasks influence the response component of the driving task and cognitive secondary tasks impact central task processing (e.g. decision making). A notable point is that a single distraction task can involve more than one of these forms of distraction, depending on a particular trigger (Regan et al., 2013; Lee, 2007). By way of illustration, let us consider the operation of a mobile phone, which may involve the four distraction forms as follows: Dialling a phone number or pressing a button to answer a call constitutes physical distraction; looking at the phone to receive a call or dial a number counts as visual distraction; the ringing of the phone or simply holding a conversation corresponds to audial distraction; and focusing on the topic of a conversation rather than monitoring changes in road environment corresponds to cognitive distraction.

2.6 A review of driver distraction studies

This section provides the thematic review of the literature on the driver distraction issues that most strongly related to the present work, namely, the prevalence and self-regulation of driver distraction.

2.6.1 Prevalence of driver distraction

Determining the degree to which a secondary task undermines road safety is challenging as this determination is a function of several factors, including the prevalence of a secondary task (i.e. exposure to the task) and the level of distraction associated with that task. Prevalence refers to how often a driver engages in a secondary task whilst driving (Young and Regan, 2009), but measurement is not anchored simply on the frequency of engagement but also extends to the amount of time spent on a task. A precise estimation of prevalence is important in extrapolating driving performance impairments in controlled settings and subsequently evaluating their influence on general safety levels (McEvoy and Stevenson, 2009).

In estimating the prevalence of a secondary task, an essential requirement is to consider the magnitude of the threat or the level of distraction imposed by the task (Young and Regan, 2009). A secondary task that imposes a high level of distraction (i.e. high relative risk) may be performed rarely or for short durations (i.e. low prevalence) and thus pose an overall low risk of crashing. Conversely, a task may be slightly risky on a task basis (i.e. low relative risk) but may be performed frequently or for long durations (i.e. high prevalence) and therefore present a high overall crash risk.

Knowledge about prevalence is important for a number of reasons. Prevalence data are essential in identifying the secondary task categories that contribute to distraction-related crashes, determining the crash risk associated with specific secondary tasks and estimating population-attributable risk or the impact of these tasks on the population as a whole (Young and Regan, 2009). Prevalence data are also vital in efforts to illuminate the conditions in which drivers choose to perform secondary tasks and which driving populations engage in these activities. Such insights uncover information about secondary task engagement patterns, which can serve as reference in developing better designs and targeted countermeasures for distraction mitigation and prevention. Finally, prevalence data factor importantly in evaluating the effectiveness of implemented countermeasures (Stelling and enHagenzieker, 2012).

The value of data on secondary task prevalence has prompted researchers to focus investigations into this matter. Many studies, however, have focused only on mobile phone use (e.g. Young et al., 2010; Fitch et al., 2013) despite the existence of data on many other distracting activities (e.g. Victor et al., 2015; Dingus et al., 2006a). The research methods that have been used to explore the prevalence of secondary tasks and patterns of engagement are surveys, roadside observations and ND studies. Each approach has its own advantages and disadvantages and, mostly, no single method can cover the full range of distraction sources.

The following sections discuss these methods within the context of prevalence examination and highlight some of the findings derived through these approaches.

2.6.1.1 Surveys

The advantage of surveys (telephone/mail/online surveys, face-to-face interviews, etc.) is that they can be carried out relatively inexpensively and quickly. They can cover a large geographical area and shed light on secondary activities that are difficult to observe using other methods (Stelling and enHagenzieker, 2012). On this basis, surveys are a useful technique for exploring the trends and patterns that underlie secondary behaviour engagement and investigating drivers' opinions or thoughts regarding the influence of these behaviours on their driving performance and safety. Numerous surveys centred on mobile phone use, reporting the behaviour as a common occurrence amongst drivers.

In Australia, an early survey of 1347 drivers showed that drivers who use their mobile phones whilst driving (at least occasionally) account for 57%, amongst whom 12% write text messages as they drive (McEvoy et al., 2006b). A survey of 796 drivers found that over 75% of drivers have used their mobile phones 'some time' whilst driving, with nearly 40% of these individuals reporting daily usage or multiple times of usage per day (White et al., 2010). More recently, an online survey of 181 drivers revealed that 57% of drivers read a text message whilst driving and that 28% send a text message. In addition, 44% of drivers answer a call, whereas 29% initiate a call. The social pressure felt by drivers is a significant predictor of response to calls and texts, but such pressure is non-significant with respect to call and text initiation tasks (Waddell and Wiener, 2014).

In the US, two surveys conducted by the American Automobile Association (AAA, 2012) and Stutts et al. (2003b) uncovered that 54% to 59% of drivers use a mobile phone whilst driving. A Swedish survey derived lower prevalence results, with approximately one-third of drivers engaging in the aforementioned activity (Thulin and Gustafsson, 2004). In Canada, mobile phone use amongst drivers increased from 25% in 2000 to 40% in 2003 (Beirness et al., 2002; Laberge-Nadeau et al., 2003), and these levels are lower than those discovered amongst drivers in New Zealand and Spain (around 60%) (Sullman and Baas, 2004; Gras et al., 2007). A higher rate was found amongst Finnish drivers (80%) (Pöysti et al., 2005). In most of these countries, the use of mobile phones is greatest amongst young drivers, and the rate of usage involving handheld phones is higher than that related to hands-free usage.

Although a high proportion of drivers admit to mobile phone use whilst driving, they perform this task infrequently and for short durations. As indicated by Beirness et al. (2002), almost 60% of drivers in Canada use their phones for less than 10 minutes per week. McEvoy et al. (2006b) found that the drivers who regularly use their phones in Australia spend nearly 10 minutes a day, or 8% of their driving time, on the phone. Thulin and Gustafsson (2004) reported that in Sweden, drivers use their phones for an average of 1.1 times per day at a 10-minute average length of phone conversation.

Surveys on the prevalence of secondary behaviours other than mobile phone use is limited. Amongst the few is the work of Huemer and Vollrath (2011), who conducted face-to-face interviews with 289 drivers in Germany and found that almost 90% of drivers engage in one to four secondary tasks in the last 30 minutes of driving. The most prevalent reported secondary tasks were passenger-related activities (39% of driving time), mobile phone use (35%), singing or daydreaming (30%), smoking (23%) and eating or drinking (8%). In the Australian context, drivers engage in one secondary task every 6 minutes of driving. The most commonly occurring secondary task during the sample's most recent trips was lack of concentration (72% of drivers), followed by adjustments to in-vehicle controls (69%) and passenger conversations (40%); only 9% of drivers reported using a mobile phone (McEvoy et al., 2006a).

In the UK, Lansdown (2010) administered a survey to 482 drivers and found that the most frequent secondary task performed on a daily or weekly basis is the adjustment of in-vehicle controls (91% of drivers), followed by interaction with passengers (81%) and eating/drinking (51%). In terms of mobile phone subtasks, 32% of drivers engage in hands-free use, and 25% and 14% of drivers read and write a text message, respectively. In an American survey of distracted driving attitudes and behaviours, Royal (2003) found that one in four drivers use a mobile phone whilst driving (at least occasionally) but that other technological secondary tasks are uncommon. The vast majority of drivers, however, talk to passengers (81%), adjust in-vehicle controls (66%) and eat/drink (49%).

Finally, in an online Australian-based survey of 287 drivers, Young and Lenné (2010) found mobile phone usage whilst driving amongst approximately 60% of drivers, out of whom almost one-third do so whilst holding their phones. A high proportion of drivers interact with audio entertainment systems (94%) and engage in non-technology-based tasks, such as eating or drinking (80%).

Although prevalence surveys are relatively inexpensive, convenient and rapidly completed, they have several limitations. They depend substantially on honesty in responses and accuracy in memory, which cannot always be guaranteed (European Commission, 2018). Participants may, for example, lean towards giving socially desirable answers, especially when the secondary tasks in which they engage are socially frowned upon or prohibited by law. This tendency may lead to self-reporting bias. Surveys are also susceptible to sample bias (e.g. online surveys reach only people who have Internet connections) and low response rates (Young and Regan, 2009). An important issue is the extent to which self-reported surveys represent what is happening in the real world.

2.6.1.2 Roadside observational studies

Roadside observational studies can be a reliable method of collecting data on the prevalence of secondary task engagement at a specific point in time. In such research, an observer who stands at a roadside directly records the number of drivers who engage or not engage in certain tasks (Edwards and Wundersitz, 2019). As with surveys, many roadside observations have been devoted to the use of mobile phones and proposed that such a behaviour is relatively widespread amongst drivers.

Early roadside observational studies of drivers' use of handheld phones revealed almost similar usage rates across countries where performing such an activity is illegal. For instance, 1.3% of drivers in the UK (Johal et al., 2005) and 1.5% to 2% of drivers in Australia (Horberry et al., 2001; Taylor, 2004) use handheld phones whilst driving. More recently, two large-scale Australian studies found that 0.6% (Wundersitz, 2014) to 3.4% of drivers (Young et al., 2010) engage in such a task as they drive. An additional 1.4% of drivers use their phones hands-free (Young et al., 2010). Moreover, the use of mobile phones is more frequent amongst drivers who travel alone (having no passengers) and who do not use seatbelts (Wundersitz, 2014).

In the US, Bernstein (2015) compared the rate of mobile phone use amongst drivers who are temporarily at rest (i.e. stationary vehicle condition) with that of drivers in motion. Overall, such usage is remarkably higher during the former than during the latter. When in motion, 5% of drivers talk on the phone, and 3% send text messages, but when they are stationary, 6.3% and 14.5% perform these activities, respectively. Bernstein (2015) also found that both the use of seatbelts and the presence of passengers are associated with reduced mobile phone usage—consistent with Wundersitz (2014).

In two studies intended to determine the prevalence of a wide array of secondary tasks in randomly selected urbanised locations in the UK, 14.4% to 16.8% of drivers occupy themselves with secondary tasks (Sullman, 2012; Sullman et al., 2015). In both studies, the most frequently observed task was talking to a passenger (ranging from 7.4%–8.8%), followed by mobile phone use (2.2%–3.4%) and smoking (1.9%–2.2%). Sullman et al. (2015) comprehensively examined mobile phone use and found that 1.7% of drivers use their phones hands-free, 1% talk on a handheld phone and 0.7% read/send text messages. Few drivers eat or drink (1.1%) and adjust in-vehicle controls (0.5%).

Kidd et al. (2016) probed into drivers' engagement in numerous secondary behaviours in the US and discovered that of the 16,556 drivers observed, almost one-quarter engage in some kind of secondary task. Although illegal, the handheld use of mobile phones is the most prevalent secondary task (observed amongst 11.5% of drivers). In detail, 5.1% of drivers hold their phones whilst driving, 4.2% talk on a handheld phone and 2.2% manipulate their phones. The next most prevalent tasks are eating/drinking (3.1%), talking to a passenger (2.7%) and smoking (1.6%). All the secondary tasks (except talking to a passenger) more likely occur when no passengers are present in a vehicle (Kidd et al., 2016).

As with many surveys, roadside observations typically identify older drivers (60 years and older) as less likely to perform secondary tasks than younger drivers (e.g. Young et al., 2010; Sullman et al., 2015; Kidd et al., 2016). Findings regarding gender differences are mixed, with a number of investigations failing to pinpoint variances in secondary task engagement between male and female drivers (e.g. Young et al., 2010; Sullman, 2012; Bernstein, 2015). A study found that female drivers exhibit higher engagement than do males (Kidd et al., 2016), whereas others indicated that engagement rates are higher amongst the latter (e.g. Taylor, 2004; Horberry et al., 2001).

Although roadside observations allow the observing of a large sample size in a relatively short period of time, it is associated with shortcomings related to the estimation of prevalence. First, data collection is typically performed only on low-speed road sections and during daytime. These constraints may lead to over- or underestimations of secondary task engagement rates (Young and Regan, 2009). Second, observations capture only a snapshot of whether a driver is engaged in secondary tasks; they cannot provide information on task duration and frequency (McEvoy and Stevenson, 2009). Third, this approach is confronted with difficulties in observing secondary behaviours which are not easily detected from outside a vehicle. The judgment of certain driver characteristics (e.g. age group) is also challenging when done from a roadside view (Sullman et al., 2015).

2.6.1.3 ND Studies

ND study is a research method that has been used to obtain prevalence data on different types of secondary behaviours. Using unobtrusive instruments installed in vehicles (video cameras and sensors), researchers can acquire exhaustive information on driver involvement in a wide range of secondary tasks during everyday driving conditions (SWOV, 2010). This information includes the duration and frequency of task performance, the driver-related factors associated with these tasks and the circumstances under which drivers perform them (a detailed description of the ND method is provided in Chapter 4). In the last two decades, several ND studies have been conducted in a number of countries to examine driver engagement in secondary tasks under natural driving environments.

In the US, Stutts et al. (2003a) examined the prevalence of engagement in secondary tasks by 70 drivers who were equally distributed across five age groups (ranging from 18 to 60 years) of males and females. Driving data of three hours per driver were coded and analysed. The findings revealed that drivers carry out secondary activities approximately 31% of the total amount of time that their vehicles are moving. Conversation with passengers is the most prevalent task, accounting for around 15% of driving time (observed amongst 77% of drivers); the remaining 16% is distributed across other tasks (Stutts et al., 2003a; 2005). These results are fairly consistent with those of Sayer et al. (2007), who reported that about one-third of reviewed five-second video clips reflect the performance of secondary tasks, of which conversation with passengers is the most frequently occurring, as evidenced by engagement amongst 15% of the sample.

In the same study, the analysis of coded driving time pointed to more than 90% of drivers reaching for objects and adjusting in-vehicle controls; these drivers spend almost 5% of their total driving time performing these tasks. A similar percentage of total driving time is devoted to eating/drinking activities (observed amongst 71% of drivers). Grooming and reading/writing activities are carried out by nearly half of the drivers, and mobile phones are used by one-third of them. The use of mobile phones account for 1.3% of total driving time. Interestingly, smoking-related activities are performed by only 7% of the drivers, with the activities accounting for 1.6% of total driving time (Stutts et al., 2003a).

Stutts et al. (2003a) also found that some secondary tasks, such as smoking, are less frequent but of much longer duration. Others, such as adjusting audio controls, are frequent but of short duration. A small age difference was found with respect to the willingness to engage in various secondary activities, but female drivers are significantly more likely than males to perform grooming tasks. The study further showed that the willingness to engage in secondary tasks distinctly varies depending on contextual variables, including whether a vehicle is moving or in a stationary condition, traffic level, road type and lighting conditions. The results of the contextual variable analysis should, however, be regarded as inconclusive given the lack of statistical testing and the relatively small sample sizes for several cells of contextual variables.

The 100-car ND study conducted by the Virginia Tech Transportation Institute (VTTI) is considered the first large-scale endeavour of this kind, in which 241 primary and secondary drivers were observed for more than a year. The data collection efforts yielded data on nearly two million vehicle miles, with nearly 43,000 hours of ND data (Dingus et al., 2006a; Neale et al., 2005). Despite the wealth of data generated on the prevalence of secondary task engagement, detailed findings have not been published. A central matter of concern has been crash risk estimation on the basis of various secondary behaviours. Only one prevalence result has been reported: that over one-half (54%) of the randomly selected 6-second baseline epochs (i.e. segments with no event crash, near-crash or incident present) reflected engagement in at least one form of secondary task (Klauer et al., 2006a).

More recently, the VTTI completed the Strategic Highway Research Program Phase-2 (SHRP2) ND project, which is the largest ND study undertaken to date. The study collected around 35 million vehicle miles of continuous ND data from more than 3500 drivers across a three-year period (Dingus et al., 2015; Campbell, 2012). Overall, 52% of selected baseline segments (6-second windows) involved engagement in at least one kind of secondary task (Dingus et al., 2016)—a finding that aligns with the results of the 100-car ND study (Klauer et al., 2006a). Dingus et al. (2016) further detailed secondary task engagement behaviours, explaining that the most prevalent secondary task is talking to a passenger (observed in 14.6% of baselines), followed by mobile phone use (6.4%), adjusting in-vehicle controls (3.5%), eating/drinking (3.1%) and grooming (1.7%). Reading/writing activities account for the lowest prevalence (0.1%).

Another recent initiative is the European Commission-funded UDRIVE project, which is regarded as the first large-scale ND research in Europe, with the endeavour involving the observation of around 280 drivers in six different countries over 18 months. The project derived voluminous data comprising more than 270,000 trips and 88,000 hours of ND data (Dotzauer et al., 2017) (detailed description in Chapter 5). On the whole, 52% of the car drivers' trips involve at least one secondary task, with these individuals spending 10.2% of their total driving time performing these activities (excluding passenger conversations). The most prominent tasks are mobile phone use (accounting for 4.2% of total driving time), smoking (2.9%), talking/singing to self (1.4%) and eating/drinking (0.6%). The study delineated mobile phone use, uncovering that drivers spend more time on hands-free phones (62% out of the total time spent on mobile phone use) than on handheld phones (38%) (Carsten et al., 2017).

According to Carsten et al. (2017), male drivers spend a slightly higher percentage of their driving time performing secondary tasks (11%) than that devoted by female drivers (9.5%). Some differences in activity patterns between male and female drivers were found: Females more willingly groom themselves and use mobile phones, whereas male drivers more likely perform smoking-associated activities. In terms of cross-country comparison, participants from Poland spend a significantly higher percentage of their driving time engaging in secondary tasks (around 20%) compared with participants from the UK and France (8%). The time allocation of the German sample accounts for the lowest percentage (2%) (Carsten et al., 2017).

Finally, in Australia, a consortium of universities, governments and industry partners (led by the Transport and Road Safety Research Centre at the University of New South Wales) conducted the first large-scale Australian ND study. The study accumulated roughly 2 million vehicle kilometres of data from 377 drivers over a period of four months (Regan et al., 2013; Williamson et al., 2015). Overall, the results revealed that drivers initiate one secondary task every 1.6 minute of driving or nine tasks per trip. Drivers occupy themselves with secondary activities for around 45% of their total driving time. The most frequently performed secondary task is adjusting in-vehicle controls, but because of the short and discrete nature of such an activity, engagement in it accounts for only 1.3% of driving time. Conversely, the tasks performed most of the time are passenger conversations (account for 25% of driving time), followed by mobile phone use (7%) and eating/drinking activities (4.2%) (Young et al., 2019).

As declared by Young et al. (2019), female drivers are significantly more willing to initiate secondary tasks per minute of driving than are male drivers, albeit no clear differences were identified between age groups. The authors also explained that drivers perform multiple secondary tasks simultaneously during around 20% of secondary task events. Passengers conversation is the activity that is typically carried out in conjunction with other task categories; 40% of all multiple task events encompass drivers talking with a passenger whilst also engaging in other secondary behaviours.

ND studies offer the opportunity to obtain precise and detailed real-world data on the prevalence levels and patterns of secondary task engagement over an extended time period. The ND approach does, however, generate a massive amount of data, which can be extremely expensive and require considerable logistical efforts to code and analyse (Carsten et al., 2013). Moreover, the highly diverse and uncontrolled situations of driving in these studies can influence data sensitivity and render data analysis a very complex undertaking. Another limitation of the ND method is that driver behaviour can be somewhat influenced by the fact that they are under observation, no matter how unobtrusive related instruments are (Young and Regan, 2009). Finally, this method cannot, at least not yet, reliably and validly record certain variables and secondary tasks that are difficult to observe, such as daydreaming and looking at external billboards. The advantages and disadvantages of ND studies are thoroughly discussed in Chapter 4.

2.6.1.4 Summary of prevalence findings derived from different methods

On the basis of the results discussed in previous sections, it is possible to gain a good estimation of the prevalence of various secondary tasks via different methods. These prevalence findings are summarised in Table 2-1. A noteworthy point is that some variations in findings occur amongst research methods because each approach is directed towards the examination of slightly different prevalence aspects. A case in point is roadside observation, which provides only a snapshot of whether a driver performs secondary tasks. In other words, roadside observations measure prevalence at a single point in time (i.e. point prevalence), thereby identifying a lower prevalence rate than those found in surveys and ND studies from which more comprehensive data (e.g. frequency, duration and percentage of driving time) are acquired owning to the adoption of a longer time frame.

Table 2-1. Prevalence estimates (% of drivers and driving time) of various secondary tasks, as derived via different prevalence methods

Type of secondary task	Surveys		Roadside observations	ND studies	
	Drivers	Driving time	Drivers	Drivers	Driving time
Overall	95.0		15.0–25.0		10.0–50.0
Mobile phone use (total)	40.0–80.0	15.0–35.0	2.0–11.0	35.0	1.5–7.0
• Hands-free phone use	35.0–80.0		1.5		2.5–3.5
• Handheld phone use	15.0–60.0		2.0–11.0		1.5–6.5
Interacting with passengers (including conversations)	40.0–80.0	40.0	3.0–9.0	75.0	15.0–25.0
Adjusting vehicle controls	65.0–95.0		0.5	100.0	1.3–3.5
Eating or drinking	50.0–80.0	10.0	1.0–3.0	70.0	1.0–5.0
Smoking		25.0	1.5–2.5	7.0	1.5–3.0
Personal grooming				45.0	0.3–2.0
Reading or writing	10.0–15.0			40.0	0.1–0.7
Reaching for objects				95.0	0.5–2.0
Talking/singing to self		30.0			1.0–2.0
External distraction	60.0	10.0		85.0	1.0–1.6

An important issue to highlight is that the prevalence findings obtained via a single method may vary considerably. In surveys, for example, the formulation of questions could exert a remarkable influence on responses. To illustrate, those that ask drivers whether they have ever been involved in secondary activities in general (e.g. Young and Lenné, 2010) are likely to yield higher prevalence estimates than those derived by surveys that inquire into what drivers do on daily and weekly bases (Lansdown, 2010). Furthermore, surveys that ask respondents about the secondary activities that they performed in their most recent trips (e.g. Huemer and Vollrath, 2011) tend to yield more precise findings than those concerned with what drivers generally do in a previous month (AAA, 2012). Such variations may also be attributed to (1) differences in the size and characteristics of samples, (2) the places where studies are conducted (drivers from different countries may behave differently), (3) the different periods at which data are collected (the occurrence of some secondary tasks may change over time) and (4) the different secondary task coding manuals adopted in each study.

Notwithstanding the broad variations in prevalence findings (Table 2-1), a constant pattern is the decision of many drivers to engage in secondary behaviours whilst driving, indicating that distractions are a common aspect of everyday driving despite the low representation of some secondary task categories in total driving time. With respect to driver characteristics, the results regarding the effect of gender on the prevalence of secondary task engagement are mixed, but the findings on older drivers (60 years and older) consistently reflected that these individuals are less likely than younger drivers to perform secondary tasks. Several studies also suggested that drivers are more likely to perform secondary tasks when they travel in urban areas (e.g. McEvoy et al., 2006a; Sullman and Baas, 2004), when they have few years of driving experience (e.g. McEvoy et al., 2007) and when they have high annual mileage rates (e.g. Gras et al., 2007; Pöysti et al., 2005).

Collectively, surveys, roadside observations and ND studies have produced substantial data regarding the prevalence rates and patterns of secondary task engagement, yet a problem is that many of these studies revolved around drivers' use of mobile phones. A crucial component of futuristic studies is the collection of prevalence data on a wide range of secondary tasks to estimate the crash risk associated with involvement in these activities and guide the development of effective countermeasures. A point worth emphasising is that prevalence findings have a short shelf-life given the increasing ownership of electronic devices (e.g. mobile phones) and the continuous proliferation of in-vehicle technologies.

Even as the aforementioned efforts have advanced research on the prevalence of secondary task engagement, the topic remains in need of more exhaustive investigations. One of the fundamental issues as regards everyday driving behaviours is how drivers behave at complex locations within roadway networks, such as intersections. The willingness of drivers to occupy their time with secondary tasks at intersections and the potential consequences of such behaviour remain unclear. Correspondingly, this research was directed primarily towards this area of knowledge.

2.6.2 Self-regulation behaviour

An essential point related to the effects of driver distraction on driving performance and safety is whether and how drivers adapt or regulate their behaviours to moderate the risk associated with the demand imposed by secondary tasks. Surprisingly, research that directly addresses this issue is lacking, with explorations predominantly revolving around measuring the influence of engagement in secondary tasks via associated performance metrics. A fundamental issue to be acknowledged, however, is that not all effects on driving performance aspects are indications of poorer safety. Research has proposed that drivers are capable, to some extent, of effectively regulating their secondary task engagement behaviours in accordance with changes in demand situations for the purpose of adequately maintaining safe driving (Haigney et al., 2000; Regan et al., 2009; Lee and Strayer, 2004; Young et al., 2007).

In the road safety literature, the term ‘behavioural adaptation’ has been extensively used to describe of unintended or unexpected changes in behaviour that result from a change in the transport system. In this thesis, such a change refers to secondary task engagement whilst driving, and the behavioural adaptation that ensues is viewed as a response to driver distraction. This distraction-related adaptation is usually called ‘self-regulation’ or ‘risk compensatory behaviour’ in the driver distraction literature. The latter has met with considerable criticism (see Evans, 1991) because ‘risk compensation’ generates an impression that the processes/mechanisms associated with behavioural change result in a safer net outcome, which is not necessarily true in every case. For this reason (and to prevent loss of generality), 'self-regulation' is the expression adopted in this thesis.

As explained by Charlton et al. (2006), self-regulation means the driving-related behavioural adjustments that drivers implement to adequately match changing sensory, cognitive and motor capacities. Self-regulation can occur when drivers are adapting their behaviour in anticipation of a distracting occurrence (i.e. preparatory approach) or in response to being distracted (i.e. reactive approach) (Young and Regan, 2013). Both preparatory and reactive self-regulatory behaviours can take place at the three levels of driving task control described by Michon (1985): strategic (highest level of control), tactical (moderate control) and operational (lowest level of control) (Lee et al., 2009a). Each of these levels reflects a different kind of driving skill that is operated over a certain timescale (Table 2-2).

Table 2-2. Breakdown of multilevel driving control process (adapted from Lee et al., 2009a)

Level of control	Description	Timescale
Strategic level	General trip planning tasks, including mode choice and route selection	Weeks to minutes
Tactical level	Implementing manoeuvres to achieve short-term goals, such as overtaking, lane changing and speed choice	Minutes to seconds
Operational level	Automatic action patterns: Lateral and longitudinal control of a vehicle (e.g. braking and steering)	Seconds to milliseconds

Research has shown that drivers self-regulate their engagement in secondary tasks at all the above-mentioned control levels (e.g. Oviedo-Trespalacios et al., 2017a; Christoph et al., 2019; Alm and Nilsson, 1995). At the strategic level, for example, self-regulation can be observed when drivers refrain from involving themselves in distracting activities (or a specific kind of activities) whilst driving (i.e. controlling exposure to distracting situations by, for instance, switching off a mobile phone or keeping it out of reach). This is a manifestation of what counts as preparatory self-regulation. At the tactical level, drivers can choose when and where to perform distracting activities (e.g. withholding involvement in secondary tasks under specific environmental conditions such as a traffic-free environment). Drivers may also prioritise the driving task by breaking down a distracting activity into multiple parts (i.e. activity timing). At the operational level, drivers can manage the accompanying risk/load arising from distracting activities (i.e. resource allocation) through operational means, such as increasing headway distance and reducing speed (Young and Regan, 2013; Lee et al., 2008). The latter is an example of what might be called reactive self-regulation.

Across the three levels of self-regulation (strategic, tactical and operational), a kind of interaction can be observed between drivers' decisions and the activities that they choose to perform. This interaction typically occurs in a feedforward manner (top–down pattern), wherein decisions at the strategic level (highest) affect tactical choices (moderate), which in turn, affect operational activities (lowest). In some unexpected driving situations, however, the interaction may occur in a feedback manner (bottom–up constitution), in which operational and tactical activities influence strategic decisions (Lee et al., 2009a).

2.6.2.1 Strategic self-regulation

A recent study conducted in Australia revealed that at the strategic level, some drivers never use their mobile phones whilst driving. This strategic decision figures prominently in the avoidance of complex mobile phone sub-tasks, such as texting and browsing (Oviedo-Trespalacios et al., 2017b). Other studies found that older drivers are less willing than younger drivers to engage in distracting activities (Sullman, 2012; Stutts et al., 2003a), particularly mobile phone use, whilst driving (Lamble et al., 2002; Alm and Nilsson, 1995). The latter may be attributed to the generally low level of technology use by the older population (Charlton et al., 2013) or may originate from the predilection of the older to strategically self-regulate as a means of minimising their exposure to risk given their reduced abilities (e.g. visual and information processing) (Eby et al., 1998).

2.6.2.2 Tactical self-regulation

In a survey, Young and Lenné (2010) found that at the tactical level, drivers report being unwilling to perform distracting activities in heavy traffic situations, when approaching an intersection, in bad weather conditions and in roadworks and school areas. Similarly, Sayer (2005) discovered that drivers infrequently occupy themselves with tasks that divert attention when braking, travelling on curved roads, driving on wet road surfaces and driving at night. A Swedish ND study revealed that drivers are unwilling to perform visual-manual (VM) mobile phone activities in the presence of a passenger, during sharp turns and at high speeds (Tivesten and Dozza, 2015). The study also reported that drivers adapt the timing of secondary task engagement by holding off activities until the completion of lane-changing and overtaking manoeuvres. In the same context, Christoph et al. (2019) found that drivers are less willing to initiate VM mobile phone tasks when driving in rural areas compared with driving in urban areas and motorways. Some other ND studies indicated that drivers more frequently execute secondary tasks when they are stationary than when they are moving (Funkhouser and Sayer, 2012; Stutts et al., 2003a; Metz et al., 2014; Charlton et al., 2013).

Although the above-mentioned findings demonstrate a degree of positive self-regulatory behaviour, some other studies found inconclusive results relating to this self-disciplinary tendency. For example, a recent simulator study found that drivers delayed the initiation of secondary tasks during increased workload but that this delay was inadequate to mitigate the effects of the workload. That is, the drivers were willing to perform secondary activities even when workload conditions had not reverted to the baseline condition (Teh et al., 2018). In addition, an ND study performed in the European context illustrated that drivers regulate their engagement in secondary activities in accordance with task duration but not with task complexity. Drivers were found to perform all secondary task complexity levels independently of the driving task complexity (Carsten et al., 2017).

2.6.2.3 Operational self-regulation

Research has found that at the operational level, drivers try to moderate the risk that accompanies secondary task engagement through a range of operational strategies, such as increasing headway distance (Strayer and Drew, 2004; Jamson et al., 2004), reducing speed (Oviedo-Trespalacios et al., 2017a; Burns et al., 2002; Rakauskas et al., 2004) and accepting a decline in performing certain non-critical driving tasks, including checking mirrors (both side and rear-view mirrors) and in-vehicle instruments (Harbluk et al., 2007; Brookhuis et al., 1991). These findings suggest a degree of positive self-regulatory behaviour, but controversy has arisen as to whether these operational outcomes are a product of drivers' initiative to increase their safety margins (i.e. compensatory behaviour) or simply a demonstration of diminished driving performance owing to the impaired attention allocated to the driving task. Each of these positions poses different implications for road safety.

2.6.2.4 What factors influence self-regulatory behaviour?

Whilst exercising self-regulation seems a positive behaviour, it is not on every occasion sufficient to offset the risk arising from a secondary task, or it is not always possible (Young and Regan, 2013). In certain situations, self-regulation can break down and considerably degrade driving performance and safety (Young et al., 2007). In their model of the factors that moderate the impact of distraction, Young et al. (2009) proposed that self-regulation (at the three levels of control) is the product of changes in driving task demand, secondary task demand and driver characteristics. These determinants influence self-regulation behaviour, which in like manner, can affect the degree to which distraction affects driving performance and safety. What has yet to be clarified, with regard to the model, is the mechanism through which this moderation occurs. Expanding our comprehension of the mechanism by which drivers self-regulate their involvement in secondary tasks is important in the development of effective countermeasures (Young et al., 2009).

Young and Regan (2013) highlighted some conditions under which drivers may face difficulties in properly self-regulating their driving in response to a distracting activity. These conditions emerge when secondary tasks are (1) non-adjustable (i.e. when a task cannot be adjusted in a way that reduces the demand that it imposes), (2) unpredictable (i.e. when task onset is unexpected), (3) uninterruptible (i.e. when a task cannot be postponed or split into multiple parts) and (4) non-ignorable (i.e. when a task is so demanding or compelling that it is difficult to disengage from it). Under these circumstances, drivers find it difficult (or impossible) to self-regulate their engagement behaviour and consequently become increasingly vulnerable to the impacts of distraction.

Another potential deterrent to self-regulation is a driver's lack of awareness concerning the consequences of secondary task engagement on driving performance and safety. Several studies reported that drivers underestimate, or are unaware of, the consequences associated with secondary task engagement (e.g. Horrey et al., 2008). This lack of awareness can influence the capability of drivers to actively adjust their behaviour to minimise any risk. Given this outcome, He et al. (2011) raised the issue of whether some or all self-regulatory behaviours (particularly those executed at the operational level) are intentional acts of drivers or unintentional tendencies by-product of dual-task interference.

2.6.2.5 Summary of self-regulation findings

Several studies have been conducted to elucidate whether and how drivers self-regulate secondary task engagement. Some found inconclusive results relating to self-regulatory tendencies (e.g. Teh et al., 2018), but the overall consensus has been that involvement in secondary tasks is not random, at least to a certain extent, with drivers implementing a variety of strategies or tactics in deciding on whether, where and when to engage (e.g. Tivesten and Dozza, 2015; Young and Regan, 2013; Young and Lenné, 2010). This observation aligns with a previously proffered explanation, wherein drivers are regarded as active receivers and processors of distraction-related information. They are seen as capable of effectively managing their behaviours in accordance with changes in demand situations, thereby mitigating the consequences of distraction on driving performance and safety (Fitch et al., 2014; Young et al., 2009; Lee and Strayer, 2004). Nevertheless, despite insights that point to the positive application of self-regulation in a range of contexts, a deficiency threatens the validity of currently published findings; that is, studies that focus on such behaviour at intersections and areas near these intersections are lacking. Additionally, few explorations have concentrated particularly on the self-regulation of secondary tasks other than mobile phone use. Correspondingly, the present research was directed primarily to filling these gaps.

Chapter Three

Background on Intersection Research

There is a wealth of intersection-related literature, but this research enquired principally into the topics that are most relevant to its aims to build a sufficient knowledge foundation regarding the issue of interest. The chapter defines what an intersection is before describing statistics on crashes occurring at such roadways, along with clarifying types of crashes and factors that contribute to these accidents. Issues that surround the determination of the physical and functional areas of intersections are then addressed. Finally, studies associated with general driver behaviours at intersections are discussed, with a particular focus on the limited research that has dealt with driver distraction at intersections.

3.1 What is an intersection?

An intersection refers to an at-grade junction or a general area of a roadway where multiple roads intersect at the same grade, including the roadway and the roadside facilities located within the area (e.g. auxiliary lanes, islands, medians and sidewalks) (Stollof, 2008). Intersections are thus one of the unique roadway elements where conflicting vehicle streams (and sometimes other road users, including pedestrians and cyclists) share the same space (American Association of State Highway and Transportation Officials [AASHTO], 2011). Intersections can be three-way (T- or Y-intersections) or four-way (X-intersections, sometimes known as crossroads) or even five or more ways (Cottrell and Mu, 2005). They can be both un-signalised and signal-controlled. Intersections include situations where a driver has priority and does not need to stop, situations drivers have no priority, and roundabouts. Most types of intersections were considered in this thesis.

Driving at intersections imposes additional demands on drivers as they are compelled to properly detect, identify and assess a wide array of visual stimuli, including several diverse moving objects (e.g. other vehicles and pedestrians) (Tawari et al., 2016). During such driving, drivers are also required to make concurrent or converging decisions, including choosing an appropriate lane, manoeuvring to reach a suitable position, selecting a safe gap, interacting with changes in traffic signals and performing deceleration/acceleration operations as needed (Werneke and Vollrath, 2010). All these closely spaced tasks render intersections one of the most demanding/complex locations within a road network. This complexity does not even encompass the possibility that some drivers engage in potentially distracting activities (secondary tasks) as they pass through an intersection—a condition that could compete increasingly for the limited cognitive resources of drivers and thereby leave them more vulnerable to committing driving errors.

3.2 Statistics on intersection crashes

Intersections are a major part of a road system and are relevant to nearly all trips that all drivers make. Intersections also feature heavily in crash statistics, thus prompting countries to accord high priority to improving intersection safety in their traffic safety strategies (Aoude et al., 2012). According to Simon et al. (2014), crashes in intersections represent approximately 45% of the total number of injury crashes in Europe. Their analysis was based on the CARE database, which is the European centralised database on road crashes that result in injuries or deaths. This considerable occurrence of intersection-related crashes is equally evident in Italy, Denmark, the Netherlands, the Czech Republic and the UK, with percentages varying from 47% to 59% of crashes that result in injuries. Amongst these nations, the UK registered the highest proportion (59%) of the aforementioned crashes (Simon et al., 2014).

In Germany, 50% of injury crashes in urban areas occur at intersections (Streubel et al., 2015). In the US, 45% of traffic injuries and 25% of traffic fatalities are attributed to intersection-related crashes (NHTSA, 2009). In Australia, such crashes represent 47% of the total number of car crashes and 48% of the overall pedestrian crashes in the country (Young et al., 2011). These differences in percentage amongst countries can be explained by several factors, including the intrinsic definition of criteria used to categorise a crash as intersection related. In the UK, for instance, a crash is classified as an intersection-related crash when it occurs within 20 metres of an intersection (Lloyd et al., 2015). This definition indicates that crashes occurring near intersections are also counted as intersection crashes.

The percentages in the UK context are consistent with those derived via a simple analysis (performed in this thesis) of the injury police-reported crash data provided by the DfT for the period 2010 to 2019. The examination of the data revealed that in 2019, around 60% of the total number of injury crashes and 38% of the overall number of fatal crashes occurred within intersections (Figures 3-1 and 3-2). These percentages also remained steady from 2010 to 2019.

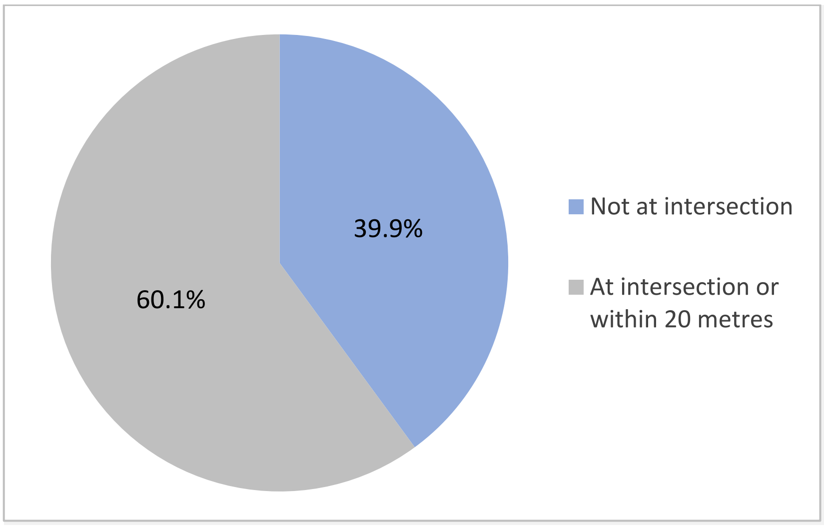

Figure 3-1. Injury crashes in the UK and their relationship with intersections (2019)

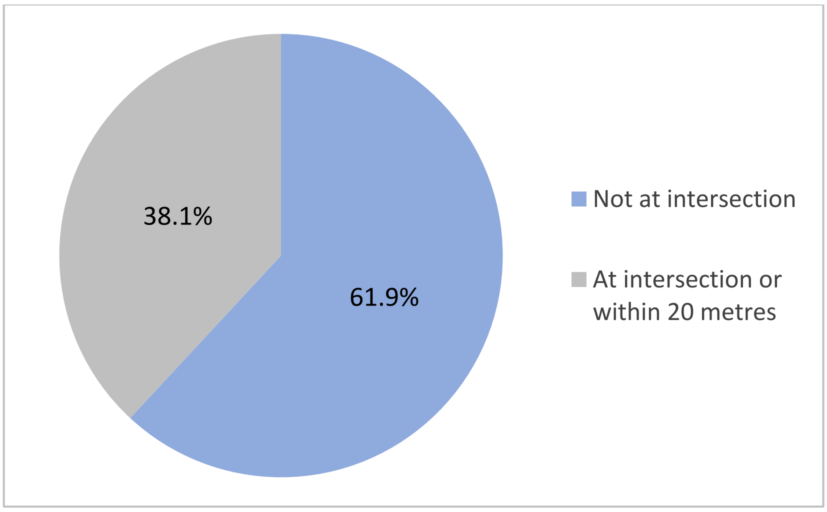

Figure 3-2. Fatal crashes in the UK and their relationship with intersections (2019)

The above-mentioned statistical data verified that intersections are one of the most common locations for crashes in a road system (with 45% to 60% of injury crashes occurring on these sites) and reflected the challenges that confront road safety in such locations. This high crash rate is commonly ascribed to the highly cognitively complex nature of intersection driving, imposing substantial visual and mental demands that may be underestimated by drivers (Stinchcombe and Gagnon, 2009). Correspondingly, understanding driver behaviour at intersections is essential to the development of countermeasures that have the potential to reduce crashes and injuries at these complicated locations (Young et al., 2011).

3.3 Intersection crashes: Types and contributory factors

With regard to specific types of crashes that occur at intersections, several studies found that the primary ones are right-angle crashes, left-turn-across-path crashes (opposite directions in the UK), rear-end crashes and crashes involving pedestrians (McLean et al., 2010; Taylor et al., 1996; Hall, 1986; Kennedy and Sexton, 2010; Anowar et al., 2008; Ogden et al., 1994; Aust et al., 2012). The findings of these studies slightly differ only in terms of percentages and sequences. Such a variance can be attributed to the intersection features covered in each study, including location (urban or rural areas), control measure (signalised or unsignalised) and layout (T-intersections, X-intersections or roundabouts). Note as well that different countries classify crash types in various ways.

According to Mayhew et al. (2006) and the Ohio Strategic Highway Safety Plan (2013), the factors that most significantly contribute to injury crashes at intersections are the failure to look properly, inaccurate gap acceptance and the failure to either stop or yield the right of way. Similarly, the data issued by the DfT (2019) showed that the leading contributor to intersection crashes is the failure to look properly, but the department also identified the failure to judge another person's speed or path, poor turning/manoeuvring and careless or reckless driving as causes. Bougler et al. (2008) pinpointed the inability of drivers to correctly evaluate and observe the risk implicit in intersections as the principal determinant of crashes at these locations, whereas Anowar et al. (2008) and Al-Ghamdi (2003) revealed excess speed and the failure to yield to be the most common causes of crashes at urban intersections.

Despite the insights provided by the above-mentioned studies, however, they did not discuss distraction as a leading contributory factor in crashes at intersections. A possibility is that some of the contributory factors discussed in previous research may have stemmed from distracted behaviours or inattention. This issue was comprehensively discussed by Brown (2005) in his study on looked-but-failed-to-see crashes. All the aforementioned studies were also based on police crash data analysis, which is regarded as susceptible to underestimation given the limitations related to corresponding data collection approaches (Stutts et al., 2001; NHTSA, 2008). This type of examination may lead to a disregard of driver distraction as a factor that accounts for a critical percentage of intersection-related crashes.

The factors that contribute to intersection crashes have also been examined via in-depth crash investigations (e.g. Aust et al., 2012). In adopting this approach, Aust et al. (2012) aimed to identify the factors that contribute to fatal intersection crashes in Norway. For each driver, the contributory factors were first coded and then sorted on the basis of a combination of conflict types and whether a driver was turning or going straight. Drivers who performed turning manoeuvres were commonly grouped under the category ‘timing: too early’, indicating an early turn and failure to yield the right of way to another vehicle. The drivers also encountered, to a large extent, two kinds of perception-related difficulties. One is that they failed to see a conflict vehicle at the time at which the decision to make a turn was needed because of a physical obstruction to view. The other is that the drivers were inattentive to the situation because of a distracting activity. In contrast to these drivers, those going straight experienced much fewer perception-related difficulties but largely expected turning drivers to yield (Aust et al., 2012). The insights provided by the authors are valuable, but the analysis was limited to motor vehicle crashes and did not cover those involving pedestrians and cyclists.

The ND study approach has been employed also to explore the patterns that underlie the factors contributing to crashes at intersections. Engström et al. (2013b), for instance, used this method to delve into the role of driver inattention in rear-end crashes and crossing-path crashes that occur at intersections. Notably, the authors adopted an alternative approach to traditional ND studies. That is, data were not continuously collected and were recorded only around safety-critical events; the recording was based on specific kinematic triggers. The analysis focused on crossing-path crashes, wherein the instrumented vehicle planned to go straight through an intersection, and rear-end crashes, in which the instrumented vehicle was positioned in the back. The findings revealed that inattention was associated with 38% of all the crossing-path crashes. Driver distraction represented almost half of these inattention cases and thus represented 19% of all crossing-path crashes. Some other key contributors to crossing-path crashes were visual occlusion, the selection of an insufficient safety margin and the failure to yield. The findings also showed that inattention was the dominant contributor to 74% of all the rear-end crashes caused by at least one form of inattention. Driver distraction represented over half of these inattention cases and was associated with 43% of all the rear-end crashes.

Moreover, an insufficient safety margin, represented by the close following to a lead vehicle, contributed to 26% of all the rear-end crashes.

In the in-depth crash investigation performed by Aust et al. (2012) and the ND study carried out by Engström et al. (2013b), driver distraction was visibly a major contributor to intersection crashes. These studies provided a clearer picture of events that precede crashes than that achieved by analyses based on police crash data. Therefore, they seemed to enable a better examination of crash causation.

3.4 Physical and functional areas of intersections

An intersection can be defined on the basis of both its physical and functional areas (see Figure 3-3). The physical area of an intersection is the fixed area which represents the space bounded by the corners of the intersection, whereas the functional area refers to the distance-based influence zone of an intersection, extending both upstream and downstream beyond the boundaries of the physical intersection area. The functional area may contain auxiliary lanes and related channelisation (Rice, 2010).

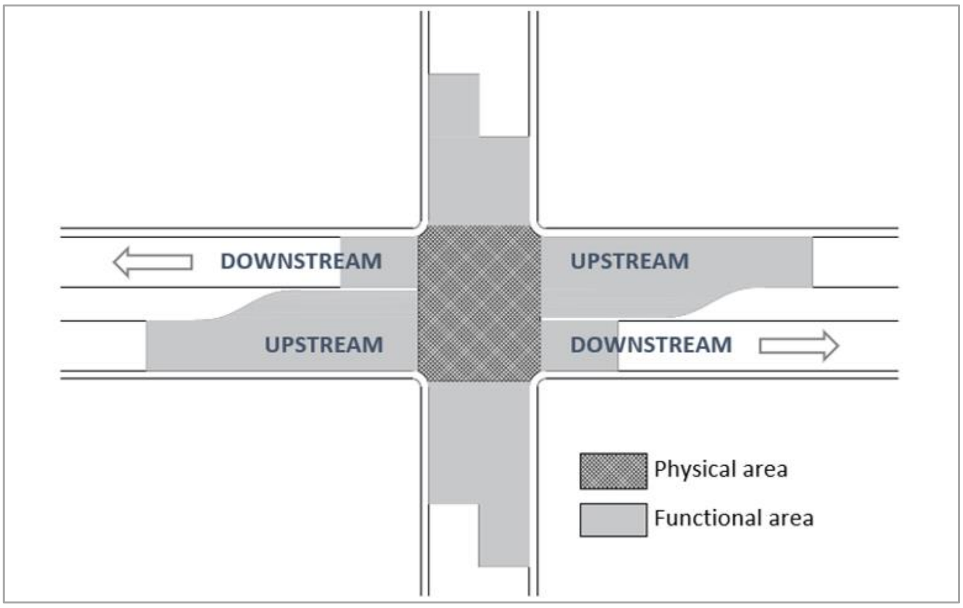

Figure 3-3. Physical and functional areas of an intersection (right-hand traffic representation) (adapted from Rice, 2010)

Stover (1996) stated that all intersections, regardless of type, have upstream and downstream functional areas. In the upstream functional phase, drivers observe and react to upcoming events, such as the presence of a yield sign or a change in traffic signal. Drivers can also decelerate and manoeuvre into turning lanes and storage queues. In the downstream functional phase, drivers accelerate, encounter turning vehicles from other approaches and may prepare to decelerate again as a response to farther downstream situations (Cottrell and Mu, 2005). The guidelines for defining the downstream functional area are less sufficiently developed within the literature than those for the upstream functional area.

For operational and safety reasons, ideally, both upstream and downstream functional areas should be protected from driveway access (Rice, 2010; AASHTO, 2011). In other words, driveways should not be located within the functional area of an intersection (upstream and downstream) to minimise the number of decisions that drivers are compelled to undertake whilst traveling through intersections. This preventive measure improves the safety level in the vicinity of intersections.

In terms of crash classification, Cottrell and Mu (2005) stated that any crash that occurs within the limits of an intersection’s physical area or at the upstream or downstream functional phases is categorised as an intersection-related crash. However, many standardisation organisations, including the AASHTO, do not present clear guidelines for the physical length that the functional area spans (Stover, 1996). The absence of clear definitions of such an area has presented several problems in the comparison of different research findings. These problems are manifested owing to the dissimilar ways by which crashes are classified (as intersection-related and non-intersection crashes) in different studies or countries. In the UK, for example, a crash is categorised as an intersection-related crash if it occurs within 20 meters of an intersection (Lloyd et al., 2015), but in the US, the criteria for classification vary between states and cover distances of 15, 30, 45, 60, 75 and 150 metres (Stollof, 2008; Cottrell and Mu, 2005).

For the purpose of the current thesis, a fundamental requirement was to specify clear distance-based boundaries for the upstream and downstream functional areas of intersections. As defined by Stover (1996) and Rice (2010), the functional area of an intersection comprises the distance travelled during the perception–reaction time (decision distance) and the distance travelled whilst braking (deceleration distance), plus any required vehicle storage length (queue length). Both decision and deceleration distances depend considerably on the prevailing travel speed or speed limit imposed over a given intersection. The length of the functional area therefore varies in accordance with speed changes; a higher speed generates longer decision and deceleration distances, thus requiring a longer functional area. The current thesis followed Stover (1996) approach in defining the physical length values of the upstream and downstream functional phases. This adoption is explained in further detail in the general methodology chapter (see Section 5.5).

3.5 General driver behaviours at intersections

Driver errors occur at all segments of a roadway system, but such mistakes can more prominently take place at intersections, where drivers are compelled to make multiple decisions under time and speed constrains. Drivers commit a considerably higher number of errors at intersections than at non-intersection segments of a network and commit fewer errors at signalised intersections than at unsignalised ones. Some of the most common intersection-related errors identified are failing to properly signal a turn, travelling excessively fast for a turn and braking late and hard (Young et al., 2011).

A number of observational studies have been undertaken to model drivers’ use of the turn signal at intersections as a function of several driver-related and situational factors, particularly those associated with the complexity of the driving environment at intersections (e.g. turning direction and road type). An example of such studies are those carried out by Sullivan et al. (2015) in the US and Faw (2013) in Canada. The overall findings of both studies showed that nearly one-quarter of the turns at intersections were made without signalling. The studies also reported that drivers perform signalling more often when turning left versus turning right (opposite directions in the UK), when a forward vehicle is present than in situations wherein no vehicle is ahead of them and when the approach to an intersection is a major road as opposed to a local or minor road. Driver-related factors, including age and gender, were found to have no significant influence on the use of the turn signal (Sullivan et al., 2015), but the presence of a dedicated turning lane reduced the propensity of drivers to use such a signal (Faw, 2013). Notwithstanding these valuable findings, the model formulation in these studies paid no heed to the potential impact of secondary task engagement by drivers—an issue that gives rise to the need for increased investigation.

Other studies that focused on driver behaviour at intersections were those conducted by Oneyear et al. (2016) in the US and Streubel et al. (2015) in Germany. These studies were aimed at developing a model of braking behaviour at the approach to unsignalised rural intersections (Oneyear et al., 2016) and urbanised intersections (Streubel et al., 2015). In the modelling, the authors used the distance before an intersection at which drivers initiate braking as the dependent variable. The results showed that young drivers (under 25 years), right turners (left turners in the UK) and drivers approaching a stop sign initiate braking later than do older drivers, left turners (right turners in the UK) and drivers approaching a yield sign, respectively (Streubel et al., 2015; Oneyear et al., 2016). The presence of countermeasures, such as overhead flashing and on-road surface marks that alert drivers to the presence of an intersection ahead, increases the distance at which drivers commence braking (Oneyear et al., 2016). Moreover, late brake reactions occur more often in T-intersections than in X-intersections, which is an understandable result given the highly complex characteristics of the latter (Streubel et al., 2015).

A number of statistical models have also been adopted to model driving behaviour at intersections in relation to many factors, including a driver's personal characteristics, a roadway's geometric features and a vehicle's speed (e.g. Aoude et al., 2012; Miller et al., 2011; Zhang et al., 2009). Similar to other studies that were earlier identified as deficient, however, these investigations disregarded distraction in model formulation. Engagement in secondary tasks can influence different kinds of intersection-related errors and behaviours, including turn signal use, braking, gap acceptance and speeding—an issue that is worth more comprehensive exploration.

3.6 Studies regarding driver distraction at intersections

Few studies have been devoted to elucidating the prevalence of secondary task engagement at intersections and its consequences on daily driving. Three of such explorations (the ones that are most strongly related to the idea behind the current thesis) were reviewed, and their limitations were specified. The first study was a roadside observational research conducted by Huisingh et al. (2015), whereas the second and third studies were ND studies carried out by Charlton et al. (2013) and Xiong et al. (2015), respectively.

