DEVELOPING DRIVING BEHAVIOUR MODELS INCORPORATING THE EFFECTS OF STRESS

by

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INTELLECTUAL PROPERTY AND PUBLICATIONS

The candidate confirms that the work submitted is his/her own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Four papers have been produced from the research that was undertaken in the context of the current thesis. Each paper is listed below including its location in the thesis and a full reference where appropriate. Also for each paper, an author contribution statement is provided.

The work in Chapter 2 of the thesis has been accepted for conference presentation:

Paschalidis, E., Choudhury, C.F., Hibberd, D.L., 2019. Investigating the effects of traits, stress and situational factors on driving performance. *World Conference on Transport Research – WCTR, 2019*. Mumbai 26-31 May 2019.

The candidate significantly contributed to the idea and design of the study, the analysis and interpretation of the data and also wrote the manuscript. The co-author CFC also had an important contribution to the idea and design of the study and also reviewed the paper prior to submission. The co-author DLH provided useful feedback during the design of the study and also substantially contributed in the data analysis.

The work in Chapter 3 of the thesis has appeared in publication as follows:

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The candidate contributed in the idea of the paper, data analysis, modelling work and also prepared the manuscript. The co-author CFC contributed in the idea of the paper. Both co-authors CFC and SH provided recommendations on the modelling work, feedback on the results their interpretation and reviewed the paper before submission.

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The candidate contributed in the idea of the paper, data analysis, modelling work and also prepared the manuscript. The co-author CFC also had an substantial contribution to the idea of the paper. Both co-authors CFC and SH provided recommendations on the modelling work, feedback on the results their interpretation and reviewed the paper before submission.

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ABSTRACT

Driving is a complex task and several factors influence drivers' decisions and performance including traffic conditions, attributes of vehicles, network and environmental characteristics, and last but not least characteristics of the drivers themselves. in an effort to better explain and represent driving behaviour, several driving behaviour models have been suggested over the years. In the existing literature, there are two main streams of driving behaviour models that can be found. The first is approaching driving behaviour from a human factors and cognitive perspective while the second is engineering-based. Driving behaviour models of the latter category are mathematical representations of drivers' behaviour at the individual level, mostly focussing on acceleration/deceleration, lane-change and gap-acceptance decisions. Many of these factors are captured by existing driving behaviour models used in microscopic simulation tools. However, while the vast majority of existing models is approximating driving behaviour, primarily focusing on the effects of traffic conditions, little attention has been given to the impact of drivers' characteristics.

The aim of the current thesis is to investigate the effects of stress on driving behaviour and quantify its impact using an econometric modelling framework. This main research question emerged as a result of a widely acknowledged research gap in existing engineering-based driving behaviour models related to the incorporation of human factors and drivers' characteristics within the model specification. The research was based on data collected using the University of Leeds Driving Simulator. Two main scenarios were presented to participants, while they were also deliberately subjected to stress induced by time pressure and various scenarios. At the same time, stress levels were measured via physiological indicators. Sociodemographic and trait data was also collected in the form of surveys.

The data has been initially analysed for each main scenario and several statistics are extracted. The results show a clear effect of time pressure in favour of speeding, however relations related to physiological responses are not always clear. Moreover, two driving behaviour models are developed, a gap-acceptance and a car-following model. In the former model, increase in physiological responses is related to higher probability of accepting a gap and time pressure has a positive effect of gap-acceptance probability as well. In the car-following model, stress is associated with increased acceleration and potentially a more aggressive driving style.

The aforementioned analysis is based on data collected in a driving simulator. Given the potential differences in driving behaviour between real and simulated driving, the transferability of a model based on the latter data to field traffic setting is also investigated. Results indicate significant differences in parameters estimated from a video and the simulator dataset, however these differences can be significantly reduced after applying parameter updating techniques.

The findings in this thesis show that stress and drivers' characteristics can influence driving behaviour and thus should be considered in the driving behaviour models for microscopic simulation applications. However, for real life applications, it is suggested that the extent of these effects should be treated with caution and ideally rescaled based on real traffic observations.

CONTENTS

Chapter 1: Introduction ... 1
1.1 Background ... 1
1.2 Driving behaviour models ... 3
1.2.1 Acceleration models ... 3
1.2.2 Lane-change and gap-acceptance models ... 8
1.3 Key limitations of driving behaviour models ... 10
1.4 The effects of human factors on driving behaviour ... 12
1.5 Stress and driving behaviour ... 15
1.5.1 Defining stress in the driving context ... 15
1.5.2 Driving-related stress occurrence ... 17
1.5.3 The effects of stress on drivers' behaviour ... 18
1.5.4 The relation between stress and human physiology ... 18
1.6 Data requirements for the development of driving behaviour models ... 20
1.6.1 Driving behaviour data ... 20
1.6.2 Drivers' characteristics data ... 21
1.7 Research objectives ... 21
1.8 Thesis outline ... 23
1.9 References ... 25
Chapter 2: Investigating the effects of traits, stress and situational factors on driving performance ... 41
2. 1 Introduction ... 42
2.2 Driving simulator experiment ... 43
2.2.1 Apparatus ... 43
2.2.2 Driving simulator scenarios ... 46
2.3 Sample characteristics ... 51
2.3.1 Descriptive statistics ... 51
2.3.2 Inferential statistics ... 53
2.4. Urban setting ... 58
2.4.1 Effect of time pressure ... 58
2.4.2 The effects of stress/arousal levels as measured by the physiological responses ... 62

2.4.3 Interaction with sociodemographic characteristics 63
2.4.4 Interaction with personality traits.. 65
2.4.5 Interaction with the driving style 66
2.5. The motorway setting... 67
2.5.1 The effects of time pressure 68
2.5.2 The effects of stress or arousal as measured by the physiological responses... 71
2.5.3 Interactions with sociodemographic characteristics....................... 72
2.5.4 Interactions with personality traits 73
2.5.5 Interactions with driving style.. 73
2.6. Summary of findings.. 74
2.7. Conclusion... 77
2.8 References 78
Chapter 3: Modelling the effects of stress on gap-acceptance decisions combining data from driving simulator and physiological sensors.................. 85
3.1 Introduction 86
3.2 Literature review 87
3.2.1. Stress and driving context 87
3.2.2 Gap-acceptance behaviour and models 89
3.3. Data collection... 91
3.3.1 Driving simulator experiment 91
3.3.2 The gap-acceptance task... 93
3.3.3. Exploratory analysis.. 95
3.4. Methodology 99
3.4.1 The gap acceptance model 99
3.4.2. Physiological data analysis.. 101
3.5. Gap-acceptance model 103
3.5.1 Parameter estimation results and interpretation 103
3.5.2. Model comparison... 107
3.5.3 Sensitivity analysis... 108
3.5.4 Substitution rates 111
3.6. Conclusion... 113
3.7 References 115

Chapter 4: Combining driving simulator and physiological sensor data in a latent variable model to incorporate the effect of stress in car-following behaviour ... 123

4.1 Introduction ... 124

4. 2 Data ... 127

4.2.1 Driving simulator experiment ... 127

4.2.2 Physiological indicator extraction ... 130

4.2.3 Sample analysis ... 131

4.3 Model framework ... 133

4.3.1 Base car-following model ... 134

4.3.2 Car-following model with sociodemographic variables ... 137

4.3.3 Car-following model with latent stress variable ... 137

4.3.4 Car-following model with both sociodemographic and latent stress variables ... 141

4.4. Estimation results ... 141

4.4.1 Base car-following models ... 141

4.4.2 Car-following models with sociodemographic variables ... 146

4.4.3 Car-following models with latent stress variable ... 148

4.4.4 Car-following models with both sociodemographic and latent stress variables ... 153

4.5 Conclusion ... 153

4.6 References ... 157

Chapter 5: From driving simulators experiments to field traffic application: improving the transferability of car-following models ... 165

5.1 Introduction ... 166

5.2 Background and methodology ... 168

5.2.1 Car-following model ... 168

5.2.2 Evaluating Model Performance and Transferability ... 172

5.2.3 Methods to Improve Transferability ... 173

5.3. Case study ... 176

5.3.1 Data ... 176

5.3.2 Preliminary analysis ... 178

5.4 Estimation results ... 180

5.4.1 Individual Models ... 180

5.4.2 Model comparison and sensitivity analysis ... 183

5.5. Model updating and joint estimation ... 186

5.5.1 Model updating ... 186
5.5.2 Joint estimation results ... 188
5.6 Conclusion ... 190
5.7 References ... 192
Chapter 6: Conclusion ... 197
6.1 Summary ... 197
6.1.1 The effects of drivers' characteristics on driving behaviour ... 197
6.1.2 The effects of traffic conditions and time pressure on driving behaviour ... 198
6.1.3 The incorporation of stress in driving behaviour models ... 199
6.1.4 The transferability of driving simulator data to the real driving context ... 200
6.2 Progress made in achieving the research objectives ... 201
6.3 Contributions to knowledge and practice ... 202
6.4 Future research directions ... 204
6.5 Concluding remarks ... 205
6.6 References ... 206
Appendix A: Appendix to Chapter 2 ... 209
Appendix B: Appendix to Chapter 4 ... 237

LIST OF TABLES

Table 1.1: The effects of stress on driving behaviour 14

Table 1.2: Transactional analysis of driver's stress 16

Table 1.3: Studies investigating driving-related issues using physiological data..... 19

Table 2.1: The motorway setting sections... 50

Table 2.2: Descriptive statistics of the sample 52

Table 2.3: Descriptive statistics of the survey responses 53

Table 2.4: Personality factors correlations 54

Table 2.5: MDSI factors correlations 55

Table 2.6: Personality-MDSI factors correlations 56

Table 2.7: Personality-MDSI factors correlations with sociodemographics 57

Table 2.8: The overtaking scenario variables 59

Table 2.9: The red traffic light scenario variables 60

Table 2.10: The amber dilemma scenario variables... 61

Table 2.11: The gap-acceptance scenario variables. 62

Table 2.12: The free driving scenario variables 62

Table 2.13: Correlation matrix of personality factors with the motorway setting variables 74

Table 2.14: Correlation matrix of MDSI factors with the motorway setting variables 76

Table 3.1: The available gaps and gaps' sizes**Σφάλμα! Δεν έχει οριστεί σελιδοδείκτης.**

Table 3.2: Descriptive statistics of the sample 95

Table 3.3: Accepted gap(s) of each participant at the two intersections.................. 97

Table 3.4: Results of the paired samples t-test and Wilcoxon test......................... 100

Table 3.5: Gap-acceptance models' parameter estimates 105

Table 3.6: Likelihood ratio tests' results 108

Table 4.1: Descriptive statistics of the sample 132

Table 4.2: Descriptive statistics of the motorway scenarios 133

Table 4.3: Parameter estimates and t-test of parameter equivalence of the base car-following models 144

Table 4.4: Parameter estimates considering sociodemographic characteristics...... 147

Table 4.5: Parameter estimates of the latent stress car-following models 149

Table 4. 6: Parameter estimates of the latent variable car-following models with sociodemographic variables 154

LIST OF TABLES

Table 5.1: Descriptive statistics of the two datasets 179

Table 5.2: Models parameter estimates, t-test of individual parameter equivalence and TTS results 181

Table 5.3: Parameters and TTS results after model updating 187

Table 5.4: Parameter estimates of the joint model 189

LIST OF FIGURES

Figure 2.1: The University of Leeds Driving Simulator (UoLDS) 44
Figure 2.2: Time pressure emoji 48
Figure 2.3: The urban setting .... **Σφάλμα! Δεν έχει οριστεί σελιδοδείκτης.**
Figure 2.4: The motorway setting 51
Figure 2.5: The motorway setting sections. 51
Figure 3.1: The University of Leeds Driving Simulator 91
Figure 3.2: Time pressure indications 93
Figure 3.3: Illustration of the intersection 94
Figure 3.4: Accepted gaps and sizes without and with time pressure 98
Figure 3.5: Example of SCRs extraction 103
Figure 3.6: Variations in gap acceptance probabilities in Models 1 and 4 109
Figure 3.7: Sensitivity plots of the dummy variables used in Model 4 on gap-acceptance probability 110
Figure 3.8: Sensitivity plot of heart rate and SCR on gap-acceptance probability 111
Figure 3.9: Marginal rates of substitution 112
Figure 4. 1: The University of Leeds Driving Simulator 128
Figure 4. 2: Time pressure emoji 129
Figure 4. 3: Example of the proposed car-following framework incorporating stress 138
Figure 4.4: Sensitivity plots of the “Aggressive drivers” car-following model 143
Figure 4.5: Reaction time distributions of the car-following models 145
Figure 4.6: Time headway sensitivity analysis of the “No events” latent variable model 150
Figure 4.7: Relative speed sensitivity analysis of the “No events” latent variable model 151
Figure 4.8: Time headway sensitivity analysis of the “Aggressive drivers” latent variable model 152
Figure 4.9: Relative speed sensitivity analysis of the “Aggressive drivers” latent variable model 152
Figure 5.1: (left) I-80 motorway data collection site, (right) Screenshots of the motorway setting of NG-DBM 177
Figure 5.2: Reaction time distributions of the car-following models 180

Figure 5.3: Sensitivity analysis of the car-following models.................................. 185
Figure 5.4: Sensitivity analysis after Bayesian updating 187
Figure 5.5: Sensitivity analysis after Combined Transfer Estimation 188

CHAPTER 1: INTRODUCTION

1.1 Background

Driving behaviour models refer to the representation of drivers' tactical manoeuvring decisions in different traffic conditions, based on mathematical approaches. These models mostly include acceleration-deceleration, lane-change and gap-acceptance decisions of each driver as a response to the surrounding traffic. Acceleration and lane-changing are related to the longitudinal and lateral interactions on the road, respectively. Gap-acceptance is related to intersection crossing but it is also a part of the lane-change process. These driving behaviour models are a core component of traffic microsimulation tools and are extensively used to investigate phenomena such as traffic breakdown, hysteresis, stop-and-go traffic etc. through explicit representation of drivers' behaviour at the individual level. Driving behaviour models can be also used to test network performance under situations of different geometric designs, traffic controls and a variety of traffic management measures (Venter et al., 2001). Thus, the accuracy of driving behaviour models in these applications is of substantial importance in order to accurately represent driving behaviour and its effects.

Over time, several driving behaviour models have been proposed and calibrated. Most of these models approach the issue of driving behaviour as a function of variables related to the surrounding traffic e.g. speed, relative speed, headway available gaps etc. A main drawback of these approaches is the limited incorporation of heterogeneity in behaviour across drivers (e.g. via desired speed) and absence of within driver heterogeneity. However, driving is a complex task and research from other fields as traffic psychology has shown that driving behaviour is influenced by factors such as drivers' individual characteristics, vehicle attributes, network characteristics, and environmental characteristics. Among the limitations of existing driving behaviour models, the impact of drivers' characteristics has already been reported in the existing literature (e.g. Saifuzzaman and Zheng, 2014; Zheng, 2014). Lancaster and Ward (2002) listed a series of factors that affect driving behaviour: gender, age, education, nationality, personality, aggression, driving confidence, thoroughness in decision-making, attitudes, risk perception, social deviance, previous accident experience, live events, stress, fatigue and physiology. These factors indicate that apart from the heterogeneity across drivers (e.g. sociodemographic characteristics), differences in driving behaviour may occur also within the same individual (e.g. stress, fatigue etc.). Drivers' imperfect behaviour can also arise as a result of their misjudgement in their own performance. For instance, Rolim and Baptista (2018) observed drivers for a given period of time and concluded that they failed to evaluate their observed behaviour, in terms of aggressiveness.

From all the above, it emerges that there is an imperative need for further research regarding the effect of individual characteristics within a driving behaviour modelling context. Thorough investigation of driving behaviour would require extended data collection approaches, the ability to capture driving behaviour in a variety of situations while at the same time, detailed information about drivers themselves is being collected. This is not easily possible in field traffic settings. The answer to this challenge may have been provided already in the field of safety research and the use of driving simulators. Amongst their advantages, driving simulators offer a controllable and repeatable environment where subjects can be tested under the same traffic conditions and scenarios in a safe manner. Also, data is collected with high accuracy such that any deficiencies of real traffic observations with respect to measurement errors are eliminated in a driving simulator environment. Moreover, it is easy to collect a plethora of information regarding drivers, such as sociodemographic characteristics, psychological and physiological indicators, amongst others. To the aforementioned benefits, it should be also added the longer observation period compared to the very short periods typically covered by field traffic data (Toledo, 2007). These benefits do not come without a price however since the behavioural validity of driving simulators has been, in some cases, criticised while other unexpected inconveniences such as simulator-related sickness have been reported.

A potential solution to the problems reported in the previous paragraph could be merging driving simulator with video data. This combination could result in model estimations that would have all the benefits from simulator data (e.g. identifying and quantifying the effects of sociodemographic characteristics, stress etc.) while at the same time acknowledging and capturing any potential realism-related deviation in observed behaviour by rescaling with real traffic data. An approximation of driving behaviour models similar to the suggested one could potentially lead to new directions in driving behaviour modelling and more behaviourally representative models. Thus, the scope of the current PhD study has been to investigate some of the aforementioned aspects, with a particular focus on: (a) The effects of drivers' stress levels and attributes on driving behaviour, (b) The estimation of driving behaviour models with specifications that incorporate drivers' characteristics , and (c) testing approaches to close the gap (if any) between models estimated with driving simulator and real traffic data.

The current chapter has been organised to present the existing driving behaviour models and highlight their limitations. Moreover, findings from the literature are reported, in order to underline the importance of drivers' characteristics that are usually omitted from these models. Finally, the research questions, and how they have been addressed via the undertaken research, are presented.

1.2 Driving behaviour models

1.2.1 Acceleration models

Acceleration models, refer to the longitudinal component of driving behaviour. They are divided in car-following and free-flow models. The former category is the most common among all types of driving behaviour models. Car-following (CF) behaviour has been extensively investigated and several approaches have been proposed. Car-following models focus on the investigation of longitudinal interactions of vehicles on the road, when moving at close headways. This concept has been initially introduced by Pipes and Reuschel (Pipes, 1953; Reuschel, 1950). Pipes assumed that the follower aims in maintaining a safe time headway of 1.02s from the leader. This value was derived from a recommendation in the California Vehicle Code. Using Laplace transformations, he developed theoretical expressions for the subject's acceleration given a mathematical function that describes the leader's behaviour.

The GM model and its extensions

The concept of CF behaviour was further elaborated and the GM Research Laboratories contextualised it into the stimulus-response framework (Chandler et al. 1958, Gazis et al. 1961). This approach considered CF behaviour as a set of reactions to the stimuli presented to the drivers. The response (acceleration) to a specific stimulus was lagged to capture the effect of reaction time as shown in Equation 1.1.

$$\text{response}_n(t) = \text{sensitivity}_n(t) \times \text{stimulus}_n(t - \tau_n) \qquad (1.1)$$

where, t corresponds to the time of a specific acceleration observation of driver n, and τ is the reaction time. In this concept, reaction time includes both perception reaction time and foot movement time. The GM model specification had several stages of development but the most common (Gazis et al, 1961), is given by the Equation 1.2:

$$a_n(t) = \alpha \frac{V_n(t)^{\beta}}{\Delta X_n(t - \tau_n)^{\gamma}} \Delta V_n(t - \tau_n) \tag{1.2}$$

where α, β, γ are parameters to be estimated, V_n is the current speed of driver n, ΔV_n is the relative speed with the lead vehicle and ΔX_n is the space headway. In this specification, the stimulus was represented by relative speed while sensitivity was a function of speed and space headway. The model was validated using real observed traffic data. In this form of the GM model, the sensitivity term is formed by the speed of the follower and the spacing between the follower and the leader. Some of the most acknowledged limitations of this specification (Saifuzzaman and Zheng, 2014) include identical reaction for all drivers, the ability of drivers to perceive very small changes in driving conditions and generic parameters that did not capture differences in between acceleration and deceleration regimes.

The GM model was further revisited and several alternative specifications were suggested. For instance, Lee (1966) introduced a memory function in the model specification to capture the reactions of drivers to the relative stimulus over a period rather than an instantaneous moment. However, one of the most significant contributions has been by Ahmed (1999). In his research, Ahmed suggested a general acceleration framework consisted of two main parts, (a) the car-following component and (b) the free-flow component. The former, was based on the GM model considering however different sets of parameters to capture acceleration-deceleration asymmetry and also accounted for the effects of traffic density. Another main contribution was the treatment of reaction time as a random variable that follows a specific distribution, rather than having an identical and fixed value for all drivers. The concept of a general acceleration model was also discussed some years earlier by Subramanian (1996). The general acceleration model of Ahmed can be summarised, as shown in Equations 1.3 and 1.4:

$$a_n^{cf,g}(t) = \alpha^g \frac{V_n\left(t - \xi\tau_n\right)^{\beta^g}}{\Delta X_n(t - \xi\tau_n)^{\gamma^g}} \, k_n(t - \xi\tau_n)^{\rho^g} \, \Delta V_n(t - \xi\tau_n)^{\lambda^g} \tag{1.3}$$

$$a_n^{ff,g}(t) = \lambda^{ff}\left[V_n^*(t - \tau_n) - V_n(t - \tau_n)\right] \tag{1.4}$$

where, V_n is subject speed, V_n^* is the desired speed, ΔV_n is relative speed, τ_n is the reaction time, ΔX_n is the space headway, k_n is the density of the traffic ahead, ξ is a parameter that indicates the update of drivers' perception during the driving process, and α^g, β^g, γ^g, ρ^g, λ^g, λ^{ff} are parameters to be estimated. The model was later extended by Toledo (2003) in an integrated framework to combine acceleration and lane-change decisions.

One of the main drawbacks in the CF component of Ahmed's specification is the assumption that drivers accelerate when the relative speed is positive and decelerate when negative. In order to address this limitation, Koutsopoulos and Farah (2012) suggested a new model specification where the desire to accelerate, decelerate or do-nothing was treated as a latent variable based on utility functions. The model component however that was capturing the probability of the acceleration observations was based on Ahmed's specification. Another variation of this model has been used to model CF behaviour on roads with weak lane discipline (Choudhury and Islam, 2016).

Alternative car-following model specifications

A further inspection of the GM model shows that if two vehicles move at the same speed, any spacing between the follower-leader pair is accepted. This assumption is not realistic however, since at short headways this is not likely to be the case. Thus, alternative CF specifications have been suggested across time. One of the most well-known approaches is the introduction of desired measures. For instance, Helly (1959) proposed the concept of desired following distance; a driver attempts to minimise both relative speed and the difference between the actual and desired space headway. Another example of a desired measures CF model is the Intelligent Driver Model (IDM) proposed by Treiber et al. (2000) where desired speed and space headway were considered.

Another category of CF models is the safety-distance models where the main assumption is that drivers consider spacing distance and not relative speed as stimulus. One of the first safety-distance models was Newell's (1961) but the most popular specification was suggested by Gipps (1981). Another also commonly known type of CF models is the Optimal Velocity (OV) models. The first OV model was proposed by Bando et al. (1995) and assumes that each vehicle has an optimal speed which depends on the distance from the preceding vehicle. The model was later updated by Bando et al. (1998) suggesting a specification that accounted for the effects of reaction time. The OV model was extended to other forms as the Full Velocity Difference (FVD) model (Jiang et al., 2001), that also accounted for the effect of relative speed or the Asymmetric Full Velocity Difference (AFVD) model (Gong et al., 2008) that also incorporated acceleration-deceleration asymmetry. The OV model and its variants have received considerable attention in the physics community. Several models have been developed to investigate hypothetical cases on simulated data. Although this approach has been widely applied in this field, owing to its feasibility in theory analysis, only few studies established their findings based on observed data (Zheng et al., 2012).

Some less common CF modelling approaches include cellular automata models (e.g. Nagel and Schreckenberg, 1992) and fuzzy-logic models (McDonalnd et al., 1997). However, the latter approach involves the definition of fuzzy sets, to capture perceptual uncertainties of drivers, which is a challenging process that makes difficult the estimation and validation process (Saifuzzaman and Zheng, 2014)

Despite any differences in specification, the models presented in the previous paragraphs share in common a specific characteristic; in all cases acceleration is approximated as a function of variables related only to traffic conditions while the major focus has been in examining the adequacy of these models to represent real traffic phenomena as oscillations capacity drop etc. The effects of traffic conditions on acceleration are usually examined with parameters estimated from observed data, but in other cases arbitrary but reasonable values are used (based on existing) and also some completely data driven approaches have been adopted that do not investigate any associations among variables (Papathanasopoulou and Antoniou, 2015; Kendziorra, 2016). However, the engineering based approach of the aforementioned models does not necessarily reflect driving behaviour accurately. As discussed in the next sections of this chapter, it is well established that driving behaviour is influenced by additional factors related to drivers' characteristics and does not follow the optimal patterns that most of the engineering-based models indicate. For instance, Laval et al. (2014) calibrated a desired acceleration CF model including a "white noise" term and found that human errors can be responsible for traffic instabilities. The potential impacts of human factors and their incorporation in CF model specifications has been discussed in several studies in the existing literature.

The human factors approach in car-following models

In their extensive literature paper, Saifuzzaman and Zheng (2014) mention that the behavioural representativeness of CF models was criticised after the historical review of Brackstone and McDonald (1999). Following this paper, Hancock (1999) published a work to highlight the deficiencies of CF models in capturing in a psychological way the human way of thinking. Some additional notable papers from this period, regarding the same issue, were also those of van Winsum (1999), Boer (1999) and Ranney (1999) while Brackstone and McDonald (2003) published a paper, a few years later, where they explicitly investigated potential drawbacks of microscopic simulation models in terms of the safety constraints imposed, data accuracy and time step. However, some of the first attempts to address specific limitations of CF models were originated more than two decades before the aforementioned studies. For instance, Wiedemann (1974) introduced the concept of perceptual thresholds, within an effort to relax the assumption of many previous CF models and establish minimum values of change in the stimulus that drivers can perceive. Each threshold was defined based on spacing distance and/or relative speed and was a part of a zone where the driver would either react or not to the stimulus. A similar model was proposed by Fritzsche (1994). However, as reported by Saifuzzaman and Zheng (2014) the calibration approaches to the perceptual threshold models are based either through existing commercial microsimulation software or the results are not reported in the studies at all.

The incorporation of human factors in CF models continued to be a considerably studied topic and several various model specifications were suggested to capture the impacts of human factors. Hamdar et al. (2008) and Hamdar et al. (2014) suggested a car-following model, based on the prospect theory of Kahneman and Tversky's (1979). The model considered car-following as a sequential risk-taking process and allowed for risk-taking manoeuvres based on a probability of being involved in a rear-end collision. The probability was estimated as a function of variables such as acceleration, spacing and relative speed. In another approach, Saifuzzaman et al. (2015) incorporated an additional term in their model, in order to represent task difficulty (TD) as expressed by the Task-Capability Interface (TCI) model (Fuller, 2005). This term was specified as a function of time headway, spacing and speed of the driver. In a rather different approach, Hoogendoorn et al. (2010) conducted a driving simulator experiment to investigate the relationships between mental workload and car-following without however incorporating the former in the model specification. Finally, Farah and Koutsopoulos (2014) modified the GM model and expressed the stimulus part as a series of socio-demographic variables. In a more recent study, Micó et al. (2018) questioned the assumptions of most CF models regarding safe following distance and conducted a driving simulator study to investigate differences between different types of following behaviour i.e. driving to keep distance and driving to keep inertia. However, no modelling approaches were implemented in this study.

1.2.2 Lane-change and gap-acceptance models

Lane-change (LC) is also an important driving behaviour that impacts safety and network performance. In his extensive literature review, Zheng (2014) grouped lane-change in two main categories: (a) models that investigate the decision making process behind a LC manoeuvre and (b) models that investigate the impact of LC manoeuvre on traffic. The latter group however, is beyond of the scope of the current research work.

Rule-based lane-change models

One of the first LC models was introduced by Gipps (1986). This model assumes that a driver focuses on balancing between two conflicting goals namely, keeping a desirable speed and desirable safety. Gipps' model is rule-based and a driver decides to execute or not a lane-change considering the possibility, necessity and desirability of it. The main factors that influence this decision are safety, obstructions on road, transit lanes, distance from turning point, presence of heavy vehicles and lane speed. The model applies a set of deterministic rules to predict lane-change behaviour based on the aforementioned variables. This rule-based approach can be also considered as the main limitation of Gipps model as every decision is deterministic. For instance, some lane-changes occur only when they are safe and the heterogeneity among drivers' preferences is not considered.

Some of the deficiencies in Gipps model were considered in other rule-based lane-change models. Hidas developed the SITRAS (2002) and the ARTEMis (2005) models. One of the main differences with Gipps model is that lane-change manoeuvres are categorised in free, cooperative and forced. This addition allows for LC manoeuvres also when the available gaps are below the safe margins as a driver "sends" a message of courtesy which is evaluated by the follower of the adjacent lane. If the following vehicle decides to provide courtesy, it decelerates in order to increase the available gap. Another rule-based model was developed by Kesting et al. (2007) under the name of MOBIL. The model is mainly defined by two rules, a safety constrain and a desirability rule.

Probabilistic lane-change models

Following the rule-based approach of the Gipps' model (1986), Yang & Koutsopoulos (1996) suggested a new LC modelling approach and applied it in the MITSIM microsimulation software. The main difference of this model is that instead of a deterministic decision making approach, a lane-change probability is introduced, in order to add stochasticity to the model. The decision making for lane-change in MITSIM is applied, similarly to Gipps' lane-change model, in terms of necessity, desire and gap-acceptance. The lane-change is divided in mandatory (MLC) and discretionary (DLC).

The probabilistic approach of Yang and Koutsopoulos (1996) was followed by Ahmed (1999) where lane-change probability was based on Random Utility Theory. The concept of mandatory (MLC) and discretionary (DLC) lane-changes was also applied in this model. The model specification also included a gap-acceptance model component where the available gap was compared with a latent critical gap to evaluate whether the LC manoeuvre will be completed. The model of Ahmed (1999) examined separately the cases of MLC and DLC. However, the distinction between MLC and DLC is not always clear and the MLC situations are not always perceived by drivers. In order to overcome this limitation, Toledo (2003) developed an integrated lane-change model where both cases were included in the same utility function. The model also incorporated acceleration decisions within the same framework. The lane-change decisions in Toledo's model considered only the adjacent lanes as potential target lanes. However, a LC manoeuvre to a specific lane does not necessary indicate that the latter is also the target lane. To address this limitation Choudhury (2007) proposed a latent plans framework where each lane had a specific probability to be the target lane. The model also used the gap-acceptance model previously used by Ahmed (1999) and Toledo (2003). The latent plans framework also introduced state-dependence via a Hidden Markov Model. Choudhury (2007) examined lane change behaviour in merging sections, considering three different states of merging behaviour: normal, courtesy and forced. The model was estimated using video trajectory data. Later, Choudhury et al. (2009) extended the framework of merging behaviour, by incorporating acceleration behaviour based on the model of Ahmed (1999). Another example of state dependence implementation in a LC model was presented by Toledo and Katz (2009).

Gap-acceptance and other driving behaviour models

A main component in some lane-change model is the gap-acceptance model. As mentioned by Toledo (2007), in his literature review paper, gap-acceptance models were initially developed to approximate intersection crossings. These models are presented more detailed in Chapter 3 of the thesis. Moreover, gap-acceptance models have been also used to represent overtaking behaviour (Farah and Toledo, 2010; Toledo and Farah, 2011). Ghods & Saccomanno (2011) divided the overtaking manoeuvre in five stages: catch-up, desire to overtake, gap acceptance, passing, and returning to lane and also cited a series of variables (e.g. speed of overtaken vehicle, vehicles' lengths, reaction time, available gaps etc.) which affect overtaking behaviour. In a rather different modelling approach, Danaf et al. (2015) estimated a series of models to predict the effect of driving anger in drivers' choices in specific situations, developed in a driving simulator. The modelled choices were drivers violations. Their modelling approach was based on the trait-state driving anger theory (Deffenbacher et al., 1994). In a similar recent work, Tarabay (2018) presented a red-light violation model, based on driving simulator data, incorporating drivers' physiological responses as indicators of stress.

1.3 Key limitations of driving behaviour models

The issue of accurately reproducing driving behaviour has been a major topic of discussion and several approximations have been proposed. Going back to Equation 1.2, it is evident that for given values of speed, headway and relative speed, the model would predict identical acceleration for all drivers. However, this would not be the case in real life as response would vary across individuals. Thus, in many cases, the research focus shifts from the traditional traffic flow theory and revolves around the effect of drivers' characteristics. In their literature papers, Saifuzzaman and Zheng (2014) and Zheng (2014) already highlighted this issue, regarding the traditional engineering driving behaviour models for car-following and lane-changing respectively. This has also been the case in some of the existing commercial microsimulation packages. Lützenberger and Albayrak (2014) reviewed a series of available commercially available software in terms of their capability to capture human factors. The most common approach in microsimulation tools is to implement a basic driving behaviour model and then establish variations of it (e.g. cautious, aggressive etc.) that use different parameters to represent driving behaviour. However, it is not clear how the different ranges in specific behaviours (e.g. speeding) of these groups are decided while in Bonsall et al. (2005) it is reported that in many cases they are derived from theory rather than observed data. The same study also questions the approach of most traffic simulation models to constrain driving behaviour in favour of safe representations and suggests that "unsafe" but more realistic parameters in these models would be more appropriate. In a quite similar study, Laagland (2005) has approached the issue of aggressive behaviour in traffic simulation. He concluded that this aspect of driving behaviour is considered only in a few packages while he also proposed a methodological approximation to deal with this issue.

As discussed also in Chapter 4 of the thesis, some engineering-based models have attempted to capture some of the drivers' characteristics (via e.g. more elaborated model specifications based on prospect theory or the task capability concepts) however, in these cases these additional terms are expressed as a function of traffic variables ignoring the drivers' actual individual characteristics. Another practice has been the use of random disturbance terms but, despite the increase in the performance of models, the added value regarding the effects of human factors can be considered limited as the source of variance in driving behaviour is not explained by the disturbance terms. However, there are also a few examples of modelling approaches incorporating human factors in the existing literature. For instance, Farah and Koutsopoulos (2014) have estimated a car-following model expressing the stimulus part as a series of variables including drivers' age. Moreover, although not strictly related to traditional forms of driving behaviour models (e.g. car-following or lane-change), the effects of human factors have been investigated in overtaking models (e.g. Farah and Toledo, 2011) and in alternative modelling approaches related to driving anger (Danaf et al. 2015) and red-light violation (Tarabay, 2018). Further to the aforementioned approaches, additional work still needs to be undertaken in order to thoroughly investigate and incorporate drivers' characteristics in traditional driving behaviour models.

It should be mentioned that apart from the engineering-focused models discussed previously, there is also another category of driving behaviour models that attempts to approximate driving behaviour from a more cognitive perspective. Vaa (2001) presented a literature review of these models that included among others, Näätänen and Summala's (1974) "Zero-Risk" model, Wilde's (1982) "Risk Homeostasis" model and Fuller's (2000) "Task-Capability Interface" model. The main concept of the latter has been adopted as a mathematical modelling approach by Saifuzzaman et al. (2015) in car-following while Varotto et al. (2018) used a later adaptation of Fuller's model (Fuller, 2011: Risk Allostasis Theory) to model control transitions and target speed of drivers using Adaptive Cruise Control systems. However, apart from the aforementioned cases, the driving behaviour models described in Vaa's (2001) work are mostly theoretical frameworks and thus not appropriate for predictions in microsimulation tools.

The inclination of researchers towards integrated approaches to approximate driving behaviour also appears in other studies. Toledo et al. (2007) stressed the need for the development of a general driving behaviour model and suggested a theoretical framework that captures both aspects of drivers' characteristics and surrounding environment data. Although this approach was not strictly related to modelling approaches, as defined in the previous sections, it still indicates that drivers' characteristics can have a significant impact. A similar holistic framework was also proposed by Rakotonirainy and Maire (2005) including variables related to environment, vehicle dynamics, drivers' psychological and physiological state. Although the use of Dynamic Bayesian Networks was suggested as a modelling tool, the whole framework was a theoretical approach and the authors did not present any application on data. A driving behaviour framework incorporating variables as personality, attitudes etc. was also suggested by Sidoumou et al. (2013) with the application of machine learning techniques. The aforementioned examples are indications that the research community has acknowledged the importance of human factors in modelling frameworks. However, in very few cases human factors have been actually considered in mathematical driving behaviour models. As discussed in Section 1.1, an obstacle to this approach is data related. In many cases models are calibrated with video trajectory, GPS or simulated data. As discussed in Section 1.6, a potential solution to this issue can be suggested driving simulator or naturalistic driving data. Also, Sections 1.4 and 1.5, focus on the effects of drivers' characteristics on driving behaviour, to provide a better understanding regarding the importance of this aspect.

1.4 The effects of human factors on driving behaviour

The previous section highlighted the lack of human factors in most of the existing driving behaviour models as one of their limitations. Their effects have been confirmed in several studies, especially in the field of traffic psychology. Some of the most studied human factors, are sociodemographic characteristics with a main emphasis on gender and age. In general, male drivers have been linked to a higher likelihood of risky driving behaviour (Oltedal & Rundmo, 2006; Lonczak et al., 2007; Rhodes & Pivik, 2011; Taubman & Yehel, 2012; Jiménez-Mejías, 2014) and violations (Blockey & Hartley, 1995; Westerman & Haigney, 2000; González-Iglesias et al., 2012; Varet et al. 2018) while it has been also the case that no gender-related differences occurred in terms of errors, lapses or violations (Özkan, & Lajunen, 2005). Further to the outcomes of the aforementioned studies that rely on self-reported surveys, Papantoniou et al. (2019) conducted a driving simulator experiment and found that female and older drivers have been more prone to errors. This finding was consistent with Westerman & Haigney (2000) where a similar gender effect was found. Regarding issues more related to driving behaviour modelling, Lyu et al. (2018) analysed naturalistic data collected at an expressway in

China, that also included driving on a deceleration lane in order to take a specific exit ramp. The authors concluded that male drivers are more aggressive in overtaking behaviour as they performed an overtaking manoeuvre at very short distance before entering in the deceleration lane. Moreover, more experienced and professional drivers, performed the lane-change to the deceleration lane earlier, indicating higher risk awareness of those drivers. The effects of age have been also investigated in a similar way and younger drivers have been generally associated to a higher propensity to risky or aggressive behaviour (Jonah, 1990; Krahé & Fenske, 2002; Iversen, & Rundmo, 2004; Rhodes & Pivik, 2011; Taubman & Yehel, 2012), violations and errors (Blockey & Hartley, 1995; Westerman & Haigney, 2000; Oppenheim et al., 2016), speeding behaviour (Quimby et al., 1999), crash rate (Ryan et al., 1998) and distracted driving (Pope et al., 2017).

Apart from the more traditional sociodemographic characteristics, the effects of individual traits have also received significant attention, where personality and attitudes have been considered the most. A common approach related to the former is based on the big five traits, else five factor model (FFM) approach (Goldberg, 1990; Goldberg, 1993) or variants of it. The various aspects of drivers' personality have been linked to different types of driving behaviour. A more detailed list of the findings related to the effects of personality is outlined in Table 1.1.

Apart from the personality traits, also the effects of attitudes on driving behaviour have been investigated. More particularly, Ulleberg & Rundmo (2002) and Ulleberg & Rundmo (2003) developed an attitudinal questionnaire scale and found that risk perception and attitudes towards traffic safety influence risky driving behaviour. The same outcome was also derived by Iversen (2004) and Musselwhite (2006).

Except for the aforementioned factors, the focus of research community has been also put on the effects of emotions, mostly anxiety and anger. It is worth mentioning that not only negative emotions have been examined, with respect to impaired driving behaviour, since also positive emotions can influence driving behaviour in a negative way e.g. slower responses in hazard detection (Zimasa et al., 2017). With respect to the latter, Jones & Jonsson (2005) reported that happier drivers are also better drivers. However, Jeon et al. (2014) compared the effect of neutral, fear, anger and happiness states in driving behaviour and found that happiness impairs driving behaviour more than fear in cases of lane keeping task and respect of traffic rules. Another outcome was that happier drivers were more confident despite their low performance. Towards the same direction, Pêcher et al. (2009) found in a driving experiment that happy distracted drivers resulting in a sharp decrease of their mean speed and impairment of vehicle control while sad music made drivers to drive more carefully. Finally, Eherenfreund-Hager et al. (2017) concluded that both positive and negative emotions increase risk-taking in a driving simulator experiment.

Table 1.1: The effects of personality traits on driving behaviour

Study	Personality trait	Effect on driving behaviour
Taubman-Ben-Ari & Yehiel, 2012	High Extraversion Low Agreeableness Low Conscientiousness	Reckless behaviour
	High Neuroticism Low Conscientiousness	Anxious behaviour
Ulleberg & Rundmo, 2003	Altruism	Increased risk perception, positive attitudes towards traffic safety
	Anxiety	Increased risk perception, more positive attitudes towards traffic safety
	Normlessness	Decreased risk perception, less positive attitudes towards traffic safety
	Sensation-seeking	Less positive attitudes towards traffic safety
	Aggression	Less positive attitudes towards traffic safety
Arnett et al., 1997	Sensation-seeking Aggression	Reckless driving behaviour in young drivers
Oltedal & Rundmo, 2006	Irritability	Positive correlation with risky driving behaviour and accident involvement
	Normlessness	Positive correlation with risky behaviour
	Aggression	Positive correlation with risky driving behaviour and accident involvement
	Anxiety	Negative correlation with risky driving behaviour
	Excitement-seeking	Positive correlation with risky driving behaviour and accident involvement
Machin & Sankey, 2008	Excitement-seeking	Increased likelihood of accident involvement, increased tendency in speeding, increased risk-taking behaviour
	Altruism	Decreased likelihood of accident involvement, decreased tendency in speeding, aversion to risk-taking
Dahlen et al., 2012	Emotional stability	Negative effect on aggressive driving
	Extraversion	Positive effect on aggressive driving
	Openness	Positive effect on aggressive driving
	Agreeableness	Negative effect on aggressive driving
	Conscientiousness	Negative effect on aggressive driving
Ge et al., 2014	Sensation-seeking	Positive effect on aggressive driving, risky driving, drunk driving and negative emotional driving
	Anger	Positive effect on aggressive driving, risky driving, drunk driving and negative emotional driving
	Altruism	Negative effect on aggressive driving, risky driving, drunk driving and negative emotional driving
Jovanović et al., 2011	Agreeableness	Driving-related anger and aggression
	Conscientiousness	Driving-related anger but negative effect on driving aggression
	Altruism	Prosocial driving behaviour
Măirean and Havârneanu (2018)	Better-than-average	Risky behaviour
Riendeau at al. (2018)	Conscientiousness	Lower risky and unsafe behaviour among middle-aged drivers
	Sensation-seeking	Risky and unsafe behaviour among young drivers
	Extraversion Neuroticism	Unsafe driving behaviour
Oppenheim et al. (2016)	Sensation-seeking	Increase in violations
Stephens et al. (2018)	Mindfulness	Decrease in driving aggressiveness

Regarding the effects of negative emotions, Steinhauser et al. (2018) related anger with increased speeding and reduced following distance in a driving simulator study. Similarly, Zhang et al. (2018) deduced similar conclusions with respect to anger and aggressive driving behaviour. Hu et al. (2013) concluded that both negative emotions and mood may decrease drivers' judgement ability and make them consider driving situations less risky. In a study based on driving simulator, Roidl et al., (2014) found that people who experienced anger drove faster after a frustrating event, but for a short period, while drivers who experienced more anxiety were influenced for a longer time after a frustrating event. Moreover, they concluded that drivers with higher levels of anger violated the speed limit for longer periods. Shahar (2009) found a positive relation between the self-reported level of anxiety and driving errors and lapses. They also reported that higher levels of anxiety are related to more distraction and violations. Similarly, Dula et al. (2010) found a correlation between anxiety and dangerous driving. Taylor et al. (2007) used on-road observations in order to investigate the effects of anxiety to driving performance. Their results indicated that fearful drivers had the same type of errors, compared to not fearful however, they did more errors than the latter. Also, fearful drivers reported increased levels of perceived anxiety and also rated lower their driving skills.

This section briefly presented some commonly examined individual factors that have been found to influence driving behaviour. In an extensive literature review related to this issue, Lancaster and Ward (2002) listed in more details a series of individual characteristics and their effects. Amongst these, stress was also included in a prominent position. However, the latter has not been presented in the current section. As one of the main aims of the current thesis had been to investigate the effects of stress on driving behaviour, it is presented separately in the next section.

1.5 Stress and driving behaviour

1.5.1 Defining stress in the driving context

A popular approach relating stress to the driving task was attempted by Gulian et al. (1989) based on Lazarus's transactional framework about stress (Lazarus and Launier, 1978). That framework suggested that stress, as a part of the driving task, can emerge in situations that test drivers' abilities, reduce their perceived control or threatens their mental or physical health. In that work, the authors distinguished two different types of stress, namely, *driving stress*, which is exclusively related to stress that is derived from the driving task and *drivers' stress*, which is a more comprehensive definition that also includes life-related stress. Moreover, they determined two types of driving-related stress. The first referred to specific situations that may be interpreted as dangerous or demanding by the drivers while the second can arise as a result of the prolonged exposure of drivers to stressful situations i.e. daily commuting or long-distance journeys. As a highlight of that work, Gulian et al. (1989) developed a questionnaire survey named *Driving Behaviour Inventory (DBI)*. In their study they combined the DBI with other existing personality tests and derived five different dimensions of drivers' stress vulnerabilities namely, driving aggression, irritation when overtaken, alertness, dislike of driving and frustration after a failed overtaking. The DBI questionnaire was further reviewed and its new form was named *Driving Stress Inventory* (DSI: Matthews et al. 1997). Later, Matthews (2002), further elaborated on the aforementioned approach of driving related stress and suggested that the environmental stimuli (stressors) are assessed by some personal factors, related to drivers' characteristics and both factors influence their cognitive stress process. The cognitive stress process results in two different types of consequences namely, subjective (e.g. anger, anxiety, tiredness) and performance changes (e.g. changes in speed, reduced control of the vehicle etc.). Based on his previous work he suggested three different aspects of drivers' stress namely, anxiety, aggression and fatigue. Each of these aspects was related to the environmental stimuli that causes them, the personality traits of drivers, the consequences to subjective stress, the changes in drivers' behaviour and the effects on safety. The basic elements of the aforementioned approach are outlined in Table 1.2.

Table 1.2: Transactional analysis of driver's stress

	Anxiety	Anger/ Aggression	Fatigue
Situational stressors	Threats to control (e.g. poor visibility)	Impedance, other traffic	Prolonged, high-workload traffic
Personality traits	Dislike of driving	Aggression	Fatigue-proneness
Key cognitions	Negative self-appraisal, low perceived control, emotion-focused coping	Negative other-appraisal, confrontive coping	Reduced effortful coping
Subjective stress	Distress, worry	Anger	Task disengagement, distress
Behavioural change	Loss of functional attention, behavioural caution	Risk-taking	Reduced control activity
Safety implications	Mixed	Impaired	Impaired

[Source: Matthews, 2002]

Drivers' stress is a multidimensional issue influenced by several different factors, both related to the demands of the driving task but also irrelevant to it. Each person has an initial tendency to get stressed while driving, which can be considered as a basic level of stress that is caused as a result of this task. That tendency is also reported as trait driver stress (Hennessy & Wiesenthal, 1997; Hennessy & Wiesenthal, 1999; Wickens et al., 2015). This type of stress is chronic and positively related to the overall perceived stress that arises during driving task (state driver stress). State driver stress arises owing to stressful factors (stressors) that occur during the driving task. However, each driver’s background is different and thus the same stressors may have different impact on strain. In other words, for a given stressful situation, drivers have different reactions. Some of the most common components of drivers’ background examined are the socio-demographic characteristics, experience, personality, mood, life stress etc. In most studies, the aforementioned characteristics are also examined in relation to the aggressive driving behaviour.

1.5.2 Driving-related stress occurrence

Stress as a part of the driving task can be directly related to its demands (e.g. lateral and longitudinal controls when following a road or another vehicle respectively), the environmental conditions (e.g. fog occurrence can reduce visibility and thus the cognitive ability of drivers), network characteristics as surface characteristics, junction frequency, and speed and flow per lane (Highways Agency, 1993; Van Treese et al., 2018) and/or potential secondary tasks e.g. use of navigation system, texting etc. (Schießl, 2007). Moreover, time urgency and the level of congestion also consist two important factors that influence state drivers’ stress (Hennessy & Wiesenthal, 1997; Hennessy & Wiesenthal, 1999; Hennessy et al., 2000). In particular, time urgency can increase the perceived state stress, even in low congestion conditions, while in heavy congestion, drivers’ stress is associated with aggressive behaviour. Some similar findings were found in a driving simulator study of Emo et al. (2016) regarding the effects of slow traffic on aggressive drivers. Finally, Hill and Boyle (2007) suggested four different situations which can induce stress namely, weather-related conditions, the interactions with other drivers (e.g. slow moving vehicles, drivers that brake constantly), conditions related to the driving task (e.g. crossing unprotected intersections, merging into heavy traffic, moving across exit lanes etc.) and limited visibility conditions (e.g. driving during the night, blocked vision by a heavy truck).

Apart from the situational induced stress, the latter can also occur from stressors not related to the driving task. For example, Rowden et al. (2011) found that the stress levels related to the work of each person have an effect on drivers’ stress as well. Also, Clapp et al. (2011) mentioned that driving performance is affected by the level of life stress. A similar outcome was also derived by Ge et al. (2014). More specifically, they found some correlations between driver’s and life (global) stress. The interpretation of this outcome indicates that someone who is stressed as a person in general, has also a higher tendency for increased driver’s stress. In the same study it is reported that some aspects of personality (sensation-seeking) also influence the levels of perceived driver's stress. Finally, Matthews et al. (1991) found an effect of mood state to drivers' stress.

1.5.3 The effects of stress on drivers' behaviour

The role of stress has been mostly investigated regarding its impact to drivers' decision-making process and aberrant driving behaviours. Drivers under stress are more likely to get involved in hazardous situations (Ge et al., 2014). With reference to Kontogiannis (2006), aberrant driving behaviour can be grouped in two main classes, namely *errors* and *violations*. Both classes are related to road accidents and incidents, therefore stress is considered as an issue related also to traffic safety. Similar findings regarding perceived stress are also reported by Westerman and Haigney (2000), Useche et al. (2015), Qu et al. (2016). Moreover, Ge et al., (2014) found that perceived stress is linked to aggressive and risky driving behaviour. Finally, Öz et al. (2010) found that the dimensions of stress related to anger and anxiety and hazard monitoring are related to accident involvement while excitement-seeking had a positive association with speeding behaviour.

It should be highlighted that although some studies imply a causal effect of stress on driving behaviour, the relationship between the two is not that straightforward, as a correlation of stress and driving behaviour does not necessarily imply that a specific driving action is an outcome of stress (Verma et al., 2019). In the same study, although the authors attempt to specify a model that captures this causality, they also acknowledge that stress can be caused as an outcome of driving behaviour.

1.5.4 The relation between stress and human physiology

The occurrence of stressors is followed by the activation of several human physiological responses. After the stressor passes however, the body relaxes and returns to a normal state (Bakker et al., 2011). The mechanism that leads the body into the state of alertness is called acute stress. Several studies have worked on this direction and tried to investigate drivers' stress through physiological responses. Some of the most commonly used physiological responses are heart rate (HR), heart rate variability (HRV), electrodermal activity (EDA), blood volume pulse (BVP), blood pressure (BP), respiration rate (RR), skin temperature (ST), electromyography (EMG) and brain-related activity via electroencephalogram (EEG). There are also eye-related measurements as pupil dilation and blinking frequency. It should be mentioned that heart-related measurements are obtained through electrocardiogram (ECG) or photoplethysmogram (PPG). A summary of some studies used such indicators is listed in Table 1.3. Although stress occurrence has been found to affect the physiological indicators, in most cases, this source of data is mainly being used to predict or detect stress, rather than investigating how these responses are linked to observed driving behaviour.

Table 1.3: Studies investigating driving-related issues using physiological data

Study	Study purpose	Data	Physiological responses
Cai et al. (2007)	Drivers' emotions	Driving simulator	HR, HRV, EDA, ST, RR, eye-related
Wang and Gong (2008)	Drivers' emotions	Driving simulator	RR, ST, BVP, EDA
Rimini et al. (2001)	Drivers' stress and fatigue	Driving simulator	ECG, EEG, ST, RR
Sun et al. (2011)	Driver fatigue	Driving simulator	HR, HRV, RR, blink frequency
Liang et al. (2007)	Driver distraction	Driving simulator	Eye-related measures
Yamaguchi et al. (2006)	Driver stress	Driving simulator	Salivary amylase activity (SAMY)
Haak et al. (2009)	Driver stress	Driving simulator	EEG, blink frequency
Johnson et al. (2011)	Comparison of physiological responses in simulator and on-road driving	Driving simulator, naturalistic	HR
Herrero-Fernández (2016)	Anger and physiological repsonses	Driving simulator	HR, EMG
Rebolledo-Mendez et al. (2014)	Drivers' emotions	Driving simulator	ECG, EDA, EEG
Pradhan et al. (2005)	Risk perception	Driving simulator	Eye-related measures
Shamsul et al. (2014)	Drivers' stress and fatigue	Driving simulator	EEG, salivary cortisol
Yamakoshi et al. (2008)	Drivers' stress	Driving simulator	BVP, ST
Thi-Hai-Ha Dang (2014)	Cognitive workload	Driving simulator	HR, EDA
Rendon-Velez et al. (2016)	Time pressure effects	Driving simulator	HR, HRV, RR, blink frequency
Chen (2013)	Drivers' stress	Driving simulator	ECG, EDA
Li et al. (2013)	Driving behaviour	Naturalistic	Eye-related measures
Singh and Queyam (2013)	Drivers' stress	Naturalistic	HR, EDA, RR, EMG
Healey and Picard (2005)	Drivers' stress	Naturalistic	HR, EDA, RR, EMG
Rigas et al. (2012)	Drivers' stress	Naturalistic	HRV, EDA
Sena et al. (2014)	Drivers' stress	Driving simulator, naturalistic	HRV
Miller and Boyle (2013)	Drivers' stress	Naturalistic	HRV
Wang et al. (2013)	Drivers' stress	Naturalistic	HRV
Singh et al. (2013)	Drivers' stress	Naturalistic	EDA, HRV
Malta et al. (2011)	Drivers' frustraation	Naturalistic	EDA
Hamaoka et al. (2005)	Drivers' stress	Naturalistic	HR
Schneegass et al. (2013)	Cognitive workload	Naturalistic	HR, HRV, EDA
Leng et al. (2007)	Drivers' emotions	Naturalistic	BVP, ST, EDA, RR, facial recognition
Healey et al. (1999)	Drivers' stress	Naturalistic	HR, EDA, RR, EMG
Mesken et al. (2007)	Drivers' emotions	Naturalistic	HR
Tarabay and Abou-Zeid (2018)	Cognitive workload	Driving simulator	HR, EDA
Tarabay (2018)	Driving behaviour	Driving simulator	HR, EDA

1.6 Data requirements for the development of driving behaviour models

1.6.1 Driving behaviour data

As described in Section 1.1, traditional driving behaviour models mostly focus on car-following and lane-change behaviour while also other forms of models have been proposed in the existing literature (e.g. gap-acceptance). The development and calibration of this type of models requires the availability of specific details e.g. speed, relative speed, headway etc. A common source is video trajectory data while the latest years, in many studies, models have been estimated using the NGSIM database (Alexiadis et al., 2004). The data was collected within an effort to assist in the development of microscopic traffic models. This data was recorded in two motorways (Interstate 80 Freeway and US Highway 101) and two urban roads (Lankershim Boulevard and Peachtree Streets). The main databases are semi-processed providing information regarding the position, speed, vehicle type, vehicle size, lane index, lead vehicle index etc. Moreover, additional information, related to the trajectories of the vehicles, such as photos, geographical data, AutoCAD-diagrams, orthocertified photos etc. are available. However, some studies (e.g. Punzo et al., 2011; Coifman and Li, 2017) showed that the NGSIM data suffer from several measurement errors while this is likely to be the case in most of the video trajectory data since the accuracy of position extraction is subject to factors as quality of videos, software used etc. Moreover, video trajectory data are limited to traffic-related variables only. The estimation of models that include additional details e.g. any information related to drivers' characteristics would require alternative sources.

A solution could be naturalistic driving data (i.e. instrumented vehicle) however, this data could have the same limitations to video trajectory data concerning accuracy.

Driving simulator data can be considered as an alternative as information is collected in high accuracy and also it is possible to acquire details regarding drivers' characteristics. Moreover, the simulator environment is completely controllable, and drivers' can be tested in very similar of not exactly the same driving conditions. Thus, the current work was based on data collected at the University of Leeds Driving Simulator (UoLDS). The attributes of UoLDS are presented in more details in Chapters 2 to 5 of the current thesis, therefore, it is not included in the current chapter. Driving simulators have been extensively used in road safety research however their behavioural validity has been questioned and investigated in several studies. The validity of driving simulators is distinguished in absolute and relative validity (Fisher et al., 2011). The former is achieved when the numerical values, related to driving behaviour, between real and simulated driving are similar, while in the latter the numerical values in the two cases are different but they follow similar patterns. The issue of validity is further discussed for modelling purposes in Chapter 4.

1.6.2 Drivers' characteristics data

In section 1.6.1 it has been briefly mentioned that the estimation of driving behaviour models augmented with drivers' characteristics would require some additional information. In the preceded literature review, a series of individual characteristics has been listed that could have an impact on driving behaviour. Among them, the present research has mostly focused on acute stress, as expressed through physiological responses. Some of the most common physiological responses used in the driving context have been reported in Section 1.3.4. For the current study, a wristband device was used to capture HR, EDA, BVP and ST. The device is presented more detailed in Chapters 2, 3 and 4.

Findings from the existing literature also indicate that individual traits can have substatial impact on driving behaviour (e.g. aggressive or risk-taking driving style). These traits are usually collected through self-report surveys. Given their latent nature, each trait is "measured" through questions-indicators related to it. For instance, in psychological research several scales have been developed regarding personality traits while similar approaches have been applied also within the driving context, related to driving stress, anger, driving styles etc. Latest advances in modelling allow these measures to be incorporated in models as latent variables and have been collected also within the context of the current thesis. Finally, sociodemographic characteristics have an important contribution in driving behaviour and it is considered useful to be collected as well.

1.7 Research objectives

The main objective of the thesis has been to suggest methodological approaches to incorporate drivers' characteristics in driving behaviour models with an explicit consideration of drivers' stress. To accomplish this aim, a driving simulator experiment has been conducted at the University of Leeds Driving Simulator (UoLDS), composed by two main scenarios, where drivers have been tested in a series of stressful simulator scenarios inducing stress with time pressure and traffic events. The thesis has been structured around chapters that investigate a series of research objectives that are ultimately all linked to the main aim of the thesis. The aforementioned objectives can be summarised as follows:

O.1: Investigate in which way and to what extent individual character traits and stress affect driving behaviour.

There are several indications in the existing literature that sociodemographic characteristics, together with traits and emotional state can have a considerable impact on driving behaviour. However, in many cases these findings are not based on observed drivers' behaviour or objective metrics but they are relying on subjective measures as self-report questionnaires and thus may suffer from measurement errors. At the same time, there are even fewer attempts to incorporate these variables within mathematical modelling frameworks that can be used for prediction. The initial objective, aims in identifying which individual characteristics, and in what manner, are influencing driving behaviour.

To answer this question, an exploratory analysis has been conducted and presented in Chapter 2. The findings are used to guide the mathematical models developed in Chapters 3 and 4.

O.2: Investigate how traffic conditions and contextual factors such as time pressure affect driving behaviour and how they are linked to stress levels.

As reported in Section 1.5.2 there is evidence that traffic environment and driving conditions as well as contextual factors (e.g. time pressure) can have an impact on perceived stress and consequently on driving behaviour. But the effect of contextual factors have not been incorporated in mathematical models of driving behaviour. The second objective of the thesis is to address this research gap.

Chapter 2 presents an initial exploratory analysis that further justifies this objective. Chapters 3 and 4 then extends it and mathematically model the effects of time pressure and traffic conditions respectively.

O.3: Investigate approaches to incorporate stress levels in driving behaviour models in order to obtain more behaviourally representative results.

This key objective, linked with O.2 and justified in Chapter 2, focuses on developing a modelling framework to incorporate the effect of stress induced from time pressure and driving environment factors in mainstream diving behaviour models.

This objective shapes the models developed in Chapters 3 and 4. The former presents a gap-acceptance model for intersection crossing while the latter is a car-following model.

O.4: Investigate in which way behaviour in the simulator environment compares to a real life and whether models estimated with simulator data are transferable to the field traffic context.

Driving simulators can be considered more advantageous compared to the conventional data sources for the estimation of driving behaviour models as they provide additional flexibility in terms of driving environment controllability and information related to drivers' individual characteristics. However, the issue of behavioural realism still remains, as already mentioned in the introduction of this chapter. The fourth objective of the thesis is to investigate this issue in the context of mathematical models of driving behaviour with special focus on how the driving behaviour models developed using the simulator data can be made more transferable to the field traffic context.

Chapter 5 focuses on this issue in a car-following modelling framework and investigates competing methods for improving the tarnsferability.

1.8 Thesis outline

The remainder of the thesis is organised in five chapters. Chapters 2 to 5 present papers that investigate the research objectives outlined in Section 1.7 while Chapter 6 is a conclusion of the thesis.

Chapter 2, presents a paper entitled "Investigating the effects of traits, stress and situational factors on driving performance". The paper presents the driving simulator experiment on which the analysis of the thesis is based. This involves the description of the experimental design, and the main outcomes derived from the analysis of the observed driving behaviour, physiological responses and survey responses via descriptives and inferential statistics analysis. The results show that time pressure has a significant impact on speeding behaviour in the urban setting of the experiment while overall they completed those scenarios faster. With respect to the motorway setting, time pressure and traffic conditions had a significant impact on speed, acceleration and lane-change behaviour of drivers. Moreover, several mild correlations with self-reported statements were found, supporting the existing literature. Finally, although no significant correlations were found between physiological responses and behaviour in the urban setting, the former correlated with higher speeds and standard deviation of acceleration in the motorway setting indicating a relationship between stress levels and risky driving behaviour.

Chapter 3, presents a paper entitled “Modelling the effects of stress on gap-acceptance decisions combining data from driving simulator and physiological sensors”. The paper is focusing on the estimation of a gap-acceptance model starting only with traffic-related explanatory variables and gradually adding variables related to socio-demographic characteristics, time pressure and physiological responses. The latter have been incorporated as direct explanatory variables in the model specifications using normalisations on the raw physiological signals. The results indicate that each newly added set of exaplanatory variables significantly improves model fit. This finding shows the importance of incorporating drivers’ characteristics and contextual factors on driving behaviour, on top of traffic-related variables. Finally, increase of physiological responses has been linked to higher probability of gap-acceptance, suggesting a positive correlation of aggressive driving behaviour and physiological activity.

Chapter 4 presents a paper entitled “Combining driving simulator and physiological sensor data in a latent variable model to incorporate the effect of stress in car-following behaviour”. In this paper, an adaptation of the GM car-following model is presented that also accounts for the effects of stress, as expressed through physiological responses. Stress is represented as a latent variable linked to the sensitivity component of the car-following model. The model accounts for inter-driver heterogeneity via reaction time and intra-heterogeneity via the stress latent variable. Moreover, the effects of socio-demographic characteristics are considered as part of the stimulus component of the model. The results show a positive correlation of the latent variable with acceleration behaviour while no significant results occurred with respect to deceleration. The findings of the paper are consistent with the results of Chapter 3 and further support the need for considering the effect of drivers’ characteristics and physiological activity in driving behaviour models.

Chapter 5 presents a paper entitled “From driving simulators experiments to field traffic application: improving the transferability of car-following models”. The paper investigates transferability of driving simulator data in a car-following model context. Given that transferability is not validated, the paper makes use of techniques for its improvement including parameter updating (Bayesian updating and Combined

Transfer Estimation) and joint model estimation. The results show that after the application of Combined Transfer Estimation, transferability between the two contexts is feasible.

Finally, Chapter 6 provides an overall summary of the thesis, highlighting the findings from each chapter. Contributions and future research directions are also discussed.

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CHAPTER 2: INVESTIGATING THE EFFECTS OF TRAITS, STRESS AND SITUATIONAL FACTORS ON DRIVING PERFORMANCE

ABSTRACT Driving behaviour is an inherently complex process affected by various factors ranging from individual characteristics to network attributes and situational factors. The current study attempts to thoroughly investigate driving behaviour under different traffic conditions and time pressure levels particularly focusing on the correlations between the behaviour and the characteristics of the driver. In terms of driver characteristics, both static (e.g. socio-demographics, personality and driving style) and dynamic (level of stress) are considered. The analysis is based on a comprehensive driving simulator experiment that included two main scenarios, namely, an urban road and a motorway setting. Participants have been subjected to carefully designed stressful scenarios induced by time pressure and traffic conditions. The physiological responses (e.g. skin conductance, heart rate and blood pressure) have been recorded alongside the driving manoeuvres, as an indication of stress levels. The analysis of the data collected from the urban task indicates that under time pressure, participants significantly increase their speed and completed specific scenarios much faster. Moreover, significant associations are found between observed behaviour and sociodemographic characteristics and traits. The analysis of the data collected from the motorway setting indicate that participants change their behaviour depending on the traffic conditions and time pressure. Moreover, physiological responses are found to be significantly correlated with observed behaviour as speeding, braking etc. though the correlations with the traits are less significant. The insights from the results can be used for designing appropriate intervention strategies to improve safety.

2. 1 Introduction

Driving behaviour is an inherently complex process affected by the driver characteristics, traffic and vehicle factors. The former corresponds to static (e.g. socio-demographics, personality, driving style) as well as dynamic (e.g. alertness, stress, etc.) characteristics of the driver. The variables related to traffic conditions include level of congestion, behaviour of the neighboring drivers, visibility, etc. The key vehicle factors include the acceleration-deceleration and braking capability of vehicles. All these factors influence drivers' performance to a varying extent.

There is a significant body of literature that has investigated the effects of sociodemographic characteristics where gender and age are the most common variables to be investigated. For instance, Westerman & Haigney, (2000) found that men reported more violations, but fewer lapses, than women and they also reported a negative correlation between age and violations. Rhodes & Pivik (2011) reported that male drivers are more likely to get involved in risky situations while a similar outcome was also found by Jiménez-Mejías et al. (2014). Also, Lonczak et al. (2007) reported male drivers as more risk takers. Regarding age, differences in risk-taking behaviour have been found between teen male and adult female drivers (Iversen and Rundmo, 2004; Taubman-Ben-Ari & Yehiel, 2012) Also, Jonah (1990) reported that younger drivers are more likely to show risky driving behaviour and also commit more violations.

The effects of individual characteristics have been also investigated in terms of traits, attitudes and emotional states. Taubman-Ben-Ari & Yehiel (2012) associated personality traits with different driving styles (e.g. anxious, aggressive, cautious etc.) while Ulleberg & Rundmo (2003) found relationships between personality, risky driving and attitudes towards driving risk and safety. The effects of personality on driving aggression and risk-taking were also examined in other studies (e.g. Dahlen et al., 2012; Ge et al., 2014). The concept of drivers' stress has been conceptualised by Gulian et al. (1989) and Matthews (2002) where it was defined as a situation that challenges drivers' abilities, reduces their perceived control or threatens their mental/physical health.

Driver stress can arise as a result of environmental conditions (e.g. foggy, icy, etc.), network characteristics (e.g. surface characteristics), junction frequency, speed and flow per lane and/or potential secondary tasks, such as use of navigation system, texting, etc. (Hill and Boyle, 2007). Moreover, time urgency and the level of congestion have been identified as two important factors influencing drivers' stress (Hennessy and Wiesenthal, 1999). Self-reported stress has been linked to aberrant driving behaviour, namely errors and violations (Kontogiannis, 2006). These types of impaired behaviour can lead to road crashes and incidents, therefore stress is considered as a key issue related to traffic safety (Westerman and Haigney, 2000; Useche et al., 2015, Qu et al., 2016). Moreover, Ge et al. (2014) found that perceived stress is linked to aggressive and risky driving behaviour.

The existing findings provide compelling evidence regarding the effects of stress on driving, however, they are mostly based on self-reported surveys and therefore prone to response bias and reporting/measurement errors. Further, they are primarily based on point measurements at the end of the task. An alternative, and potentially more reliable, approach to detect drivers' level of stress and study its effects, is through its implications on human physiology. Recent advances in sensor technologies and affective computing have made it possible to measure drivers' stress levels through physiological responses, e.g. changes in heart rate, Electrodermal Activity (EDA), blood volume pulse, etc. There are several existing studies related to driving stress that use this type of data (some examples Healey and Picard, 2005; Singh and Queyam, 2013; Rigas et al., 2012). However, the aforementioned studies have primarily focused on detecting stress rather than investigating its effects on observed driving behaviour.

The current study focuses on a thorough investigation of drivers' behaviour where the latter is examined in different network environments with various driving conditions and time pressure states. Moreover, drivers' individual characteristics are considered in terms of socio-demographics, traits and stress levels. To accomplish this aim, a comprehensive driving simulator study has been conducted where participants have been subjected to a series of stressful scenarios, including time pressure, while at the same time their physiological responses have been observed. Sociodemographic characteristics and traits have been also collected in the form of surveys. Ultimately, the study has attempted to examine how drivers' behaviour can change under different traffic conditions and time pressure, and how different factors affect speed and risk-taking behaviour.

2.2 Driving simulator experiment

2.2.1 Apparatus

The University of Leeds Driving Simulator (UoLDS)

The data used in this study was collected as part of a comprehensive driving simulator study (Next Generation Driving Behaviour Models – NG-DBM) for investigating the effect of stress in different driving decisions (e.g. acceleration-deceleration, overtaking, red light violation, gap acceptance, etc.). The experiments have been conducted using the University of Leeds Driving Simulator (UoLDS). The UoLDS (Figure 2.1) is a high fidelity, dynamic simulator. The vehicle cab is a 2005 Jaguar S-type with all driver controls available and fully operational. This includes the steering wheel and braking pedal, and there is also a fully operational dashboard. The vehicle is placed in a 4m diameter spherical projection dome. The dome provides fully textured 3-D graphical scene with a horizontal field of view of 250^o and 45^o vertical and it is placed on an 8 degrees of freedom motion system. The model of vehicle dynamics has been extensively validated to capture accurate vehicle behaviour on high-friction surfaces (Markkula et al., 2018). The raw data output consists of observations of 60Hz frequency.

Figure 2.1: The University of Leeds Driving Simulator (UoLDS)

The E4 wristband

Drivers' physiological data, across the whole experiment, has been collected using the Empatica E4 wristband which is a non-intrusive device that provides information about heart rate (HR), Electrodermal Activity (EDA), blood volume pulse (BVP) and temperature (TEMP). Each of the physiological indicators has been collected with a different frequency, depending on the attributes of the wristband. EDA and temperature have a 4Hz frequency, blood volume pulse 64Hz and heart rate 1Hz.

The Empatica E4 wristband has been used in several studies. With respect to the reliability of the obtained signal, it has been mentioned an issue of missing IBI (intra-beat interval) data for studies that involve strong movement (Enewoldsen, 2016; Koskimäki et al., 2017; Lam et al., 2018). This issue poses a challenge in conducting heart rate variability analysis (Ollander et al., 2016), however, when IBI values are missing or unrealistic, the wristband is using an algorithm and is able to provide HR values (Enewoldsen, 2016). These values are considered acceptable to be used for analysis (Ollander et al., 2016). Moreover, a very small proportion of the EDA signal is identified as noise (Enewoldsen, 2016; Lam et al., 2018) however open and humid environment can have a severe effect on the quality of the signals (Lam et al., 2018).

Within the context of the NG-DBM study, it was also aimed to obtain participants' physiological data in real life, outside the context of driving simulator (however, this analysis extends the scope of the current paper). Thus, the wristband was selected for its flexibility as it would be easier to be provided to participants for use several days before the actual simulator study. The device was used within the members of the research group to test for changes in physiological responses during daily activities (travelling on train, working, relaxing at home etc.) and after some basic visual analysis of the outputs, it was decided to proceed with its use.

Questionnaires and participants' paperwork

Participants were provided with a series of documents, some days before participating in the driving simulator experiment. The documents included:

a) A participant's information sheet where details about the driving simulator and the experiment itself were provided

b) The multidimensional driving style inventory (MDSI; Taubman-Ben-Ari, 2004) that is a 44-item scale developed to identify driving styles. Each item has been evaluated with a 6-point Likert scale of agreement that extends from "Not at all" (1) to "Very much" (6). In the original study, the authors derived 8 different driving styles, namely:

Dissociative driving style: This style represents easily distracted drivers who commit errors or show cognitive gaps.

Anxious driving style: This style is related to drivers that feel distress or anxiety during driving or have lack of confidence with respect to their driving skills.

Risky driving style: This style refers to drivers who seek for sensation or show risk taking behaviour

Angry driving style: This style represents driver that show hostile or aggressive driving behaviour and feel anger while driving.

High-velocity driving style: This style represents drivers that tend to drive fast or show signs of feeling time pressure.

Distress-reduction driving style: This style is about drivers that engage in relaxing activities to reduce distress while driving.

Patient driving style: This driving style is about drivers that are polite towards other drivers, feel no time pressure and are patient.

Careful driving style: This style represents drivers that drive careful, planning their trajectory in advance and adopt a problem-solving attitude towards driving task-related issues.

c) A personality survey based on items derived from the International Personality Item Pool – IPIP (Goldberg, 1999: http://ipip.ori.org), that participants completed before arriving at the simulator. In particular, the Anger, Anxiety, Vulnerability and Excitement seeking components were derived from the NEO-PI-R of Costa & McCrae (1992). The first three are parts of the Neuroticism component while the latter is part of the Extraversion component of the 5-factor personality model. Those components have been selected because existing literature has mentioned the relationship between Neuroticism, Extraversion and Conscientiousnes with driving related outcomes (Dahlen and White, 2006).

In related literature where similar subscales of the NEO-PI-R have been used (Ulleberg & Rundmo, 2003; Chen, 2009; Lucidi et al., 2010; Mallia et al., 2015), the items were evaluated with a 5-point Likert scale. In the present paper, a 6-point Likert scale has been used, not only for consistency with the MDSI questionnaire but also to avoid reported issues of odd-numbered Likert response scales. Kulas et al. (2008) used items from the NEO-PI-R scale and found that preference of the mid-point can be actually used as "dumping ground" or instead of non-applicable responses. Moreover, Garland (1991) reported that mid-point use can be evidence of social desirability bias while Grondin & Blais (2010) also mentioned that the mid-point choice can be result of a satisficing strategy i.e. a quick response. In order to avoid the aforementioned issues of potential extensive use of the mid-point, that could also cause issues in future analysis, because of less variance in the responses and small sample size (e.g. modelling driver behaviour including latent variables), an even number of points was decided. Moreover, responses could be later merged in less categories, following approaches in literature (e.g. Grondin & Blais, 2010). The personality items used in the analysis range from Strongly disagree (1) to Strongly agree (6).

d) A survey of perceived stress that was completed after each driving simulator task.

The documents mentioned in b, c, and d can be found in Appendix A.

2.2.2 Driving simulator scenarios

Procedure

The whole experiment has included approximately 90 minutes of total driving in the simulator for each individual. Participants initially have had a short briefing session about the simulator and its operation followed by a practice session around 15 minutes to familiarise themselves with the simulated environment and vehicle dynamics (i.e. motion system). For safety reasons, participants have been accompanied by a researcher during the practice run, positioned in the back seat. After the practice session, participants started the main driving scenarios, composed of two different settings: an urban and a motorway. After completing the urban setting, participants have had a short break during which they completed a feedback form. They have also completed a similar feedback form after finishing the second setting.

General details of the driving simulator scenarios

The driving simulator settings have been designed in order to investigate driving behaviour, and the effects of traits and stress on it, under a variety of traffic conditions, events and situational factors. To this end, two different main scenarios have been developed, an urban setting and a motorway setting. Given the different nature of the main settings, different scenarios have been designed and tested in each of them. It should be mentioned that both of the main settings, and the scenarios within, have been presented to participants with the same order and have not been randomised as a counterbalancing approach. The rationale behind this design have been mostly related to the recording of the physiological observations; the induction of stressful events at the very early stages of the experiment could possibly increase physiological responses and then it might not be possible for these indicators to return to baseline levels. Thus, it has been preferred to steadily increase the stressors during the experiment.

Apart from the stress induced by the traffic conditions or the events that took place in each setting, time pressure has been also applied as a stressor. Time pressure have had the following form: During their briefing session, participants have been instructed that they have had to reach their destination within 35 minutes (in each setting separately) and they could see an emoji placed on the dashboard (Figure 2.2) as an indicator of their performance. Moreover, they have been informed that the emoji displayed to them has been determined based on expected arrival time which was computed and constantly updated using a sophisticated algorithm running in the background and uses variables such as current speed, speed limit, distance to the end, an average estimated delay that will be caused by the events ahead etc. as inputs. This has been then used to determine which of the three emoji to show. Participants have been instructed that the green state indicated they have been doing well, in terms of remaining time, while the red would have meant that they have been late. The intermediate amber emoji would have meant that they have been marginally fine in terms of time. That is, they would have received a red emoji if they had further delay in the remaining driving tasks. The introduction of an amber state has been decided to make the shift from green to red emoji more convincing to the participants.

Figure 2.2: Time pressure emoji

In point of fact, the state of the time pressure emoji has not been related to participants' actual performance but has been pre-decided in order to induce time pressure in specific road segments. It may be noted that the choice of 3 different emoji to indicate time pressure, has been preferred to a conventional countdown timer since it would have been easier to manipulate. In order to increase the likelihood that participants would consider time pressure indications, they have been instructed that a penalty would be imposed on the monetary reward for their participation in case they have been late at the end of the motorway (red emoji). However, this has never been the case since both main scenarios of the experiment have been programmed to end in the amber time pressure state. The piloting stage of the study was mainly used to get feedback with respect to the experimental design and scenarios; driving behaviour was not analysed with respect to the emoji state changes. The potential monetary penalty together with literature findings regarding stress occurrence under time pressure (Hennessy and Wiesenthal, 1999) and changes in driving behaviour (Rendon-Velez et al., 2016) were considered as indications that the various emoji would affect and change driving behaviour. The next sections present a more detailed description of the two main motorway settings.

Excluded participants

The UoLDS is a dynamic driving simulator and thus there is always some risk to affect people with motion sickness. This has been the case for three participants that reported motion sickness during the practice session or at the very early stages of the urban setting and have been completely removed from the analysis. Moreover, the E4 device has failed to record any physiological data from one participant which has also been removed from the analysis. The remaining participants are in total 42. However, because of a software failure, the urban setting was interrupted for one participant and therefore the total sample size was 41. Finally, some participants normally started the motorway setting however they dropped out without finishing it mostly owing to dizziness. Regardless their progress in this setting, these participants have been completely removed from the sample and 36 were finally considered in the analysis. The required sample size was not determined by any sample size calculation approach rather motivated by literature review of similar studies. In particular, some examples as Jamson et al., 2015 (22 participants), Li et al., 2018 (35 participants), Xue et al., 2018 (46 participants) and Zimasa et al., 2019 (40 participants) motivated us that a sample size of 36 or 41 participants would be sufficient to proceed with the analysis.