3.6.1 Huisingh et al. (2015)

Huisingh et al. (2015) used a roadside observational technique to estimate the prevalence of secondary task engagement amongst passenger vehicle drivers at 11 selected intersections in Alabama in the US. Trained observers observed a random sample of 3625 passing-by drivers and recorded their secondary task engagement behaviours, their characteristics (e.g. gender and age group) and some associated contextual variables, such as traffic flow and vehicle speed. In general, the study revealed that almost one-third of the observed drivers were involved in at least one kind of distracting activity whilst driving. The most frequently observed secondary tasks were interacting with passengers and mobile phone talking, followed by external vehicle distraction and mobile phone dialling/texting. The female drivers more frequently used their mobile phones than did the males, and the young drivers (younger than 30 years) were engaged in secondary tasks more frequently than were the older age groups. The drivers were also more likely to involve themselves in secondary tasks when their vehicles were stationary than when they were moving.

As with any roadside observational study, the strengths of Huisingh et al. (2015) work were the observation of many types of secondary activities (from a reasonably large sample of drivers) and the documentation of occurrences in the real world. However, a number of limitations are worth noting. First, the findings reflected daytime behaviours only, as the observations were scheduled in the mornings and early afternoons. Second, each observation was carried out by a single observer, thereby precluding the testing of data reliability. Third, the observations were constrained by the availability of time and the accuracy of discrimination by the observer. This potentially caused miscategorisation bias because some secondary tasks are difficult to detect given the short observation window. Some illegal secondary tasks may also have been missed, especially amongst drivers who tried to disguise their actions (e.g. Some drivers may have kept their phones down low, below the level of the car window). These matters may have obscured observations of the prevalence of certain secondary activities, especially those of short durations and most illegal ones. Additionally, the observations were performed at intersection approaches only (upstream functional areas), so neither intersection physical areas nor downstream functional areas were included within the observation window. Lastly, no distraction-related comparison of various intersection-related variables, such as intersection control and layout, was conducted.

3.6.2 Charlton et al. (2013)

Charlton et al. (2013) looked into the willingness of older drivers (65 years and older) to engage in secondary tasks at intersections in Australia. In the study, 10 drivers were asked to drive an instrumented vehicle on their regular trips for two weeks, and 200 intersection manoeuvres (20 manoeuvres per driver) were randomly selected for the in-depth analysis. Approximately 30% of the examined intersection manoeuvres involved some kind of distracting behaviours, amongst which the most frequently occurring were grooming, talking/singing and interacting with a vehicle’s control panel. Some other secondary tasks, such as reading, using a mobile phone and reaching for an object, were performed only whilst a vehicle was stationary at intersections.

The authors developed a logistic generalised estimating equation model to determine the effects of driver-related and contextual factors on the percentage of intersection manoeuvring time that is occupied by engagement in secondary tasks. The results showed that the older drivers were significantly more willing to perform secondary activities in a stationary vehicle than in a moving one (four times higher), in fully controlled (signalised) intersections than in uncontrolled (three times higher) ones and under moderate to high traffic density than in low traffic density (two times higher). Gender, turning direction and road type were non-significantly associated with secondary task engagement. These findings suggest that drivers engage selectively in secondary tasks in accordance with driving and roadway conditions (at least to a certain extent) and that older drivers self-regulate by limiting their secondary task engagement under more complicated driving conditions.

A number of limitations in Charlton et al.’s (2013) study are worth discussing. To begin with, the drivers drove an instrumented vehicle instead of their own vehicles, therefore presenting a potential impact of the lack of vehicle familiarity on driving behaviour. Additionally, the sample size was small (10 drivers), and only 20 intersection manoeuvres per driver were analysed. Care should hence be taken in generalising the study's findings to the wider population of older drivers. The exploration into the effects of the drivers' personal characteristics on their willingness to engage in secondary tasks would have benefitted from a larger sample. Finally, the study centred only on an older sample and did not compare these drivers with younger driver groups. Studies that involve a broader age range are needed to comprehensively scrutinise changes across age spans. Moreover, expanding the dataset variables (e.g. the presence of passengers, intersection layout) would have reinforced the explanation of secondary task engagement at intersections.

3.6.3 Xiong et al. (2015)

Xiong et al. (2015) inquired into the effects of mobile phone use on speeding behaviours at signalised intersections in Michigan, USA. Driving speed whilst using mobile phones at intersections, for both conversation and VM tasks, was compared with driving speed at the baseline (normal conditions at intersections). A total of 108 drivers of different ages were asked to drive an instrumented vehicle for six weeks. Overall, the prevalence of mobile phone conversation at intersections was significantly higher than that of VM task engagement, suggesting that drivers avoid engaging in exceedingly challenging distracting activities under high-driving-demand conditions. The drivers drove more slowly when using their mobile phones compared with the baseline condition for both conversation and VM task engagement. A higher decrement in speed occurred with engagement in VM tasks than with participation in conversation. A deeper scrutiny of the conversation tasks indicated that the drivers tended to drive at a slower speed during night-time driving than during daytime driving and in dense traffic than in low-traffic conditions. With respect to VM task involvement, the maximum speed was significantly lower than the baseline in low-traffic situations but slightly higher than the baseline in dense traffic.

The results suggest that to minimise risk, drivers self-regulate on the basis of the demand imposed by a secondary task and current driving situations. These can provide insight into the development of driver distraction guidelines, but such value is moderated by the limitations of the work. The drivers drove an instrumented vehicle rather than their own vehicles—a condition that may have affected their behaviours. The study was also limited to secondary tasks related to mobile phones, light vehicle drivers, signalised intersections and effects on speeding behaviour. No comparison of the drivers' personal characteristics was made. Taken together, these deficiencies highlight the need for a cautious generalisation of the findings. More comprehensive studies are required to illuminate various other types of secondary tasks, different types of intersection control measures and layouts and varying effects on other driving behaviours at intersections (e.g. turn signal use, braking and headway selection behaviours).

3.7 Summary

The aim of this chapter was to cast as much light as possible on the intersection literature relevant to the current thesis to elevate the understanding of traffic safety challenges and driver behaviours at intersections. The main points are summarised as follows:

- An intersection refers to the general area where two or more roads intersect at grade and is defined by both its physical and functional areas.
- Intersections are an integral part of the road system that also feature prominently in crash statistics.
- Many studies focused on general driving behaviours at intersections, but they disregarded driver distraction in model formulation.
- There is a lack of studies that revolve around the prevalence of secondary task engagement and the self-regulation of such behaviour at intersections.

- Understanding driver behaviour at intersections is essential to the development of countermeasures that can reduce crashes and enhance safety levels at these highly demanding locations.

Chapter Four

Tools and Research Questions

This chapter provides a detailed description of the ND approach, which was the method adopted in the current thesis to address the research questions. It then outlines the overall goals and research questions pursued in the thesis.

4.1 The ND approach

ND study is a relatively new research observational method that was developed following the advent of technology that enables the collection, storing, management and analysis of massive volumes of data with increasingly smaller instruments (SWOV, 2010). The approach is designed to provide insight into the everyday driver behaviours of individuals through the continuous recording of information on vehicle movements (e.g. speed or acceleration), driver behaviours (e.g. engagement in secondary tasks) and external conditions (e.g. weather, road and traffic characteristics); recording is to be carried out with advanced instruments attached to a vehicle (van Schagen et al., 2011). These instruments typically include a host of sensors and various cameras. The cameras often provide over-the-shoulder views of a driver's hands, views of a driver's face and views of the road on which a vehicle travels. Instruments should be installed as unobtrusively as possible so that a driver forgets his or her involvement in continuous observation whilst driving; this also prevents other drivers from changing their behaviours after noticing that a nearby vehicle is instrumented (Carsten et al., 2013).

Preferably, drivers who participate in an ND study should be required to use their own vehicles, in which recording instruments are installed. The drivers are then instructed to drive as they normally do, without imposing for any kind of experimental control (e.g. specific instructions or interventions) during observation (SWOV, 2010). Through this approach, an

ND study provides essential and very interesting data on the interrelationships amongst driver, vehicle, road and the surrounding environment in normal baseline conditions and in safety critical events situations. This type of information is useful not only from the road safety perspective (e.g. reduction of road injuries and fatalities) but also from the environmental and traffic management perspectives (van Schagen and Sagberg, 2012).

ND projects can vary widely with respect to number of recruited drivers and observational periods covered. Ideally, a large-scale study would involve a relatively large number of instrumented vehicles for a relatively long period of observation; collected data are then used to answer a wide variety of questions. Study efforts can also be concentrated on answering a limited number of questions, for which driver samples and instruments are specifically tailored (Thomas et al., 2013).

According to Klauer et al. (2006a), ND studies commonly serve several purposes, including the collection of normal baseline data and the examination of the association between various variables, such as engagement in specific secondary tasks whilst driving, and crash risk. Normal baseline data can be used to measure the prevalence of specific driver behaviours (e.g. driver engagement in certain secondary tasks) and behavioural changes over time. They can also be employed in exploring the association between specific driver behaviours and surrounding environmental factors, such as road type, road locality and road layout (Carsten et al., 2013). Carsten et al. (2013) explained that the ND approach involves more diagnostic features of the problem and does not systematically explore the role of countermeasures in preventing crashes. As the nature of ND studies is rather exploratory, research questions in these studies lean towards being more open-ended compared to other research types.

4.1.1 ND study in relation to field operational test (FOT)

An FOT is a research method which is related to the ND approach. The slightly longer used FOT is closely related to the ND approach (SWOV, 2010). It is defined as:

> a study undertaken to evaluate a function, or functions, under normal operating conditions in environments typically encountered by the host vehicle(s) using quasi-experimental methods (FESTA Consortium, 2008, p.1).

One of the main aims of an FOT is to evaluate new in-vehicle technologies and market-ready products. The evaluation covers when and how drivers use the aforementioned technologies and how their traffic behaviours are affected by these technologies. An FOT in real-life situations is often conducted as an ND study, in which similar instruments and techniques are used. In an ND study, however, no specific interventions or instructions are provided to drivers. Contrastingly, an FOT usually includes interventions represented in driver guidance to turn on or turn off a technology for a specific period of study; the latter represents the baseline (van Schagen et al., 2011). The data extracted from FOT baselines are considered to correspond to the data derived from a purely ND study (Green et al., 2007). Note, however, that the durations of FOT baselines are often shorter than those of ND studies (Carsten et al., 2013).

In ND studies, drivers commonly use their private vehicles, which are equipped with instruments, whereas in FOTs, drivers usually drive instrumented vehicles owned by a research institute. The observational period of ND studies is typically longer than that of FOTs partially because of the high costs incurred from installing instruments to private vehicles, which means that frequently moving instruments from one vehicle to another would be uneconomical. The longer duration of ND studies provides a good basis for evaluating long-term effects, such as the learning effects of novice drivers and seasonal variation effects (Carsten et al., 2013).

4.1.2 Added value of the ND approach

Thus far, the most widespread methods for studying driver behaviours are simulator studies, instrumented car studies, self-report studies, crash data analysis and in-depth crash investigations (van Schagen and Sagberg, 2012). Although these methods extensively enhance knowledge regarding several aspects of driver behaviours and other crash-related factors, they are encumbered with a number of limitations, summarised as follows:

- The results of simulator studies may be difficult to apply to real-world traffic conditions given that vehicle characteristics and the surrounding environment do not completely reflect reality. This is especially true in studies that use simple static-based simulators (SWOV, 2010; Regan et al., 2009). Moreover, simulator studies are extremely difficult to use as a method of measuring the prevalence and self-regulation of secondary task engagement within the everyday driving context.
- In instrumented car studies, individuals are asked to drive in real-world traffic conditions, but their driving behaviours may be affected by the apparent devices installed in their vehicles and the presence of an experimenter in some cases, which may increase a driver's awareness of the experimental nature of the situation (van Schagen and Sagberg, 2012).
- The outcomes of self-report studies may be biased given memory and perceptual limitations and the tendency of individuals to provide socially desirable responses. These problems raise doubt as to the extent to which reported behaviour corresponds to actual behaviour (van Schagen et al., 2011; SWOV, 2010).
- Crash data analysis is insufficient to elucidate why and how a crash occurs. Furthermore, the documentation of non-fatal crashes is far from complete because of underreporting (van Schagen and Sagberg, 2012).

- In-depth crash investigations provide important information about the factors that contribute to crashes, but such explorations are grounded in data collected after the occurrence of a crash (e.g. witness reports and post-hoc self-reports). This method also fails to provide information on normal driving behaviour and thus cannot be relied on to reveal insights into the conditions in which a crash can be prevented (SWOV, 2010).

The ND approach has several advantages over the above-mentioned research methods, most notable of which is the higher external validity of ND research as well as the possibility to study behaviour over a long time frame (Carsten et al., 2013). Experimenters do not accompany participants in ND studies and the context is non-experimental (no instructions or interventions) (Boyle et al., 2012). ND studies provide a much wider perspective of comprehending normal driving behaviour in the everyday driving context. They also offer an opportunity to directly observe safety critical events, including conflicts, near-crashes and real-world crashes, without generating the potential biases occurring in some traditional research methods (van Schagen et al., 2011; SWOV, 2010). Correspondingly, ND studies can contribute to illustrating the prevalence of (for instance) engagement in secondary tasks amongst drivers, the crash risk related to understanding the interaction between road user behaviour and traffic and road conditions and many other aspects of road user behaviour that are not easily examined with other research methods.

4.1.3 Limitations of the ND approach

Although the advantages of the ND approach exceed the disadvantages related to the illumination of many research questions, these limitations are worth discussing. First, using the approach to establish causal relationships or causal conclusions is difficult because no experimental control is exercised over the various variables that influence road user behaviour (SWOV, 2010). An ND study is therefore ill-suited for explorations into how a specific driver assistance system or any other kind of treatment influences behaviour in a given situation (Carsten et al., 2013). Second, ND studies espouse the general assumption that participant drivers will behave as they normally do and quickly forget that they are being constantly observed. Although ND studies in the US elucidate that drivers revert quickly to their natural behaviours within an hour or so (Dingus et al., 2006a), this assertion is not supported by stringent scientific evidence (van Schagen et al., 2011).

Third, the voluntary nature of participation in ND studies may introduce self-selection bias. Therefore, the behaviours of participants may not always be representative of the manner by which an entire population conducts itself. A carefully designed background questionnaire can be used to control such bias (Regan et al., 2013). Finally, a practical disadvantage of ND studies is that they are costly to establish and difficult to manage (Carsten et al., 2013). To ensure cost-effectiveness in ND-projects, researchers should address as many research questions as possible in a single investigation. Data should also be accessible for additional analysis once studies are completed. The present thesis is an example of that in which the raw data collected from the UDRIVE project was used to address the questions pursued in the current work. Accordingly, this thesis did not involve a data collection stage and, thus, did not incur the high costs associated with the implementation of ND studies.

4.1.4 Previous ND studies

During the last two decades, the ND approach has gained ground as a method of road safety research. In the US, for instance, several large-scale ND projects have been undertaken, the first being the 100-car ND study conducted by the VTTI, which observed 100 car drivers for more than a year (Dingus et al., 2006a). The most recent is the ND study carried out for the SHRP2 project, for which 3000 vehicles were observed for two years to unravel the much wider variety of challenges that confront roadway safety (Victor et al., 2015; Campbell, 2012).

Another recent initiative was the European Commission-funded UDRIVE project, which is regarded as the first large-scale ND study in Europe; around 200 vehicles were observed over a period of 18 months (Carsten et al., 2017; Eenink et al., 2014) (detailed description provided in Chapter 5). A large-scale ND study was also conducted in Japan, with 60 vehicles providing data that cover two years of observations (Uchida et al., 2010). Australia and Canada have followed suit in intensifying efforts to undertake their first exhaustive ND study programmes (Regan et al., 2013; Hankey, 2014).

Prior to the UDRIVE project, several small-scale projects that are based on ND methodologies have been initiated in Europe. Some of these projects (those funded by the European Commission) are presented in Table 4-1.

Table 4-1. Small-scale European projects (using the ND methodologies)

Project	Aim
PROLOGUE	Assess the usefulness and feasibility of conducting a large-scale ND study in Europe (van Schagen et al., 2011)
INTERACTION	Enhance the understanding of driver interaction with in-vehicle technologies (Bruyere and Brusque, 2013)
2BeSafe	Improve the understanding of the behaviour and safety of powered two wheelers (Laporte, 2010)
DaCoTA	Evaluate the usefulness of the ND approach in collecting representative data on safety performance indicators and exposure (Thomas et al., 2013)

An objective consideration of the ND literature (small- and large-scale studies) suggested that the majority of studies conducted thus far have focused on road safety issues. Various aspects of road safety have been explored, including the driving behaviours of novice teen drivers and their involvement in crashes (Foss and Goodwin, 2014; Prato et al., 2010; Lee et al., 2011); older drivers' behaviours and loss of skills (Aksan et al., 2013; Guo et al., 2015; Charlton et al., 2013); driver distraction and inattention (e.g. Risteska et al., 2021; Dingus et al., 2016; Victor et al., 2015; Klauer et al., 2006a); driver fatigue (Dingus et al., 2006b); the interaction between light and heavy vehicles (Hanowski et al., 2006; Hanowski et al., 2007);

lane change and overtaking behaviours (Johnson et al., 2016; Chen et al., 2015); driver interaction with driver assistance technologies (Sayer et al., 2007); and the use of recorded data as feedback to drivers for the improvement of their driving behaviours (Toledo et al., 2008).

Studies that addressed the topic of driver distraction typically investigated how distraction was related to safety-critical events, and many of them were carried out to estimate the crash risk associated with engagement in certain secondary behaviours whilst driving. Notwithstanding the value provided by these studies, however, estimating the relative likelihood of a crash whilst drivers perform secondary tasks without considering both the prevalence of these tasks and how drivers self-regulate their engagement addresses only part of the safety problem.

4.2 Research questions

Given the gaps in knowledge identified in Chapters 2 and 3, this thesis sought a deeper understanding of drivers' engagement in secondary behaviours whilst driving through intersections and endeavoured to gain insight into why, how and when secondary tasks are performed at these locations as well as in what contexts drivers carry these activities out. The key research questions answered were as follows:

- How prevalent is secondary task engagement at intersections?
- What specific categories of secondary tasks do drivers typically engage in?
- What driver-related and contextual factors predict the willingness of drivers to engage in secondary tasks, and are any of these factors associated with certain secondary activities?
- Do drivers self-regulate secondary task engagement at intersections, and what strategies and tactics (if any) do they adopt in this respect?
- Are there certain groups of drivers who do not self-regulate?
- Is there a disparity in self-regulation across secondary task types?

- Are there differences in the willingness of drivers to engage in secondary tasks between intersection and non-intersection segments?
- Does engagement in secondary tasks influence rates of turn signal use at intersections?

By answering all these research questions, the current thesis illuminated part of the background that can inform future attempts to improve intersection safety. The findings can serve as guidelines for the development and targeting of distraction countermeasures and policies related to safe driving strategies and managing distractions.

Chapter Five

General Methodology

This chapter begins with a brief methodological description of the UDRIVE project, which served as the major source of preliminary data for the current thesis. This chapter then describes the methodological issues that were central to the entire work undertaken in this thesis. These issues encompassed aspects related to data management and protection, data reduction, data sampling and data coding. Details relating to the data analysis methods are provided in later chapters that discuss the results.

5.1 UDRIVE project

UDRIVE is the first large-scale and most comprehensive ND project undertaken to date in Europe. It was built on the experience gained from various European FOTs (e.g. Benmimoun et al., 2013; Victor et al., 2010) and the PROLOGUE feasibility study (van Schagen et al., 2011). It was funded by the European Commission under the 7th EU framework programme, launched in 2012 and completed in 2017. The project was a collaboration of 19 partners across Europe (including the University of Leeds as a car operation and analysis site) in the collection, management and analysis of ND data on cars, trucks and powered two-wheelers (Barnard et al., 2016).

The main purpose of the UDRIVE project was to expand the understanding of road user behaviours in everyday driving situations, and the objectives pursued in service of this purpose were twofold: to improve road safety through the identification of well-founded and appropriate measures and to ascertain approaches for reducing fuel consumption and harmful emissions and thus establish a more sustainable traffic system (Eenink et al., 2014). From technical and scientific points of view, the project was aimed (1) at describing and quantifying road user behaviours under normal baseline conditions and safety critical events, as well as estimating the risk arising from specific safety-critical behaviours, with particular focus on determining the prevalence and effects of driver states, such as inattention and distraction, and interactions between drivers and vulnerable road users. UDRIVE was also intended (2) to describe and quantify road user behaviours in relation to fuel consumption and emission, with concentration directed especially towards driving styles, the characteristics of road networks and traffic situations, such as congestion (Barnard et al., 2016).

The design of the study plan for UDRIVE was based on research questions that were meant to address a variety of factors and cut across five thematic areas of the project: crash causation and risk, everyday driving, distraction and inattention, vulnerable road users and driving style/eco-driving (Barnard et al., 2016).

5.1.1 UDRIVE dataset

The UDRIVE project involved 200 vehicles (cars, trucks and powered two-wheelers) operated across six European countries: the UK, Poland, France, Germany, the Netherlands and Spain. To recruit more participants, the project team allowed the involvement of multiple drivers per vehicle, thereby generating data on a total of 280 participants (185 car drivers, 48 truck drivers and 47 powered two-wheelers riders), who were observed continuously over 12 to 21 months using a state-of-the-art data acquisition system (DAS) (see Section 5.1.2 for more details on the DAS). The project ended up with a wealth of information on over 270,000 trips and nearly 88,000 hours of ND data represented by an overall dataset size of almost 61 terabytes. The number of trips and driving hours per vehicle type are shown in Table 5-1. For the car driver sample, the UK has the largest number of drivers and trips.

Table 5-1. Size of the UDRIVE dataset

Vehicle type	Country	Number of vehicles*	Number of drivers/riders	Number of trips	Hours of data collected
Car	UK	30	51	59,584	45,591
	France	30	43	49,764	
	Poland	30	31	27,928	
	Netherlands	10	33	13,309	
	Germany	20	27	23,495	
Truck	Netherlands	40	48	88,686	41,389
Powered two-wheelers	Spain	40	47	7,487	891
Total		200	280	270,253	87,871

* Based on the number of DASs installed

5.1.2 Data acquisition system (DAS)

A DAS was fitted in each participant's vehicle to collect necessary data for at least 12 months per vehicle. The DAS was designed to fulfil the information needs of UDRIVE and enable modifications that fit the different vehicle types investigated in the project (Dotzauer et al., 2017). Basically, the system consisted of (1) a set of sensors [a GPS, an internal controller area network (CAN) and an accelerometer] that automatically and continuously provided time-series vehicular information (10 Hz), including location coordinates, speed, acceleration, braking and gear position; (2) a smart Mobileye central forward-facing camera that recorded continuous signals related to the presence of other road users (e.g. other vehicles, cyclists and pedestrians) and the frontward distance between the equipped vehicle and other road users; and (3) multiple other cameras (five to eight, depending on vehicle type) that were positioned in a vehicle in such a way that enabled the broad video coverage of both external and interior scenes but with minimal disruption to a driver's view (Jansen et al., 2017). The camera arrangements in the cars are described below (Figure 5-1):

- Cameras 1, 2 and 3 are forward-facing cameras (left, centre and right, respectively) designed to capture around 180 degrees of front-vehicle situations.

- Camera 4 is the blind-spot camera intended to record the movements/activities of other possible road users at the right side of the equipped vehicle.
- Camera 5 is the face camera, which was used to capture the head movements and visual attention of drivers.
- Camera 6 is the camera designed to capture the feet activity of drivers.
- Camera 7 is the interior cabin camera intended to detect passenger presence and their interactions.
- Camera 8 is the over-the-shoulder camera meant to record the hand activity and actions of drivers, including secondary task engagement.

Figure 5-1. UDRIVE car camera views (Utesch et al., 2014). Note that the driver shown in the figure is a member of the UDRIVE project team and has given permission to share this image.

The videos recorded by the above-mentioned cameras were useful in dealing with variables that could not be acquired automatically by the sensors, such as a driver's engagement in secondary activities. Measuring these variables, however, necessitates a wide range of video annotations after data acquisition. A major challenge here is the sheer mass of video material that requires processing (Utesch et al., 2014).

The DAS equipment was operated automatically and was ignition-controlled, so, data recording began upon engine start-up and ended on engine shutoff. Engine shutoff initiates the automatic shutdown of the system and the storage of data files for a given trip according to the time and date of travel. The DAS also had a feature that enabled the drivers to temporarily deactivate the camera recording system for whatever purpose by pressing a dedicated button. This deactivation could be implemented either at the beginning of a trip or whilst driving. This feature was also a critical requirement in adhering to ethical principles (Eenink et al., 2014).

5.1.3 Additional data sources

Within UDRIVE, some information from other databases was used to enrich the data obtained from the DAS. The DAS data were first supplemented with map-based data (with OpenStreetMap), which were derived from the map-matching process for the time-series location coordinates acquired after data acquisition (Utesch et al., 2014). This supplementation yielded information on speed limits, road types, locality types (e.g. rural, urban) and intersection presence, amongst other aspects. The data were then augmented with information from UDRIVE-designed questionnaires that were filled out by the participants in the recruitment phase; the information covered components such as attitudes, personalities, driving behaviours and demographics (e.g. age and driving experience) (Jansen et al., 2017). The data gathered from these questionnaires were available in a separate set of tables linked with the ND data through a driver identification number.

In addition to the above-mentioned UDRIVE data sources, the Street View tool in the Google Earth software was used in the current thesis to manually code some infrastructural roadway variables (e.g. intersection layout and number of lanes) that were difficult to code directly using the forward-facing camera views from the DAS. Figure 5-2 shows Google Earth views of a signalised four-way intersection (in the UK) with three approaching lanes from each direction.

Figure 5-2. Google Earth views of a four-way intersection in the UK (Source: Google Earth, Image © 2021 CNES / Airbus)

5.1.4 Data management and protection in UDRIVE

The amount of data collected in UDRIVE and their distributed nature called for an efficient data management procedure. The raw data were collected at six operational sites (OSs; i.e. the UK, Germany, Poland, France, the Netherlands and Spain), pre-processed at three local data centres (LDCs; i.e. Sweden, Germany and France) and then delivered to the central data centre (CDC) in Sweden (Dotzauer et al., 2017).

In the OSs, researchers monitored the data collection process, including the installation and de-installation of the DAS and the periodic replacement of hard drives during the data collection phase. The LDCs were responsible for conducting map matching and the pre-processing of data that cover aspects related to data conversion, encryption, harmonisation and synchronisation. Lastly, all the pre-processed data were sent and stored at the CDC, to which project partners (including the University of Leeds) have remote access. This entire process (data collection, transfer and pre-processing) was tracked through a smart online monitoring tool developed in UDRIVE (Bärgman et al., 2017).

With respect to data protection, the UDRIVE team established a well-defined concept for ethical adherence and data security. The concept covers the constraints and requirements of the OSs, LDCs, the CDC and analysis sites, as well as those pertaining to post-project data usage. It was directed towards ensuring that data security satisfied all national and international ethical and legal considerations (particularly privacy considerations) and subsequent requirements. The concept was also intended to realise a satisfactory comprehension of data protection issues amongst the UDRIVE partners and guarantee that data usage is restricted to research areas permitted by the UDRIVE participants via signed consent forms (Bärgman et al., 2017).

5.1.5 Data visualisation and processing tool (SALSA)

To manage the data and the entire data reduction process, the UDRIVE project team developed a MATLAB-based visualisation and processing tool known as the Smart Application for Large-Scale Analysis (SALSA). This tool separates analysis tasks from data management activities, thereby eliminating the need for researchers to deal with data storage or the low-level architecture of the dataset (Eenink et al., 2014). Instead, the researchers were required, through SALSA, to establish and implement algorithms (using MATLAB scripts) for identifying segments of interest across the UDRIVE dataset (i.e. part of trips), calculating derived measures and creating annotation panels (Jansen et al., 2017). Figure 5-3 provides a shot of the user interface in SALSA.

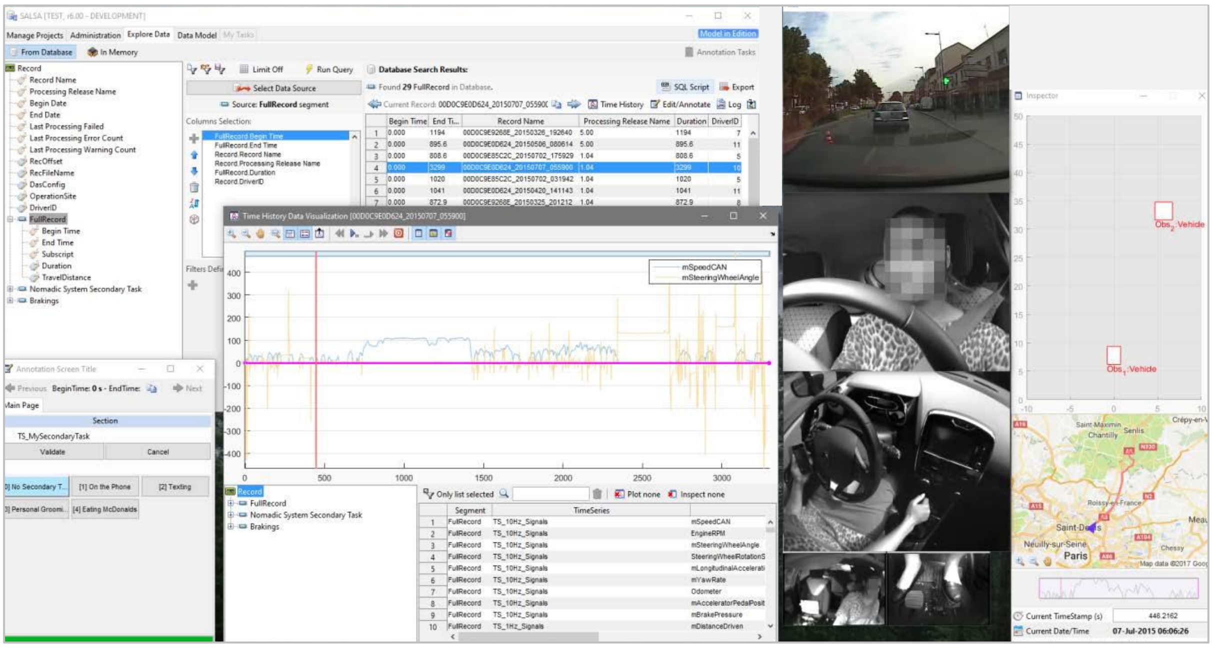

Figure 5-3. SALSA user interface (Bärgman et al., 2017)

To facilitate the data viewing and coding process in the current thesis, the decision was made to use the SALSA tool as the data viewing/coding platform. SALSA was generally suited to the purpose of this research, but it suffered from a very slow user interface on many occasions—an issue that slowed down the data coding process in the current work.

5.2 UDRIVE data limitations and issues, as determined from the perspective of the current thesis

Despite the richness and diversity of the UDRIVE dataset, a range of limitations and quality issues were encountered by the researcher with respect to the data. Knowledge about these issues was important before committing to use the data and before data sampling was carried out. The key issues are briefly described thus:

- All the car drivers involved in the UDRIVE project drove Renault Mégane, Renault Clio 3 or Renault Clio 4 cars. Accordingly, the project has limited generalisability with regard to car types (i.e. only one brand of cars was represented in the dataset). This was due to the fact that Renault, as a partner in the UDRIVE project, has provided access to a wide range of information available in the in-vehicle network.

- For some of the drivers, there was no satisfactory synchronisation between the video channels and the continuous vehicular information (with up to a 3-second offset found).
- For certain drivers, some sensor data were missing either a single information or the full DAS output. This was attributed to hardware issues in the DAS or mistakes in hardware installation.
- For some of the drivers, not all the camera views were available or properly directed. For this reason, the video data on these drivers were insufficient to allow a good view of the interior or exterior scenes needed for annotation.
- Some of the trips documented in the dataset were fragmented into several short records rather than stored as one record of the entire trip. This was attributed to the occasional rebooting of the DAS as the participants were driving.

In addition to the drawbacks related to the UDRIVE dataset, a major challenge facing this research was that such a dataset was not tailored specifically to the objectives formulated in this work. This was evident, for example, in the poor definition of intersections within the dataset and the absence of some important time-series signals, such as the distance to the next intersection signal, which were necessary in carrying out the present exploration. For this reason, intensive efforts were extended to configure and code the UDRIVE data, with a view to ensuring their suitability as bases in answering the research questions.

5.3 Data access and ethical approval for this thesis

As mentioned earlier, the entire UDRIVE dataset was hosted at the CDC, which the project partners can access using a remote desktop service. This research was classified as a University of Leeds partner research and was thus granted access to the dataset. Such access, however, was granted only after the researcher signed a strict non-disclosure agreement and received relevant training on data integrity and protection. The non-disclosure agreement mandates conformity to security requirements for the use of UDRIVE data. The major stipulations are listed below (see Appendix A for more details on the agreement):

- The UDRIVE coding room should be physically protected upon exit from the room (the PCs, all doors and windows should be locked).
- No photos of the PC screens are allowed to be captured or taken.
- Non-project staff are prohibited from entering the coding room and accessing data.
- No attempt should be made to store UDRIVE data outside the remote environment. If a portion of the data need to be extracted, the UDRIVE procedure for this purpose should be followed.
- UDRIVE data should not be posted online or on any social media platforms.
- UDRIVE data should be used solely for the thesis, and information should be disclosed only via the agreed-upon channels: thesis report, paper, poster, presentation.

In addition to the non-disclosure agreement and as a means of certifying the ethical conformity of the current thesis protocols, ethical approval was received from the research ethics committee of the University of Leeds (Reference number: AREA 16-193).

5.4 Training on the use of UDRIVE data

After access to the UDRIVE dataset was granted, a necessary task was to acquire adequate training on the general use of the data and the SALSA tool, which was used in the current thesis as the data viewing and coding platform. The head of the analysis site at the University of Leeds provided the initial training on how to access the data from the server and how to operate SALSA. Preliminary training was also provided on all relevant administrative and operational procedures. A data user manual was then supplied as a guide to in-depth self-learning related to data reduction and coding procedures.

To expand training and coding experience, a decision was made by the researcher to work part of the time with the UDRIVE data annotation team for several weeks. The team assigned the researcher a number of tasks for completion:

(1) A driver identification task was assigned to verify whether a driver had given consent and assign him/her a driver identifier for recording. Only records that reflected consent were included in the dataset.

(2) The researcher was instructed to accomplish general secondary task annotation to manually identify and categorise secondary task interactions in broad categories.

(3) The researcher was asked to comprehensively annotate mobile phone interactions to pinpoint which specific sub-tasks drivers perform as they are engaged on their phones.

Given that SALSA is a MATLAB-based tool, appropriate instruction on MATLAB programming, especially on how to create and apply algorithms (using MATLAB scripts) to the UDRIVE dataset was essential. A 12-hour course offered by the University of Leeds was accordingly completed by the researcher.

Taken together, the above-mentioned training practices constituted a sufficient and fair experience for the researcher as regards the general usage of the UDRIVE dataset and the cultivation of skills critical to the completion of the thesis (i.e. data reduction, coding and annotation).

5.5 Identification of intersection segments

In this thesis, an intersection was defined on the basis of both its physical and functional areas. The physical area refers to the general segment where multiple roads intersect at-grade, whereas the functional area pertains to the distance-based influence zone of an intersection which extends both before and after the boundaries of the physical intersection area (Cottrell and Mu, 2005; Stover, 1996). On this basis, entire intersection segments consist of three successive phases: (1) the pre-intersection phase (upstream functional area), (2) the within-intersection phase (intersection physical area) and (3) the post-intersection phase (downstream functional area). These phases were compared in an exhaustive analysis of the issues covered by the research questions.

As a starting point in identifying intersection segments, a map-matched signal called 'Map_Intersection' was used through SALSA to locate intersection physical areas across the entire UDRIVE dataset. Next, a distance-based window was drawn before and after the boundaries of these physical intersection areas to delineate the full intersection influence zone (upstream, within and downstream intersection phases). This thesis adopted the physical length values of the upstream and downstream phases published in the Design Manual for Roads and Bridges (DMRB, 2002) and Stover's (1996). These values were varied in accordance with the speed limits at intersections (Table 5-2).

Table 5-2. Length-based values of the intersection functional area

Speed (km/h)	Physical length (m)
30	25
40	35
50	50
60	70
70	90
80	115
90	140
100	160

An important consideration is that a single trip may involve passing over numerous intersection segments, on which corresponding distance-based windows may overlap. The current thesis concentrated on isolated intersections segments, thus intersections with overlapping distance-based windows were excluded.

5.6 Sampling choices

Given the magnitude of the complete UDRIVE car dataset (nearly 46,000 hours of ND data, nearly 174,000 trips and over 1 million intersection cases identified on the basis of map matching), an essential preparative task in this thesis was to develop a robust sampling strategy for acquiring a good-quality representative sample of the intersection cases.

The first choice in sampling scheme was the representation of as full a range of participating UDRIVE car drivers as possible. This choice was undertaken to maintain the maximum diversity allowable and give as many drivers as possible an opportunity to be represented in the analyses. As disclosed earlier, however, certain drawbacks and quality problems emerged in regard to data on some drivers (described in Section 5.2). Correspondingly, a set of driver inclusion standards were formulated. Specifically, inclusion hinged on (1) the existence of fully functional and properly directed camera channels in a given vehicle, (2) existing and perfectly synchronised vehicular information from sensors and (3) at least 20 trips made by a driver (minimum trip length = 1 kilometre). The implementation of these standards resulted in a sample of 163 car drivers, and 22 drivers who fell short of the standards were excluded from further sampling and analysis.

Two-stage data sampling was performed on the intersection cases involving the 163 remaining drivers. The procedure was executed as follows:

- Stage 1: For each driver, trips were sampled equally (163 drivers, 10 trips each), with all trips made by an individual driver sampled at random without replacement (minimum trip length = 1 kilometre).
- Stage 2: Within each trip, only one intersection case was randomly selected for coding. That is, each intersection case was selected from a unique trip.

This procedure produced a total sample of 1630 intersection cases (10 intersection cases per driver)—a total number that was decided on the grounds of the resources available (time and budget) for the thesis and the sample size needed for a robust analysis within the research timeframe.

5.7 Final sample

5.7.1 Participants

Amongst the 163 drivers, 78 were females (47.9%) and 85 were males (52.1%), whose ages ranged from 18 to 80 years [mean = 43.8, standard deviation (SD) = 13.1]. The participants were distributed location-wise across five countries (the UK, France, Germany, Poland, the Netherlands). The distributions of age and gender across the five countries are described in Table 5-3. The UDRIVE dataset did not contain any information about the driving experience of the participants. For this reason, this variable was not included among the driver characteristics in the current thesis.

Table 5-3. Gender and age and distributions of drivers across countries

Country	Drivers	Gender		Age (in years)			
		Female	Male	Minimum	Maximum	Mean	SD
UK	46	26	20	18	69	44.6	14.5
France	36	19	17	23	70	43.8	11.7
Germany	21	7	14	23	80	46.5	16.3
Poland	31	12	19	20	65	40.1	8.9
Netherlands	29	14	15	26	70	45.7	13.3
Total	163	78	85	18	80	43.8	13.1

5.7.2 Intersection cases

The analysis was directed towards a pool of 1630 intersection cases (10 intersection cases per driver), which amounted to a total travel time of 678.8 minutes. The average duration of an intersection case was 25 seconds (shortest case: 7 seconds, longest case: 230 seconds). Table

5-4 displays the distribution of the intersection cases per country, and Figure 5-4 illustrates the distribution by travel time. As observed in the figure, the majority of the intersection cases (n = 844) lasted between 10 and 20 seconds. Only 64 intersection cases were shorter than 10 seconds and 88 cases lasted longer than a minute.

Table 5-4. Coded intersection cases per country

Country	Total number of intersections	Total travel time (minutes)	Average duration (seconds)
UK	460	189.5	24.7
France	360	137.6	22.9
Germany	210	85.9	24.6
Poland	310	147.1	28.5
Netherlands	290	118.7	24.6
Total	1630	678.8	25.0

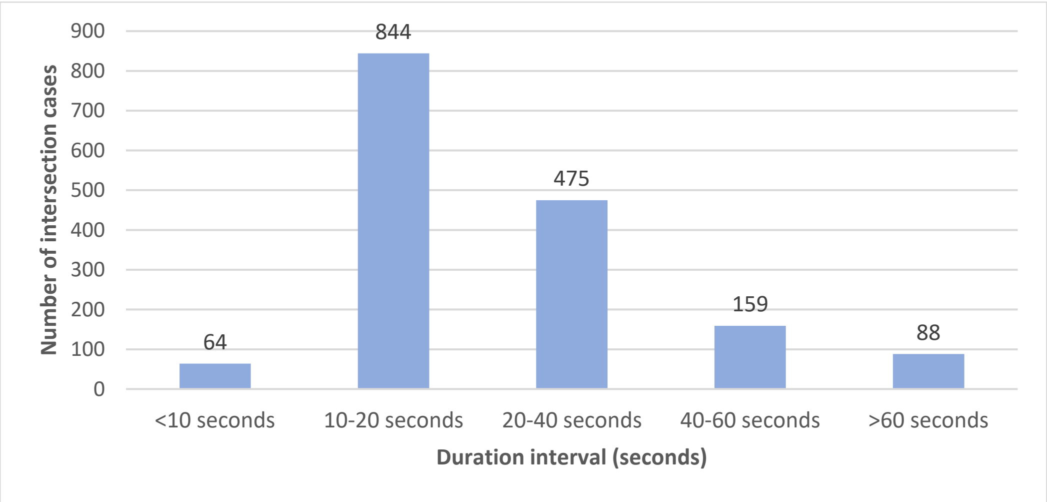

Figure 5-4. Distribution of intersection cases by travel time

With respect to the intersection phases, the total 678.8 minutes of travel time was divided into 373.2, 161.2 and 144.4 minutes for the upstream, within and downstream intersection phases, respectively. In relation to vehicle motion conditions, such overall travel duration was split into 536 minutes of moving time and 142.8 minutes of stationary time. A vehicle was considered stationary when it was at a complete stop (when speed dropped to zero). Note that 98.3% of the total stationary time occurred in the upstream phase and the remaining proportion occurred in the within-intersection (1.6%) and downstream phases (0.1%).

5.8 Coding procedure

The data collection in the UDRIVE project did not comprise the automatic coding of secondary task interactions. Accordingly, it was necessary to manually code video recordings via SALSA to identify such behaviours. The preparatory activities here were to define in detail the manual annotation process and finalise the secondary task coding scheme before the start of the coding. For comparability and consistency with other ND studies, this thesis was based largely on the same secondary task coding principles as those to which the UDRIVE project adhered (see Carsten et al., 2017). The only additional refinement applied was the inclusion of passenger conversations in the secondary tasks to be annotated—an activity that was disregarded in UDRIVE. This decision was prompted by the fact that passenger conversation was part of the coding scheme in many other ND studies (e.g. Dingus et al., 2016; Stutts et al., 2003a) as well as by what had been initially observed in the current work that drivers exercised some sort of self-regulation when it came to interacting with passengers.

The coding procedure for the selected intersection cases involved a four-pass coding approach to data collection (Passes A–D). The first three passes focused on detecting and categorising secondary task engagement, whereas the fourth revolved around characterising surrounding contextual variables, including intersection-related and environmental factors. These consecutive passes are thoroughly explained in the succeeding sections.

5.8.1 Pass A: General secondary task annotation

This pass was aimed at coding whole intersection segments to broadly categorise secondary tasks such as mobile phone use, drinking/eating, personal grooming and smoking. Table 5-5 summarises the secondary task categories that were coded (refer to Appendix B for more information on the operational definition of each task).

Table 5-5. Secondary task categories for annotation (Pass A)

Task category	Description
No task	The driver is not engaging in any secondary tasks that can be observed.
Mobile phone use	The driver interacts with a mobile phone (e.g. locating/searching, holding, dialling, pressing buttons; texting and talking either hands-free or hand-held).
Electronic device engagement	The driver interacts with an electronic device (e.g. iPad, camera, calculator).
Smoking	The driver glances around and reaches for a cigar/cigarette or electronic cigarette, lights it, smokes it or extinguishes it.
Personal grooming	The driver interacts with any item related to health, personal hygiene or accessories.
Eating and drinking	The driver performs an action related to food or drink (e.g. reaching for food or a cup, drinking and eating, putting a food/drink item away).
Reading and writing	The driver is writing or reading material that is in the vehicle but is not part of the vehicle or a mobile phone interaction. This category includes activities such as reading paper materials or packaging.
Engagement with in-vehicle control system	The driver interacts with in-vehicle control systems (e.g. manipulating in-vehicle climate controls, radio buttons or other buttons on the centre stack display).
Passenger conversations	The driver participates in any exchange with a passenger; at the minimum, he/she utters a word.
Talking/singing in the absence of passengers	The driver is talking or singing (moving his/her lips) in the absence of passengers. There is a need to ensure that drivers are not talking on a mobile phone hands-free.
Other	The driver interacts with some other object that is not included in the above-mentioned categories or interacts with objects that cannot be clearly identified from the videos.

The secondary task classification mentioned above was conducted to detect and categorise the secondary tasks being performed. The operational definition of tasks was then adopted to locate the start and end points of each task to the nearest 0.1 second interval. In general, engagement with secondary tasks was considered to commence when a driver began an interaction (i.e. first-hand movement or gaze towards a specific object or the first instance of lip movement) and regarded as concluded when physical/visual contact or lip movement stopped.

Figure 5-5 illustrates how coding of secondary tasks was performed with respect to the intersection phases (upstream, within and downstream intersection phases). In scenarios A to

C, the secondary task engagement occurred in a single intersection phase, while in scenarios D to G, such engagement took place in two or three phases. In scenarios D to G, the secondary task interaction was counted as a single task but representing varying percentages of time spent at each intersection phase. Note that the coding did not cover an entire engagement in cases wherein such interaction was initiated before an intersection segment or when it continued beyond this segment (Figure 5-5).

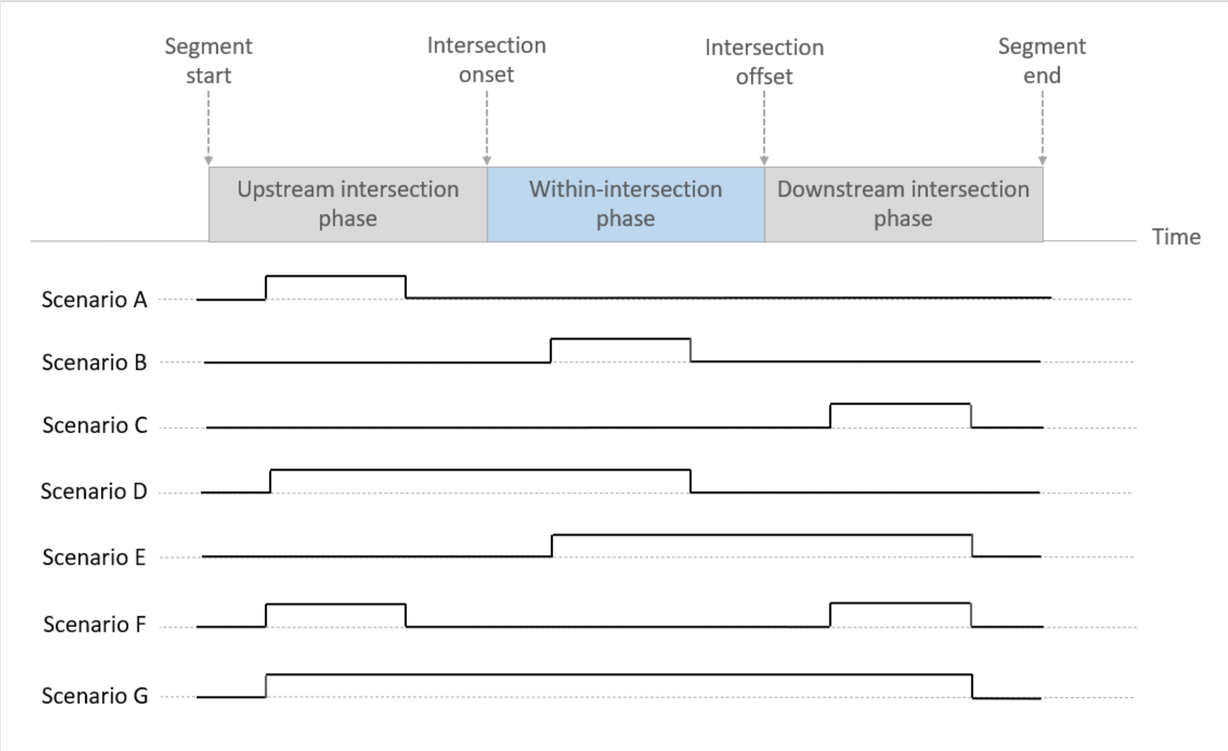

Figure 5-5. Coding of secondary tasks by intersection phases (Scenario A, secondary tasks annotated in the upstream phase; Scenario B, secondary tasks annotated in the within-intersection phase; Scenario C, secondary tasks annotated in the downstream phase; Scenario D, secondary tasks annotated in both the upstream and within phases; Scenario E, secondary tasks annotated in both the within and downstream phases; Scenario F, secondary tasks annotated in both the upstream and downstream phases; Scenario G, secondary tasks annotated across the three phases)

Successive secondary task engagement falling under the same category was coded as being a single secondary task if the interval between the interactions was less than 5 seconds. No minimum task duration was applied, with any task interaction annotated and included in the analysis. To take into consideration the possibility of engagement in simultaneous tasks, each secondary activity was annotated in a different layer within the annotation panel. This strategy allowed the use of the same principles to code both single- and multi-task situations (e.g. a driver talking on a mobile phone and manipulating radio controls at the same time).

5.8.2 Pass B: Detailed coding of sub-categories of mobile phone interactions

Each part of the intersection segment where a driver was engaged in a mobile phone-related task (from Pass A) was viewed a second time to break down mobile phone usage into specific sub-categories on the basis of the nature of the interaction. These sub-categories were handheld interaction, hands-free interaction, handheld conversation, hands-free conversation, phone holding and other mobile phone-related activities (Table 5-6, Appendix B).

Table 5-6. Sub-categories for mobile phone interactions for annotation (Pass B)

Sub-category	Description
Handheld interaction	The driver is touching the screen of a mobile phone or pressing buttons. The driver could be browsing the Internet or typing a text message. These are mostly physical interactions that alternate with small pauses (i.e. looking back at the road).
Hands-free interaction	The driver is looking regularly at a mobile phone without holding it. This can occur if drivers are receiving navigational guidance through the phone.
Handheld conversation	The driver is talking on a handheld phone or has the phone up to his/her ear as if listening to a phone conversation or waiting for a person they are calling to pick up the phone.
Hands-free conversation	The driver is talking or listening on a phone hands-free (e.g. using the mobile phone speaker, a headset or an in-vehicle integrated system).
Phone Holding	The driver is simply holding his/her mobile phone but not interacting with it. The phone could be in his/her hand or lap, or the driver may be holding the device in some other way.
Related	The driver is interacting with a mobile phone in a way that is not covered by the categories above (e.g. cleaning the screen, plugging the phone into a charger).

5.8.3 Pass C: Secondary task in relation to VM complexity and technological aspects

Each part of the intersection segment where a secondary task was carried out was viewed one more time to break down each secondary task instance in relation to VM complexity level and the existence of any associated technological aspect.

With respect to VM complexity, the observed secondary tasks were grouped in accordance with the classification method developed by Klauer et al. (2006b) in the 100-car study. That is, the tasks were arranged into three groups: simple, moderate and complex tasks. Simple tasks are those that require a single or no button press or a single glance off the forward roadway. Moderate tasks are those that require up to two button presses or up to two glances off the forward roadway. Complex tasks are those that require multiple steps, such as multiple button presses or multiple glances off the forward roadway. The importance of this classification approach lies in the fact that the primary driving task itself is essentially a VM task and thus it is likely to be increasingly affected as drivers engage in more complex secondary activities (from a VM perspective). This phenomenon can be linked to the multiple resource theory developed by Wickens (2008) (described in Chapter 2), which elucidates that dual-task interference tends to transpire when simultaneous tasks are characterised by similar modalities.

Concerning technological aspects, each secondary task was classified on the basis of Young et al. (2003) categorisation technique. Specifically, the tasks were labelled as either technology-based tasks (e.g. mobile phone use and electronic device interaction) or non-technology-based tasks (e.g. smoking, eating and passenger conversation).

5.8.4 Pass D: Contextual variable coding

In addition to the secondary task coding approach described in Passes A to C, a variety of contextual variables were incorporated into the coding scheme executed in this research. These variables consisted of several environmental and intersection-related factors that were coded for entire intersection segments regardless of the presence of secondary task engagement. Table 5-7 presents the variables that were coded alongside their utilised categories.

The selection of these variables was informed by the literature review and the extent to which these factors can be obtained from the available data sources. These variables were also seen as important in describing situations under which drivers engage in secondary tasks—information that can advance the drawing of key inferences regarding how drivers self-regulate involvement in secondary activities according to driving situation.