The urban setting

As shown in Figure 2.3, the urban setting has been composed of a two-lane road (one lane per direction) where the driving has been interrupted by a series of intersections (signalised or unsignalised). The main concept is based on observing drivers' behaviour at the intersections, where particular events have been taking place. These have been presented in the following sequence: an encounter with a slow-moving lead vehicle that participants could have decided to overtake or not, a traffic light with a red indication of long duration that has aimed to cause frustration, an amber dilemma scenario where participants could have decided to accelerate or brake and a gap-acceptance scenario where participants have had to cross a junction. These scenarios have been repeated twice (initially without and then under the presence of time pressure) while at the end of the setting there has also been a right-turn manoeuvre

Figure 2.3: The urban setting

scenario which has been the last task of the urban road. Moreover, in the first sequence of the scenarios there has been also presented an additional intersection where a vehicle has been violating priority and crossing in front of the participant, however, this scenario has not been analysed in the current study. Within an effort to minimize any potential residual effects from the previous tasks, some straight road segments without any critical events have been inserted, in between the main tasks. The average duration of these segments has been 2-3 minutes and participants have not met any traffic in these (only occasionally from the opposite direction), however, at the second half of the urban setting they have been deliberately subjected to time pressure. The main scenarios are presented more detailed in Section 2.4.

The motorway setting

The motorway setting has had a 3-lane road (where the right-most lane has been the fastest) composed by several scenarios that have been distributed along the different segments (Figure 2.4). These have been based on variations of the traffic conditions and time pressure. In the initial road section, no specific events have been taking place and the time pressure indicator has been green. This has been followed by a road section with "aggressive" surrounding traffic. This scenario has been implemented by allowing the driving simulator drones (vehicles controlled by the simulator software) to accept shorter gaps while performing a lane change. This has resulted in the occurrence of lane change manoeuvres at short headways with respect to participants' position. The scenario has been repeated at the next main road segment as well, but this time under the presence of time pressure (amber or red). In the next scenario participants have faced traffic at slow speeds which aimed to create a sense of congestion. This scenario has been time based (as opposed to all the rest which have been position based) with an approximate duration of 5.5 minutes. During this scenario, participants have faced all possible time pressure states. The last two segments of the motorway have not included any specific events apart from changes in the emoji states. As an exception, at the last segment a hard-braking scenario has been programmed but it has not been initiated for all participants as specific requirements with the lead vehicles should have been met, with respect to distance and headway. It should be mentioned that for purposes of convenience, each motorway segment has been given a specific code that is used in the analysis presented in the next paragraphs. The main details of the motorway setting are summarised in Table 2.1 while a visual representation is provided in Figure 2.5.

Table 2.1: The motorway setting sections.

Code	Scenario	Time pressure state
M1	No events	Green
M2	Aggressive traffic	Green
M3	Aggressive traffic	Amber – Red
M4	Slow traffic	Green – Amber – Red
M5	No events	Amber – Red
M6	No events – Hard braking	Green – Amber – Red

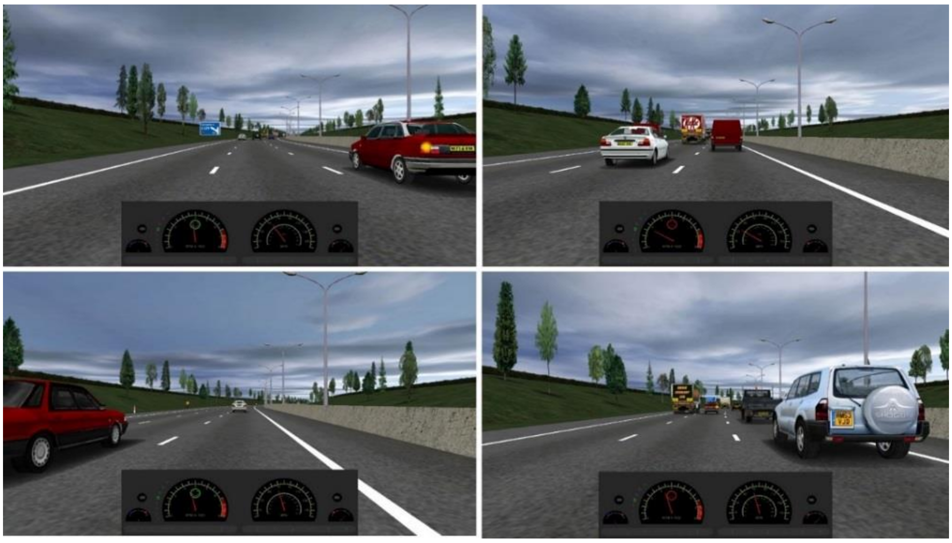

Figure 2.4: The motorway setting

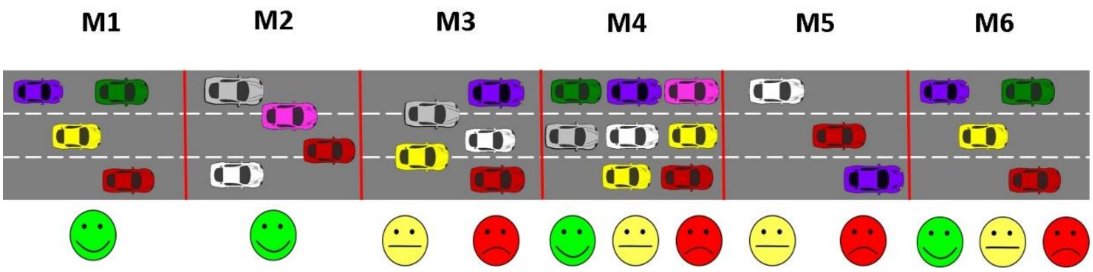

Figure 2.5: The motorway setting sections.

2.3 Sample characteristics

2.3.1 Descriptive statistics

Before proceeding further into the analysis of the simulator settings and scenarios, the sample has been analysed, in order to obtain some initial insights. The total sample consists of 42 participants that successfully completed the full or at least one of the two settings of the experiment. Participants has been excluded from each setting as described in Section 2.2. Table 2.2 presents the overall descriptive statistics. In total, 22 male and 20 female participants took part in the study with average age 34 years old approximately. The driving experience of the sample is almost 13.5 years while half of the participants stated driving on a daily basis. The effects of age have been investigated in the analysis using a dummy variable for drivers below 40 or 40 and above years old. The age groups have been split based on literature that has considered drivers above and below 40 years as different groups (Yee, 2010; Shanmugaratnam et al., 2010; Reimer et al., 2013). It should be mentioned that elder drivers may be considered as a different age group but give the small sample size, only two age groups were considered in the current study. Similarly, drivers with 10 years of experience and above, were considered as a different driving experience group (Chisholm et al., 2006; Wallis & Horswill, 2007). Also, two-thirds have reported 10,000 miles per year and below while only a minority of the sample have reported accident involvement and tickets for speeding.

As per the approach used by the original study of the MDSI, which linked driving style with socio-demographic characteristics, for each participant, the responses belonging to the same factor have been averaged to get a certain driving style score. The same approach has been also applied for the personality trait items. The average scores of each factor are presented in Table 2.3 and have also been used to the rest of the analysis.

Table 2.2: Descriptive statistics of the sample

Variable	Intervals	Frequency	%
Gender	Male	22	52.4
	Female	20	47.6
Age	Below 40	28	66.7
	40 and above	14	33.3
Driving experience	Below 10 years	22	52.4
	10 years and above	20	47.6
Frequency of driving	Everyday	22	52.4
	2-3 days a week	12	28.6
	About once a week	4	9.5
	Less often	4	9.5
Miles per year	Less than 5000	14	33.3
	5000 - 10,000	14	33.3
	10,000 - 15,000	9	21.4
	15,000 - 20,000	3	7.1
	Over 20,000	2	4.8
Minor accident involvement	No	36	85.7
	Yes	6	14.3
Major accident involvement	No	38	90.5
	Yes	4	9.5
Ticket for speeding	No	35	83.3
	Yes	7	16.7
Life stress	Moderately stressed	15	35.7
	A little stressed	21	50.0
	Not at all	6	14.3

Similarly to the original paper that introduced the MDSI (Taubman-Ben-Ari, 2004), the highest average values occurred for the Patient and Careful styles while the lowest for the Risky style. Similar outcomes have been found in other studies that used this scale (Holland et al., 2010; Bellem et al., 2016). Given the change of scale, the values of personality subscales can only be compared relatively with existing literature examples (Ulleberg & Rundmo, 2003; Chen, 2009; Lucidi et al., 2010; Mallia et al., 2015). The values of the Anxiety component in the current study are slightly lower, compared to the aforementioned examples. Moreover, the Anger component is also at lower levels, with respect to existing findings as in most of the aforementioned studies it has been slightly above the average value of 2.5 (2.38-2.88). Finally, Excitement seeking follows the trend of previous studies with a higher score, compared to the other personality subscales, although it is smaller, in a relative sense, compared to other literature.

Table 2.3: Descriptive statistics of the survey responses

Variable	Mean	Std. deviation
MDSI scores		
Dissociative	2.1	0.7
Anxious	2.6	0.8
Risky	1.7	0.7
Angry	2.4	0.8
High-velocity	2.6	0.6
Distress-reduction	2.6	0.6
Patient	4.5	0.7
Careful	4.8	0.6
Personality scores		
Anxiety	3.1	0.8
Anger	3.0	0.7
Vulnerability	2.6	0.7
Excitement seeking	3.4	0.9

2.3.2 Inferential statistics

A further analysis of the sample statistics has indicated some additional relationships between participants' characteristics and the survey responses. First, a correlation analysis has been conducted to examine the latter in more detail. Table 2.4 shows the correlation analysis of the personality factors (significant correlations marked with bold). Anxiety, Anger and Vulnerability factors have been all positively correlated while no significant associations have occurred with respect to Excitement seeking.

The same pairwise comparison approach has been also applied for the MDSI factors, as shown in Table 2.5. Dissociative driving style has been positively correlated with the Distress-reduction driving style and as expected negatively correlated with the Careful driving style. Anxious driving style has been negatively correlated with the

Risky driving style while the latter has been also positively associated with the High-velocity driving style and negatively with the Patient and the Careful styles. Moreover, a positive correlation has occurred between the Angry and the High-velocity driving styles while the former was negatively correlated with the Patient style. As expected, High-velocity factor is negatively correlated with Patient and Careful driving styles while one final positive correlation occurred between the latter driving styles as well. The correlation has been found to be the highest for the Dissociative-Distress reduction pair, followed by the negative correlation between the Risky and Anxious driving styles.

Table 2.4: Personality factors correlations

		Anxiety	**Anger**	**Vulnerability**	**Excitement seeking**
Anxiety	r	1			
	p-value				
Anger	r	**.568**	1		
	p-value	**0.000**			
Vulnerability	r	**.770**	**.504**	1	
	p-value	**0.000**	**0.001**		
Excitement-seeking	r	-0.251	0.053	-0.056	1
	p-value	0.109	0.739	0.724	

One final investigation related to the survey items focuses on the relationship the personality and the MDSI items as presented in Table 2.6. Anxiety has been positively correlated with the Anxious driving style and negatively with the Risky driving style. Moreover, Anger has been positively associated with Angry and High-velocity driving styles while a negative correlation has occurred with the Patient driving style. The Vulnerability personality factor has been positively correlated only with the Anxious driving style. Finally, Excitement-seeking has been positively correlated with Risky, High-velocity and Distress-reduction driving styles while negative correlations arose with the Patient and Careful driving styles. Out of the aforementioned correlations, only the Excitement-seeking and Distress-reduction pair has been not anticipated while all the rest are consistent with expectations. Overall, the relationships found within and between scales provide some useful insights with respect to personality and driving styles, showing that personality traits can play an important role shaping up the driving style. The next sections further investigate the survey responses and their relationship with the observed behaviour to the various driving simulator tasks.

Table 2.5: MDSI factors correlations

		Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Careful
Dissociative	r	1							
	p-value								
Anxious	r	0.177	1						
	p-value	0.263							
Risky	r	0.121	**-.500**	1					
	p-value	0.444	**0.001**						
Angry	r	-0.161	-0.236	0.202	1				
	p-value	0.308	0.132	0.199					
High-velocity	r	**0.297**	-0.208	**.493**	**.462**	1			
	p-value	**0.057**	0.185	**0.001**	**0.002**				
Distress-reduction	r	**.503**	0.116	0.189	-0.066	0.208	1		
	p-value	**0.001**	0.464	0.232	0.679	0.187			
Patient	r	**-0.265**	-0.035	**-.313**	**-.344**	**-.470**	-0.082	1	
	p-value	**0.090**	0.825	**0.044**	**0.026**	**0.002**	0.607		
Careful	r	**-.375**	0.167	**-.461**	0.004	**-.414**	**-0.289**	**.473**	1
	p-value	**0.014**	0.290	**0.002**	0.979	**0.006**	**0.063**	**0.002**	

Table 2.6: Personality-MDSI factors correlations

		Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Careful
Anxiety	r	0.192	**.579**	**-.330**	-0.040	0.018	-0.033	-0.189	0.024
	p-value	0.224	**0.000**	**0.033**	0.801	0.912	0.835	0.230	0.882
Anger	r	-0.149	0.244	-0.022	**.308**	**.308**	-0.057	**-.364**	-0.146
	p-value	0.347	0.120	0.888	**0.047**	**0.048**	0.720	**0.018**	0.356
Vulnerability	r	**0.278**	**.569**	-0.242	-0.129	0.146	0.076	-0.211	-0.112
	p-value	**0.075**	**0.000**	0.123	0.415	0.355	0.633	0.179	0.480
Excitement-seeking	r	0.146	-0.194	**.668**	0.101	**.441**	**.320**	**-.313**	**-.446**
	p-value	0.358	0.218	**0.000**	0.526	**0.003**	**0.039**	**0.043**	**0.003**

As a last step, the differences in personality and MDSI factors have been examined with respect to the sociodemographic characteristics presented in Table 2.7. Given the small sample size of each sub-group that derived from each sociodemographic attribute, nonparametric tests have been preferred to ANOVA. In particular the Mann-Whitney U test has been used for grouping variables with two categories while the Kruskal-Wallis H test was preferred for three or more categories. Significant outcomes with respect to gender have been found with respect to Anxiety (Z=-1.829,

Table 2.7: Personality-MDSI factors correlations with sociodemographics

	Anxiety	Anger	Vulnerability	Excitement-seeking	Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Carefu
Gender	(+)		+				(+)	(+)				
Age					(+)		(+)					
Driving experience											(+)	
Frequency of driving	(+)	(+)										
Miles per year												
Minor accident involvement												
Major accident involvement		+										
Ticket for speeding	(+)			++			++					
Life stress	++		++									

(+) Association at the 0.1 level
+ Association at the 0.05 level
++ Association at the 0.01 level

p=0.067) and Vulnerability (Z=-2.308, p=0.021) personality items with female participants having higher average scores. Moreover, some outcomes of weak significance have arised concerning Risky (Z=-1.777, p=0.076) and Angry (Z=-1.865, p=0.062) driving styles and male drivers. Age has been examined as a dummy variable for participants below and above 40 years old. The latter reported in general lower scores in the Dissociative (Z=-1.874, p=0.061) and Risky (Z=-1.691, p=0.091) driving styles.

In a similar way to age, driving experience has been also treated as a dummy variable for participants driving for less or more than 10 years and only a weak negative relationship has occurred between this variable and the Patient driving style (Z=-1.653, p=0.098). With respect to driving frequency, significant results have been found with Anxiety (KW=7.719, p=0.052) and Anger (KW=6.707, p=0.082). In particular, participants driving 2-3 days a week have in general lower scores in these factors compared to the rest. Another interesting finding that has been found regarding major accident involvement and higher scores in the Anger personality factor (Z=-2.275, p=0.023). Moreover, reported ticket for speeding is related to lower scores in the Anxiety personality factor and higher scores in Excitement-seeking and the Risky driving style. Finally, participants that reported higher levels of life stress also have higher scores in the Anxiety and Vulnerability personality factors. Following the relationships found within and between personality and MDSI scales, sociodemographic characteristics have provided some further initial insights regarding their effects of driving style behaviour.

2.4. Urban setting

The current section presents the analysis of the urban setting. The analysis is revolving around the main scenarios described in Section 2.2.2. Driving behaviour in these scenarios is initially investigated with respect to the effects of time pressure. Then, the relationship of the observed driving behaviour in these scenarios is examined compared to stress levels, socio-demographic characteristics, personality traits and driving style.

2.4.1 Effect of time pressure

This section presents the analysis of the urban setting of the driving simulator experiment. Given the repetition of the urban scenarios, the differences in behaviour and choices of drivers have been examined via comparing the effects of time pressure on a series of observed outcomes. The repeated measures ANOVA has been initially applied but when the normality assumption of the residuals has not been met, Wilcoxon Signed Ranks Test has been ultimately preferred, that can be considered as a non-prametric alternative for paired populations (Washington et al., 2010). Normality has been tested with the Shapiro-Wilk (1965) test.

The overtaking task

The overtaking task has been the first that participants faced in the urban setting. Drivers encountered a lead vehicle moving at 20mph-8.94m/s (speed limit 40mph-17.88m/s) and they could have decided to either overtake or not. The slow vehicle has been programmed to take a left turn at a specific intersection after approximately 500m, in case participants have decided not to overtake.

The variables considered with respect to the overtaking task are a dummy variable indicating if participants have performed an overtaking manoeuvre or not, time taken to overtake, minimum headways on the left and right (opposite direction) lanes and maximum speed during overtaking. The average values of the aforementioned variables are presented in Table 2.8 without (NTP) and under time pressure (TP) cases. It is worth mentioning that only 14 participants accomplished an overtaking manoeuvre in both cases, thus, most of the examined variables refer to this subgroup only.

Table 2.8: The overtaking scenario variables

Descriptive Statistics				**Wilcoxon Signed Ranks Test**	
	Mean	Std. Deviation	N	Test Statistics	
All drivers					
Overtaking manoeuvre NTP	0.34	0.480	41	Z	-3.000
Overtaking manoeuvre TP	0.56	0.502	41	p-value	0.003
Overtaking drivers					
Time to overtake NTP (s)	65.60	38.575	14	Z	-2.417
Time to overtake TP (s)	47.27	32.236	14	p-value	0.016
Left lane min headway NTP (s)	0.508	0.190	14	Z	-2.291
Left lane min headway TP (s)	0.400	0.151	14	p-value	0.022
Right lane min headway NTP (s)	2.680	0.747	14	Z	-2.668
Right lane min headway TP (s)	3.263	0.801	14	p-value	0.008
Max speed during overtake NTP (m/s)	18.639	1.623	14	Z	-2.354
Max speed during overtake TP (m/s)	19.657	2.060	14	p-value	0.019

The red traffic light task

This task involves a traffic light that has remained in the red phase approximately 45-50 seconds, depending when the participants have arrived at a specific location that triggers the activation of the scenario. The purpose of the scenario has been to investigate whether the combination of waiting time and time pressure would have an impact of the speeding behaviour of participants. The variables considered are scenario mean speed, maximum and end speed, as well as mean and maximum acceleration. All variables have been calculated excluding stationary time. The scenario area has included the intersection where the traffic light was placed and an area approximately 100m before and 350m after. These distances have been defined based on the approach that the road environment has been constructed. The road segments have been either single carriageway tiles approximately 250m long or segments coded as intersection where the total length varies. With respect to the red traffic light task, the intersection area started approximately 100m before the traffic light. Moreover, for the end of the scenario, one additional tile after the intersection was considered. These distances have been selected for a more straightforward data processing however, their impact needs to be further investigated with additional analysis. The average values of the considered variables are presented in Table 2.9. In all cases, participants adopted higher speed and acceleration under time pressure and apart from the mean acceleration, all differences are statistically significant.

Table 2.9: The red traffic light scenario variables

Descriptive Statistics				**Repeated measures ANOVA**	
	Mean	Std. Deviation	N		
Scenario mean speed NTP (m/s)	13.659	1.056	41	F	55.257
Scenario mean speed TP (m/s)	14.919	1.528	41	p-value	0.000
				η^2	0.580
Max acceleration NTP (m/s^2)	2.004	0.597	41	F	30.906
Max acceleration TP (m/s^2)	2.479	0.690	41	p-value	0.000
				η^2	0.436
				Wilcoxon Signed Ranks Test	
Scenario max speed NTP (m/s)	18.490	1.549	41	Z	-4.749
Scenario max speed TP (m/s)	20.209	2.493	41	p-value	0.000
Scenario end speed NTP (m/s)	18.180	1.498	41	Z	-4.283
Scenario end speed TP (m/s)	19.827	2.573	41	p-value	0.000
Scenario mean acceleration NTP (m/s^2)	0.115	0.066	41	Z	-1.678
Scenario mean acceleration TP (m/s^2)	0.143	0.084	41	p-value	0.093

The amber dilemma scenario

In the amber dilemma scenario, a traffic light that has been switching to the amber indication 3 seconds before they have arrived at the junction area has been presented to participants. Drivers could have decided whether to accelerate or brake. As the mean values in Table 2.10 indicate, only 7 participants have stopped without time pressure and 4 under time pressure, this difference has not been significantly different. However, after crossing the junction (whether stopped or not) participants have adopted significantly higher speeds under time pressure.

Table 2.10: The amber dilemma scenario variables

Descriptive Statistics				Wilcoxon Signed Ranks Test	
	Mean	Std. Deviation	N	Test Statistics	
Stopped NTP	0.171	0.381	41	Z	-1.134
Stopped TP	0.098	0.300	41	p-value	0.257
End speed NTP (m/s)	17.010	3.674	41	Z	-3.79
End speed TP (m/s)	19.381	4.783	41	p-value	0.000

The gap-acceptance scenario

In the gap-acceptance task, participants have faced a junction where they have had to stop while vehicles have been crossing from the priority perpendicular stream. They could have decided to either accept one of the gaps and cross or wait until all vehicles had passed. Ten gaps of varying lengths have been presented at both intersections. The task has been analysed considering an area covering from approximately 100m before the intersection to 500m after. The variables related to speed have been generated considering only the area after the junction while several other time-related variables were calculated. In particular, the latter include time from stopping to crossing the junction (time to clear), the time from crossing to the end of the scenario (junction to finish) area and the total scenario time. As shown in Table 2.11, participants adopted significantly higher speeds and completed the task faster under time pressure.

Free driving

The previous sections have presented some basic findings with respect to the main scenarios of the urban setting. The performance of participants has been also examined in one additional road segment, without any specific scenarios, between the long duration traffic light and the amber dilemma task. Similarly to the previous analysis, two different cases have been tested, without and under time pressure. Four variables related to speed have been calculated and the results are presented in Table 2.12. The values under time pressure were in all cases significantly higher.

Table 2.11: The gap-acceptance scenario variables.

Descriptive Statistics				Wilcoxon Signed Ranks Test	
	Mean	Std. Deviation	N	Test Statistics	
Time to clear NTP (s)	34.674	14.021	41	Z	-4.101
Time to clear TP (s)	26.539	17.397	41	p-value	0.000
Junction to finish NTP (s)	27.802	2.945	41	Z	-3.726
Junction to finish TP (s)	26.192	3.602	41	p-value	0.000
Mean speed after junction NTP (m/s)	22.453	2.367	41	Z	-3.816
Mean speed after junction TP (m/s)	23.972	3.166	41	p-value	0.000
Max speed after junction NTP (m/s)	27.848	3.756	41	Z	-4.62
Max speed after junction TP (m/s)	30.623	4.573	41	p-value	0.000
Total scenario time NTP (s)	76.022	15.398	41	Z	-4.788
Total scenario time TP (s)	64.665	20.677	41	p-value	0.000

Table 2.12: The free driving scenario variables

Descriptive Statistics				Wilcoxon Signed Ranks Test	
	Mean	Std. Deviation	N	Test Statistics	
Mean speed NTP (m/s)	18.439	1.365	41	Z	-4.529
Mean speed TP (m/s)	19.861	2.699	41	p-value	0.000
Max speed NTP (m/s)	20.105	1.578	41	Z	-3.751
Max speed TP (m/s)	21.709	3.587	41	p-value	0.000
% above 40mph NTP	64.008	34.015	41	Z	-2.844
% above 40mph TP	77.738	31.294	41	p-value	0.004
% above 60mph NTP	0.048	0.309	41	Z	-2.023
% above 60mph TP	4.127	13.486	41	p-value	0.043

2.4.2 The effects of stress/arousal levels as measured by the physiological responses

Following the same methodological approach, each scenario described in the previous section has been also investigated in terms of the physiological responses of participants. For this analysis, heart rate (HR) and skin conductance (SC) have been considered. Regarding the former, average values have been calculated for each scenario from the original observations and also their z-scores that were calculated following the example of Picard et al. (2001). The SC signals have been processed using the Matlab package Ledalab (Karenbach, 2005) to extract the skin conductance responses. Based on findings in existing literature (Sano et al., 2014), a critical value equal to 0.01μS has been selected as the minimum critical SCR. The skin conductance responses (SCRs) have been obtained applying trough-to-peak (TTP) and continuous decomposition analysis (CDA). Thereafter, the frequency and the mean amplitude of responses have been calculated for each scenario. A mean value has been also calculated for the z-scores of the responses' amplitude. However, before this calculation, the signal has been transformed from a standard normal variable N[0,1] to a random variable with mean equal to 5 and standard deviation 1, as N[5,1]. This transformation has been applied owing to the approach that the means have been calculated. For instance, if no SCRs have been detected in an area, it would result in a zero value, concerning the original signal. However, for the normalised signal, the absence of any responses could not be replaced with zero since this value corresponds to the mean of a standard normal variable. Thus, after transforming the original z-scores into a normal random variable N[5,1] all values have been positive, and it has been more reasonable to replace with zero the cases where no SCRs have been detected.

The results of this analysis are presented detailed in Appendix A (Tables A.1-A.3). A main finding has been that almost in all cases HR has been higher in the first half of the urban setting, without the induction of time pressure. Although this finding is not consistent with expectations, it can be ascribed to learning effects and also familiarisation of participants with the simulator environment. As explained in Section 2.2.2, participants had a practice session before starting the main experiment, however, familiarisation effects might have significantly influenced also the urban driving session. The findings from the TTP and CDA analysis of the SC signal also resulted in ambiguous results as no clear conclusions could be drawn. Overall, physiological responses have not provided any clear insights regarding drivers' behaviour in the urban setting while the majority of significant differences occurred in favour of the area without time pressure.

2.4.3 Interaction with sociodemographic characteristics

The effects of the sociodemographic characteristics have been investigated with the nonparametric Mann-Whitney U and Kruskal-Wallis H tests. The tests have been applied to all variables of the urban scenarios. Given the high number of all combinations, the detailed tables are provided in Appendix A.2, (Tables A.4-A.8) while only some important associations are mentioned in the current section. The results are reported up to 0.1 level of significance.

With respect to gender, males have been more likely to attempt an overtaking manoeuvre both without and under time pressure. Moreover, under time pressure males have accomplished the manoeuvre in less time while they also had higher maximum speed during the passing. Finally, female participants have had higher values of minimum headway on the right lane which indicates that they have been withdrawing faster from the opposite lane after completing their manoeuvre. Age has been investigated as a dummy variable with 40 years as critical value. Participants below 40 have been in general more likely to accomplish an overtaking manoeuvre while without time pressure, they have attempted the passing earlier. Additionally, their minimum following distance have been also smaller, compared to older drivers. Participants with driving experience less than 10 years have been also more likely to do a passing under time pressure and adopted shorter following headway however, regarding this finding there might be some confound with age. It is worth mentioning that under time pressure, participants that reported major accident involvement, had smaller maximum speed while overtaking however, given that this sample consisted only by three people this outcome should be treated with some caution. The same applies for participants that reported a ticket for speeding. For the latter, the time to overtake has been shorter but they also had shorter minimum time headway on the opposite lane which indicates that they completed the manoeuvre faster.

Regarding the red traffic light scenario, males have had higher mean, maximum and end speed under time pressure. Moreover, male participants have had higher values of maximum acceleration both without and under time pressure. Age has also a significant effect since for all variables related to speed, both without and under time pressure, drivers below 40 years had significantly higher values. Participants that reported involvement in major accident and a ticket for speeding have had higher average speed without time pressure. The latter also had higher maximum acceleration without time pressure. One last interesting outcome regarding this scenario has been that participants reported the highest life stress also had higher maximum acceleration under time pressure.

In the amber dilemma scenario, male drivers have applied higher scenario end speed under time pressure. Moreover, drivers below 40 years have had higher scenario end speed both without and under time pressure. Also, participants with driving experience above 10 years, are more likely to stop at the intersection under time pressure and also have smaller maximum scenario end speed. Finally, participants with major accident involvement have been more likely to stop at the intersection without under time pressure, although this outcome should be treated again with caution because of the small sample size.

The amber dilemma scenario has been followed by the gap-acceptance task. In the latter, males have had shorter junction to finish times while they also have applied higher mean and maximum speeds. Moreover, participants below 40 years have shorter junction to finish times and higher mean speeds in the same area both without and under time pressure. Also, participants that reported daily driving have crossed the junction faster in both cases while they have completed the total scenario faster without time pressure. Regarding drivers that reported involvement in minor accident, they have higher maximum speed after crossing the junction. Additionally, participants having being fined for speeding have crossed the junction and completed the total scenario significantly faster under time pressure.

Finally, with respect to the free driving segment, males have had higher mean and maximum speed and proportion spent above 40mph. Some similar findings have occurred for participants below 40 years. In particular, they have had higher mean speed and proportion above 40mph both without and under time pressure. The miles driven per year also have a significant effect on this scenario as, without time pressure, participants that reported 10,000 and above had higher values of mean, maximum and proportion spend above 40mph. Moreover, participants that reported major accident involvement have higher mean speed without time pressure while as expected, those who reported a ticket for speeding, have had a significantly higher proportion spent above 60mph. The same applies also for participants that reported the lowest levels of life stress.

2.4.4 Interaction with personality traits

Following the same approach with the previous section, also the effects of personality have been investigated for each scenario. Pearson correlation analysis has been applied to compare the mean scores of each personality factor with observed behaviour. All the significant correlations are presented in detail in Appendix A.2 (Tables A.9-A.13)

With respect to the overtaking scenario, only one significant and positive correlation has been found between Anxiety and minimum headway on the right lane without time pressure. This might indicate that more anxious participants have attempted to complete the manoeuvre faster.

More correlations have been found between personality items and the variables of the red-light scenario. Most of them are related to the Excitement-seeking and the Anxiety factors. In particular, the former was related to higher mean speed both without and under time pressure. Also, Excitement-seeking has been positively related to maximum acceleration under time pressure. On other hand, Anxiety has been negatively correlated with the maximum speed without and under time pressure and also speed at the end of the scenario. Finally, Vulnerability has been negatively associated with the scenario maximum speed under time pressure.

With respect to the amber dilemma scenario under time pressure, Excitement-seeking has been negatively related to stop at the intersection and positively related to the speed at the end of the junction. No other significant correlations have been found regarding the rest of the personality factors.

Excitement-seeking also has had a significant effect on most variables of both gap-acceptance tasks. In particular, participants with higher scores in this personality factor completed the task faster, after crossing, while they also have had higher mean and maximum speeds. A non-expected outcome has been related to the total time of scenario as it has been positively correlated with Excitement-seeking. This finding implies that these participants waited more time at the intersection to accept a gap. However, Anxiety has been negatively related to the total scenario time which indicates that the effect of this factor has had a positive effect on accepting a gap faster.

Excitement-seeking and Anxiety have had a major role also in the free driving task. More specifically, the former has been related to higher mean speed, maximum speed and proportion spent above 60mph. On the other hand, Anxiety has been negatively correlated with mean and maximum speed under time pressure and proportion spent above 60mph for both time pressure states.

Overall, the most influential personality factor has been Excitement-seeking which was in general related to increased speed and acceleration. The opposite effect has occurred with respect to Anxiety and this factor seems to be related with more cautious behaviour.

2.4.5 Interaction with the driving style

The same approach of Pearson correlations has been also adopted between the variables of each scenario and the driving style factors of the MDSI scale. All significant correlations are reported in Appendix A.2 (Tables A.14-A.18)

Regarding the overtaking scenario, Patient driving style has been negatively associated with accomplishing a passing manoeuvre without time pressure. Moreover, another significant and negative correlation have occurred between time to overtake without time pressure and the High-velocity driving style.

Multiple significant correlations have occurred between the red traffic light scenario and various reported driving styles. In brief, the Risky driving style has been related to higher speeds both without and under time pressure and also with maximum acceleration. Some similar positive and significant effects have been found with respect to the Angry driving style while also the High-velocity driving style has been positively related to mean speed under time pressure. On the other hand, the Patient driving style has been negatively correlated with speed and acceleration variables. It is worth mentioning that some non-expected outcomes have occurred regarding the Distress-reduction driving style since it has been found to have a positive effect on some variables related to speed and acceleration.

Regarding the amber dilemma scenario, the Dissociative driving style has been negatively related to stopping at the intersection under time pressure while on the other hand Careful driving style has been positively correlated with the same variable. Moreover, the Dissociative and Risky styles have been positively correlated with speed at the end of the junction, under time pressure, while Patient and Careful styles have had a significantly negative effect.

The various reported driving styles also have had some significant effects on the gap-acceptance tasks variables. More specifically, risky drivers have completed the task faster in both cases and also have had significantly higher speeds. Some similar findings have also occurred for the High-velocity and Angry driving styles while the opposite effects were found regarding the Patient and Careful styles. Finally, Distress-reduction driving styles have exhibited some findings closer to the more risk-taking styles as, without time pressure, a positive correlation occurred regarding maximum speed after junction and a negative with the junction to scenario end time.

2.5. The motorway setting

The current section is organised similarly to Section 2.4. The analysis revolves around a series of driving behaviour-related variables, as calculated for each of the six main motorway sections. Differences in behaviour are initially examined with respect to time pressure and stress levels while the interaction with socio-demographic characteristics, personality traits and self-reported driving style are also investigated.

2.5.1 The effects of time pressure

As explained in Section 2.2.2, the motorway scenario has been composed of several segments with various traffic conditions and time pressure levels. These differences have been expected to influence drivers' behaviour, thus some basic variables have been calculated and compared among the various motorway sections. The variables have been related to speeding and acceleration behaviour, lane-changes, car-following and pedal depression. A series of repeated ANOVA tests have been applied, in order to investigate variations in driving behaviour across the various motorway segments. When the assumption of normality has not been met, it has been replaced by Wilcoxon Signed Ranks Test. It should be mentioned that only the main areas have been considered in the analysis and the intermediate intersection sections have been excluded.

Speeding and acceleration behaviour

The main variables considered, with respect to speeding and acceleration behaviour, have been mean speed, maximum speed, percentage spent above the speed limit, standard deviation of acceleration, mean and standard deviation of positive and negative acceleration. All results are summarised in Appendix A.2, (Tables A.19-A.22)

The observed patterns regarding speed, have showed a series of relatively consistent outcomes with respect to the expected effects of each scenario on driving behaviour. In particular, the lowest average speed has been observed in the M4 motorway segment while the highest have occurred in the M1 segment. Although no time pressure has been applied in the latter area, the traffic environment has been still being formulated and thus participants have experienced more free-flow conditions. The average speed in M1 has been significantly higher compared to all the rest segments, apart from M5. Interestingly, although time pressure has been applied also in M6, participants adopted lower speeds in that area. Although this might seem as an unexpected outcome at first glance, it should be considered that participants have been aware that they have been driving at the final segment and have had to pull over at the next intersection. Participants have not been familiar with the exact location of the next intersection thus, they possibly have adapted their speed accordingly. This finding may imply that path-plan has a stronger effect on driving behaviour compared to time pressure. Another outcome regarding the effects of time pressure has been observed between segments M2 and M3. The average speed has been higher in the latter however, the difference was not statistically significant. Similar patterns have been also observed in the rest of the variables related to speed. A notable mention regards the difference in the percentage above the speed limit between segments M3 and M5. Although time pressure has been applied in both cases, the average value has been smaller in M3 are indicating safety concerns owing to the differences in the behaviour of the surrounding traffic. However, this difference has not been statistically significant.

The next indicator of drivers' performance across the various motorway segments has been the standard deviation of acceleration. As expected, a significantly higher variation in acceleration have been noticed for areas M2 and M3, given the nature of the scenarios there. A high value has also occurred in section M6. Considering that the average acceleration is always expected to be around zero (e.g. the typical example of the NGSIM trajectory data; Alexiadis et al., 2004), and thus not very instructive, the differences in acceleration patterns have been investigated more explicitly in terms of positive and negative values. This latter distinction has been also applied in traffic microsimulation studies (e.g. Ahmed, 1999). With regards to the average values of both positive and negative acceleration, the patterns have been close to those presented for the standard deviation. The higher rates took place in areas M2 and M3 indicating that drivers have had more disturbed behaviour there. The smallest average value of positive acceleration has been noticed in the M1 area where no time pressure was applied and traffic conditions were milder.

Similar outcomes have been also derived from the standard deviation of positive and negative acceleration. The higher values were observed in sections M2, M3 and M6. The implications of these findings are further investigated in the next sections combined with additional variables considered.

Lane choice and lane change behaviour

The various motorway segments have yielded different lane-change behaviour. This has been investigated with the frequency of lane-changes and lane choice. It should be mentioned that another variable to be considered could have been the total number of lane-changes, but the lane-change frequency has been preferred given the differences in the duration spent on each segment.

An interesting outcome has been that on average, lane changes have occurred more frequently in section M4. This finding has been potentially a result of drivers' efforts to take advantage of potential breakthroughs and manoeuvre through slow traffic. The lane-change rate has also remained high in segments M5 and M6, compared to the three first ones. The rationale behind this behaviour could be related to the presence of time pressure in these areas; drivers attempted to avoid following slower moving vehicles. Interestingly, the lowest lane-change frequency has taken place in area M2 where the presence of aggressive neighbouring traffic increased cautiousness. However, under the same traffic conditions, participants carried out lane-changes more frequently in section M3.

A more detailed investigation of the lane choice behaviour is presented in Appendix A.2, Tables A.23-A.24 where the proportion spent in each lane is outlined. The use of the leftmost lane has been significantly higher in the last motorway segment. As discussed previously, path-plan effects could have driven the participants towards this behaviour as the exit lane to pull over at the end of the experiment was at that side of the motorway. The use of the leftmost lane has been also significantly higher in section M4, compared to most of the other segments. This could be a result of the higher lane-change rate in this area since, as already explained, drivers attempted to manoeuvre more to avoid slow traffic.

Following behaviour

Following behaviour has been investigated with variables related to mean time and space headway and also the proportion of time headway spent below 1.5 seconds. As expected, the highest mean time headway occurred in section M4, given the slow speeds of the traffic. Moreover, high time headways have been observed in the M1 segment while as expected, the shortest headways have been found in section M3, given the aggressive nature of the traffic and the time pressure. Similar trends have been also noticed regarding the proportion spent under 1.5 seconds and also space headway. With respect to the latter, short space headways have been also observed in the last motorway segment. A potential interpretation could be that, given participants' awareness that they were driving on the last section, and the presence of time pressure, willingness to adopt shorter following distances might have been increased, in order to avoid finishing the motorway task late.

Pedal depression

The last indicators of participants' performance have been related to pedal depression. The variables considered are standard deviation of accelerating and braking (Appendix A.2, Table A.26). In sections M1 and M4 participants have had significantly smaller values compared to M2 and M3 while the same applied also regarding braking. The latter has been potentially a result of the aggressive traffic in these areas which forced participants to accelerate and brake more frequently. The high braking value in braking at section M6 could be a result of the braking scenario. This finding could be also supported by the high value of standard deviation observed regarding the negative acceleration of the same section.

2.5.2 The effects of stress or arousal as measured by the physiological responses

Physiological responses at the scenario level

Physiological responses have been initially investigated similarly to the urban setting through pairwise comparisons between motorway segments. The tested variables have been extracted the same way described in Section 2.4.2. Moreover, the sum of amplitudes has been also calculated but, given the differences in the duration of each motorway area, the mean values were preferred at this stage of the analysis. The detailed results are presented in Appendix A (Tables A.27-A.29). The patterns of physiological responses have been different, depending on which variable was being examined. For instance, both HR variables (raw and normalised) have had higher values at the first two segments and gradually decreasing until section M4 (slow traffic). After this section, HR patterns have started increasing again. Similar outcomes also occurred regarding the mean values of SCRs both with TTP and CDA analysis. However, the frequency of responses has had a slightly different pattern as it started from lower values and has an increasing trend across the motorway. Moreover, the normalised mean amplitudes have been highest during M4 area which is not consistent with the previous findings. Overall, there has been some ambiguity regarding physiological responses in each road segment while almost all associations were not significantly different.

Physiological responses and driving behaviour

The differences in physiological responses have not been insightful at the scenario level however, given the duration of the motorway setting and the constant interaction of participants with traffic, they have been also compared to the variables presented in section 2.5.1 with Pearson correlation analysis. This analysis refers to all the areas e.g. mean speed in each of the six main areas for each participant was compared with the respective physiological responses. The detailed findings of the significant results are presented in Appendix A.2, Table A.30.

Significance levels might be different, whether raw or normalised responses are considered. With respect to HR, some positive correlations have occurred with the mean and the maximum speed and also with the standard deviation of acceleration. Moreover, some additional positive associations have been found with the proportion spent on the right-most lane, the standard deviation of negative acceleration and braking and finally, a negative correlation with the mean negative acceleration. These findings indicate that increase of HR can possibly lead to a more agitated driving style.

The same approach has been also applied to the SC analysis but in this case, also the sum of responses has been considered. The CDA analysis shows a number of positive correlations regarding some of the SC variables with the proportion spend above the speed limit and the standard deviation of acceleration. Moreover, a positive association has been found with the total number of lane changes and the proportion of time spent on the left-most and right-most lane while a negative relationship occurred regarding the use of the middle lane. This finding might imply that increased SC activity could have resulted to either more aggressive or more cautious behaviour. Additionally, a series of relationships have been found with the mean values and standard deviation of positive and negative acceleration. In particular, increase in SC amplitude has associated with higher acceleration, smaller deceleration and increase of both standard deviations. Also, a positive correlation has occurred with the standard deviation of the gas pedal depression.

The TTP analysis of the SC signal has resulted on very similar significant outcomes. The main difference has been a positive correlation also with brake pedal depression. In general, increase of SC variables has been also correlated with less steady driving style supporting to some extent the findings from HR. Finally, it might be worth mentioning that the frequency of responses has resulted only in one significant correlation and thus, at this level of aggregation, it might not be an informative indicator.

2.5.3 Interactions with sociodemographic characteristics

The effects of the sociodemographic characteristics have been investigated with the nonparametric Mann-Whitney U and Kruskal-Wallis H tests. Although different relationships could be found at the various sections, given that the whole motorway was continuous and there has not been any clear indication to participants regarding the changes in traffic conditions, it was decided to investigate the relationship of sociodemographic characteristics and the motorway as a whole. The reported results refer to significance either at the 0.05 or 0.1 level.

Some significant gender effects have occurred on the average speed ($Z=-2.012$, $p=0.024$) and percentage above speed limit ($Z=-2.297$, $p=0.022$). In both cases, the values for male drivers are higher. It is worth mentioning that regarding the latter, the average value for male participants has been almost twice as high as the one for females (18.56% and 9.38% respectively). Moreover, males have had significantly higher mean ($Z=-2.012$, $p=0.044$) and standard deviation ($Z=-2.329$, $p=0.020$), regarding positive acceleration, and also higher standard deviation in the gas pedal depression ($Z=-2.646$, $p=0.008$). Moreover, some additional relationships have been found between minor accident involvement and higher mean headway ($Z=-1.740$, p=0.082) and lane-change frequency (Z=-1.783, p=0.075). This finding could indicate that these participants preferred to change lanes more frequently in order to avoid following vehicle at closer time headways. No other significant relationships have been found regarding the effects of sociodemographic characteristics. However, as already mentioned, it is likely that an investigation of sociodemographic characteristics at scenario-motorway segment level would result in more significant relationships and would be something to be considered.

2.5.4 Interactions with personality traits

The relationship of personality factors with the various variables has been investigated for the whole length of the motorway experiment with Pearson correlation analysis. The significant results are presented in Table 2.13.

Regarding speeding behaviour, Anxiety has been related to smaller maximum speed and proportion above the speed limit. Another interesting outcome has been that Angry personality trait is also related to a steadier driving style in terms of acceleration while, as expected, Excitement-seeking is positively correlated with the percentage spent above the speed limit.

Regarding lane-change behaviour, Anxiety has been negatively correlated with lane-change number and frequency while Vulnerability has been positively associated with more time spent in the middle lane. With respect to following behaviour, Excitement-seeking has resulted in associations with shorter headways and higher proportion spend below 1.5 seconds. The same factor has been also associated with higher rates of gas and brake pedal depression while on the other hand, some negative correlations occurred, regarding Anxiety and Anger and some pedal depression variables.

2.5.5 Interactions with driving style

The same approach as personality traits has been also applied for the driving style factors of the MDSI scale, however, fewer significant correlations were found in this case. The significant results are included in Table 2.14. In particular, Risky driving style has been associated positively with mean speed, maximum speed and proportion spent above the speed limit. On the other hand, Patient driving style has been negatively correlated with mean speed and Careful style with maximum speed. Also, Patient style is positively correlated with higher proportion spent on the left-most lane and negatively correlated with the right-most lane. The proportion spend on the middle lane has been positively associated with the Anxious and the Distress-reduction styles. Finally, Risky driving style has been positively correlated with the standard deviation of gas pedal depression.

Table 2.13: Correlation matrix of personality factors with the motorway setting variables

		Anxiety	Anger	Vulnerability	Excitement
Maximum speed	r	**-.396**	-0.141	-0.149	0.161
	p-value	**0.017**	0.411	0.387	0.347
% above speed limit	r	**-.350**	-0.228	-0.152	**.404**
	p-value	**0.036**	0.181	0.377	**0.015**
Std. deviation of acceleration	r	-0.265	**-0.288**	-0.124	0.184
	p-value	0.118	**0.089**	0.471	0.282
Mean of negative acceleration	r	**0.285**	0.263	0.129	-0.139
	p-value	**0.092**	0.121	0.452	0.418
Std. Dev. of positive acceleration	r	**-.359**	**-0.287**	**-0.280**	0.231
	p-value	**0.032**	**0.090**	**0.098**	0.175
Std. Dev. of negative acceleration	r	-0.245	**-0.289**	-0.083	0.133
	p-value	0.149	**0.087**	0.630	0.438
Total lane-changes	r	**-0.293**	-0.230	-0.027	-0.065
	p-value	**0.083**	0.178	0.875	0.705
Lane-change frequency	r	**-0.305**	-0.241	-0.029	-0.009
	p-value	**0.070**	0.156	0.867	0.959
% spent on the middle lane	r	0.180	0.021	**.341**	-0.101
	p-value	0.293	0.902	**0.042**	0.557
Mean time headway	r	0.232	0.146	0.174	**-.408**
	p-value	0.173	0.395	0.309	**0.013**
% spent at time headway < 1.5 secs	r	-0.159	-0.201	-0.150	**0.317**
	p-value	0.353	0.239	0.383	**0.059**
Std. deviation acceleration pedal depression	r	**-0.296**	-0.172	-0.156	**.382**
	p-value	**0.079**	0.316	0.365	**0.021**
Std. deviation of braking	r	-0.248	-0.168	0.014	**0.320**
	p-value	0.145	0.326	0.935	**0.057**

2.6. Summary of findings

The current analysis has been based on an extensive driving simulator experiment that presented to participants two different settings, in terms or road characteristics, an urban road and a motorway. Given the differences in the nature of the two settings, different outcomes were extracted about driving behaviour (as presented more detailed in Sections 2.4 and 2.5) which can have useful practical applications.

In the urban scenario, driving behaviour has been tested with respect to specific events that have been taking place along the road. Interestingly, participants' behaviour have been almost in all cases significantly different under time pressure. This difference has been expressed, under time pressure, via higher speeds and acceleration rates, while in other cases participants completed the scenarios faster. For instance, under time pressure, more participants have accomplished a passing manoeuvre and they have started overtaking earlier at the overtaking scenario. Moreover, less participants have stopped at the amber dilemma scenario while the time to complete to gap-acceptance task was shorter under time pressure. Findings in existing literature (Cœugnet et al., 2013; Naveteur et al., 2013) have showed that drivers perceive speed differently under time pressure and become more impatient. The outcomes from the urban setting have supported the results of the aforementioned studies. Regarding sociodemographic characteristics, the results have been expected with respect to gender and age. Moreover, some additional significant findings have been found regarding involvement in minor accident and having received a fine for speeding, showing that these can also be indicators of risky driving behaviour. An interesting finding has been that several traits as e.g. excitement-seeking and anxiety or other self-reported driving styles have been correlated with observed behaviour. In recent literature (van Huysduynen et al., 2018) some modest correlations have been also found between the MDSI scale and driving simulator behaviour indicating that self-reported scales can be insightful about the actual driving behaviour. However, in the urban scenario no significant correlations have occurred between time pressure and stress levels. Although this could have been a result of familiarisation with the simulated environment and learning effects, it could have also been the case that stress levels have not been affected by time pressure in the urban setting.

The motorway setting has been investigated in terms of speeding, lane choice and lane-change behaviour, following behaviour and pedal depression. Most of the differences across the various segments have been expected while also significant correlations have been found with some traits. However, the most interesting finding regarding this scenario has been that some of the physiological responses have been correlated with the examined traffic variables. In particular, increase of physiological variables has been positively correlated with higher speeds and standard deviation of acceleration. This might be an indication for a bidirectional relationship between stress levels and agitated or risky driving behaviour which may also have safety implications.

Table 2.14: Correlation matrix of MDSI factors with the motorway setting variables

		Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Careful
Mean speed	r	0.037	-0.034	**.379**	-0.024	0.101	0.034	**-0.298**	-0.247
	p-value	0.831	0.845	**0.023**	0.888	0.557	0.846	**0.077**	0.146
Maximum speed	r	-0.033	-0.186	**0.284**	0.063	0.050	0.081	-0.206	**-.422**
	p-value	0.850	0.276	**0.093**	0.717	0.773	0.639	0.229	**0.010**
% above speed limit	r	-0.013	-0.085	**.451**	-0.019	0.097	0.091	-0.190	-0.244
	p-value	0.938	0.620	**0.006**	0.913	0.573	0.597	0.267	0.152
% spent on the left-most lane	r	0.005	-0.119	-0.133	0.044	-0.111	-0.041	**0.285**	0.066
	p-value	0.976	0.489	0.439	0.797	0.518	0.810	**0.093**	0.701
% spent on the middle lane	r	0.198	**.349**	-0.228	-0.233	0.016	**0.281**	0.041	0.242
	p-value	0.246	**0.037**	0.181	0.172	0.926	**0.097**	0.814	0.154
% spent on the right-most lane	r	-0.144	-0.137	0.277	0.124	0.088	-0.161	**-0.282**	-0.228
	p-value	0.401	0.424	0.102	0.472	0.611	0.348	**0.096**	0.181
Std. deviation acceleration pedal depression	r	0.085	-0.095	**0.329**	0.014	0.021	0.152	-0.085	-0.198
	p-value	0.621	0.582	**0.050**	0.935	0.902	0.377	0.621	0.248

2.7. Conclusion

The current study has attempted to investigate driving behaviour and the effects of traffic conditions, time pressure and individual characteristics (both static and dynamic). Driving behaviour has been observed within a driving simulator environment while at the same time, also physiological responses of drivers were collected.

Driving behaviour was studied over a series of various situations and significant differences have been found with regarding the effects of time pressure and traffic conditions. These outcomes highlight the potential and significance of the use of driving simulators to investigate several aspects of driving behaviour. Moving a step forward, driving simulators can be used for the estimation of typical microscopic traffic simulation models (see Toledo, 2007 for an extended review), augmented with drivers' attributes or situational factors that are usually omitted. This may lead to the improvement in the representation of driving behaviour since, as found in the existing literature, and also in the current study, individual characteristics, traits and stress may significantly influence driving behaviour. Thus, the incorporation of these variables in the existing models could increase their behavioural representativeness and accuracy.

Another focus of the current work has been to invstigate the relationship of driving behavior with physiological responses. Considering the latest developments in the field of artificial emotional intelligence (Emotion AI), it is possible to device interventions to reduce stress (Hernandez et al., 2016) and significantly increase road safety. For instance, advances in vehicle operation technologies offer the opportunity for designing interventions to warn/advise drivers, limit acceleration- deceleration capabilities, introduce calming measures and even take over full control of the vehicle.

Despite the promising nature of the results, the study has a series of limitations that should be acknowledged. First, the data has been collected in a simulated environment and thus may be behaviourally incongruent due the experimental nature. Moreover, it should be noted that in the urban-rural scenario, time pressure has been always induced at the second half of the road without counterbalancing between the two tasks. Though this approach has been also applied in other stress-related research (see Rendon-Velez et al., 2016 for example) and the learning effect is likely to be minimal given the experimental design, this is yet to be tested. Similarly, the order of scenarios and time pressure in the motorway setting has been always fixed for all participants. This experimental design might has influenced driving behaviour, especially in the last segments (e.g. owing to fatigue or impatience). Moreover, the emoji has been always green during the first part of the motorway for purposes of realism, as the drivers would not have expected to see an amber or red indication at the very early stages. For the same reason, there was some type of time pressure at the last motorway segments. In terms of each individual scenario, it has been decided to present to participants a green to red sequence of time pressure indicators within an effort to minimise the risk of increasing their physiological responses at the beginning of a specific scenario that would potentially influence and prevent them from returning to the baseline levels. Also, it should be mentioned that no baseline levels of physiological responses were collected. This practice is advised for signal normalisation to reduce inter-individual differences (Healey & Picard, 2005; Singh & Queyam, 2013) or to compare changes across different emotional states (e.g. Yin et al., 2018). However, baseline measurements are not essential as there are several examples in literature that signal normalisation has been applied using the whole range of the signal, rather than comparing with values during rest (Picard et al., 2001; Wang et al., 2013; Handouzi et al., 2014). Given that the most important has been the detection of relative changes in physiological responses for different driving conditions in the simulator environment, the main trends and findings are not expected to be affected by the lack of comparison with baseline levels. To the aforementioned limitations, it should be added a potential bias from the rescaling of the NEO-PI-R scale.

The results presented in the current paper encourage us for a deeper analysis of driving behaviour. Driving behaviour can be separately examined in terms of e.g. overtaking behaviour, gap-acceptance behaviour, car-following and lane-change. For each component of driving behaviour, it is e.g. possible to estimate models based on existing microscopic simulation approaches. At the same time, drivers’ characteristics as socio-demographics and stress levels can be incorporated, extending this way the traditional model specifications. This approach, is possible to provide further insights and a better understanding on driving behaviour and how it is influenced by individual and contextual factors.

2.8 References

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CHAPTER 3: MODELLING THE EFFECTS OF STRESS ON GAP-ACCEPTANCE DECISIONS COMBINING DATA FROM DRIVING SIMULATOR AND PHYSIOLOGICAL SENSORS

ABSTRACT Driving behaviour is an inherently complex process affected by various factors ranging from network topography, traffic conditions and vehicle features to driver characteristics like age, experience, aggressiveness and emotional state. Among these, the effects of emotional state and stress have received considerable attention in the context of crash analysis and safety research where driving behaviour has been found to be affected by drivers' mental state/stress, cognitive workload and distraction. However, these studies are mostly based on questionnaire surveys and self-reports which can be prone to response bias and reporting/measurement errors. The analyses are also often descriptive in nature. In a parallel stream of research, advances in sensor technologies have made it possible to observe drivers' stress through human physiological responses, e.g. heart rate, electro-dermal activity etc. However, these studies have primarily focused on detecting stress rather than quantifying or modelling its effects on driving decisions. The present paper combines these two approaches in a single framework and investigates the gap-acceptance behaviour of drivers during an intersection crossing, using data collected using a driving simulator. The participants are deliberately subjected to stress induced by time pressure, and their stress levels are measured using two physiological indicators, namely Electrodermal Activity (skin conductance) and heart rate. In addition to statistical analyses, discrete choice models are developed to link the accept-reject choices of a driver with the driver demographics, traffic conditions and stress levels. The results of the models indicate that increased stress levels significantly increase the probabilities of accepting a gap. The improvement in model fit and safety implications derived from model estimates are also discussed. The insights from the results can be used for designing appropriate intervention strategies to improve safety.

3.1 Introduction

Road safety continues to be an important issue with road crashes among the leading causes of death - accounting for more than 1.2 million fatalities and 50 million injuries globally each year (World Health Organization, 2015). Driver behaviour is a factor in over 90% of crashes, with speeding as one of the major contributors (World Health Organization, 2015). Driving behaviour models, which provide mathematical representations of drivers' decisions involving acceleration-deceleration, lane-changing, overtaking, etc., are increasingly being used for evaluation and prediction of road safety parameters and formulating remedial measures (e.g. Farah et al., 2009; Barceló, 2010; Hoogendoorn at el., 2010; Farah & Koutsopoulos, 2014). Reliable driving behaviour models are also critical for accurate prediction of congestion levels in microscopic traffic simulation tools) and analyses of emissions.

Driving decisions are affected by various factors, including network topography, traffic conditions and driver characteristics - which include, among others, demographics, personality traits and emotional state. Existing driving behaviour models address many of these factors, either fully or partially, where the effects of surrounding traffic conditions have received considerable attention (Ossen and Hoogendoorn, 2005; Toledo, 2007; Choudhury, 2007; Marczak et al., 2013 to name a few). However, in most cases, the models do not adequately capture the sophistication of driver behaviour and the causal mechanism behind their observed decisions. In particular, research in other realms, in the context of crash analysis and safety research, has confirmed that driving behaviour is significantly affected by drivers' mental state/mood (e.g. anger) (Garrity and Demick, 2001), cognitive workload (Hoogendoorn et al., 2010), distraction (Young et al., 2007) and fatigue (Thiffault and Bergeron, 2003). Existing work on drivers' stress has mainly focused on the investigation of the relationship between stress and aberrant behaviour and its impact on safety (Ge et al., 2014; Westerman and Haigney, 2000; Hill and Boyle, 2007). However, these studies primarily examined the effects of stress based on self-reported surveys which can be prone to response bias and reporting errors. Indeed, at best, a driver can report an indication of stress levels, but not an objective measure of a physiological state. In addition, many of these studies are largely descriptive rather than relying on detailed modelling work.

In a parallel stream of research, recent advances in sensor technologies have made it possible to measure drivers' stress levels through human physiological responses, e.g. changes in heart rate, electrodermal activity etc. (Healey and Picard, 2005; Ahmed et al., 2015). However, these studies have primarily focused on detecting stress rather than quantifying or modelling its effects on driving decisions in detail.

This paper aims to fill in this research gap by developing gap acceptance models with explicit consideration of the effect of stress on driving behaviour. The gap-acceptance models developed in this research are based on an extensive experimental study in the University of Leeds Driving Simulator (UoLDS) where the drivers have been intentionally subjected to stressful driving conditions caused by time pressure and surrounding traffic conditions. Their choices of accepted gaps have been recorded alongside physiological measurements of stress indicators (Electrodermal Activity and heart rate) and socio-demographic characteristics (age, gender, experience). A series of gap acceptance models are developed and augmented by continuous physiological measurements.

The remainder of the paper is organised as follows. We first present a review of the literature, followed by the experimental setting and the data analyses. This is followed by a description of the methodological approach of the study. We then present estimation results followed by concluding remarks where insights from the models are discussed.

3.2 Literature review

3.2.1. Stress and driving context

'Driver stress' has been defined as a situation that challenges drivers' abilities, reduces their perceived control or threatens their mental/physical health (Gulian et al., 1989). Driver stress can be a consequence of several factors including the direct demands of the driving task, the environmental conditions (e.g. foggy, icy, etc.), network characteristics (e.g. surface characteristics), junction frequency, speed and flow per lane and/or potential secondary tasks, such as use of navigation system, texting, etc. (Hill and Boyle, 2007). Moreover, time urgency and the level of congestion have been identified as two important factors influencing drivers' stress (Hennessy and Wiesenthal, 1999).

There is a substantial body of literature that investigates the effects of stress on driving behaviour. Drivers under stress may be overwhelmed by negative emotions and thus are more likely to get involved in hazardous situations (Ge et al., 2014). Self-reported stress has been linked to aberrant driving behaviour, namely errors and violations

(Kontogiannis, 2006). These types of impaired behaviour are related to road crashes and incidents, therefore stress is considered as an issue related to traffic safety (Westerman and Haigney, 2000; Useche et al., 2015, Qu et al., 2014). Moreover, Ge et al. (2014) found that perceived stress is linked to aggressive and risky driving behaviour. Also, Clapp et al. (2011), grouped reactions under stressful situations in three main categories which are the extremely cautious driving behaviour, aberrant behaviour and aggressive (or hostile) behaviour. The aforementioned findings provide compelling evidence regarding the effects of stress on driving, however, they are based on self-reported survey results and therefore prone to response bias and reporting/measurement errors.

An alternative, and potentially more reliable, approach to detect drivers' level of stress and study its effects, is through its implications on human physiology. Recent advances in sensor technologies and affective computing have made it possible to measure drivers' stress levels through physiological responses, e.g. changes in heart rate, Electrodermal Activity (EDA), blood volume pulse, etc. There are several existing studies related to driving stress that use this type of data (some examples Healey and Picard, 2005; Singh and Queyam, 2013; Rigas et al., 2012). However, the aforementioned studies mostly focused on detecting stress rather than investigating its effects on observed driving behaviour.

Two of the most widespread physiological indicators - also used in the present study - are heart rate and Electrodermal Activity (EDA). Heart rate represents the observed heartbeats per minute. Lower heart rate is generally linked to a relaxed state while it increases under the presence of emotional stimuli or mental effort (Katsis et al., 2011). EDA is related to the sweat gland activity and it is an indicator that increases or decreases proportionally to stress effort (Katsis et al., 2011). EDA is composed of two different parts, namely the skin conductance level (SCL – tonic part) and skin conductance response (SCR – phasic part). While SCL is slowly varying and related to individual characteristics, SCRs are expressed as a sudden and fast increase of skin conductance owing to the presence of a specific stimulus and thus have been linked to acute stress. SCRs are identified if the increase in skin conductance activity exceeds specific critical values.

Before proceeding, let us just expand on the argument of why such physiological measurements are superior to self-reported measures. The two most apparent issues with self-reported data are perception bias and measurement error. For the former, a respondent to a questionnaire may perceive to be more or less stressed than he/she actually is, and this can be amplified in the case of recall surveys. For the latter, it is difficult for a survey respondent to quantify the level of stress in an objective manner.

An additional reason, which is mentioned less often, is that of strategic bias. A respondent in a survey may purposefully overstate or understate his/her actual stress levels for example to make an experienced situation seem more stressful or play down the effect of his/her own mental state. None of these issues should in theory arise with physiological measurements as they are driven by subconscious factors that cannot be easily biased by the respondent and are also measured objectively.

3.2.2 Gap-acceptance behaviour and models

Driving behaviour models primarily include car-following, lane-change and gap-acceptance (Toledo, 2007). The latter of the aforementioned concepts focuses on two different aspects; the decision of drivers to change lane and the attempt of a turning or crossing manoeuvre at an intersection. In the literature, several methodological approaches have been developed in order to predict the intersection crossing decisions of drivers. This type of gap acceptance behaviour is of prime importance when studying issues such as network capacity, delays and road safety (Ashton, 1971; Fitzpatrick, 1991). The majority of these methodologies are based on the critical gap concept, which is defined as the minimum time gap in the priority stream which a driver moving on the minor road is willing to accept in order to cross through the conflict zone. According to Brilon et al., (1999), there are at least 20-30 different methods related to gap-acceptance decisions. Some of the most cited are the Raff method (Raff and Hart, 1950), the Greenshields method (Greenshields et al., 1946), the lag method (see Brilon et al., 1999), the logit method (Maze, 1981) - which is a method based on traditional choice modelling techniques (see Ben-Akiva and Lerman, 1985), the Ashworth’s method (Ashworth, 1969), and the maximum likelihood method (Miller and Pretty, 1968). The main limitations regarding some of the existing methodologies in the context of unsignalised intersections are the assumptions of consistency and homogeneity (Bottom and Ashworth, 1978; Pollatschek et al., 2002). The former indicates that a driver, in all similar situations, would have a specific critical gap value t_c and accept all gaps with a value greater than this (and reject the rest). Based on this assumption, a driver waiting to cross a junction, cannot reject a specific gap and later accept a shorter one. The assumption of consistency is not however accurate since e.g. risk tolerance of an individual might change during waiting time leading to acceptance of a shorter gap compared to the ones rejected earlier (Pollatschek et al., 2002). Moreover, the various t_c values of different consistent drivers are treated as a random variable that follows a specific distribution $\varphi(t_c)$ and cumulative distribution $\Phi(t_c)$ (Brilon et al., 1999). Sub-groups of drivers are assumed to follow the same density and cumulative distribution functions resulting within-group homogeneity of the driver population.

The assumptions of homogeneity and consistency of gap-acceptance methodologies raise limitations in the representation of drivers' behaviour since they both ignore their sophisticated decision-making process. For instance, critical gap varies among and within drivers, in different situations, and should be treated as a random variable (Guo et al., 2014). The drawbacks imposed by these assumptions have been relaxed in gap-acceptance models developed in the context of lane-changing, where critical gaps are assumed to follow statistical distributions with means being functions of influencing variables like speed of the lead and lag vehicles (e.g. Ahmed 1999, Toledo 2003, Choudhury 2007). These models are also extended to incorporate the effect of driver demographics (age, gender) and driving style (e.g. Farah et al. 2009). Another competing approach is to model the gap accept-reject decisions based on 'Utility maximization theory' – logit models for example. In Logit models, the probability of accepting or rejecting a gap is a function of different variables (e.g. gap size, the speed of the approaching vehicles, waiting time, etc.) and captures the trade-off among different influencing factors (e.g. Amin and Maurya, 2015).

A review of the gap-acceptance literature showed that drivers' behaviour is influenced by various factors. Most of the variables are related to traffic conditions such as gap size (Bottom & Ashworth, 1978; Nabaee et al., 2011), waiting time in the queue (Pollatschek et al., 2002) or at the stop line (Mahmassani and Sheffi, 1981) and the queue behind the driver while waiting at the stop line (Nabaee et al., 2011; Tupper et al., 2011). Apart from the aforementioned factors, Bottom & Ashworth (1978) mention that inter-individual variance is worth being investigated in terms of variables as extroversion (personality), age, annual mileage and vehicle type.

Despite the advances in gap-acceptance model structures, the full range of variables influencing the decisions of the drivers has not yet been fully investigated. Some of the aspects which are not yet addressed include drivers' strategies when deciding to cross an intersection or not, the motivation behind an observed "inconsistent" action and finally the effects of individual traits and characteristics (e.g. personality, attitudes, state of mind, level of stress etc.). The aim of the present study is to provide an extended gap-acceptance framework, through the development of a model that accounts for variables related to driver's individual characteristics, with explicit consideration of drivers' acute stress levels, and contribute to filling in this gap of driving behaviour modelling research.

3.3 Data collection

3.3.1 Driving simulator experiment

The data used in this research is based on primary data collected as part of a comprehensive driving simulator study (Next Generation Driving Behaviour Models – NG-DBM) for investigating the effect of stress in different driving decisions (e.g. acceleration-deceleration, overtaking, red light violation, gap acceptance, etc.). The experiments have been conducted using the University of Leeds Driving Simulator (UoLDS). The UoLDS (Figure 3.1) is a high fidelity, dynamic simulator. The vehicle cab is a 2005 Jaguar S-type with all driver controls available and fully operational. This includes the steering wheel and braking pedal, and there is also a fully operational dashboard. The vehicle is positioned in a 4m diameter spherical projection dome. The dome provides fully textured 3-D graphical scene with a horizontal field of view of 250^{o} and 45^{o} vertical and it is placed on an 8 degrees of freedom motion system. The model of vehicle dynamics has been extensively validated to capture accurate vehicle behaviour on high-friction surfaces (Markkula et al., 2018). The raw data output consists of observations of 60Hz frequency. The relative validity of UoLDS has been confirmed in several studies (e.g. Jamson et al., 2010; Markkula et al., 2018). While driving simulator data, given its 'experimental' flavour, has the risk to be prone to behavioural incongruence, it offers the flexibility to fully control the surrounding traffic and driving contexts (e.g. inducing time pressure and stressful scenarios) which are crucial for this particular study.

Figure 3.1: The University of Leeds Driving Simulator

[sources: University of Leeds, University of Leeds Driving Simulator]

The full data collection process involved around 90 minutes of total driving in the simulator for each individual. Participants initially had a short briefing session about the simulator and its operation followed by a practice session of approximately 15 minutes duration to familiarise themselves with the simulated environment and vehicle dynamics (i.e. motion system). For safety reasons, participants were accompanied by a researcher during the practice run, positioned in the back seat. After the practice session, participants started the main driving sessions, composed of two different environments, using an urban setting and a motorway setting, with a short break in between.

The urban setting was composed by several tasks. These included an encounter with a slow-moving lead vehicle that participants could decide to overtake or not, a traffic light with a red indication of long duration that aimed to cause frustration, an amber dilemma scenario where participants could decide to accelerate or brake and the gap-acceptance scenario presented in the current analysis. These scenarios were repeated twice (without and under the presence of time pressure) while in the end there was also a right-turn manoeuvre scenario which was the last task of the urban setting. Within an effort to minimize any potential residual effects from the previous tasks, some straight road segments without any critical events were included, in between the main tasks. The average duration of these dummy segments was 2-3 minutes and participants did not meet any traffic in these, however, at the second half of the urban setting they were deliberately subjected to time pressure. The latter needs some more explanation. As mentioned above, the majority of the scenarios had two variants - one without and one with time pressure. Before each of the two main driving simulator settings, participants were instructed that they had to reach the destination within 35 minutes and they could see an emoji placed on the dashboard (Figure 3.2) denoting their performance with respect to time. Participants were told that the emoji displayed to them was determined based on expected arrival time which is computed and constantly updated using a sophisticated algorithm running in the background and uses variables such as current speed, speed limit, distance to the end, an average estimated delay that will be caused by the events ahead etc. as inputs. This was then used to determine which of the three emoji to show. Participants were instructed that the green state would indicate they were doing well, in terms of time, while the red would mean that they were late. The intermediate amber emoji meant that they were marginally fine in terms of time. That is, they will receive a red emoji if they have further delay in the remaining driving tasks. An amber state was introduced to make the shift from green to red emoji (and vice versa) more convincing to the participants. In reality, the state of the time pressure emoji was not related to their actual performance but was pre-decided in order to induce time pressure in specific road segments. It should be mentioned that the amber was always shown before/after the critical sections (e.g. in straight segments) as opposed to near intersections. Therefore, the data used for gap-acceptance model development only include red and green phases. It may be noted that the choice of 3 different emoji to indicate time pressure, was preferred to a conventional countdown timer since it would be easier to manipulate. In order to increase the likelihood that participants would consider time pressure indications, they were instructed that a penalty would be imposed on the monetary reward they received for their participation in case they were late at the end of a scenario (red emoji). Again, this was never the case since both main scenarios were programmed to end in the amber time pressure state.

Figure 3.2: Time pressure indications

Drivers' physiological data, across the whole experiment, was collected using the Empatica E4 wristband which is a non-intrusive device that provides information about heart rate (HR), Electrodermal Activity (EDA), blood volume pulse (BVP) and temperature (TEMP). Each of the physiological indicators was collected with a different frequency, depending on the attributes of the wristband. EDA and temperature have a 4Hz frequency, blood volume pulse 64Hz and heart rate 1Hz. The device can be automatically synchronised with the clock of any computer when plugged in.

3.3.2 The gap-acceptance task

In the present study, the gap-acceptance task was presented twice, as a part of the urban driving scenario. Drivers faced the first gap-acceptance task without time pressure (green emoji) followed by the same scenario with time pressure (red emoji). The scenario itself consisted of two groups of vehicles. At first, six blocking vehicles were shown to participants, moving at short headway distances. These vehicles were used to force drivers to stop before the main gap acceptance task. This first group of vehicles was followed by eleven vehicles that created 10 gaps. The gaps had an increasing trend in general. The increasing trend of gaps was chosen in order to secure that drivers would not face a large gap at the beginning of the scenario and miss information related to their willingness to accept a shorter one. However, to increase realism, some shorter gaps were also introduced in between (as 3rd, 5th, 7th and 8th gaps). The full set of available gaps were identical for both intersections and across participants. For each gap-acceptance task, the drivers could choose to accept the available gap and cross or reject the immediate gap and wait for a better one or even reject them all (i.e. wait till all 11 vehicles had crossed). The drivers, however, had no a priori knowledge regarding the number of the oncoming vehicles or the waiting time required. For the sake of simplicity, it was decided to constrain the gap-acceptance scenario by developing a case where cars were shown only coming from the left side of the driver. It may be noted that the time pressure was always applied at the second intersection albeit the fact that there might be confounding with learning[1] and fatigue effects. The main reason for this design was related to drivers' physiology, since we aimed to minimise the risk of increasing their responses at the beginning of the driving task by inducing additional stressors (e.g. time pressure) that would potentially influence and prevent them from returning to the baseline levels. Also, it would be more realistic for the participants to receive a red face indication closer to the end of the driving task, rather than during the first part. A general outline of the gap-acceptance scenario setting is illustrated in Figure 3.3, while the presented gap sizes are shown in Table 3.1.

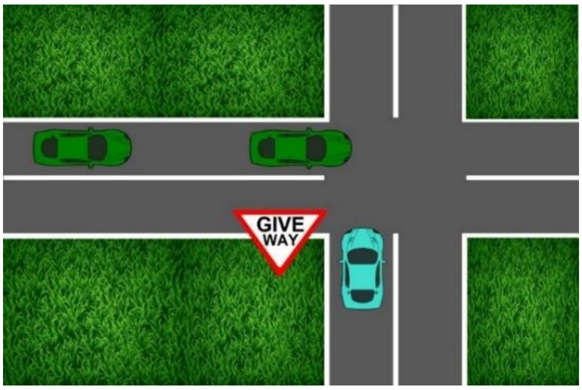


Figure 3.3: Illustration of the intersection

Table 3.1: The available gaps and gaps' sizes

Gap ID	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Gap size (s)	2.8	3.45	3.4	4.4	4	5.4	5	4.7	6	6.8

[1] Since the two scenarios occurred with a time gap of approximately 15 minutes in between where the drivers had to tackle other difficult situations, the learning effect is not expected to be significant.

3.3.3. Exploratory analysis

Sample analysis

The sample of the current analysis consists of 41 (22 male, 19 female) staff members or students at the University of Leeds, holding a valid driving licence, that successfully completed the urban task. Three participants were removed from the analysis, since they reported motion sickness during the practice session while also an additional participant was removed because the wristband device failed to collect physiological data. The mean age of participants is approximately 34 years and the corresponding standard deviation is 11 years. Almost half of the participants stated that they are driving on a daily basis. The average driving experience of participants is almost 14 years. Regarding accident involvement, 6 participants have reported involvement in minor accidents while 4 have reported involvement in serious accidents. It is worth mentioning that a serious (or major) accident is defined as one where at least one person required medical treatment and/or there was property damage above £500. Finally, 7 participants stated that they had at least once received a ticket penalty for speeding behaviour. The descriptive statistics of the sample are also outlined in Table 3.2.

Table 3.2: Descriptive statistics of the sample

Variable	Intervals	Frequency	%	mean	std. dev.	min	max
Gender	Female	19	0.46	-	-	-	-
	Male	22	0.54	-	-	-	-
Age	-	-	-	34.39	10.86	19	57
Driving experience	-	-	-	13.63	11.48	1	39
Frequency of driving	Everyday	21	0.51	-	-	-	-
	2-3 times/week	12	0.29	-	-	-	-
	Once/ week	4	0.10	-	-	-	-
	Less often	4	0.10	-	-	-	-
Minor accident involvement	No	35	0.85	-	-	-	-
	Yes	6	0.15	-	-	-	-
Major accident involvement	No	37	0.90	-	-	-	-
	Yes	4	0.10	-	-	-	-
Ticket for speeding	No	34	0.83	-	-	-	-
	Yes	7	0.17	-	-	-	-

Gap-acceptance task analysis

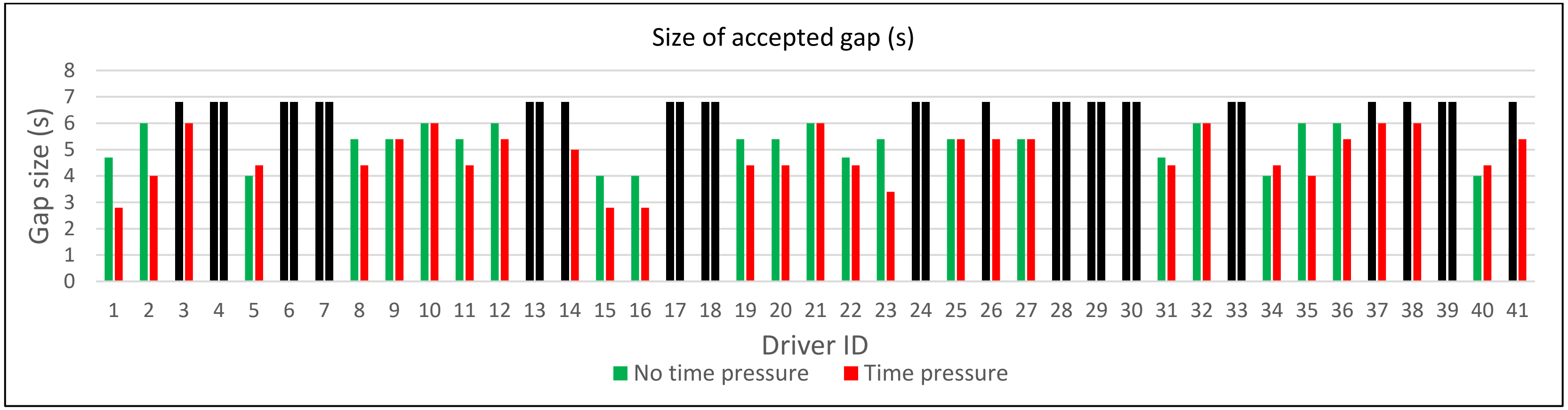
Before the development of the model, participants' gap-acceptance behaviour has been examined with respect to the effects of time pressure. Table 3.3 presents the accepted gaps of each individual, and their respective size (a value n/a is given if no gap is accepted). A similar illustration is also provided in Figure 3.4. It should be mentioned that 12 out of 41 participants did not accept any of the gaps presented to them (i.e. waited for all vehicles to pass), in both cases. On the other hand, six participants accepted a gap only under the time pressure conditions while they had not done so without time pressure. The remaining 23 participants accepted a gap at both intersections. The latter group of participants always accepted the same gap in the second run or a gap that was shown earlier, compared to the one accepted without the external stressor. To further investigate this outcome, a paired samples t-test is applied to compare the significance of the difference of the accepted gap sizes at the two intersections. Given the small sample size, this difference has been also investigated with the non-parametric Wilcoxon test (De Winter 2013). The results (Table 4) show that the mean size of the accepted gaps is smaller at the second intersection, and this difference is statistically significant. As mentioned in the data collection section, participants faced a series of additional tasks involving at least 15min of driving in between the two intersections, thus the learning effect is not likely to be a major influencing factor behind these choices. A similar approach related to the impact of learning effects is found in a study conducted by Ali et al. (2018). The authors investigate behaviour in a mandatory lane-changing scenario in drives of 10-12min long. With respect to learning effects, they mention that because of the occurrence of multiple events, participants are less likely to remember the details of a specific event as time passes. We, therefore, conclude that time pressure had a major influence on acceptance of smaller gaps, which we further test empirically in Section 3.5, although it is still likely to have carryover effects at the second intersection. The mean values in Table 3.4 are smaller than some reported in the existing literature (e.g. Bottom & Ashworth, 1978; Fitzpatrick, 1991) however, they are very close to the median values reported by Ashton (1971) and Amin and Maurya (2015). It may be noted that given the simulated nature of our experiment and the scope to show a limited number of gaps to each participant, the presented gaps were on the shorter range on purpose. Otherwise, there would have been risk of missing the minimum acceptable gap.