Table 5-7. Key contextual variables for coding (Pass D)

Variable	Description	Source
Intersection layout	Categories: Roundabouts and intersections Roundabouts were further broken down into mini roundabouts, single-lane roundabouts and multiple-lane roundabouts. Intersections were further broken down into X-intersections, T-intersections, intersections with more than four arms and other complex junctions.	Video annotation and Google Earth
Intersection control	Categories: Controlled by traffic lights or managed with traffic signs and road markings	Video annotation
Intersection priority	Categories: Subject vehicle (SV) has priority or no priority The intersection approaches were annotated in accordance with the priority (right of way) given to the SV in passing through an intersection (i.e. an SV has priority versus an SV has no priority) regardless of the presence of any other vehicle in the other traffic streams at the intersection.	Video annotation
Turning direction	Categories: Left turn, right turn and straight on (no turn) The UK is the only left-side driving country amongst the sampled countries; hence, the left and right turn categorisations were reversed to match the type of manoeuvres allowed in the other countries.	DAS and Video annotation
Intersection locality	Categories: Rural and urban Locality of intersection approaches based on map matching data	Map matching
Road type	Categories: Single carriageway/undivided/single-track/one-way road and dual carriageway (divided road) Road type at intersection approach	Map matching
Number of lanes	Categories: Single lane, two lanes, three lanes, four or more lanes Number of lanes at intersection approach	Video annotation and Google Earth
Lighting conditions	Categories: Darkness (unlighted), darkness (lighted), dawn or dusk and daylight	Video annotation
Weather conditions	Categorise: No adverse weather conditions (good weather), light rain, moderate rain, heavy rain, foggy and snowy	Video annotation
Trip length	Categories: 0 to 1000, 1000 to 2000, 2000 to 3000 and ≥ 3000 seconds Length of trip from which an intersection case was selected	DAS
Passengers presence	Categories: No passenger or with passenger Passengers are either present in the vehicle or not.	Video annotation
Seat belt usage	Categories: Wearing or not wearing Driver wearing a seatbelt	Video annotation

Table 5-8 breaks down the 1630 intersection cases (the total number of intersection cases included in this research) with reference to the coded contextual factors.

Table 5-8. Contextual factors acquired from coding

Contextual factor	Categories	% of 1630 intersection cases
Intersection layout	Roundabouts	26.0
	Intersections	74.0
Intersection control	Traffic signs and road markings	62.9
	Traffic lights	37.1
Intersection priority	Priority allocated to SV	50.6
	No priority allocated to SV	49.4
Turning direction	Turning left	32.5
	Going straight	35.9
	Turning right	31.6
Intersection locality	Rural	24.7
	Urban	75.3
Road type	Single carriageway or undivided road	72.9
	Dual carriageway or divided road	27.1
Number of lanes	Single lane	53.9
	Two lanes	28.7
	Three lanes	11.3
	Four or more lanes	6.1
Lighting conditions	Daylight	68.3
	Dawn or dusk	10.8
	Darkness (lighted)	19.6
	Darkness (no lighting)	1.3
Weather condition	No adverse conditions	86.7
	With adverse conditions	13.3
Trip length	0 to 1000 seconds	61.0
	1000 to 2000 seconds	26.5
	2000 to 3000 seconds	8.2
	≥ 3000 seconds	4.3
Passenger presence	No passenger	68.2
	With passenger	31.8
Seat belt usage	Not wearing	2.1
	Wearing	97.9

5.9 Inter-rater reliability

Inter-rater checks were conducted to assess the reliability of the coded data, for which a random selection of nearly 10% of the intersection cases coded by a second independent coder. The inter-rater reliability analysis was essential in demonstrating consistency amongst the data coding implemented by the two independent coders for both the categorical variables (e.g. weather conditions) and the continuous variables (e.g. the time at which secondary tasks were initiated). The analysis was defined as fully crossed because exactly the same observations were coded by the two coders using the same coding scheme. Consequently, it was justified to examine inter-rater reliability using Cohen's kappa coefficient for the categorical variables and intraclass correlations coefficient (ICC) for the continuous variables (Mackey and Gass, 2005; Hallgren, 2012). What follows is a brief methodological description of these reliability coefficients, after which the reliability testing outcomes are delineated.

5.9.1 Cohen's kappa coefficient

Unweighted Cohen's kappa coefficients were estimated to measure the levels of agreement between the two coders as regards categorical ratings of the 16 variables used to classify secondary tasks and contextual factors (Table 5-9). The sample size was 177 cases for each categorical variable based on observations of 177 intersection cases.

The method of estimating kappa ± 95% Confidence Intervals (CI) with SPSS (Statistical Package for the Social Sciences) version 24.0 followed the protocol outlined by TexaSoft (2008). Possible kappa coefficients range from −1 to 1, where 1 indicates perfect agreement, 0 indicates completely random agreement and −1 indicates perfect disagreement. The conventional interpretation of kappa coefficients was originally proposed by Landis and Koch (1977), who explained that values of 0.0 to 0.20 indicate slight agreement, 0.21 to 0.40 indicate fair agreement, 0.41 to 0.60 indicate moderate agreement, 0.61 to 0.80 indicate good agreement, 0.81 to 0.90 indicate strong agreement and 0.91 to 1.0 indicate almost perfect agreement. In practice, however, the interpretation of the kappa coefficient of any given variable depends on measurement method, research questions and the extent of rigor imposed by a researcher in illuminating the results of subsequent statistical analyses using this variable (Hallgren, 2012).

In this thesis, a more conservative guideline was applied because a slight to good level of agreement with respect to a given variable using the lower levels of Landis and Koch (1977) interpretation (i.e. kappa coefficient = 0.0 to 0.80) might compromise succeeding statistical examinations conducted using that variable. If a kappa coefficient is less than 0.80, then the 95% CIs of the kappa are sufficiently wide to conclude that over 20% of analysed data are incorrect (McHugh, 2012). In this research, therefore, incorrect conclusions were prevented by using a kappa coefficient of at least 0.80 as the threshold that manifests an adequate level of agreement between two coders. If the kappa coefficient of a given variable is less than 0.80, then any conclusions based on a subsequent statistical analysis of that variable could be compromised, therefore invalidating this variable as grounding for definitive conclusions.

5.9.2 Intraclass correlation coefficient (ICC)

Three ICCs ±95% CI were estimated to measure the levels of agreement between the two coders concerning the measurements of three continuous variables (start time, end time and duration) on the basis of observed secondary tasks. The sample size was 85 cases for each continuous variable (based on 85 secondary task instances observed from the 177 intersection cases).

The analysis was underlain by the assumptions that (a) the start time, end time and duration of each secondary task were continuous variables, that (b) each secondary task was observed by the two coders and that (c) the two coders were representative of a larger population of similar coders. The research applied a two-way random effects model, wherein the effects of the two coders and the continuous variables were assumed to be random. The ICCs were computed with SPSS using an absolute agreement definition, in keeping with the protocol described by Landers (2015).

The relative magnitudes of ICCs were interpreted in line with the guidelines formulated by McGraw and Wong (1996), who suggested that ICC values can be classified as follows: "excellent" (≥ 0.81); "good" (0.61 - 0.80); "moderate" (0.41 - 0.60); or "poor: (≤ 0.40). In this thesis, an ICC of less than 0.80 was assumed to represent an unreliable measurement; thus, conclusions based on a subsequent statistical analysis of such measurement could be compromised, preventing the maintenance of the variable as a component of the analysis.

5.9.3 Reliability testing outcomes

Table 5-9 presents the results of the inter-rater reliability analysis of the categorical variables using Cohen's kappa coefficient. Amongst the kappa statistics, 13 exceeded the value 0.90 (almost perfect agreement), and two generated less than 0.90 but exceeded 0.80 (strong agreement). All these categorical variables (15 variables) satisfied the stated criterion, thereby signifying adequate agreement between the two coders. All such variables were hence retained for subsequent statistical analysis.

However, the kappa statistic of the special condition variable was the only element generating a kappa of less than 0.80 (inadequate level of agreement between the two coders) (Table 5-9). A review of this variable by the two coders revealed that the second coder did not rate the presence of roadworks as a special condition category. To correct this issue, the special condition variable was re-coded by the second coder across the sample. The kappa coefficient of the re-coded special condition variable was 0.865 (95% CI, 0.814 to 0.905)—a value that warranted retaining for the subsequent examination.

Table 5-9. Inter-rater agreement between the two coders for the categorical variables

Categorical variable	Kappa	95% CI (lower)	95% CI (upper)	No. of disagreements
Secondary task presence	0.976	0.943	1.000	2
Secondary task category	0.981	0.956	1.000	2
Intersection layout	0.973	0.948	0.998	3
Intersection control	0.976	0.943	1.000	2
Intersection priority	0.947	0.902	0.992	5
Turning direction	0.990	0.974	1.000	1
Intersection locality	0.891	0.805	0.977	6
Road type	0.893	0.815	0.971	7
Number of lanes	0.926	0.875	0.977	8
Lighting condition	0.918	0.859	0.977	7
Weather condition	0.904	0.810	0.998	4
Passenger presence	0.972	0.933	1.000	2
Passenger seating	0.962	0.919	1.000	3
Passenger age group	0.974	0.939	1.000	2
Seat belt wearing	1.000	1.000	1.000	0
Special condition	0.770	0.615	0.925	8
Special condition (re-coded)	0.865	0.814	0.905	4

Table 5-10 shows the findings of the inter-rater reliability analysis of the three continuous variables using ICC. All the variables satisfied the stated criterion for reflecting an excellent level of agreement between the two coders. Consequently, these items were retained in the subsequent statistical analysis.

Table 5-10. Intraclass correlation between the two coders for the continuous variables

Continuous variable	ICC	95% CI (lower)	95% CI (upper)
Start time of secondary tasks	0.987	0.979	0.993
End time of secondary tasks	0.985	0.977	0.990
Duration of secondary tasks	0.982	0.964	0.990

5.10 Selection and coding for non-intersection segments

Additional data were coded, with concentration on driver behaviours at non-intersection segments. The use of a non-intersection dataset was aimed at shedding light on what constitutes typical driver behaviours or normal driving outside intersections and generating a comparison benchmark for driver conduct at intersections.

For each intersection case (1630 intersection cases coded), one matched non-intersection segment was randomly selected for coding using the same coding procedure described in Section 5.8. This procedure produced a total sample of 1630 non-intersection segments. Note that some of the contextual variables described in Table 5-7 are intersection-specific variables (e.g. intersection layout and intersection control) and are therefore unrelated to non-intersection segments. Each of the matched non-intersection segment was coded regardless of whether the intersection case involved any kind of secondary task engagement.

The selected matching criteria were the following: the same driver, the same speed limit (more or less 10 km/h), the same locality, the same driving time duration (i.e. the time duration of each matching non-intersection segment equal to the time duration of each corresponding intersection segment) and the same trip. The use of the same trip as a criterion contributed to the compatibility of many other factors, including passenger presence, weather conditions, lighting conditions and other internal driver-related factors, such as mood. At least a 2-minutes gap difference between the intersection and its matched non-intersection case should exist.

Chapter Six

Prevalence and Main Self-regulatory Strategies of Drivers' Secondary task Engagement

This chapter represents the first of four result chapters and is considered the cornerstone of the findings derived in this thesis. It reports on the prevalence levels and patterns of secondary task engagement whilst drivers are driving through intersections and what main self-regulatory strategies, if any, drivers adopt to manage such an engagement. The analyses focused on exploring trends and patterns that underlie secondary behaviour engagement at intersections, but these aspects were also investigated in the context of non-intersection segments to generate a comparison benchmark for driver conduct at intersections.

6.1 Aims and hypotheses

The aims of the investigation discussed in this chapter were as follows:

- To determine the overall prevalence of secondary task engagement by drivers as they pass through intersections.
- To identify the categories/types of secondary tasks that drivers typically perform and examine their occurrence in everyday driving.
- To examine whether drivers regulate their secondary activities across intersection phases (upstream, within and downstream) and motion conditions (moving and stationary).
- To explore how changes in speed influenced the drivers' propensity to engage in secondary tasks.
- To explore whether there are differences in the willingness to engage in secondary activities between intersection and non-intersection segments.

The primary hypothesis advanced in this chapter is that drivers exercise self-regulation by reducing engagement in typical secondary tasks in general and more complex secondary tasks in particular during challenging intersection-driving situations. This reduction is expected to take place specifically in areas falling within intersections rather than at upstream and downstream regions. Such a reduction is also anticipated to occur when drivers are in motion as opposed to when they are stationary and when they travel at high speeds in contrast to low speeds. It is likewise hypothesised that when passing through intersections, drivers reduce secondary task engagement to a level lower than that observed in non-intersection segments.

6.2 Methods

The analysis used a sample of 163 drivers (78 females, 85 males), whose driving trajectories spanned a total of 1630 intersection cases (10 intersection cases per participant) across five countries (the UK, Germany, the Netherlands, France, Poland) (refer to Section 5.7 for more details on the sample). The average duration of an intersection case was around 25 seconds, and the total observation time across all the intersection cases was 678.8 minutes. For vehicle motion status, the total observation time was divided into 536 minutes of moving condition and 142.8 minutes of stationary condition. In terms of intersection phases, the total observation time was segmented into 373.2, 161.2 and 144.4 minutes of driving across upstream, within- and downstream intersection phases, respectively. The description of these intersection phases, as well as the secondary task coding procedures and their respective inter-rater checks, is presented in detail in the general methodology chapter (Sections 5.8 and 5.9).

SPSS (version 24) was used for the data analysis, in which secondary task events were treated as independent units and pooled across drivers. Various descriptive and inferential examinations were carried out to determine the frequency, duration and prevalence of engagement in secondary activities. The descriptive analyses were aimed at exploring the data and summarising the distribution of variables, whereas the inferential statistical tests were conducted to identify statistically significant relationships between variables. The proportion of intersection cases involving secondary task engagement, and the percentage of total intersection driving time accounted for by such engagement was the major metric used to evaluate prevalence. The other metrics employed were the percentages of time spent in the upstream intersection, within-intersection and downstream intersection phases and the total stationary and moving times during which secondary tasks were performed. A paired-samples t-test was performed for the distraction-related comparison of motion status conditions, and one-way repeated-measures ANOVA was carried out to compare the three intersection phases. Spearman's rank-order correlation was determined to assess the relationship between the percentage of time involving secondary tasks and driving speed.

A distraction-related comparison of intersection and non-intersection segments was also performed (discussed in this chapter) to explore whether drivers behaved differently across these roadway locations. As described in the methodology chapter, each of the 1630 intersection cases was matched with a non-intersection segment selected from the same trip. The matching produced an equal sample (i.e. 1630) of non-intersection segments. Because all the non-intersection segments involved vehicular moving conditions only, secondary tasks that occurred at intersections in stationary conditions were excluded from the comparison. Paired-samples t-tests and OR analyses were used for the comparison. An alpha (significance level) of 0.05 was used as a cut-off point for identifying statistical significance. Note that between-driver variability was not considered in the statistical analyses used in the current thesis. In other words, it was assumed that there is no between-driver variability in the dependant variables.

6.3 Results

The results are presented in order of the aims listed above.

6.3.1 How prevalent is secondary task engagement at intersections?

6.3.1.1 Overall prevalence (all secondary tasks)

The descriptive analysis revealed that 47.7% of the intersection cases involved at least one secondary task interaction (778 intersections of the 1630 that were coded), amounting to a total of 1050 secondary task events identified. On average, the drivers initiated one secondary task every 39 seconds of driving and spent 26.5% of their total driving time at intersections engaged in one or more secondary tasks.

Almost all the drivers (97.5%) engaged in a secondary task in at least one out of the 10 intersection cases coded for them, showing that this behaviour was a frequent and common occurrence. Four drivers did not engage in any secondary activity under any conditions, and another four performed some type of secondary task in all the coded intersections associated with them (Figure 6-1).

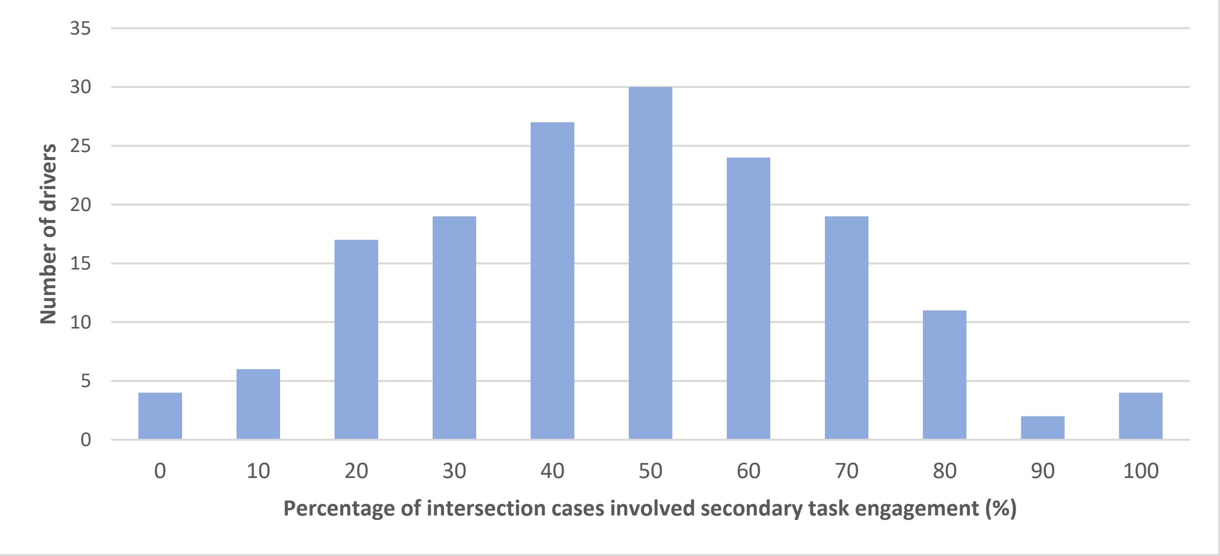

Figure 6-1. Percentages of intersection cases with secondary task engagement by number of drivers

Across the 1630 intersections coded, the drivers performed a single secondary task in 543 cases (33.3%), two secondary tasks in 198 cases (12.1%) and three or more secondary tasks in 37 cases (2.3%) (Figure 6-2). Amongst the 1050 secondary task events, 48% represented less than 10% or more of the 90% total intersection driving time (Figure 6-3). This result indicated that almost one-half of the secondary tasks carried out by the drivers were either relatively short (ranging from 0%–10%) or long (90%–100%), as determined from the percentage of intersection time having a mean of 43.4%.

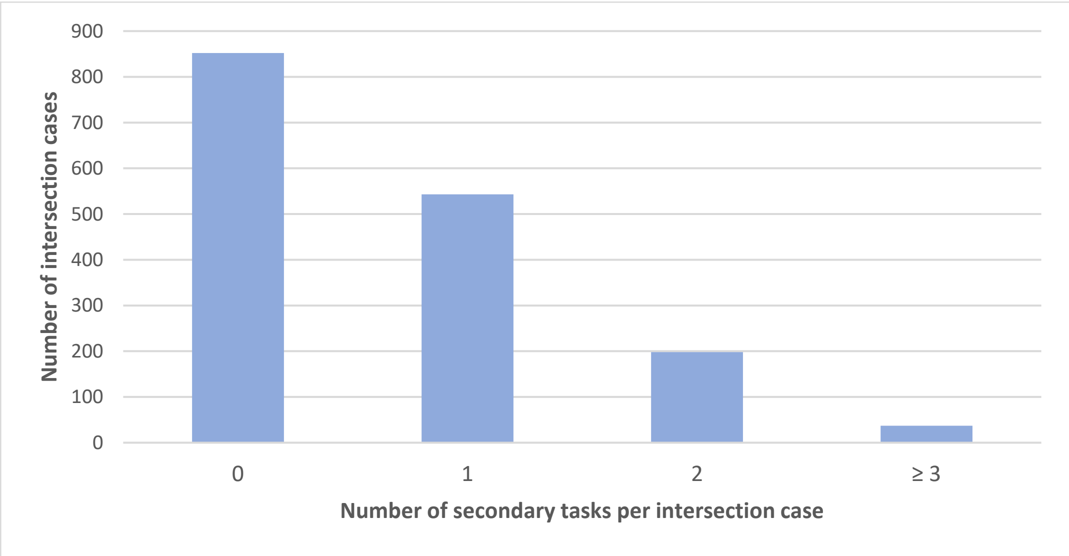

Figure 6-2. Distribution of annotated intersection cases by number of observed secondary tasks

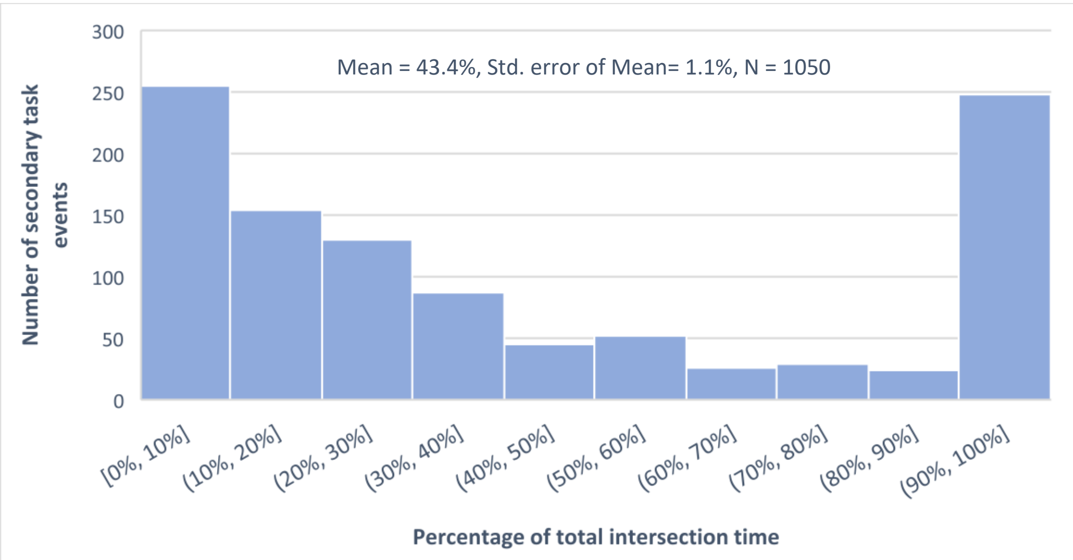

Figure 6-3. Percentages of total intersection time devoted to secondary task events (n = 1050)

6.3.1.2 Prevalence by task category

The first step in delving into the categories of secondary task engagement was counting the frequency of engagement in each task category (Table 6-1). The most commonly observed category was conversation with a passenger (n = 456, observed in 23% of intersections), followed by talking/singing in the absence of passengers, mobile phone use and adjustment of in-vehicle controls. The tasks in which drivers least commonly engaged were those related to reading and writing (n = 6, observed across 0.2% of intersections).

Table 6-1 also presents the percentage of drivers involved in each task category in at least one intersection case. Over 80% of the drivers talked with a passenger, and around one-third used a mobile phone and performed personal grooming activities. Only 12 and 4 drivers out of the total 163 carried out smoking and reading/writing activities, respectively.

Table 6-1. Secondary task engagement by category, as determined from data coding

Secondary task category	N	% of drivers observed	% of intersection cases with task engagement
All tasks	1050	97.5	47.7
Passenger conversations	456	82.8	22.9
Talking/singing in the absence of passengers	149	46.0	8.3
Mobile phone use	132	33.7	7.0
Adjusting in-vehicle controls	100	39.3	5.5
Smoking	74	7.4	3.6
Personal grooming	73	33.1	4.1
Eating and/or drinking	29	12.3	1.5
Reading and/or writing	6	2.5	0.2
Other	31	16.6	1.9

Second, the amount of time that the drivers spent on performing each secondary task was compared with the total observed intersection time (678.8 minutes) (Figure 6-4). The task category performed most of the time was passenger conversation (13.2%), followed by mobile phone use (6.6%) and smoking-related tasks (3.7%). The task category performed the least was reading or writing, accounting for only 0.2% of the total observed time.

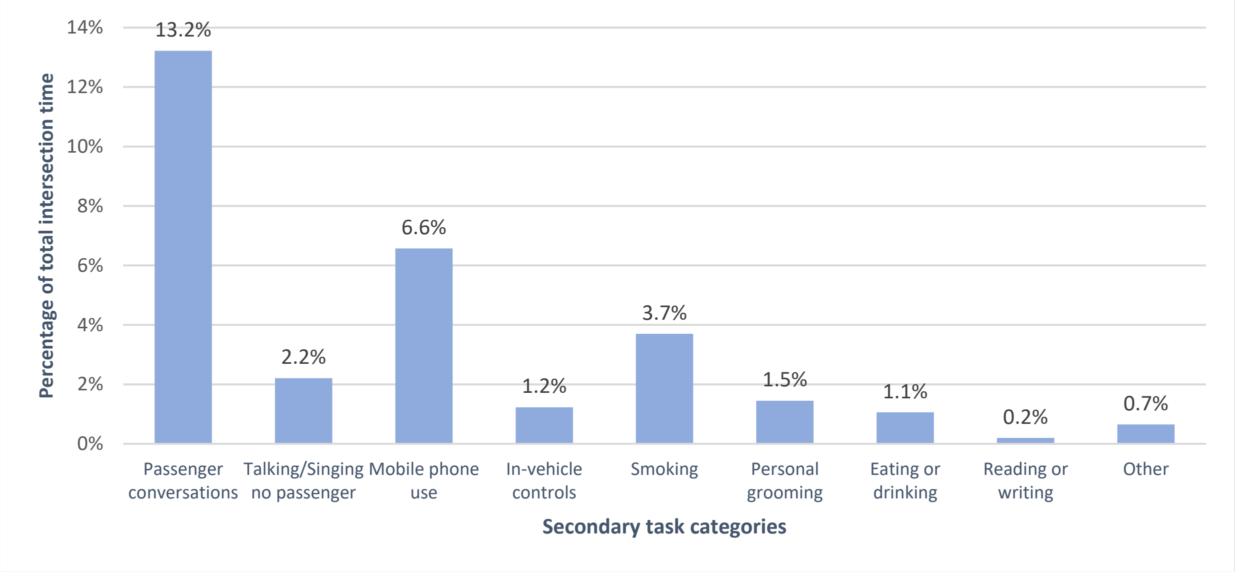

Figure 6-4. Percentage of total intersection time by category of secondary task

Third, the relationship between each task's frequency and mean duration accounted for within intersection boundaries was investigated (Figure 6-5). Both smoking and mobile phone use were carried out for the longest mean duration (nearly 20 seconds), but the latter was a more frequently exercised activity. Conversely, both adjustment of in-vehicle controls and talking/singing in the absence of passengers on board were accorded the shortest mean durations (ranging from 5–6 seconds). Talking to a passenger went on for a moderate mean duration (approximately 12 seconds) but was by far the most frequently observed activity.

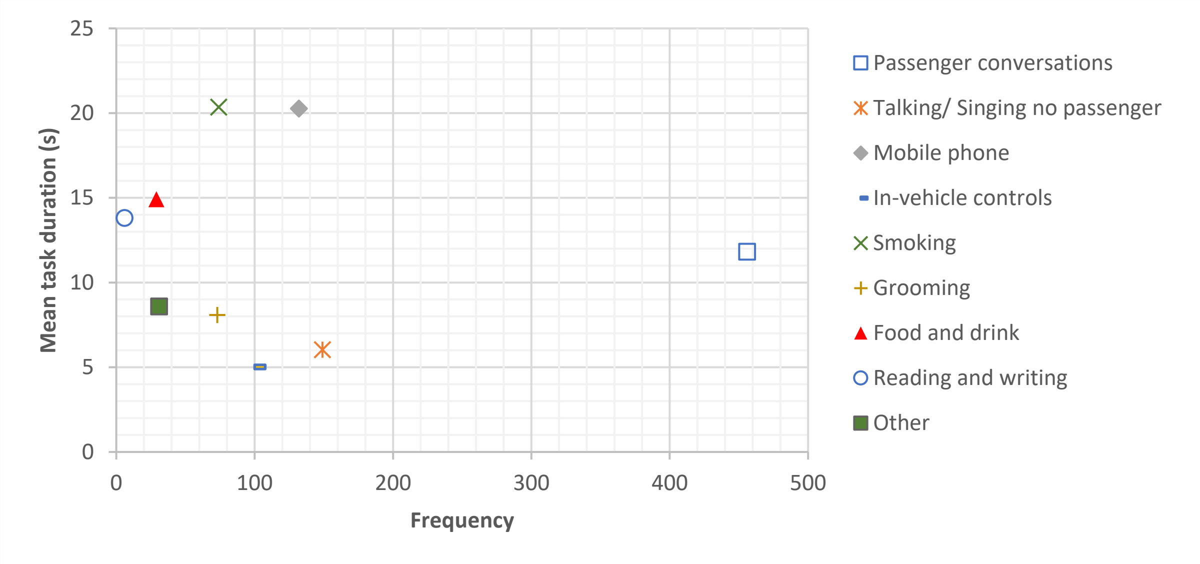

Figure 6-5. Mean duration vs. frequency by task category

6.3.1.3 Prevalence of mobile phone sub-tasks

As described in Table 6-1, 7% of the intersection cases involved mobile phone use (114 intersections of the 1630 coded), with 132 distinct interactions observed. Overall, such a usage accounted for 6.6% of the total intersection driving time and was observed amongst nearly one-third of the drivers. To better understand what drivers do as they manipulate their mobile phones, this task category was broken down into several sub-tasks (Table 6-2).

The most commonly observed sub-task was hands-free interaction (n = 44, observed amongst 13.5% of the drivers), followed by hands-free conversation and handheld interaction. Handheld conversation was rarely performed at intersections (n = 6, observed amongst five drivers only). The percentage of intersection driving time during which the drivers engaged in each mobile phone sub-task was also considered. The drivers devoted the majority of their time to hands-free interactions, although the proportion remained low when evaluated against the total driving time (2.4%). Handheld conversation accounted for the lowest percentage of intersection driving time (0.3%) (Table 6-2).

Table 6-2. Mobile phone use by sub-task, as determined from data coding

Mobile phone sub-task	N	% of drivers observed	% of total driving time
Total mobile phone use	132	33.7	6.6
Hands-free interaction	44	13.5	2.4
Handheld interaction	29	15.3	1.2
Hands-free conversation	32	14.1	1.7
Handheld conversation	6	3.1	0.3
Holding	12	5.5	0.7
Related	9	5.5	0.3

The relationship between the frequency at which each mobile phone sub-task was carried out and mean duration was examined (Figure 6-6). Both hands-free interaction and hands-free conversation were performed more frequently and for longer mean durations than were handheld interaction and handheld conversation, respectively. Simply holding a phone, hands-free conversation and hands-free interaction were the activities that accounted for the longest mean duration (ranging from 22–24 seconds), but hands-free interaction was a more frequently exercised task.

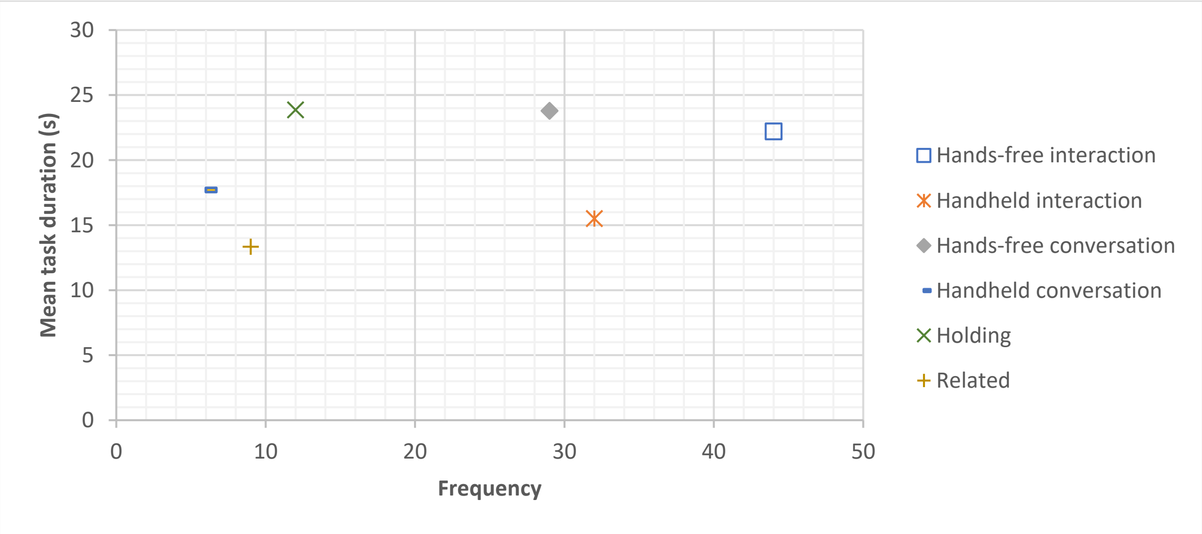

Figure 6-6. Mean duration vs. frequency by mobile phone sub-task

6.3.1.4 Prevalence in relation to VM complexity and technological classifications

This section summarises the findings on secondary task prevalence in relation to VM complexity level and the existence of associated technological aspects. With respect to VM complexity, the secondary tasks were grouped into simple, moderate and complex tasks (Table 6-3) in accordance with the classification of Klauer et al. (2006b). Simple tasks were, by far, the most frequent and common amongst the drivers, representing 23.9% (162.2 minutes) out of the total intersection time (678.8 minutes). Conversely, only 3.7% and 2.7% of the drivers' total driving times were devoted to moderate and complex tasks, respectively.

Table 6-3. Secondary tasks by VM complexity level

VM complexity of secondary tasks	N	% of drivers observed	% of total driving time
Simple tasks	859	96.9	23.9
Moderate tasks	113	39.9	3.7
Complex tasks	78	33.1	2.7

With regard to differences in task duration amongst the VM complexity groups, the findings indicated that task duration decreased as task involvement proceeded from simple (mean = 14.3 seconds) to moderate (mean = 13.2 seconds) and complex (mean = 11.1 seconds) tasks (Figure 6 7). Spearman's rank-order correlation analysis was carried out to assess whether this trend induced the formation of a significant relationship between the two variables. There was a statistically significant but small correlation between task durations and VM complexity groups, $r_s(1048) = -0.118$, $p < 0.001$. This correlation was negative, suggesting that task duration decreased as task complexity increased.

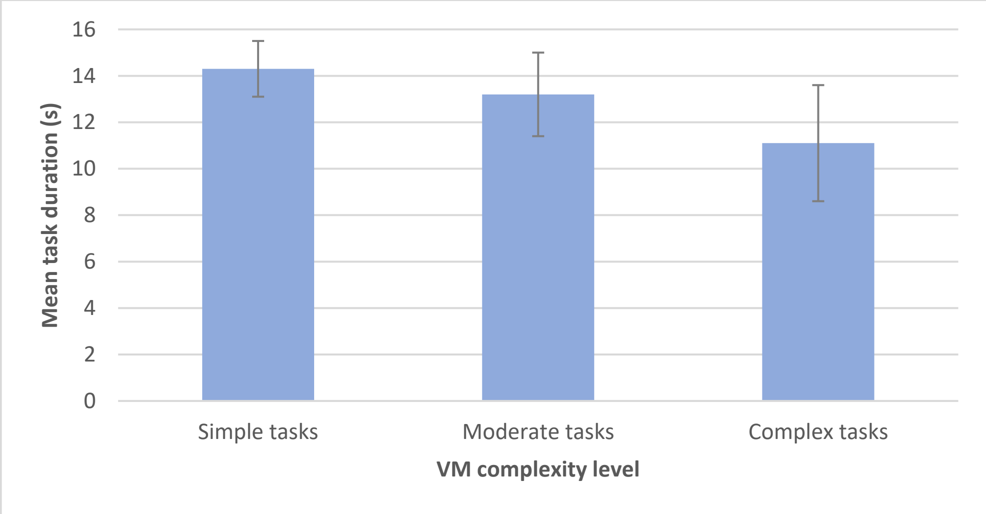

Figure 6-7. Secondary task mean duration by VM complexity level (95% CI error bars)

Concerning technological aspects, each secondary task event was classified into technology- and non-technology-based tasks on the basis of Young et al. (2003) categorisation technique. Non-technology-based tasks were more frequent (n = 233) and more common amongst the drivers (observed out of 95.7% of the sample) and were performed overall for a greater amount of time (22.5%) compared with technology-based tasks (Table 6-4).

Table 6-4. Secondary tasks by the existence of technological aspects

Technological aspect classification of tasks	N	% of drivers observed	% of total driving time	Mean duration (seconds)
Non-technology-based tasks	817	95.7	22.5	11.2
Technology-based tasks	233	60.7	7.8	13.7

An independent-samples t-test was run to determine whether there were differences in durations between technology- and non-technology-based tasks. The duration at which the former tasks were carried out (mean = 13.7 seconds) was significantly higher than that at which the latter were performed (mean = 11.2 seconds), $t(1048) = 2.485$, $p = 0.013$.

6.3.1.5 Prevalence of multiple task engagement

When drivers perform multiple secondary tasks at once, they need to divide their attention not only between the driving function and a secondary task but also between the driving function and two (or more) secondary activities. The investigation was aimed at ascertaining how often drivers engage in multiple non-driving tasks in parallel and exploring the patterns of such an engagement.

Approximately one-third of the drivers (32%) involved themselves in multiple tasks in at least one out of the 10 intersection cases coded for them, with 72 distinct multiple task events observed. Nevertheless, multiple task engagement represented only 1.5% of the total intersection driving time. The secondary task that was most frequently shared with other activities was conversation with a passenger, with over 60% of all the multiple task events involving this act carried out simultaneously with other tasks. The next most commonly shared tasks were mobile phone use (36%) and adjustment of in-vehicle controls (29%) (Table 6-5).

Table 6-5. Driver performance of multiple tasks

Secondary task category	% multiple tasks
Passenger conversations	62.5
Talking/singing in the absence of passenger	13.9
Mobile phone use	36.1
Adjusting in-vehicle controls	29.2
Smoking	20.8
Personal grooming	23.6
Eating and/or drinking	5.6
Reading and/or writing	1.4
Other	6.9

Table 6-6 shows the frequency of combinations of task categories performed in parallel. The most frequent combinations were talking to a passenger and adjusting in-vehicle controls (n = 13), talking to a passenger and using a mobile phone (n = 11) and talking to a passenger and grooming (n = 10). With respect to the VM complexity of tasks, Table 6-7 illustrates the three-by-three combinations of complexity groups. Simple tasks were the activities most frequently shared with others (appearing in 96% out of all multiple task events). The most commonly shared combination was constituted by two simple tasks (n = 46), followed by engagement in a simple and a moderate task (n = 15) and a simple and a complex task (n = 9). Other complexity combinations were either rare or did not occur at all.

Table 6-6. Multiple task events by task category

Combinations of task categories	Count
Passenger conversations & Adjusting in-vehicle controls	13
Passenger conversations & Mobile phone use	11
Passenger conversations & Personal grooming	10
Passenger conversations & Smoking	5
Mobile phone use & Personal grooming	5
Mobile phone use & Talking/singing no passenger	4
Passenger conversations & Eating and/or drinking	3
Adjusting in-vehicle controls & Talking/singing no passenger	3
Smoking & Adjusting in-vehicle controls	3
Smoking & Mobile phone use	3
Smoking & Talking/singing no passenger	2
Smoking & Other	2
Passenger conversations & Other	2
Passenger conversations & Reading and/or writing	1
Mobile phone use & Adjusting in-vehicle controls	1
Mobile phone use & Eating and/or drinking	1
Mobile phone use & Other	1
Personal grooming & Adjusting in-vehicle controls	1
Personal grooming & Talking/singing no passenger	1

Note: The counts for all other combinations of task categories were zero

Table 6-7. Multiple task events by VM complexity

Combinations of complexity groups	Count
Simple task & Simple task	46
Simple task & Moderate task	15
Simple task & Complex task	9
Moderate task & Moderate task	0
Moderate task & Complex task	2
Complex task & Complex task	0

With regard to the technological classification of tasks, the most frequent combination was engagement in a non-technology-based task and a technology-based task (n = 45), followed by the performance of two non-technology-based tasks (n = 25). The drivers were rarely observed performing two technology-based tasks in parallel (n = 2).

6.3.2 Did drivers regulate their secondary activities across intersection phases?

As mentioned earlier, the drivers engaged in secondary tasks on average for 26.5% of the total intersection driving time. Figure 6-8 breaks down the percentage ± 95% CI by intersection phase (upstream, within and downstream).

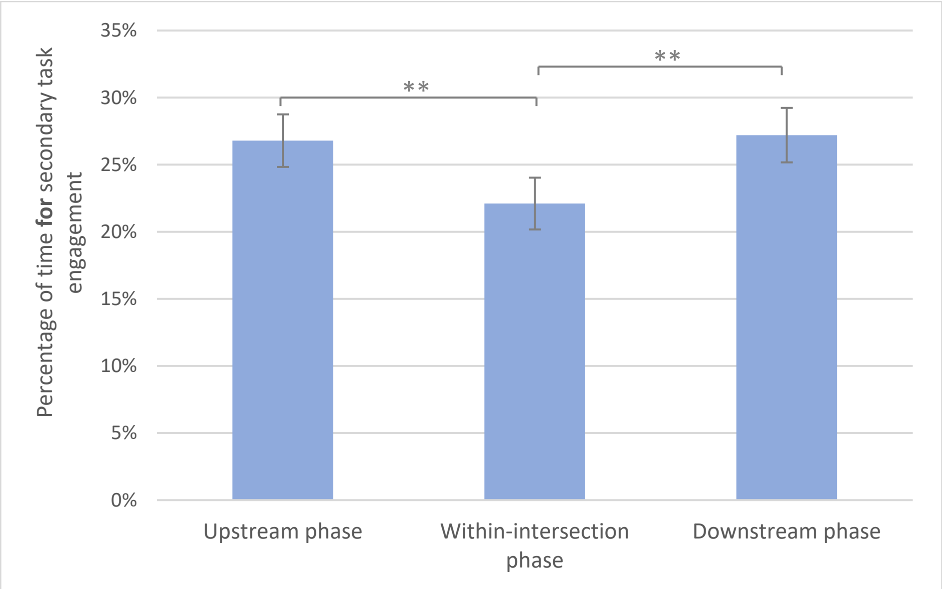

Figure 6-8. Secondary task engagement by intersection phase ($p < 0.001$)**

A one-way repeated measures ANOVA was conducted to look into the differences in the percentages of time allocated to secondary task engagement amongst the intersection phases. Pairwise comparisons were carried out with Bonferroni correction for multiple comparisons. The percentages statistically significantly differed across the intersection phases, $F(2, 3258) = 37.258$, $p < 0.001$. The pairwise comparisons showed a significantly lower level of secondary task engagement at the within-intersection phase (mean = 22.1%) than at the upstream (mean = 26.8%) and downstream phases (mean = 27.2%) ($p < 0.001$), but no significant difference was found between the upstream and downstream phases (Figure 6-8). These findings constitute what can be called a V-shaped relationship between secondary task engagement and the three intersection phases. A subsequent analysis was conducted to determine whether this V-shaped relationship held over varying driver groups and secondary task types.

6.3.2.1 Analysis of different driver groups

A series of one-way repeated-measures ANOVA were performed to determine whether the V-shaped relationship was sustained across different driver groups in terms of gender, age and country of recruitment. The findings indicated that the V-shaped trend was applicable to both the males and females (Figure 6-9), all the age groups (18–34 years, 35–54 years, 55+ years) (Figure 6-10) and all the countries (Figure 6-11). The drivers in all the groups appeared to execute secondary tasks at significantly higher rates during the upstream and downstream phases than at the within-intersection phase.

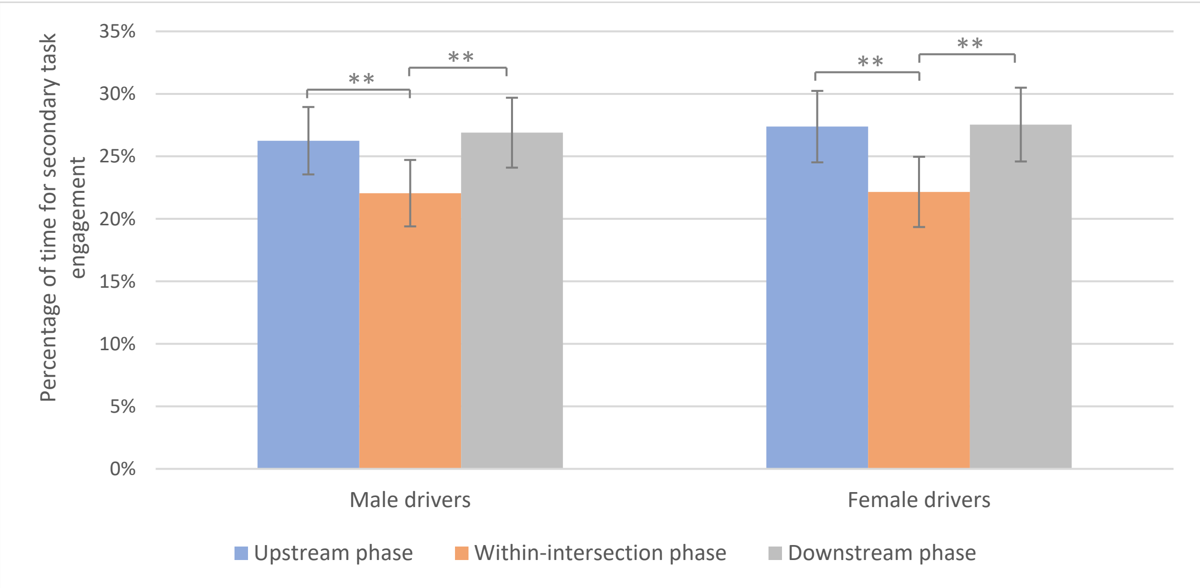

Figure 6-9. Secondary task engagement by intersection phase and gender (*p* < 0.001)**

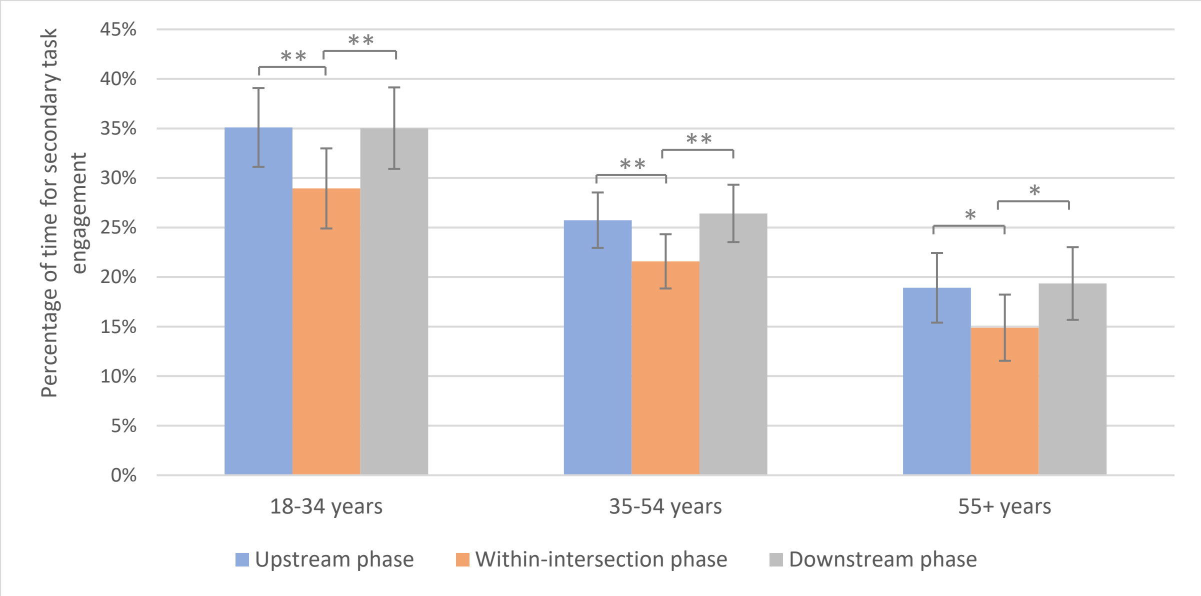

Figure 6-10. Secondary task engagement by intersection phase and age group (**p* < 0.05, *****p* < 0.001)**

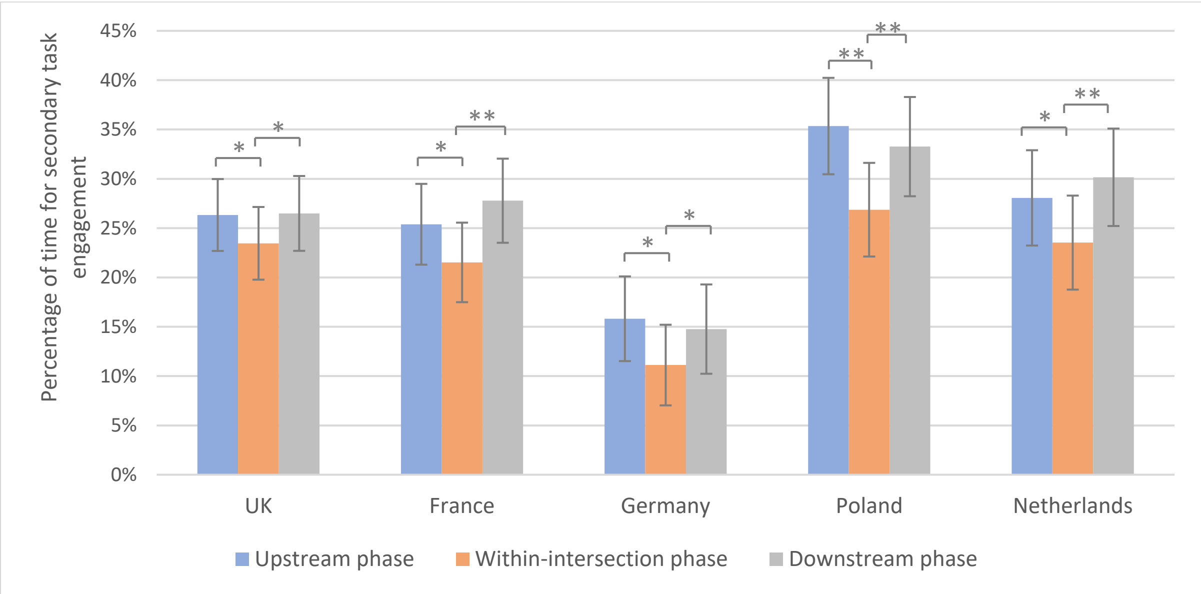

Figure 6-11. Secondary task engagement by intersection phase and country (**p* < 0.05, *****p* < 0.001)**

6.3.2.2 Analysis per secondary task type

When task performance was broken down per secondary task category, a smaller difference in such performance arose across the three intersection phases. Figure 6-12 illustrates that both passenger conversation and adjustment of in-vehicle controls were significantly (or clearly) the least commonly occurring within-intersections compared with the upstream and downstream phases (forming the V-shaped relationship). However, this relationship did not emerge in connection with mobile phone use, smoking and grooming. The trend characterising these tasks was higher engagement on the approach to intersections, with lower but almost similar engagement rates in the within-intersection and downstream phases (Figure 6-12).

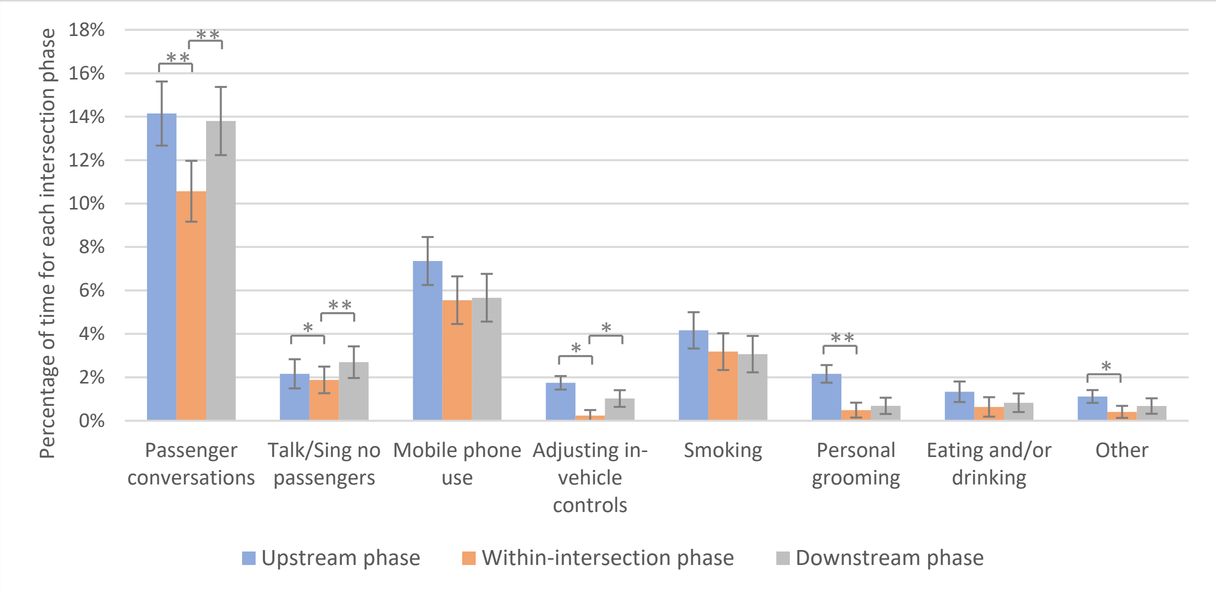

Figure 6-12. Percentage of time allocated to each secondary task category across intersection phases (*p < 0.05, **p < 0.001)

When performance was broken down per mobile phone sub-task, little difference in performance occurred across the three intersection phases, except with respect to handheld interaction. Figure 6-13 shows that this behaviour was significantly most common on the approach to intersections but that engagement dropped sharply in the within-intersection and downstream phases.