Furthermore, with reference to Table 3.3, under the time pressure conditions, three of the participants accepted the first gap they faced. These drivers did not actually behave as expected during the task (stop at the intersection and wait for a gap, or not, to cross) but drove through the streaming of oncoming vehicles without stopping. This indicates that external stressors could increase risk-taking – however, such extreme behaviour may not be frequently observed in real life. Moreover, it is worth mentioning that the 10th gap was never accepted in the current experiment, although

Table 3.3: Accepted gap(s) of each participant at the two intersections

ID		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**
First intersection (without time pressure)	Gap ID	8	9	11	11	5	11	11	6	6	9	6	9	11	11	5	5	11	11	6	6	9
	Gap size (s)	4.7	6	n/a	n/a	4	n/a	n/a	5.4	5.4	6	5.4	6	n/a	n/a	4	4	n/a	n/a	5.4	5.4	6
Second intersection (under time pressure)	Gap ID	1	5	9	11	4	11	11	4	6	9	4	6	11	7	1	1	11	11	4	4	9
	Gap size (s)	2.8	4	6	n/a	4.4	n/a	n/a	4.4	5.4	6	4.4	5.4	n/a	5	2.8	2.8	n/a	n/a	4.4	4.4	6

ID		**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**
First intersection (without time pressure)	Gap ID	8	6	11	6	11	6	11	11	11	8	9	11	5	9	9	11	11	11	5	11
	Gap size (s)	4.7	5.4	n/a	5.4	n/a	5.4	n/a	n/a	n/a	4.7	6	n/a	4	6	6	n/a	n/a	n/a	4	n/a
Second intersection (under time pressure)	Gap ID	4	3	11	6	6	6	11	11	11	4	9	11	4	5	6	9	9	11	4	6
	Gap size (s)	4.4	3.4	n/a	5.4	5.4	5.4	n/a	n/a	n/a	4.4	6	n/a	4.4	4	5.4	6	6	n/a	4.4	5.4



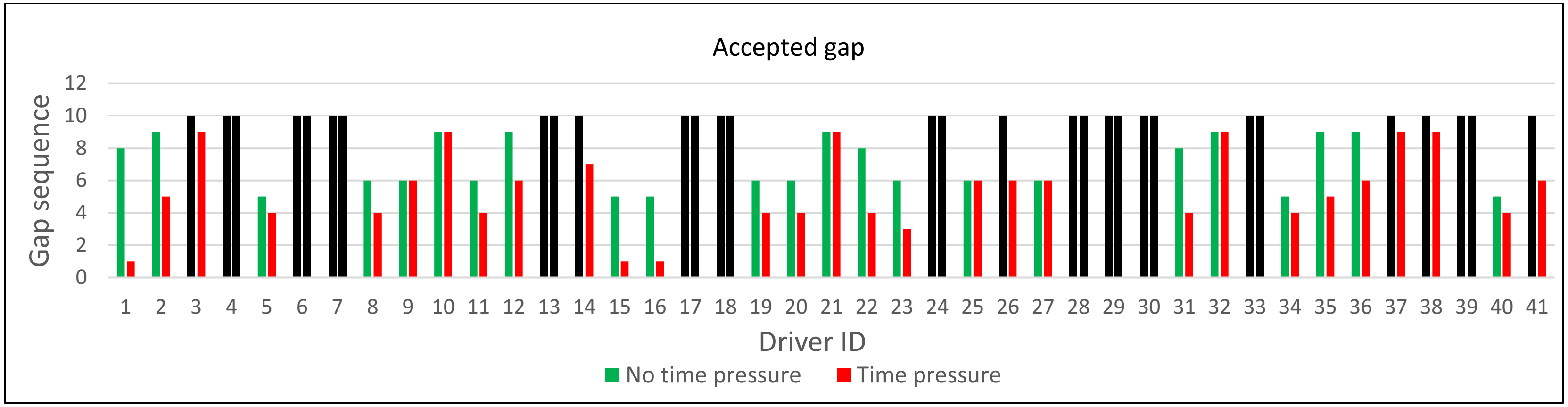


Figure 3.4 Accepted gaps and sizes without and with time pressure

it is the largest one in terms of headway size. This behaviour maybe shows anticipation effects in gap-acceptance behaviour; drivers that wait until the last available gap also prefer to wait the additional time need until being able to cross when the intersection is clear rather than engaging in crossing under the presence of oncoming traffic. As mentioned above, almost one-third of participants follow this behaviour, without being influenced by time pressure in the second task.

3.4. Methodology

3.4.1 The gap acceptance model

The gap-acceptance approach of the current paper has been formulated as a binary choice model, where each gap is considered as a different accept/reject decision. This approach is a modification of the Logit method mentioned in the literature section. The model assumes that the probability of accepting a gap increases with the increase in the utility. The utility associated with a particular gap is a function of the attributes of the gap (e.g. gap size, order, etc.), characteristics of the driver (e.g. socio-demographics) and their state. The utility U_{nt} associated with the decision of a driver *n* to accept/reject a gap *t* can therefore be expressed as follows:

$$U_{nt} = \beta X_{nt} + \gamma Z_n + \theta W_{nt} + \alpha \nu_n + \varepsilon_{nt} \qquad (3.1)$$

where X_{nt} is a vector of gap-specific variables, Z_n are individual-specific and situation-independent variables (e.g. socio-demographics), W_{nt} is a vector of physiological variables that are used to capture drivers' mental state, ν_n represents the effect of unobserved variables that vary across individual drivers but is same for a specific driver (referred as individual specific error term), and ε_{nt} is the random error term (assumed to be independent and identically distributed). Finally, β, γ, θ and α are vectors of parameters to be estimated.

Following the aforementioned assumptions, the probability of gap-acceptance conditional on individual specific error term is defined as (Equation 3.2):

Table 3.4: Results of the paired samples t-test and Wilcoxon test

	Descriptives			Paired samples t-test						
									95% CI for Mean Difference	
	Mean	**SD**	**SE**	**T**	**df**	**P**	**Mean Difference**	**SE Difference**	**Lower**	**Upper**
First intersection (no time pressure)	5.191	0.768	0.16							
Second intersection (under time pressure)	4.558	0.978	0.204	3.752	22	0.001	0.633	0.169	0.283	0.983
Wilcoxon test p-value: 0.002										

$$P_{nt}^{GA}|\nu = \frac{e^{(\beta X_{nt}+\gamma Z_n+\theta W_{nt}+\alpha \nu_n)}}{1+e^{(\beta X_{nt}+\gamma Z_n+\theta W_{nt}+\alpha \nu_n)}} \tag{3.2}$$

If the observed choice of a driver to accept a gap is set as Y_{nt}=1, the conditional full probability of an observed driver's decision can be expressed, as shown in Equation 3.3:

$$P_{nt}|\nu = (P_{nt}^{GA}|\nu)^{Y_{nt}}(1-P_{nt}^{GA}|\nu)^{1-Y_{nt}} \tag{3.3}$$

The conditional probability of a sequence of T_n observed decisions of the same driver takes the form indicated by Equation 3.4:

$$P_n|\nu = \prod_{t=1}^{T_n}(P_{nt}|\nu) \tag{3.4}$$

The unconditional joint probability of the observations of a given driver can be expressed as follows:

$$P_n = \int_{-\infty}^{+\infty}(P_n|\nu)\varphi(\nu)d\nu \tag{3.5}$$

where a $\varphi(\nu)$ is the probability density function of the individual specific error term assumed to have a standard normal distribution. The model parameters are jointly estimated using the Simulated Maximum Likelihood approach using 1000 Halton draws (Halton 1960). The model has been specified and estimated in R based on the code framework provided by the Choice Modelling Centre, University of Leeds.

3.4.2. Physiological data analysis

The model described in the previous section has been augmented by continuous physiological measurements. These observations have been used as direct explanatory variables, in order to investigate whether the gap-acceptance model would be more behaviourally representative when stress has been included. Two different responses have been considered, namely, heart rate and Electrodermal Activity (EDA). Before turning to the actual implementation, it is worth briefly discussing our use of these measures as direct explanators. Recent work in choice modelling (Abou-Zeid and Ben-Akiva, 2014) has focussed on the use of hybrid choice models to incorporate additional indicators of heterogeneity such as answers to attitudinal questions. This type of approach is not critical in our case as the physiological measures are direct measures of physiological states and should thus not be affected by the same concerns of measurement error.

The physiological variables have been initially processed and transformed before their incorporation in the model. Transformation or standardisation of physiological variables is a common practice in relevant research (e.g. Zhai and Barreto, 2006; Singh et al., 2013; Kalimeri & Saitis,2016), within an effort to reduce the inter-individual differences in physiological responses, while it has also been found to improve the distinction among the various physiological states (Ben-Shakhar, 1985). In the current approach, each gap is considered as a different discrete stimulus, rather than assuming the whole sequence as a single continuous stimulus (differences between the two approaches are explained in Cacioppo et al. (2007)). Thus, physiological responses used in the model have been calculated with reference to the initiation of each gap (i.e. when the lead vehicle associated with the gap reaches the beginning of the intersection).

Instead of using the raw observations, the heart rate data have been normalised at the individual level, applying a z-score transformation $\left(\frac{x-\mu}{\sigma}\right)$, where x is a heart rate observation, μ is the heart rate mean value across the whole urban task and σ is its standard deviation (Picard et al., 2001; Healey and Picard, 2005; Maaoui and Pruski, 2010). The normalized heart rate in the beginning of each gap is then considered as a variable in the model.

The EDA observations have been processed using the Matlab package Ledalab (Karenbach, 2005). The skin conductance responses (SCRs) have been obtained applying trough-to-peak analysis, where the amplitude of a response is calculated as the difference in the EDA values between a peak in the signal and its preceding trough (Benedek and Kaernbach, 2010). The amplitude is then considered as an explanatory variable in the models. The EDA analysis is based on event-related response activation; each gap has been considered as a different stimulus. The initiation of each gap has been used as the starting point and responses are detected 1-4s after that moment. Moreover, since we are interested to capture the stress level at the beginning of a gap (when the lead vehicle corresponding to the gap reaches the intersection), the amplitudes corresponding to the immediately preceding gap has been used as an explanatory variable. An example of SCRs analysis is illustrated in Figure 3.5. Following literature indications (e.g. Sano et al., 2014), a critical value equal to 0.01μS is selected as a minimum critical SCRs. Moreover, each significant amplitude (above 0.01μS) has been divided by the maximum observed SCR amplitude, during the simulator experiment, to minimise the effects of individual differences (Lykken, 1972).

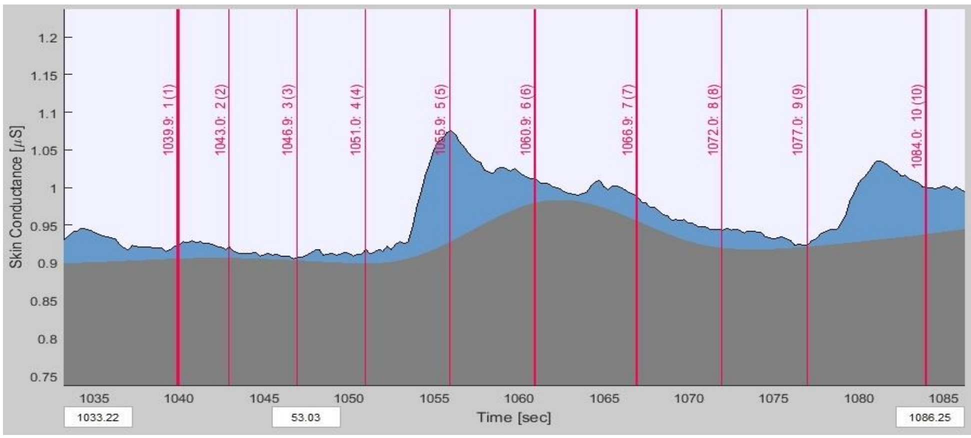


Figure 3.5: Example of SCRs extraction

3.5. Gap-acceptance model

3.5.1 Parameter estimation results and interpretation

A series of gap-acceptance models have been estimated based on the methodology presented in Section 3.4.1. The first model includes only traffic-related variables, while the socio-demographics, time pressure dummy, and the physiological observations are eventually added. Thus, each new model includes all the previous variables plus one or more new ones. The aim of this approach is to compare model fit and investigate the incremental improvement (if any) of adding a specific group of variables. Four different models have been estimated in total, as follows:

- Model 1: Traffic-related variables only
- Model 2: Socio-demographics variables included
- Model 3: Time pressure considered
- Model 4: Physiological variables included

The results of all four models are presented in Table 3.5. All parameter estimates are significant at 95% level (|t-ratio|>1.96).

With reference to Table 3.5, gap size, speed, position, skin conductance response (SCR) and heart rate are continuous variables explained in the next paragraphs. Moreover, a series of dummy variables have been included in the models.

Model 1: Traffic-related variables only

The first model includes the gap size (in seconds), the position of the vehicle during the waiting time, vehicle speed when arriving at the intersection area, a dummy variable indicating whether there is another gap following, or not, and the standard normal disturbance term (Model 1) as explanatory variables.

As expected, gap size has a positive effect on gap acceptance behaviour showing that drivers' probability to accept a gap increases with its size.

Vehicle position is a variable that captures a vehicle's position at the intersection area (the value zero denoting the start of the intersection area) with an increase in value as the vehicle moves forward. If a participant has been outside of the intersection area during the task (it is the case for some participants during the first shown gap), the variable could also take negative values. The inclusion of this variable attempts to capture drivers' behaviour to better position themselves and increase the likelihood of accepting the next available gap. This variable was considered in the model as, during data collection, a proportion of drivers was observed to slowly move their car forward during the period they were waiting for an acceptable gap. As expected, the effect of this variable is positively related to the gap-acceptance probability and drivers are more likely to accept a gap the closer to or further inside the intersection their vehicle is.

The variable vehicle speed is considered in the utility function only for the first gap of each intersection and is ignored for all the rest. It is used to capture the behaviour of not stopping at all at the junction and accepting the first gap – the likelihood of which is expected to increase if the driver is travelling at a high speed.

Finally, the dummy variable of the last gap (which is 1 if there are no further approaching vehicles on sight) has a negative effect denoting a reduction in the probability of accepting a gap which is the last one. This confirms that drivers' gap-acceptance decisions are not short-sighted or focused on the current gap only, rather, the drivers further consider the next available gaps before deciding whether to accept the immediately available gap or not (anticipation effect). The variable sign is thus intuitive.

Table 3.5: Gap-acceptance models' parameter estimates

Variable	Traffic related variables only model Model 1		Socio-demographics included model Model 2		Time pressure included model Model 3		Physiological observations included model Model 4	
	Estimate	t-ratio	estimate	t-ratio	estimate	t-ratio	estimate	t-ratio
Constant	-24.39	-3.74	-25.92	-3.92	-33.56	-5.14	-59.05	-7.32
Gap size	1.14	2.50	1.28	2.87	1.99	3.66	2.87	3.23
Last gap dummy	-9.01	-15.16	-9.17	-14.78	-10.24	-14.69	-13.57	-7.31
Speed (first gap)	2.09	3.77	1.98	3.90	2.18	4.54	3.96	6.10
Position	2.92	3.40	2.77	3.48	3.15	3.92	6.13	5.04
α^{acc}	4.59	4.38	3.47	3.92	4.70	4.48	8.89	4.93
Age>45 dummy	-	-	-5.87	-4.16	-7.89	-4.29	-11.38	-3.79
Regular driver dummy	-	-	5.00	3.05	6.50	3.18	10.08	3.27
Time pressure dummy	-	-	-	-	2.45	2.96	3.75	2.94
Skin conductance response	-	-	-	-	-	-	11.90	2.62
Heart rate	-	-	-	-	-	-	2.40	2.13
LL0		-426.29		-426.29		-426.29		-426.29
LL		-83.53		-75.82		-71.61		-64.90
ρ^2		0.80		0.82		0.83		0.85
adjusted ρ^2		0.79		0.80		0.81		0.82
observations		615		615		615		615

In gap-acceptance situations, waiting time would be expected to have a significant impact. The effect of waiting time was included both as time in seconds and also as a number of gaps that participants waited to accept a gap. However, none of those variables had a significant impact and thus, they were dropped from the model.

Model 2: Socio-demographics variables included

Model 2 included all of the Model 1 variables as well as the variables related to the sociodemographic characteristics of the drivers. Among the several sociodemographic variables tested, those with a statistically significant effect are Age>45 (which is 1 if the driver is older than 45 years, 0 otherwise) and Regular driver dummy (which is 1 if the driver typically drives every day, 0 otherwise). It may be noted that these variables are used in the dummy variable form, since it provides a better model fit with this coding, rather than having a continuous or ordinal form. The Age>45 dummy has a negative effect on gap-acceptance probability, indicating that older drivers are less likely to accept an available gap compared to younger. Moreover, all else being equal, participants that drive every day are more likely to accept a gap. It may be noted that the effects of gender, accident records and fine for speeding have also been tested but not found to have a statistically significant effect. The signs of the variables common with Model 1 were found to be the same but the magnitudes were different. Such changes in sensitivity are expected as the socio-demographic variables are adding further insights in the observed behaviour potentially leading to more representative sensitivity values.

The results of the gap-acceptance model(s) of this study support the existing literature findings. For instance, previous research (e.g. Matthews et al., 1999) used driving frequency as a measure of driving exposure and positively related it to crashes and speed violations. In the present case, participants driving on a daily basis – and thus with higher exposure - were more likely to accept a gap and therefore might be considered as more risk-takers. Similarly, in existing research elder drivers are found to have a less risk-taking propensity (e.g. Jonah, 1990; Krahé and Fenske, 2002; Rhodes and Pivik, 2011; Taubman-Ben-Ari and Yehel, 2012) which is in agreement with our findings.

Model 3: Time pressure considered

The third gap-acceptance model (Model 3) includes all the variables of Model 2 and also accounts for the time pressure conditions induced at the second gap-acceptance task. The time pressure parameter has a positive effect indicating that drivers were more likely to accept a gap if they are subjected to time pressure. Again, the signs of the variables common with Model 2 were found to be the same but the magnitudes were different.

Model 4: Physiological variables included

Finally, the model is enhanced by physiological variables related to heart rate and SCRs. The extraction and transformation/normalization of the physiological responses is described in Section 3.4.2. Both variables have a significant a positive effect. This outcome, together with the effect of time pressure conditions, confirm that drivers' (gap-acceptance) behaviour is not only influenced by traffic conditions but also by external stressors (time pressure in this case) or acute stress levels. In the current case, drivers' stress is reflected through physiological responses during gap-acceptance choices, where a rise in the indicator values also implies an increase in the probability of crossing. However, the crossing behaviour, as examined in the present study can be also interpreted as an action that involves risk-taking propensity. Drivers' physiological responses can hence be seen as indicators of potential aberrant or risky behaviour that could lead to a crash.

The main findings of the presented models are in accordance with literature findings, in terms of the effect of gap size on drivers' behaviour, as participants were more likely to accept larger gaps. The effect of waiting time was also investigated, but no statistically significant outcomes were found. Moreover, potential queuing effects were not examined as we controlled for this effect and there was no other traffic on the minor road. Finally, literature findings (e.g. Bottom & Ashworth, 1978; Nabaee et al., 2011) suggest that older drivers tend to accept larger gaps. This outcome is in line with our results since older drivers had a smaller probability of accepting a gap.

3.5.2. Model comparison

As shown in Table 3.6, while the gap-acceptance model is being enriched with new parameters, measures of model improve, both for the final log-likelihood (LL) and the ρ^2 and adjusted ρ^2 values.

All models are next compared using the likelihood ratio test (e.g. Ben-Akiva and Lerman, 1985). In brief, the test can be defined as:

$$LR = -2(LL^R - LL^U)$$

where L^R is the LL value of the restricted model (the one with fewer variables) and L^U is the LL of the unrestricted model (the model that includes the extra variables). The resulting LR statistic is asymptotically χ^2-distributed and is compared with a critical value which depends on the degrees of freedom (difference in estimated parameters). If the LR statistic exceeds that threshold value then the null hypothesis that both models perform equally is rejected.

The results of the various likelihood ratio tests are presented in Table 3.6. In all cases, the null hypothesis is rejected at 99% level which implies that the models with more variables have a significantly better goodness-of-fit compared to the simpler models re-confirming the hypotheses that driving is a complex task affected by factors beyond traffic conditions. Furthermore, since Model 4 has a significantly better goodness-of-fit compared to Model 3 - indicating statistically significant improvements in the model fit due to the incorporation of physiological variables.

Table 3.6: Likelihood ratio tests' results

Models	LR	Degrees of freedom (df)	$\chi^2_{(99\%,df)}$	Null hypothesis
Model 2 vs Model 1	15.41	2	9.21	Rejected
Model 3 vs Model 2	8.43	1	6.64	Rejected
Model 4 vs Model 3	13.42	2	9.21	Rejected

3.5.3 Sensitivity analysis

The effect of each variable on the gap-acceptance probabilities is investigated first. In this regard, each variable is varied within the predefined bounds (specified by the range of values observed in the experimental data) while keeping all other variables constrained to the sample averages. The fixed values of the continuous variables used are 4.295s for gap size, 0.96m/s for speed, 4.0543m for the position (median value), -0.15 for the normalised heart rate and 0.038 for the normalised SCRs. For the dummy variables, sample average values are also used (varying between zero and one): 0.18 for age, 0.46 for driving frequency, 0.45 for time pressure and 0.05 for the last gap. Based on these values, the probabilities of gap-acceptance are estimated for the variables common in the Model 1[2] and the Model 4 (based on model fit results in section 5.2) as presented in Figure 3.6.

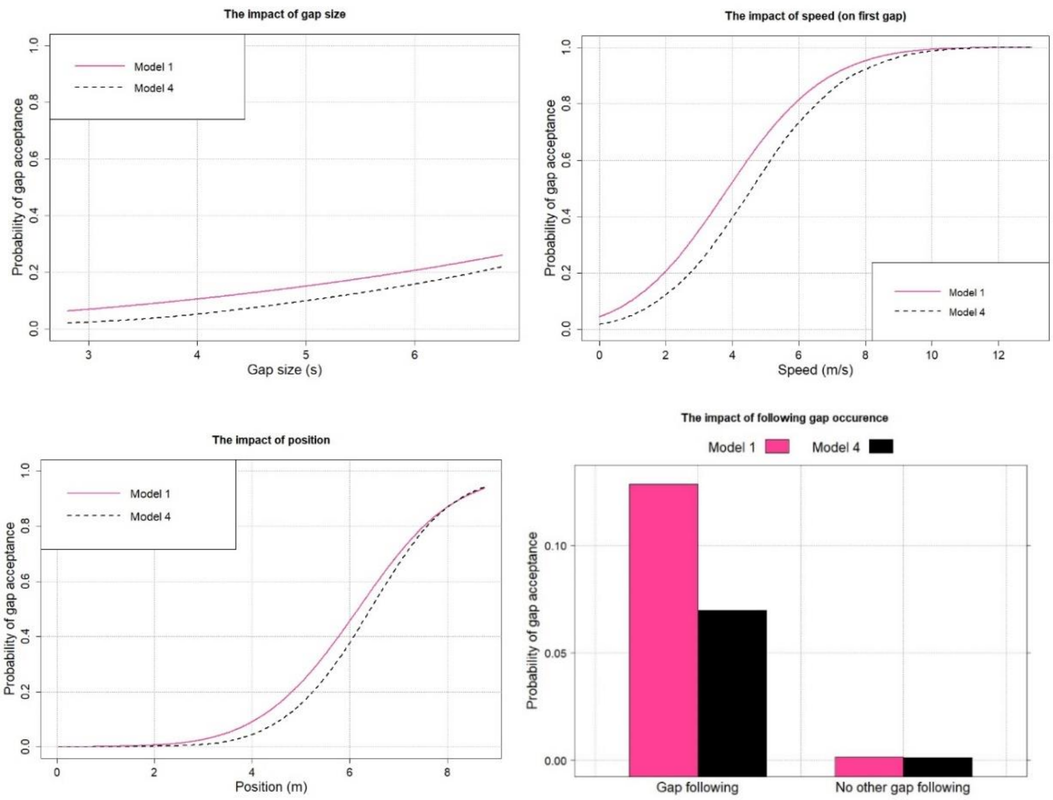


Figure 3.6: Variations in gap acceptance probabilities in Models 1 and 4

A general observation from Figure 3.6 is that in case of all traffic variables, the general trends of change in the probabilities are similar for both Model 1 and Model 4. For example, all else being equal, the probability of accepting a gap increases with gap size, speed (for the first gap), the position with respect to the intersection and the gap being the last gap. However, all else being equal, the probabilities of accepting a gap are always higher for Model 1, denoting overprediction of accepting a gap if the driver characteristics and stress levels are not included in the model.

[2] It may be noted that the state-of-the-art traffic simulation tools are based on the principles of Model 1.

Figure 3.7 depicts the effect of the socio-demographic variables used in the Model 4[3]. With respect to the age dummy variable, the probability for accepting a gap, for a driver above 45 years, has a value close to zero while gap-acceptance probability increases for younger drivers. In a similar way, the gap-acceptance probabilities for participants who drive on a daily basis, are higher compared to the rest. Finally, as expected, the probability for accepting a gap under time pressure conditions is almost double compared to no time pressure.

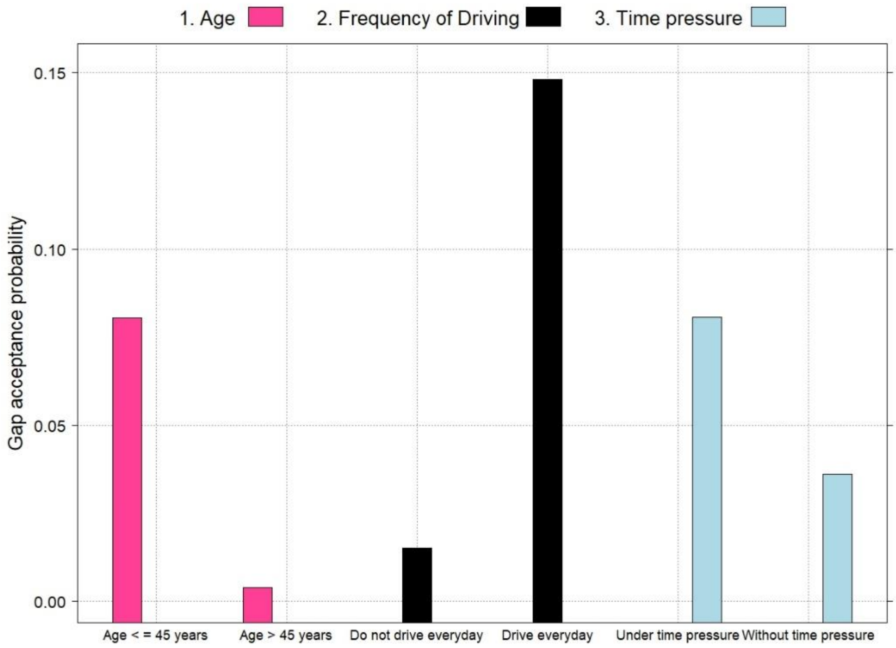


Figure 3.7: Sensitivity plots of the dummy variables used in Model 4 on gap-acceptance probability

The effect of the physiological measurement variables is shown in Figure 3.8. The results show that the gap acceptance probabilities increase in a similar pattern as the values of heart rate and increase in SCR.

[3] Since these variables are not included in the Model 1, their effect on gap-acceptance probabilities have not been investigated across models but only for Model 4.

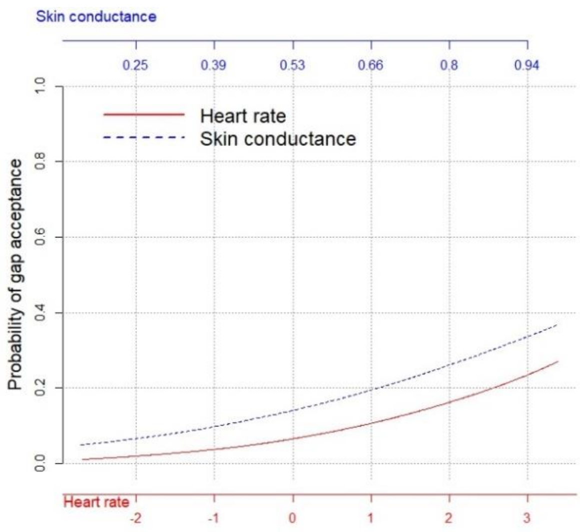


Figure 3.8: Sensitivity plot of heart rate and SCR on gap-acceptance probability

3.5.4 Substitution rates

At the final part of the analysis, an alternative approach is attempted to compare Model 1 and the Model 4. The approach is based on the marginal rates of substitutions (MRS) that also assists in avoiding issues of differences in scales across models. The MRS investigates the required change in a specific variable, in order to counterbalance the change in another variable and keep the total utility constant. The MRS is calculated as the ratio of the parameter estimates (β_i/β_j), where i and j denote two different variables of the model. In most studies, MRS has been used to calculate marginal willingness-to-pay, using the marginal utility of price in the denominator and another variable (travel time for instance) in the numerator. In this case, the parameter of gap size has been used as the denominator and the ratios are computed using each of the other parameters as numerators. The results are illustrated in Figure 3.9 where the calculated MRS values represent the relative effect of each parameter with respect to the gap size parameter in each model.

It should be mentioned that since the parameter of gap size is positive, the ratios with negative parameter are expected to be negative while positive ratios are expected when the opposite holds. Thus, when interpreting the MRS values, what is important is whether the absolute ratio value is higher than unity, rather than the sign of the ratio itself. For instance, |MRS|>1 shows that the change in utility, from a one-unit shift from the baseline of a given variable, is greater than the change corresponding to an increase in gap size by 1s. The opposite applies for |MRS|<1.

As observed in Figure 3.9, the absolute values of MRS are larger than unity denoting all these variables have a higher contribution to the utility (in absolute terms) compared to the gap size variable (i.e. per second). Moreover, in all cases, the absolute values are higher for the Model 1. The MRS for the last gap dummy indicates that the effect of the current gap being the last in the sequence of gaps is almost 8 times as negative as the increase of 1s in the gap size in the utility of gap acceptance in Model 1. However, in Model 4, it is 6 times as negative as the increase of 1s in gap size. For the approach speed, in the utility of gap acceptance in Model 1, the effect of an increase in approach speed of 1m/s is twice as positive as an increase of 1s in gap size. The same ratio in the Model 4 denotes that 1 m/s increase in approaching speed is approximately 1.4 times as positive as 1s gap increase. Likewise, the effect of a 1m increase in vehicle’s position (denoting proximity to the start of the intersection) is approximately 3.5 times and 2 times as positive as a 1s increase in gap size for Model 1 and Model 4 respectively. For the individual specific error term, the MRS values indicate the contribution of these in the utility are 4 and 3 times more than the contribution of gap size in Model 1 and Model 4 respectively. This reduction is expected as Model 4 captures the heterogeneity among the driver by means of the socio-demographic and physiological sensor variables leading to a reduction in unobserved heterogeneity.

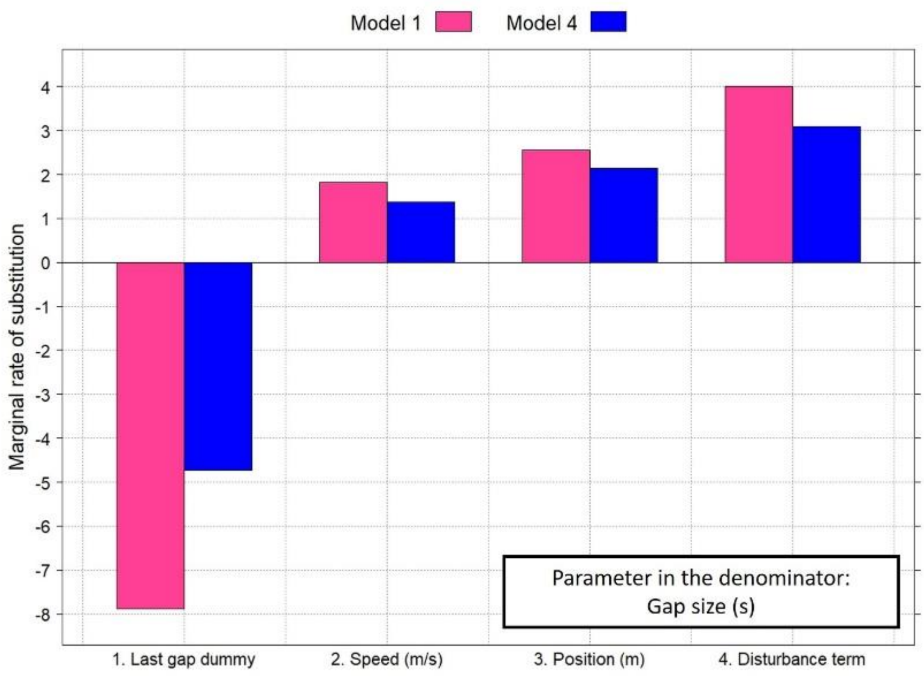


Figure 3.9: Marginal rates of substitution

3.6. Conclusion

The results of both the statistical analyses and the discrete choice model indicate a significant impact of time pressure on the gap-acceptance decision. The time pressure variable has an expected positive sign denoting that also else being equal, the probability of accepting a gap more than doubles in presence of time pressure. As expected, increasing gap size has a positive effect in acceptance probability. Moreover, socio-demographics as age and driving frequency, influence gap-acceptance probability. The effects of gap size and age are in line with the findings of previous literature. Further, empirical analyses demonstrate that the explanatory power of the models increases when the models are augmented with EDA and heart rate data. The gap acceptance probability was found to increase non-linearly with the increase with the skin conductance response and heart rates resulting significant increase in the probability (up to 40%) of accepting a gap. In addition, using the choice modelling framework made it possible to quantify the impact of time pressure and stress on sensitivities towards the traffic-related variables. Results indicate that the inclusion of the physiological sensor measurements reduced the sensitivities towards the traffic-related variables, which can have important safety implications. These findings indicate the need for an additional dimension that should be considered in driving behaviour models for more realistic representation of reality.

Despite the promising nature of the results, there are some limitations in this study that can be investigated in future research. First of all, the data was collected in a simulated environment and thus may be behaviourally incongruent due the experimental nature. However, it is not possible to control the driving situation to isolate the stress effects in a field study. We are investigating the transferability of models developed using the driving simulator to the field in separate research (Papadimitrou and Choudhury 2017) and ways to correct for the potential scale differences (Paschalidis et al. 2018) which will help to make the model coefficients more applicable in the field. Secondly, it should be noted that time pressure was always induced at the second intersection without counterbalancing between the two tasks. Though this is a standard approach in stress research (see Rendon-Velez et al., 2016 for example) and the learning effect is likely to be minimal given the experimental design, this is yet to be tested empirically. Moreover, it is worth mentioning that physiological responses actually represent ‘arousal’ which may be a reflection of other emotional states, positive or negative. Given the experimental setting of the current study, and the expected impact on drivers’ behaviour, we decided to conceptualize physiological responses as an expression of stress though it can be confounded with other forms of arousals as well. Finally, another potential source of bias could be self-selection however, it is very likely that it is uncorrelated with stress levels and thus does not affect the results.

It terms of model validation, the approach of investigating model performance on a hold out sample has not been applied in the current paper. Given the relatively small sample size (41 individuals) and the data structure (at most one acceptance observation per person per junction, while all the rest have been coded as rejection) it has been decided to use the most possible observations for the model estimation part. Also, in terms of the model structure, there is scope to use more advanced model structures (e.g. treating stress as a latent variable for instance) as well as enhance the models with ‘life stress’ and ‘trait stress’ data. Development of other driving behaviour models (signal violation, overtaking) and cross-comparison of the stress effects across scenarios will also be an interesting direction for future research.

In terms of practical application of the models for prediction, the challenge lies in inferring the presence of time pressure and/or stress levels in real-life driving. However, with advances in ubiquitous computing technologies, it is now becoming feasible to measure stress levels in a very non-intrusive manner – wearable wristbands (as used in this study) and smartphone technologies that can detect stress levels from pitch and intervals of voice conversations (Sharma and Gedeon 2012, Lu et al. 2012). Given the extremely steep growth rate of wearables and smartphones, as well as advent of semi-autonomous cars (which have a wide range of sensors for inferring the surrounding traffic conditions), it is likely to be possible in near future to establish sophisticated models to sense stress levels of the driver and correlate it with potential influencing factors. Such prediction models for stress levels in real-world conditions will be very useful in widespread applications of the proposed model. This, coupled with the advances in the field of artificial emotional intelligence (Emotion AI) which has made it possible to device interventions to reduce stress (Fletcher et al. 2010, Picard et al. 2011), can make a significant contribution in increasing road safety. For instance, advances in vehicle operation technologies offer the opportunity for designing interventions to warn/advise drivers, limit acceleration- deceleration capabilities, introduce calming measures and even take over full control of the vehicle. The proper value addition of such novel technologies requires quantification of the safety impacts of stress. Our models can be used for such evaluations and/or subsequent willingness-to-pay. Applications may be also extended in the field of microsimulation to capture and better reflect driver heterogeneity. For example, there are emerging microsimulation models that combine activity models with traffic microsimulation (e.g. SimMobility (Adnan et al. 2016)). In these new types of tools, it is possible to include schedule delays in the traffic simulation component and our models can contribute to more realistic representation of driving behaviour in such simulation tools and hence increase their accuracy.

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CHAPTER 4: COMBINING DRIVING SIMULATOR AND PHYSIOLOGICAL SENSOR DATA IN A LATENT VARIABLE MODEL TO INCORPORATE THE EFFECT OF STRESS IN CAR-FOLLOWING BEHAVIOUR

ABSTRACT Car-following models, which are used to predict the acceleration-deceleration decisions of drivers in the presence of a closely spaced lead vehicle, are critical components of traffic microsimulation tools and useful for safety evaluation. Existing car-following models primarily account for the effects of surrounding traffic conditions on a driver's decision to accelerate or decelerate. However, research in human factors and safety has demonstrated that driving decisions are also significantly affected by individuals' characteristics and their emotional states like stress, fatigue, etc. This motivates us to develop a car-following model where we explicitly account for the stress level of the driver and quantify its impact on acceleration-deceleration decisions. An extension of the GM stimulus-response model framework is proposed in this regard, where stress is treated as a latent (unobserved) variable, while the specification also accounts for the effects of drivers' sociodemographic characteristics. The proposed hybrid models are calibrated using data collected with the University of Leeds Driving Simulator where participants are deliberately subjected to stress in the form of aggressive surrounding vehicles, slow leaders and/or time pressure while driving in a motorway setting. Alongside commonly used variables, physiological measures of stress (i.e. heart rate, blood volume pulse, skin conductance) are collected with a non-intrusive wristband. These measurements are used as indicators of the latent stress level in a hybrid model framework and the model parameters are estimated using Maximum Likelihood Technique. Estimation results indicate that car-following behaviour is significantly influenced by stress alongside speed, headway and drivers' characteristics. The findings can be used to improve the fidelity of simulation tools and designing interventions to improve safety.

4.1 Introduction

Car-following (CF) refers to the acceleration-deceleration decisions of a driver with respect to the behaviour of a closely spaced lead vehicle. CF models are critical components of microsimulation tools and are also used in safety analyses (Ahmed, 1999). Over the past decades, there has been significant research that focuses on the development and improvement of car-following models (Toledo, 2007). Saifuzzaman and Zheng (2014) classified the car-following models into two groups based on the modelling perspective: 1) engineering and 2) human factors based models. In the former type, the effects of surrounding traffic are used to model the acceleration-deceleration decisions of drivers (e.g. Toledo, 2003; Ossen. and Hoogendoorn, 2005; Choudhury et al., 2009; Marczak et al., 2013 to name a few). However, the adequacy of engineering CF models, in terms of cognitive and behavioural representativeness, has been criticised by several researchers who approached the issue from its human perspective. For instance, Brackstone and McDonald (2003) stressed the limitations of CF models and suggested the need to incorporate motivational and attitudinal factors to explain the heterogeneity among drivers. In the same direction, Hancock (1999) questioned engineering CF models for representing car-following task as an optimal rather than a satisficing task and criticized the use of noise terms to explain variations across behaviours. Further, van Winsum (1999) suggested a model framework based on psychological findings and highlighted the importance of accounting for human factors.

Based on literature findings (retrieved from Hamdar, 2012; Treiber and Kesting, 2013), Saifuzzaman and Zheng (2014) provided a list of human factors that have been found to influence car-following behaviour including sociodemographic characteristics, reaction time, contextual sensitivity, aggressiveness and risk-taking propensity, desired speed, desired headway etc. Researchers in psychology have also identified that moods and stress have significant impacts on driving behaviour (Westerman and Haigney, 2000; Garrity and Demick, 2001; Hill and Boyle, 2007). The concept of incorporating human factors in microscopic driving behaviour models has been already reported and considered in some microsimulation tools (Rathi and Santiago, 1990; Liu et al., 1995; Dias et al., 2013). The main attention has been focused on the integration of groups of drivers with different characteristics and accounting for aggressive drivers. The aggressive drivers are expected, amongst others, to apply more abrupt rates of acceleration-deceleration, accept shorter gaps and have shorter desired headways (Laagland, 2005). Thus, in existing applications, the “aggressive” proportion of traffic is assigned different desired values compared to the rest. However, in many cases, the values assigned to the various drivers’ groups are derived from theory, rather than observations (Bonsall et al., 2005). Based on these capabilities of specific microscopic simulation tools, Soria et al. (2014) calibrated car-following models using naturalistic driving data. Moreover, Mubasher et al. (2017) associated a Big Five Factors Model of Personality, as derived from traffic psychology (Herzberg, 2009), to specific parameters of the IDM model (Treiber et al., 2000) and developed car-following models for different patterns of personality utilising existing software. The importance of drivers' characteristics has been also underscored in non-related to microscopic simulation driving behaviour modelling approaches; Anastasopoulos and Mannering (2016) modelled the effect of speed limit on speed choice and found several effects of sociodemographic characteristics (e.g. gender, age, income etc.).

Apart from the base model specifications, where only the parameters' values among drivers vary, there are also more sophisticated examples of car-following models. In order to increase the behavioural realism, Hamdar et al. (2008) and Hamdar et al. (2014) suggested a car-following model, based on the prospect theory of Kahneman and Tversky's (1979). The model considers car-following as a sequential risk-taking process and allows for risk-taking manoeuvres based on a probability of being involved in a rear-end collision. This probability is estimated as a function of variables such as acceleration, spacing and relative speed. In another approach, Saifuzzaman et al. (2015) incorporated an additional term in their model, in order to represent task difficulty (TD) as expressed by the Task-Capability Interface (TCI) model (Fuller, 2005). This term is specified as a function of time headway, spacing and speed of the driver. Although the aforementioned model specifications aim to indirectly account for human factors, the relevant terms are still expressed as a function of traffic related variables and do not refer to characteristics of the drivers per se; drivers are still assumed to behave in the same way for given traffic conditions. The unobserved heterogeneity in car-following behaviour has been investigated across drivers (e.g. Ossen and Hoogendoorn, 2011; Kim et al., 2013) and within drivers (e.g. Pariota et al., 2016). However, it has taken the form of statistical distributions and random parameters rather than being linked to individual characteristics. In a recent application, van Lint and Calvert (2018), used the IDM model to incorporate task demand and awareness (i.e. focus, distraction etc.). In a rather different approach, Hoogendoorn et al. (2010) conducted a driving simulator experiment to investigate the relationships between mental workload and car-following without however incorporating the former in the model specification. Finally, Farah and Koutsopoulos (2014) modified the GM model and expressed the stimulus part as a series of socio-demographic variables – incorporating the effect of stress and/or the state-of-mind was however beyond the scope of their paper. It is worth mentioning that the importance of accounting for the unobserved heterogeneity has been also highlighted in modelling approaches from other streams of driving behaviour research. For instance, Sarwar at al. (2017b) considered unobserved heterogeneity in a model specification for the simultaneous estimation of discrete and continuous dependent variables while Mannering et al. (2016) also emphasised the importance of this issue in the analysis of accident data.

Driving stress has been defined as a situation that challenges drivers' abilities, reduces their perceived control or threatens their mental/physical health (Gulian et al., 1989). It can be a consequence of several factors including the direct demands of the driving task, the environmental conditions, network characteristics, traffic conditions, secondary tasks (e.g. use of navigation system, texting), etc. (Hill and Boyle, 2007). It is worth mentioning, that traffic, weather and road conditions have been also linked to accident occurrence (Norros et al., 2016), which can be an outcome of the increased demands of the driving task in some occasions. Moreover, time urgency and congestion levels have been identified as two factors influencing drivers' stress (Hennessy and Wiesenthal, 1999). In many studies, stress has been measured with self-reported surveys, however, an alternative, and potentially more reliable, approach to detect drivers' level of stress and study its effects, is through its implications on human physiology. While traditionally, stress levels are detected using levels of cortisol (e.g. Mather et al. 2009) which limits measurement of stress at a single or few time points, recent advances in sensor technologies and *affective computing* have made it possible to measure stress levels through physiological responses, e.g. changes in heart rate (HR), electrodermal activity (EDA), blood volume pulse (BVP), etc. on a continuous basis and in a non-intrusive way. There are several existing studies related to driving stress that use this type of data (Healey and Picard, 2005; Singh and Queyam, 2013). However, the aforementioned studies mostly focused on detecting the stress level of the driver rather than investigating its effects on driving behaviour.

This study aims to filling in the research gap in the state-of-the-art car-following models by bridging the engineering and human-factor based approaches to include the full ranges of variables influencing the decisions and bring a safety-related perspective via drivers' stress. A novel framework has been proposed in this regard to quantify the relative impact of driving stress in car-following decisions. The models are estimated using data from the University of Leeds Driving Simulator (UoLDS) where the participants were intentionally subjected to stressful driving conditions caused by time pressure and surrounding traffic conditions. Their driving actions were recorded alongside physiological measurements of stress indicators (electrodermal activity, heart rate and blood volume pulse) and socio-demographic characteristics. The detailed data collected from different scenarios are used to estimate the car-following model parameters.

The remainder of the paper is organised as follows: The next section presents the data collection efforts and exploratory analyses of the data. This is followed by the model structures and estimation results. We conclude the paper with the summary of the research and directions of future research.

4.2 Data

4.2.1 Driving simulator experiment

The use of driving simulators, originally used primarily for human-factors research, is gaining popularity in the context of driving behaviour modelling. The driving simulator data has been used in development of car-following (Hoogendoorn et al., 2010), overtaking (Farah et al., 2009), and signal crossing (Danaf et al., 2015) behaviour for instance. Further, there have been driving simulator-based studies focussing on aggression (Sarwar at al., 2017a) and risk-taking (Lavrenz et al., 2014; Tran et al., 2015) to evaluate the safety impacts.

The data used in this research is based on primary data collected as part of a comprehensive driving simulator study (Next Generation Driving Behaviour Models – NG-DBM) for investigating the effect of stress in different driving decisions. The experiments were conducted using the University of Leeds Driving Simulator (UoLDS). The UoLDS (Figure 4.1) is a high fidelity, dynamic simulator. The vehicle cab is a 2005 Jaguar S-type with all driver controls available and fully operational. This includes the steering wheel and braking pedal, and there is also a fully operational dashboard. The vehicle is positioned in a 4m diameter spherical projection dome. The dome provides fully textured 3-D graphical scene with a horizontal field of view of 250^{o} and 45^{o} vertical. The raw data output consists of observations of 60Hz frequency.

The full data collection process involved around 90 minutes of driving in the simulator for each individual. Participants initially had a short briefing session regarding the simulator and its operation followed by a practice session of approximately 15 minutes to familiarise themselves with the simulated environment and vehicle dynamics (i.e. motion system). For safety reasons, participants were accompanied by a researcher during the practice run. Thereafter, participants started the main driving sessions, composed of two different environments, using an urban setting and a motorway setting of approximately same duration each, with a short break in between. For the main part of the data collection, they were instructed to drive and behave as they would normally do in real life driving.

The current analysis focused only on the motorway setting. The motorway was composed of six main sections approximately 6km long each, connected with some shorter road segments specified as intersections. In each of the main road segments, different traffic scenarios were implemented, while the role of intersections was to provide a smoother transition and also reduce potential residual effects from previous road segments, as no specific events were planned in these locations.

Figure 4. 1: The University of Leeds Driving Simulator

[source: University of Leeds, University of Leeds Driving Simulator]

Before explaining more detailed the traffic scenarios in each motorway segment, it is worth mentioning that one of the main objectives of the study had also been to examine drivers' behaviour under time pressure. Hence, participants were deliberately subjected to time pressure. During their briefing session, participants were instructed that they had to reach their destination within 35 minutes and they could see an emoji placed on the dashboard (Figure 4.2) as an indicator of their performance. Moreover, they were informed that the emoji displayed to them was determined based on expected arrival time which was computed and constantly updated using a sophisticated algorithm running in the background and uses variables such as current speed, speed limit, distance to the end, an average estimated delay that will be caused by the events ahead etc. as inputs. This was then used to determine which of the three emoji to show. Participants were instructed that the green state would indicate they were doing well, in terms of time, while the red would mean that they were late. The intermediate amber emoji meant that they were marginally fine in terms of time. That is, they would receive a red emoji if they had further delay in the remaining driving tasks. The introduction of an amber state was decided to make the shift from green to red emoji more convincing to the participants.

Figure 4. 2: Time pressure emoji

In reality, the state of the time pressure emoji was not related to participants' actual performance but was pre-decided in order to induce time pressure in specific road segments. It may be noted that the choice of 3 different emoji to indicate time pressure, was preferred to a conventional countdown timer since it would be easier to manipulate. In order to increase the likelihood that participants would consider time pressure indications, they were instructed that a penalty would be imposed on the monetary reward for their participation in case they were late at the end of the motorway (red emoji). However, this was never the case since both main scenarios of the experiment were programmed to end in the amber time pressure state.

Regarding the motorway scenario itself, it has been already mentioned that it was composed by various traffic scenarios. In the initial road section, no specific events were taking place and the time pressure indicator was green. This was followed by the road section with "aggressive" surrounding traffic. This scenario was implemented by allowing the driving simulator car drones (vehicles controlled by the simulator software) to accept shorter gaps while performing a lane change. This resulted in the occurrence of lane change manoeuvres at short headways with respect to participants' position. The scenario was repeated at the next main road segment as well but this time under the presence of time pressure (amber or red). In the next scenario participants faced traffic at slow speeds which aimed to create a sense of congestion. This scenario was time based (as opposed to all the rest which were position based) with an approximate duration of 5.5 minutes. During this scenario, participants faced all possible time pressure states. The last segment of the motorway did not include any specific events apart from changes in the emoji states.

It should be mentioned that the order of scenarios/time pressure states was always fixed and the same for all participants. It is acknowledged that this experimental design might have impacted driving behaviour, especially in the last segments of the motorway (e.g. owing to fatigue or impatience). The order of scenarios was always the same as it was easier to develop the motorway following this approach. Moreover, the emoji was always green during the first part of the motorway for purposes of realism, as the drivers would not expect to see an amber or red indication at the very early stages. For the same reason, there was some type of time pressure at the last motorway segments. In terms of each individual scenario, it was decided to present to participants a green to red sequence of time pressure indicators within an effort to minimise the risk of increasing their physiological responses at the beginning of a specific scenario that would potentially influence and prevent them from returning to the baseline levels.

Drivers' physiological data, across the whole experiment, was collected using the Empatica E4 wristband. The device is very similar to a common smart-watch and thus offers a non-intrusive manner to obtain physiological data. The Empatica E4 wristband provides information about heart rate (HR), Electrodermal Activity (EDA), blood volume pulse (BVP) and temperature (TEMP). Each of the physiological indicators was collected with a different frequency, depending on the attributes of the wristband. EDA and temperature have a 4Hz frequency, blood volume pulse 64Hz and heart rate 1Hz.

4.2.2 Physiological indicator extraction

As stated previously, participants used a wristband device that collected physiological responses. One of the main objectives of the study was the incorporation of these responses in a car-following model framework in order to investigate the possibility of obtaining more behaviourally representative outcomes. Following findings from existing literature (Picard et al., 2001; Katsis et al., 2011), the raw signals were transformed, and a series of indicators were extracted. The indicators were calculated based on 10s moving windows (Katsis et al., 2011; Kushki et al., 2011) centred at each acceleration observation.

Heart rate (HR): The HR signal was transformed into z-scores to reduce inter-individual differences and obtain more comparable values (Picard et al., 2001). The mean transformed HR values were than calculated for each window. The basic z-score transformation can be described as $\left(\frac{x - \mu}{\sigma}\right)$, where x is a heart rate observation, μ is the heart rate mean value across the whole motorway task and σ is its standard deviation.

Blood volume pulse (BVP): The same transformation as HR was also applied to the BVP signal and from the z-scores it was calculated, for each 10s window, the mean of the first absolute difference (FAD) as Equation 4.1:

$$\mathrm{FAD_X} = \frac{1}{\mathrm{N - 1}} \sum_{\mathrm{n=1}}^{\mathrm{N}} |\mathrm{X_{n+1} - X_n}| \tag{4.1}$$

The aforementioned BVP indicator was normalised using a min-max transformation in order to always obtain values between 0-1. This transformation is common practice in literature (Zhai and Barreto, 2006; Sun et al., 2010) to reduce the inter-individual differences. In brief, the transformation can be summarised as shown in Equation 4.2:

$$\mathrm{FAD_{X\,norm}} = \frac{\mathrm{FAD_X} - \mathrm{FAD_{X\,min}}}{\mathrm{FAD_{X\,max}} - \mathrm{FAD_{X\,min}}} \tag{4.2}$$

Electrodermal activity (EDA): The EDA observations were processed using the Matlab package Ledalab (Karenbach, 2005). The skin conductance responses (SCRs) were obtained applying trough-to-peak analysis, where the amplitude of a response is calculated as the difference in the EDA values between a peak in the signal and its preceding trough (Benedek and Kaernbach, 2010). The number of responses and the sum of their z-scores in each 10s window were then considered as additional EDA indicators. The min-max transformation was also applied in the sum of amplitudes indicator. Based on findings in existing literature (Sano et al., 2014), a critical value equal to 0.01μS was selected as the minimum critical SCR.

4.2.3 Sample analysis

In total, 45 participants were recruited through the UoLDS recruitment list. The only eligibility criteria was having a valid UK driving licence. However, 3 of the participants reported nausea at the practice drive of the experiment and thus completely removed from the analysis. Out of the remaining participants that successfully completed the urban scenario, that was presented to them first, only 36 (19 male, 17 female) fully completed the motorway setting as the rest dropped out because of sickness. Motion sickness was also investigated with a yes/no question in a post driving survey. In total, 11 of 36 participants reported motion sickness however, given that they completed the experiment and their behaviour was not found to significantly differ, in terms of speed, acceleration etc. from those who did not report motion sickness, it was decided to include them in the analysis. The mean age of participants was approximately 35 years and the corresponding standard deviation was 11 years. Half of the participants stated that they were driving on a daily basis. The average driving experience of participants was almost 15 years. Regarding accident involvement, 6 participants reported involvement in minor accidents while 3 reported involvement in serious accidents. It is worth mentioning that a major accident was defined as one where at least one person required medical treatment and/or there was property damage above £500. Finally, 6 participants stated that they had at least once received a ticket penalty for speeding behaviour. The descriptive statistics of the sample are presented in Table 4.1.

Table 4.1: Descriptive statistics of the sample

Variable	Intervals	Frequency	%	Mean	Std. Dev.	Min	Max
Gender	Female	17	0.47	-	-	-	-
	Male	19	0.53	-	-	-	-
Age	-	-	-	35.06	10.99	19	57
Driving experience	-	-	-	14.83	11.73	1	39
Frequency of driving	Everyday	18	0.5	-	-	-	-
	2-3 times/week	11	0.31	-	-	-	-
	Once/ week	4	0.11	-	-	-	-
	Less often	3	0.08	-	-	-	-
Minor accident involvement	No	30	0.83	-	-	-	-
	Yes	6	0.17	-	-	-	-
Major accident involvement	No	33	0.92	-	-	-	-
	Yes	3	0.08	-	-	-	-
Ticket for speeding	No	30	0.83	-	-	-	-
	Yes	6	0.17	-	-	-	-

Physiological indicators	**Min**	**Mean**	**Max**	**Std. Dev.**
HR mean	-3.55	-0.09	4.48	0.91
BVP first absolute difference mean	0.00	0.08	0.47	0.04
SCR Sum Amplitude	0.00	0.09	1.00	0.15
SCR no of responses	0.00	0.81	12.00	1.42

In Table 4.2, we also present the descriptive statistics of the key traffic variables. For an in-depth insight, the full data is split into three parts:

- *No events zone:* This segment was composed of the initial and the last segment of the motorway. As a result, this segment involved, in total, motorway parts where no specific events took place apart from time pressure in the last segment.
- *Aggressive neighbour zone:* This part was composed of the two motorway segments where the surrounding vehicles (car drones) could show aggressive behaviour, mostly accepting shorter gaps during their lane-change

manoeuvres. Also, in this case, participants faced all possible time pressure states.

- *Slow traffic zone:* This zone included the motorway segment where traffic was intentionally slowed to give the impression of congestion. All emoji were shown to participants during this segment.

It is worth mentioning that in order to ensure that only car-following behaviour was captured (and also exclude free-flow), the conditions to include an observation in the analysis had been that a participant has not attempted a lane-change for a duration of 4s before the observation and also always had a time headway shorter than 4s with the leader (based on Hoogendoorn, 2005). All other observations were excluded from the data. Table 4.2 presents the descriptive statistics of the data included in the main analyses. An in-depth descriptive and inferential statistics analysis of the whole driving simulator experiment has been carried out by Paschalidis et al. (2019).

Table 4.2: Descriptive statistics of the motorway scenarios

Traffic variables	Min	Mean	Max	Std. Dev.
No events				
Acceleration (m/s^2)	-10.09	-0.02	2.18	0.72
Speed (m/s)	9.04	26.95	40.98	3.86
Relative speed with lead vehicle (m/s)	-26.63	-0.49	11.25	2.89
Spacing with lead vehicle (m)	5.56	49.07	145.16	24.37
Time headway with lead vehicle (s)	0.27	1.83	4.00	0.84
Aggressive drivers				
Acceleration (m/s^2)	-10.23	-0.03	2.94	0.92
Speed (m/s)	6.30	26.77	40.86	3.63
Relative speed with lead vehicle (m/s)	-20.03	-0.34	17.43	2.82
Spacing with lead vehicle (m)	0.81	46.75	140.57	25.00
Time headway with lead vehicle (s)	0.11	1.75	4.00	0.88
Slow traffic				
Acceleration (m/s^2)	-10.04	-0.09	1.90	0.67
Speed (m/s)	7.67	14.79	35.93	4.83
Relative speed with lead vehicle (m/s)	-21.76	-0.96	8.99	2.70
Spacing with lead vehicle (m)	5.79	26.16	113.90	14.51
Time headway with lead vehicle (s)	0.42	1.82	3.98	0.69

4.3 Model framework

We first present the basic structure of the state-of-the-art car-following model followed by the novel extension to incorporate the effect of stress. Each of the models was estimated without and with the consideration of sociodemographic variables. This approach resulted in four main model specifications which can be summarised as:

- Base car-following model (no sociodemographic variables) (Section 4.3.1)
- Car-following model with sociodemographic variables (but no latent stress variable) (Section 4.3.2)
- Car-following model with latent stress variable (but no sociodemographic variables) (Section 4.3.3)
- Car-following model with both sociodemographic and latent stress variables (Section 4.3.4)

4.3.1 Base car-following model

Basic structure

The model structure is based on the stimulus-response GM car-following model (Gazis et al., 1961). In the original GM model, acceleration choices for a vehicle are a function of its speed, space headway and relative speed with the lead vehicle. The original specification is (Equation 4.3):

$$a_n(t)|\tau_n = \alpha \frac{V_n(t)^{\beta}}{\Delta X_n(t)^{\gamma}} \Delta V_n(t - \tau_n) \tag{4.3}$$

where: ΔX_n is the space headway at time t, V_n is the following vehicle speed, ΔV_n is the relative speed between the following and the lead vehicle and τ_n is the driver specific reaction time. Finally, α, β and γ are constants.

Based on the GM model, several extensions have been suggested. Herman and Rothery (1965) were the first to highlight that passenger cars have different acceleration and deceleration capacity. In order to address this shortcoming in the GM model, Ahmed (1999) introduced acceleration-deceleration asymmetry within a stimulus-response framework (Equation 4.4):

$$a_n^g(t)|\tau_n = s\,[X_n^g(t - \tau_n)] \times f\,[\Delta V_n(t - \tau_n)] + \varepsilon_n^g(t) \tag{4.4}$$

where: s[.] represents sensitivity, as a vector of explanatory variables and f[.] represents the stimulus, given as the relative speed. Also, ε^g is a normally distributed disturbance term while g represents the car-following regime (acceleration or deceleration). In the present study, the sensitivity and stimulus parts are analysed in (Equations 4.5 and 4.6):

$$s[X_n^g(t - \tau_n)] = \alpha^g \frac{1}{\Delta T_n(t)^{\gamma^g}} \tag{4.5}$$

$$f\,[\Delta V_n(t - \tau_n)] = \Delta V_n(t - \tau_n)^{\lambda^g} \tag{4.6}$$

where: ΔT_n is the time headway, ΔV_n is the relative speed between the subject and the lead vehicle and τ_n is the reaction time. Finally, α^g, γ^g and λ^g are parameters to be estimated and g indicates the type of regime. The GM model offers several computational advantages – both in estimation and application. It is a well identified/specified model and the likelihood function can be estimated without the need for any parameter normalisations. Therefore, it was considered as a suitable car-following model for the purpose of the current paper. It is worth highlighting that instead of applying the original GM model specification, the sensitivity part was modified in order to consider only time headway, as in Papadimitriou and Choudhury (2017).

The reaction time distribution

The current model specification also allows for the incorporation of reaction time. Following examples in literature (Ahmed, 1999), the reaction time is assumed to follow a log-normal truncated distribution (Equation 4.7):

$$\varphi(\tau_n) = \begin{cases} \dfrac{\dfrac{1}{\tau_n \sigma_\tau}\varphi\left(\dfrac{\ln(\tau_n) - \mu_\tau}{\sigma_\tau}\right)}{\Phi\left(\dfrac{\ln(\tau^{max}) - \mu_\tau}{\sigma_\tau}\right) - \Phi\left(\dfrac{\ln(\tau^{min}) - \mu_\tau}{\sigma_\tau}\right)} & \text{if } \tau^{min} < \tau_n \leq \tau^{max} \\ 0 & \text{otherwise} \end{cases} \tag{4.7}$$

where: $\varphi(.)$ is the standard normal distribution density function, $\Phi(.)$ is the cumulative normal distribution, τ_n is the reaction time of driver n, μ_τ is the mean of the distribution of $\ln(\tau_n)$, σ_τ is the standard deviation and τ^{max}, τ^{min} are the bounds of truncation. Truncation is required since reaction time is finite. The bounds are set deterministically while the mean and the standard deviation are estimated simultaneously with the rest of the model parameters. The bounds of reaction time were set between 0 and 4 seconds (Ahmed, 1999; Kusuma, 2015).

Likelihood Function

In Equation 4.3, assuming that the disturbance terms are normally distributed, the probabilities of accelertion-deceleration decisions can be expressed using the standard normal density function (Equation 4.8):

$$\varphi\left(a_n^g(t)|\tau_n\right)=\frac{1}{\sigma_{\varepsilon^g}}\varphi\left(\frac{a_n^g(t)\text{-}s[X_n^g(t\text{-}\tau_n)]\times f[\Delta V_n(t\text{-}\tau_n)]}{\sigma_{\varepsilon^g}}\right) \tag{4.8}$$

where: g ∈ {acc,dec}.

Also, the assumption of the GM car-following model is that a driver accelerates if the relative speed is positive and decelerates if negative. Given this, the distribution of acceleration decisions is given, conditionally on reaction time τ, as (Equation 4.9):

$$\varphi(a_n(t)|\tau_n)=\varphi(a_n^{acc}(t)|\tau_n)^{\delta[\Delta V_n(t\text{-}\tau_n)]}\varphi\left(a_n^{dec}(t)|\tau_n\right)^{(1\text{-}\delta[\Delta V_n(t\text{-}\tau_n)])} \tag{4.9}$$

where:

$$\delta[\Delta V_n(t\text{-}\tau_n)]=\begin{cases} 1 & \text{if } \Delta V_n(t - \tau_n)\geq 0 \\ 0 & \text{otherwise} \end{cases}$$

In the current specification, the acceleration observations of each driver n are assumed to be independent while the heterogeneity in driving behaviour is captured through the reaction time distribution. Thus, the conditional joint density of the acceleration sequential observations, of a driver n, is the product of the conditional densities of the acceleration decisions (Equation 4.10):

$$\varphi(a_n(1),a_n(2),\dots,a_n(T_n)|\tau_n)=\prod_{t=1}^{T_n}\varphi(a_n(t)\,|\tau_n) \tag{4.10}$$

The unconditional form of the distribution above is (Equation 4.11):

$$\varphi\big(a_n(1),a_n(2),\ldots,a_n(T_n)\big)=\int_{\tau^{min}}^{\tau^{max}} \varphi\big(a_n(1),a_n(2),\ldots,a_n(T_n)|\tau_n\big)\,\varphi(\tau_n)d\tau \qquad (4.11)$$

At the final step, the model is estimated by maximizing the log-likelihood function of the acceleration observations (Equation 4.12):

$$LL=\sum_{n=1}^{N}\ln\Big[\varphi\big(a_n(1),a_n(2),\ldots,a_n(T_n)\big)\Big] \qquad (4.12)$$

4.3.2 Car-following model with sociodemographic variables

An important component of driving behaviour heterogeneity is also drivers' sociodemographic characteristics. As mentioned in the Introduction section, this has been a disregarded issue in the vast majority of existing models. An interesting approach to incorporate these variables has been suggested by Farah and Koutsopoulos (2014), where sociodemographic characteristics are a part of the stimulus component. In brief, following the aforementioned work, Equation 4.6 is extended to (Equation 4.13):

$$f\,[\Delta V_n(t-\tau_n)]=\Delta V_n(t-\tau_n)^{\lambda^g+\beta^g Z_n} \qquad (4.13)$$

where: Z_n is a vector of sociodemographic variables and β^g is the vector of the corresponding parameters. The inclusion of these variables is expected to enhance the explanatory power of the models and provide improved behavioural representation of the car-following process. The remaining of the model specification and estimation follows the same process presented in Section 4.3.1.

4.3.3 Car-following model with latent stress variable

In the current study, stress levels are not directly measured but instead, their effects on physiological responses are observed. Thus, the suggested framework incorporates stress as a latent variable in the car-following model. The structure of the new model specification is based on the hybrid choice modelling approach (see Abou-Zeid and Ben-Akiva, 2014 for details).

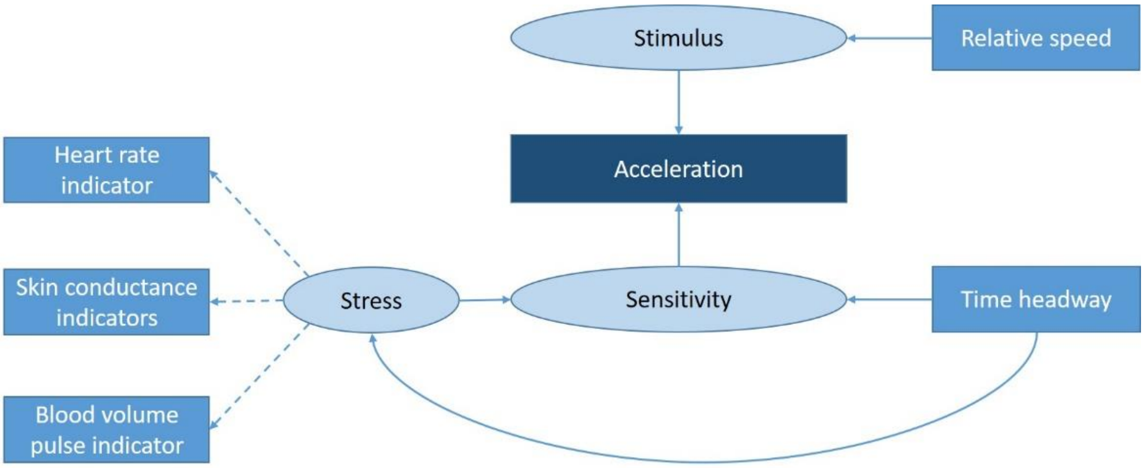

Figure 4. 3: Example of the proposed car-following framework incorporating stress

The new latent variable model (presented in Figure 4.3) is composed by two main parts, the structural equation, which describes the latent variable specification and the measurement component which is linking the latent variable to the indicators (Joreskog and Sorbom, 1984). In a car-following context, stress levels are expected to affect drivers' sensitivity to the presented stimulus (relative speed in the case of GM model). Hence, the latent variable that represents stress is incorporated as a shift to the sensitivity through an additive term.

At the same time, the stress levels may be also influenced by the traffic conditions. For example, a driver may be more stressed if the driver in the front is too close or too slow. For this reason, stress in turn was expressed as a function of time headway and relative speed, following the formulation in Equation 4.14. However, as shown in a later section, our results indicated that only the time headway had a statistically significant effect on stress and thus, relative speed was dropped from the specification. The overview of the suggested model specification is depicted in Figure 4.3. Latent variables are shown in ovals and observed variables are shown in rectangles. The solid and the broke lines represent structural and measurement relationships respectively.

The overall specification of the suggested latent variable car-following model can be summarised as (Equations 4.14-4.16):

Structural equations:

$$Stress_n(t)= \xi Y_n(t) + \eta_n(t), \qquad \eta_n(t)=N\sim(0,1) \qquad (4.14)$$

$$a_n^g(t)|\tau_n = \{s[X_n^g(t)] + \theta^g \,\text{Stress}_n(t)\} \times f\,[\Delta V_n(t-\tau_n)] + \varepsilon_n^g(t) \tag{4.15}$$

Measurement equations:

$$I_{k,n}(t) = \beta_{I_k} + \zeta_{I_k}\,\text{Stress}_n(t) + u_{k,n}(t) \qquad u_{k,n}(t) = N \sim (0, \sigma_{I_k}^2) \tag{4.16}$$

where: $\text{Stress}_n(t)$, is the latent variable representing stress which is expressed as a function of $Y_n(t)$ explanatory variables with a vector ξ of parameters to estimate and $\eta_n(t)$ is a standard normal disturbance term. Also, θ^g is a set of parameters capturing the effect of the latent variable in the acceleration-deceleration regimes, $I_{k,n}(t)$ is an indicator k of individual n at time t, as extracted from the raw physiological responses, β_{I_k} is a constant of the k^{th} indicator, ζ_{I_k} is a parameter that captures the effect of the latent variable on the k^{th} indicator and $u_{k,n}(t)$ is a normally distributed disturbance term. If the mean value is subtracted from each continuous indicator, then the $\beta_{I_k}\ \forall\ k$ does not need to be estimated.

Given the assumption of normality for the disturbance term of each indicator, a measurement equation takes the form (Equation 4.17):

$$\varphi\left(I_{k,n}(t)\right) = \frac{1}{\sigma_{I_k}}\,\varphi\left(\frac{I_{k,n}(t) - \zeta_{I_k}\,\text{Stress}_n(t)}{\sigma_{I_k}}\right) \tag{4.17}$$

where: $\varphi(.)$ denotes the probability density function (pdf) of a standard normal distribution. For an individual n, the total likelihood of observing a specific pattern of indicators is given as the product of the pdf values at time *t* as shown in Equation 4.18:

$$L\left(I_{k,n}(t)|\,\zeta_{I_k}, \text{Stress}_n(t), \sigma_{I_k}, t\right) = \prod_{k=1}^{K} \varphi\left(I_{k,n}(t)\right) \tag{4.18}$$

The car-following model in its basic specification, captures heterogeneity across drivers through reaction time. However, the latent variable is expected to influence acceleration observations within the same individual n. Thus, following Hess and Train (2011) the new model specification accounts for heterogeneity both at the inter-individual (reaction time) and intra-individual level (latent variable for stress). The new log-likelihood function then takes the following form, as presented in Equation 4.19:

$$LL=\sum_{n=1}^{N}\ln\left[\int_{\tau_{min}}^{\tau_{max}}\left(\prod_{t=1}^{T}\left(\int_{\eta}\varphi\left(\alpha_n(t)\right)L\left(I_{k,n}(t)|\ \zeta_{I_k},Stress_n(t),\sigma_{I_k},t\right)\ \varphi(\eta)d\eta\right)\right)\varphi(\tau)d\tau\right] \tag{4.19}$$

Given the nature of a stimulus-response car-following model formulation (a driver reacts to the stimulus of relative speed with a specific sensitivity), the specification presented in Section 4.3.2 is reasonable in terms of behavioural interpretation; stress levels could affect drivers' sensitivity to a presented stimulus.

It may be noted that additional model specifications (presented in Equations 4.20 to 4.22) have been tested and compared with the proposed model specification.

$$a_n^g(t) = s[X_n^g(t)]\times f\,[\Delta V_n(t\text{-}\tau_n)] + \theta^g\ Stress_n(t) + \varepsilon_n^g(t) \tag{4.20}$$

$$a_n^g(t) = (\alpha^g+\theta^g\ Stress_n(t))\,\frac{1}{\Delta T_n(t)^{\gamma^g}}\times f\,[\Delta V_n(t\text{-}\tau_n)] + \varepsilon_n^g(t) \tag{4.21}$$

$$a_n^g(t) = \alpha^g\,\frac{1}{\Delta T_n(t)^{\gamma^g+\theta^g\ Stress_n(t)}}\times f\,[\Delta V_n(t\text{-}\tau_n)] + \varepsilon_n^g(t) \tag{4.22}$$

Each variant presented above represents different approximations regarding the effects of stress on car-following behaviour. For instance, Equation 4.20 assumes that stress has an overall shift on acceleration values, Equations 4.21 and 4.22 assume that stress interacts with the constant term and the time headway respectively. It should be mentioned that these specifications resulted in either worse log-likelihood values or unrealistic predictions in the sensitivity analysis (as performed in Section 4.4.3) and thus were not selected as the recommended specifications.

4.3.4 Car-following model with both sociodemographic and latent stress variables

The last of the model specifications presented in the current paper focuses on the estimation of the latent variable car-following model, while it also accounts for the effects of sociodemographic characteristics. The incorporation of these variables is following the specification presented in Section 4.3.2 while the rest of the process remains the same as in Section 4.3.3. This approach provides the benefit to investigate the effects of stress within a car-following model framework, on top of the sociodemographic variables and thus obtain more robust outcomes.

4.4. Estimation results

The current section presents the results of the various car-following model specifications. We first estimated base models (i.e. car-following models without socio-demographic and stress latent variables) and tested for significant differences among the various segments (Section 4.4.1). Based on these results, we retained separate models for each of the scenarios and developed the following four sets of models, as presented in Section 4.3. These can be summarised to the base car-following models without sociodemographic variables (Section 4.4.1), car-following models with sociodemographic variables, but no latent stress variable (Section 4.4.2), car-following models with latent stress variable, but no sociodemographic variables (Section 4.4.3) and car-following models with both sociodemographic and latent stress variables (Section 4.4.4). The final equations, including the parameter estimates for all models, are presented in Appendix B.

4.4.1 Base car-following models

Parameter estimates

As described previously, three different segments were extracted from the motorway scenario and investigated separately to examine for significant differences in car-following behaviour due to the different nature of traffic conditions. Three separate models were then estimated from these segments. These were: a model from the segments without specific events (“No events” model), a model from the aggressive drivers’ zone (“Aggressive drivers” model) and a model from the slow traffic zone (“Slow traffic” model). As an initial step, the various models were estimated following the basic GM model specification presented in Section 4.3.1. The parameter estimates are presented in Table 4.3. All parameters of the car-following components have expected values and signs while most of them are significant at the 95% level. For instance, all acceleration constants are positive while the deceleration ones are negative. Moreover, the stimulus parameters (relative speed) have values smaller or close to 1, as expected, owing to the limited acceleration/deceleration a driver can apply (Ahmed, 1999). It should be mentioned that the "No events" model was also estimated using data only from the motorway segment without time pressure, but almost all parameter estimates did not significantly differ from those presented in Table 4.3.

Sensitivity analysis

The sensitivity analysis of the "Aggressive drivers" model is presented in the current section as an example of model interpretation. In particular, the effect of each explanatory variable is illustrated (Figure 4.4) with respect to the estimated parameters of acceleration-deceleration regimes. For purposes of consistency, the ranges of acceleration/deceleration were kept constant across explanatory variables. It is worth mentioning that despite the differences in the parameter estimates, similar patterns were in general observed for all three segments.

The observed trends are consistent with expectations and findings in the existing literature. When in acceleration regime, drivers tend to apply lower rates of acceleration as time headway increases, since traffic conditions are more likely to be closer to free flow. On the other hand, deceleration rate increases in absolute terms, as time headway decreases, implying safety concerns from the perspective of drivers to avoid a potential crash. Finally, an approximately linear relationship is observed between acceleration-deceleration rates and relative speed.

Reaction time

The estimated reaction time distributions are illustrated in Figure 4.5. The mean reaction time is largest for the slow traffic scenario as expected and consistent with literature findings (Törnros, 1995). The mean and the standard deviation for the reaction time is smaller for aggressive driving scenario (as drivers are more alerted).