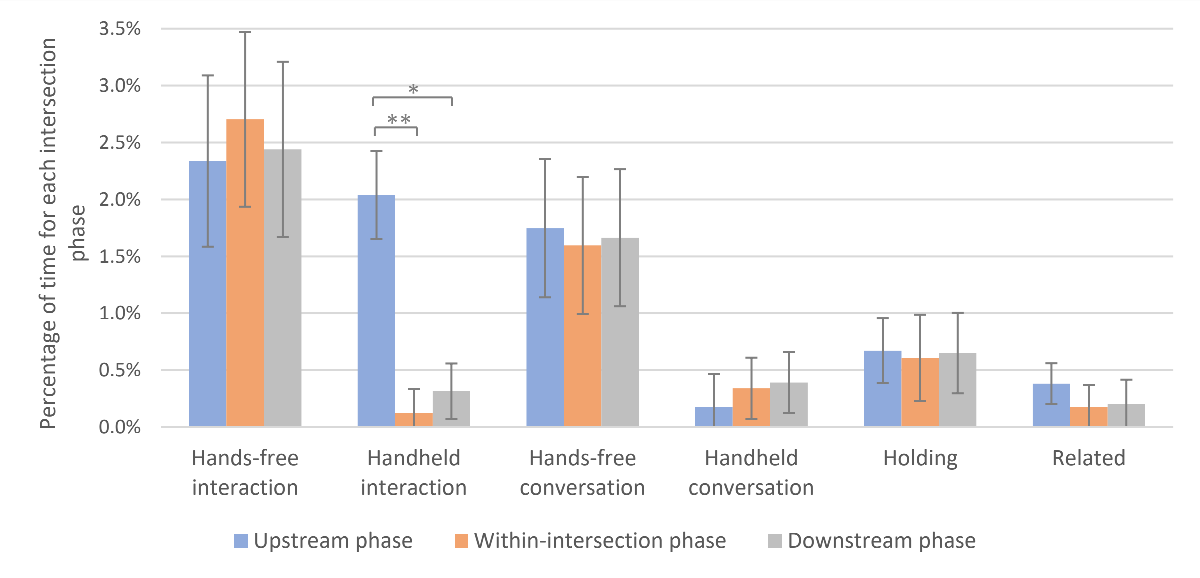

Figure 6-13. Percentage of time allocated to each mobile phone sub-task across intersection phases (*p < 0.05, **p < 0.001)

With respect to the VM complexity of secondary tasks, the drivers appeared to perform all kinds of tasks less commonly at the within-intersection phase than in the other phases; thus, the V-shaped relationship held over all the task complexity groups. A result worth noting was that the complex task group was significantly most common in the upstream phase but that involvement declined extremely sharply in the within-intersection (10 times lower) and downstream phases (four times lower) (Figure 6-14).

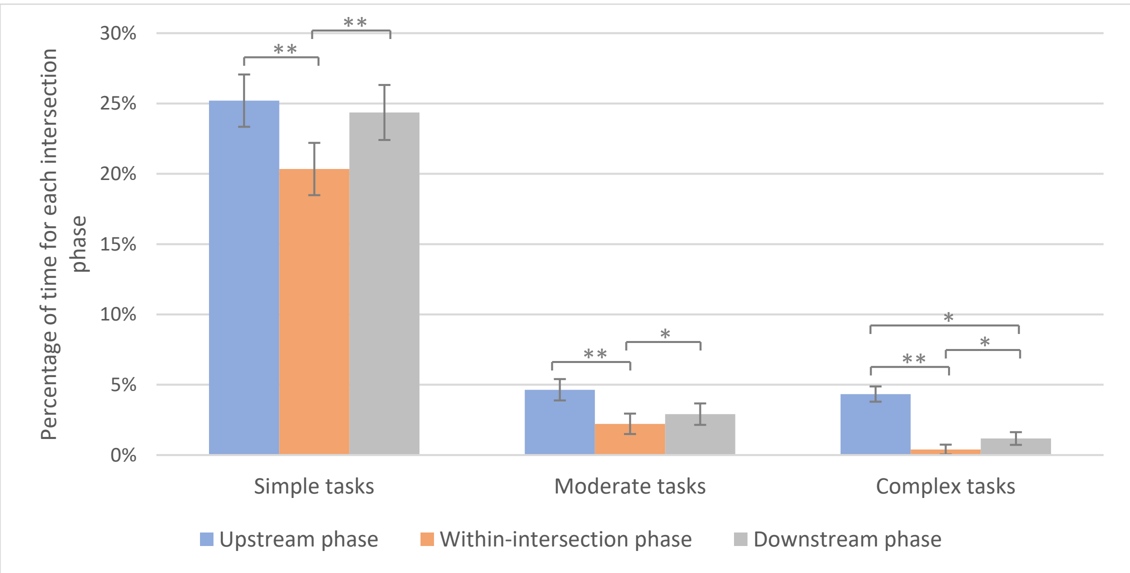

Figure 6-14. Percentage of time associated with each task complexity group across intersection phases (*p < 0.05, **p < 0.001)

Regarding task classification grounded in technological aspects, the V-shaped relationship remained over both the technology- and non-technology-based tasks, but the relationship was more obvious in the latter group (Figure 6-15).

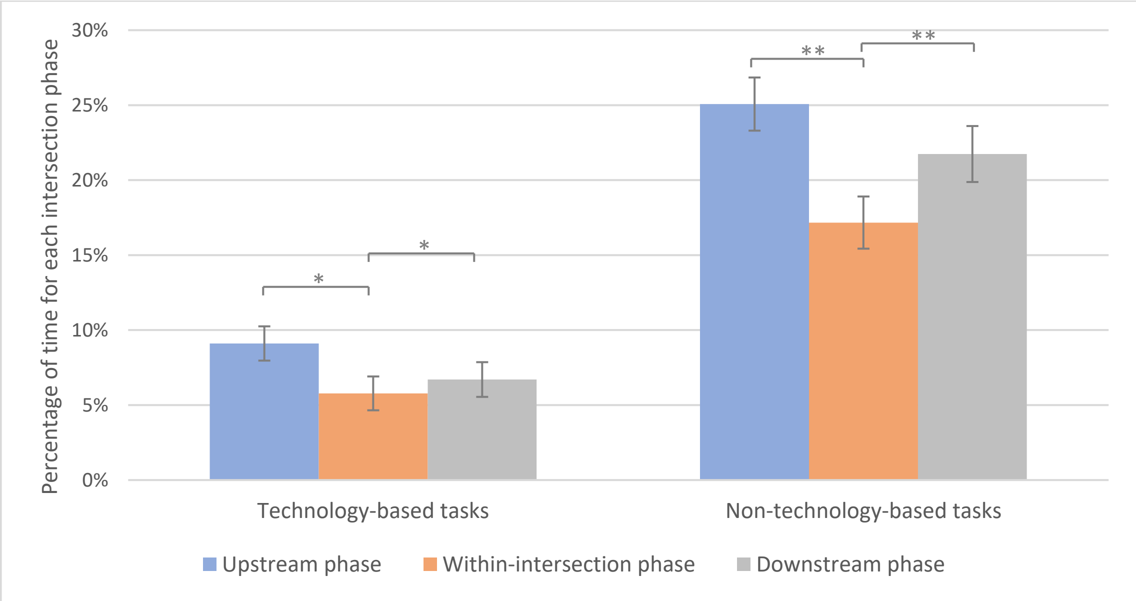

Figure 6-15. Percentage of time allocated to technology- vs. non-technology-based tasks across intersection phases (*p < 0.05, **p < 0.001)

6.3.3 Did drivers regulate their secondary activities across motion conditions?

Figure 6-16 presents a breakdown of the mean percentage ± 95% CI of total intersection travel time associated with secondary task engagement by vehicle motion status (moving and stationary). On the whole, the drivers in the sample considerably increased the percentage of time devoted to secondary tasks when their vehicles were stationary (mean = 34.8%) compared with when they were moving (mean = 25.1%). On the basis of the paired-samples t-test, this mean percentage difference between the stationary and moving conditions was statistically significant, $t(434) = 8.958$, $p < 0.001$ (Figure 6-16).

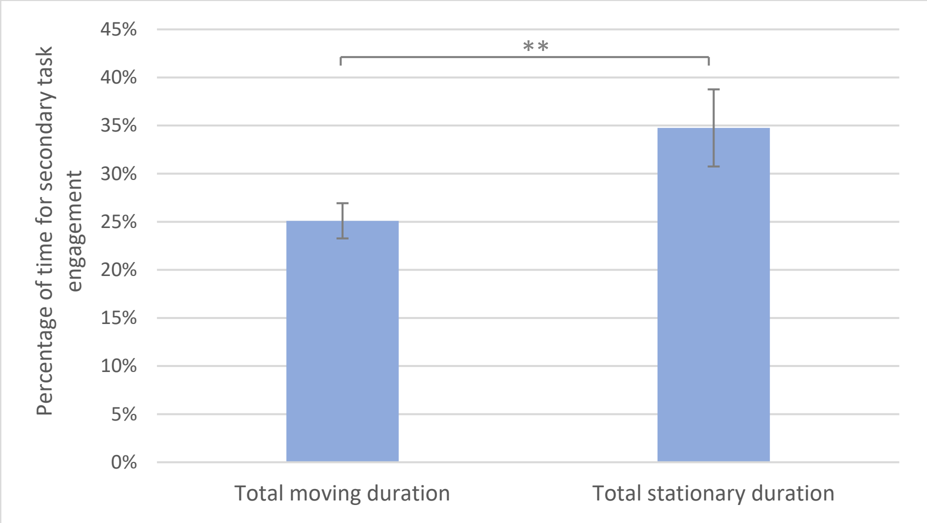

Figure 6-16. Secondary task engagement by motion status (p < 0.001)**

6.3.3.1 Analysis of different driver groups

A series of paired-samples t-tests were conducted to determine whether the trend in Figure 6-16 was maintained over the different driver groups. The findings indicated that the trend was applicable to the males and females (Figure 6-17), all the age groups (Figure 6-18) and all the countries (Figure 6-19). The drivers in all the groups significantly decreased the percentage of time devoted to secondary activities whilst their vehicles were moving compared with when they were stationary.

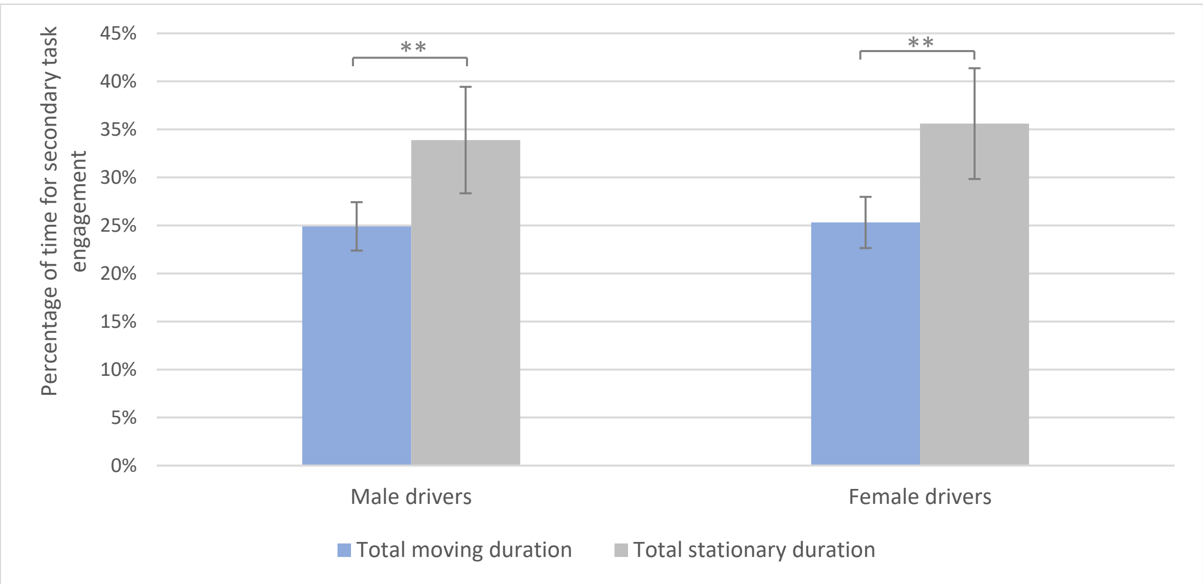

Figure 6-17. Secondary task engagement by motion status and gender (p < 0.001)**

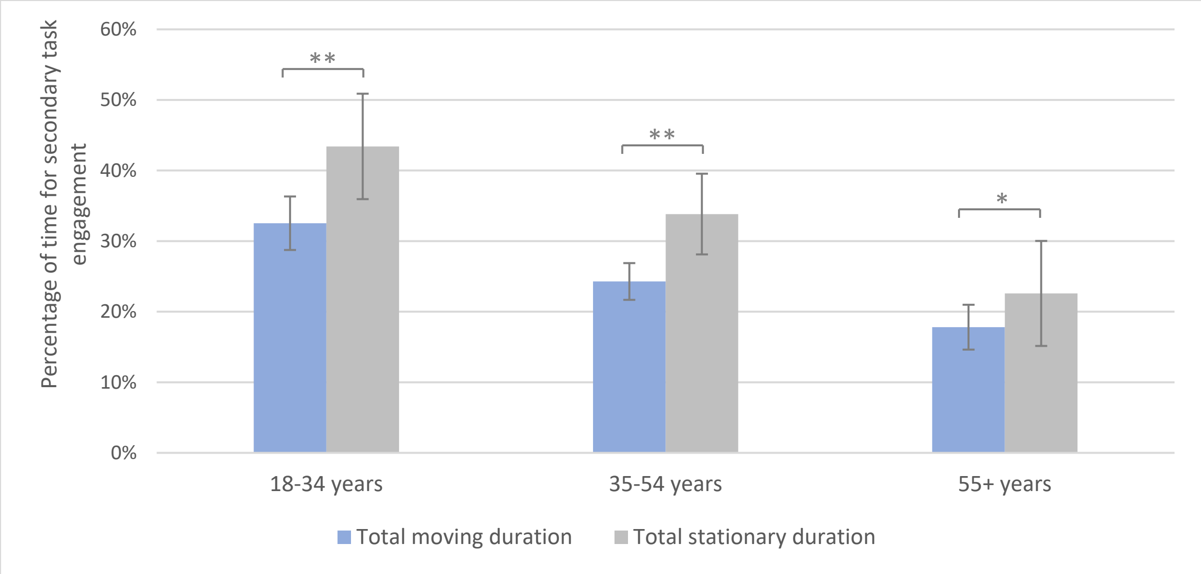

Figure 6-18. Secondary task engagement by motion status and age group (*$p < 0.05$, **$p < 0.001$)

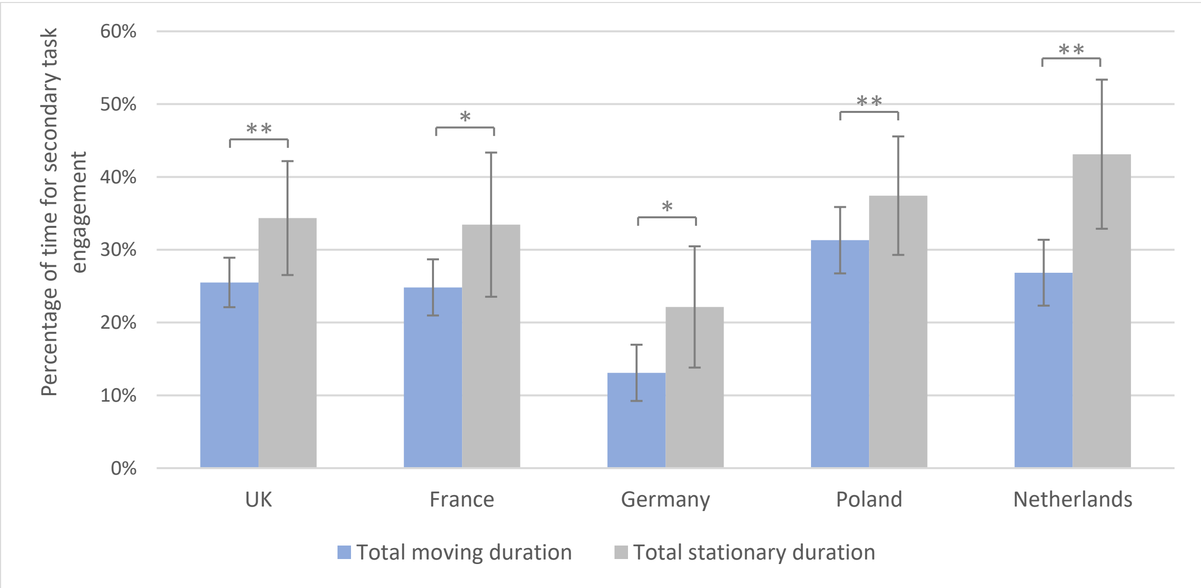

Figure 6-19. Secondary task engagement by motion status and country (*$p < 0.05$, **$p < 0.001$)

6.3.3.2 Analysis per secondary task type

When a break down per secondary task category was implemented, the same stationary–motion trend applied to most of the task categories as shown in Figure 6-20. The only exception was talking/singing in the absence of passengers, on which the drivers spent a lower percentage of time when stationary. The drivers showed nearly five times an increase in the amount of time devoted to personal grooming and adjustments to in-vehicle controls when they were stationary compared with when they were moving. The increment in stationary time was 1.5 to 2 times higher for passenger conversation, mobile phone use and eating/drinking-related tasks. However, the amount of time devoted to smoking activities did not significantly differ between moving and stationary situations.

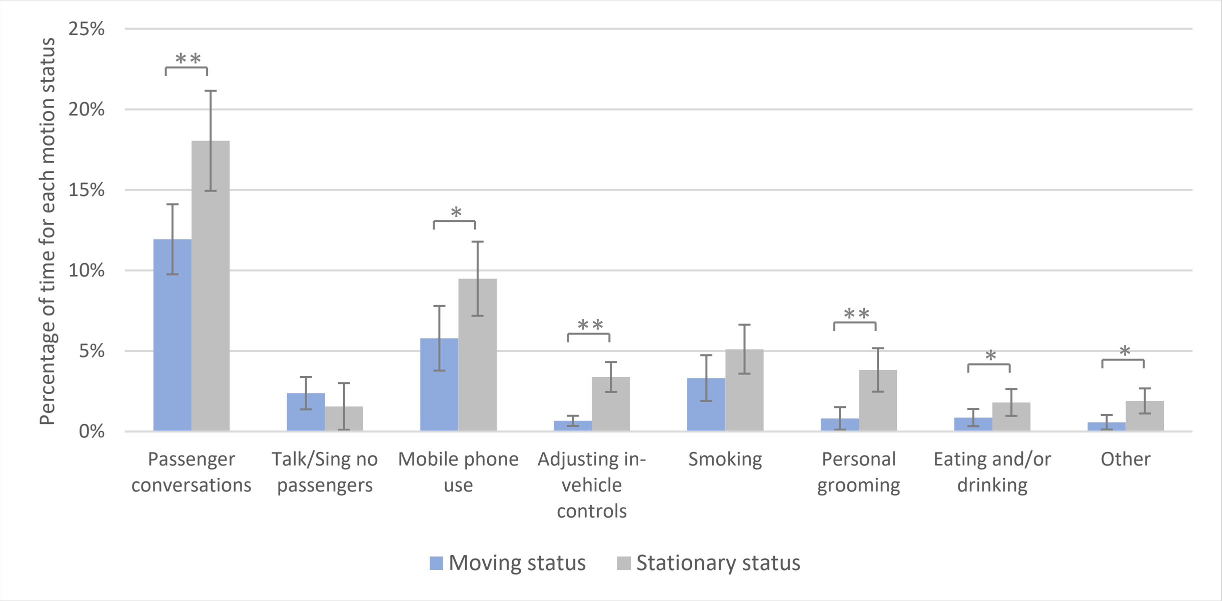

Figure 6-20. Percentage of time allocated to each secondary task category across motion status (*p < 0.05, **p < 0.001)

The same trend characterised most of the mobile phone sub-tasks shown in Figure 6-21, with the sole exception being the hands-free interaction sub-task, to which the drivers devoted a higher percentage of time as their vehicles were moving. Of note was the remarkably significant increase in the percentage of time that the drivers allocated to handheld interaction activities whilst their vehicles were stationary (nearly nine times higher than when their vehicles were moving). All the other sub-tasks did not significantly differ across motion conditions (Figure 6-21).

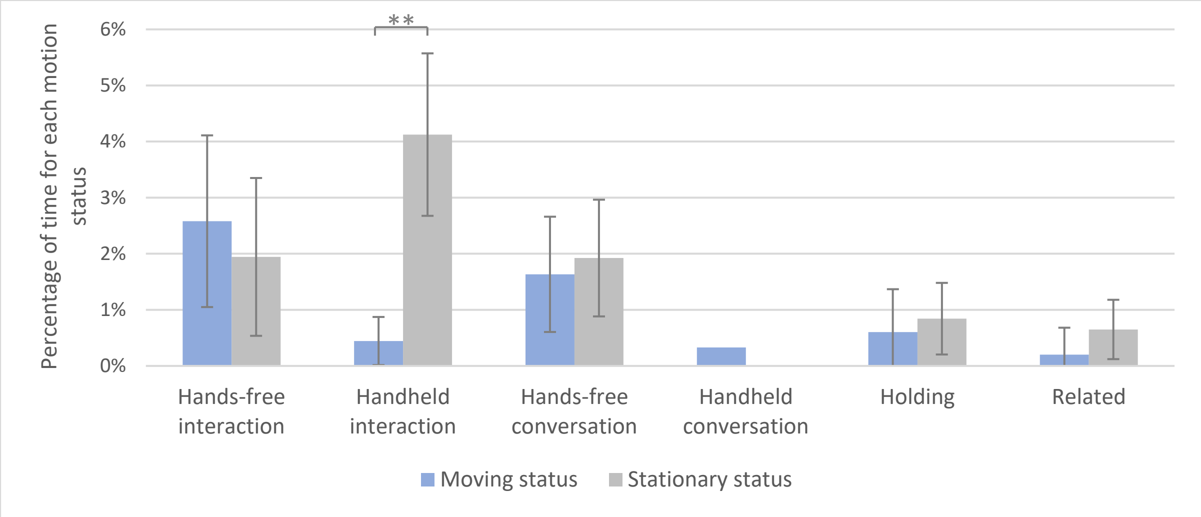

Figure 6-21. Percentage of time allocated to each phone sub-task across motion status (p < 0.001)**

In terms of the VM complexity-based classification of tasks, the stationary–motion trend held across different complexity groups (all p values < 0.001) (Figure 6-22). A result worth noting was the that drivers increased the amount of time that they devoted to complex tasks by seven times when they were stationary compared with when they were moving. For moderate and simple tasks, this increment was nearly 3 times and 1.5 times higher in the stationary condition, respectively. The same trend was observed in the technology- and non-technology-based activities (Figure 6-23), for which the drivers showed a 1.6 to 2 times increase in engagement whilst stationary compared with the rates observed as they were moving.

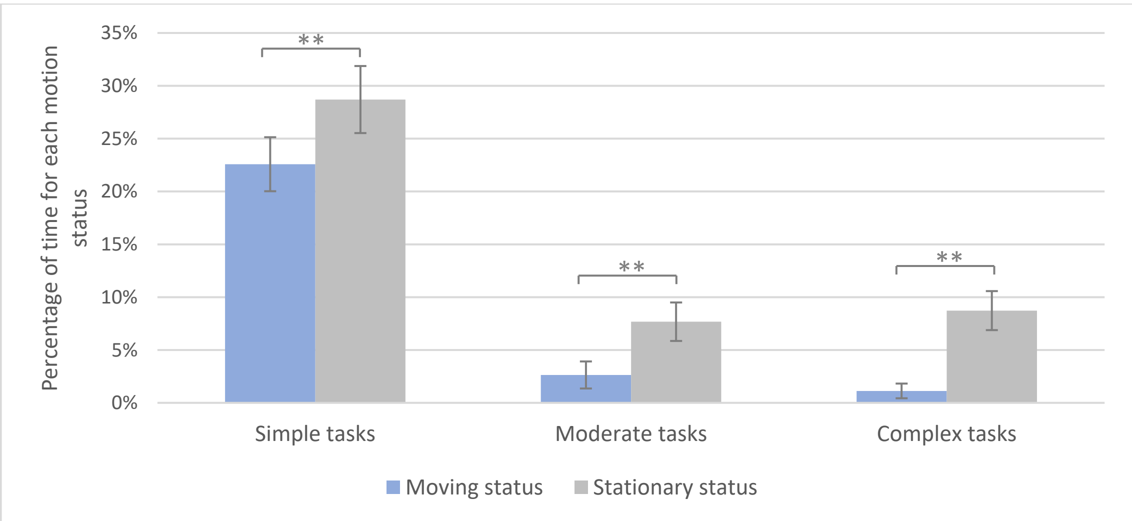

Figure 6-22. Percentage of time associated with each task complexity group across motion status (p < 0.001)**

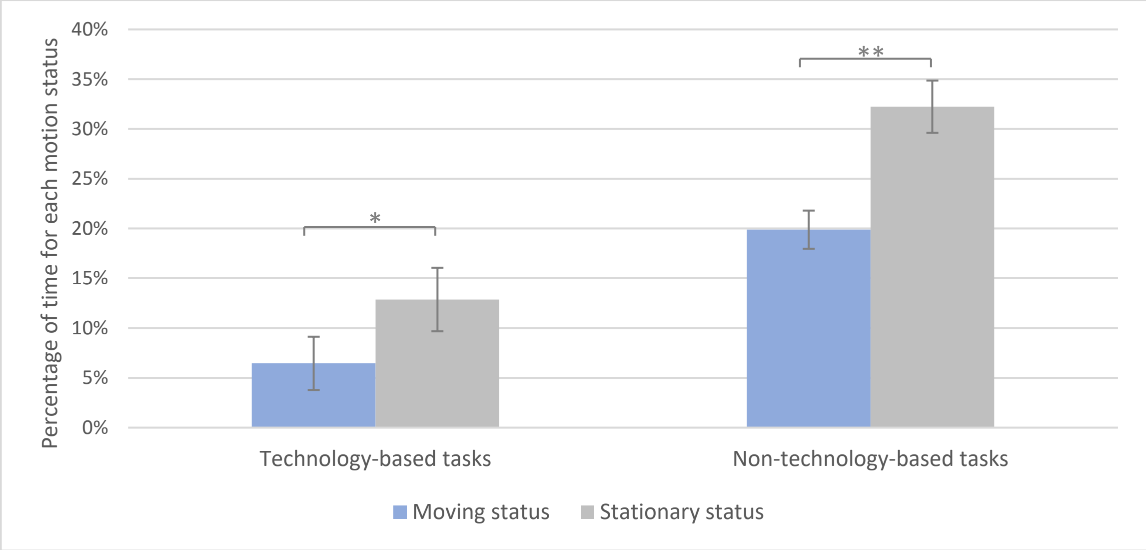

Figure 6-23. Percentage of time allocated to technology- vs. non-technology-based tasks across motion status (*p < 0.05, **p < 0.001)

6.3.4 Does being stationary influence self-regulation behaviour?

Figure 6-24 compares secondary task engagement over the three intersection phases for the cases with (n = 436) and without (n = 1194) stationary time on an intersection approach (knowing that the opportunity for stationary time most likely emerged in the upstream phase). The one-way repeated-measures ANOVA revealed a significant difference amongst the intersection phases, both with and without stationary time, $F(2, 870) = 45.854$, $p < 0.001$ and $F(2, 2386) = 28.484$, $p < 0.001$, respectively. Where no stationary time occurred, a significantly greater amount of time was spent performing secondary tasks in the downstream phase (mean = 28.7%) than in the within-intersection (mean = 23.1%) and upstream (mean = 25.1%) phases ($p < 0.001$). Where a vehicle stopped in the upstream phase, a significantly greater amount of time was consumed engaging in secondary tasks in the upstream phase (mean = 31.4%) than in the within-intersection (mean = 19.3%) and downstream (mean = 23.1%) phases ($p < 0.001$) (Figure 6-24).

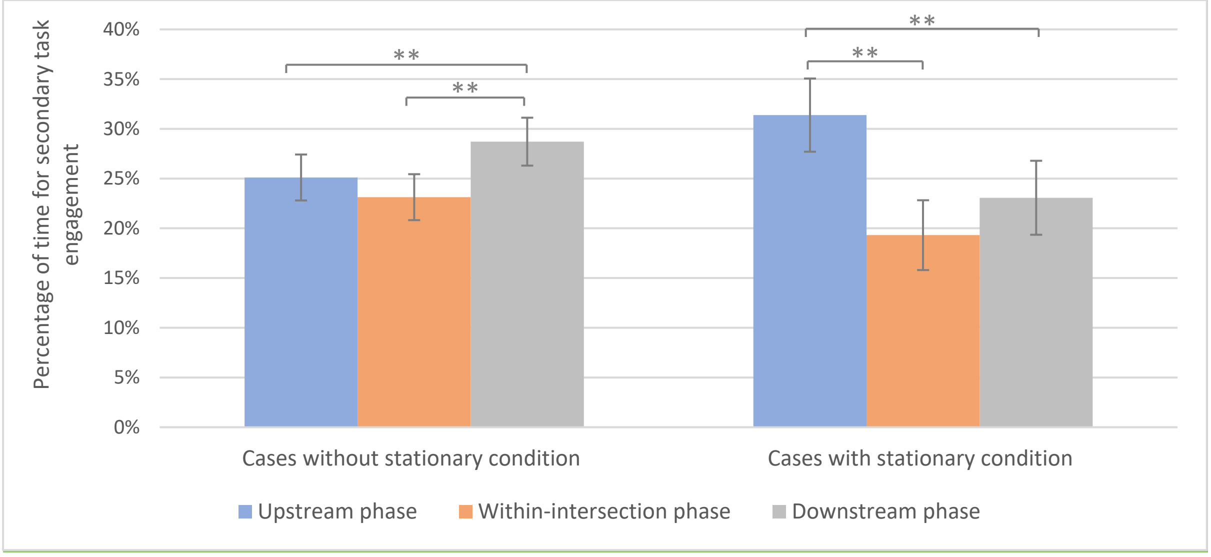

Figure 6-24. Secondary task engagement on the basis of stationary presence (*p* < 0.001)**

6.3.5 How do changes in speed influence the willingness to engage in secondary tasks?

As described in Section 6.3.4, the drivers were more likely to occupy themselves with secondary tasks when their vehicles were stationary than when they were moving. To better understand how changes in speed influenced the drivers' propensity to engage in secondary tasks, the findings on moving status were broken down to represent several speed groups (Figure 6-25).

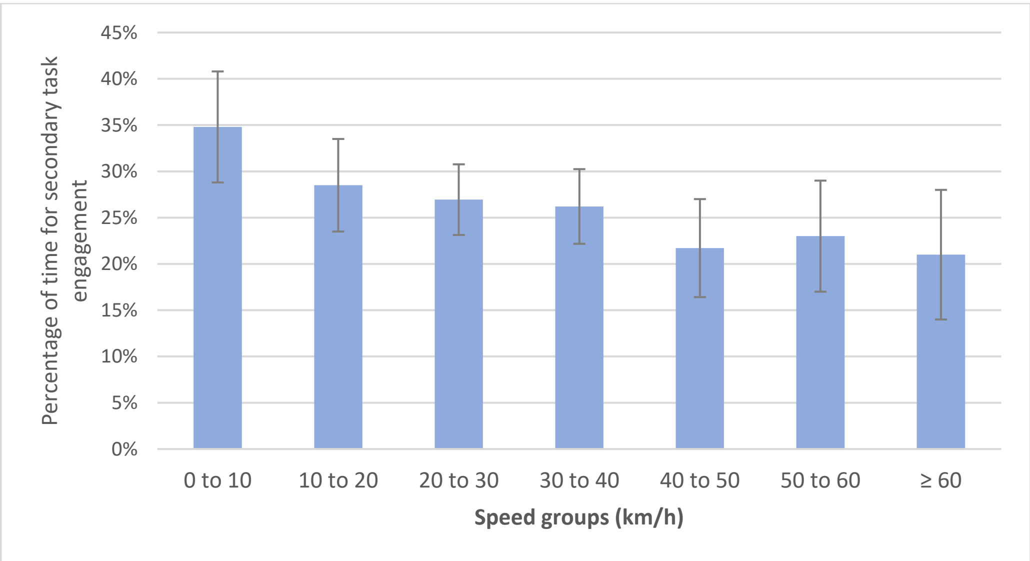

Figure 6-25. Secondary task engagement by speed group (95% CI error bars)

A one-way ANOVA was conducted to determine whether the percentage of time allocated to secondary tasks differed amongst the groups at varying speeds. The percentage was statistically significantly different amongst the speed groups, $F(6,1623) = 2.126$, $p = 0.048$, with the trend being decreasing time allocated to secondary activities with increasing speed. Tukey's post hoc analysis revealed that the decrease in time allocation in the 0–10 km/h speed group differed to a statistically significant extent from that of the other groups ($p < 0.05$) (except for the 10–20 km/h group), but no other group differences exhibited such a significance.

Spearman's rank-order correlation was carried out to assess whether the above-mentioned trend formed a significant association between the two variables. The analysis unravelled a statistically significant, weak/small correlation between the percentage of time involving secondary tasks and speed, $r_s(1628) = –0.150$, $p < 0.001$. This correlation was negative, suggesting that as speed increased, the proportion of time devoted to secondary task engagement decreased (Figure 6-25).

6.3.6 Are there differences in the willingness to engage in secondary tasks between intersection and non-intersection segments?

Secondary task engagement in intersection and non-intersection segments was compared to explore whether the drivers adjusted their behaviours or behaved differently across these roadway locations. As described in the methodology chapter, each of the 1630 intersection cases was matched with a non-intersection segment that was selected from the same trip. This produced a total sample of 1630 non-intersection segments. Because all the non-intersection segments involved moving conditions only, secondary tasks that occurred at intersections in stationary conditions were excluded from the analysis.

Broadly speaking, the analysis revealed that a significantly higher percentage of non-intersection segments involved secondary task interaction (50.6%) compared with intersections (43.2%). The odds ratio (OR) of secondary task occurrence in non-intersection segments versus intersections was 1.348 (95% CI, 1.159–1.568). In addition, the drivers initiated a significantly greater number of tasks per minute of driving and accorded a significantly higher percentage of their total travel time to secondary task execution at non-intersection segments compared with intersections (Table 6-8).

Table 6-8. Comparison of secondary task engagement in non-intersection and intersection segments

Segments	% of cases involving task	No. of tasks initiated per min of driving	% of driving time with task
Non-intersections	50.6	2.2	31.3
Intersections	43.2	1.9	25.7
Statistical test	OR*= 1.348 (95% CI, 1.159 to 1.568)	** $t(1629) = 1.971$, $p = 0.045$	** $t(1629) = 5.504$, $p < 0.001$
Sig.	Significant	Significant	Significant

* Odds ratio of non-intersections vs. intersections

** Paired-samples t-test

When a breakdown per secondary task type was carried out, the tendency of the drivers to occupy themselves in most of the task types was more prevalent in non-intersection segments than intersections (Table 6-9). The only exceptions were hands-free interaction and hands-free conversation sub-tasks, which the drivers were more willing to perform at intersections. Nevertheless, most of these differences were not statistically significant (p values > 0.05). The only significant findings were as follows:

- The drivers were 2.5 times more willing to adjust in-vehicle controls at non-intersection segments than intersections ($p < 0.001$).
- They were 2.7 times more willing to engage in personal grooming activities at non-intersection segments than intersections ($p < 0.001$).

- The drivers were 1.3 times more willing to perform complex tasks at non-intersection segments compared with intersections ($p < 0.001$).
- The drivers were 1.6 times more willing to perform multiple tasks (in parallel) at non-intersection segments compared with intersections ($p = 0.031$).

Table 6-9. Non-intersection vs. intersection segments by secondary task type

Classification	Tasks	OR*	95% CI (LCL–UCL)	Sig.
Secondary task categories	Passenger conversations	1.067	0.887–1.283	0.492
	Talking/singing in the absence of passengers	1.294	0.968–1.728	0.082
	Mobile phone use	1.070	0.787–1.454	0.666
	Adjusting in-vehicle controls	2.452	1.666–3.607	< 0.001**
	Smoking	1.101	0.737–1.644	0.638
	Personal grooming	2.743	1.724–4.362	< 0.001**
	Eating and/or drinking	1.505	0.796–2.847	0.208
	Other (including reading/writing tasks)	1.339	0.715–2.507	0.361
Mobile phone sub-tasks	Hands-free interaction	0.963	0.602–1.541	0.875
	Handheld interaction	1.197	0.607–2.362	0.604
	Hands-free conversation	0.844	0.473–1.507	0.567
	Handheld conversation	1.449	0.457–4.587	0.529
	Holding	1.714	0.642–4.573	0.282
	Related	1.081	0.340–3.438	0.895
Task VM complexity	Simple tasks	1.244	0.788–1.962	0.348
	Moderate tasks	1.328	0.944–1.867	0.104
	Complex tasks	1.255	1.076–1.463	< 0.001**
Technological classification	Technology-based tasks	1.095	0.889–1.349	0.394
	Non-technology-based tasks	1.057	0.917–1.217	0.444
Multiple task engagement		1.564	1.042–2.349	0.031**

* Odds ratio of non-intersection segments vs. intersections

** Significant result

6.4 Discussion

On the basis of ND data, this chapter looked into the prevalence of secondary task engagement whilst driving through intersections and investigated what main self-regulatory strategies the drivers adopted to manage such engagement. Inquiry was also directed towards whether there were differences in the propensity of the drivers to engage in secondary tasks between intersection and non-intersection segments. The results revealed a number of interesting findings regarding the prevalence levels and patterns of secondary task engagement as well as the drivers' attempts to self-regulate this behaviour across different roadway conditions. During the within-intersection phase, for instance, the drivers moderated secondary task engagement to a level lower than that observed in the phases located immediately upstream or downstream of intersections. These findings should be considered in the development of countermeasures to road traffic crashes, including training/education programmes, media campaigns, infrastructure design and advanced driver assistance systems.

6.4.1 Prevalence of secondary task engagement at intersections

Out of the 1630 intersections coded, nearly half of the intersections (47.7%) and one-quarter of the total observed intersection time (26.5%) involved interaction with a secondary task. These figures indicate that secondary task engagement is common and frequent amongst drivers. The one-quarter time percentage outcome is inconsistent with the findings of Carsten et al. (2017; i.e. the UDRIVE project), Young et al. (2019) and Dingus et al. (2016), who discovered 10.2%, 44.4% and 51.9% engagement, respectively. These differences are likely due to coverage — the present analyses were restricted to intersections, whereas the previous investigations mentioned were aimed at the full range of driving contexts. The differences can also be attributed to some cross-country behavioural differences of drivers as well as differences in sample demographic characteristics between studies. Moreover, the different coding schemes applied in these studies renders solid comparisons difficult. For example, the current work included passenger conversations as a type of secondary task engagement, but this category was not covered in the UDRIVE project.

Across the 1630 intersection cases, the most frequently observed task categories were passenger conversations, followed by talking/singing in the absence of passengers and mobile phone activities. Notably, the least frequently observed activities were those associated with reading/writing, which was unsurprising because these tasks require taking one's eyes completely off the road. Smoking also minimally occurred, but it was the task characterised with the longest mean duration throughout an entire intersection zone. This result was unsurprising because smoking tasks were annotated as long as the cigarette was burning independent of the position of the cigarette (e.g. hand, mouth). Conversely, interactions with an in-vehicle control system entailed the shortest average duration, which was as expected given the brief period required to accomplish this type of task.

The highest prevalence registered by passenger conversations is consistent with the findings of earlier ND studies (Young et al., 2019; Dingus et al., 2016; Stutts et al., 2003a). In the UDRIVE project, mobile phone usage and talking/singing were the most frequent, whereas reading/writing was the lowest-frequency task (Carsten et al., 2017), in line with the findings of the current study (accounting for the absence of passenger conversations from their coding scheme). The only dissimilarity between the outcomes of the two studies is the relative frequency of personal grooming activities and eating/drinking tasks. These categories were observed to a lesser extent in the present intersection-focused work in contrast to the results of the full-trip analysis in the UDRIVE study. This leads to the possibility that abstinence from eating-, drinking- and grooming-related tasks is a form of self-regulation exercised by drivers. Overall, this research provided evidence that drivers refrain from carrying out certain secondary activities as they travel through intersections (perhaps what the drivers perceive as non-essential or non-time-critical tasks).

The use of mobile phones (hands-free and handheld) accounted for 13% of all the secondary tasks observed and was performed in approximately 7% of the total intersection driving time. The most frequent phone activity was hands-free interaction (accounting for over one-third of all phone activities executed), followed by hands-free conversation and handheld interaction activities. The phone activity with which the drivers least frequently occupied themselves was handheld conversation. These results reflect that hands-free phone use more commonly occurs than handheld phone use in intersections, contradicting the full-trip findings derived by Hibberd et al. (2020). The authors found that hands-free and handheld phone use occur at a similar frequency. Nevertheless, it is important to note the low frequency of phone use instances throughout both datasets. The increased demand imposed by driving through an intersection appeared to decrease the drivers' inclination to use their mobile phones in a handheld manner. This was unsurprising because at intersections, drivers have a greater need to use their hands, particularly when turning or shifting gears, and are therefore less inclined to occupy their hands simultaneously with a handheld phone activity. The drivers nonetheless did not abstain entirely from this task at intersections. It is worth noting that all the drivers in the UDRIVE project were driving manual transmission cars.

The detailed findings on mobile phone use also showed that both hands-free interaction and hands-free conversation activities were performed for considerably longer mean durations than were handheld interaction and handheld conversation, respectively. This suggests that drivers are aware of the illegality of handheld phone use and accordingly try to keep these types of activities brief to minimise the chances of being observed or caught (knowing that handheld phone interaction is prohibited by law in all the countries in the sample). However, caution should be exercised before generalising this trend given that few mobile phone interactions were made, making it difficult to draw strong conclusions on behavioural trends. Future work should acquire a larger sample of phone interaction cases to establish whether this trend takes place on a wider scale.

In terms of the VM complexity-based classification of tasks, the simple tasks were the most frequent and common amongst the drivers, accounting for over 80% of all secondary tasks performed. These tasks had the longest mean duration and were executed for nearly 24% of the total intersection driving time. Task frequency and duration decreased as task involvement proceeded from simple to moderate to complex; thus, the associated percentage of total driving time decreased as task complexity increased. This trend is somewhat consistent with the full-trip findings of Klauer et al. (2006b), but the drop in time percentage across the task complexity groups was steeper and more obvious in the current work. This was expected given the increased demand for focus on driving through intersections, which appeared to further diminish the inclination of the drivers to engage in the most complex secondary activities. As with handheld phone usage, however, the complex tasks did not disappear entirely at intersections.

Of particular interest was that engagement in multiple secondary tasks in parallel was observed across nearly 4% of the intersection cases and accounted for 1.5% of the total intersection driving time. The current study and that of Young et al. (2019) both uncovered that conversation with a passenger was the secondary task category most commonly shared with other activities, with 50% to 60% of all the multiple task events involving simultaneity between this act and other tasks. The present analyses further revealed that multiple task engagement most often involved activities that required different resources. For example, the most frequently combined multiple tasks were talking to a passenger (i.e. a vocal and auditory task) and adjusting in-vehicle controls (i.e. a VM task). Categorising the tasks in accordance with the VM complexity-based classification indicated, as expected, that the simple tasks were the activities most frequently combined with others (appearing in 96% out of all multiple task events), with the most recurrently shared combinations involving two simple tasks (accounting for 64% of all multiple task events). Therefore, the more complex a secondary task, the less likely that it will be carried out simultaneously with other activities.

6.4.2 Secondary task engagement across intersection phases

As was hypothesised in the present chapter, the percentage of time that involved secondary task engagement was greater during the upstream and downstream phases than during the within-intersection phase. A V-shaped self-regulation relationship existed between secondary task engagement and progress through the intersection phases, implying that drivers minimise secondary task engagement as a response to a high driving demand or risk related to the within-intersection phase (where conflicts with other streams of traffic are more likely to occur). This understanding is strengthened by the fact that the V-shaped relationship was sustained across different driver groups in terms of gender, age and country of recruitment. The relationship also held over most of the secondary task types and was especially pronounced with respect to the more complex secondary behaviours (e.g. handheld phone interaction), as expected.

Few of the secondary task types, including smoking and hands-free phone interaction, showed no such relationship, in which little difference in performance occurred amongst the three intersection phases. This was unsurprising given the continuous nature of these tasks and the way in which they were annotated. As previously described, smoking tasks were annotated the entire time a cigarette burned independently from the position of the cigarette (e.g. hand, mouth), whereas hands-free phone interactions (i.e. mostly occurring when drivers were receiving navigational guidance through the phone) were annotated throughout the period during which a phone screen could be seen independently from the interaction modality. Mobile phone calls (hands-free and handheld) were also associated with little difference in performance rates across the three intersection phases, suggesting that the drivers were less willing to relinquish involvement as they travelled through intersections. However, generalisation should be undertaken with caution given that few phone calls were made, making it difficult to generate definitive conclusions regarding behavioural trends.

The above-mentioned V-shaped relationship varied, depending on whether the upstream phase involved a vehicle being stationary at some point. Where a vehicle did not stop in the intersection, the drivers were more willing to postpone initiating secondary activities until the driving task demand declined at the downstream phase. Where stopping occurred, the drivers were more likely to perform secondary tasks during stationary at the upstream phase and then relinquish activities to keep pace with the growing demand/risk encountered after movement. These outcomes imply that being stationary highly influences drivers' decisions on when to initiate or abandon secondary tasks across the intersection phases. Ultimately, then, this behaviour can be deemed another form of self-regulation.

6.4.3 Secondary task engagement across motion conditions

The comparison of behaviours under movement versus stationary conditions likewise suggested that the drivers, overall, had a considerably lower rate of secondary task engagement when their vehicles were moving compared to when they were stationary. This outcome confirms the hypothesis presented in the current chapter and agrees with previous ND studies (e.g. Young et al., 2019; Tivesten and Dozza, 2015; Funkhouser and Sayer, 2012; Metz et al., 2014; Stutts et al., 2003a). This result points yet again to self-regulatory discipline by drivers, this time in response to high demand during motion compared with the demand under stationary conditions. The drivers were at least somewhat aware of the increased risk posed by some secondary tasks, and they made a strategic decision to wait until they were stationary to occupy themselves with a higher number of tasks. What reinforces this comprehension is that the trend applied to the males and females, all the age groups and all the countries.

The same stationary–motion trend applied to most of the secondary task types and was particularly prominent with regard to the most complex secondary behaviours (i.e. the high-risk tasks). The more complex a secondary task, the lower the chances of occurrence whilst moving and the higher the possibility of occurrence whilst stationary. However, it is important to note that the drivers did not entirely refrain from engaging in complex tasks under movement. Equally noteworthy was that the drivers initiated several secondary tasks whilst braking just before they came to a full stop, yet in a number of other cases, they disengaged from secondary activities that were commenced during a standstill shortly after the start of movement; however, this engagement strategy was not captured in the current analysis. Advancing or delaying secondary task engagement towards stationary vehicle conditions, whilst likely to reduce risk, is far from a solution to the distracted driving problem. In fact, previous research (e.g. Strayer et al., 2015; Winzer et al., 2017) indicated that residual interference from secondary activities may have already begun before task initiation and may persist beyond task completion.

The only exceptions from the stationary–motion trend were talking/singing in the absence of passengers and the hands-free phone interaction tasks, to which the drivers devoted a slightly (but not significantly) higher percentage of time as their vehicles were moving compared to when they were stationary. This was unsurprising given the simplicity of the talking/singing task category and the continuous nature of the hands-free phone interaction task.

6.4.4 The influence of speed on the willingness to engage in secondary tasks

The findings on moving status were further broken down across speeds to cast light on whether and how changes in speed influenced the drivers' inclination to engage in secondary tasks. The analysis suggested a negative correlation between speed and the percentage of time involving secondary tasks. Put differently, the higher the speed, the lower the percentage of time spent carrying out secondary activities; thus, the hypothesis presented in the current chapter was confirmed. This result implies another kind of self-regulation exercised by drivers. A plausible explanation here is that the drivers managed their behaviours, realising that high-speed conditions are more demanding and riskier periods in which to perform secondary behaviours. This explanation corresponds with the mobile phone use findings of Funkhouser and Sayer (2012) and Tivesten and Dozza (2015), who unravelled that drivers in the US and Sweden, respectively, are less likely to initiate phone conversations and VM phone activities when driving at high speeds than when driving at low speeds.

6.4.5 Secondary task engagement in intersections and non-intersection segments

The comparison of secondary task engagement in intersections and non-intersection segments suggested that the drivers behaved differently across these roadway locations. Specifically, they were significantly less predisposed towards performing secondary tasks when they passed through intersections compared with non-intersection segments (as was hypothesised in this chapter). This finding suggested a level of self-regulation in which the drivers were, at least to some extent, aware of the increased demand/risk of driving through intersections and reduced their secondary task engagement on that basis. What strengthens this interpretation is that the same trend applied to most of the secondary task types and that the reduction in task engagement rates at intersections (compared with non-intersection segments) was more obvious/steeper with respect to the more complex secondary activities and multiple task engagement.

Given such a kind of self-regulatory discipline by the drivers, however, an essential issue for consideration is that the drivers still spent around one-quarter of their total driving time doing secondary tasks at intersections. They also devoted a higher percentage of time performing secondary tasks whilst stationary at intersections (34.8%) compared with non-intersection segments (31.3%). These findings highlight the work that still needs to be done to reduce drivers' secondary task engagement rates at intersections.

Only the hands-free mobile phone interaction and conversation sub-tasks exhibited a reverse non-significant trend with higher engagement rates at intersections. This was not surprising considering the continuous and hands-off nature of such activities. However, the generalisation of this trend must be approached with care given the low number of phone activities performed, rendering the drawing of definitive conclusions challenging.

6.5 Summary and conclusion

This chapter presented the analysis of ND data for an investigation into the prevalence and patterns of secondary task engagement whilst driving through intersections and exploration of what self-regulatory strategies the drivers adopted to manage such an engagement. The findings on prevalence revealed that secondary task engagement was common amongst the drivers, who nevertheless also exercised self-regulation by reducing engagement during certain roadway conditions that were assumed/considered to be more challenging. This self-regulatory discipline was shown by the drivers' diminished willingness to perform secondary activities when their vehicles were moving and the V-shaped relationship between the percentage of time dedicated to secondary task tasks and the three intersection phases (upstream, within and downstream). Self-regulatory behaviour was also represented by the reduced willingness of the drivers to perform secondary tasks when driving at high speeds (compared with driving at low speeds) and when travelling through intersections (compared with travel over non-intersection segments. A particularly important finding is that these self-regulatory practices were especially pronounced with respect to the more complex and therefore more demanding secondary behaviours.

Although this chapter shed light on several findings regarding the prevalence and self-regulation of drivers' secondary task engagement, there is still a need for additional research on some relevant aspects that were not covered in the current chapter. Exploring these aspects is vital to gain a precise and more comprehensive picture of self-regulation behaviours before implications are drawn. These aspects include the extent to which a wider array of driver-related (e.g. age and gender) and contextual variables (e.g. intersection control and weather conditions) influence the willingness of drivers to occupy themselves with secondary activities. This research direction is covered in the next results chapter (Chapter 7).

Chapter Seven

What Driver-related and Contextual Factors Predict the Willingness of Drivers to Engage in Secondary Tasks?

After the determination of the types of secondary tasks that drivers typically engage in and the prevalence of these behaviours in Chapter 6, this chapter was intended to ascertain whether the aforementioned engagement is influenced by driver-related factors (e.g. age and gender) and contextual variables, particularly those associated with the complexity of the driving task at intersections (e.g. intersection control and weather conditions). The analyses in this chapter focused on exploring whether drivers manage or self-regulate their secondary task engagement at intersections, but this behaviour was also investigated in the context of non-intersection segments to generate a comparison benchmark for driver conduct at intersections.

7.1 Aims and hypotheses

This chapter describes the inferential statistical methods implemented in this work and presents the results meant to address the following research question: What driver-related and contextual factors predict the willingness of drivers to engage in secondary tasks? This query includes two secondary questions:

- Research Question A: What driver-related and contextual factors predict the decision of drivers to engage in secondary tasks (with task/no task)?
- Research Question B: What driver-related and contextual factors predict the percentage of driving time allocated to secondary task engagement?

Tables 7-1 and 7-2 list the names, descriptive definitions and measurement levels of the binary categories (analysed using multilevel binary logistic regression) and continuous level measures (analysed using multilevel multiple linear regression) that were used to address the sub-questions. Tables 7-3 and 7-4 define the predictor variables.

Multilevel modelling (also known as hierarchical modelling) is quite a complex subject, but here is a brief explanation of it drawn from Hox et al. (2010):

> The term 'multilevel' refers to a hierarchical or nested data structure, usually subjects within organisational groups, but the nesting may also consist of repeated measures within subjects, or respondents within clusters, as in cluster sampling. The expression multilevel model is used as a generic term for all models for nested data. Multilevel analysis is used to examine relations between variables measured at different levels of the multilevel data structure . . . multilevel modelling has contributed to the analysis of traditional individuals within groups data, repeated measures and longitudinal data, sociometric modelling, twin studies, meta-analysis and analysis of cluster randomised trials (Hox et al., 2010. p. 8).

Unlike standard modelling in which all the independent variables are entered into the regression equation at the same time, multilevel modelling allows the independent variables to be entered into the regression equation in a specific order. This has a number of advantages, such as allowing the analyst to: (a) control for the effects of covariates on the results; and (b) take into account the possible causal effects of independent variables when predicting a dependent variable. Nonetheless, all multilevel regressions answer the same statistical question: How much extra variation in the dependent variable can be explained by the addition of one or more independent variables? (Gelman and Hill, 2006). Multilevel modelling is explained in further detail in Section 7.2.