Model comparison

In order to examine whether traffic conditions affect car-following behaviour, the three models were compared in terms of individual parameters and overall model fit. The former was investigated with the t-test of parameter equivalence which is summarised as (Equation 4.23):

$$t_{diff,k} = \frac{\beta_{1,k} - \beta_{2,k}}{\sqrt{\left(\frac{\beta_{1,k}}{t_{1,k}}\right)^2 + \left(\frac{\beta_{2,k}}{t_{2,k}}\right)^2}} \tag{4.23}$$

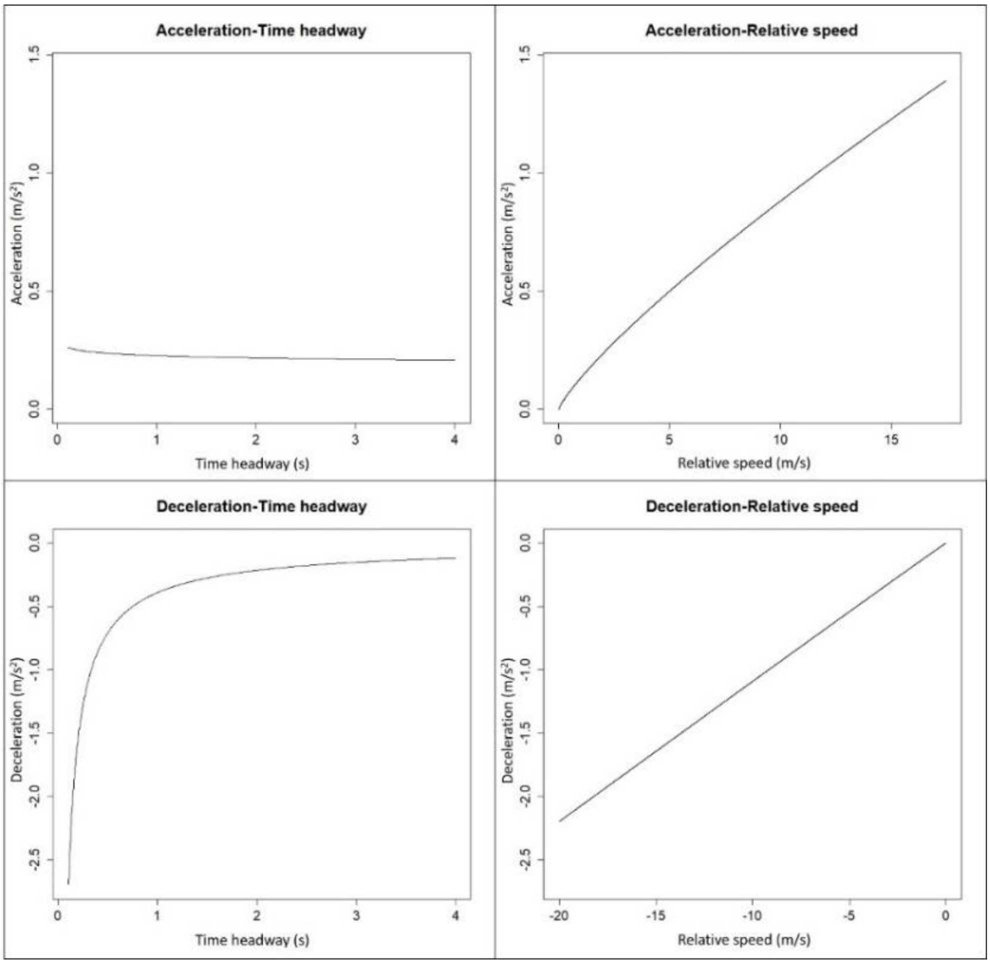

Figure 4.4: Sensitivity plots of the "Aggressive drivers" car-following model

where $\beta_{1,k}$ and $\beta_{2,k}$ are the parameter estimates of the k^{th} parameter of the two models and $t_{1,k}$ and $t_{2,k}$ are corresponding t-statistics. The null hypothesis of parameter equivalence is rejected at 95% level of confidence if $|t_{diff,k}|>1.96$. The three base models were compared pairwise, and the results of the t-test are presented in Table 4.3.

Table 4.3: Parameter estimates and t-test of parameter equivalence of the base car-following models

	No events model (1)		Aggressive drivers model (2)		Slow traffic model (3)		t-test of parameter equivalence		
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	(1) and (2)	(2) and (3)	(1) and (3)
Reaction time distribution									
μ_t	0.297	1.58	-0.068	-0.22	0.655	14.63	1.01	**-1.86**	**-2.31**
σ_t	0.725	7.40	0.746	4.30	0.350	2.73	-0.10	**2.32**	**1.83**
Car-following acceleration									
Constant	0.193	8.39	0.139	7.93	0.347	6.97	**1.85**	**-2.82**	**-3.94**
Time headway (s)	0.400	3.76	0.063	0.49	0.275	1.77	**2.03**	0.67	-1.05
Relative speed (m/s)	0.707	10.15	0.818	10.84	0.674	9.73	-1.08	0.34	1.41
σ^{acc}	0.447	22.03	0.634	15.78	0.337	25.72	**-4.16**	**4.53**	**7.02**
Car-following deceleration									
Constant	-0.219	-5.65	-0.174	-4.98	-0.255	-5.43	-0.86	0.59	1.38
Time headway (s)	1.192	4.05	0.857	8.31	0.486	2.73	1.07	**2.05**	**1.80**
Relative speed (m/s)	0.786	4.15	1.009	9.28	0.709	9.5	-1.02	0.38	**2.29**
σ^{dec}	0.770	15.64	0.985	17.25	0.694	17.06	**-2.85**	1.19	**4.16**
LL(β)	-9278.67		-13622.58		-5681.67				
ρ^2	0.22		0.10		0.32				
N	36		36		36				
Observations	10105		11325		7236				

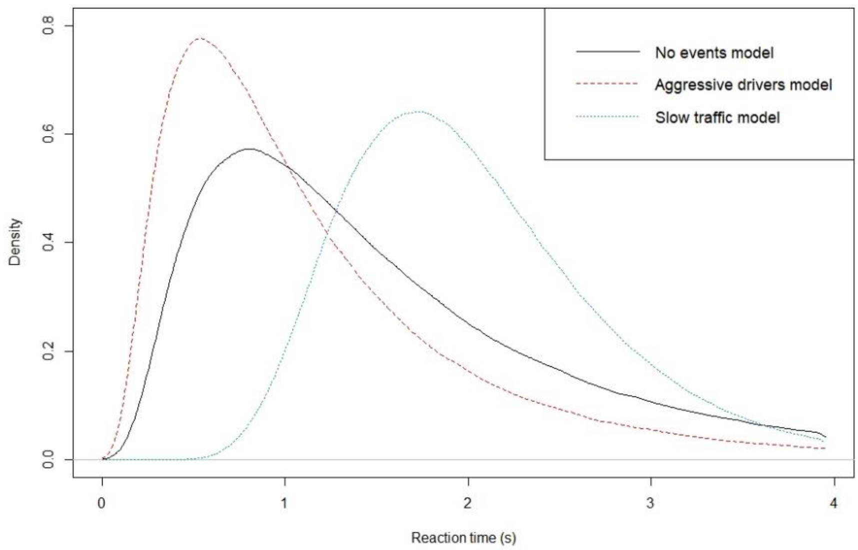

Figure 4.5: Reaction time distributions of the car-following models

With reference to the results of the t-tests, some of the parameters among the three models significantly differ either at the 90% or 95% level, indicating significant differences in car-following behaviour (e.g. acceleration constants significantly differ in all examined pairs). However, some of the variables (mean of reaction time and time headway) were retained in the 'Aggressive Driver' model in spite of being insignificant at 90% level of significance for the sake of consistency and ease of comparison. It may be noted that inclusion of these insignificant variables may have some effect on the efficiency of the estimation.

Estimation results indicate that there is a significant difference in the reaction time distribution of "Slow traffic" model which may show that drivers perceive stimulus differently in various traffic conditions. As a final step, all models were also investigated pairwise, in terms of total fit, using the likelihood ratio test (Ben-Akiva & Lerman, 1985) that compares the log-likelihood (LL) values between a restricted and an unrestricted model, with degrees of freedom equal to the difference in model parameters. For every set of two models, from those presented in Table 4.3, the sum of LL was considered as the unrestricted model while a model estimated using the same data points of these two models, but only a single set of parameters was considered as the restricted model. In essence, the restricted model assumes that the effect of explanatory variables on acceleration is the same for both the examined motorway areas. The results of these likelihood ratio tests showed that in all cases, the null hypothesis was rejected indicating the restricted models were significantly worse compared to the unrestricted. Following the findings also from the t-tests of individual parameter equivalence, this outcome further indicates that a single set of parameters, for model estimation from different segments of the motorway, does not capture the heterogeneity in car-following behaviour and the differences should be considered with additional parameters. Based on these results, the stress effects are investigated separately for each segment in the next section.

4.4.2 Car-following models with sociodemographic variables

The models presented in the previous section were extended to also consider heterogeneity across drivers via sociodemographic characteristics. Based on the findings of Farah and Koutsopoulos (2014), these variables were incorporated as a part of the stimulus term (relative speed parameter) as detailed in Section 4.3.2. The parameter estimates are presented in Table 4.4. It should be mentioned that different sociodemographic variables were found to be significant in the three models and only the variables statistically significant at 90% level of confidence have been retained in the model. This led to addition of gender, age, driving frequency and accident involvement variables in models, while driving experience, speed violation history, education level and employment status were dropped as they were not statistically significant in any of the models. In the model specification, as accident involvement were considered both minor and major reported accidents while, with respect to driving frequency, the best fit occurred when driving 2-3 days per week or every day were combined as a single category.

All models were compared with the respective car-following models without sociodemographic characteristics using the likelihood-ratio test. In all cases, the difference was significantly higher from the critical values at the 99% level of significance. This finding shows that in all cases, model fit was significantly improved when drivers' characteristics were considered. As expected, the smallest improvement occurred for the "Aggressive drivers" model where only the female dummy in the deceleration regime was found to be significant. Moreover, similar values were obtained for the reaction time distributions' moments and the acceleration and deceleration constants kept their expected signs. The effects of the significant sociodemographic characteristics (90% level of significance or above) on acceleration/deceleration behaviour were investigated through sensitivity analyses (appended in Appendix B).

The model where largest number of sociodemographic variables were found to be statistically significant was the "No events" model. In particular, gender, had significant effects on both acceleration and deceleration with male drivers applying higher acceleration and lower (absolute) decelerations. Age had a significant impact on acceleration only. More specifically, increase in age was associated with decrease in acceleration values. The effects of driving frequency had similar trends to those of gender on both acceleration and deceleration regimes. Moreover, higher driving frequency was related to higher acceleration and lower deceleration values. Also, participants who reported accident involvement also applied lower deceleration.

Table 4.4: Parameter estimates considering sociodemographic characteristics.

	No events model (1)		Aggressive drivers model (2)		Slow traffic model (3)	
	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
Reaction time distribution						
μ_t	0.322	1.68	-0.023	-0.12	0.610	11.41
σ_t	0.760	6.38	0.766	7.66	0.338	2.77
Car-following acceleration						
Constant	0.190	8.92	0.139	8.06	0.332	7.14
Time headway (s)	0.389	3.65	0.055	0.44	0.223	1.56
Relative speed (m/s)	0.942	7.18	0.815	11.1	1.449	7.64
σ^{acc}	0.447	23.24	0.634	15.92	0.337	25.08
Car-following deceleration						
Constant	-0.100	-3.66	-0.163	-5.86	-0.250	-5.22
Time headway (s)	1.801	6.25	0.907	9.43	0.504	3.33
Relative speed (m/s)	1.695	11.25	0.950	8.89	0.941	6.57
σ^{dec}	0.727	16.5	0.979	17.53	0.686	17.21
Sociodemographic characteristics						
Female dummy acceleration	-0.192	-1.79	0	NA	-0.436	-2.33
Female dummy deceleration	0.503	2.73	0.289	2.26	0	NA
Accident involvement dummy deceleration	-1.050	-6.35	0	NA	-0.152	-1.83
Age acceleration	-0.008	-2.35	0	NA	-0.012	-3.51
Driving frequency dummy acceleration	0.176	1.99	0	NA	0	NA
Driving frequency dummy deceleration	-0.387	-3.34	0	NA	-0.203	-2.30
LL(β) – (LR test)	-8968.31 (620.72 - $\chi^2_{(99\%,df)}$: 16.81)		-13588.98 (67.20 - $\chi^2_{(99\%,df)}$: 6.63)		-5628.68 (105.97 - $\chi^2_{(99\%,df)}$: 13.28)	
ρ^2	0.25		0.11		0.32	
N	36		36		36	
Observations	10105		11325		7236	

Regarding the “Aggressive drivers” model, only gender in the deceleration regime was found to be significant. The type of effect was the same of the “No events” model.

In the “Slow traffic” model, the coefficients corresponding to female drivers for deceleration and to frequent drivers for acceleration were not found to be statistically significant. The statistically significant coefficients were found to have the same sign as the "No events model" though the difference in magnitudes resulted slightly different trends in the sensitivity plots.

4.4.3 Car-following models with latent stress variable

Following the suggested methodological framework from Section 4.3.3, a series of car-following models incorporating stress as a latent variable were estimated. The estimation results of the latent variable car-following model based on Equation 4.15 are presented in Table 4.5. The estimates of the other specifications (Equations 4.20-4.22) are not presented in detail as they either resulted in inconsistent values during the sensitivity analysis (e.g. negative values in the acceleration regime, non-realistic deceleration rates etc.) and/or worse LL scores for the car-following component compared to the presented model.

Measurement equation component:

The parameters of the measurement components are of similar magnitude and same trend in all three models. There is a positive and significant effect of the latent variable almost on all indicators; that is, as stress increases, the value of each indicator increases too. This is in line with the a-priori expectations. The statistical significance is in general higher for the electrodermal response indicators (Sum of SCR amplitudes and Number of SCR responses exceeding the threshold) compared to the indicators corresponding to HR and BVP. Finally, the effect of the latent variable was not significant on the HR indicators of the "No events" and "Slow traffic" models.

Structural equation component:

The parameter estimates, for all three models, are similar to the base specifications. The latent variable was expressed in all models as a function of time headway; its effect was always negative and significant at the 90% or 95% level. The effect of the latent variable on acceleration was positive indicating that as stress increases, drivers tend to accelerate more. The coefficient of the latent stress was found to be statistically significant in the acceleration components of the "No events" and "Aggressive drivers" models, which is an indirect indication that the models are behaviourally more robust than the models without stress. The effect of stress was however not significant in the "Slow traffic" model. This is likely to be due to the fact that in the "Slow traffic" segment, even if drivers desired to accelerate, they were constrained by the slow speeds of the surrounding traffic. For the sake of compatibility, the variable was retained in the model though. It may be noted that inclusion of these insignificant variables may have some affect the efficiency of the estimation. Interestingly, the effect of stress on deceleration was not statistically significant in any of the models and removed from the model.

Table 4.5: Parameter estimates of the latent stress car-following models

	No events model (1)		Aggressive drivers model (2)		Slow traffic model (3)	
	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
Reaction time distribution						
μ_t	0.294	1.57	-0.057	-0.19	0.655	14.56
σ_t	0.730	7.59	0.752	4.31	0.35	2.73
Car-following acceleration						
Constant	0.190	8.21	0.137	7.82	0.349	7.18
Time headway (s)	0.409	3.83	0.042	0.33	0.282	1.85
Relative speed (m/s)	0.731	9.99	0.829	11.25	0.695	8.35
σ^{acc}	0.446	22.18	0.633	15.74	0.34	25.54
Car-following deceleration						
Constant	-0.219	-5.64	-0.173	-4.97	-0.255	-5.43
Time headway (s)	1.190	4.05	0.856	8.32	0.486	2.72
Relative speed (m/s)	0.787	4.17	1.011	9.30	0.708	9.50
σ^{dec}	0.770	15.67	0.985	17.25	0.693	17.06
Effects of stress						
Stress acceleration	0.018	2.01	0.023	2.35	-0.012	-0.57
Latent variable specification						
Time headway (s)	-0.041	-2.38	-0.036	-1.80	-0.046	-4.37
Measurement equations						
HR mean	0.089	1.54	0.093	2.10	0.065	1.47
σ_{HR}	0.972	15.24	0.864	15.48	0.844	15.04
BVP first absolute difference mean	0.016	6.23	0.015	4.13	0.016	5.29
σ_{BVP}-FAD	0.044	15.17	0.042	16.44	0.042	20.11
SCR Sum Amplitude	0.168	29.6	0.164	14.63	0.159	27.46
σ_{SCR}-sum	0.037	13.25	0.038	12.52	0.038	4.10
SCR no of responses	1.625	6.87	1.384	8.00	1.370	12.54
σ_{SCR}-no	0.531	5.27	0.489	4.18	0.396	3.00
LL(β) – car-following component	-9273.54		-13620.52		-5681.805	

Sensitivity analysis

This section presents the sensitivity analysis for the “No events” and “Aggressive drivers” models considering the effects of the stress latent variable. As opposed to the sensitivity analysis presented in Section 4.4.1, where acceleration patterns arise as a single curved line, either as a function of time headway or relative speed, the incorporation of the latent variable introduces a third dimension to be considered. This approach results in a “surface” of predicted values, where acceleration patterns vary also depending on the stress levels alongside traffic variables. Moreover, the values derived from the current sensitivity analyses, depend on parameter estimates of stress weighted by the distribution assumption of the latent variable, as explained in Section 4.3.3. Compared to the deterministic approach of the base car-following model, the suggested latent variable specification allows for a wider range of acceleration patterns and better match the reality. The sensitivity analysis of the latent variable models is presented in Figures 4.6 to 4.9. It may be noted that since the parameter estimates of stress for the deceleration regime were not statistically significant, only the acceleration regime is analysed in detail.

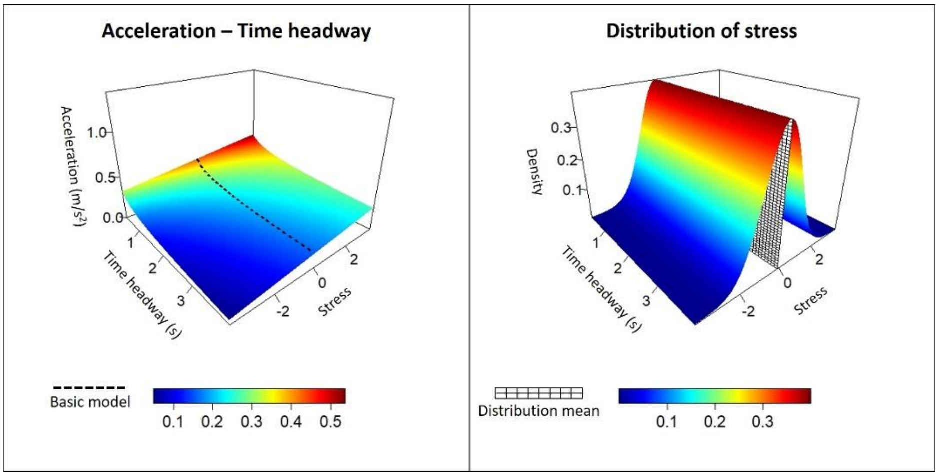

Figure 4.6: Time headway sensitivity analysis of the "No events" latent variable model

Regarding the derived acceleration patterns per se, Figure 4.6 shows the results of the "No events" latent variable model, with respect to the time headway. On the left part of the figure, the plot corresponds to the Acceleration-Time headway plot presented in Figure 4.4, accounting also for the effects of the latent variable. Moreover, the base car-following model is highlighted with a dashed line. Given the model specification (latent variable is an additive disturbance to the sensitivity term) and also the similarity in the parameter estimates between the base and latent car-following models, the base model occurs as a line at the zero value of stress. The acceleration trend is in general similar to the one presented in the sensitivity analysis of the base model. For instance, higher acceleration values are observed at shorter time headways, while the values decrease as headway increases (and traffic conditions potentially approach free-flow). However, in addition, there is also a slope variation due to the stress effects. Hence, for the same value of time headway, acceleration increases as stress rises while similar values of acceleration can result for other specific combinations of time headway and stress. It may be noted that given the distribution of the latent variable (presented on the right part of Figure 4.6) the stress values are gathered around zero indicating that there is higher frequency of obtaining acceleration values from this zone compared to the tail end of the stress distribution.

Similar impacts of stress also occur in Figure 4.7 where the sensitivity plot with respect to relative speed and stress is presented. It is worth mentioning that the figure has been rotated around the z-axis for a better illustration of the results. Again, the overall pattern is similar to the one presented in the sensitivity analysis of the base model i.e. acceleration increases as relative speed becomes larger while the effects of the latent variable distribution apply in this case as well. Moreover, this plot shows that the latent variable model results in higher upper range of acceleration compared to the base model (though with lower probabilities, owing to the distribution assumption of stress).

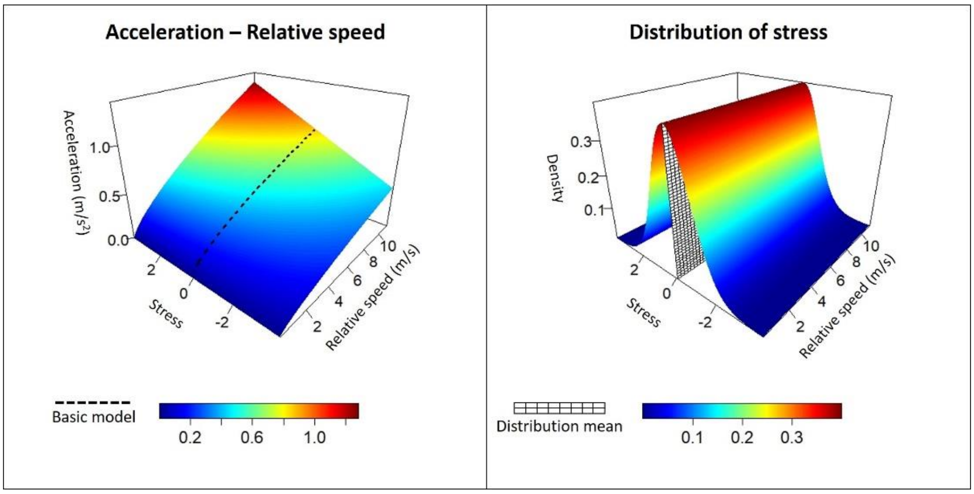

Figure 4.7: Relative speed sensitivity analysis of the "No events" latent variable model

The outcomes presented regarding the "No events" model also extend to the "Aggressive drivers" model, as congruous patterns are observed (Figure 4.8 and 4.9) and all the acceleration trends are in line with expectations. Moreover, Figure 4.8 is an additional example that highlights the difference between the base and the latent variable model, as it is obvious that the latter provides a larger variability in acceleration values while the former is restricted only to the average band. This seems to be the case also in Figure 4.9, where the latent variable model also allows for acceleration values beyond the range of the base model providing potentially wider heterogeneity of drivers' behaviour.

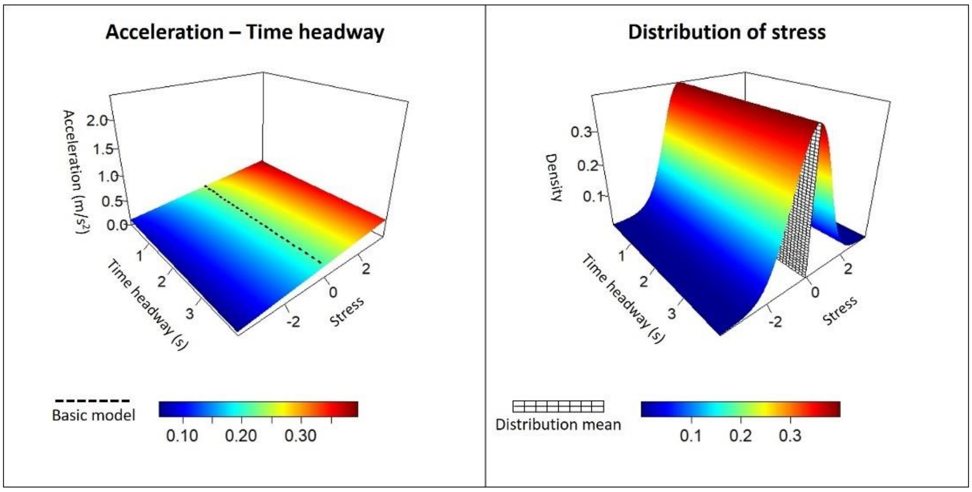

Figure 4.8: Time headway sensitivity analysis of the "Aggressive drivers" latent variable model

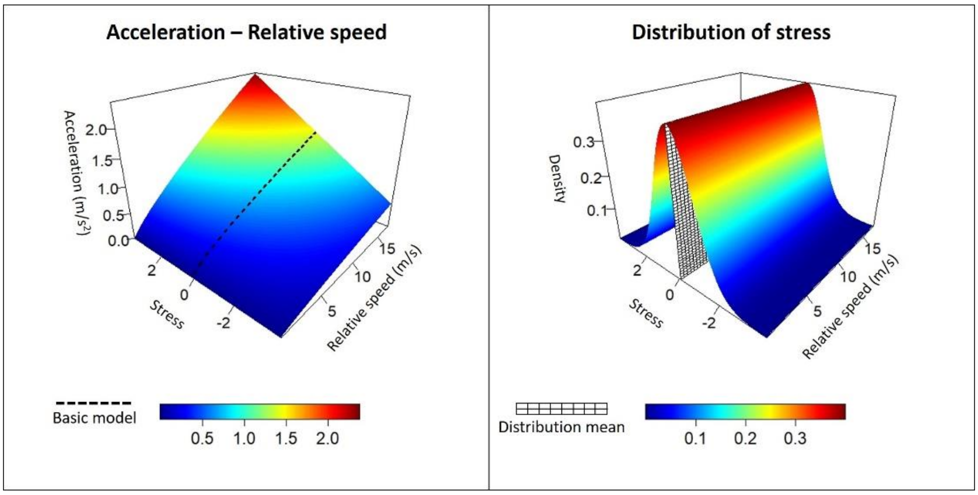

Figure 4.9: Relative speed sensitivity analysis of the "Aggressive drivers" latent variable model

Overall, our sensitivity analyses indicates that as stress increases, there is a significant increase of the acceleration rate, for both the "No events" and "Aggressive drivers" models. From a behavioural point of view, drivers under higher levels of physiological stress express similar characteristics with the "aggressive" drivers used in some microsimulation tools. However, while the current microsimulation tools assume that an aggressive driver will always have higher acceleration values, the proposed model captures the intra-driver heterogeneity in a more robust manner. Moreover, from a road safety perspective, the increase of stress levels points out safety concerns regarding the performance of drivers.

4.4.4 Car-following models with both sociodemographic and latent stress variables

The last part of model estimation focused on the estimation of the latent variable car-following model also considering drivers' sociodemographic characteristics. The model specification combined the models presented in Sections 4.3.2 and 4.3.3. The parameter estimates are outlined in Table 4.6.

Similar to the models presented in Section 4.4.3, stress was found to have a positive effect only on the acceleration regimes of the "No events" and "Aggressive drivers" models – however, statistical significance dropped to the 90% level in the former. The effect of time headway on stress remained negative and significant in all models. On top of these findings, the same effects of sociodemographic characteristics were also captured in the latent variable model with their levels of significance remaining the same, compared to the base cases. The detailed sensitivity analyses (generated assuming a sample average value for the sociodemographic variables) are presented in Appendix B. They show similar trends to those illustrated in Figures 4.6-4.9.

4.5 Conclusion

Car-following is a crucial component of driving behaviour both in terms of traffic flow replication and road safety analyses. The existing literature has highlighted the importance of incorporating human factors and the mental states of the driver in car-following models – but to the best of our knowledge, this had not been done in any previous study. This paper fills in this research gap with a special focus on driving stress by suggesting a framework for their incorporation in a modelling framework. The study is based on data collected from a motorway scenario developed at the University of Leeds Driving Simulator, as part of a comprehensive driving simulator study, where participants were deliberately subjected to stressful conditions.

Different car-following models were estimated based on an adaptation of the traditional GM model for three different motorway traffic scenarios. Our findings suggest that various traffic conditions yielded different car-following behaviours emphasizing the need to investigate the effect of stress independently for each motorway segment. For the incorporation of stress, a latent variable was introduced in the model specification, capturing heterogeneity at the intra-individual level. It may be noted that although the benefits of accounting for unobserved inter-intra heterogeneity have been demonstrated in other contexts using mixed logit (e.g. Hess and Train, 2011; Hess and Giergiczny, 2015) and hybrid choice models (e.g. Calastri et al., 2018), these efforts have often only led to minor changes in results. In the present work, the panel/dynamic nature of the indicators seems to have contributed to a greater ability to capture inter-intra heterogeneity, possibly due to more intra-individual variation in the experienced scenarios.

Table 4. 6: Parameter estimates of the latent variable car-following models with sociodemographic variables

	No events model (1)		Aggressive drivers model (2)		Slow traffic model (3)	
	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
Reaction time distribution						
μ_t	0.339	1.70	-0.018	-0.09	0.611	11.32
σ_t	0.773	6.27	0.770	7.58	0.338	2.76
Car-following acceleration						
Constant	0.188	8.69	0.137	7.90	0.333	7.23
Time headway (s)	0.394	3.72	0.033	0.27	0.226	1.58
Relative speed (m/s)	0.956	7.36	0.827	11.47	1.479	7.98
σ^{acc}	0.446	23.39	0.633	15.90	0.337	24.10
Car-following deceleration						
Constant	-0.099	-3.65	-0.163	-5.86	-0.250	-5.13
Time headway (s)	1.800	6.26	0.907	9.42	0.503	3.32
Relative speed (m/s)	1.696	11.27	0.955	8.89	0.942	6.48
σ^{dec}	0.727	16.49	0.979	17.54	0.686	17.24
Effects of stress						
Stress acceleration	0.016	1.74	0.023	2.38	-0.011	-0.47
Latent variable specification						
Time headway (s)	-0.041	-2.38	-0.036	-1.80	-0.046	-4.37
Sociodemographic characteristics						
Female dummy acceleration	-0.188	-1.83	0	NA	-0.407	-1.85
Female dummy deceleration	0.502	2.73	0.290	2.27	0	NA
Accident involvement dummy deceleration	-1.050	-6.36	0	NA	-0.152	-1.82
Age acceleration	-0.008	-2.38	0	NA	-0.013	-3.22
Driving frequency dummy acceleration	0.171	1.97	0	NA	0	NA
Driving frequency dummy deceleration	-0.387	-3.35	0	NA	-0.203	-2.29
Measurement model						
HR mean	0.089	1.54	0.093	2.10	0.065	1.47
σ_{HR}	0.972	15.24	0.864	15.48	0.844	15.04
BVP first absolute difference mean	0.016	6.23	0.015	4.13	0.016	5.29
σ_{BVP}-FAD	0.044	15.17	0.042	16.44	0.042	20.08
SCR Sum Amplitude	0.168	29.62	0.164	14.63	0.159	27.46
σ_{SCR}-sum	0.037	13.26	0.038	12.52	0.038	4.02
SCR no of responses	1.625	6.87	1.384	8.00	1.370	12.51
σ_{SCR}-no	0.531	5.27	0.489	4.18	0.396	2.95
LL(β) – car-following component	-8964.19		-13586.81		-5629.05	

Regarding the effects of stress, a positive effect on acceleration was found which was statistically significant in all cases other than the slow leader scenario (where the driver had restricted movement). From a behavioural perspective, drivers with higher levels of stress (as manifested in the physiological responses), express similar characteristics with the “aggressive” drivers used in some microsimulation tools. But while in the current state-of-the-art simulation tools, an aggressive driver is assumed to have the same level of aggression throughout the entire simulation, our findings indicate that there is significant within-driver heterogeneity which needs to be accounted for in the simulation. Ignoring the within-driver heterogeneity in levels of aggression can have substantial impact on safety analyses. Interestingly, the effect of stress on deceleration was not found to be statistically significant in any scenario. A final remark regarding our findings, is the positive contribution of sociodemographic characteristics in the model fit. The latter were considered as a part of the stimulus term and their significance remained on both the base and the latent variable model highlighting the importance of incorporating human factors in driving behaviour models.

However, while interpreting the results, it should be acknowledged that the research is based on data from a driving simulator experiment as opposed to real driving due to the infeasibility of controlling the surrounding traffic environment in the latter. Though utmost attention has been given to make the scenarios as realistic as possible, there is a possibility of behavioural incongruence owing to the “experimental flavour” of the simulated driving. Thus, there is a possibility of behavioural bias as a result of the lack of actual risk but also Hawthorne-like effects i.e. some participants may adapt their driving style closer to what they believe the observer perceives as desirable. Moreover, although participants were asked to drive as they would normally do, the absence of genuine possibility for physical harm and/or penalisation due to illegal driving may also lead to unrealistic behaviour e.g. in excessive speeding or lateral manoeuvring. However, this latter issue is not expected to significantly influence the outcomes of the current study as only car-following observations were considered and overtaking behaviour was excluded. In addition to the aforementioned issues, stress levels might be different when comparing simulated and real driving, and it will be interesting to combine the current data with real world data in future research. Another potential source of bias could be self-selection however, it is unlikely that it is correlated with stress levels and thus does not affect the results. Finally, the fixed order of scenarios/time pressure might have caused behavioural bias, as discussed in Section 4.2.1.

Based on the findings of the current study, there is scope for further research. This involves the incorporation of stress in further aspects of driving behaviour (e.g. lane-change behaviour) but also more elaborated model specifications, regarding the effects of stress, are being considered. For instance, stress levels are expected to have different effects across individuals while drivers' traits and perceptions towards the driving task vary as well. These characteristics have been found to significantly influence drivers' behaviour, in the research field of road safety, and their integration in a modelling context could improve models' performance. Another interesting aspect will be to investigate potential temporal shifts of parameter estimates that have been highlighted in recent safety research (Mannering 2018).

In terms of practical application of the models, the challenge lies in inferring the presence of stress levels in real-life driving. However, with advances in ubiquitous computing technologies, it is now becoming feasible to measure stress levels in a non-intrusive manner – wearable wristbands and smartphone technologies that can detect stress levels from pitch and intervals of voice conversations (Sharma and Gedeon, 2012). Given the steep growth rate of wearables and smartphones, as well as advent of semi-autonomous cars (which have a wide range of sensors for inferring the surrounding traffic conditions), it is likely to be possible in near future to establish sophisticated models to sense stress levels of the driver and correlate it with potential influencing factors. Such prediction models for stress levels in real-world conditions will be very useful in widespread applications of the proposed model. This, coupled with the advances in the field of artificial emotional intelligence (Emotion AI) which has made it possible to device interventions to reduce stress (Hernandez et al., 2014), can make a significant contribution in increasing road safety. The proper value addition of such novel technologies requires quantification of the safety impacts of stress. Our models can be used for such evaluations and/or subsequent willingness-to-pay.

Applications may be also extended in the field of microsimulation to better reflect driver heterogeneity. For example, there are emerging microsimulation models that combine activity models with traffic microsimulation (e.g. SimMobility (Adnan et al., 2016)). In these new types of tools, it is possible to include schedule delays in the traffic simulation component and our models can contribute to more realistic representation of driving behaviour in such simulation tools and hence increase their accuracy.

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CHAPTER 5: FROM DRIVING SIMULATORS EXPERIMENTS TO FIELD TRAFFIC APPLICATION: IMPROVING THE TRANSFERABILITY OF CAR-FOLLOWING MODELS

ABSTRACT Over the last few decades, there have been two different streams of data used for driving behaviour research: trajectory data collected from the field (using video recordings, GPS, etc.) and experimental data from driving simulators (where the behaviours of the drivers are recorded in controlled laboratory conditions). Previous research has shown that the parameters of car-following models developed using simulator data are not directly transferable to the field. In this research, we investigate the differences in details and compare alternative methods to overcome the problem. Two types of approaches are tested in this regard: 1) econometric approaches for increasing model transferability: Bayesian updating and Combined Transfer Estimation, 2) joint estimation using both data sources simultaneously. Car-following models based on 'stimulus-response framework' are developed in this regard using experimental data collected from the University of Leeds Driving Simulator (UoLDS) and detailed trajectory data collected from Interstate 80 (I-80), CA, USA. Performances of the proposed approaches for improving transferability are evaluated using t-tests for individual parameter equivalence and Transferability Test Statistic (TTS). The results indicate that the transferability can be improved after parameter updating and Combined Transfer Estimation is found to outperform the other approaches. The findings of this study will enable more effective usage of driving simulator data for the estimation of mainstream mathematical models of driving behaviour.

5.1 Introduction

Driving decisions and consequently vehicle interactions, are crucial factors for evaluating traffic performance and driving safety. Driving behaviour models, which are mathematical approximations of drivers' decisions regarding longitudinal and lateral movements (e.g. acceleration-deceleration, lane-changing, etc.), have been widely studied in the past few decades (see Toledo, 2007; Zheng 2014 and Saifuzzaman and Zheng 2014 for details). Of particular interest are car-following models, which aim to replicate the accelerations and decelerations of the driver while closely following a lead vehicle in the front. Such models are crucial for increasing the realism of the microsimulation tools as well as safety and emission analyses.

Car-following (and microscopic driving behaviour models in general) are typically developed using two types of data, (a) driving simulator (where drivers drive an instrumented vehicle in a simulated roadway) and (b) road traffic data. Driving simulator data are collected following standardised procedures and are more controllable and reproducible compared to actual road traffic. Furthermore, driving simulators allow researchers to manipulate the surrounding conditions (e.g. geometric layout of the road, number and type of vehicles etc.) as well as driver specific conditions (e.g. level of distraction and fatigue). They also allow analysts to run multiple hypothetical scenarios for the same driver and observe driving behaviour for longer time horizons.

The advantages of driving simulators can allow researchers to shift from the development of models completely based on a Newtonian laws of motion approach (i.e. considering only speed, headway etc.) and incorporate further aspects of driving behaviour. For instance, Saifuzzaman and Zheng (2014) highlighted in their literature paper the need to incorporate human factors in existing car-following model specifications. Also, researchers in psychology (e.g. Van Winsum, 1999; Hancock, 1999; Brackstone & McDonald, 2003) have questioned the existing engineering car-following modelling approaches that omit the effects of drivers' characteristics. Along the same direction, Laagland (2005) suggested a series of approaches to incorporate drivers' aggression in microscopic driving behaviour models. Driving simulators offer a research environment where many of the aspects of driving behaviour related to human factors can be investigated, recorded and potentially used in modelling approaches.

However, there is scepticism regarding simulator fidelity (physical and behavioural) and how well drivers' behaviour in a simulator matches with their behaviour on real roads (Lee, 2003). On the other hand, traffic data collected from the field best represents true driving behaviour, but have several limitations: short observation time, measurement errors, complex confounding of influencing factors, less control on the external factors and absence of driver characteristics in particular. It may be noted that besides these two sources, naturalistic driving data collected using instrumented vehicles (e.g UDRIVE, SHRP2 etc.) have also been used in research, but given the very high costs involved, the availability of these data is still limited. Moreover, similar to driving simulator data, naturalistic data are likely to be prone to behavioural incongruence; and similar to real road traffic data, the external variables are often not fully controllable and it is not possible to test the effects of hypothetical scenarios.

Several studies have attempted to investigate the validity of driving simulators concerning drivers' behaviour. Driving simulators' behavioural validity is usually approached in terms of absolute (when the patterns and the magnitude of values are similar to real driving) or relative validity (when the patterns are similar but the magnitudes differ). Godley et al. (2002) investigated behavioural validity in terms of speed. Their research included two types of driving tasks (instrumented vehicle and driving simulator). While their results showed a similar pattern of deceleration in both environments, they noted that drivers adopted faster speed in naturalistic driving conditions and only relative validity prevails. In the same direction, Yan et al. (2008) developed a scenario based on a real signalised intersection and studied simulator validity in terms of speeding and surrogate safety measures. The results showed absolute validity regarding speeding, however, participants adopted riskier behaviours in the driving simulator, thus the safety measures had only relative validity. Bella et al. (2007) reproduced a real two-lane road section composed of 11 parts and tested validity in speed. This study confirmed relative but also absolute validity for most of the examined cases. Risto and Martens (2014) compared the differences in headway choice between an instrumented vehicle and driving simulator without finding significant deviations. Finally, McGehee et al. (2000) compared drivers' reaction times in real and simulated environment and found statistical equivalence between the two cases.