Table 7-1. Binary dependent variables used to address Research Question A

Variables	Descriptive definitions	Categories
Total intersection segment	Secondary task engagement in the total intersection segment	Binary categories: 0 = No task 1 = With task
Upstream intersection phase	Secondary task engagement in the upstream-intersection phase only	Binary categories: 0 = No task 1 = With task
Within-intersection phase	Secondary task engagement in the within-intersection phase only	Binary categories: 0 = No task 1 = With task
Downstream intersection phase	Secondary task engagement in the downstream-intersection phase only	Binary categories: 0 = No task 1 = With task
Moving intersection status	Secondary task engagement only while moving along an intersection	Binary categories: 0 = No task 1 = With task
Stationary intersection status	Secondary task engagement only while stationary at an intersection	Binary categories: 0 = No task 1 = With task
Total non-intersection segment	Secondary task engagement in the total non-intersection segment	Binary categories: 0 = No task 1 = With task

Table 7-2. Continuous dependent variables used to address Research Question B

Variables	Descriptive definitions	Measures
Total intersection time	Percentage of time in which drivers engaged in secondary tasks along the total intersection segment	0.0% to 100.0%
Upstream intersection time	Percentage of time in which drivers engaged in secondary tasks in the upstream phase only	0.0% to 100.0%
Within-intersection time	Percentage of time in which drivers engaged in secondary tasks in the within-intersection phase only	0.0% to 100.0%
Downstream intersection time	Percentage of time in which drivers engaged in secondary tasks in the downstream phase only	0.0% to 100.0%
Moving intersection time	Percentage of time in which drivers engaged in secondary tasks in the moving intersection status only	0.0% to 100.0%
Stationary intersection time	Percentage of time in which drivers engaged in secondary tasks in the stationary intersection status only	0.0% to 100.0%
Total non-intersection time	Percentage of time in which drivers engaged in secondary tasks along the total non-intersection segment	0.0% to 100.0%

Table 7-3. Predictor variables (driver-related factors) used to address RQs A and B

Variables	Descriptions	Measures
Age	Age of driver	One continuous variable: 18 to 80 years
Country	Country of driver	Five dummy variables coded as 1 or 0: France; Poland; United Kingdom; Netherlands; Germany (reference)
Gender	Gender of driver	Two nominal categories: 0 = Female; 1 = Male

Table 7-4. Predictor variables (contextual factors) used to address RQs A and B

Variables	Descriptions	Measures
Trip length	Length of trip in which the intersection case was chosen	Four ordinal categories: 1 = 0 to 1000 seconds 2 = 1000 to 2000 seconds 3 = 2000 to 3000 seconds 4 $\geq$ 3000 seconds
Intersection layout	Layout of intersection	Two nominal categories: 0 = Roundabouts 1 = Intersections (T, X or other)
Intersection control	Control at intersection	Two nominal categories: 0 = Traffic lights 1 = Traffic signs and road markings
Intersection priority	Priority at intersection	Two binary categories: 0 = SV having no priority 1 = SV having priority
Turning direction	Turning direction at intersection (Turning directions in the UK were flipped to match data on other countries)	Three dummy variables coded as 1 or 0: Turning left; Going straight on; Turning right (reference)
Locality	Locality of segment based on map matching data	Two nominal categories: 0 = Urban; 1 = Rural
Road type	Type of road at intersection approach	Two ordinal categories: 1 = Single carriageway/undivided/single-track or one-way road 2 = Dual carriageway or divided road
Number of lanes	Number of lanes at intersection approach	For ordinal categories: 1, 2, 3, 4 or more lanes
Lighting conditions	Lighting conditions, rated using a four-point hierarchical scale, increasing in logical order from the darkest to the lightest conditions	Four ordinal categories: 1 = Darkness (no lighting) 2 = Darkness (lighted) 3 = Dawn or dusk 4 = Daylight
Weather conditions	Weather conditions at segment	Two binary categories: 0 = Good weather (no adverse conditions) 1 = Poor weather (with adverse conditions including rain, snow or fog)
Passenger presence	Passengers present in vehicle	Two binary categories: 0 = No passenger; 1 = With passenger
Seat belt usage	Driver of vehicle wearing a seat belt	Two binary categories: 0 = Not wearing; 1 = Wearing

Note that some of the contextual variables described in Table 7-4 are intersection-specific variables (e.g. intersection layout and intersection control) and are therefore unrelated to non-intersection segments.

The primary hypothesis advanced in this chapter is that drivers exercise self-regulation by reducing engagement in secondary tasks during more challenging driving situations compared with less challenging circumstances. Such a reduction would be expected to take place, for example, when drivers do not have priority in passing through an intersection (which requires more gap-associated judgments) compared with instances when they have priority and when they are driving under adverse weather conditions as opposed to driving in good weather. Older drivers are also hypothesised to be less inclined than younger drivers to perform secondary tasks—a supposition that should arise more broadly as a driving situation becomes more challenging.

7.2 Methods

7.2.1 Multilevel binary logistic regression

Hierarchical or multilevel binary logistic regression was implemented to address Research Question A. The regression was carried out using SPSS and following the protocol outlined by Mertler and Reinhart (2016). Seven binary logistic regression models were constructed to predict the log odds of the seven binary categorical dependent variables (coded as 1 vs. 0) listed in Table 7-1. The predictors were the driver-related and contextual variables listed in Tables 7-3 and 7-4. The models were defined using the generalised equation below:

$$\ln \pi/(1\text{-}\pi) = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

where π denotes probability, $\log \pi/(1-\pi)$ is the logit function or log odds of the dependent variable (i.e. the outcome that the researcher wanted to predict) and β_1, $\beta_2 \ldots \beta_k$ are the logistic regression (β) coefficients of *k* predictor (X) variables (Menard, 2010). The binary dependent variables (Table 7-1) represented two possible observations, coded as either 1 (meaning that a secondary task was executed at a segment) or 0 (indicating that no secondary task engagement occurred at a segment).

The predictor variables (Tables 7-3 and 7-4) were incorporated into the regression analysis as a hierarchy via classification into two levels. The driver-related factors were entered first (level 1), after which the contextual factors that were nested within the driver-related factors were entered second (level 2). Correspondingly, each hierarchical model consisted of one primary level, within which a subsequent level was nested. Although level 2 was an independent model, it still accounted for the effects of all the other variables in level 1.

Each logistic regression model was constructed to predict the logit function or log odds of the highest coded value of a dependent variable (i.e. with task = 1) relative to the lowest coded outcome (i.e. no task = 0) in an iterative procedure called the maximum likelihood method, which was cycled through multiple repetitions to find the best fit with the data. The models were verified to have an overall good fit with the logistic function, with a $p < .05$, derived using the Omnibus test statistic, and a $p > .05$, determined using the Hosmer–Lemeshow test statistic (Hosmer and Lemeshow, 2000). These fit statistics were reported for each model, alongside the Nagelkerke R^2 and percentage accuracy in classification (PAC) values.

The regression statistics were interpreted to identify the most important factors that predicted the drivers' decision to engage in secondary tasks. A binary regression coefficient for a predictor variable was assumed more likely to deviate from zero if a $p < .05$ was derived using the Wald statistic. However, as emphasised in the formal statement issued by the American Statistical Association (Wasserstein and Lazar, 2016), scientific conclusions or policy decisions should never be based only on whether or not a *p*-value passes a specific threshold (e.g. $p < .05$). Furthermore, a *p*-value indicating statistical significance is a 'fickle' measurement that does not pinpoint the size of an effect or the importance of statistical analysis results. By itself, a *p*-value is an unreliable measure for confirming a model, testing a hypothesis or addressing a research question (Nuzzo, 2014). Other forms of statistical evidence (e.g. effect sizes) are essential to interpret the results of inferential statistical tests (McShane and Gal, 2017; Rosenthal, 1996).

The OR was interpreted as an effect size to address Research Question A, and the statistic indicated the extent to which each factor predicted whether or not a driver will engage in secondary tasks. The crude or unadjusted OR was inapplicable to the current context because this statistic does not consider the effects of confounding variables (Menard, 2010). Instead, the OR was adjusted to take into account the combined effects of multiple confounding variables within a multiway cross-tabulation (unlike the situation with the unadjusted OR, which considers only the univariate effect of one predictor variable on one dependent variable within a two-way cross-tabulation) (Agresti, 2018). The adjusted OR of each predictor variable was then computed, with the effect size reflected by estimating that much of the log odds of the dependent variables would change with a one-unit change in each predictor variable. The OR values were interpreted to compare the relative effects of each factor on the dependent variables. An OR = 1.0 meant that a predictor variable had no effect, an OR > 1.0 indicated that the predictor variable increased the log odds and an OR < 1.0 denoted a decrease in the log odds. If the 95% CIs of the OR did not cover 1.0, then the OR was evaluated as significantly different from 1.0 at $p < .05$. If the 95% CIs of the OR included 1.0, then the OR was interpreted as not significantly different from 1.0 at $p > .05$.

Fractional odds were also used to interpret the results of the binary logistic regression. The fractional odds were expressed as a percentage and computed using the formula (OR – 1) × 100. For example, an OR = 2.0 would yield a fractional odds = (2.0 – 1.0) × 100 = 100%, implying that for every one unit increase in a predictor variable, the likelihood of engagement in a secondary task rose by 100%. However, an OR = 0.5 would result in a fractional odds = (0.5 – 1.0) × 100 = –50%, suggesting that for every one unit increase in the predictor variable, the likelihood of secondary task execution decreased by 50%.

7.2.2 Multilevel multiple linear regression

Hierarchical or multilevel multiple linear regression was applied to address Research Question B, with modelling directed towards the driver-related and contextual determinants of the percentage of total driving time associated with secondary task engagement. As with the binary logistic regression, the multiple regression analysis was conducted using SPSS and in adherence to the procedures recommended by Mertler and Reinhart (2016). Seven multiple linear regression models were constructed to predict the seven continuous level variables listed in Table 7-2 on the basis of the driver-related and contextual factors (Tables 7-3 and 7-4) as predictors. The models were defined via the generalised equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 ... \beta_k X_k$$

where Y is the dependent variable (i.e. the percentage of time allocated to secondary task engagement), and β_1, $\beta_2 ... \beta_k$ represent the standardised partial regression (β) coefficients (or β weights) of *k* independent predictor (X) variables. The predictor variables were classified into a hierarchy with two levels, as was done in the binary logistic regression.

In the multiple regression, the effects of each predictor variable on the dependent variable measured by each regression coefficient were net effects, which enabled simultaneous control for the effects of all the other predictor variables in the model. The SPSS outputs included unstandardised (*b*) and standardised (β) coefficients. This research focused on interpreting β alongside *b* coefficients because not all the factors were measured with a common scale. The *b* coefficients were measured using different units, rendering the comparison of the relative effect of each predictor variable on the dependent variable difficult. The β coefficients were based on variables that were measured using a common metric (z-scores), thus allowing for their direct comparison using a standardised scale ranging from –1 through 0 to +1. These coefficients were also measured in standard deviation units. A predictor characterised by a large standardised partial coefficient magnitude is a strong determinant, whereas a predictor typified by a small magnitude is a weak determinant. For example, if $\beta = 0.5$ for a predictor variable, then every one standard deviation unit increase in the predictor variable will translate to a 0.5 standard deviation unit increase in the dependent variable. The β coefficients were interpreted subjectively using Cohen's (1992) criteria: 0.10 = small, 0.30 = medium and 0.50 = large.

The four main theoretical assumptions of the multiple regression analysis (Osborne and Waters, 2002), namely, those on reliability, residual normality, linearity and homoskedasticity (homogeneity of variance of the predictors across the dependent variables), were tested and found to be slightly deviating from the norm (not violated). Linearity and homoskedasticity were checked by plotting the standardised residuals against the standardised predicted values of the dependent variables. Non-linearity would be reflected by a cloud of points with a curved shape. Heteroskedasticity (i.e. non-homogeneity of variance) would be indicated by a cloud of points distributed non-horizontally on either side of the mean (zero) value. A straight line of points directed upwards or downwards would imply that the variance increases or decreases systematically. The residual plots in this research indicated that the assumptions of linearity and homoskedasticity deviated only slightly from the standard. Residual normality was reflected by the approximately bell-shaped frequency distribution of the standardised residuals. The Mahalanobis distance test detected no multivariate outliers (i.e. extremely large or extremely small values, non-contiguous with or outside expected limits of a normal distribution).

The regression statistics were interpreted to determine the extent to which each of the predictor variables predicted the seven dependent variables presented in Table 7-2. Each β coefficient was assumed to differ from zero if $p < .05$ in the t-test and if the 95% CI of the *b* coefficient did not capture zero (McShane and Gal, 2017). The dichotomisation of *p*-values did not provide definitive evidence for the interpretation of the results.

The effect sizes (adjusted R^2) were computed to indicate the proportion of the variance in the dependent variables explained by the predictor variables in each model, reflecting the practical significance of the results. The R^2 values (adjusted according to the number of variables in the model) were interpreted using the subjective criteria suggested by Cohen (1992) on the basis of $f^2 = R^2 / 1– R^2$, where 0.02 = small, 0.15 = medium and 0.35 = large.

7.2.3 Multicollinearity

The binary logistic and multiple linear regression analyses assumed that that the predictor variables were not multicollinear, meaning that they were not strongly correlated, dependent on or conceptually related to one another. Multicollinearity inflates the standard error (SE) of regression coefficients and thereby compromises statistical inferences. In this work, multicollinearity was tested using the variance inflation factor (VIF) shown in Table 7-5 (where √VIF = the degree by which standard errors were inflated). A convention widely adhered to is that the assumption of non-multicollinearity is satisfied if VIF < 5 (Yoo et al., 2014). None of the predictor variables in Table 7-5 had a VIF > 5.

All the individual categories within the nominal variables (e.g. country of recruitment) that were defined as two or more dummy variables using Boolean indicators (i.e. 0 or 1 for each category) could not be used in the regression analyses given their multicollinearity. The treatment conformed to the following rule: The number of binary dummy variables representing a nominal variable with three or more categories was k–1, where k refers to the total number of binary categories within the nominal variable (Mertler and Reinhart, 2016).

Table 7-5. VIF statistics for testing multicollinearity

Levels	Predictors	VIF
1	Driver age	1.094
	Country: France	2.150
	Country: Poland	2.087
	Country: UK	2.339
	Country: Netherlands	1.972
	Gender	1.069
2	Driver age	1.147
	Country: France	2.286
	Country: Poland	2.156
	Country: UK	2.454
	Country: Netherlands	2.063
	Gender	1.112
	Trip length	1.057
	Intersection layout	1.723
	Intersection control	2.594
	Intersection priority	2.351
	Turning direction: Left	1.675
	Turning direction: Going straight	1.279
	Locality	1.098
	Road type	1.810
	Number of lanes	2.530
	Lighting conditions	1.030
	Weather conditions	1.022
	Passenger presence	1.059
	Seat belt usage	1.056

To avoid multicollinearity, all the Boolean indicators contained within each nominal variable with three or more categories (e.g. country of recruitment) were incorporated with an excluded variable that served as a baseline or reference category to which all the other categories were compared. Regardless of which dummy variable was selected as the reference category, exactly the same regression model was fitted (Hardy, 1993). For example, each model was calculated by entering the data on five countries (France, the Netherlands, Poland, the UK and Germany) that were coded using Boolean variables (where 1 = the country; 0 = not the country). However, Germany was chosen as the reference category, which explains why the statistics for Germany did not appear explicitly in the SPSS output. Nevertheless, such statistics remained hidden in the output within the intersect of the regression equation (termed the 'constant' in the output).

7.3 Results

The results of the binary logistic and multiple linear regression analyses are presented in the following sections.

7.3.1 Multilevel binary logistic regression results

This section discusses the results of the hierarchical or multilevel binary logistic regression intended to determine the driver-related and contextual factors that predict drivers' decision to engage in secondary tasks (Research Question A). Two regression models were constructed for each of the seven dependent variables listed in Table 7-1. The use of SPSS involved entering the predictor variables in Tables 7-3 and 7-4 into the regression procedure as a hierarchy by classifying them into two levels. As previously described, the driver-related factors were incorporated before the contextual factors (levels 1 and 2, respectively). This meant that level 1 was an independent model, which described the effects of the driver-related factors on the drivers' decision to engage in secondary tasks whilst disregarding the effects of the contextual factors, and that level 2 accounted for the effects of all of the predictor variables, in which the contextual factors were nested with the driver-related factors.

The levels 1 and 2 models (alongside their fit statistics) are presented in Tables 7-6 to 7-12 to illustrate the secondary task engagement predictions, classified by total intersection segment (Table 7-6), upstream intersection phase (Table 7-7), within-intersection phase (Table 7-8), downstream intersection phase (Table 7-9), moving intersection status (Table 7-10), stationary intersection status (Table 7-11) and total non-intersection segment (Table 7-12). The goal of the logistic regression was to construct the most parsimonious model containing only the most useful predictors (Menard, 2010). Because the predictors with $\beta = 0$ and OR = 1 were useless and represented only the effects of random noise or unexplained variance, parsimonious models that comprised only the predictors with $\beta \neq 0$ and OR $\neq 1$ ($p < .05$) were constructed (Table 7-13).

Table 7-6. Model for predicting secondary task engagement along the total intersection segment

Models	Predictors	Reference	β	*p*	OR	95% CI for OR	
						LCL	UCL
Level 1	(Constant)		.200	.396	1.222		
	Driver age in years (continuous)		–.018	<.001*	.982	.974	.990
	Country: France	Germany	.454	.012*	1.574	1.105	2.243
	Country: Poland	Germany	.567	.002*	1.763	1.222	2.544
	Country: UK	Germany	.463	.008*	1.589	1.129	2.236
	Country: Netherlands	Germany	.451	.016*	1.570	1.087	2.268
	Gender: Male	Female	.152	.142	1.165	.950	1.427
	The model was statistically significant, $\chi^2(6) = 36.360$, $p < .001$ (Nagelkerke R^2 = 2.9%, PAC = 56.1%).						
Level 2	(Constant)		–.135	.820	.874		
	Driver age in years (continuous)		–.027	<.001*	.974	.965	.983
	Country: France	Germany	.576	.006*	1.778	1.179	2.683
	Country: Poland	Germany	.602	.005*	1.827	1.201	2.778
	Country: UK	Germany	.485	.016*	1.623	1.096	2.405
	Country: Netherlands	Germany	.468	.030*	1.597	1.048	2.436
	Gender: Male	Female	–.165	.163	.848	.673	1.069
	Trip length		.145	.037*	1.156	1.009	1.325
	Intersection layout: Intersections	Roundabouts	–.081	.661	.922	.641	1.326
	Intersection control: Traffic signs	Traffic lights	–.438	.009*	.645	.464	.897
	Intersection priority: With	No priority	.305	.048*	1.397	1.070	2.013
	Turning direction: Left	Right	.133	.395	1.142	.841	1.552
	Turning direction: Going straight	Right	–.227	.098	.797	.609	1.043
	Locality: Rural	Urban	–.024	.861	.976	.748	1.275
	Road type		.010	.952	1.010	.728	1.402
	Number of lanes		.028	.778	1.028	.848	1.246
	Lighting conditions		–.039	.557	.962	.844	1.096
	Weather conditions: Poor	Good	–.355	.046*	.705	.495	0.990
	Passenger presence: Yes	No	2.034	<.001*	7.645	5.878	9.942
	Seat belt use: Yes	No	–.072	.856	.931	.429	2.021
	The model was statistically significant, $\chi^2(19) = 369.295$, $p < .001$ (Nagelkerke R^2 = 27.0%, PAC = 69.8%).						

Note: * $\beta \neq 0$ and OR $\neq 1$ ($p < .05$)

Table 7-7. Model for predicting secondary task engagement in the upstream intersection phase

Models	Predictors	Reference	β	*p*	OR	95% CI for OR	
						LCL	UCL
Level 1	(Constant)		–.046	.851	.955		
	Driver age in years (continuous)		–.019	<.001*	.982	.974	.990
	Country: France	Germany	.279	.140	1.322	.912	1.916
	Country: Poland	Germany	.617	.001*	1.853	1.270	2.704
	Country: UK	Germany	.373	.041*	1.451	1.015	2.075
	Country: Netherlands	Germany	.350	.047*	1.420	1.005	2.085
	Gender: Male	Female	.054	.608	1.056	.858	1.300
	The model was statistically significant, $\chi^2(6) = 38.078$, $p < .001$ (Nagelkerke R^2 = 3.1%, PAC = 61.2%).						
Level 2	(Constant)		–.585	.326	.557		
	Driver age in years (continuous)		–.023	<.001*	.977	.968	.986
	Country: France	Germany	.478	.026*	1.614	1.058	2.460
	Country: Poland	Germany	.621	.004*	1.860	1.217	2.842
	Country: UK	Germany	.446	.030*	1.562	1.045	2.337
	Country: Netherlands	Germany	.331	.134	1.392	.903	2.144
	Gender: Male	Female	–.203	.089	.816	.646	1.031
	Trip length		.206	.003*	1.229	1.072	1.409
	Intersection layout: Intersections	Roundabouts	–.111	.550	.895	.622	1.288
	Intersection control: Traffic signs	Traffic lights	–.303	.074	.738	.530	1.030
	Intersection priority: With	No priority	.225	.199	1.252	.888	1.765
	Turning direction: Left	Right	–.090	.567	.914	.671	1.244
	Turning direction: Going straight	Right	–.215	.121	.806	.614	1.059
	Locality: Rural	Urban	–.105	.449	.900	.685	1.182
	Road type		.166	.324	1.181	.849	1.644
	Number of lanes		.086	.379	1.090	.899	1.321
	Lighting conditions		–.061	.363	.941	.825	1.073
	Weather conditions: Poor	Good	–.111	.509	.895	.643	1.245
	Passenger presence: Yes	No	1.648	<.001*	5.198	4.051	6.670
	Seat belt use: Yes	No	–.263	.506	.769	.354	1.668
	The model was statistically significant, $\chi^2(19) = 322.258$, $p < .001$ (Nagelkerke R^2 = 24.4%, PAC = 69.3%).						

Note: * $\beta \neq 0$ and OR $\neq 1$ ($p < .05$)

Table 7-8. Model for predicting secondary task engagement in the within-intersection phase

Models	Predictors	Reference	β	*p*	OR	95% CI for OR	
						LCL	UCL
Level 1	(Constant)		–.836	.003*	.433		
	Driver age in years (continuous)		–.020	<.001*	.980	.971	.989
	Country: France	Germany	.709	.002*	2.031	1.306	3.159
	Country: Poland	Germany	.777	.001*	2.175	1.391	3.402
	Country: UK	Germany	.755	.001*	2.127	1.385	3.267
	Country: Netherlands	Germany	.697	.003*	2.008	1.272	3.171
	Gender: Male	Female	.095	.413	1.099	.876	1.379
	The model was statistically significant, $\chi^2(6) = 38.205$, $p < .001$ (Nagelkerke $R^2 = 3.4\%$, PAC = 72.8%).						
Level 2	(Constant)		–1.106	.085	.331		
	Driver age in years (continuous)		–.028	<.001*	.973	.963	.983
	Country: France	Germany	.762	.002*	2.142	1.324	3.464
	Country: Poland	Germany	.845	.001*	2.328	1.438	3.770
	Country: UK	Germany	.800	.001*	2.226	1.400	3.538
	Country: Netherlands	Germany	.672	.008*	1.958	1.194	3.210
	Gender: Male	Female	–.208	.099	.812	.634	1.040
	Trip length		.124	.087	1.132	.982	1.305
	Intersection layout: Intersections	Roundabouts	–.107	.588	.898	.609	1.325
	Intersection control: Traffic signs	Traffic lights	–.317	.073	.728	.515	1.030
	Intersection priority: With	No priority	.155	.404	1.168	.811	1.683
	Turning direction: Left	Right	.170	.311	1.186	.852	1.650
	Turning direction: Going straight	Right	.170	.252	1.186	.886	1.586
	Locality: Rural	Urban	–.014	.924	.986	.740	1.313
	Road type		.137	.441	1.147	.809	1.626
	Number of lanes		.075	.471	1.078	.879	1.322
	Lighting conditions		–.082	.247	.922	.803	1.058
	Weather conditions: Poor	Good	–.226	.225	.798	.554	1.149
	Passenger presence: Yes	No	1.566	<.001*	4.788	3.725	6.154
	Seat belt use: Yes	No	.386	.376	1.471	.625	3.461
	The model was statistically significant, $\chi^2(19) = 221.704$, $p < .001$ (Nagelkerke $R^2 = 18.4\%$, PAC = 73.9%).						

Note: * $\beta \neq 0$ and OR $\neq 1$ ($p < .05$)

Table 7-9. Model for predicting secondary task engagement in the downstream intersection phase

Models	Predictors	Reference	β	*p*	OR	95% CI for OR	
						LCL	UCL
Level 1	(Constant)		–.521	.048*	.594		
	Driver age in years (continuous)		–.023	<.001*	.977	.968	.985
	Country: France	Germany	.826	<.001*	2.285	1.497	3.487
	Country: Poland	Germany	.913	<.001*	2.493	1.647	3.774
	Country: UK	Germany	.811	<.001*	2.250	1.500	3.374
	Country: Netherlands	Germany	1.003	<.001*	2.726	1.779	4.177
	Gender: Male	Female	.160	.143	1.174	.947	1.455
	The model was statistically significant, $\chi^2(6) = 59.093$, $p < .001$ (Nagelkerke $R^2 = 4.9\%$, PAC = 65.6%).						
Level 2	(Constant)		–1.059	.086	.347		
	Driver age in years (continuous)		–.035	<.001*	.966	.956	.975
	Country: France	Germany	.896	<.001*	2.450	1.534	3.911
	Country: Poland	Germany	.915	<.001*	2.497	1.572	3.966
	Country: UK	Germany	.793	.001*	2.209	1.411	3.458
	Country: Netherlands	Germany	1.048	<.001*	2.852	1.774	4.587
	Gender: Male	Female	–.190	.120	.827	.650	1.051
	Trip length		.212	.002*	1.237	1.078	1.418
	Intersection layout: Intersections	Roundabouts	.163	.399	1.177	.806	1.718
	Intersection control: Traffic signs	Traffic lights	–.214	.209	.807	.578	1.127
	Intersection priority: With	No priority	.200	.261	1.221	.862	1.731
	Turning direction: Left	Right	.082	.610	1.085	.793	1.486
	Turning direction: Going straight	Right	–.160	.264	.852	.644	1.128
	Locality: Rural	Urban	.018	.897	1.018	.774	1.340
	Road type		–.098	.574	.907	.644	1.276
	Number of lanes		.087	.395	1.091	.893	1.333
	Lighting conditions		–.030	.666	.971	.849	1.111
	Weather conditions: Poor	Good	–.369	.041*	.691	.485	.985
	Passenger presence: Yes	No	1.808	<.001*	6.099	4.744	7.841
	Seat belt use: Yes	No	.146	.724	1.157	.515	2.599
	The model was statistically significant, $\chi^2(19) = 308.837$, $p < .001$ (Nagelkerke $R^2 = 23.9\%$, PAC = 71.5%).						

Note: * $\beta \neq 0$ and OR $\neq 1$ ($p < .05$)

Table 7-10. Model for predicting secondary task engagement in the moving intersection status

Models	Predictors	Reference	β	*p*	OR	95% CI for OR	
						LCL	UCL
Level 1	(Constant)		–.133	.583	.876		
	Driver age in years (continuous)		–.019	<.001*	.981	.973	.989
	Country: France	Germany	.700	<.001*	2.014	1.380	2.939
	Country: Poland	Germany	.725	<.001*	2.065	1.430	2.980
	Country: UK	Germany	.715	<.001*	2.045	1.434	2.917
	Country: Netherlands	Germany	.647	.001*	1.911	1.305	2.797
	Gender: Male	Female	.203	.052	1.225	.998	1.504
	The model was statistically significant, $\chi^2(6) = 46.171$, $p < .001$ (Nagelkerke $R^2 = 3.7\%$, PAC = 59.0%).						
Level 2	(Constant)		–.598	.313	.550		
	Driver age in years (continuous)		–.029	<.001*	.971	.962	.980
	Country: France	Germany	.789	<.001*	2.200	1.443	3.355
	Country: Poland	Germany	.794	<.001*	2.213	1.441	3.399
	Country: UK	Germany	.743	<.001*	2.103	1.403	3.151
	Country: Netherlands	Germany	.677	.002*	1.967	1.275	3.034
	Gender: Male	Female	–.145	.220	.865	.686	1.091
	Trip length		.138	.046*	1.148	1.002	1.314
	Intersection layout: Intersections	Roundabouts	–.055	.769	.947	.658	1.363
	Intersection control: Traffic signs	Traffic lights	–.380	.023*	.684	.493	.948
	Intersection priority: With	No priority	.183	.290	1.201	.855	1.686
	Turning direction: Left	Right	–.024	.877	.976	.720	1.324
	Turning direction: Going straight	Right	–.205	.088	.790	.591	1.035
	Locality: Rural	Urban	.061	.656	1.063	.814	1.387
	Road type		.010	.951	1.010	.728	1.402
	Number of lanes		.010	.921	1.010	.833	1.224
	Lighting conditions		–.031	.646	.970	.851	1.105
	Weather conditions: Poor	Good	–.279	.098	.757	.544	1.053
	Passenger presence: Yes	No	2.028	<.001*	7.601	5.878	9.829
	Seat belt use: Yes	No	.263	.508	1.301	.597	2.838
	The model was statistically significant, $\chi^2(19) = 350.538$, $p < .001$ (Nagelkerke $R^2 = 25.9\%$, PAC = 70.8%).						

Note: * $\beta \neq 0$ and OR $\neq 1$ ($p < .05$)

Table 7-11. Model for predicting secondary task engagement in the stationary intersection status

Models	Predictors	Reference	β	*p*	OR	95% CI for OR	
						LCL	UCL
Level 1	(Constant)		.518	.252	1.678		
	Driver age in years (continuous)		–.016	.044*	.984	.968	1.000
	Country: France	Germany	.258	.465	1.295	.647	2.591
	Country: Poland	Germany	.464	.181	1.590	.806	3.137
	Country: UK	Germany	.028	.930	1.028	.550	1.924
	Country: Netherlands	Germany	.199	.543	1.220	.643	2.316
	Gender: Male	Female	.006	.974	1.006	.683	1.483
	The model was not statistically significant, $\chi^2(6) = 7.807$, $p = .253$ (Nagelkerke $R^2 = 2.4\%$, PAC = 54.0%).						
Level 2	(Constant)		–.649	.543	.523		
	Driver age in years (continuous)		–.023	.014*	.977	.959	.995
	Country: France	Germany	.248	.548	1.281	.571	2.877
	Country: Poland	Germany	.348	.391	1.416	.640	3.133
	Country: UK	Germany	–.144	.704	.866	.413	1.817
	Country: Netherlands	Germany	.175	.643	1.191	.569	2.493
	Gender: Male	Female	–.345	.138	.708	.449	1.117
	Trip length		.376	.011*	1.456	1.088	1.948
	Intersection layout: Intersections	Roundabouts	.468	.282	1.597	.680	3.749
	Intersection control: Traffic signs	Traffic lights	–.210	.205	0.802	.565	1.997
	Intersection priority: With	No priority	1.441	<.001*	4.226	2.011	8.878
	Turning direction: Left	Right	.277	.343	1.319	.744	2.335
	Turning direction: Going straight	Right	–.150	.602	.861	.490	1.512
	Locality: Rural	Urban	.223	.471	1.250	.681	2.296
	Road type		.067	.836	1.069	.566	2.022
	Number of lanes		–.136	.431	.873	.622	1.225
	Lighting conditions		–.067	.638	.935	.708	1.236
	Weather conditions: Poor	Good	–.227	.490	.797	.418	1.517
	Passenger presence: Yes	No	1.933	<.001*	6.910	3.974	12.015
	Seat belt use: Yes	No	–.498	.436	.607	.173	2.130
	The model was statistically significant, $\chi^2(19) = 107.002$, $p < .001$ (Nagelkerke $R^2 = 29.1\%$, PAC = 70.1%).						

Note: * $\beta \neq 0$ and OR $\neq 1$ ($p < .05$)

Table 7-12. Model for predicting secondary task engagement along the total non-intersection segment

Models	Predictors	Reference	β	*p*	OR	95% CI for OR	
						LCL	UCL
Level 1	(Constant)		.120	.615	1.127		
	Driver age in years (continuous)		–.016	<.001*	.984	.977	.992
	Country: France	Germany	.412	.023*	1.510	1.058	2.156
	Country: Poland	Germany	.568	.003*	1.766	1.220	2.554
	Country: UK	Germany	.541	.002*	1.718	1.218	2.422
	Country: Netherlands	Germany	.496	.008*	1.643	1.136	2.376
	Gender: Male	Female	.210	0.054	1.230	.995	1.509
	The model was statistically significant, $\chi^2(6) = 32.010$, $p < .001$ (Nagelkerke $R^2 = 2.7\%$, PAC = 56.8%).						
Level 2	(Constant)		–.115	.826	.891		
	Driver age in years (continuous)		–.023	<.001*	.977	.968	.986
	Country: France	Germany	.378	.056	1.459	.991	2.149
	Country: Poland	Germany	.601	.003*	1.824	1.220	2.728
	Country: UK	Germany	.576	.002*	1.778	1.225	2.581
	Country: Netherlands	Germany	.563	.006*	1.756	1.173	2.629
	Gender: Male	Female	.016	.890	1.016	.812	1.272
	Trip length		.074	.274	1.077	.943	1.229
	Locality: Rural	Urban	.140	.281	1.150	.892	1.482
	Lighting conditions		–.097	.137	.907	.798	1.032
	Weather conditions: Poor	Good	–.369	.023*	.691	.503	.950
	Passenger presence: Yes	No	1.676	<.001*	5.343	4.153	6.875
	Seat belt use: Yes	No	.434	.308	1.544	.670	3.560
	The model was statistically significant, $\chi^2(12) = 238.814$, $p < .001$ (Nagelkerke $R^2 = 18.8\%$, PAC = 65.4%)						

Note: * $\beta \neq 0$ and OR $\neq 1$ ($p < .05$)

In Table 7-13, the ORs of the predictors in the parsimonious models are presented alongside the computed fractional odds (OR – 1 × 100). The fractional odds were important in indicating whether the chances of engagement in a secondary task were positive or negative. Positive fractional odds translated to an increased chance of engagement in a secondary task, whereas negative fractional odds translated to a decreased chance of engagement in a secondary task.

Table 7-13. Summary of ORs and fractional odds (%) of predictors in parsimonious logistic regression models[a]

Levels	Predictors	Reference	Intersection phases and motion conditions						Non-intersection segment
			Total	Upstream	Within	Downstream	Moving	Stationary	
1	Driver age		.982 (–1.8%)	.982 (–1.8%)	.980 (–2.0%)	.977 (–2.3%)	.981 (–1.9%)	.984 (–1.6%)	.984 (–1.6%)
	Country: France	Germany	1.574 (57.4%)		2.031 (103.1%)	2.285 (128.5%)	2.014 (101.4%)		1.510 (51.0%)
	Country: Poland	Germany	1.763 (76.3%)	1.853 (85.3%)	2.175 (117.5%)	2.493 (149.3%)	2.065 (106.5%)		1.766 (76.6%)
	Country: UK	Germany	1.589 (58.9%)	1.451 (45.1%)	2.127 (112.7%)	2.250 (125.0%)	2.045 (104.5%)		1.718 (71.8%)
	Country: Netherlands	Germany	1.570 (57.0%)	1.420 (42.0%)	2.008 (100.8%)	2.726 (172.6%)	1.911 (91.1%)		1.643 (64.3%)
2	Driver age		.974 (–2.6%)	.977 (–2.3%)	.973 (–2.7%)	.966 (–3.4%)	.971 (–2.9%)	.977 (–2.3%)	.977 (–2.3%)
	Country: France	Germany	1.778 (77.8%)	1.614 (61.4%)	2.142 (114.2%)	2.450 (145.0%)	2.200 (120.0%)		
	Country: Poland	Germany	1.827 (82.7%)	1.860 (86.0%)	2.328 (132.8%)	2.497 (149.7%)	2.213 (121.3%)		1.824 (82.4%)
	Country: UK	Germany	1.623 (62.3%)	1.562 (56.2%)	2.226 (122.6%)	2.209 (120.9%)	2.103 (110.3%)		1.778 (77.8%)
	Country: Netherlands	Germany	1.597 (59.7%)		1.958 (95.8%)	2.852 (185.2%)	1.967 (96.7%)		1.756 (75.6%)
	Trip length		1.156 (15.6%)	1.229 (22.9%)		1.237 (23.7%)	1.148 (14.8%)	1.456 (45.6%)	
	Intersection control: Traffic signs	Traffic lights	.645 (–35.5%)				.684 (–31.6%)		N/A
	Intersection priority: With	No priority	1.397 (39.7%)					4.226 (322.6%)	N/A
	Weather conditions: Poor	Good	.705 (–29.5)			.691 (–30.9%)			.691 (–30.9%)
	Passenger presence: Yes	No	7.645 (664.5%)	5.198 (419.8%)	4.788 (378.8%)	6.099 (509.9%)	7.601 (660.1%)	6.910 (591.0%)	5.343 (434.3%)

Note: [a] Including only the predictors with $\beta \neq 0$ and OR $\neq 1$ ($p < .05$)

In the level 1 models (Table 7-13), the most consistent predictor of a reduced chance of engagement in a secondary task across all the observations was driver age. Because age was entered into the model as a continuous variable, the possibility of such engagement declined by 1.6% to 2.3% for every one-year increase in age. Country was also a consistent predictor. The samples from Poland, France, the UK and the Netherlands registered significantly higher secondary task engagement than that observed in the reference category (the German sample). This finding was applicable across the complete intersection and non-intersection datasets, except with respect to stationary intersection status. At stationary intersection conditions, no significant differences in task engagement were found between the German sample and the samples from the other countries. However, the level 1 models were not representative of the full set of data because the related analysis disregarded the effects of the contextual factors. For this reason, the findings of the level 1 models should be interpreted with caution, especially given the small Nagelkerke R^2 values associated with the models.

The level 2 models were the most representative of the dataset given their consideration of the effects of the contextual factors nested within each driver-related factor. As shown in Table 7-13, the strongest and most consistent predictor of engagement in a secondary task across all the observations was the presence of passengers. The odds of engagement in a secondary task when passengers were present in a vehicle (relative to when passengers were not present) ranged from a minimum of 4.8 times higher (in the within-intersection phase) to a maximum of 7.6 times higher (in the total intersection segment). Driver age was also a consistent predictor, but the direction of prediction proceeded in the negative direction. For every one-year increase in age, the likelihood of engagement in a secondary task decreased by 2.3% to 3.4%. The next most consistent predictor was country. The German sample registered significantly lower secondary task engagement compared with the rest of the samples. The trend was that the Polish sample exhibited the highest secondary task engagement level, followed by convergent values for the Dutch, the UK and the French samples; the lowest engagement was observed amongst the German sample. This trend was evident across the complete intersection and non-intersection datasets, except in regard to stationary intersection status, for which no significant differences in task engagement were found between countries.

The other significant fractional odds in the level 2 models were smaller or less consistent across the observations in relation to trip length, stationary at approach, intersection control, intersection priority, turning direction and weather conditions:

- For every single ordinal unit increase in trip length, the chance of engagement in a secondary task increased by 15.6% in the total intersection segment, 22.9% in the upstream phase, 23.7% in the downstream phase and 14.8% under the moving status. This likelihood increased by a larger amount (45.6%) in the stationary status. Trip length exerted no significant impact on the likelihood of engagement in secondary tasks in the within-intersection phase and the non-intersection segment.
- In relation to intersections controlled by traffic signs compared with intersections managed by traffic lights, the chance of secondary task engagement decreased by 35.5% and 31.6% in the total intersection segment and under the moving status, respectively.
- When drivers had priority in passing through an intersection (compared with cases wherein they had no priority), the likelihood of secondary task engagement increased by 39.7% in the total intersection segment (1.4 times higher) and 322.6% in the stationary status (4.2 times higher).
- When driving was done under adverse weather conditions versus driving in good weather, the chance of secondary task engagement declined by 29.5% in the total intersection segment and 30.9% in both the downstream-intersection phase and the non-intersection segment.

Gender, intersection layout, turning direction, locality (urban/rural), road type, number of lanes, lighting conditions and seat belt use exerted no significant impact on the drivers' decision to engage in secondary tasks (p values > 0.05).

7.3.2 Multilevel multiple linear regression results

This section details the statistical evidence used to ascertain what driver-related and contextual factors predict the percentage of driving time associated with secondary task engagement (Research Question B). Two regression models were developed for each of the seven dependent variables listed in Table 7-2. SPSS entailed the incorporation of the predictor variables in Tables 7-3 and 7-4 into the regression procedure as a hierarchy, again by classifying the driver-related factors first (level 1) and the contextual factors second (level 2).

Tables 7-14 to 7-20 present the levels 1 and 2 models (alongside their fit statistics) for the predictions of the percentage of time allocated to secondary tasks, classified by total intersection segment (Table 7-14), upstream phase (Table 7-15), within-intersection phase (Table 7-16), downstream phase (Table 7-17), moving intersection status (Table 7-18), stationary intersection status (Table 7-19) and total non-intersection segment (Table 7-20). The goal of the multiple regression was to construct the most parsimonious model containing only the most useful predictors (Chatterjee and Hadi, 2015). The predictors with zero regression coefficients were useless and represented only the effects of random noise or unexplained variance. They were thus eliminated. The parsimonious models including only the predictors with $\beta \neq 0$ ($p < .05$) are presented in Table 7-21.

Table 7-14. Model for predicting the percentage of time allocated to secondary tasks along the total intersection segment

Models	Predictors	Reference	*b*	SE b	β	*p*
Level 1	(Constant)		33.757	4.957		<.001*
	Driver age in years (continuous)		–.459	.074	–.158	<.001*
	Country: France	Germany	9.380	3.256	.103	.004*
	Country: Poland	Germany	14.246	3.391	.147	<.001*
	Country: UK	Germany	10.850	3.130	.129	.001*
	Country: Netherlands	Germany	12.917	3.382	.130	<.001*
	Gender: Male	Female	1.734	1.907	.023	.363
	The model was statistically significant, $F(6, 1623) = 11.782$, $p < .001$, adjusted $R^2 = .038$ (small).					
Level 2	(Constant)		–.340	15.988		.983
	Driver age in years (continuous)		–.501	.070	–.173	<.001*
	Country: France	Germany	8.779	3.137	.096	.005*
	Country: Poland	Germany	12.977	3.220	.134	<.001*
	Country: UK	Germany	9.520	2.996	.113	.002*
	Country: Netherlands	Germany	10.305	3.233	.104	.001*
	Gender: Male	Female	–3.145	1.817	–.041	.084
	Trip length		3.640	1.082	.079	.001*
	Intersection layout: Intersections	Roundabouts	–.308	2.869	–.004	.915
	Intersection control: Traffic signs	Traffic lights	–5.294	2.575	–.048	.045*
	Intersection priority: With	No priority	4.008	2.639	.053	.129
	Turning direction: Left	Right	.424	2.400	.005	.860
	Turning direction: Going straight	Right	–1.432	2.124	–.019	.500
	Locality: Rural	Urban	–1.873	2.091	–.021	.370
	Road type		2.162	2.605	.025	.407
	Number of lanes		1.589	1.525	.038	.298
	Lighting conditions		–1.483	1.034	–.033	.152
	Weather conditions: Poor	Good	–5.106	2.561	–.046	.046*
	Passenger presence: Yes	No	27.487	1.902	.338	<.001*
	Seat belt use: Yes	No	5.042	6.188	.019	.415
	The model was statistically significant, $F(19, 1609) = 16.564$, $p < .001$, adjusted $R^2 = .160$ (medium).					

Note: * $\beta \neq 0$ ($p < .05$)

Table 7-15. Model for predicting the percentage of time allocated to secondary tasks in the upstream phase

Models	Predictors	Reference	*b*	SE $_b$	β	*p*
Level 1	(Constant)		35.331	5.289		<.001*
	Driver age in years (continuous)		–.456	.079	–.148	<.001*
	Country: France	Germany	8.140	3.474	.084	.019*
	Country: Poland	Germany	15.374	3.618	.149	<.001*
	Country: UK	Germany	9.516	3.340	.106	.004*
	Country: Netherlands	Germany	11.630	3.609	.110	.001*
	Gender: Male	Female	1.266	2.035	.016	.534
	The model was statistically significant, $F(6, 1623) = 10.869$, $p < .001$, adjusted $R^2 = .035$ (small).					
Level 2	(Constant)		5.168	17.164		.763
	Driver age in years (continuous)		–.472	.076	–.153	<.001*
	Country: France	Germany	8.016	3.368	.082	.017*
	Country: Poland	Germany	13.363	3.457	.130	<.001*
	Country: UK	Germany	8.279	3.216	.092	.010*
	Country: Netherlands	Germany	8.790	3.471	.083	.011*
	Gender: Male	Female	–3.447	1.951	–.043	.077
	Trip length		4.862	1.162	.098	<.001*
	Intersection layout: Intersections	Roundabouts	–4.127	2.765	–.045	.136
	Intersection control: Traffic signs	Traffic lights	–1.267	3.081	–.015	.681
	Intersection priority: With	No priority	2.413	2.834	.030	.395
	Turning direction: Left	Right	–.481	2.577	–.005	.852
	Turning direction: Going straight	Right	–2.359	2.280	–.029	.301
	Locality: Rural	Urban	–3.878	2.245	–.041	.084
	Road type		3.189	2.796	.035	.254
	Number of lanes		1.732	1.638	.038	.290
	Lighting conditions		–1.918	1.110	–.040	.084
	Weather conditions: Poor	Good	–3.936	2.750	–.033	.153
	Passenger presence: Yes	No	26.988	2.042	.311	<.001*
	Seat belt use: Yes	No	.871	6.643	.003	.896
	The model was statistically significant, $F(19, 1609) = 15.079$, $p < .001$, adjusted $R^2 = .147$ (medium).					

Note: * $\beta \neq 0$ ($p < .05$)

Table 7-16. Model for predicting the percentage of time allocated to secondary tasks in the within-intersection phase

Models	Predictors	Reference	*b*	SE $_b$	β	*p*
Level 1	(Constant)		26.262	5.228		<.001*
	Driver age in years (continuous)		–.410	.078	–.135	<.001*
	Country: France	Germany	9.393	3.434	.098	.006*
	Country: Poland	Germany	12.086	3.577	.119	.001*
	Country: UK	Germany	11.774	3.302	.133	<.001*
	Country: Netherlands	Germany	12.068	3.568	.116	.001*
	Gender: Male	Female	2.584	2.011	.032	.199
	The model was statistically significant, $F(6, 1623) = 8.330$, $p < .001$, adjusted $R^2 = .026$ (small).					
Level 2	(Constant)		–1.101	17.344		.949
	Driver age in years (continuous)		–.455	.076	–.150	<.001*
	Country: France	Germany	8.373	3.403	.087	.014*
	Country: Poland	Germany	11.453	3.493	.113	.001*
	Country: UK	Germany	10.501	3.250	.119	.001*
	Country: Netherlands	Germany	9.557	3.507	.092	.006*
	Gender: Male	Female	–1.622	1.971	–.020	.411
	Trip length		2.958	1.174	.061	.012*
	Intersection layout: Intersections	Roundabouts	–3.182	2.794	–.035	.255
	Intersection control: Traffic signs	Traffic lights	–.057	3.113	–.001	.985
	Intersection priority: With	No priority	1.919	2.863	.024	.503
	Turning direction: Left	Right	–.421	2.604	–.005	.872
	Turning direction: Going straight	Right	.845	2.304	.010	.714
	Locality: Rural	Urban	–.923	2.268	–.010	.684
	Road type		2.001	2.826	.022	.479
	Number of lanes		2.132	1.655	.048	.198
	Lighting conditions		–1.626	1.122	–.035	.147
	Weather conditions: Poor	Good	–2.962	2.779	–.025	.287
	Passenger presence: Yes	No	22.167	2.064	.260	<.001*
	Seat belt use: Yes	No	8.159	6.712	.029	.224
	The model was statistically significant, $F(19, 1609) = 10.141$, $p < .001$, adjusted $R^2 = .101$ (small).					

Note: * $\beta \neq 0$ ($p < .05$)

Table 7-17. Model for predicting the percentage of time allocated to secondary tasks in the downstream phase

Models	Predictors	Reference	*b*	SE $_b$	β	*p*
Level 1	(Constant)		33.441	5.479		<.001*
	Driver age in years (continuous)		–.470	.081	–.147	<.001*
	Country: France	Germany	11.702	3.599	.116	.001*
	Country: Poland	Germany	14.878	3.739	.136	<.001*
	Country: UK	Germany	10.898	3.460	.117	.002*
	Country: Netherlands	Germany	14.250	3.748	.134	<.001*
	Gender: Male	Female	2.195	2.108	.026	.298
	The model was statistically significant, $F(6, 1623) = 10.187$, $p < .001$, adjusted $R^2 = .033$ (small).					
Level 2	(Constant)		–.991	17.705		.955
	Driver age in years (continuous)		–.556	.078	–.174	<.001*
	Country: France	Germany	9.336	3.474	.093	.007*
	Country: Poland	Germany	13.157	3.566	.124	<.001*
	Country: UK	Germany	8.610	3.317	.093	.010*
	Country: Netherlands	Germany	12.067	3.580	.110	.001*
	Gender: Male	Female	–3.498	2.012	–.042	.082
	Trip length		3.181	1.198	.062	.008*
	Intersection layout: Intersections	Roundabouts	–3.828	2.852	–.040	.180
	Intersection control: Traffic signs	Traffic lights	–2.678	3.178	–.031	.400
	Intersection priority: With	No priority	4.417	2.923	.053	.131
	Turning direction: Left	Right	1.079	2.658	.012	.685
	Turning direction: Going straight	Right	–1.345	2.352	–.016	.568
	Locality: Rural	Urban	–.460	2.315	–.005	.843
	Road type		.650	2.884	.007	.822
	Number of lanes		1.587	1.689	.034	.348
	Lighting conditions		–.560	1.145	–.011	.625
	Weather conditions: Poor	Good	–7.088	2.837	–.058	.013*
	Passenger presence: Yes	No	30.372	2.106	.338	<.001*
	Seat belt use: Yes	No	6.481	6.852	.022	.344
	The model was statistically significant, $F(19, 1609) = 15.668$, $p < .001$, adjusted $R^2 = .153$ (medium).					

Note: * $\beta \neq 0$ ($p < .05$)

Table 7-18. Model for predicting the percentage of time allocated to secondary tasks in the moving intersection status

Models	Predictors	Reference	*b*	SE $_b$	β	*p*
Level 1	(Constant)		29.898	4.932		<.001*
	Driver age in years (continuous)		–.434	.073	–.151	<.001*
	Country: France	Germany	10.573	3.240	.116	.001*
	Country: Poland	Germany	14.307	3.374	.149	<.001*
	Country: UK	Germany	11.708	3.114	.140	<.001*
	Country: Netherlands	Germany	13.319	3.365	.135	<.001*
	Gender: Male	Female	2.286	1.897	.030	.228
	The model was statistically significant, $F(6, 1623) = 11.121$, $p < .001$, adjusted $R^2 = .036$ (small).					
Level 2	(Constant)		3.267	16.011		.838
	Driver age in years (continuous)		–.484	.071	–.168	<.001*
	Country: France	Germany	9.068	3.142	.100	.004*
	Country: Poland	Germany	13.089	3.225	.136	<.001*
	Country: UK	Germany	10.027	3.000	.120	.001*
	Country: Netherlands	Germany	10.468	3.238	.106	.001*
	Gender: Male	Female	–2.571	1.820	–.034	.158
	Trip length		3.761	1.084	.082	.001*
	Intersection layout: Intersections	Roundabouts	–3.626	2.579	–.042	.160
	Intersection control: Traffic signs	Traffic lights	.175	2.874	.002	.951
	Intersection priority: With	No priority	2.472	2.643	.033	.350
	Turning direction: Left	Right	–.987	2.404	–.012	.682
	Turning direction: Going straight	Right	–1.796	2.127	–.023	.399
	Locality: Rural	Urban	–1.620	2.094	–.019	.439
	Road type		2.342	2.608	.028	.369
	Number of lanes		1.479	1.528	.035	.333
	Lighting conditions		–1.417	1.035	–.032	.171
	Weather conditions: Poor	Good	–4.555	2.565	–.041	.076
	Passenger presence: Yes	No	26.108	1.905	.323	<.001*
	Seat belt use: Yes	No	4.731	6.197	.018	.445
	The model was statistically significant, $F(19, 1609) = 15.085$, $p < .001$, adjusted $R^2 = .147$ (medium).					

Note: * $\beta \neq 0$ ($p < .05$)

Table 7-19. Model for predicting the percentage of time allocated to secondary tasks in the stationary intersection status

Models	Predictors	Reference	*b*	SE b	β	*p*
Level 1	(Constant)		51.453	10.750		<.001*
	Driver age in years (continuous)		–.691	.165	–.204	<.001*
	Country: France	Germany	9.074	7.284	.078	.214
	Country: Poland	Germany	18.876	7.101	.170	.008*
	Country: UK	Germany	11.319	6.554	.118	.085
	Country: Netherlands	Germany	9.443	6.740	.096	.162
	Gender: Male	Female	1.543	4.070	.018	.705
	The model was statistically significant, *F*(6, 428) = 4.507, *p* < .001, adjusted R^2 = .046 (small).					
Level 2	(Constant)		–14.758	28.415		.604
	Driver age in years (continuous)		–.715	.152	–.211	<.001*
	Country: France	Germany	7.201	6.730	.062	.285
	Country: Poland	Germany	16.130	6.668	.145	.016*
	Country: UK	Germany	8.805	6.178	.092	.155
	Country: Netherlands	Germany	8.605	6.125	.087	.161
	Gender: Male	Female	–5.693	3.761	–.067	.131
	Trip length		6.887	2.395	.126	.004*
	Intersection layout: Intersections	Roundabouts	7.724	6.849	.053	.260
	Intersection control: Traffic signs	Traffic lights	–2.849	6.678	–.029	.670
	Intersection priority: With	No priority	16.853	6.021	.190	.005*
	Turning direction: Left	Right	6.168	4.711	.071	.191
	Turning direction: Going straight	Right	.621	4.791	.007	.897
	Locality: Rural	Urban	2.596	5.034	.023	.606
	Road type		.904	5.390	.010	.867
	Number of lanes		–.997	2.842	–.023	.726
	Lighting conditions		–2.549	2.308	–.048	.270
	Weather conditions: Poor	Good	–3.921	5.524	–.031	.478
	Passenger presence: Yes	No	36.882	4.154	.389	<.001*
	Seat belt use: Yes	No	6.552	10.979	.026	.551
	The model was statistically significant, *F*(19, 415) = 7.972, *p* < .001, adjusted R^2 = .234 (medium).					

Note: * β ≠ 0 (*p* < .05)

Table 7-20. Model for predicting the percentage of time allocated to secondary tasks along the total non-intersection segment

Models	Predictors	Reference	*b*	SE $_b$	β	*p*
Level 1	(Constant)		30.519	5.334		<.001*
	Driver age in years (continuous)		–.504	.079	–.163	<.001*
	Country: France	Germany	14.379	3.511	.147	<.001*
	Country: Poland	Germany	18.993	3.638	.180	<.001*
	Country: UK	Germany	18.517	3.380	.206	<.001*
	Country: Netherlands	Germany	17.795	3.650	.173	<.001*
	Gender: Male	Female	3.224	1.863	.040	.081
	The model was statistically significant, $F(6, 1623) = 14.320$, $p < .001$, adjusted $R^2 = .048$ (small).					
Level 2	(Constant)		–2.708	15.798		.864
	Driver age in years (continuous)		–.570	.076	–.185	<.001*
	Country: France	Germany	12.576	3.330	.129	<.001*
	Country: Poland	Germany	17.549	3.469	.167	<.001*
	Country: UK	Germany	17.303	3.196	.192	<.001*
	Country: Netherlands	Germany	16.901	3.472	.164	<.001*
	Gender: Male	Female	–.251	1.974	–.003	.899
	Trip length		3.323	1.162	.068	.004*
	Locality: Rural	Urban	–1.683	2.221	–.018	.449
	Lighting conditions		–2.251	1.124	–.047	.045*
	Weather conditions: Poor	Good	–5.524	2.761	–.047	.046*
	Passenger presence: Yes	No	28.255	2.063	.325	<.001*
	Seat belt use: Yes	No	8.612	7.229	.028	.234
	The model was statistically significant, $F(12, 1561) = 25.502$, $p < .001$, adjusted $R^2 = .157$ (medium).					

Note: * $\beta \neq 0$ ($p < .05$)

The standardised (β) and unstandardised (*b)* coefficients of the predictors in the parsimonious models are presented in Table 7-21. Because not all the predictors were measured with a common scale, the β coefficients were essential to exploring which of the predictors exerted a greater effect on the dependent variable (i.e. the percentage of time involving secondary task engagement). A predictor with a large β magnitude is a strong determinant, whereas one with a small β magnitude is a weak determinant. The *b* coefficients were interpreted to probe into whether a change in the percentage of time allocated to secondary task engagement was positive or negative. A positive *b* coefficient meant a percentage increase by the value of *b* for every one unit increase in a predictor. A negative *b* coefficient pointed to a percentage decrease by the value of *b* for every one unit increase in the predictor.

In the level 1 models (Table 7-21), the strongest and most consistent predictor of the percentage of time allocated to secondary task engagement (indicated by the highest β magnitude) was driver age. Hence, age was entered into the model as a continuous variable, after which the percentage of secondary task engagement decreased by an unstandardised coefficient of 0.4% to 0.7% for every one-year increase in age. Country was also a consistent predictor. The German sample registered a significantly lower percentage of secondary task engagement than did the other samples across the complete intersection and non-intersection datasets, with the exception of stationary intersection status. At stationary intersection conditions, only the Polish sample registered a significantly higher secondary task engagement level than that shown by the German sample. Nevertheless, the level 1 models had low practical significance with small R^2 values because they were not representative of the full dataset and disregarded the effects of the contextual factors that were nested within each driver-related factor in the level 2 models.

Table 7-21. β coefficients (and *b* coefficients) in parsimonious multiple regression models[a]

Levels	Predictors	Reference	Intersection phases and motion conditions						Non-intersection segment
			Total	Upstream	During	Downstream	Moving	Stationary	
1	Driver age		–.158 (–.459)	–.148 (–.456)	–.135 (–.410)	–.147 (–.470)	–.151 (–.434)	–.204 (–.691)	–.163 (–.504)
	Country: France	Germany	.103 (9.380)	.084 (8.140)	.098 (9.393)	.116 (11.702)	.116 (10.573)		.147 (14.379)
	Country: Poland	Germany	.147 (14.246)	.149 (15.374)	.119 (12.086)	.136 (14.878)	.149 (14.307)	.170 (18.876)	.180 (18.993)
	Country: UK	Germany	.129 (10.850)	.106 (9.516)	.133 (11.774)	.117 (10.898)	.140 (11.708)		.206 (18.517)
	Country: Netherlands	Germany	.130 (12.917)	.110 (11.630)	.116 (12.068)	.134 (14.250)	.135 (13.319)		.173 (17.795)
2	Driver age		–.173 (–.501)	–.153 (–.472)	–.150 (–.455)	–.174 (–.556)	–.168 (–.484)	–.211 (–.715)	–.185 (–.570)
	Country: France	Germany	.096 (8.779)	.082 (8.016)	.087 (8.373)	.093 (9.336)	.100 (9.068)		.129 (12.576)
	Country: Poland	Germany	.134 (12.977)	.130 (13.363)	.113 (11.453)	.124 (13.157)	.136 (13.089)	.145 (16.130)	.167 (17.549)
	Country: UK	Germany	.113 (9.520)	.092 (8.279)	.119 (10.501)	.093 (8.610)	.120 (10.027)		.192 (17.303)
	Country: Netherlands	Germany	.104 (10.305)	.083 (8.790)	.092 (9.557)	.110 (12.067)	.106 (10.468)		.164 (16.901)
	Trip length		.079 3.640	.098 4.862	.061 2.958	.062 3.181	.082 3.761	.126 6.887	.068 3.323
	Intersection control: Traffic signs	Traffic lights	–.048 (–5.294)						N/A
	Intersection priority: With	No priority						.190 (16.853)	N/A
	Lighting conditions								–.047 (–2.251)
	Weather conditions: Poor	Good	–.046 (–5.106)			–.058 (–7.088)			–.047 (–5.524)
	Passenger presence: Yes	No	.338 (27.487)	.311 (26.988)	.260 (22.167)	.338 (30.372)	.323 (26.108)	.389 (36.882)	.325 (28.255)

Note: [a] Including only the predictors with $\beta \neq 0$ ($p < .05$)

The level 2 models were the most representative of the dataset, as manifested by the fact that the effects of the contextual factors nested within each driver-related factor were taken into account. This finding was corroborated by the high R^2 values, reflecting a medium level of practical significance. The strongest and most consistent predictor of the percentage of time allocated to secondary task engagement (indicated by the highest β magnitude) was the presence of passengers. Time allocation in the presence of passengers in a vehicle (relative to the absence of passengers) increased by a minimum unstandardised coefficient of 22.2% (in the within -intersection phase) to a maximum of 36.9% (in the stationary intersection status). The second strongest and most consistent predictor was driver age. Across the seven dependent variables, the percentage of secondary task engagement was reduced by 0.5% to 0.7% for every one-year increase in age. Country was the next strongest predictor. Amongst all the samples, the German sample registered the lowest percentage of secondary task engagement across the complete intersection and non-intersection datasets, except as regards stationary intersection status. Under such a status, the Polish sample was the sole group that significantly exceeded the German sample in terms of secondary task engagement (16.1% higher).

The other significant β coefficients were either smaller or less consistent in relation to trip length, stationary at approach, intersection control, intersection priority, lighting conditions and weather conditions:

- For every single ordinal unit increase in trip length, the percentage of time allocated to secondary task involvement rose by an unstandardised coefficient of 3.6% in the total intersection segment, 4.9% in the upstream phase, 3.0% in the within-intersection phase, 3.2% in the downstream phase, 3.8 in the moving intersection status, 6.9% in the stationary intersection status and 3.3% in the total non-intersection segment.

- In intersections controlled by traffic signs versus intersections managed by traffic lights, the percentage of time dedicated to secondary task engagement decreased by 5.3% in the total intersection segment.
- When SVs had priority versus the cases wherein SVs had no priority, the percentage of time allocated to secondary task engagement increased by 16.9% in the stationary intersection status.
- An increase in lighting conditions by one ordinal unit on a four-point scale ranging from 1 (the darkest condition, no lighting) to 4 (the lightest condition, daylight) translated to a decrease by 2.3% in the percentage of time associated with secondary task engagement in the non-intersection segment.
- When driving under adverse weather conditions compared with driving in good weather, the percentage of time allocated to secondary task engagement declined by 5.1%, 7.1% and 5.5% in the total intersection segment, downstream phase and non-intersection segment, respectively.

Gender, intersection layout, turning direction, locality (urban/rural), road type, number of lanes and seat belt use did not have a clear influence on the percentage of time allocated to secondary task engagement (p values > 0.05).

7.4 Discussion

This chapter discusses the ND data-based examination of the role played by various driver-related and contextual variables in influencing the overall willingness of drivers to engage in secondary tasks. This willingness was evaluated using the following metrics: the likelihood that a secondary task was executed at a segment (analysed via binary logistic regression) and the percentage of time associated with secondary task engagement along the segment (analysed through multiple linear regression). The analyses for each metric were classified by total intersection segment, upstream intersection phase, within-intersection phase, downstream intersection phase, moving intersection status, stationary intersection status and total non-intersection segment. The results revealed a number of interesting findings regarding the factors that influenced the drivers' propensity to engage in secondary tasks as well as their attempts to self-regulate this behaviour in response to variations in roadway and environmental conditions.

In terms of the influence of driver-related factors, both the binary logistic regression and the multiple linear regression results indicated that driver age was the most powerful predictor of involvement in secondary tasks, with task engagement decreasing as the drivers became older. This pattern indicated that the older drivers were less likely to occupy themselves with secondary tasks than the younger drivers—a pattern that was consistent across the entire intersection (encompassing all the intersection phases and vehicle motion conditions) and non-intersection datasets. This outcome confirms the proposed hypothesis of the inverse relationship between age and secondary task engagement and aligns with the findings of several studies within the distracted driving literature (e.g. Sullman et al., 2015; Funkhouser and Sayer, 2012; Stutts et al., 2003a).

The lower secondary task engagement rates of the older drivers may be explained by the predilection of these individuals to strategically self-regulate as a means of minimising their exposure to risk given their reduced abilities (e.g. sensory and information processing abilities) (Eby et al., 1998) and the complexity of the driving task specifically at intersections. It is also an expected outcome because of older drivers' greater awareness of distraction-related risks whilst driving as well as their higher sense of social responsibility compared with younger drivers (Rhodes and Pivik, 2011). Another plausible explanation is that older drivers are less inclined to engage in technology-based secondary tasks (Pickrell, 2015; Sullman, 2012; Young and Lenné, 2010) and therefore appear less involved in all secondary tasks as a group.

That the younger drivers were the group most frequently involved in secondary tasks is likewise unsurprising, as these individuals are more likely than their older counterparts to speed and commit other violations (Gras et al., 2009), have more negative attitudes towards traffic safety in general (Iversen and Rundmo, 2004) and appear to be the group most susceptible to distraction-related crashes (Buckley et al., 2014). Thus, targeting enforcement and educational resources particularly towards younger drivers is again pointed out in this thesis. However, before proposals to target countermeasures or policies are made, further investigation is needed to look into differences across age groups in terms of varying types of secondary tasks performed. This issue is covered in the next results chapter (Chapter 8).

With respect to a cross-country comparison, both regression analyses uncovered that the highest secondary task engagement level was registered by the Polish sample, followed by the Dutch, the UK and the French samples, which exhibited convergent values. The lowest engagement was observed amongst the German sample. This trend was evident across the intersection and non-intersection datasets, except in regard to stationary intersection status, for which the differences in task engagement between countries were smaller—nevertheless, the same trend was sustained. This trend is compatible with the findings reported in the UDRIVE project (even with the absence of the Dutch sample from their analysis) (Carsten et al., 2017). These cross-country differences may be attributed to variations in traffic culture as drivers in some countries are more sensitive to risk, more law-abiding (Nordfjærn et al., 2011) and more conscious about the dangers of distracting tasks than others.

The Polish sample accounting for the highest task engagement is unsurprising owing to the fact that the country had the worst road safety record (highest road traffic fatality rate) amongst the five countries (WHO, 2018). An association may therefore exist between engagement in secondary tasks and road traffic crash occurrence. Further investigation of the between-country differences that are reflected in the results is needed before implications are drawn. For example, an important complementary analysis is the comprehensive exploration of who engages in which secondary task types—an examination covered in the next results chapter (Chapter 8).

With reference to gender, no clear difference in secondary task engagement was observed between the male and female drivers, either in the intersection or non-intersection dataset. This finding is expected, as it is consistent with previous self-report, observational and ND studies that have typically found no gender differences in the overall rate of secondary task engagement (e.g. Chen et al., 2016; Sullman et al., 2015; Young et al., 2010; Charlton et al., 2013). A subsequent analysis of the data was carried out (see Chapter 8), with the aim of looking into gender differences in terms of various secondary tasks performed to determine whether this angle might provide more insight into the matter.

With regard to the influence of contextual factors, the binary logistic and the multiple linear regression results both denoted the presence of passengers to be the strongest and most consistent predictor of secondary task engagement across all observations. The rate of secondary task engagement was significantly higher when passengers were present relative to when they were not. This result contrasts with those of Metz et al. (2015) and Tivesten and Dozza (2015), who reported that drivers are more willing to engage in mobile phone-related activities in the absence of passengers. This contradiction in outcomes can be ascribed to the fact that the analysis in the current chapter was directed to all secondary tasks as a group (including passenger conversation), whereas the two above-mentioned studies examined the use of mobile phones only. It is possible that the drivers limited their involvement in complex secondary activities (e.g. handheld mobile phone interaction) when passengers were present but were likely to perform just as many, if not more, other secondary task types in the company of passengers. Additional inquiry is required to explore whether the influence of passengers on secondary task engagement differs across task types (a research direction covered in Chapter

8). Potentially, the drivers refrained from carrying out certain secondary activities, such as conversing on a mobile phone, because they already had a person to talk with in the vehicle.

The length of trips from which intersection/non-intersection cases were selected also significantly affected secondary task engagement, with such an engagement increasing as trips lengthened. This relationship was applicable across the complete intersection and non-intersection datasets and was particularly prominent at stationary intersection conditions. A possible explanation for this relationship is that the drivers, on short trips, may have exhibited a greater tendency to postpone the initiation of some secondary tasks until the trips ended, but on longer trips, they may have had reduced propensity for such postponement. Another explanation could be that the drivers tried to overcome the boredom and monotony associated with longer trips by choosing to engage more frequently in secondary tasks. The data should be further examined to ascertain whether the impact of trip length on secondary task engagement varies across secondary task types. This analysis is addressed in Chapter 8.

The regression modelling also cast light on a number of other contextual variables, particularly those associated with the complex aspects of driving at intersections. The analysis revealed some indication engagement level was significantly influenced by intersection control, intersection priority and weather conditions. Secondary task engagement was lower at intersections managed with traffic signs than at those controlled by traffic lights. Such a difference was particularly pronounced with regard to the totality of an intersection segment. This finding suggested that the drivers were less likely to engage in secondary tasks at intersections that require more gap judgment and where potential conflicts between vehicles moving in different directions are not separated in time. This outcome aligns with the results of an earlier ND study (Charlton et al., 2013). In terms of intersection priority, the drivers were more willing to perform secondary tasks when they had priority in passing through an intersection compared with cases when they did not have such priority. This finding was applicable across all intersection phases and motion conditions but was especially pronounced at stationary status. This result is plausible considering that drivers in non-priority locations are compelled to evaluate gaps and choose the best option for crossing an intersection (high decision-making demand). With reference to weather conditions, the drivers (either at intersections or non-intersection segments) were more reluctant to perform secondary tasks in poor weather situations than in good weather situations, which agrees with previous studies (Sayer, 2005; Young and Lenné, 2010).

The findings related to intersection control, intersection priority and weather conditions pointed to positive self-regulatory behaviour, wherein the drivers realised the greater driving task demands associated with certain driving context factors and consequently adjusted their involvement in secondary tasks. This phenomenon confirms the proposed hypothesis in the current chapter and agrees with previous studies that demonstrated the reluctance of drivers to undertake secondary activities under challenging driving scenarios (e.g. Tivesten and Dozza, 2015; Funkhouser and Sayer, 2012).

Lighting conditions also exerted a significant influence on secondary task engagement, but this influence was limited to the non-intersection segments. The percentage of time allocated to secondary tasks along the non-intersection segments was higher at night-time driving relative to daytime driving. This finding is surprising considering the risks associated with the former as well as its being one of the most challenging driving situations (Wood, 2020). Although this result can be viewed as a negative self-regulatory tendency, the positive point here is that (at the least) such a predisposition was not in play during intersection driving. At intersections, the drivers did not appear to consider lighting conditions in deciding when to execute secondary tasks—a result that aligns with a previous ND study (Young et al., 2019). Returning to the higher task engagement level in non-intersection segments, this issue may be ascribed to the drivers more frequent involvement in specific secondary activities (e.g. smoking and mobile phone-related tasks) to maintain alertness and stay awake as they drive at night (Kagabo et al., 2020).

Neither locality (urban/rural) nor the number of lanes at intersection approach, nor intersection layout, significantly influenced the drivers' willingness to engage in secondary tasks. The latter finding suggested that the drivers perceived roundabouts the same way as non-roundabout intersections. Moreover, no significant difference in secondary task engagement was found between the drivers who wore a seat belt and those who did not. Similarly, no significant association was discovered between turning directions (left/right/straight) and the level of secondary task engagement. This outcome, although unexpected, is consistent with the outcome derived by Charlton et al. (2013), albeit their analysis did not involve straight drives through intersections. A lower level of secondary task engagement during left turns (across traffic flow with many conflict points) compared with right turns was hypothesised. This unexpected outcome can be attributed to the method adopted in the current analyses; that is, the dependent variables used in the comparisons did not precisely delineate the start and end of turning manoeuvres. Closer scrutiny is needed to determine whether different dependent variables are suitable for the examination of turning moves.

Some of the findings in this chapter suggested that the drivers, at least to some extent, reduced the relative risk associated with secondary task engagement by choosing to perform more tasks in situations considered/assumed to present relatively lower decision-making demands. Nevertheless, this does not mean that such a behaviour is safe practice. The concern emerging from this situation is that drivers may underestimate the risk related to secondary task involvement, particularly when driving at intersections. As discussed in the literature (Chapter 3), intersections pose more demands on drivers than do other types of roadways and figure prominently in crash statistics (Simon et al., 2014). In these distracting situations at intersections, drivers are required to use additional cognitive resources to process different sources of information, which in turn, may reduce situation awareness or slow down driver decision making to risky levels and eventually lead to safety errors and increase crash risk.

7.5 Summary and conclusion

This chapter looked into the influence of various driver-related and contextual factors on the overall propensity of drivers to engage in secondary tasks. The results indicated that the drivers exercised self-regulation by limiting their engagement in secondary tasks during certain roadway and environmental conditions that were assumed/considered to be challenging. This self-regulatory behaviour was shown, for example, by the reduced willingness of drivers to perform secondary tasks when they did not have priority in passing through an intersection compared to when they had priority and when they were driving in adverse weather conditions as opposed to driving under fine weather. However, the drivers appeared to have disregarded some contextual variables that may impact risks, such as intersection layout and turning direction, in their self-regulatory discipline. A particularly important finding is that the level of secondary task engagement decreased as the drivers became older and as the trips became shorter.

Although the results discussed in this chapter provide preliminary information that can be useful in targeting enforcement and refining driver training/awareness programmes on managing distractions and applying safe driving strategies, the results should be seen in light of the fact that the analysis was directed to all secondary tasks as a group. Instead of combining all secondary tasks, individual secondary tasks can be examined to investigate whether there are differences between task types in how driver-related and contextual variables affect the engagement. Exploring these differences is essential to gaining a more precise understanding of self-regulation behaviours before distraction countermeasures or policies can be proposed. For example, do drivers postpone riskier secondary tasks until they encounter periods of low driving demand, and are they willing to carry out simpler secondary tasks during high-demand situations? Chapter 8 is intended to provide an answer to these and other related questions.

Chapter Eight

Exploring the Relationship Between Secondary Task Types and Driver-related and Contextual Factors

The previous chapter recounts the examination of the role that various driver-related and contextual factors play in influencing the overall propensity of drivers to engage in secondary tasks. The current chapter details how the findings presented in Chapter 7 were extended through an enquiry into whether any of the driver-related and contextual variables were associated with certain types of secondary activity. In other words, this chapter reports on the investigation of who engaged in which secondary task types and what contextual situations involved specific secondary behaviours.

8.1 Aims and hypotheses

The aims of the investigation discussed in this chapter were as follows:

- To determine whether any driver-related factors were associated with particular types of secondary activity.
- To determine whether any contextual factors were associated with particular types of secondary activity.

The driver-related and contextual factors that were included in the analysis were the same ones used to develop the regression models in Chapter 7 (Tables 7-3 and 7-4). The four classifications of secondary tasks that were explored in respect of their association with the different factors were (1) the general classification of task categories (e.g. mobile phone use, smoking, personal grooming), (2) the detailed classification of mobile phone sub-tasks, (3) the VM complexity-based classification of tasks (simple, moderate and complex) and (4) the technological classification of tasks (technology- and non-technology-based tasks). These classifications and their respective coding procedures are described in detail in the general methodology chapter (Section 5.8).

The core hypothesis examined in this chapter is that drivers exercise self-regulation by reducing engagement in more complex secondary activities as a driving situation becomes more challenging. Such a reduction is expected to take place, for example, when driving under adverse weather conditions compared with driving in good weather and when drivers do not have priority in passing through an intersection compared with situations when they have priority. Moreover, older drivers are posited to exhibit a lower propensity than younger drivers to engage in technology-based tasks and more complex secondary behaviours. On this basis, then, a negative relationship arises between driver age and the complexity of secondary tasks being performed.

8.2 Methods

The analysis documented in this chapter was grounded on the same dataset used in the investigations discussed in the previous chapters. Such an examination was directed towards a pool of 1630 intersection cases, which involved a total of 1050 distinct secondary task events, including 132 mobile phone interactions (refer to Section 5.7 for more details on the dataset).

To determine whether any of the driver-related and contextual factors were significantly associated with certain secondary task types and explore the nature of such an association, a series of OR analyses were carried out using SPSS. An OR is a popular measure of association between an exposure and an outcome; it represents the likelihood of an outcome occurring given a particular exposure compared with the likelihood of occurrence in the absence of that exposure (Szumilas, 2010). In this work, the OR was interpreted as an effect size, and the statistic indicated the extent to which each factor predicted whether or not a driver will engage in specific secondary behaviours (with task/no task). An OR = 1.0 meant that a factor had no effect, an OR > 1.0 indicated that the factor increased the odds of outcome occurrence and an OR < 1.0 denoted a decrease in the odds. In situations wherein the 95% CIs of the OR did not include 1.0, then the OR was evaluated as significantly different from 1.0 at $p < 0.05$. If the 95% CIs included 1.0, then the OR was interpreted as not significantly different from 1.0 at $p > 0.05$.

8.3 Results

The results on gender, age and country of recruitment as the driver-related factors and the contextual variables are presented in the succeeding sections.

8.3.1 Driver-related factors

8.3.1.1 Gender

A series of OR comparisons were carried out to determine whether a statistically significant difference existed between the male and female drivers as regards secondary task behaviours. The analysis with reference to the secondary task categories revealed some suggestion of significant gender differences in behaviour (Table 8-1). For example, 6.4% of the segments coded for the female drivers involved personal grooming activities, whereas only 2% of the segments coded for the male drivers reflected engagement in these activities. This result can be expressed as an OR, whereby the female drivers were 3.4 times more likely than the male drivers to engage in personal grooming tasks ($p < 0.001$). The female drivers were also 1.7 times more willing than the male drivers to talk/sing in the absence of passengers ($p = 0.005$), whereas the male drivers were 1.8 times more willing than the female drivers to talk to a passenger ($p < 0.001$). Other non-significant differences were that the males had higher incidences of smoking-related activities compared with the females, whereas the females had higher rates of mobile phone use and in-vehicle control adjustment.

Table 8-1. Engagement in each secondary task type by gender

Classifications	Tasks	Proportions of segments with task (%)		OR*	95% CI (LCL–UCL)	Sig.
		Female	Male			
Secondary task categories	Passenger conversations	17.7	27.8	0.559	0.441–0.709	< 0.001**
	Talking/singing in the absence of passengers	10.4	6.5	1.675	1.172–2.394	0.005**
	Mobile phone use	8.1	6.0	1.377	0.939–2.018	0.102
	Adjusting in-vehicle controls	6.0	5.1	1.203	0.786–1.842	0.394
	Smoking	3.1	4.1	0.739	0.436–1.254	0.263
	Personal grooming	6.4	2.0	3.356	1.919–5.871	< 0.001**
	Eating and/or drinking	1.8	1.2	1.535	0.678–3.477	0.304
	Other (including reading/writing tasks)	2.4	1.9	1.301	0.664–2.549	0.442
Mobile phone sub-tasks	Hands-free interaction	2.3	3.1	0.749	0.407–1.376	0.351
	Handheld interaction	2.4	1.4	1.744	0.841–3.616	0.135
	Hands-free conversation	2.6	1.1	2.459	1.113-5.433	0.026**
	Handheld conversation	0.3	0.5	0.544	0.099–2.977	0.482
	Holding	1.0	0.4	2.926	0.773–11.068	0.114
	Related	0.4	0.7	0.543	0.135–2.179	0.389
VM complexity	Simple tasks	41.0	43.5	0.902	0.741–1.099	0.307
	Moderate tasks	6.7	6.2	1.074	0.723–1.595	0.723
	Complex tasks	5.5	3.5	1.595	0.990–2.569	0.055
Technological classification	Technology-based tasks	13.5	11.1	1.251	0.930–1.684	0.139
	Non-technology-based tasks	38.5	41.2	0.893	0.732–1.089	0.264

* Odds ratio of female drivers vs. male drivers

** Significant result

When analysed on the basis of the mobile phone sub-tasks, the findings in Table 8-1 suggest that the male drivers had slightly higher incidences of handheld conversation and hands-free interaction than the female drivers, whereas the female drivers had higher rates of handheld interaction and hands-free conversation. Amongst all the mobile phone sub-tasks, only hands-free conversation reflected a significant difference in engagement between the gender groups (p = 0.026). The OR of participating in hands-free conversation amongst the female drivers versus the male drivers was 2.459 (95% CI, 1.113–5.433).

With respect to the VM complexity-based classification of tasks, Table 8-1 indicates that the female drivers tended more strongly to perform complex tasks relative to the male drivers (1.6 times higher), but this difference fell just short of significance at the 0.05 level ($p = 0.055$). As for the simple and moderate tasks, the differences in engagement between the gender groups were slight and nowhere near significant proportions.

The task classification grounded in technological aspects showed that the male drivers were somewhat more prone to engaging in non-technology-based activities, whereas the female drivers were slightly more willing to occupy themselves with technology-based tasks. These differences, however, were not statistically significant and thus provided no support for an existing association between gender and technologically oriented task classification (Table 8-1).

8.3.1.2 Age

To determine whether age was significantly associated with any of the secondary task types, the drivers were categorised into three ordinal age groups: younger (18–34 years, $n = 46$), middle-aged (35–54 years, $n = 79$) and older (55+ years, $n = 38$) drivers. This categorisation was dictated by the constraints arising from the demographic data from the overall UDRIVE sample and was conducted to ensure sufficient and fairly balanced proportions of drivers in each group. Broadly speaking, the results presented in Chapter 7 revealed that age significantly influenced the overall willingness of drivers to engage in secondary tasks, with task engagement decreasing as the drivers became older. The subsequent analyses here were performed to determine whether the same pattern held across varying secondary task types.

When analysed on the grounds of the secondary task categories, involvement in most of the tasks appeared to decrease with age (Table 8-2). The only exception was conversation with a passenger, in which the possibility of engagement rose by nearly 20% for every single ordinal unit increase in age ($p = 0.025$). A noteworthy result was that the likelihood of engagement in smoking-related activities decreased by around 60% for every single ordinal unit increase in age ($p < 0.001$) and that the drivers older than 55 years had zero engagement in such activities. The decrement in the likelihood of engagement for every ordinal unit increase in age was 56.9% for mobile phone use ($p < 0.001$), 34.4% for talking/singing in the absence of passengers ($p = 0.001$) and 36.8% for personal grooming activities ($p = 0.011$). Although incidences of in-vehicle control adjustment and eating/drinking tasks were the least occurring amongst the older drivers, the trend of decline in these tasks were not statistically significant as these categories were slightly more prevalent amongst the middle-aged drivers compared with the other age groups.

When performance was broken down per mobile phone sub-task, all the sub-tasks seemed to decrease with age (Table 8-2). Of note was the prominent reduction in the likelihood of executing handheld interaction and hands-free interaction as age increased. The probability of engagement in handheld interaction and hands-free interaction decreased by 73.4% and 63.4%, respectively, for every single ordinal unit increase in age ($p < 0.001$). The same relationship applied to all the other sub-tasks, but the trend of decline with age was not statistically significant.

Concerning the secondary task classification grounded in VM complexity, the pattern was that engagement in the three task complexity groups (simple, moderate and complex) significantly decreased with age; however, this decrement was steepest for complex tasks, followed by moderate tasks and then simple tasks. For every single ordinal unit increase in age, the decrement in the likelihood of engagement was 39.6% for complex tasks, 30.3% for moderate tasks and 19.9% for simple tasks (Table 8-2). Evidently, the older the drivers, the less likely they were to engage in more complex secondary activities.

Table 8-2. Engagement in each secondary task type by age

Classifications	Tasks	Proportions of segments with task (%)			OR*	95% CI (LCL–UCL)	Sig.
		18–34 years	34–54 years	55+ years			
Secondary task categories	Passenger conversations	20.2	22.7	26.8	1.203	1.024–1.414	0.025**
	Talking/singing in the absence of passengers	12.0	7.5	5.8	0.656	0.509–0.845	0.001**
	Mobile phone use	12.0	6.6	1.8	0.431	0.321–0.579	< 0.001**
	Adjusting in-vehicle controls	5.2	5.9	5.0	0.987	0.733–1.328	0.930
	Smoking	5.9	4.1	0.0	0.406	0.269–0.611	< 0.001**
	Personal grooming	5.9	3.9	2.4	0.632	0.443–0.900	0.011**
	Eating and/or drinking	1.5	1.8	0.8	0.790	0.447–1.398	0.419
	Other (including reading/writing tasks)	1.8	2.7	1.5	0.907	0.568–1.447	0.682
Mobile phone sub-tasks	Hands-free interaction	4.8	2.8	0.0	0.366	0.225–0.595	< 0.001**
	Handheld interaction	4.3	1.3	0.3	0.266	0.141–0.500	< 0.001**
	Hands-free conversation	2.2	1.9	1.1	0.727	0.431–1.228	0.233
	Handheld conversation	0.7	0.4	0.0	0.376	0.103–1.372	0.139
	Holding	1.1	0.6	0.3	0.522	0.214–1.269	0.151
	Related	0.9	0.4	0.5	0.707	0.277–1.807	0.469
VM complexity	Simple tasks	47.8	41.6	37.1	0.801	0.697–0.919	0.002**
	Moderate tasks	7.8	7.1	3.4	0.697	0.525–0.925	0.012**
	Complex tasks	6.3	4.6	2.1	0.604	0.429–0.851	0.004**
Technological classification	Technology-based tasks	16.7	12.3	6.6	0.616	0.496–0.763	< 0.001**
	Non-technology-based tasks	43.0	40.0	35.8	0.860	0.749–0.988	0.034**

* Odds ratio of every single ordinal unit increase in age

** Significant result

With respect to the classification of secondary tasks via technological aspects, the data in Table 8-2 imply that participation in both the technology- and non-technology-based tasks significantly decreased with age. However, the pattern of decrement as regards the technology-based activities was steeper, reflecting a 38.4% reduction in likelihood for every single ordinal unit increase in age versus a 14% reduction in likelihood with respect to non-technology-based activities. As can be seen, the older the drivers, the more reluctant they were to occupy themselves with technology-based activities.

8.3.1.3 Country of recruitment

A series of comparisons were carried out to determine whether a statistically significant difference existed amongst the countries as regards secondary task behaviours. When explored on the basis of the secondary task categories (Table 8-3), the data suggested such a difference with respect to mobile phone use and in-vehicle control adjustment ($p < 0.05$). The trend of mobile phone use was that the Polish sample exhibited the highest engagement level (with 13.5% out of the total segments coded for them involving this activity), followed by the Dutch (7.6%) and the French (7.2%) samples, as evidenced by their convergent values. The lowest engagement in mobile phone use was observed amongst the UK (3.9%) and the German (2.9%) samples. The German sample were also the least likely to adjust in-vehicle controls (2.9%), whereas the French sample were the most likely to execute such a task (9.4%). A result worth noting was that the German sample did not engage in smoking-related activities and that the French sample rarely performed eating/drinking tasks. All the other task categories had convergent engagement rates across the samples from the five countries.

On the subject of the mobile phone sub-tasks, the data in Table 8-3 imply a significant association between country and both the hands-free interaction ($p = 0.002$) and the handheld interaction ($p = 0.040$) sub-tasks. For both these sub-tasks, the highest engagement rate was exhibited by the Polish sample, followed by the French, the Dutch and the UK samples; the lowest engagement rate was observed amongst the German sample. This trend also applied to the hands-free conversation sub-task, but the differences amongst the countries were smaller and did not reach a level of significance. The Polish sample manifested a slightly higher participation level than that observed in the four other samples with respect to handheld conversation.

Table 8-3. Engagement in each secondary task type by country

Classifications	Tasks	Proportions of segments with task (%)					Sig.
		FR	NL	PL	UK	GE	
Secondary task categories	Passenger conversations	20.8	23.4	24.2	24.3	21.0	0.698
	Talking/singing in the absence of passengers	8.1	5.9	8.1	10.4	8.1	0.290
	Mobile phone use	7.2	7.6	13.5	3.9	2.9	0.000*
	Adjusting in-vehicle controls	9.4	5.9	4.2	4.3	2.9	0.005*
	Smoking	5.3	3.1	4.2	3.9	0.0	0.146
	Personal grooming	4.2	4.8	4.5	3.5	3.8	0.907
	Eating and/or drinking	0.3	3.1	1.6	1.5	1.4	0.154
	Other (including reading/writing tasks)	1.9	2.1	3.2	1.7	1.9	0.705
Mobile phone sub-tasks	Hands-free interaction	3.6	2.8	5.8	0.9	0.5	0.002*
	Handheld interaction	1.7	2.1	4.2	1.3	0.0	0.040*
	Hands-free conversation	2.2	2.6	2.8	0.9	0.5	0.173
	Handheld conversation	0.3	0.3	1.3	0.2	0.5	0.364
	Holding	0.3	1.3	0.3	0.2	1.0	0.089
	Related	0.3	0.3	1.0	0.7	1.0	0.758
VM complexity	Simple tasks	41.7	42.4	47.7	42.8	34.3	0.065
	Moderate tasks	7.5	7.1	8.3	5.0	4.3	0.231
	Complex tasks	4.7	4.8	7.7	3.3	1.4	0.013*
Technological classification	Technology-based tasks	16.1	13.4	17.1	8.0	5.7	< 0.001*
	Non-technology-based tasks	38.6	39.0	42.3	43.0	32.9	0.122

* Significant difference in task type engagement level amongst the country samples

The analysis anchored in the VM complexity of tasks suggested a significant difference in engagement rate between the countries with respect to complex tasks (p = 0.013). In detail, the German sample registered the lowest engagement level (with 1.4% out of the total segments coded for them involving complex tasks), whereas the Polish sample had the highest engagement level (7.7%). This tendency held over the simple and moderate tasks, but the differences across the samples were not significant (Table 8-3).

With respect to the technological classification of tasks, country-oriented differences in behaviour occurred (Table 8-3). The French, Dutch and Polish samples tended more strongly towards technology-based tasks compared with the UK and German samples. The German sample, furthermore, were the least likely to engage in non-technology-based activities.

8.3.2 Contextual factors

A series of OR comparisons were carried out to evaluate the relationship between the contextual factors and the types of secondary task engagement. Five of the contextual factors were not significantly associated with any of the secondary task types ($p > 0.05$). These factors were intersection layout, turning direction (left, right, straight), locality (urban, rural), road type (single, dual carriageway) and number of lanes. The other contextual factors were significantly associated with at least one of the secondary task types. These factors and their related relationships are elucidated in the succeeding sub-sections.

8.3.2.1 Trip length

To perform OR comparisons and determine whether trip length (from which the intersection cases were sampled) was significantly associated with any of the secondary task types, the trips were categorised into three ordinal groups: short (less than 15 minutes, n = 994), medium-length (15–30 minutes, n = 432) and long (30+ minutes, n = 204) trips. Broadly speaking, the analysis from the previous chapter revealed that the overall willingness of the drivers to engage in secondary tasks increased as a trip lengthened. A subsequent analysis was conducted to determine whether this relationship held across varying secondary task types.

When a breakdown per secondary task category was implemented, the same trend manifested in most of the task categories (Table 8-4). What warrants attention was the significant increase in the likelihood of engagement in mobile phone-related tasks, with around a 73% increase in likelihood for every single ordinal unit increase in trip length ($p < 0.001$). All the other task categories were not significantly associated with trip length ($p > 0.05$).

The same trend characterised most of the mobile phone sub-tasks (Table 8-4), with the sole exception being the handheld conversation sub-task, to which the drivers devoted slightly lower engagement during long trips. Of particular interest was that the drivers showed a nearly 67% increase in the likelihood of engaging in handheld interaction for every single ordinal unit increase in trip length ($p = 0.023$). This possibility strengthened by a larger proportion (91% to 94%) with respect to the hands-free interaction and phone holding sub-tasks.

Table 8-4. Engagement in each secondary task type by trip length

Classifications	Tasks	Proportions of segments with task (%)			OR*	Sig.
		Short trips	Medium-length trips	Longer trips		
Secondary task categories	Passenger conversations	23.0	22.0	24.5	1.02	0.850
	Talking/singing in the absence of passengers	8.4	7.9	9.3	1.03	0.808
	Mobile phone use	4.4	11.1	10.8	1.73	< 0.001**
	Adjusting in-vehicle controls	4.7	6.5	7.4	1.29	0.076
	Smoking	3.0	4.9	3.9	1.24	0.218
	Personal grooming	3.6	5.1	4.4	1.18	0.335
	Eating and/or drinking	1.4	1.4	2.0	1.14	0.636
	Other (including reading/writing tasks)	1.5	2.3	2.2	1.01	0.623
Mobile phone sub-tasks	Hands-free interaction	1.4	4.9	4.4	1.91	0.001**
	Handheld interaction	1.4	2.1	3.9	1.67	0.023**
	Hands-free conversation	1.2	2.8	2.5	1.55	0.066
	Handheld conversation	0.4	0.5	0.0	0.65	0.533
	Holding	0.5	0.5	2.0	1.94	0.074
	Related	0.3	1.4	0.0	1.32	0.522
VM complexity	Simple tasks	40.3	44.9	46.6	1.15	0.044**
	Moderate tasks	4.9	8.8	8.8	1.44	0.005**
	Complex tasks	3.8	5.3	5.9	1.28	0.114
Technological classification	Technology-based tasks	9.0	17.2	17.4	1.55	< 0.001**
	Non-technology-based tasks	38.9	41.2	41.7	1.07	0.351

* Odds ratio for every single ordinal unit increase in trip length

** Significant result

In connection with the VM complexity-based classification of tasks, the relationship held across different complexity groups. A result worth noting was that the likelihood of engagement in complex and moderate tasks increased by 28% and 44%, respectively, for every single ordinal unit increase in trip length. This possibility of engagement increased by a smaller amount (15%) with respect to simple tasks. In regard to the task classification grounded in technological aspects, the same relationship was sustained over both the technology- and non-technology-based tasks, but the upward relationship was steeper in the former, with a 55% increase in engagement likelihood for every ordinal unit increase in trip length (Table 8-4).

8.3.2.2 Intersection control

When explored on the basis of the secondary task categories (Table 8-5), the drivers were more likely to engage in all the task categories in intersections managed by traffic lights (i.e. signalised intersections) than in intersections controlled by traffic signs (i.e. unsignalised intersections). A noteworthy result was that the drivers showed nearly four times an increase in the likelihood to engage in eating/drinking and personal grooming tasks at signalised intersections compared with unsignalised ones ($p < 0.001$). The increment at signalised intersections was 3.1 times higher as regards in-vehicle control adjustment ($p < 0.001$) and 1.7 times higher for mobile phone use ($p = 0.006$). However, the likelihood of engagement in passenger conversation, talking/singing in the absence of passengers and smoking-related activities did not significantly differ between signalised and unsignalised intersections.

The same trend persisted over most of the mobile phone sub-tasks and was especially pronounced with respect to the handheld interaction category, which the drivers were approximately three times more willing to perform at signalised intersections ($p = 0.007$). Only the handheld conversation sub-task exhibited a reverse trend, with execution rate slightly higher at unsignalised intersections (Table 8-5).

Table 8-5. Engagement in each secondary task type by intersection control

Classifications	Tasks	Proportions of segments with task (%)		OR*	95% CI (LCL–UCL)	Sig.
		Signalised	Unsignalised			
Secondary task categories	Passenger conversations	23.3	22.7	1.033	0.814–1.311	0.790
	Talking/singing in the absence of passengers	8.6	8.2	1.053	0.734–1.512	0.778
	Mobile phone use	9.3	5.7	1.701	1.161–2.491	0.006**
	Adjusting in-vehicle controls	9.4	3.2	3.127	2.011–4.861	< 0.001**
	Smoking	3.6	3.6	1.008	0.589–1.725	0.978
	Personal grooming	7.4	2.1	3.664	2.177–6.164	< 0.001**
	Eating and/or drinking	2.8	0.7	4.205	1.733–10.198	< 0.001**
	Other (including reading/writing tasks)	3.3	1.5	2.302	1.170–4.531	0.016**
Mobile phone sub-tasks	Hands-free interaction	3.6	2.1	1.720	0.944–3.134	0.076
	Handheld interaction	3.1	1.2	2.737	1.319–5.679	0.007**
	Hands-free conversation	1.8	1.8	1.036	0.486–2.208	0.927
	Handheld conversation	0.3	0.4	0.847	0.155–4.636	0.848
	Holding	1.2	0.4	2.988	0.871–10.249	0.082
	Related	0.8	0.4	2.127	0.569–7.952	0.262
VM complexity	Simple tasks	46.8	39.7	1.335	1.089–1.635	0.005**
	Moderate tasks	9.9	4.4	2.398	1.606–3.578	< 0.001**
	Complex tasks	7.4	2.7	2.861	1.765–4.638	< 0.001**
Technological classification	Technology-based tasks	17.7	9.0	2.179	1.616–2.939	< 0.001**
	Non-technology-based tasks	43.6	37.7	1.282	1.045–1.572	0.017**

* Odds ratio of signalised vs. unsignalised intersections

** Significant result

In the matter of the VM complexity-based classification of tasks, the findings in Table 8-5 indicate that the drivers were 1.3 times more likely to engage in simple tasks at signalised intersections relative to unsignalised intersections (p = 0.005). This pattern of engagement increased to 2.4 times for moderate tasks ($p < 0.001$) and 2.9 times for complex tasks ($p < 0.001$). Thus, the more complex the secondary task, the greater the likelihood that it will be carried out at signalised intersections and the lower the possibility that it will be performed at unsignalised intersections.

In relation to the technological classification of tasks, the drivers appeared to be more strongly inclined towards executing both the technology- and non-technology-based tasks at signalised intersections relative to unsignalised intersections. However, the difference was greater for the technology-based activities, with the chance of occurrence at signalised intersections higher by 2.2 times compared with the 1.3-fold increase in the possibility of involvement in the non-technology-based activities (Table 8-5).

8.3.2.3 Intersection priority

As regards the secondary task categories, the drivers were significantly more likely to use their mobile phones (1.5 times higher, $p = 0.028$), adjust in-vehicle controls (2.1 times higher, $p = 0.001$) and engage in eating/drinking tasks (5 times higher, $p = 0.003$) when they had priority in passing though intersections compared with situations when they had no such priority. This relationship was sustained but not significant in connection to passenger conversation and personal grooming tasks. Only talking/singing in the absence of passengers and smoking-related activities had a reverse non-significant trend, with a higher engagement rate under the absence of priority (Table 8-6). When a breakdown per mobile phone sub-task was implemented, the tendency of the drivers to occupy themselves with all the phone interactions was slightly more prevalent when they had priority in passing through intersections than in cases when they had no such priority. However, the priority groups did not significantly differ across all the phone sub-tasks (all $p > 0.05$) (Table 8-6).

When explored on the basis of the VM complexity of tasks, the data in Table 8-6 suggest that the drivers exhibited a stronger predilection to engage in moderate and complex tasks when they had priority in passing through intersections (1.7 to 2 times higher compared with cases wherein they had no priority). The same trend characterised the simple tasks, but the difference in occurrence between the two priority groups was not statistically significant. These findings indicated that the drivers were more reluctant to engage in moderate and complex activities under the absence of priority. Nevertheless, involvement in moderate and complex tasks did not disappear entirely in these conditions.

Table 8-6. Engagement in each secondary task type by intersection priority

Classifications	Tasks	Proportions of segments with task (%)		OR*	95% CI (LCL–UCL)	Sig.
		With priority	No priority			
Secondary task categories	Passenger conversations	23.3	22.6	1.042	0.827–1.312	0.730
	Talking/singing in the absence of passengers	7.5	9.2	0.805	0.566–1.145	0.227
	Mobile phone use	8.4	5.6	1.546	1.048–2.280	0.028**
	Adjusting in-vehicle controls	7.4	3.6	2.142	1.361–3.370	0.001**
	Smoking	3.3	4.0	0.819	0.486–1.381	0.454
	Personal grooming	4.7	3.5	1.380	0.841–2.266	0.202
	Eating and/or drinking	2.4	0.5	4.988	1.697–14.657	0.003**
	Other (including reading/writing tasks)	2.7	1.6	1.673	0.837–3.345	0.145
Mobile phone sub-tasks	Hands-free interaction	3.0	2.4	1.296	0.708–2.372	0.401
	Handheld interaction	2.2	1.6	1.362	0.663–2.799	0.400
	Hands-free conversation	2.1	1.5	1.394	0.661–2.937	0.383
	Handheld conversation	0.5	0.2	1.961	0.358–10.736	0.438
	Holding	1.1	0.2	4.439	0.956–20.610	0.057
	Related	0.8	0.2	3.444	0.713–16.630	0.124
VM complexity	Simple tasks	43.1	41.6	1.064	0.874–1.295	0.535
	Moderate tasks	8.4	4.5	1.955	1.290–2.961	0.002**
	Complex tasks	5.7	3.4	1.685	1.005–2.599	0.048**
Technological classification	Technology-based tasks	15.0	9.3	1.727	1.273–2.342	< 0.001**
	Non-technology-based tasks	40.2	39.6	1.025	0.841–1.250	0.807

* Odds ratio of situations with vs. without priority

** Significant result

In respect of the technological classification of tasks, the drivers appeared significantly more willing to occupy themselves with technology-based tasks when they had priority in passing through intersections (1.7 times higher relative to non-priority situations, $p < 0.001$). However, the two priority groups exhibited an almost similar rate of engagement in the non-technology-based activities (Table 8-6).

8.3.2.4 Lighting conditions

To perform the OR comparisons and determine whether lighting conditions were significantly associated with any of the secondary task types, the conditions were categorised into two groups: daytime driving (covering dawn to dusk, n = 1291) and night driving (encompassing lighted darkness and unlighted darkness, n = 339) (Table 8-7). This categorisation was prompted by the constraints arising from the sample and was performed to ensure sufficient proportions of conditions in each group.

Table 8-7. Engagement in each secondary task type by lighting conditions

Classifications	Tasks	Proportions of segments with task (%)		OR*	95% CI (LCL–UCL)	Sig.
		Daytime	Night			
Secondary task categories	Passenger conversations	22.4	25.1	0.862	0.653–1.138	0.295
	Talking/singing in the absence of passengers	7.9	10.0	0.770	0.512–1.157	0.208
	Mobile phone use	6.6	8.6	0.753	0.485–1.169	0.207
	Adjusting in-vehicle controls	5.7	5.0	1.135	0.660–1.952	0.646
	Smoking	2.9	6.2	0.459	0.266–0.794	0.005**
	Personal grooming	4.6	2.1	2.312	1.047–5.105	0.038**
	Eating and/or drinking	1.5	1.5	0.998	0.370–2.692	0.997
	Other (including reading/writing tasks)	2.1	2.4	0.884	0.398–1.963	0.762
Mobile phone sub-tasks	Hands-free interaction	2.7	2.7	1.022	0.486–2.147	0.955
	Handheld interaction	2.1	1.9	1.114	0.476–2.604	0.805
	Hands-free conversation	1.5	2.7	0.577	0.260–1.279	0.176
	Handheld conversation	0.4	0.3	1.314	0.153–11.286	0.803
	Holding	0.6	0.9	0.698	0.184–2.647	0.597
	Related	0.5	0.9	0.523	0.130–2.102	0.361
VM complexity	Simple tasks	42.1	45.9	0.791	0.622–1.006	0.096
	Moderate tasks	6.4	6.8	0.932	0.577–1.504	0.773
	Complex tasks	4.6	3.8	1.222	0.663–2.254	0.520
Technological classification	Technology-based tasks	12.1	12.9	0.915	0.639–1.309	0.630
	Non-technology-based tasks	38.5	45.1	0.761	0.598–0.969	0.027**

* Odds ratio of daytime vs. night-time driving

** Significant result

When analysed by category of secondary task engagement, the findings suggest that the drivers were significantly more likely to occupy themselves with personal grooming activities when driving during the daytime relative to driving at night (2.3 times higher, $p = 0.038$). They were significantly more likely to perform smoking-related activities during night-time driving than daytime driving (2.2 times higher, $p = 0.005$). Lighting conditions were not significantly associated with either the other task categories or any of the mobile phone sub-tasks (Table 8-7).

In terms of the VM complexity-based classification of tasks, the drivers were slightly more willing to engage in simple tasks when driving at night compared with daytime driving, whereas they were slightly more inclined to choose daytime periods to engage in complex tasks. These differences, however, were not statistically significant and thus provided no support for the presumed relationship between lighting conditions and task complexity. With regard to the technological classification of tasks, the drivers appeared significantly more predisposed towards non-technology-based activities as they drove at night than during the day (1.3 times higher, $p = 0.027$). Even so, the rate at which technology-based activities occurred was almost similar during daytime and night-time driving (Table 8-7).

8.3.2.5 Weather conditions

When a breakdown per secondary task category was carried out, the tendency of the drivers to occupy themselves in most of the task categories was less prevalent when they were driving under adverse weather conditions versus when they were driving in good weather (Table 8-8). The only exception was the passenger conversation category, which had a slightly higher occurrence rate under adverse weather situations. Of note was the significant decline in the willingness of drivers to adjust in-vehicle controls when driving under adverse weather conditions (a 78.6% lower chance of occurrence than that observed during driving in good weather, $p = 0.009$). This lower engagement rate occurred at a non-significant level with respect to personal grooming (48.6%), mobile phone use (39.2%) and smoking (27%).

The same trend persisted across all the mobile phone sub-tasks and was especially pronounced with regard to the handheld interaction and hands-free conversation sub-tasks (Table 8-8). The chances of engagement in these sub-tasks declined by around 52% to 55% as the drivers drove under adverse weather conditions compared with the levels observed as they drove in good weather. Nonetheless, engagement in these sub-tasks as well as all the other sub-tasks did not significantly differ across weather conditions.

Table 8-8. Engagement in each secondary task type by weather conditions

Classifications	Tasks	Proportions of segments with task (%)		OR*	95% CI (LCL–UCL)	Sig.
		Poor	Good			
Secondary task categories	Passenger conversations	23.1	22.9	1.006	0.717–1.413	0.971
	Talking/singing in the absence of passengers	8.3	8.4	0.993	0.591–1.666	0.978
	Mobile phone use	4.6	7.4	0.608	0.313–1.183	0.143
	Adjusting in-vehicle controls	1.4	6.2	0.214	0.067–0.682	0.009**
	Smoking	2.8	3.8	0.730	0.310–1.718	0.471
	Personal grooming	2.3	4.4	0.514	0.204–1.293	0.157
	Eating and/or drinking	1.4	1.5	0.929	0.275–3.142	0.906
	Other (including reading/writing tasks)	1.8	2.2	0.837	0.293–2.395	0.740
Mobile phone sub-tasks	Hands-free interaction	2.3	2.8	0.831	0.324–2.132	0.700
	Handheld interaction	0.9	2.1	0.444	0.105–1.874	0.269
	Hands-free conversation	0.9	1.9	0.478	0.113–2.022	0.316
	Handheld conversation	0.4	0.5	0.767	0.089–6.579	0.809
	Holding	0.5	0.7	0.650	0.083–5.099	0.681
	Related	0.4	0.6	0.786	0.095–5.215	0.854
VM complexity	Simple tasks	38.2	43.0	0.822	0.613–1.103	0.192
	Moderate tasks	4.6	6.7	0.670	0.344–1.307	0.240
	Complex tasks	1.8	4.9	0.366	0.132–0.985	0.048**
Technological classification	Technology-based tasks	6.5	13.1	0.458	0.261–0.804	0.007**
	Non-technology-based tasks	36.4	40.4	0.844	0.628–1.135	0.262

* Odds ratio of poor vs. good weather conditions

** Significant result

In a scrutiny anchored in the VM complexity of tasks, the data in Table 8-8 suggest that the drivers were significantly less likely to engage in complex tasks when driving under adverse weather conditions (63.4% lower compared with driving in good weather, $p = 0.048$). The same trend typified the moderate tasks (33% lower) and simple tasks (17.8% lower), but the differences in occurrence under the two weather conditions were not statistically significant (p values > 0.05). These findings implied that the drivers were more reluctant to engage in more complex activities when driving in adverse weather conditions. Simply put, the more complex the task, the lower the chance that it will be carried out in unfavourable weather conditions. However, the drivers did not entirely refrain from engaging in complex tasks in these conditions.

Regarding the task classification grounded in technological aspects, the rate of participation in both the technology- and non-technology-based tasks was lower when driving under adverse weather conditions compared with driving in good weather. However, the drop was steeper and more obvious for the technology-based tasks, with a 54.2% lower likelihood of engagement in adverse weather conditions ($p = 0.007$) compared with a non-significant 15.6% drop with respect to the non-technology-based tasks (Table 8-8).

8.3.2.6 Passenger presence

Because passenger conversations can occur only when a driver travels in the presence of a passenger and because talking/singing in the absence of passengers is restricted to solo trips, both tasks were excluded from the analysis of passenger presence as a factor for secondary task engagement.

Table 8-9 indicates a significant relationship between passenger presence and many of the secondary task types ($p < 0.05$). An analysis based on the secondary task categories showed that the drivers were more predisposed to engage in all the task categories when travelling alone relative to travelling in the presence of a passenger. A notable result is that the drivers were 3.3 and 4.3 times more likely to occupy themselves with mobile phones and smoking-related activities, respectively, when they were travelling alone than when they were in the company of a passenger ($p < 0.001$).

Table 8-9. Engagement in each secondary task type by passenger presence

Classifications	Tasks	Proportions of segments with task (%)		OR*	95% CI (LCL–UCL)	Sig.
		No passenger	With passenger			
Secondary task categories	Mobile phone use	8.9	2.9	3.277	1.884–5.700	< 0.001**
	Adjusting in-vehicle controls	5.8	4.8	1.224	0.762–1.966	0.402
	Smoking	4.8	1.2	4.271	1.824–10.000	< 0.001**
	Personal grooming	4.3	3.7	1.185	0.689–2.037	0.540
	Eating and/or drinking	1.7	1.0	1.784	0.662–4.803	0.252
	Other (including reading/writing tasks)	2.8	0.8	3.685	1.294–10.494	0.015**
Mobile phone sub-tasks	Hands-free interaction	2.9	2.3	1.249	0.638–2.446	0.516
	Handheld interaction	2.7	0.2	14.335	1.949–105.40	0.009**
	Hands-free conversation	2.5	0.2	13.354	1.812–98.420	0.011**
	Handheld conversation	0.5	0.0	N/A		
	Holding	1.0	0.0	N/A		
	Related	0.6	0.4	1.634	0.338–7.895	0.541
VM complexity	Simple tasks	17.4	6.9	2.826	1.456–5.487	0.002*
	Moderate tasks	7.7	3.7	2.201	1.324–3.659	0.002**
	Complex tasks	5.8	1.5	3.958	1.885–8.311	< 0.001**
Technological classification	Technology-based tasks	14.4	7.5	2.064	1.430–2.979	< 0.001**
	Non-technology-based tasks	13.5	5.6	2.659	1.273–5.552	0.009*

* Odds ratio of no passenger absence vs. passenger presence

** Significant result

On the subject of the mobile phone sub-tasks, the drivers were less strongly inclined to perform all the mobile phone activities when passengers were present, as was the case with most of the secondary task categories. The mobile phone sub-tasks undertaken in the presence of passengers included only one handheld interaction, one hands-free conversation, no handheld conversation and no phone holding. Almost all (97.5%) these four phone interactions occurred when a driver was not carrying a passenger. The OR of occurrence during solo travel versus travel in the presence of a passenger was 14.3 with respect to handheld interaction (p = 0.009) and 13.4 with respect to hands-free conversation (p = 0.011).

The analysis anchored in the VM complexity of tasks implied that the drivers were significantly more likely to engage in simple (2.8 times higher, p = 0.002), moderate (2.2 times higher, p = 0.002) and complex tasks (4 times higher, $p < 0.001$) during solo travel relative to travelling in the presence of a passenger. Pertaining to the secondary task classification based on technology, the findings suggest that the drivers were significantly more likely to perform technology-based (2.1 times higher, $p < 0.001$) and non-technology-based tasks (2.7 times higher, p = 0.009) in the absence of a passenger than when a passenger is present (Table 8-9).

8.3.2.7 Seat belt usage

A series of comparisons were carried out to determine whether a significant difference existed between the drivers who wore a seat belt and those who did not in relation to the engagement in secondary task types. Overall, minor differences were found in the tendency of the drivers to occupy themselves with most of the secondary task types between cases wherein seat belts were worn versus cases wherein seat belts were not worn. Few such activities were significantly related to seat belt usage, and the pattern typifying all these task types was that the unseat-belted drivers engaged in activities to a greater extent. These task types are described below (Table 8-10):

- Personal grooming activities were 3.2 times more likely to occur in cases wherein seat belts were not worn versus cases where seat belts were worn (p = 0.032).
- Eating/drinking-related tasks registered 4.5 times more likelihood to be executed in cases wherein seat belts were not worn versus cases where seat belts were worn (p = 0.049).

- Mobile phone handheld interaction had 5.4 times more chance to be performed in situations where seat belts were not worn relative to cases wherein seat belts were worn (p = 0.008).
- Mobile phone handheld conversation was 9.6 times more likely to be performed in cases wherein seat belts were not worn than in situations where seat belts were worn (p =0.041).
- Complex tasks were 4.9 times more likely to be executed in circumstances of no seat belts usage relative to seat belt-wearing cases (p = 0.001).

Table 8-10. Engagement in each secondary task type by seat belt usage

Classifications	Tasks	Proportions of segments with task (%)		OR*	95% CI (LCL–UCL)	Sig.
		Seat belt not worn	Seat belt worn			
Secondary task categories	Passenger conversations	17.6	23.1	0.715	0.294–1.740	0.460
	Talking/singing in the absence of passengers	11.8	8.3	1.479	0.513–4.261	0.469
	Mobile phone use	11.8	6.9	1.801	0.623–5.205	0.277
	Adjusting in-vehicle controls	5.9	5.5	1.071	0.253–4.541	0.926
	Smoking	5.9	3.6	1.687	0.395–7.214	0.480
	Personal grooming	11.8	3.9	3.244	1.109–9.490	0.032**
	Eating and/or drinking	5.9	1.4	4.472	1.009–19.826	0.049**
	Other (including reading/writing tasks)	2.9	2.2	1.352	0.180–10.162	0.770
Mobile phone sub-tasks	Hands-free interaction	2.9	2.7	1.094	0.146–8.188	0.930
	Handheld interaction	8.8	1.8	5.419	1.564–18.776	0.008**
	Hands-free conversation	2.9	1.8	1.637	0.217–12.381	0.633
	Handheld conversation	2.9	0.3	9.642	1.096–84.834	0.041**
	Holding	0.0	0.7	N/A		
	Related	0.0	0.6	N/A		
VM complexity	Simple tasks	50.0	42.2	1.371	0.695–2.706	0.362
	Moderate tasks	6.5	2.9	2.299	0.312–16.949	0.414
	Complex tasks	17.6	4.2	4.890	1.959–12.210	0.001**
Technological classification	Technology-based tasks	17.6	12.1	1.558	0.637–3.810	0.331
	Non-technology-based tasks	47.1	39.7	1.349	0.683–2.665	0.389

* Odds ratio of seat belt usage vs. non-usage

** Significant result

8.4 Discussion

The aim of the work described in this chapter was to gain insight into who engaged in which secondary task types and what contextual situations involved specific secondary behaviours. The results uncovered a number of interesting findings, which can serve as a reference in guiding and targeting driver distraction countermeasures and policy development. These findings are discussed in the succeeding sections.

8.4.1 Driver-related factors

In general, the results revealed numerous differences amongst the driver groups regarding their levels of engagement in various secondary task types. Those with the greatest disparities were the age groups, followed by the country groups; the differences between the gender groups were limited.

Engagement in most of the secondary task types appeared to decrease with increasing age, suggesting that the younger drivers had a generally higher inclination to perform activities than the older drivers. Such a difference was especially pronounced in connection with technology-based activities (specifically, mobile phone use) and the most complex tasks (i.e. tasks assessed as high risk from a VM perspective, such as handheld mobile phone interaction). These outcomes confirmed the hypothesis presented in the current chapter.

The higher propensity of the younger drivers to participate in technology-based activities in general and mobile phone use in particular is consistent with the findings of previous studies (e.g. Pickrell, 2015; Young and Lenné, 2010; Stutts et al., 2005). It is also an expected outcome, given that younger generations are normally more aware of technology and more likely to use it than older generations(Olson et al., 2011). That the younger drivers were the group most frequently involved in the most complex tasks (including handheld phone interaction) is particularly concerning, as these individuals, unlike their older counterparts, are also more likely to commit speeding and other driving violations (Lucidi et al., 2019), espouse more negative attitudes towards road safety in general (Iversen and Rundmo, 2004) and appear to be the most vulnerable to distraction-related crashes (Buckley et al., 2014). Therefore, targeting educational and enforcement resources for the benefit of younger drivers is again highlighted in this chapter, but this time, resource targeting should be specific to technology-based and complex secondary behaviours.

The pattern of decrease in task engagement level with age was also evident in the analysis of smoking-related activities. The likelihood of engagement in these activities decreased by 60% for each single ordinal unit increase in age category (from younger to middle-aged to older). This pattern aligns with the results of several studies (e.g. Stutts et al., 2003a; Charlton et al., 2013). In contrast, conversation with passengers was the only task type that had an age-related counter-pattern from all the other task types, with task engagement increasing as the drivers became older. The probability of participation in this activity rose by nearly 20% for every single ordinal unit increase in age category. It should however be noted that the older drivers carried passengers more often than did the younger drivers in the sample; hence, differences in behaviour may not be attributable to age alone.

Although the age-related results in this chapter illustrated substantial dissimilarities between the age groups with respect to many secondary task types, there remains a need for additional research into this matter for improved understanding and reliable explanations of disparities. A possibly appropriate strategy is to conduct a long-term cohort study, with a view to investigating behavioural changes in drivers over time (preferably over many years, which should adequately reflect an increase in drivers' ages).

Considerable differences by country were evident amongst the drivers in relation to their participation in a number of secondary task types. The most notable of these cross-country differences occurred in the range of the technology-based activities (specifically, mobile phone use) and the most complex tasks (specifically, handheld mobile phone interaction). The trend emerging in respect of these activities was that the Polish sample exhibited the highest engagement level, whereas the German sample showed the lowest. The British, Dutch and French samples registered levels falling somewhere in between. These cross-country differences may be attributed to variations in traffic culture, as drivers in some countries are more sensitive to risk (Nordfjærn et al., 2011) and more law-abiding than others (seeing as handheld phone interaction is prohibited by law in all the countries in the sample). The latter is supported by the fact that the Polish sample accounted for the highest engagement in the most complex secondary tasks (specifically, handheld phone interaction). This behaviour is likely attributable to the generally lower compliance with traffic laws and rules in the country. Such a high engagement rate is also unsurprising when we consider that Poland had the worst road safety record (the highest rate of road traffic crash occurrence) amongst the five countries (WHO, 2018).

With reference to the German sample, future research is required to discover why these drivers registered the lowest engagement in secondary tasks in general and the lowest involvement in complex activities in particular. Extracting the best lessons from the German experience can be a gateway to refining distraction-related prevention strategies (e.g. enforcement and regulation) in other countries.

With regard to gender groups, the findings on secondary task types suggested a few gender differences in behaviour. The most prominent dissimilarity was related to personal grooming tasks, with the female drivers being 3.4 times more likely than the male drivers to perform such an activity—a result that coincides with the findings of earlier ND studies (e.g. Carsten et al. 2017; Stutts et al., 2005). This finding is expected, considering that females (in a general context) participate more frequently in tasks such as applying make-up and exhibit more interest in their appearance than do males (Cash et al., 2004; Brown et al., 1990). The difference between the gender groups in the matter of grooming-related tasks contributed to the higher engagement in complex tasks amongst the female drivers relative to their male counterparts (1.6 times higher). Nevertheless, this difference fell just short of significance.

8.4.2 Contextual factors

On the basis of the findings presented in Section 8.3.2, some of the contextual factors studied did not show significant associations with any of the secondary task types. These factors were intersection layout, turning direction, locality, road type and number of lanes. Other contextual factors showed some significant relationships. These factors were passenger presence, intersection control, intersection priority, weather conditions, lighting conditions and seat belt usage.

Returning to the matter of passenger presence, this factor was amongst the most influential on the nature of secondary task engagement, with the drivers being less predisposed towards most activity involvement when there were passengers aboard their vehicles. Under such a condition, engagement in smoking, mobile phone use (specifically, handheld phone interaction) and, in general, the most complex tasks considerably declined. The current work and previous studies (e.g. Kidd et al., 2016; Tivesten and Dozza, 2015; Bernstein; 2015) agree on the result related to mobile phone use. A possible explanation for why drivers refrain from performing specific secondary behaviours is that a certain social pressure to restrain engagement arises owing to the presence of passengers, or this may simply be a situation that allows for drivers to request passengers to handle some of these tasks for them. Such restraint can also be ascribed to the emergence of ‘replacement activities’ for the driver, such as conversations with passengers. These findings can pose implications for targeting policy aspects, such as media campaigns (refer to Section 10.3 for more details on the implications).

The analysis in this chapter likewise casts light on a number of other contextual variables, particularly those relating to the complex aspects of driving at intersections. The nature of secondary task engagement was substantially influenced by intersection control, intersection priority and weather conditions. The drivers tended to perform most of the secondary task types less frequently at intersections managed by traffic signs (which require more gap judgment) than those controlled by traffic lights (where potential conflicts between vehicles moving in different directions are separated in time), when they did not have priority compared with when they had priority and when they were travelling in adverse weather conditions compared to fine weather conditions. These findings indicated that involvement in most of the secondary activities was lower in situations that drivers most likely considered to be more demanding—a phenomenon that points to the positive self-regulatory behaviours exercised by the drivers. Note that these self-regulatory practices were exercised in a particularly prominent way when it came to the most complex secondary behaviours. To illustrate, the more complex a secondary task, the lower the chances that it will be carried out under highly challenging conditions, thus confirming the hypothesis presented in this chapter. Nevertheless, involvement in complex tasks did not disappear entirely under these circumstances.

The length of trips from which the intersection cases were selected was also amongst the factors that exerted some form of influence on the nature of secondary task engagement. The level of participation in most of the secondary activities increased (at least minimally) as the trips became longer. This upward pattern was steepest and most obvious with respect to technology-based activities and mobile phone use, specifically hands-free and handheld phone interactions. The result related to hands-free phone interaction (i.e. occurring mostly when drivers were receiving navigational guidance through a phone) was unsurprising, as in the long trips, the drivers were more likely to need navigational guidance. The finding on handheld phone interaction may be accounted for by the possibility that on short trips, the drivers exhibited a greater tendency to postpone the initiation of this task until the trips ended; long trips may have diminished their resistance against engagement. Therefore, keeping a mobile phone out of easy reach during long trips (e.g. in a glove compartment or a handbag) may reduce the temptation of drivers to use this device in this manner whilst driving.

Influence on engagement level originated as well from seat belt usage (albeit the results in Chapter 7 showed this factor to be irrelevant to the overall level of involvement in secondary activities). The drivers who did not wear seat belts exhibited a significantly greater tendency to engage in personal grooming tasks, eating/drinking activities, mobile phone use (specifically, handheld phone interaction and conversation) and, on the whole, the most complex tasks. With these findings as basis, drivers who do not adhere to traffic regulations, specifically wearing a seat belt, have a higher inclination to engage in both risky and prohibited (i.e. handheld phone use) secondary behaviours whilst driving. This can be attributed to some personality factors or a lack of awareness of the danger and consequences of these complex tasks. However, the association of personal characteristics with secondary task engagement is beyond the scope of this thesis. The current analysis highlighted the importance of these factors, which are thus recommended for further study. It should be noted that the seat belt non-usage was confined to few drivers (only 8 drivers out of the total 163 drivers were observed not wearing seat belts at least once in all of the intersection cases coded for them), therefore, these results should be viewed with caution and considered indicative results instead of conclusive findings.

8.5 Summary and conclusion

The aim of the work documented in this chapter was to determine whether driver-related and contextual variables were associated with certain types of secondary behaviours. The key findings are listed below:

- The younger drivers showed stronger inclination to perform most of the secondary activities than did the older drivers. This difference was largest with respect to complex tasks, technology-based activities, smoking and mobile phone use (specifically, handheld phone interaction).
- The Polish sample registered the highest engagement in complex tasks and mobile phone use (specifically, handheld phone interaction), in contrast to the German sample, who minimally engaged in such activities.
- The drivers showed a lower inclination to carry out most of the secondary task types when they were travelling in the presence of a passenger relative to when they were on solo trips. This reduction was steepest in regard to complex tasks, smoking and mobile phone use (specifically, handheld phone interaction).
- The drivers were more reluctant to engage in most of the secondary activities in highly demanding situations than under less challenging circumstances. This reluctance was more evident with respect to complex secondary behaviours.
- Non-seat belt users showed a considerably greater inclination to engage in personal grooming, eating/drinking, mobile phone use (specifically, handheld phone interaction and conversation) and, in general, the most complex tasks.

The results discussed in this chapter provide some preliminary information that can be useful in refining and targeting driver distraction countermeasures and policies (e.g. driver education/training, awareness programmes and media campaigns) as well as in determining the effectiveness of these countermeasures and policies in managing distractions. Some of the implications stemming from the findings in this chapter are presented in Chapter 10.

Chapter Nine

The Influence of Secondary Task Engagement on Turn Signal Usage at Intersections

This chapter represents the last of four chapters that discuss the results derived in this thesis. The previous chapters focus on the investigation of how different driver-related and contextual variables influence secondary task engagement. In the current chapter, concentration falls on illuminating how this engagement affects certain non-critical driving tasks, namely, the use of the turn signal. The aim of the analysis presented here was to examine turn signal use (for both left and right turns) at intersections and its association with driver involvement in secondary tasks on the approach to intersections.

9.1 Introduction

Dewar and Olson (2007) stated that 'driving a vehicle' is 'by its very nature . . . a cooperative venture' (p.260). This view was based on the fact that every driver shares the same physical space with other road users (e.g. other drivers, pedestrians and cyclists), thereby requiring mutual cooperation in road use. One of the most prominent aspects of such cooperation is productive communication between road users, and an effective, ongoing means of communication between a driver and other road users is the use of turn signals (Faw, 2013). Signalling alerts other road users to a driver's intention to turn or change lanes, providing them sufficient time to perform essential adjustments. The consistent and appropriate use of turn signals can be a potential contributor to enhanced traffic flow as well as the collective safety of all road users (Ponziani, 2012).

Despite the importance of turn signalling and its availability as a standard feature in all vehicles, however, a number of studies have found a general weakness in drivers' commitment to use the turn signal, at least in some situations. For example, Ponziani's (2012) on-road investigation uncovered that 48% of drivers neglect turn signal usage when changing lanes. A survey conducted by Response Insurance (2006) revealed that 57% of drivers admit to disregarding turn signalling when executing a lane change manoeuvre. Justifications by the participants ranged from consideration of turn signals as unimportant and laziness to a similar lack of adherence by other drivers, but they did not cite excuses related to involvement in any kind of secondary behaviour. The survey also showed that male and younger drivers have lower turn signal usage rates than those exhibited by female and older drivers, respectively (Response Insurance, 2006).

Other observational studies have been carried out to model drivers' use of the turn signal when executing a turning manoeuvre at intersections. Examples are those undertaken by Faw (2013) in Canada and Sullivan et al. (2015) in the US. The overall findings of both studies showed that nearly 25% of turns at intersections are made without signalling. The authors also reported that drivers perform signalling more often when turning left than when turning right (opposite directions in the UK), when a forward vehicle is present than in situations wherein no vehicle is ahead of drivers and when the approach to an intersection is a major road as opposed to a local or minor road. Driver-related factors, including age and gender, have no significant influence on the use of the turn signal (Sullivan et al., 2015), but the presence of a dedicated turning lane reduces the propensity of drivers to use such a signal (Faw, 2013).

Notwithstanding these valuable findings, a deficiency in this area of knowledge is the lack of inquiries into the relationship between turn signal use and secondary task engagement by drivers. The model formulation in the above-mentioned studies paid no heed to the potential impact of driver involvement in secondary tasks—an issue that warrants more comprehensive exploration. This matter was addressed in the current work, with the aim of providing solid evidence on whether turn signal use (for both left and right turns) at intersections varies with engagement in secondary tasks.

9.2 Aims and hypotheses

The aims of the investigation discussed in this chapter were as follows:

- To determine the rates of turn signal use intended to indicate the intention to turn left or right at intersections.
- To examine whether engagement in secondary tasks during the approach to intersections influences rates of turn signal use.
- To explore how changes in the complexity-based classification of secondary tasks performed (simple, moderate and complex) influence rates of turn signal use.

The primary hypothesis advanced in this chapter is that the rate of turn signal usage decreases when drivers engage in secondary behaviours compared with levels of usage when they are not engaging in such behaviours. Such a reduction is expected to take place at a higher degree when drivers are occupied themselves with complex secondary activities (i.e. tasks that require multiple steps, such as multiple button presses or multiple hand movements) than when they are executing simple tasks (i.e. tasks that require a single or no button press or hand movement). This expectation was based on the fact that the use of turn signals is essentially a manual task and that usage rates are thus likely to be increasingly affected as drivers engage in more manually complex secondary activities.

9.3 Methods

The dataset used in the analysis is the same as that used in the investigations discussed in the previous chapters, except that the intersection cases wherein no turns were performed (i.e. cases of drivers going straight) were excluded. This yielded a sample of 978 intersection cases that involved either right or left turns executed by 163 drivers. The demographic characteristics of the drivers are described in detail in the general methodology chapter (Section 5.7). Note that the UK is the only left-side driving country amongst the sampled countries; hence, left and right turn categorisation was reversed to match the type of manoeuvres made in the other countries (France, Poland, Germany and the Netherlands).

As a starting point in identifying the use of turn signals in the selected intersection cases, a time-series CAN signal called 'turn indicator signal' was used through SALSA to identify whether or not a driver used the turn signal at some point before or within turn execution. For most of the turns, signals were activated before turn initiation, although the drivers sometimes began signalling after a turn has commenced. For the analysis in this chapter, both kinds of signal actuation were regarded as signalling. Next, the video recording of each turn was manually checked to ensure the accuracy of the data on determining automated signalling as well as to confirm that signalling was executed specifically for the turning manoeuvre that needed to be coded. The over-the-shoulder camera view (Figure 9-1) was ascertained as the best perspective for monitoring the hand-based activities performed by the drivers, including their use of the turn signal.

Figure 9-1. UDRIVE over-the-shoulder camera view (Utesch et al., 2014)

The selected intersection cases were also coded in terms of involvement in secondary tasks before and within turn execution. If a secondary task was carried out, the segment was viewed one more time to break down the task instance in relation to the complexity-based classification of tasks into simple, moderate and complex activities. This secondary task classification, alongside its respective coding procedures, is described in detail in the general methodology chapter (Section 5.8).

To determine whether the dependent variable, that is, turn signal use (signalled/unsignalled), was significantly associated with either turning direction (left/right) or secondary task engagement (no task/with task) and understand the nature of the associations, stacked bar charts were plotted and OR comparisons were performed. These OR comparisons were carried out given that the variables were of the categorical dichotomous variety. If the 95% CIs of the OR did not include 1.0, then the OR was evaluated as significantly different from 1.0 at $p < 0.05$. If the 95% CIs included 1.0, then the OR was interpreted as not significantly different from 1.0 at $p > 0.05$.

The Cochran–Armitage test of trend was also performed to delve into and assess the linear trend between the ordinal independent variable, namely, secondary task complexity, and the dichotomous dependent variable, turn signal use. This test determines whether the binomial proportions for each category of the ordinal variable are the same or increase/decrease with increasing category of the ordinal variable. An alpha of 0.05 was adopted as a measure of significance, wherein a *p* less than 0.05 was regarded as indicative of a statistically significant relationship.

9.4 Results

The results are presented in order of the aims listed above.

9.4.1 What are the typical rates of turn signal use that indicate drivers' intention to turn at intersections, and does signalling rate for left and right turns differ?

Overall, the descriptive analysis revealed that 80.2% of the turning manoeuvres executed at intersections were preceded by a signal (784 turning manoeuvres of the 978 that were coded). In other words, the drivers neglected the use of the turn signal in about 20% of the turns. The breakdown of turn signal use by turning direction is shown in Figure 9-2. Signalling occurred in around 82% of the left turns and 78% of the right turns. The OR of turn signal implementation for left versus right turns was 1.328 (95% CI = 0.968–1.822), which approaches the borderline of significance ($p = 0.078$).

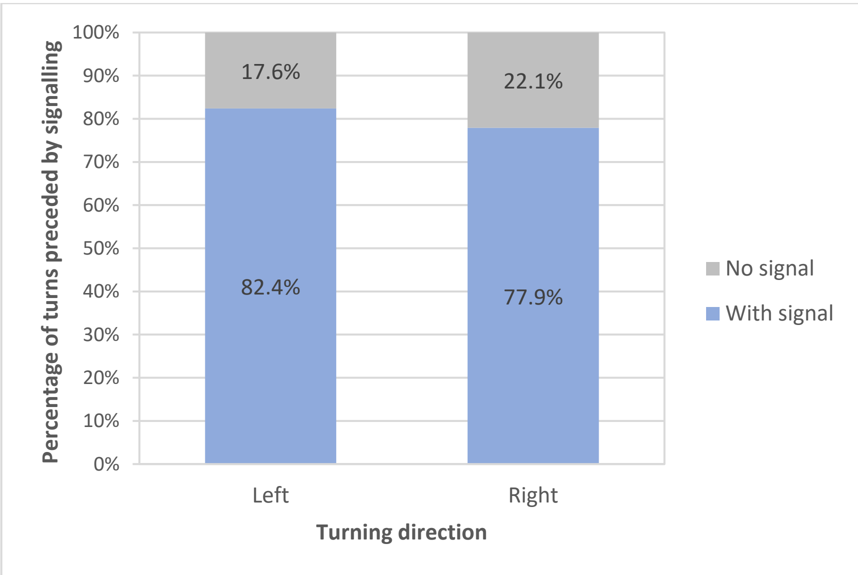

Figure 9-2. Turn signal use by turning direction

9.4.2 Does engagement in secondary tasks whilst approaching intersections influence rates of turn signal use?

The findings indicated that signalled turns occurred in about 88% of cases that did not involve any kind of secondary task engagement but that such a signal occurred in about 73% of cases that involved engagement (Figure 9-3). This can be expressed as an OR, whereby the drivers were around 2.5 times more likely to execute turn signal when they were not occupied with a secondary activity than when they were occupied with such activity (95% CI for OR = 1.824–3.557, $p < 0.001$). Put differently, the drivers were significantly more predisposed to neglect turn signal use when they are engaged in secondary behaviours compared with situations when they are not engaged in any secondary behaviour.

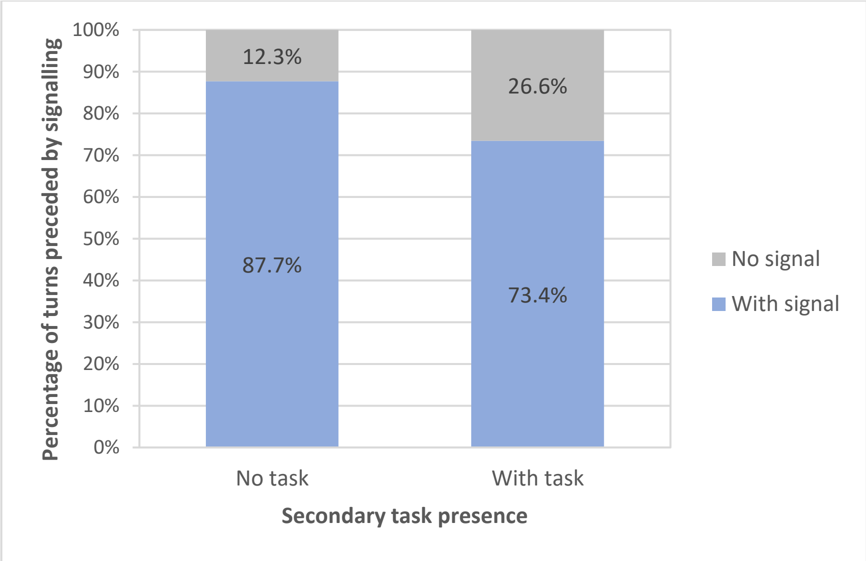

Figure 9-3. Turn signal use by secondary task engagement

9.4.3 How do changes in the complexity of secondary tasks influence rates of turn signal use?

The Cochran–Armitage test of trend was conducted to determine whether a linear trend existed between the complexity of secondary tasks performed and the percentage of intersection turns accompanied by signalling. Complexity was categorised into three ordinal groups: simple task (n = 302), moderate task (n = 48) and complex task (n = 34), to which the corresponding percentages of turns made with signalling were 78.5%, 62.5% and 47.1%, respectively. The test showed a statistically significant linear relationship, ($p < 0.001$), with higher task complexity associated with a lower percentage of turns accompanied by signalling. That is, the more complex the task performed, the greater the chances that turn signalling is abandoned (Figure 9-4).

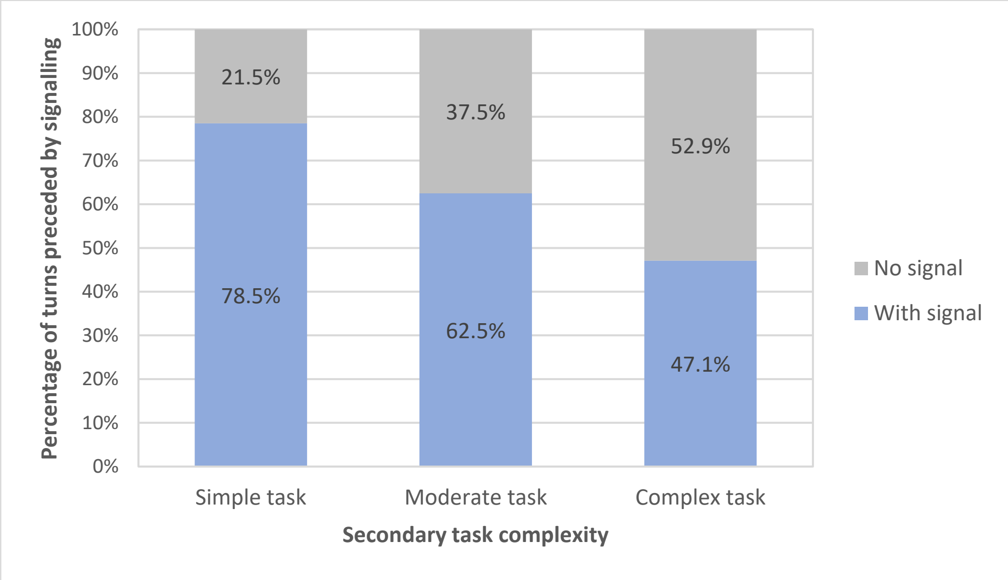

Figure 9-4. Turn signal use by secondary task complexity

The OR of turn signal implementation for every single ordinal unit increase in secondary task complexity was 0.496 (95% CI = 0.408–0.604, $p < 0.001$), thus generating a fractional odds [(OR – 1) × 100] of –50.4%. These results mean that the likelihood of signalling a turn decreased by 50.4% for every single ordinal unit increase in task complexity.

9.5 Discussion

On the basis of ND data, this chapter looked into the rates of turn signal use (for both left and right turns) at intersections and examined whether driver engagement in secondary tasks had an influence on these rates. On the whole, the analysis showed that nearly 80% of the turns were preceded by a signal. This outcome is generally compatible with the findings derived by Sullivan et al. (2015) and Faw (2013), who discovered approximately 75% and 77% levels of turn signal usage at intersections, respectively. The rates of signalling upon turns at intersections (75%–80%) were considerably higher than those found by Ponziani (2012) and Response Insurance (2006) amongst drivers changing lanes (43%–52%). This prominent difference gives the impression that drivers are more inclined to use turn signals when turning than when changing lanes—a tendency that is perhaps due to the higher risk associated with executing a turning manoeuvre.

With regard to the influence of turning direction on turn signal usage, the findings revealed that more signalling occurred in left-turn manoeuvres than in right-turn manoeuvres. The drivers were 1.3 times more likely to signal a left turn than a right turn. This result is largely consistent with the studies of Sullivan et al. (2015) and Faw (2013), who both found that left-turn signalling was approximately 1.4 times as likely to occur as right-turn signalling. This outcome may reflect different perceptions amongst drivers regarding the importance of signalling in each turning direction. When turning left at an intersection, more potential conflicts arise amid traffic approaching from different directions (right, left and opposite directions) than during right turns wherein conflicting traffic approaches from the left. A plausible explanation here is that the drivers perceived the higher complexity and greater risk associated with left turns and were therefore more willing to implement signalling in these turns.

In terms of the general effect of secondary task engagement on turn signal usage, the drivers were 2.5 times more likely to use turn signals when they were not occupied with a secondary activity than when they were engaged in such a task. This result demonstrates how involvement in secondary tasks negatively affects the rates of turn signal use; thus, the proposed hypothesis in the current chapter was confirmed. This outcome supports the general notion gained from a large body of previous research that secondary task engagement adversely affects many aspects of driving task performance, including the execution of some non-critical driving tasks (e.g. turn signal use).

The complexity of the secondary tasks performed also appeared to be a powerful predictor of turn signal usage. As was hypothesised in the present chapter, the more complex the secondary task performed, the greater the decline in turn signal usage rates. This relationship can be explained by the fact that the use of turn signals is essentially a manual task and that usage rates are thus likely to be increasingly affected as drivers engage in more complex secondary activities (from a manual perspective). This phenomenon can be linked to the multiple resource theory developed by Wickens (2008) (described in Chapter 2), which elucidates that dual-task interference tends to transpire when simultaneous tasks are characterised by similar modalities. The relationship can also be explained on the basis of the fact that the more complex the secondary tasks performed whilst driving, the greater the degree of possible inattention and, thus, the more likely that drivers will experience performance degradation in turn signal usage.

9.6 Summary and conclusion

The findings in the present chapter extend the current state of knowledge about rates of turn signal use at intersections by illuminating the influencing role of secondary tasks in these rates. The drivers showed less inclination to use turn signals when they were engaged in secondary tasks compared with normal baseline situations. This decline in usage occurred to a higher extent when the drivers occupied themselves with complex secondary behaviours than when they were performing simpler tasks.

Although the results discussed in this chapter were useful in the understanding of the nature of association between secondary task engagement and turn signal use, there remains a need for additional research aimed at formulating a comprehensive model of turn signal use that should involve, alongside secondary task engagement, a wide array of driver-related and driving context variables (e.g. other traffic). This model can improve the understanding of turn signal usage behaviour and can be used to determine whether the use of such signals (as an indicator of drivers' intention to turn) is sufficient to reliably forecast a driver's trajectory at an intersection. Future research should also broaden the scope of investigations to encompass the influence of secondary task engagement on different kinds of intersection-related errors and behaviours, including braking and gap acceptance.

Chapter Ten

Conclusions and Recommendations

10.1 Overview

In contrast to previous ND studies that delved into the sources of driver distraction and the associated increase in crash risk (e.g. Dingus et al., 2016; Young, 2015; Hickman et al., 2010; Olson et al., 2009; Klauer et al., 2006a), the present thesis investigated the prevalence of secondary task engagement at intersections and the attempts of drivers to self-regulate this behaviour. Particular attention was given to when drivers choose to perform secondary tasks, what types of tasks they carry out, which drivers engage in such activities and whether they adjust their engagement in response to variations in the demands imposed by roadway and environmental situations. The possible association between the use of turn signals (as a non-critical driving task) and secondary task engagement on approach to intersections was also examined.

The analysis was based on ND data from the large-scale European Commission-funded UDRIVE project, which offered a unique opportunity to gain insights into the prevalence and self-regulation of a wide range of secondary behaviours across a diverse sample of drivers from several countries. In exploring the self-regulatory patterns that underlie engagement in secondary tasks, this thesis focused on intersections, but these aspects were also examined in the context of non-intersection segments to generate a comparison benchmark for driver conduct at intersections. The following key questions were answered:

- **How prevalent is secondary task engagement at intersections?**

The findings on overall prevalence (Chapter 6) showed that secondary task engagement was common and frequent amongst the drivers as they travelled through intersections, with around half of the observed intersection cases and one-quarter of the total driving time involving participation in a secondary task. These prominent figures are of concern and should be taken seriously, regardless of whether secondary task engagement outside intersections is higher or lower than that within intersections. The problem is that drivers may underestimate the danger and demand imposed by secondary tasks, specifically when driving at highly challenging and risky locations such as intersections. Under potentially distracting conditions at these roadways, drivers are compelled to use additional cognitive resources to process different sources of information, which in turn, may slow down driver decision making or reduce situation awareness to risky levels and eventually cause safety errors and increase crash risk. These findings highlight the work that still needs to be done to minimise the secondary task engagement rates of drivers at intersections. Any future attempts to improve intersection safety in general should take into consideration the prevalence of involvement in secondary behaviours during everyday driving conditions at these locations.

- **Which driver populations are most willing to perform secondary tasks?**

The results reported in Chapters 7 and 8 indicated substantial differences in the level of secondary task engagement amongst various driver groups. As for age groups, the younger drivers showed a higher overall inclination to perform secondary tasks than did the older drivers. This outcome characterised most of the secondary task types, but the difference between the younger and older drivers was largest with respect to complex tasks, technology-based activities, smoking and mobile phone use (specifically handheld phone interaction).

There were also considerable differences by country amongst the drivers, with the Polish sample being the most frequently involved overall in task engagement. The German sample exhibited the lowest engagement level, and the British, Dutch and French samples registered levels falling somewhere in between. What attracted attention in the cross-country comparison was that the Polish sample registered a much higher participation level than did the four other samples with respect to complex tasks and handheld phone interaction. With regard to gender groups, no clear difference in the overall level of secondary task engagement was observed between the male and female drivers. The findings on secondary task types, however, somewhat suggested gender differences in behaviour. The most prominent dissimilarity was related to personal grooming tasks, with the female drivers being 3.4 times more likely than their male counterparts to perform such an activity.

The above-mentioned findings revealed the crucial role played by driver-related factors in influencing the propensity to engage in secondary tasks. These results clarified who engaged most frequently in secondary tasks (in general) and who carried out which task types—a comprehension that is essential to targeting distraction countermeasures and policy aspects.

- **Do drivers self-regulate their engagement in secondary tasks?**

On the basis of the findings discussed in Chapters 6 and 7, secondary task engagement was non-random, at least to a certain extent. The drivers appeared to self-regulate their involvement in secondary tasks according to driving situation and driving task demand. Specifically, they self-regulated themselves by limiting engagement during certain roadway and environmental situations that are considered to be more challenging.

On the whole, this self-regulatory behaviour was represented by the reduced willingness of the drivers to engage in secondary tasks when travelling through intersections relative to travel over non-intersection segments. When focusing on intersection driving, self-regulatory discipline was manifested by the V-shaped relationship between the percentage of time dedicated to secondary tasks across the three intersection phases (upstream, within-intersection and downstream) and the diminished willingness of the drivers to perform these activities when their vehicles were moving than when these were stationary. Self-regulatory behaviour was also reflected by the drivers' reduced inclination to execute secondary tasks when driving at high speeds (compared with driving at low speeds), when driving in adverse weather conditions (compared with driving under fine weather) and when they did not have priority in passing through an intersection (compared with when they had priority). All these self-regulatory manifestations support the notion that drivers, in general, carry out a number of strategic decisions on when and where to engage in secondary tasks. They are regarded as active receivers and processors of distraction-related information and seen as capable of effectively adjusting their behaviours in response to changes in demand situations, thereby mitigating the impact of distraction on safety and driving performance.

Although the findings discussed above demonstrated an overall positive self-regulatory tendency by the drivers, it should be borne in mind that they still spent time (albeit a little) on secondary task engagement in high-demand driving situations. In other words, the drivers did not entirely refrain from involvement in these activities under the aforementioned situations. An essential issue to also consider is that as the drivers exercised self-regulation, they appeared to disregard some driving context variables that may have affected risk (e.g. intersection layout, turning direction and lighting conditions). The findings on these contextual variables were inconclusive with respect to their association with self-regulation. These two issues underscore that further efforts are necessary to support and possibly enhance drivers' self-regulation behaviour at both strategic and tactical levels.

- **Are there certain groups of drivers who do not self-regulate?**

The results discussed in Chapters 6 and 7 suggested that all the driver groups (with respect to age, gender and country of recruitment) have exercised some sort of self-regulation by reducing engagement in secondary tasks during challenging driving situations. For example, they appeared to perform secondary tasks at lower rates during the within-intersection phase than at the upstream and downstream phases. All the groups were also less likely to occupy themselves with secondary activities when their vehicles were moving compared with when they were stationary. These positive self-regulatory actions reinforce the widespread notion that self-regulation is a natural tendency for drivers.

- **Is there a disparity in self-regulation across secondary tasks types?**

The findings on secondary task types (Chapters 6 and 8) indicated that the majority of the self-regulatory practices were exercised in a particularly prominent way when it came to the most complex secondary behaviours (i.e. high-risk tasks). To illustrate, the drivers were more reluctant to engage in complex secondary tasks when driving under highly challenging situations (e.g. driving under adverse weather conditions). Put differently, the more complex the secondary task, the lower the chances that it will be carried out under highly demanding conditions. Nevertheless, the drivers did not entirely refrain from engaging in complex tasks in these circumstances.

- **What other factors greatly influence the nature of secondary task engagement?**

On the basis of the results discussed in Chapters 7 and 8, passenger presence and trip length were amongst the factors that considerably influenced the level and nature of secondary task engagement. The drivers were less inclined to carry out most of the task types when travelling in the presence of a passenger relative to travelling alone. The tasks that were most substantially reduced under such a condition were smoking, mobile phone use and, in general, complex tasks. A possible explanation is that when passengers are in a vehicle, drivers feel some social pressure not to engage in certain secondary behaviours, or they may simply ask passengers to handle some of these tasks for them. As for trip length, the overall level of secondary task engagement increased as the trips became longer. This trend was sustained over most of the secondary task types, but the upward trend was steepest with respect to technology-based activities and mobile phone use (specifically hands-free and handheld phone interactions).

The above-mentioned findings highlight that work remains to be done to minimise the secondary task involvement of drivers when travelling alone as well as when travelling on long trips. The results present vital implications for targeting policy aspects (e.g. media campaigns).

- **Does engagement in secondary tasks influence rates of turn signal use?**

The results on turn signal use (Chapter 9) showed that the drivers were less predisposed to use turn signals when they were engaged in secondary tasks compared with situations when they were not performing these tasks. This reduction in usage took place to a higher degree when the drivers occupied themselves with complex secondary activities (from a manual perspective) than when they were executing simple tasks. This outcome revealed how performing concurrent tasks of a similar modality negatively affects the performance of one or both tasks.

10.2 Methodological reflections

On the basis of the work carried out in this thesis and the experience gained in observing, coding and analysing ND data, it can be argued that the ND method is one the most (if not the most) suitable methods for expanding the understanding as regards the prevalence and self-regulation of secondary task engagement during everyday trips. What accords advantage to the ND method is its high external validity and the possibility of studying different types of behaviour over an extended period. By contrast, other research methods typically suffer from drawbacks that diminish their utility and appropriateness for research that focuses on the prevalence and patterns of task involvement. For example, self-reports tend to be disadvantaged by personal bias, and experimental research conducted with driving simulators and even on test tracks is negatively affected by the instruction effect, in that participants are typically instructed to perform an activity at a given moment. Thus, such experimental research can provide insight into how driver attention, driver information processing and driving performance are influenced by secondary tasks, but are less useful when research is focused on driver management of task activity. These weaknesses raise doubt as to the extent to which behaviours in self-report and experimental studies correspond to actual conduct.

Although the ND method was particularly effective in facilitating the kind of investigations undertaken in this thesis, the major criticism regarding the use of this method in the literature is the possibility that behaviour can be somewhat influenced by the fact that drivers are under observation. In this thesis, however, the drivers were generally unconcerned about being constantly observed as they participated in various activities whilst driving; these activities included many instances of illegal tasks (e.g. mobile phone texting). There was no indication that they evaded notice whilst they were performing specific activities, except in rare cases when, for instance, a driver turned off the cameras to smoke in the presence of a child on board. These results give the impression that the ND method near-accurately reflects real driver behaviours, with the possibility of a slight underestimation owing to some secondary actions that are difficult to observe (e.g. looking at external billboards).

Another criticism of ND studies is that they are extremely expensive and require considerable logistical efforts to conduct. To ensure cost-effectiveness, researchers should address as many research questions as possible in a single investigation. Data should also be accessible for additional analysis once studies are completed. The present thesis is an example of that in which the raw data collected from the UDRIVE project was used to illuminate the questions that guided the current work, thereby eliminating the need for a data collection stage and, thus, the high costs associated with the implementation of ND studies. Additional criticism of using the ND approach lies in the difficulty of establishing causal relationships or causal conclusions because no experimental control is exercised over the various variables that influence road user behaviour.

Given the above-mentioned strengths and limitations of the ND approach and the other research methods (i.e. experimental and self-report studies), it would seem reasonable to suggest that a combination these methods should be used to provide a better and more comprehensive picture on how drivers self-regulate and manage their secondary task engagement.

10.3 Implications of the research findings

The thesis findings provide some preliminary evidence that can be useful in refining driver training, education and awareness programmes on safe intersection driving strategies and distraction management. This utility can be reflected, for instance, in the direction of media campaigns towards driver groups who are most habitually engaged in potentially distracting activities in general and the most complex tasks (i.e. riskier tasks) in particular (e.g. younger drivers and the Polish sample). The result that engagement in riskier tasks (e.g. handheld phone interaction) is less frequent in the presence of a passenger can also be a potential target theme in a media campaign, encouraging drivers to deliberate on activity engagement by, say, communicating that the danger of handheld phone interaction persists even in solo travel. Keeping a mobile phone out of easy reach during long trips (e.g. in a glove compartment or a handbag) is also a favourable matter of focus in media campaigns, which may contribute to a reduction in the temptation to use such devices whilst driving.

The results likewise offer preliminary information for targeting enforcement. For example, intersections and areas near intersections can be assigned as priority locations for the installation and enforcement of the distracted driving enforcement system—a new technology developed by Acusensus (Australia) that enables the automated recognition/detection of illegal mobile phone actions. Another option is to produce and use in-vehicle technology to detect the most complex secondary tasks performed (those that require multiple button presses or multiple glances off a forward roadway) and then warn drivers to cease engagement in these activities, particularly pre-approach to intersections.

The findings should be equally helpful in the creation of guiding principles for categorising intersections in relation to the prevalence of secondary task engagement. Such principles can be determined on the basis of the insight gained into when/where secondary activities are carried out and what types of activities drivers undertake.

Given that most of the driver groups in this thesis appeared to self-regulate secondary task engagement (at least to a certain extent), road safety stakeholders can put this information to advantage by identifying the self-regulatory practices that most effectively mitigate the negative effects of distraction on driving performance. Such information can also be leveraged in awareness campaigns and training designed to motivate drivers (particularly those driver groups who showed a relatively lower inclination towards self-regulation) to implement these practices when engaging in secondary behaviours.

Although this thesis has provided insights into the drivers' self-regulation behaviour (specifically, at both strategic and tactical levels), it has raised several areas that deserve further research to reinforce our understanding of the complexities of this behaviour (refer to Section 10.3). Gaining a further comprehension of how and why drivers engage in secondary tasks and what factors motivate or moderate this behaviour is vital to guide the development of effective countermeasures. Such knowledge can, for instance, help target awareness programmes for driver groups who are less aware of the negative effects of distraction on driving safety and provide them with information on how they can regulate their behaviour to reduce risk. It can also help guide the design of in-vehicle driver assistance and distraction mitigation technologies so that they support drivers in a way that lowers the level of demand encountered, but not to the degree that drivers become bored and look out for other activities. With the development of more effective distraction countermeasures, particularly those that facilitate positive self-regulation in response to distraction, the potential negative outcomes from this form of regulation can be minimised.

10.4 Limitations

The following limitations should be taken into account when interpreting the findings of the thesis:

- The participant drivers in each of the countries did not constitute a representative sample of the driving population. For this reason, the results of the cross-country comparisons should be viewed with caution and considered indicative results instead of conclusive findings.
- Given time and resource constraints, the analyses were based on a small subset of the data available from UDRIVE. A sample of 10 intersection cases and 10 matched non-intersection segments was used for each driver. Further work is needed to demonstrate whether the findings are robust with respect to a larger and more representative sample of cases.
- The results on mobile phone sub-tasks showed that some of these activities rarely occurred amongst the drivers (e.g. handheld phone conversation). In some of the analyses, such scarcity presented difficulties in the detection of statistical differences across driver groups. A larger dataset on mobile phone use is needed to augment analytical power.
- Certain ethical considerations in UDRIVE prevented the recording of continuous audio for the video streams used in the coding. Accordingly, the secondary task types in which sound was involved (e.g. passenger conversation and hands-free phone conversation)

were coded on the basis of the drivers' lip movements. Nevertheless, the successful use of this coding technique and the improved comprehension stemming from it did not completely resolve the diminished accuracy owing to the absence of audio; this situation still slightly hindered the accurate determination of the start and end points of the secondary audio-based activities. Any future ND study aimed at collecting audio data should consider the ethical issues associated with this decision; at the very least, any such data would need to be anonymised or scrambled.

- The UDRIVE dataset, and possibly other ND datasets, does not provide a good basis for reliably and validly recording certain variables and secondary tasks that are difficult to observe, such as looking at external billboards and daydreaming. For this reason, the coding scheme in the current thesis did not cover these secondary behaviours and they were regarded as falling beyond the scope of the research.

10.5 Future work

This thesis has offered insights into the prevalence and self-regulation of drivers' secondary task engagement. However, it has raised several areas that deserve further research; some of which are identified below:

- Future work with the UDRIVE and other ND datasets should look into computer vision techniques for automating the coding of secondary task events. This can improve the efficiency of the coding process as well as produce larger secondary task datasets that can be studied without the expense and burden associated with manual coding. Computer vision can also be used to process data from face-oriented cameras to automatically capture drivers' gaze directions, head movements and facial expressions—variables that are expected to enhance the understanding of distraction management.

- An additional research direction was suggested by the outcome that the increased demand imposed by manoeuvring at intersections reduced the drivers' inclination to engage in secondary tasks. Perhaps this situation emerged because the drivers, when travelling through intersections, had greater need to use their hands for steering and gear shifting. It is worth noting, however, that all the drivers in the UDRIVE project were driving manual transmission cars. Do drivers of automatic transmission cars have a higher inclination to engage in secondary tasks? This question cannot be answered on the grounds of the UDRIVE data. Nonetheless, the proliferation of automatic transmission cars in the US may facilitate engagement in secondary tasks and could thus partly clarify the greater secondary task engagement rates reported in this country.
- Another important direction for research is the issue of self-driving cars or fully autonomous vehicles. How would self-driving cars influence drivers' secondary task engagement behaviours? Will drivers be permitted by law to engage in what are currently classified as illegal secondary activities (e.g. mobile phone texting) when driving these cars? Will drivers sustain self-regulation when driving these cars? These questions present important opportunities for discussion.
- Future work should also inquire into the links between drivers' secondary task engagement and some driving context variables that were not included in the current thesis, either because they were outside the scope of the work or because the UDRIVE dataset was inappropriate for the precise coding of these variables. These variables involve the presence of pedestrians, cyclists and other traffic in the area surrounding a vehicle as well as relevant to details about the age and seating of passengers on-board.
- The present thesis found increased mobile phone use whilst driving (with 7% of the drivers' driving time spent on mobile phone usage in some form)—a topic that deserves further exploration to reinforce our comprehension of the complexities of this behaviour.

The ND data can be put to advantage in answering the following and other related questions: Where do drivers keep their phones in their vehicles, and how do these locations influence their usage? Is there a blurred line between illegal and legal mobile phone use? Is phone use a planned or habitual behaviour? What makes the German sample significantly less likely to use their phones whilst driving, and what lessons can be learned from that?

- The current thesis illuminated the patterns and prevalence of secondary task engagement amongst car drivers. An extension of the dataset to include truck drivers (who often have to use devices for their work) or even other vehicle types would enable the examination of secondary tasks across a more representative sample of the driving population. This extension will also enable an investigation of behavioural differences amongst drivers of various vehicle types. This would then clear the way for policy measures to be more efficiently targeted towards certain driver groups.

10.6 Thesis summary

This thesis illustrated a novel application of the ND method in the investigation of driver engagement in secondary tasks at intersections. It is also one of only a handful of research that has focused on the prevalence and self-regulation of secondary tasks beyond mobile phone use. The results showed that secondary task engagement was common amongst the studied drivers, with these individuals spending nearly one-quarter of their driving time at intersections engaging in potentially distracting activities. The drivers likewise made a number of strategic decisions on when to engage or disengage in secondary tasks. They exercised self-regulation by reducing their engagement under certain roadway and environmental conditions that are assumed/considered to be more demanding. These findings provide preliminary evidence for the targeting of policies and interventions related to safe driving strategies and distraction management.

Overall, it is hoped that this thesis offered insight into why, how, when and where individuals perform secondary tasks whilst driving. This work was also carried out with a view to providing potential solutions to high secondary task engagement at intersections as well as supporting and possibly enhancing drivers' adaptation of secondary behaviours. Finally, it is anticipated that the proposed ideas for future work will encourage further investigation and perhaps the refinement of the current findings.

References

AAA. 2012. Cell phones and driving: Research update. Washington, USA: American Automobile Association.

AASHTO. 2011. A policy on geometric design of highways and streets, 6th ed. Washington, DC: American Association of State Highway and Transportation Officials.

Agresti, A. 2018. An introduction to categorical data analysis. 3rd ed. NewYork: Wiley & Sons.

Aksan, N., Dawson, J.D., Emerson, J.L., Yu, L., Uc, E.Y., Anderson, S.W. and Rizzo, M. 2013. Naturalistic distraction and driving safety in older drivers. Human Factors: The Journal of Human Factors and Ergonomics Society. 55(4), pp.841-853.

Al-Ghamdi, A.S. 2003. Analysis of traffic accidents at urban intersections in Riyadh. Accident Analysis & Prevention. 35(5), pp.717-724.

Alm, H. and Nilsson, L. 1995. The effects of a mobile telephone task on driver behaviour in a car following situation. Accident Analysis & Prevention. 27(5), pp.707-715.

Anowar, S., Alam, M.D. and Raihan, M.A. 2008. Analysis of accident patterns at selected intersections of an urban arterial. In: Proceedings of the VI ICTCT Extra (International Cooperation on Theories and Concepts in Traffic Safety) Workshop. 14–15 April 2008. Melbourne, Australia.

Aoude, G.S., Desaraju, V.R., Stephens, L.H. and How, J.P. 2012. Driver behavior classification at intersections and validation on large naturalistic data set. IEEE Transactions on Intelligent Transportation Systems. 13(2), pp.724-736.

Ashley, S. 2001. Driving the info highway. Scientific American. 285(4), pp.52-58.

Aust, M.L., Fagerlind, H. and Sagberg, F. 2012. Fatal intersection crashes in Norway: Patterns in contributing factors and data collection challenges. Accident Analysis & Prevention. 45, pp.782-791.

Bärgman, J., van Nes, N., Christoph, M., Jansen, R., Heijne, V., Carsten, O. and Fox, C. 2017. The UDRIVE dataset and key analysis results. UDRIVE Deliverable 41.1. EU FP7 Project UDRIVE Consortium.

Barnard, Y., Utesch, F., Nes, N., Eenink, R. and Baumann, M. 2016. The study design of UDRIVE: The naturalistic driving study across Europe for cars, trucks and scooters. European Transport Research Review. 8(2), pp.1-10.

Basacik, D. and Stevens, A. 2008. Scoping Study of Driver Distraction. Road Safety Research Report No. 2008/95. London, UK: Department for Transport.

Beanland, V., Fitzharris, M., Young, K.L. and Lenné, M.G. 2013. Driver inattention and driver distraction in serious casualty crashes: Data from the Australian National Crash In-depth Study. Accident Analysis & Prevention. 54, pp.99-107.

Beirness, D.J., Simpson, H.M. and Pak, A. 2002. The road safety monitor: Driver distraction. Ottawa, Ontario: The Traffic Injury Research Foundation.

Benmimoun, M., Pütz, A., Zlocki, A. and Eckstein, L. 2013. EuroFot: Field operational test and impact assessment of advanced driver assistance systems: Final results. In: Proceedings of the FISITA 2012 World Automotive Congress: Springer, pp.537-547.

Bernstein, J.J. 2015. Texting at the light and other forms of device distraction behind the wheel. BMC Public Health. 15(1), pp.968-972.

Bougler, B., Cody, D. and Nowakowski, C. 2008. California intersection decision support: A driver-centered approach to left-turn collision avoidance system design. California Partners for Advanced Transit and Highways (PATH).

Boyle, L.N., Hallmark, S., Lee, J.D., McGehee, D.V., Neyens, D.M. and Ward, N.J. 2012. Integration of analysis methods and development of analysis plan. SHRP 2 Report S2–S02-RW-1. Washington: Transportation Research Board of the National Academies.

Brace, C.L., Young, K.L. and Regan, M.A. 2007. Analysis of the literature: The use of mobile phones while driving. Health. 27, pp.112-113.

Brookhuis, K.A., de Vries, G. and De Waard, D. 1991. The effects of mobile telephoning on driving performance. Accident Analysis & Prevention. 23(4), pp.309-316.

Brown, I.D. 2005. A review of the ‘looked-but-failed-to-see’ accident causation factor. Department of Environment, Transport and the Regions Conference on Driver Behaviour at the University of Manchester.

Brown, T.A., Cash, T.F. and Mikulka, P.J. 1990. Attitudinal body-image assessment: Factor analysis of the Body-Self Relations Questionnaire. Journal of Personality Assessment. 55(1-2), pp.135-144.

Bruyere, M. and Brusque, C. 2013. INTERACTION project final report: Differences and similarities in driver INTERACTION with in-vehicle technologies. EU Seventh Framework Programme.

Buckley, L., Chapman, R.L. and Sheehan, M. 2014. Young driver distraction: State of the evidence and directions for behavior change programs. Journal of Adolescent Health. 54(5, Supplement), pp.S16-S21.

Burns, P., Parkes, A., Burton, S., Smith, R. and Burch, D. 2002. How dangerous is driving with a mobile phone? Benchmarking the impairment to alcohol. Crowthorne, UK: TRL Limited.

Caird, J. and Dewar, R. 2007. Driver distraction. Human Factors in Traffic Safety. 2, pp.195-229.

Campbell, K.L. 2012. The SHRP 2 naturalistic driving study: Addressing driver performance and behavior in traffic safety. TR News. (282).

Carsten, O., Hibberd, D., Bärgman, J., Kovaceva, J., Pereira Cocron, M. and Dotzauer, M. 2017. Driver Distraction and Inattention. UDRIVE Deliverable 43.1. EU FP7 Project UDRIVE Consortium.

Carsten, O., Kircher, K. and Jamson, S. 2013. Vehicle-based studies of driving in the real world: The hard truth? Accident Analysis & Prevention. 58, pp.162-174.

Carsten, O.M. and Brookhuis, K.A. 2005. The relationship between distraction and driving performance: Towards a test regime for in-vehicle information systems. Transportation Research Part F: Traffic Psychology and Behaviour. 8(2), pp.75-77.

Cash, T.F., Melnyk, S.E. and Hrabosky, J.I. 2004. The assessment of body image investment: An extensive revision of the Appearance Schemas Inventory. International Journal of Eating Disorders. 35(3), pp.305-316.

Charlton, J.L., Catchlove, M., Scully, M., Koppel, S. and Newstead, S. 2013. Older driver distraction: A naturalistic study of behaviour at intersections. Accident Analysis & Prevention. 58, pp.271-278.

Charlton, J.L., Oxley, J., Fildes, B., Oxley, P., Newstead, S., Koppel, S. and O'Hare, M. 2006. Characteristics of older drivers who adopt self-regulatory driving behaviours. Transportation Research Part F: Traffic Psychology and Behaviour. 9(5), pp.363-373.

Chatterjee, S. and Hadi, A.S. 2015. Regression analysis by example. Hoboken, New Jersey: John Wiley & Sons.

Chen, H.-Y.W., Donmez, B., Hoekstra-Atwood, L. and Marulanda, S. 2016. Self-reported engagement in driver distraction: An application of the Theory of Planned Behaviour. Transportation Research Part F: Traffic Psychology and Behaviour. 38, pp.151-163.

Chen, R., Kusano, K.D. and Gabler, H.C. 2015. Driver behavior during overtaking maneuvers from the 100-Car naturalistic driving study. Traffic Injury Prevention. 16(S2), pp.S176-S181.

Chisholm, S.L., Caird, J.K., Lockhart, J., Fern, L. and Teteris, E. 2007. Driving performance while engaged in MP-3 player interaction: Effects of practice and task difficulty on PRT and eye movements. In: Proceedings of the 4th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design. University of Iowa, Iowa City, IA, pp.238-245.

Christoph, M., Wesseling, S. and van Nes, N. 2019. Self-regulation of drivers' mobile phone use: The influence of driving context. Transportation Research Part F: Traffic Psychology and Behaviour. 66, pp.262-272.

Cohen, J. 1992. A power primer. Psychological bulletin. 112(1), pp.155-159.

Cottrell, W.D. and Mu, S. 2005. Utah Intersection Safety recurrent Crash Sites: Identification, Issues and Factors. Salt Lake City: University of Utah.

Damiani, S., Deregibus, E. and Andreone, L. 2009. Driver-vehicle interfaces and interaction: Where are they going? European Transport Research Review. 1(2), pp.87-96.

Dewar, R. and Olson, P. 2007. Human factors in traffic safety. 2nd ed. Tucson, AZ: Lawyers & Judges Publishing Company.

DfT. 2019. Reported road casualties Great Britain 2018: Annual report. London, UK: Department for Transport.

Dhondt, S., Macharis, C., Terryn, N., Van Malderen, F. and Putman, K. 2013. Health burden of road traffic accidents: An analysis of clinical data on disability and mortality exposure rates in Flanders and Brussels. Accident Analysis & Prevention. 50, pp.659-666.

Dingus, T. 1995. Moving from measures of performance to measures of effectiveness in the safety evaluation of ITS products or demonstrations. Paper presented at the safety evaluation workshop, University of Iowa.

Dingus, T.A., Guo, F., Lee, S., Antin, J.F., Perez, M., Buchanan-King, M. and Hankey, J. 2016. Driver crash risk factors and prevalence evaluation using naturalistic driving data. Proceedings of the National Academy of Sciences. 113, pp.2636-2641.

Dingus, T.A., Hankey, J.M., Antin, J.F., Lee, S.E., Eichelberger, L. and Stulce, K.E. 2015. Naturalistic driving study: Technical coordination and quality control. SHRP2 Report S2-S06-RW-1. Washington, DC: Transportation Research Board.

Dingus, T.A., Hanowski, R.J. and Klauer, S.G. 2011. Estimating crash risk. Ergonomics in Design. 19(4), pp.8-12.

Dingus, T.A., Klauer, S.G., Neale, V.L., Petersen, A., Lee, S., Sudweeks, J., Perez, M., Hankey, J., Ramsey, D. and Gupta, S. 2006a. The 100-car naturalistic driving study: Phase II-results of the 100-car field experiment, DOT HS 810 593, Washington, DC.

Dingus, T.A., Neale, V.L., Klauer, S.G., Petersen, A.D. and Carroll, R.J. 2006b. The development of a naturalistic data collection system to perform critical incident analysis: An investigation of safety and fatigue issues in long-haul trucking. Accident Analysis & Prevention. 38(6), pp.1127-1136.

DMRB. 2002. Design manual for roads and bridges. Vol.6, Road geometry. Section 1, Links. Part 1, TD 9/93, Highway link design. London: The Highways Agency.

Dotzauer, M., Stemmler, E., Utesch, F., Bärgman, J., Hibberd, D., Fox, C. and Carsten, O. 2017. Risk factors, crash causation and everyday driving. UDRIVE Deliverable 42.1. EU FP7 Project UDRIVE Consortium.

Eby, D.W., Trombley, D.A., Molnar, L.J. and Shope, J.T. 1998. The assessment of older drivers' capabilities: A review of the literature. Report No.UMTRI-98-24. . Michigan, USA: The University of Michigan, Transportation Research Institute.

Edwards, S. and Wundersitz, L. 2019. Distracted driving: Prevalence and motivations. Accident Analysis and Prevention. 54, pp.99-107.

Eenink, R., Barnard, Y., Baumann, M., Augros, X. and Utesch, F. 2014. UDRIVE: The European naturalistic driving study. In: Proceedings of the 2014 Transport Research Arena Conference. Paris, France.

Engström, J., Johansson, E. and Östlund, J. 2005. Effects of visual and cognitive load in real and simulated motorway driving. Transportation Research Part F: Traffic Psychology and Behaviour. 8(2), pp.97-120.

Engström, J., Monk, C., Hanowski, R., Horrey, W., Lee, J., McGehee, D. and Regan, M. 2013a. A conceptual framework and taxonomy for understanding and categorizing driver inattention. Brussels, Belgium: European Commission.

Engström, J., Werneke, J., Bärgman, J., Nguyen, N. and Cook, B. 2013b. Analysis of the role of inattention in road crashes based on naturalistic on-board safety monitoring data. In: Proceedings of the 3rd International Conference on Driver Distraction and Inattention, Gothenburg, Sweden.

European Commission. 2015. Cell phone use while driving. European Commission, Directorate General for Transport.

European Commission. 2018. Driver distraction. European Commission, Directorate General for Transport.

Evans, L. 1991. Traffic safety and the driver. Bloomfield Hills, Michigan: Science Serving Society.

Evans, L. 2004. Traffic safety. Bloomfield Hills, Michigan: Science Serving Society.

Faw, H.W. 2013. To signal or not to signal: That should not be the question. Accident Analysis & Prevention. 59, pp.374-381.

FESTA Consortium. 2008. FESTA handbook Version 2. Deliverable 6.4. The Field Operational Test Support Action Consortium.

Fitch, G.M., Grove, K., Hanowski, R.J. and Perez, M.A. 2014. Compensatory behavior of drivers when conversing on a cell phone: Investigation with naturalistic driving data. Transportation research record. 2434(1), pp.1-8.

Fitch, G.M., Soccolich, S.A., Guo, F., McClafferty, J., Fang, Y., Olson, R.L. and Perez, M.A. 2013. The impact of hand-held and hands-free cell phone use on driving performance and safety-critical event risk. Report No. DOT HS 811757. Washington, DC: National Highway Traffic Safety Administration.

Foss, R.D. and Goodwin, A.H. 2014. Distracted driver behaviors and distracting conditions among adolescent drivers: Findings from a naturalistic driving study. Journal of Adolescent Health. 54(5), pp.S50-S60.

Funkhouser, D. and Sayer, J. 2012. Naturalistic census of cell phone use. Transportation Research Record. 2321(1), pp.1-6.

Gras, M.E., Cunill, M., Sullman, M.J., Planes, M., Aymerich, M. and Font-Mayolas, S. 2007. Mobile phone use while driving in a sample of Spanish university workers. Accident Analysis & Prevention. 39(2), pp.347-355.

Gras, M.E., Sullman, M.J., Cunill, M., Planes, M., Aymerich, M. and Font-Mayolas, S. 2009. Spanish drivers and their aberrant driving behaviours. Transportation Research Part F: Traffic Psychology and Behaviour. 9(2), pp.129-137.

Green, P.E., Wada, T., Oberholtzer, J., Green, P.A., Schweitzer, J. and Eoh, H. 2007. How do distracted and normal driving differ: An analysis of the ACAS naturalistic driving data. Report No. UMTRI-2006-35. Ann Arbor, MI: University of Michigan Transportation Research Institute.

Guo, F., Fang, Y.J. and Antin, J.F. 2015. Older driver fitness-to-drive evaluation using naturalistic driving data. Journal of Safety Research. 54, pp.49-54.

Haigney, D., Taylor, R. and Westerman, S. 2000. Concurrent mobile (cellular) phone use and driving performance: Task demand characteristics and compensatory processes. Transportation Research Part F: Traffic Psychology and Behaviour. 3(3), pp.113-121.

Hall, R. 1986. Accidents at four-arm single carriageway urban traffic signals. TRRL, Contractor Report 65.

Hallgren, K.A. 2012. Computing inter-rater reliability for observational data: An overview and tutorial. Tutorials in Quantitative Methods for Psychology. 8(1), p23.

Hancock, P., Mouloua, M. and Senders, J. 2008. On the philosophical foundations of driving distraction and the distracted driver. In M. A. Regan, J. D. Lee, & K. L. Young (Eds.), Driver distraction: Theory, effects, and mitigation (pp. 11-31). Boca Raton, FL: CRC Press.

Hancock, P.A., Lesch, M. and Simmons, L. 2003. The distraction effects of phone use during a crucial driving maneuver. Accident Analysis & Prevention. 35(4), pp.501-514.

Hankey, J.M. 2014. Canadian Naturalistic Driving Study. Fourth International Symposium on Naturalistic Driving Research. Virginia Tech Transportation Institute. Blacksburg, VA.

Hanowski, R.J., Hickman, J.S., Wierwille, W.W. and Keisler, A. 2007. A descriptive analysis of light vehicle–heavy vehicle interactions using in situ driving data. Accident Analysis & Prevention. 39(1), pp.169-179.

Hanowski, R.J., Olson, R.L., Hickman, J.S. and Dingus, T.A. 2006. The 100-car naturalistic driving study: A descriptive analysis of light vehicle-heavy vehicle interactions from the light vehicle driver's perspective, data analysis results. National Highway Traffic and Safety Administration.

Harbluk, J.L., Noy, Y.I. and Eizenman, M. 2002. The impact of cognitive distraction on driver visual behaviour and vehicle control. Transport Canada Technical Report.

Harbluk, J.L., Noy, Y.I., Trbovich, P.L. and Eizenman, M. 2007. An on-road assessment of cognitive distraction: Impacts on drivers' visual behavior and braking performance. Accident Analysis & Prevention. 39(2), pp.372-379.

Hardy, M.A. 1993. Regression with dummy variables. Vol. 93. Sage.

He, J., Becic, E., Lee, Y.-C. and McCarley, J.S. 2011. Mind wandering behind the wheel: Performance and oculomotor correlates. Human Factors. 53(1), pp.13-21.

Hedlund, J., Simpson, H.M. and Mayhew, D.R. 2006. International Conference on Distracted Driving: Summary of proceedings and recommendations: October 2-5, 2005. In: CAA.

Hibberd, D., Batool, Z., Carsten, O. and Ismaeel, R. 2020. A naturalistic study of mobile phone distraction during driving: An analysis of the UDRIVE project database. Institute for Transport Studies, University of Leeds.

Hibberd, D.L. 2012. Driver distraction: Managing the timing of in-vehicle tasks to improve driver safety. thesis, University of Leeds.

Hickman, J.S., Hanowski, R.J. and Bocanegra, J. 2010. Distraction in commercial trucks and buses: Assessing prevalence and risk in conjunction with crashes and near-crashes. Report No. 10-049. Washington, DC: Federal Motor Carrier Safety Administration.

Horberry, T., Bubnich, C., Hartley, L. and Lamble, D. 2001. Drivers' use of hand-held mobile phones in Western Australia. Transportation Research Part F: Traffic Psychology and Behaviour. 4(3), pp.213-218.

Horrey, W.J., Lesch, M.F. and Garabet, A. 2008. Assessing the awareness of performance decrements in distracted drivers. Accident Analysis & Prevention. 40(2), pp.675-682.

Hosmer, D.W. and Lemeshow, S. 2000. Applied logistic regression. New York: Wiley New York.

Hox, J.J. 2010. Multilevel analysis : techniques and applications. Second edition. ed. New York: Routledge.

Huemer, A.K. and Vollrath, M. 2011. Driver secondary tasks in Germany: Using interviews to estimate prevalence. Accident Analysis & Prevention. 43(5), pp.1703-1712.

Huisingh, C., Griffin, R. and McGwin Jr, G. 2015. The prevalence of distraction among passenger vehicle drivers: A roadside observational approach. Traffic Injury Prevention. 16(2), pp.140-146.

Iversen, H. and Rundmo, T. 2004. Attitudes towards traffic safety, driving behaviour and accident involvement among the Norwegian public. Ergonomics. 47(5), pp.555-572.

Jamson, A.H. and Merat, N. 2005. Surrogate in-vehicle information systems and driver behaviour: Effects of visual and cognitive load in simulated rural driving. Transportation Research Part F: Traffic Psychology and Behaviour. 8(2), pp.79-96.

Jamson, A.H., Westerman, S.J., Hockey, G.R.J. and Carsten, O.M. 2004. Speech-based e-mail and driver behavior: Effects of an in-vehicle message system interface. Human Factors. 46(4), pp.625-639.

Jansen, R., Lotan, T., Winkelbauer, M., Bärgman, J., Kovaceva, J., Donabauer, M. and Van Nes, N. 2017. Interactions with vulnerable road users. UDRIVE Deliverable 44.1. EU FP7 Project UDRIVE Consortium.

Johal, S., Napier, F., Britt-Compton, J. and Marshall, T. 2005. Mobile phones and driving. Journal of Public Health. 27(1), pp.112-113.

Johnson, T., Sherony, R. and Gabler, H.C. 2016. Driver lane keeping behavior in normal driving using 100-car naturalistic driving study data. In: Proceedings of the 2016 IEEE Intelligent Vehicles Symposium (IV), 19-22 June 2016, Gothenburg, Sweden. pp.227-232.

Kagabo, R., Thiese, M.S., Eden, E., Thatcher, A.C., Gonzalez, M. and Okuyemi, K. 2020. Truck drivers' cigarette smoking and preferred smoking cessation methods. Substance Abuse: Research & Treatment. 14.

Kahneman, D. 1973. Attention and effort. Englewood Cliffs, New Jersey: Prentice-Hall Inc.: Citeseer.

Kennedy, J. and Sexton, B. 2010. Literature review of road safety at traffic signals and signalised crossings. TRL Report No. 436. Crowthorne: Transport Research Laboratory.

Kidd, D.G., Tison, J., Chaudhary, N.K., McCartt, A.T. and Casanova-Powell, T.D. 2016. The influence of roadway situation, other contextual factors, and driver characteristics on the prevalence of driver secondary behaviors. Transportation Research Part F: Traffic Psychology and Behaviour. 41, pp.1-9.

Kircher, K. 2007. Driver distraction: A review of the literature. VTI Rapport 594A. VTI Linköping, Sweden.

Kircher, K., Patten, C. and Ahlström, C. 2011. Mobile telephones and other communication devices and their impact on traffic safety: A review of the literature. VTI Report 729A. Sweden: VTI.

Klauer, S.G., Dingus, T.A., Neale, V.L., Sudweeks, J.D. and Ramsey, D.J. 2006a. The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data. NHTSA Report No. DOT HS 810 594. Blacksburg, VA: Virginia Tech Transportation Institute.

Klauer, S.G., Sudweeks, J., Hickman, J.S. and Neale, V.L. 2006b. How risky is it? An assessment of the relative risk of engaging in potentially unsafe driving behaviors.

Laberge-Nadeau, C., Maag, U., Bellavance, F., Lapierre, S.D., Desjardins, D. and Messier, S. 2003. Wireless telephones and the risk of road crashes. Accident Analysis & Prevention. 35(5), pp.649-660.

Lamble, D., Kauranen, T., Laakso, M. and Summala, H. 1999. Cognitive load and detection thresholds in car following situations: Safety implications for using mobile (cellular) telephones while driving. Accident Analysis & Prevention. 31(6), pp.617-623.

Lamble, D., Rajalin, S. and Summala, H. 2002. Mobile phone use while driving: Public opinions on restrictions. Transportation. 29(3), pp.223-236.

Landers, R.N. 2015. Computing intraclass correlations (ICC) as estimates of interrater reliability in SPSS. The Winnower. 2, pp.500-518.

Landis, J.R. and Koch, G.G. 1977. The measurement of observer agreement for categorical data. Biometrics. pp.159-174.

Lansdown, T.C. 2010. Frequency and severity of in-vehicle distractions—a self-report survey. In: Proceedings of the First International Conference on driver distraction and Inattention, pp.28-29.

Laporte, S. 2010. Literature review of naturalistic driving studies. Deliverable 4.2. 1. Paris, France: Europe Research Transport.

Lee, J., McGehee, D., Brown, T. and Marshall, D. 2008. Rear end crash avoidance system (RECAS) algorithm and alerting strategies: Effects of adaptive cruise control and alert modality on driver performance. Final report, DOT HS 810. Iowa: Public Policy Center, The University of Iowa.

Lee, J.D. 2007. Technology and teen drivers. Journal of Safety Research. 38(2), pp.203-213.

Lee, J.D., Regan, M.A. and Young, K.L. 2009a. What drives distraction? Distraction as a breakdown of multilevel control. CRC Press, Boca Raton, Fla, USA.

Lee, J.D. and Strayer, D.L. 2004. Preface to the special section on driver distraction. Human Factors. 46(4), pp.583-586.

Lee, J.D., Young, K.L. and Regan, M.A. 2009b. Defining driver distraction. In: M.A. Regan, J. D. Lee and K. L. Young (Eds.) Driver distraction: Theory, effects, and mitigation. Boca Raton, FL: Taylor & Francis Group.

Lee, S.E., Simons-Morton, B.G., Klauer, S.E., Ouimet, M.C. and Dingus, T.A. 2011. Naturalistic assessment of novice teenage crash experience. Accident Analysis & Prevention. 43(4), pp.1472-1479.

Lloyd, D., Graves, F., Wilson, D., Mais, D., Deda, W. and Bhagat, A. 2015. Reported road casualties Great Britain: Annual report. London, UK: Department for Transport.

Lucidi, F., Girelli, L., Chirico, A., Alivernini, F., Cozzolino, M., Violani, C. and Mallia, L. 2019. Personality traits and attitudes toward traffic safety predict risky behavior across young, adult, and older drivers. Frontiers in Psychology. 10(536).

Mackey, A. and Gass, S.M. 2005. Second language research: methodology and design. Mahwah, NJ: Lawrence Erlbaum Associates.

Mayhew, D.R., Simpson, H.M. and Ferguson, S.A. 2006. Collisions involving senior drivers: High-risk conditions and locations. Traffic Injury Prevention. 7(2), pp.117-124.

McEvoy, S. and Stevenson, M. 2009. Measuring exposure to driver distraction. In: M.A. Regan, J. D. Lee and K. L. Young (Eds.) Driver distraction: Theory, effects, and mitigation. Boca Raton, FL: Taylor & Francis Group.

McEvoy, S.P., Stevenson, M.R. and Woodward, M. 2006a. The impact of driver distraction on road safety: Results from a representative survey in two Australian states. Injury Prevention. 12(4), pp.242-247.

McEvoy, S.P., Stevenson, M.R. and Woodward, M. 2006b. Phone use and crashes while driving: A representative survey of drivers in two Australian states. Medical Journal of Australia. 185(11-12), pp.630-634.

McEvoy, S.P., Stevenson, M.R. and Woodward, M. 2007. The prevalence of, and factors associated with, serious crashes involving a distracting activity. Accident Analysis & Prevention. 39(3), pp.475-482.

McGraw, K.O. and Wong, S.P. 1996. Forming inferences about some intraclass correlation coefficients. Psychological Methods. 1(1), p30.

McHugh, M.L. 2012. Interrater reliability: The kappa statistic. Biochemia Medica. 22(3), pp.276-282.

McLean, J., Croft, P., Elazar, N. and Roper, P. 2010. Safe intersection approach treatments and safer speeds through intersections: Final report: Phase 1. Transportation Research Board.

McShane, B.B. and Gal, D. 2017. Statistical significance and the dichotomization of evidence. Journal of the American Statistical Association. 112(519), pp.885-895.

Menard, S. 2010. Logistic regression: From introductory to advanced concepts and applications. Sage.

Mertler, C.A. and Reinhart, R.V. 2016. Advanced and multivariate statistical methods: Practical application and interpretation. Taylor & Francis.

Metz, B., Landau, A. and Hargutt, V. 2015. Frequency and impact of hands-free telephoning while driving: Results from naturalistic driving data. Transportation Research Part F: Traffic Psychology and Behaviour. 29, pp.1-13.

Metz, B., Landau, A. and Just, M. 2014. Frequency of secondary tasks in driving: Results from naturalistic driving data. Safety Science. 68, pp.195-203.

Michon, J.A. 1985. A critical view of driver behavior models: What do we know and what should we do? Human Behavior and Traffic Safety. Springer, pp.485-524.

Miller, J., Garber, N. and Korukonda, S. 2011. Understanding causality of intersection crashes: Case study in Virginia. Transportation Research Record: Journal of the Transportation Research Board. (2236), pp.110-119.

Navon, D. and Gopher, D. 1979. On the economy of the human-processing system. Psychological Review. 86(3), p214.

Neale, V.L., Dingus, T.A., Klauer, S.G., Sudweeks, J. and Goodman, M. 2005. An overview of the 100-car naturalistic study and findings. In: Proceedings of the 19th International Technical Conference on Enhanced Safety of Vehicles (ESV), Washington, DC, June 6–9, 2005.

NHTSA. 2008. Driver distraction: A review of the current state-of-knowledge. Report No. DOT HS 810 787. Washington, DC: National Highway Traffic Safety Administration.

NHTSA. 2009. Fatality Analysis Reporting System Encyclopedia. Washington, DC: National Highway Traffic Safety Administration

NHTSA. 2019. Traffic safety facts research note: Distracted driving in fatal crashes. Report No. DOT HS 812 700. Washington DC: National Highway Traffic Safety Administration.

Nordfjærn, T., Jørgensen, S. and Rundmo, T. 2011. A cross-cultural comparison of road traffic risk perceptions, attitudes towards traffic safety and driver behaviour. Journal of Risk Research. 14(6), pp.657-684.

Norman, D.A. and Bobrow, D.G. 1975. On data-limited and resource-limited processes. Cognitive Psychology. 7(1), pp.44-64.

North, R.A. 1977. Task functional demands as factors in dual-task performance. In: Proceedings of the Human Factors Society Annual Meeting, Los Angeles, CA. SAGE Publications, pp.367-371.

Nuzzo, R. 2014. Statistical errors: P values, the'gold standard'of statistical validity, are not as reliable as many scientists assume. Nature. 506(7487), pp.150-153.

Ogden, K., Newstead, S., Ryan, P. and Gantzer, S. 1994. Factors affecting crashes at signalised intersections. Melbourne, Australia: Monash University Accident Research Centre.

Ohio Strategic Highway Safety Plan. 2013. Intersection data fact sheet: Overview of intersection-related crashes. Ohio, US: Ohio Strategic Highway Safety Plan.

Olson, K.E., O'Brien, M.A., Rogers, W.A. and Charness, N. 2011. Diffusion of Technology: Frequency of use for Younger and Older Adults. Ageing International. 36(1), pp.123-145.

Olson, R.L., Hanowski, R.J., Hickman, J.S. and Bocanegra, J.L. 2009. Driver distraction in commercial vehicle operations. Report No. FMCSA-RRR-09-042. Washington, DC: U.S. Department of Transportation.

Oneyear, N.L., Hallmark, S.L. and Wang, B. 2016. Evaluating the relationship between the driver and roadway to address rural intersection safety using the SHRP2 naturalistic driving study data. Report No. 13-476. Iowa Department of Transportation and Federal Highway Administration.

Osborne, J.W. and Waters, E. 2002. Four assumptions of multiple regression that researchers should always test. Practical Assessment, Research, and Evaluation. 8(1), p2.

Östlund, J., Nilsson, L., Carsten, O., Merat, N., Jamson, S., Janssen, W. and Mouta, S. 2004. Deliverable 2 – HMI and safety-related driver performance (No. GRD1/2000/25361 S12.319626). Human Machine Interface and the Safety of Traffic in Europe (HASTE) Project.

Oviedo-Trespalacios, O., Haque, M.M., King, M. and Washington, S. 2017a. Effects of road infrastructure and traffic complexity in speed adaptation behaviour of distracted drivers. Accident Analysis & Prevention. 101, pp.67-77.

Oviedo-Trespalacios, O., King, M., Haque, M.M. and Washington, S. 2017b. Risk factors of mobile phone use while driving in Queensland: Prevalence, attitudes, crash risk perception, and task-management strategies. PLoS One. 12(9).

Pashler, H. 1994. Dual-task interference in simple tasks: data and theory. Psychological Bulletin. 116(2), p220.

Pashler, H.E. 1998. The psychology of attention. Cambridge, UK: MIT Press.

Pettitt, M., Burnett, G.E. and Stevens, A. 2005. Defining driver distraction. In: Proceedings of the 12th World Congress on Intelligent Transport Systems.

Pickrell, T.M. 2015. Driver electronic device use in 2013. Report No. DOT HS 811 884. Washington, DC: National Highway Traffic Safety Administration.

Ponziani, R. 2012. Turn signal usage rate results: A comprehensive field study of 12,000 observed turning vehicles. SAE Technical Paper.

Pöysti, L., Rajalin, S. and Summala, H. 2005. Factors influencing the use of cellular (mobile) phone during driving and hazards while using it. Accident Analysis & Prevention. 37(1), pp.47-51.

Prato, C.G., Toledo, T., Lotan, T. and Taubman-Ben-Ari, O. 2010. Modeling the behavior of novice young drivers during the first year after licensure. Accident Analysis & Prevention. 42(2), pp.480-486.

Rakauskas, M.E., Gugerty, L.J. and Ward, N.J. 2004. Effects of naturalistic cell phone conversations on driving performance. Journal of Safety Research. 35(4), pp.453-464.

Ranney, T.A. 2008. Driver distraction: A review of the current state-of-knowledge.

Reed, M.P. and Green, P.A. 1999. Comparison of driving performance on-road and in a low-cost simulator using a concurrent telephone dialling task. Ergonomics. 42(8), pp.1015-1037.

Regan, M., Williamson, A., Grzebieta, R., Charlton, J., Lenneb, M., Watson, B. and Haworth, N. 2013. The Australian 400-car Naturalistic Driving Study: Innovation in road safety research and policy. In: Proceedings of the 2013 Australasian Road Safety Research, Policing & Education Conference, Brisbane, Queensland.

Regan, M.A. and Hallett, C. 2011. Driver distraction: Definition, mechanisms, effects, and mitigation. Handbook of traffic psychology. Amsterdam: Elsevier.

Regan, M.A., Hallett, C. and Gordon, C.P. 2011. Driver distraction and driver inattention: Definition, relationship and taxonomy. Accident Analysis & Prevention. 43(5), pp.1771-1781.

Regan, M.A., Lee, J.D. and Young, K.L. 2009. Driver distraction: theory, effects, and mitigation. CRC Press Taylor & Francis Group, Boca Raton, FL, USA.

Response Insurance. 2006. Survey explains why drivers are not turned on by using signals.

Rhodes, N. and Pivik, K. 2011. Age and gender differences in risky driving: The roles of positive affect and risk perception. Accident Analysis & Prevention. 43(3), pp.923-931.

Rice, E. 2010. Access management in the vicinity of intersections. Report No. FHWA-SA-10-002. Federal Highway Administration.

Risteska, M., Kanaan, D., Donmez, B. and Winnie Chen, H.-Y. 2021. The effect of driving demands on distraction engagement and glance behaviors: Results from naturalistic data. Safety Science. 136.

Rosenthal, J.A. 1996. Qualitative descriptors of strength of association and effect size. Journal of Social Service Research. 21(4), pp.37-59.

Royal, D. 2003. National survey of distracted and drowsy driving attitudes and behavior. Report No. DOT HS 809 566. Washington, DC: National Highway Traffic Safety Administration.

Sayer, J., Devonshire, J. and Flanagan, C. 2007. Naturalistic driving performance during secondary tasks. In: Proceedings of the Fourth International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design, pp.224-230.

Sayer, J.R. 2005. The effects of secondary tasks on naturalistic driving performance. Report No. UMTRI-2005-29. Michigan, US: The University of Michigan, Transportation Research Institute.

Simon, M., Hermitte, T. and Page, Y. 2014. Intersection road accident causation: A European view. In: Proceedings of 21st International Conference on the Enhanced Safety of Vehicles, pp.1-10.

Stelling, A. and enHagenzieker, M. 2012. Distraction in traffic: An overview of the literature. Report R-2012-4. Leidschendam: Institute for Road Safety Research SWOV.

Stinchcombe, A. and Gagnon, S. 2009. Estimating workload demands of turning left at intersections of varying complexity. In: Proceedings of the 5th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design, pp.440–446.

Stollof, E.R. 2008. Intersection and junction fatalities in the context of access management. In: Proceedings of the 8th National Conference on Access Management, July 13–16 2008, Washington, DC.

Stover, V. 1996. Discussion paper No. 7: Functional intersection area. Oregon, US: Transportation Research Institute, Oregon State University.

Strayer, D.L., Cooper, J.M., Turrill, J., Coleman, J.R. and Hopman, R.J. 2015. Measuring cognitive distraction in the automobile III: A comparison of ten 2015 in-vehicle information systems. Washington, DC: AAA Foundation for Traffic Safety.

Strayer, D.L. and Drew, F.A. 2004. Profiles in driver distraction: Effects of cell phone conversations on younger and older drivers. Human Factors. 46(4), pp.640-649.

Streubel, T., Rittger, L., Hoffmann, K. and Krems, J. 2015. Naturalistic driving behavior at inner-city intersections. In: In Proceedings of 22nd ITS World Congress, France.

Stutts, J., Feaganes, J., Reinfurt, D., Rodgman, E., Hamlett, C., Gish, K. and Staplin, L. 2005. Driver's exposure to distractions in their natural driving environment. Accident Analysis & Prevention. 37(6), pp.1093-1101.

Stutts, J., Feaganes, J., Rodgman, E., Hamlett, C., Meadows, T., Reinfurt, D. and Gish, K. 2003a. Distractions in everyday driving. Washington, DC: AAA Foundation for Traffic Safety.

Stutts, J.C., Hunter, W.W. and Huang, H.F. 2003b. Cell phone use while driving: Results of a statewide survey. In: Transportation Research Board, 2003. Annual Meeting (CD-ROM).

Stutts, J.C., Reinfurt, D.W., Staplin, L. and Rodgman, E.A. 2001. The role of driver distraction in traffic crashes. Washington, DC: AAA Foundation for Traffic Safety.

Sullivan, J.M., Bao, S. and Goudy, R. 2015. Characteristics of turn signal use at intersections in baseline naturalistic driving. Accident Analysis & Prevention. 74, pp.1-7.

Sullman, M.J. 2012. An observational study of driver distraction in England. Transportation Research Part F: Traffic Psychology and Behaviour. 15(3), pp.272-278.

Sullman, M.J. and Baas, P.H. 2004. Mobile phone use amongst New Zealand drivers. Transportation Research Part F: Traffic Psychology and Behaviour. 7(2), pp.95-105.

Sullman, M.J., Prat, F. and Tasci, D.K. 2015. A roadside study of observable driver distractions. Traffic Injury Prevention. 16(6), pp.552-557.

SWOV. 2010. Naturalistic Driving: observing everyday driving behaviour. Leidschendam, the Netherlands: The SWOV Institute for Road Safety Research.

Szumilas, M. 2010. Explaining odds ratios. Journal of the Canadian Academy of Child and Adolescent Psychiatry. 19(3), p227.

Tawari, A., Misu, T. and Fujimura, K. 2016. Predicting unexpected maneuver while approaching intersection. In: Proceedings of the 19th International Conference on Intelligent Transportation Systems (ITSC): IEEE, pp.2225-2229.

Taylor, D.M. 2004. Mobile telephone use among Melbourne drivers: A preventable exposure to injury risk. Medical Journal of Australia. 180(1), pp.43-45.

Taylor, M.C., Hall, R. and Chatterjee, K. 1996. Accidents at 3-arm traffic signals on urban single carriageway roads. TRL Report No. 135.

Teh, E., Jamson, S. and Carsten, O. 2018. Mind the gap: Drivers underestimate the impact of the behaviour of other traffic on their workload. Applied Ergonomics. 67, pp.125-132.

TexaSoft. 2008. Interrater reliability (kappa) using SPSS. [Online]. Available from: http://www.stattutorials.com/SPSS/TUTORIAL-SPSS-Interrater-Reliability-Kappa.htm

Thomas, P., Muhlrad, N., Hill, J., Yannis, G., Dupont, E., Martensen, H. and Hermitte, T. 2013. Final Project Report, Deliverable 0.1 of the EC FP7 project DaCoTA. Loughborough, UK: Transport Safety Research Centre, Loughborough University.

Thulin, H. and Gustafsson, S. 2004. Mobile phone use while driving: Conclusions from four investigations. Report No. VTI 490A. Linkoping, Sweden: Swedish National Road and Transport Research Institute.

Tivesten, E. and Dozza, M. 2015. Driving context influences drivers' decision to engage in visual-manual phone tasks: Evidence from a naturalistic driving study. Journal of Safety Research. 53, pp.87-96.

Toledo, T., Musicant, O. and Lotan, T. 2008. In-vehicle data recorders for monitoring and feedback on drivers’ behavior. Transportation Research Part C: Emerging Technologies. 16(3), pp.320-331.

Treat, J.R. 1980. A study of precrash factors involved in traffic accidents: Research Review. Ann Arbor, MI: University of Michigan, Highway Safety Research Institute.

Trezise, I., Stoney, E., Bishop, B., Eren, J., Harkness, A., Langdon, C. and Mulder, T. 2006. Report of the road safety committee on the inquiry into driver distraction. Report No. 209. Melbourne, Australia: Australia Road Safety Committee.

TRL, TNO and Rapp Trans. 2015. Study on good practices for reducing road safety risks caused by road user distractions. Final report. Brussels: European Commission.

Uchida, N., Kawakoshi, M., Tagawa, T. and Mochida, T. 2010. An investigation of factors contributing to major crash types in Japan based on naturalistic driving data. IATSS Research. 34(1), pp.22-30.

Utesch, F., Bärgman, J., Carsten, O., Christoph, M., Engström, J., Guyonvarch, L. and Lai, F. 2014. Preliminary Analysis Plan. Deliverable 11.2. EU FP7 Project UDRIVE Consortium.

van Schagen, I. and Sagberg, F. 2012. The potential benefits of naturalistic driving for road safety research: Theoretical and empirical considerations and challenges for the future. Procedia - Social and Behavioral Sciences. 48, pp.692-701.

van Schagen, I., Welsh, R., Backer-Grondahl, A., Hoedemaeker, M., Lotan, T., Morris, A. and Sagberg, F. 2011. Towards a large scale European naturalistic driving study: Main findings of PROLOGUE. Deliverable D4.2. Leidschendam, the Netherlands: SWOV Institute for Road Safety Research.

Victor, T., Bärgman, J., Hjälmdahl, M., Kircher, K., Svanberg, E., Hurtig, S. and Gellerman, H. 2010. Sweden-michigan naturalistic field operational test (semifot) phase 1: Final report. SAFER Report. 2.

Victor, T., Dozza, M., Bärgman, J., Boda, C.-N., Engström, J., Flannagan, C., Lee, J.D. and Markkula, G. 2015. Analysis of naturalistic driving study data: Safer glances, driver inattention, and crash risk. SHRP2 Report S2-S08A-RW-1. Transportation Research Board.

Waddell, L.P. and Wiener, K.K. 2014. What's driving illegal mobile phone use? Psychosocial influences on drivers' intentions to use hand-held mobile phones. Transportation Research Part F: Traffic Psychology and Behaviour. 22, pp.1-11.

Wang, J., Knipling, R.R. and Goodman, M. 1996. The role of driver inattention in crashes: New statistics from the 1995 Crashworthiness Data System. In: 40th Annual Proceedings: Association for the Advancement of Automotive Medicine, pp.377-392.

Wasserstein, R.L. and Lazar, N.A. 2016. The ASA statement on p-values: Context, process, and purpose. Taylor & Francis.

Werneke, J. and Vollrath, M. 2010. Where did the car come from? Attention allocation at intersections. In: Proceedings of the 2nd European Conference on Human Centred Design for Intelligent Transport Systems, Berlin, Germany.

White, K.M., Hyde, M.K., Walsh, S.P. and Watson, B. 2010. Mobile phone use while driving: An investigation of the beliefs influencing drivers' hands-free and hand-held mobile phone use. Transportation Research Part F: Traffic Psychology and Behaviour. 13(1), pp.9-20.

WHO. 2011. Mobile phone use: A growing problem of driver distraction. Geneva, Switzerland: World Health Organization.

WHO. 2013. Projections of mortality and causes of death, 2015 and 2030. Geneva, Switzerland: World Health Organisation.

WHO. 2018. Global status report on road safety 2018. Geneva, Switzerland: World Health Organization.

Wickens, C. 1984. Processing resources in attention. I Parasuraman, R. & Davies, DR (Eds): Varieties of Attention. Academic Press, London.

Wickens, C.D. 2002. Multiple resources and performance prediction. Theoretical Issues in Ergonomics Science. 3(2), pp.159-177.

Wickens, C.D. 2008. Multiple resources and mental workload. Human Factors: The Journal of the Human Factors and Ergonomics Society. 50(3), pp.449-455.

Williamson, A., Grzebieta, R., Eusebio, J., Zheng, W.Y., Wall, J., Charlton, J.L. and Lenné, M. 2015. The Australian naturalistic driving study: From beginnings to launch. In: Proceedings of the 2015 Australasian Road Safety Conference, Australia.

Winzer, O.M., Conti, A.S., Olaverri-Monreal, C. and Bengler, K. 2017. Modifications of driver attention post-distraction: A detection response task study. In: Proceedings of the International Conference on HCI in Business, Government, and Organizations: Springer, pp.400-410.

Wood, J.M. 2020. Nighttime driving: Visual, lighting and visibility challenges. Ophthalmic and Physiological Optics. 40(2), pp.187-201.

Wundersitz, L.N. 2014. Phone use while driving: Results from an observational survey. Traffic Injury Prevention. 15(6), pp.537-541.

Xiong, H.M., Bao, S., Sayer, J. and Kato, K. 2015. Examination of drivers' cell phone use behavior at intersections by using naturalistic driving data. Journal of Safety Research. 54, pp.89-93.

Yoo, W., Mayberry, R., Bae, S., Singh, K., He, Q.P. and Lillard Jr, J.W. 2014. A study of effects of multicollinearity in the multivariable analysis. International Journal of Applied Science and Technology. 4(5), p9.

Young, K., Regan, M. and Hammer, M. 2007. Driver distraction: A review of the literature. Victoria, Australia: Monash University Accident Research Centre.

Young, K.L. and Lenné, M.G. 2010. Driver engagement in distracting activities and the strategies used to minimise risk. Safety Science. 48(3), pp.326-332.

Young, K.L., Osborne, R., Koppel, S., Charlton, J.L., Grzebieta, R., Williamson, A. and Haworth, N. 2019. What contextual and demographic factors predict drivers' decision to engage in secondary tasks? IET Intelligent Transport Systems. 13(8), pp.1218-1223.

Young, K.L. and Regan, M.A. 2009. Driver distraction exposure research: A summary of findings. In: M.A. Regan, J. D. Lee and K. L. Young (Eds.) Driver distraction: Theory, effects, and mitigation. Boca Raton, FL: Taylor & Francis Group., pp.319-331.

Young, K.L. and Regan, M.A. 2013. Defining the relationship between behavioural adaptation and driver distraction. In: Behavioural Adaptation and Road Safety.Theory, Evidence and Action. CRC Press Taylor and Francis Group, Boca Raton.

Young, K.L., Regan, M.A. and Hammer, M. 2003. Driver distraction: A review of the literature. Public Health. 81, pp.102-106.

Young, K.L., Regan, M.A. and Lee, J.D. 2009. Factors moderating the impact of distraction on driving performance and safety. In M.A. Regan, J.D. Lee, and K.L. Young (eds.) Driver Distraction: Theory, Effects, and Mitigation. Boca Raton, FL: CRC Press.

Young, K.L., Rudin-Brown, C.M. and Lenné, M.G. 2010. Look who's talking! A roadside survey of drivers' cell phone use. Traffic Injury Prevention. 11(6), pp.555-560.

Young, K.L., Salmon, P.M. and Lenné, M.G. 2011. An on-road examination of driver errors at intersections. In: Proceedings of the Australian Road Safety Research, Policing and Education Conference, Australia. Monash University.

Young, R. 2015. Revised odds ratio estimates of secondary tasks: A re-analysis of the 100-car naturalistic driving study data. SAE Technical Paper.

Zhang, L., Zhou, K., Zhang, W.-b. and Misener, J. 2009. Prediction of red light running based on statistics of discrete point sensors. Transportation Research Record: Journal of the Transportation Research Board. (2128), pp.132-142.

Appendix A: The data non-disclosure agreement

UDRIVE
European Naturalistic Driving Study

UNIVERSITY OF LEEDS

Non-disclosure agreement

I will conform to all security requirements relating to the use of the UDRIVE data:

a. I will maintain the security of the UDRIVE coding room, locking my PC and all doors and windows when I exit.
b. I will not use my mobile phone in the UDRIVE room.
c. I will not use the screen capture function on the PC or attempt to take a photograph of any UDRIVE data or materials.
d. I will not allow non-project staff or students to have access to the UDRIVE room.
e. I will not allow non-project staff or students to have access to the UDRIVE data.
f. I will not attempt to store UDRIVE data outside of the remote database.
g. I will not post UDRIVE data or related materials online or on any social media platform.
h. I will use the UDRIVE data only for my dissertation work and will only disclose information via the agreed channels: dissertation report, presentation, poster.
i. I understand the violating any of the above rules will result in termination of my access to the UDRIVE data.

Name: Rashed Ismaeel

Signed: Rashed Ismaeel

Date: 25/07/2016

Appendix B: Secondary task coding scheme

Pass A: General secondary task annotation

Value	Category	Description	Annotation start	Annotation end
0	No Task	The driver is not engaging in any secondary tasks that can be observed.	Start of record (value set by default in the annotation panel).	Start of other secondary task or end of record.
1	Mobile phone use	The driver interacts with a mobile phone (e.g. locating/searching, holding, dialling, pressing buttons; texting and talking either hands-free or hand-held).	First glance or hand movement towards the phone. Code whichever occurred first.	Phone is put down or last hand movement to end the call or first sign that conversation has ended (e.g. lips do not move anymore).
2	Electronic device engagement	The driver interacts with an electronic device (e.g. iPad, camera, calculator). Annotate only electronic devices that are not integral to the vehicle. All types of interaction count: locating/searching; reaching or starting to glance around; manual interaction; visual interaction; putting away.	First glance or hand movement towards the device. Code whichever occurred first.	Device is put down or last hand movement to end interaction with device or first sign that vocal interaction has ended.
3	Smoking	The driver glances around and reaches for a cigar/cigarette or electronic cigarette, lights it, smokes it or extinguishes it. The interaction with smoking related items should also be annotated in this category.	First glance to or movement towards the cigar/cigarette or related item. Code whichever occurred first.	Discards the cigar/cigarette or related device.
4	Personal grooming	The driver interacts with any item related to health, personal hygiene or accessories. This includes: reaching for comb, brush, make-up, razor, dental floss, contact lenses, glasses (not currently being worn), hat (not currently being worn). Removing, adjusting, or putting on clothing or jewellery are also included in this category. Personal grooming activities are annotated if the driver has an object in the hand. If there is not object it should not be annotated.	First glance to or movement towards the object. Code whichever occurred first.	Puts the object down or last glance towards the mirror to end personal grooming action.

5	Eating and drinking	The driver performs an action related to food or drink (e.g. reaching for food or a cup, drinking and eating, putting a food/drink item away). Chewing only does not count as a secondary task (e.g. chewing gum). However, if driver reaches for chewing gum, this has to be counted as secondary task that ends when the driver puts away the chewing gum package.	First glance to or movement towards the food/drink-related item. Code whichever occurred first.	Driver's hand releases item for the last time.
6	Reading and writing	The driver is writing or reading material that is in the vehicle but is not part of the vehicle or a mobile phone interaction. This category includes activities such as reading paper materials or packaging.	First eye glance towards the reading material or first physical motion towards the reading material. Code whichever occurred first.	Puts down the reading material or the driver does not perform glances towards the reading material for at least 10 seconds.
7	Engagement with in-vehicle control system	The driver interacts with in-vehicle control systems (e.g. manipulating in-vehicle climate controls, radio buttons or other buttons on the centre stack display). Interactions should be annotated when the driver touches the control buttons, glances or adjusts related objects. Does not include driving-critical tasks, such as turn signal, wipers, headlights, gear shift, speedometer.	First glance or hand movement towards the control system. Code whichever occurred first.	Driver's hand releases the control system.
8	Passenger conversations	The driver participates in any exchange with a passenger; at the minimum, he/she utters a word. The passenger could be child or adult and could be sitting in the front seat, rear seat or both.	Driver’s first lips movement.	First sign that conversation (e.g. lips do not move anymore).
9	Talking/singing in the absence of passengers	The driver is talking or singing (moving his/her lips) in the absence of passengers. There is a need to ensure that drivers are not talking on a mobile phone hands-free.	Driver’s first lips movement.	First sign that talking/ singing ended (e.g. lips do not move anymore)
10	Other	The driver interacts with some other object that is not included in the above-mentioned categories or interacts with objects that cannot be clearly identified from the videos.		

Pass B: Detailed coding of sub-categories of mobile phone interactions

Value	Category	Description	Annotation start	Annotation end
1	Searching	The driver is reaching or glancing around to find his/her mobile phone.	First glance towards or hand movement towards the phone. Code whichever occurred first.	Phone is in driver's possession or conversation has begun or start of another category (e.g. hold, interaction or even put the phone down).
2	Handheld interaction	The driver is touching the screen of a mobile phone or pressing buttons. The driver could be browsing the Internet or typing a text message. These are mostly physical interactions that alternate with small pauses (i.e. looking back at the road).	First hand movement across phone screen.	Last hand movement across phone screen.
3	Hands-free interaction	The driver is looking regularly at a mobile phone without holding it. This can occur if drivers are receiving navigational guidance through the phone.		
4	Handheld conversation	The driver is talking on a handheld phone or has the phone up to his/her ear as if listening to a phone conversation or waiting for a person they are calling to pick up the phone.	Button press to answer call or if not visible, first mouth movement of call.	Button press to hang up phone or put down the phone.
5	Hands-free conversation	The driver is talking or listening on a phone hands-free (e.g. using the mobile phone speaker, a headset or an in-vehicle integrated system).	Headset or in-vehicle system button press to answer or first lips movement of call.	Last lips movement of call or button push to end call.
6	Phone Holding	The driver is simply holding his/her mobile phone but not interacting with it. The phone could be in his/her hand or lap, or the driver may be holding the device in some other way.	First body contact with phone not considered to be reaching for or interacting with it.	Phone is put down or start of another phone category.
7	Related	The driver is interacting with a mobile phone in a way that is not covered by the categories above (e.g. cleaning the screen, plugging the phone into a charger).	First manual contact with phone-related item e.g. charger.	Last manual contact with phone-related item e.g. charger.