The development of driving behaviour models based on simulator data has already been reported in literature (Farah et al., 2009, Hou et al., 2014). However, since only relative validity has been established, it remains questionable whether this type of data is suitable for direct use in microsimulation tools for traffic flow and policy analysis. Recent research has shown that the parameters of car-following models developed using simulator data are not directly transferable to the field, although the models as a whole are transferable (Papadimitriou & Choudhury, 2017). However, the Papadimitriou & Choudhury study acknowledges a major limitation - the model framework used in evaluating transferability ignores reaction time and driver heterogeneity – which have been identified as a crucial factor affecting car-following behaviour (e.g. Ahmed 1999, Toledo 2007, Koutsopoulos and Farah 2012, Van Hinsbergen et al., 2015, etc.). Further, the paper does not provide any guidance on how to close the gap between the models developed using the simulator and the real road data.

In this research, we aim to address the research gaps in the previous studies by investigating alternative methods to improve the transferability of car-following models. A better understanding of the differences between the two sources of driving behaviour data (video trajectories and driving simulator) could allow for the estimation of car-following models from driving simulator data adjusted by real traffic data. This correction could potentially increase the behavioural realism of these models, assuming that the latter data represents the ground truth with respect to drivers' behaviour. At the same time, driving simulator data allows for the implementation of extreme scenarios while information regarding drivers' attributes can also be available (see e.g. Paschalidis et al., 2019) and can be incorporated in the model specifications. In this paper, advanced model structures that incorporate the reaction time (and acknowledges the associated heterogeneity) are used in this regard to address the limitations of the previous study (Papadimitriou & Choudhury, 2017). Experimental data collected from the University of Leeds Driving Simulator (UoLDS) and detailed trajectory data collected from Interstate 80 (I-80), CA, USA are used for this purpose. Based on a review of the literature, two main approaches are tested:

1. Econometric approaches for improving model transferability
2. Joint Estimation using both data sources simultaneously

The remainder of the paper is organised as follows: Section 5.2 describes the methodological background. This is followed by the case study description and some preliminary analysis of data. In section 5.4 are presented the results of the model estimation and in section 5.5 the transferability and joint estimation results. The paper concludes with a discussion section.

5.2 Background and methodology

5.2.1 Car-following model

Basic structure

The model structure is based on the stimulus-response GM car-following model (Gazis et al., 1961). In the original GM model, acceleration choices for a vehicle are a function of its speed, space headway and relative speed with the lead vehicle. The original specification is as follows (Equation 5.1):

$$\alpha_n(t) = \alpha \, \frac{V_n(t)^{\beta}}{\Delta X_n(t)^{\gamma}} \Delta V_n(t - \tau_n) \tag{5.1}$$

where: ΔX_n is the space headway at time t, V_n is the following vehicle speed, ΔV_n is the relative speed between the following and the lead vehicle and τ_n is the reaction time. Finally, α, β and γ are constants.

Based on the GM model, several extensions have been suggested. Herman and Rothery (1965) were the first to highlight that passenger cars have different acceleration and deceleration capacity. In order to address this shortcoming in the GM model, Ahmed (1999) introduced acceleration-deceleration asymmetry within a stimulus-response framework as presented in Equation 5.2:

$$a_n^{cf,g}(t) = s\left[X_n^{cf,g}(t-\tau_n)\right] \times f\left[\Delta V_n(t - \tau_n)\right] + \varepsilon_n^{cf,g}(t) \tag{5.2}$$

where: s[.] represents sensitivity, as a vector of explanatory variables and f[.] represents the stimulus, given as the relative speed. Also, $\varepsilon^{cf,g}$ is a normally distributed disturbance term while g represents the car-following regime (acceleration or deceleration). In the present study, an adaptation of the GM model is applied where the sensitivity and stimulus parts are represented by Equations 5.3 and 5.4 respectively:

$$s\left[X_n^{cf,g}(t - \tau_n)\right] = \alpha^g \frac{1}{\Delta T_n(t)^{\gamma^g}} \tag{5.3}$$

$$f\left[\Delta V_n(t - \tau_n)\right] = \Delta V_n(t - \tau_n)^{\lambda^g} \tag{5.4}$$

where ΔT_n: is the time headway, ΔV_n is the relative speed between the subject and the lead vehicle and τ_n is the reaction time. Finally, α^g, γ^g and λ^g are parameters to be estimated and g indicates the type of regime. It is worth highlighting that instead of applying the original GM model specification, the sensitivity part was modified in order to consider only time headway, as per the recent literature (Papadimitriou & Choudhury, 2017).

The reaction time distribution

The current model specification also allows for the incorporation of reaction time. Following examples in the existing literature (Ahmed, 1999; Kusuma, 2015), reaction time is assumed to follow a log-normal truncated distribution as presented in Equation 5.5:

$$f(\tau_n)=\begin{cases} \dfrac{\dfrac{1}{\tau_n\sigma_\tau}\varphi\left(\dfrac{\ln(\tau_n)-\mu_\tau}{\sigma_\tau}\right)}{\Phi\left(\dfrac{\ln(\tau^{max})-\mu_\tau}{\sigma_\tau}\right)-\Phi\left(\dfrac{\ln(\tau^{min})-\mu_\tau}{\sigma_\tau}\right)} & \text{if } \tau^{min}<\tau_n\leq\tau^{max} \\ 0 & \text{otherwise} \end{cases} \tag{5.5}$$

where: $\varphi(.)$ is the standard normal distribution density function, $\Phi(.)$ is the cumulative normal distribution, τ_n is the reaction time of driver n, μ_τ is the mean of the distribution of $\ln(\tau_n)$, σ_τ is the standard deviation and τ^{max}, τ^{min} are the bounds of truncation. Truncation is required since reaction time is finite. The bounds are set deterministically while the mean and the standard deviation are estimated simultaneously with the rest of the model parameters. The bounds of reaction time were set between 0 and 4 seconds (Ahmed, 1999; Kusuma, 2015).

Likelihood Function

The assumption of the car-following model is that a driver accelerates if the relative speed is positive and decelerates if it negative. Given this, the distribution of acceleration decisions, conditional on reaction time τ, is presented as follows:

$$f\left(a_n^{cf,g}(t)|\tau_n\right)=f\left(a_n^{cf,acc}(t)|\tau_n\right)^{\delta[\Delta V_n(t-\tau_n)]}f\left(a_n^{cf,dec}(t)|\tau_n\right)^{(1-\delta[\Delta V_n(t-\tau_n)])} \tag{5.6}$$

where:

$$\delta[\Delta V_n(t-\tau_n)]=\begin{cases} 1 & \text{if } \Delta V_n(t-\tau_n)\geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Assuming that the disturbance terms are normally distributed, the acceleration decisions can be expressed as follows:

$$f\left(a_n^{cf,g}(t)|\tau_n\right)=\frac{1}{\sigma_{\varepsilon^{cf,g}}}\varphi\left(\frac{a_n^{cf,g}(t)-s\left[X_n^{cf,g}(t-\tau_n)\right]\times f\left[\Delta V_n(t-\tau_n)\right]}{\sigma_{\varepsilon^{cf,g}}}\right) \tag{5.7}$$

where, $g \in \{acc,dec\}$.

In the current specification, the acceleration observations of each driver n are assumed to be independent while the correlation among the decisions of the same driver (i.e. inter-respondent heterogeneity in driving behaviour) is captured through the reaction time distribution. Thus, the conditional joint density of the acceleration sequential observations, of a driver n, is the product of the conditional densities of the acceleration decisions is expressed as follows:

$$f\left(a_n(1),a_n(2),\ldots,a_n(T_n)|\tau_n\right)=\prod_{t=1}^{T_n} f\left(a_n(t)\,|\tau_n\right) \tag{5.8}$$

The unconditional form of the distribution above is expressed as follows:

$$f\left(a_n(1),a_n(2),\ldots,a_n(T_n)\right)=\int_{\tau^{min}}^{\tau^{max}} f\left(a_n(1),a_n(2),\ldots,a_n(T_n)|\tau_n\right) f(\tau_n)d\tau \tag{5.9}$$

At the final step, the model is estimated by maximizing the log-likelihood function of the acceleration observations as expressed in Equation 5.10:

$$LL=\sum_{n=1}^{N} \ln\left[f\left(a_n(1),a_n(2),\ldots,a_n(T_n)\right)\right] \tag{5.10}$$

The log-likelihood function was maximised using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm implemented in the software R.

5.2.2 Evaluating Model Performance and Transferability

The basic concept of transferability refers to the transfer of a model estimated in one context to a different one. Although there are limited studies of transferability in the domain of driving behaviour modelling, it has been investigated in detail in several other fields of transportation and beyond. The lion's share is dedicated to the investigation of transferability with the application of discrete choice modelling e.g. (Atherton & Ben-Akiva, 1976; Galbraith & Hensher, 1982; Koppelman & Wilmot, 1982; Ben-Akiva & Bolduc, 1987), however, other modelling approaches can also be found (Wilmot, 1995; Hadayeghi et al., 2006).

A review of the literature revealed several formal statistical tests of transferability (Sikder et al., 2013) among which the *t-tests of individual parameter equivalence* and *Transferability Test Statistic* (TTS) have been found to be most widely used and were thus selected for this study.

The t-tests of individual parameter equivalence compare parameter estimates of equivalent variables between the two models as e.g. in (Galbraith & Hensher, 1982). The t-stat differences can be expressed as follows (Equation 5.11):

$$t_{diff,k}=\frac{\beta_{est,k}-\beta_{appl,k}}{\sqrt{\left(\frac{\beta_{est,k}}{t_{est,k}}\right)^2+\left(\frac{\beta_{appl,k}}{t_{appl,k}}\right)^2}} \qquad (5.11)$$

where: $\beta_{est,k}$ is the the parameter estimate of the k^{th} parameter of the transferred (simulator data) model and $t_{est,k}$ is its t-statistic while $\beta_{appl,k}$ is the the parameter estimate of the k^{th} parameter of the application context (video trajectory data) model and $t_{appl,k}$ is its t-stat. The null hypothesis of parameter equivalence is rejected at the 95% level of confidence if $|t_{diff,k}|>1.96$.

The TTS (Atherton & Ben-Akiva, 1976) assesses whether the null hypothesis of statistical equivalence between the transferred and the application context model is rejected or not (Equation 5.12):

$$TTS_{appl} = -2\left[LL_{appl}(\beta_{est}) - LL_{appl}\left(\beta_{appl}\right)\right] \qquad (12)$$

where, $LL_{appl}(\beta_{est})$ is log-likelihood on the application context data using transferred context parameters and $LL_{appl}(\beta_{appl})$ is the log-likelihood on the application context data using application context parameters, i.e. new estimates. The TTS value follows a chi-squared (χ^2) distribution and the degrees of freedom are equal to the number of model parameters, assuming that the parameters of the transferred model are fixed (Koppelman & Wilmot, 1982). At 95% level of confidence, the models are classified statistically different (i.e. non-transferable) if $\chi^2 > \chi^2_{critical}$.

5.2.3 Methods to Improve Transferability

The direct transferability of parameters from a transferred to an application context is not always feasible, as models are never perfectly specified (e.g. omission of important variables) or contextual factors that affect a phenomenon e.g. over time or across areas (Badoe & Miller, 1995). Thus, a series of techniques has been proposed to update the parameter estimates of the transferred context in order to be closer to the application context. Based on a literature review conducted regarding studies that have dealt with transferability (Badoe & Miller, 1995; Sikder et al., 2013; Chingcuanco & Miller 2014), the following updating techniques have been distinguished:

Adjustment of Alternative-Specific Constants

The Adjustment of Alternative-Specific Constants (ASCs) has been suggested in the area of discrete choice modelling (see Koppelman & Wilmot, 1982). The ASCs are in general included in the utility function to capture the average effect of omitted variables. The assumption behind this updating approach is that this effect varies between the transferred and the application context and thus a model can be improved if the ASCs are updated with values derived from the latter. In this case, the deterministic part of utility function of the application context is specified as (Equation 5.13):

$$V_{in,appl} = ASC_{i,appl} + \beta_{est} X_{in,appl} \tag{5.13}$$

where $ASC_{i,appl}$ is the alternative specific constant of alternative i, β_{est} is a vector of parameters from the estimation context and $X_{in,appl}$ is a vector of explanatory variables of alternative i of individual n.

Transfer scaling

Transfer Scaling, is another approach used in discrete choice modelling (Badoe & Miller, 1995). The ASCs are estimated from a small subset of the application context data while the rest of the utility functions' parameters are assumed to be transferable from the estimation (transferred) context up to a specific scale to be estimated. The utility specification in this is as shown in Equation 5.14:

$$V_{in,appl} = ASC_{i,appl} + \gamma_{i,appl}\, \beta_{est}\, X_{in,appl} \tag{5.14}$$

where $ASC_{i,appl}$ is the alternative specific constant of alternative i, β_{est} is a vector of parameters from the estimation context, $\gamma_{i,appl}$ is a vector of scale factors for the parameters to be scaled and $X_{in,appl}$ is a vector of explanatory variables of alternative i of individual n.

Bayesian updating

The Bayesian updating process follows the Bayes theorem in which prior information about the model is combined with a random sample from the application context to obtain updated information that is important in reducing doubt during prediction (Dey & Fricker, 1994). The parameters estimated with the trajectory data can be used as the prior information in this case and the following formula can be used (Equation 5.15):

$$\beta_{upt} = \left(\frac{\beta_{est}}{\sigma_{est}^2} + \frac{\beta_{appl}}{\sigma_{appl}^2}\right)\left(\frac{1}{\sigma_{est}^2} + \frac{1}{\sigma_{appl}^2}\right)^{-1} \tag{5.15}$$

where β_{est} is the parameter of the estimation (driving simulator) context model, σ_{est} is its standard deviation, β_{appl} is the parameter of the application (real driving) context model and σ_{appl} is its standard deviation.

Combined Transfer Estimation

The Combined Transfer Estimation (CTE) method (Ben-Akiva & Bolduc, 1987) can be considered as an extension of Bayesian updating, as it accounts for the impact of the transfer bias (the difference between the real values in the parameter vectors of the estimation and the application context) in the updating process. If the transfer bias does not exceed a critical point, Combined Transfer Estimation is considered as a more efficient estimator, compared to the estimator of the application context only (direct estimator). The updated parameters are estimated as (Equation 5.16):

$$\beta_{upt}=\left(\frac{\beta_{est}}{\sigma_{est}^2+\alpha\alpha'}+\frac{\beta_{appl}}{\sigma_{appl}^2}\right)\left(\frac{1}{\sigma_{est}^2+\alpha\alpha'}+\frac{1}{\sigma_{appl}^2}\right)^{-1} \tag{5.16}$$

where: $\alpha = \beta_{est}-\beta_{appl}$ and $\alpha'=\beta_{appl}-\beta_{est}$.

The CTE is more efficient than the direct estimator if $\Delta^2<\delta\left(\sigma_{est}^2+\sigma_{appl}^2\right)$, where Δ is the transfer bias, and δ is a parameter that the authors calculated with a Monte-Carlo approach (Ben-Akiva et al., 1995). In the same study, a test is also provided to assess the size of transfer bias and whether CTE is a better estimator.

Joint Estimation

The joint estimation of models using various data sources was introduced in the discrete choice modelling field (Ben-Akiva et al., 1994) and mostly refers to the combination of stated-preference (SP) and revealed-reference (RP) data. The motivation for data combination is the estimation of enhanced models that exploit the advantages of the various data sources while at the same time minimising their shortcomings, by allowing variations in their scales. A basic example regarding the application of this approach could be the reduction of hypothetical bias of a SP survey and improvement of the accuracy of parameter estimates, through joint estimation with RP data. The joint estimation process provides estimates of the common parameters but since the variances of the disturbance terms between SP and RP are likely to be different, an additional scale parameter is introduced to capture this variation. For model identification purposes, the scale of RP is normalised to one while only the scale of SP is estimated. Within a car-following context, Hoogendoorn & Hoogendoorn (2010) provided a methodological framework for joint estimation of driving simulator and real traffic data and suggested a weighting correction to account for the differences in sample sizes. However, in their estimation, they considered the contribution of driving simulator data as equal and did not investigate any potential behavioural bias deriving from its hypothetical nature.

Comparison of updating techniques

In existing literature, there are studies that compare the aforementioned parameter updating techniques. For instance, Koppelman et al., 1985 found that the Transfer Scaling approach provides better log-likelihood scores compared to the Adjustment of Alternative-Specific Constants. This outcome is expected, since the former approach is adding at least on more parameter in model estimation, compared to the latter, based on Equations 5.13 and 5.14. Similar outcomes were found by Santoso & Tsunokawa (2010). Bayesian updating, has been the most deficient technique, compared to Transfer scaling, CTE and joint estimation in a study conducted by Badoe & Miller (1995) while Santoso & Tsunokawa (2010) found that it performs worse than the Adjustment of Alternative-Specific Constants approach for high transfer bias. This outcome, is a result of the inability of Bayesian updating to account for the effects of the latter.

Regarding the most efficient approach, Badoe & Miller (1995) report that CTE produces the best predictive performance in the application context, however, joint estimation results are more parsimonious. Thus, they suggest that if the estimation data is available, researchers should proceed with the latter approach. Moreover, they mention that for small sample sizes, Transfer scaling is comparable to these two techniques. Santoso & Tsunokawa (2010) found that CTE is the most superior technique of updating however, they did not include joint estimation in their study. Similarly, Flavia & Choudhury (2019), reported that CTE performs better compared to Bayesian Updating. Finally, Karasmaa (2007), concluded that joint estimation provides the best results. In this study, authors also found that Bayesian updating provided significant outcomes but they highlight that it should be avoided for cases of large transfer bias. Based on the aforementioned literature review, there is not an optimum transferability method but the best solution can be data and case specific.

5.3 Case study

The datasets used for the model estimation are described in the present section. Initially, the characteristics and attributes of each site are provided followed by a preliminary descriptive analysis.

5.3.1 Data

Video trajectory data

The vehicle trajectories data, used in the analysis, has been collected at the Interstate 80 (I-80), CA, USA, within the framework of the Next Generation SIMulation (NGSIM) project (Halkias & Colyar, 2006) and have been extensively used in other studies (e.g. Koutsopoulos and Farah,2012; Aghabayk et al., 2012). The observations took place on 13 April 2005. The length of the road segment is approximately 500 meters (1650 feet) and comprises of five lanes plus a high occupancy vehicle (HOV) lane (Figure 1-left). The vehicles' trajectories referring to the observations from 4.00 p.m. to 4.15 p.m. have been further processed by Punzo et al. (2011) and Montanino and Punzo (2013). The final dataset includes information regarding the position, speed, acceleration, lane, size and type of each vehicle.

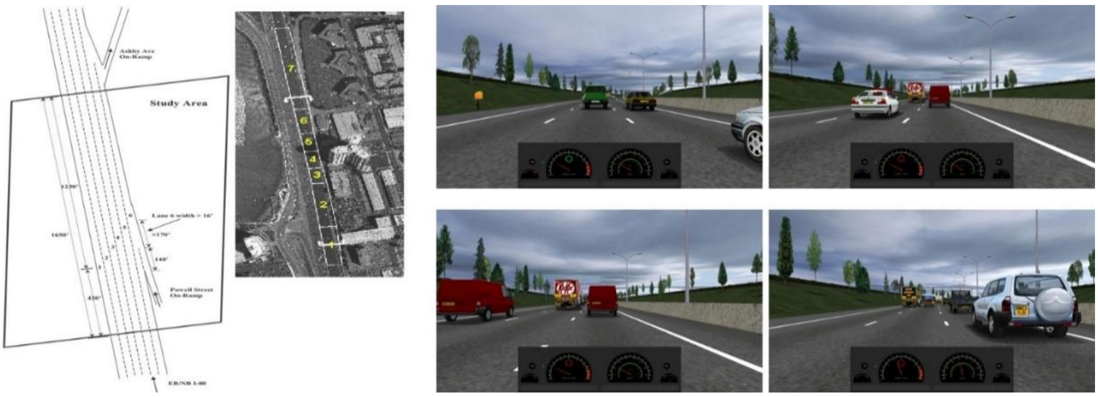

Figure 5.1: (left) I-80 motorway data collection site, (right) Screenshots of the motorway setting of NG-DBM

Driving simulator data

The driving simulator data has been collected at the University of Leeds Driving Simulator (UoLDS). The UoLDS is a high fidelity, dynamic simulator (eight degree of freedom motion system), with all driver controls, such as steering wheel and breaking pedal, available and fully functional, while there is also a fully operating dashboard. The vehicle is placed in a 4m diameter spherical projection dome. The dome provides fully textured 3-D graphical scene with a horizontal field of view of 250^{o} and 45^{o} vertical. The raw data output consits of observations of 60Hz frequency.

The data collection has taken place in the context of the "Next Generation Driving Behaviour Models" project (NG-DBM). The full data collection process involves around 90 minutes of total driving. Participants have had first a short briefing about the simulator and its operation followed by a practice session of approximately 15 minutes duration to get familiarised with the simulated environment and vehicle dynamics (i.e. motion system). For safety reasons, participants have been accompanied by a researcher, during the practice run, in the back seat. After the practice session, participants started the main driving sessions; an urban and a 3-lane motorway environment, with a short break in between. In total, 36 drivers (17 females, 19 males) aged from 19 to 57 years old have successfully completed the motorway setting that has been used in the current analysis (Figure 1-right) for the model specification and estimation.

5.3.2 Preliminary analysis

The raw datasets have been further processed to better meet the requirements for the estimation of a car-following model. As a first step, relationships regarding the surrounding traffic such as relative speed, acceleration of lead vehicle etc. have been extracted from both datasets.

Regarding the I-80 trajectory dataset, only cars that have not attempted a lane-changing manoeuvre during the observation period are included in the analysis. The driving simulator data has been first investigated in terms of its similarity to the trajectory data, in order to have more comparable cases. The full motorway setting is composed of several smaller sections, approximately 6.3km each, of varying traffic characteristics and surrounding vehicles behaviour. Each of the sections has been compared to the available trajectory dataset. The examined variables were acceleration, speed and relative speed with the lead vehicle and the simulated motorway section with the best match (in terms of descriptive statistics) in speed was used for model estimation.

For both datasets, the considered observation frequency is 1 observation/sec. Also, in order to avoid free-flow observations and following the findings in (Hoogendoorn, 2005), an upper bound of 4s has been applied in the observed time headway; all the values above that threshold, are treated as free-flow and excluded from the analysis. For the final estimation, the trajectory dataset is composed of 469 individuals and 14,826 observations while the driving simulator dataset 36 individuals and 7,191 observations. Table 5.1 summarises the descriptive statistics for some variables of the two datasets.

The descriptive statistics indicate that there are differences in the examined variables of the two datasets. These differences are further investigated with an independent samples t-test (Table 5.1). The p-values of the Levene's test are significant for all variables, apart from time headway, which indicates that the variances of all the variables are different between the video trajectory and the driving simulator datasets.

Table 5.1: Descriptive statistics of the two datasets

Variable	I-80 Video trajectory data				Driving simulator data				Levene's test for equality of variances	t-test for equality of means
	Min	Mean	Max	sd	Min	Mean	Max	sd	p-value	p-value
Speed (m/s)	1.524	8.418	26.078	3.581	7.668	14.713	35.928	4.742	0.000	0.000
Acceleration (m/s^2)	-4.728	-0.039	2.897	0.926	-10.038	-0.087	1.900	0.670	0.000	0.000
Time headway (s)	0.576	2.338	3.998	0.678	0.422	1.821	3.977	0.686	0.801	0.000
Space headway (m)	4.235	18.941	80.136	8.696	5.786	25.933	106.699	14.128	0.000	0.000
Relative speed (m/s)	-5.802	-0.0477	5.401	1.203	-19.232	-0.8111	8.982	6.106	0.000	0.000

Additionally, the results of the t-test for the equality of means shows that the means of all variables are significantly different as well. These findings point out that there are variations in the traffic variables (and thus in traffic conditions) between the two datasets which may affect the models' results. Though these differences impose extra challenge in the transferability of the models, in practical cases, this is very likely to be the reality (i.e. the simulator data being available for a small subset of participants, fixed variations in simulated traffic whereas actual road traffic will have larger variability or difficulties in reproducing observed traffic flow patterns in simulator).

5.4 Estimation results

The estimation results are summarized in Table 5.2. The individual models are further explained and compared in Sections 5.4.1 and 5.4.2 respectively. Moreover, the estimated reaction time distributions are illustrated in Figure 5.2. The reaction time distribution from the video data ranges between 0-2s and is mainly centered slightly above 0.5s. On the other hand, the estimated distribution based on the simulator data covers almost the whole range of truncation with a peak between 1.5s and 2s. This may be an indication of different response patterns for the relative speed stimulus between the two contexts. Some further discussion with respect to their differences is presented in Section 5.4.1.

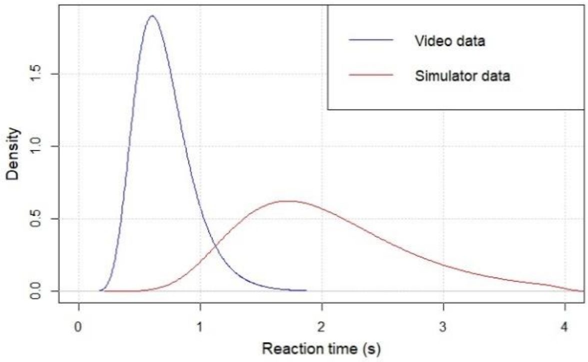

Figure 5.2: Reaction time distributions of the car-following models

5.4.1 Individual Models

Model 1: Car-following model based on driving simulator data

The estimated car-following acceleration of Model 1 is shown in Equation 5.17:

$$a_n^{cf,acc}(t) = 0.3506 \frac{1}{\Delta T_n(t)^{0.2856}} \left|\Delta V_n(t - \tau_n)\right|^{0.6787} + \varepsilon_n^{cf,acc}(t) \tag{5.17}$$

where, $\varepsilon_n^{cf,acc}(t) \sim N(0, 0.3367^2)$.

Table 5.2: Models parameter estimates, t-test of individual parameter equivalence and TTS results

Variable	Driving simulator data (Model 1) Parameter estimate	Driving simulator data (Model 1) Robust t-ratio	Video trajectory data (Model 2) Parameter estimate	Video trajectory data (Model 2) Robust t-ratio	t-tests of individual parameter equivalence Difference t-stat
Reaction time distribution					
μ_t	0.6640	14.66	-0.3973	-16.42	20.67
σ_t	0.3536	2.69	0.3257	66.48	0.21
Car-following acceleration					
Constant	0.3506	6.96	0.8304	13.77	-6.11
time headway (s)	0.2856	1.85	0.792	8.99	-2.85
relative speed (m/s)	0.6787	9.71	0.8982	20.58	-2.66
σ^{acc}	0.3367	25.26	0.7318	76.71	-24.10
Car-following deceleration					
Constant	-0.2550	-5.47	-0.5128	-16.03	4.56
time headway (s)	0.4798	2.66	0.1941	2.36	1.44
relative speed (m/s)	0.7043	9.38	0.9280	25.98	-2.69
σ^{dec}	0.6893	16.61	0.8007	75.16	-2.60
	LL = -5610.845 $\rho^2 = 0.320$ Adj. $\rho^2 = 0.319$ obs = 7191		LL = -17240.88 $\rho^2 = 0.138$ Adj. $\rho^2 = 0.137$ obs = 14826		
Transferability Test Statistic (TTS)					
Summary statistics	Simulator to real driving transferability				
Degrees of freedom (Dof)	10				
LLest (β_{transf})	-27126.16				
LLapplic(β_{appl})	-17240.88				
-2[LLapplic(β_{transf}) -LLapplic(β_{appl})]	19770.56				

In a similar way, Equation 5.18 presents the deceleration component of Model 1:

$$a_n^{cf,dec}(t) = -0.255 \frac{1}{\Delta T_n(t)^{0.4798}} |\Delta V_n(t - \tau_n)|^{0.7043} + \varepsilon_n^{cf,dec}(t) \tag{5.18}$$

where, $\varepsilon_n^{cf,dec}(t) \sim N(0, 0.6893^2)$.

The acceleration and deceleration constants both have the expected signs and are statistically significant at 0.05 level. Moreover, the parameters of time headway both have positive signs but the parameter for acceleration regime is significant at the 0.1 level. The positive sign for the time headway parameter of the acceleration regime implies that drivers tend to react less to the leader's speed as time headway increases and they get closer to a free-flow state. Regarding the deceleration regime, the positive sign of the time headway parameter indicates that drivers adopt smaller decelerations at larger headways. The schematic interpretation of the aforementioned parameters and their effects on acceleration/deceleration are illustrated in the next section. Finally, the parameters of relative speed are significant for both acceleration and deceleration regimes. It is worth mentioning that the estimates are in accordance with the a-priori expected values (smaller than 1) as the acceleration or deceleration capabilities of the driver are constrained by the vehicle capability. The impact of each parameter is depicted more explicitly in the sensitivity analyses presented in the next section. Finally, Figure 5.2 shows the reaction time distribution as expressed by the estimated mean and standard deviation. The distribution extends approximately to the whole 0-4s range and its peak is between 1.5s and 2s. The estimated distribution of reaction time is (Equation 5.19):

$$f(\tau_n) = \begin{cases} \dfrac{1}{0.3536\,\tau_n}\,\varphi\left(\dfrac{\ln(\tau_n) - 0.664}{0.3536}\right) & \text{if } 0 < \tau_n \leq 4 \\ 0 & \text{otherwise} \end{cases} \tag{5.19}$$

Model 2: Car-following model based on video trajectory data

The estimated car-following acceleration of Model 2 is presented in Equation 5.20:

$$a_n^{cf,acc}(t) = 0.8304\,\frac{1}{\Delta T_n(t)^{0.792}}\,|\Delta V_n(t - \tau_n)|^{0.8982} + \varepsilon_n^{cf,acc}(t) \tag{5.20}$$

where, $\varepsilon_n^{cf,acc}(t) \sim N(0, 0.7318^2)$.

Finally, the deceleration component of Model 2 is shown in Equation 5.21:

$$a_n^{cf,dec}(t) = -0.5128 \frac{1}{\Delta T_n(t)^{0.1941}} |\Delta V_n(t - \tau_n)|^{0.928} + \varepsilon_n^{cf,dec}(t) \tag{5.21}$$

where, $\varepsilon_n^{cf,dec}(t) \sim N(0, 0.8007^2)$.

The results of the car-following model estimation based on the video trajectory data are presented in Table 5.2. All the parameters have expected signs and are significant at 0.05 level. Moreover, the values of relative speed parameters are below 1, as a-priori expected. The reaction time distribution (Figure 5.2) extends between 0-2s while its peak is approximately after 0.5s. This outcome suggests that drivers' reaction time in real traffic is smaller compared to simulated driving (i.e. the drivers respond faster to the relative speed stimulus in field traffic conditions. This might be a potential indication that drivers perceive changes in traffic conditions differently in the simulator compared to field traffic driving (where a crash occurrence would have genuine consequences). The estimated distribution of reaction time is shown in Equation 5.22:

$$f(\tau_n) = \begin{cases} \frac{1}{0.3257\, \tau_n} \varphi\left(\frac{\ln(\tau_n) + 0.3973}{0.3257}\right) & \text{if } 0 < \tau_n \leq 4 \\ 0 & \text{otherwise} \end{cases} \tag{5.22}$$

5.4.2 Model comparison and sensitivity analysis

The initial evaluation of the estimated parameters shows that their signs are expected while all of them are significant. The current section investigates the effects of models' variables in the car-following acceleration (deceleration) to further assess the parameter estimates and ultimately compare the extent and nature of differences between the two models. Figure 5.3 depicts the sensitivity analysis for all parameters.

Focusing on the driving simulator case, the results indicate that the value of acceleration slightly decreases with the increase of time headway. This pattern reflects drivers' expected behaviour in acceleration state, as explained in Section 5.4.1. On the other hand, the absolute value of deceleration increases with the decrease of time headway. This outcome meets the expectations, since drivers will decelerate to a higher extent when time headway is short and relative speed is negative (deceleration regime), while it also indicates drivers' safety concerns; as time headway decreases, drivers decelerate to avoid collision. These interpretations also apply for the patterns related to time headway of Model 2. The steeper slopes in the latter case, which also result in higher absolute acceleration/deceleration values, better highlight the differences in drivers' sensitivity between simulated and real driving. In the acceleration regime, the aforementioned differences may indicate a higher variance in traffic conditions – which influences applied acceleration - or suggest that drivers have higher sensitivity in the decrease of time headway during real road traffic conditions. A similar trend is also observed in the deceleration regime of this model - as the plots show that deceleration rate is in general higher - compared to the driving simulator case. This outcome might be an effect of the smaller variance in traffic conditions of the simulated scenario (as happens in the acceleration regime), but given the higher value of the standard deviation parameter in the deceleration regime, and thus a potentially higher variance in observed behaviour, it might also indicate that drivers assess or perceive risk in a different way (e.g. absence of real danger) and this behaviour could influence their deceleration decisions.

Regarding relative speed, acceleration and deceleration reach their maximum absolute values when the former is maximum and minimum, respectively, in both models. The obtained acceleration-regime trends follow the underlying theory of the current car-following model as drivers' acceleration tends to increase while lead vehicle moves faster. In the same way, the increase in absolute deceleration as relative speed declines, is consistent with the safety implications reported about the effect of time headway, as a driver is expected to decelerate to a higher degree when relative speed gets smaller. Moreover, the same differences in sensitivities, reported with respect to the effects of time headway, are also observed in the relative speed plots.

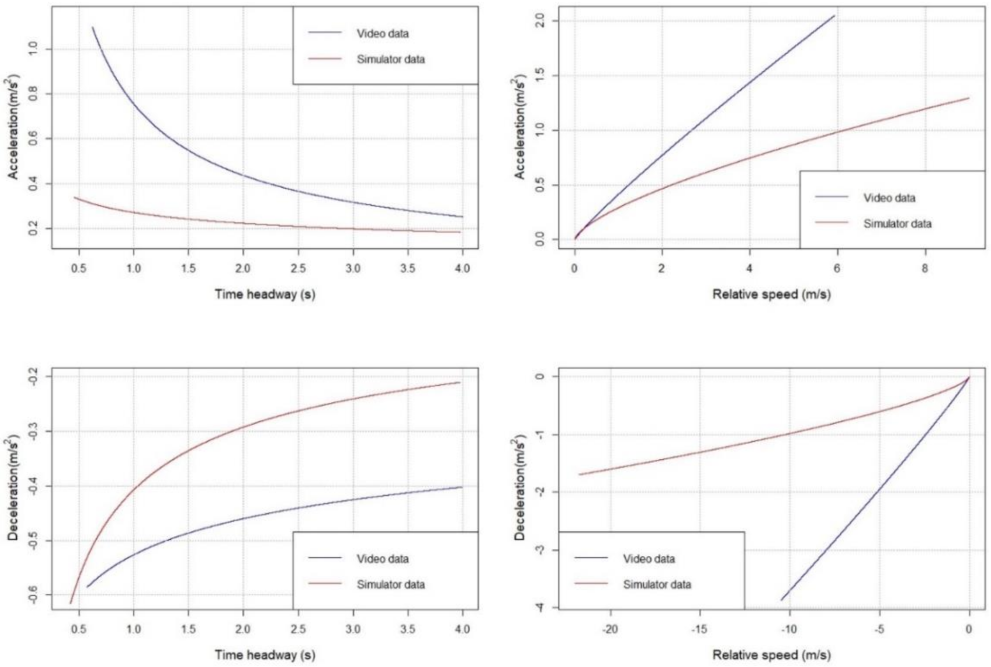

Figure 5.3: Sensitivity analysis of the car-following models

The different patterns in acceleration (deceleration) that the sensitivity analysis revealed, are further investigated through model comparison, in terms of parameter equivalence and model transferability. The results of the t-test of individual parameter equivalence (Table 5.2) show that for most of the parameters, the null hypothesis of equivalence is rejected (|t-value|>1.96). The t-stat of the difference is non-significant only for the standard deviation of reaction time distribution and the time headway parameter of the deceleration regime. Moreover, the results of TTS regarding transferability from driving simulator to real driving context show that the null hypothesis of equivalence between the two models is rejected at 0.05 level ($\chi^2_{critical}$ =18.31), thus, transferability from simulated to real traffic driving cannot be validated. It may be noted that while testing transferability with simpler models (see Papadimitriou & Choudhury, 2017 for details), though majority of the parameters were not found to be transferable, the null hypothesis of equivalence was not rejected. Albeit the space headway and subjects' speed, of the data used in the current study, have a closer match with the NGSIM data in comparison with the sim data used in the previous study, this may indicate that incorporation of reaction time heterogeneity increases the gap between the two sets of models in terms of transferability.

Considering all the above, it is evident that the results of a car-following model developed by driving simulator data cannot be directly used for real-driving applications (e.g. in microsimulation). In the next section is investigated a series of approaches to address this drawback.

5.5 Model updating and joint estimation

The analysis described in the previous section highlights the lack of transferability from driving simulator models to the field. The current section investigates two different updating approaches that aim to reduce the potential behavioural bias of driving simulator data and identify the most suitable of them in order to develop a context for its application in a real driving framework. Moreover, the results of the two car-following models are compared with the results of a joint model estimated using both datasets.

5.5.1 Model updating

The parameters of the driving simulator model have been updated using the Bayesian updating (Dey & Fricker, 1994) and Combined Transfer Estimation (Ben-Akiva & Bolduc, 1987) approaches. The updated parameters and the results of the TTS after the application of model updating are presented in Table 5.3. The TTS value after applying Bayesian updating indicates that the null hypothesis of model equivalence is rejected at 0.05 level ($\chi^2_{critical}$ =18.31). However, the TTS value of the combined transfer estimation shows that after updating, the null hypothesis is not rejected and thus, driving simulator data can be considered transferable. This finding is consistent with existing literature, where Combine Transfer Estimation outperforms Bayesian updating.

The effects of the updating techniques and the amendments of each on the parameters of Model 1 can be demonstrated more rigorously with the application of the sensitivity analysis described in Section 5.4.2. The results of both approaches are illustrated in Figures 5.4 and 5.5. The parameters after applying Bayesian updating (Figure 5.4) on Model 1, result in the occurrence of lines which are closer to Model 2 – compared to the initial sensitivity analysis as presented in Figure 5.3 – but still there is a distinct difference between the two cases. On the other hand, the new set of parameters, after Combined Transfer Estimation, produces very similar outcomes. In particular, the acceleration regime of both models is almost identical while some differences can be noticed in the deceleration regime. The results of the sensitivity analysis are consistent with the outcomes presented in Table 5.3 and provide an expanded investigation regarding the effects of each updating technique on each of the elements of the car-following model based on driving simulator data.

Table 5.3: Parameters and TTS results after model updating

	Bayesian updating	Combined Transfer Estimation
Variable	Parameter estimate	Parameter estimate
Reaction time distribution		
μ_t	-0.162	-0.398
σ_t	0.326	0.326
Car-following acceleration		
Constant	0.548	0.838
time headway (s)	0.667	0.809
relative speed (m/s)	0.837	0.908
σ^{acc}	0.598	0.732
Car-following deceleration		
Constant	-0.430	-0.517
time headway (s)	0.243	0.149
relative speed (m/s)	0.887	0.935
σ^{dec}	0.794	0.802
Transferability Test Statistic (TTS)		
Summary statistics	Bayesian updating	Combined Transfer Estimation
Degrees of freedom (Dof)	10	10
LLapplic (βtransf)	-17884.1	-17245.46
LLapplic(βapplic)	-17240.88	-17240.88
-2[LLapplic(βtransf) -LLapplic(βapplic)]	1286.44	9.16

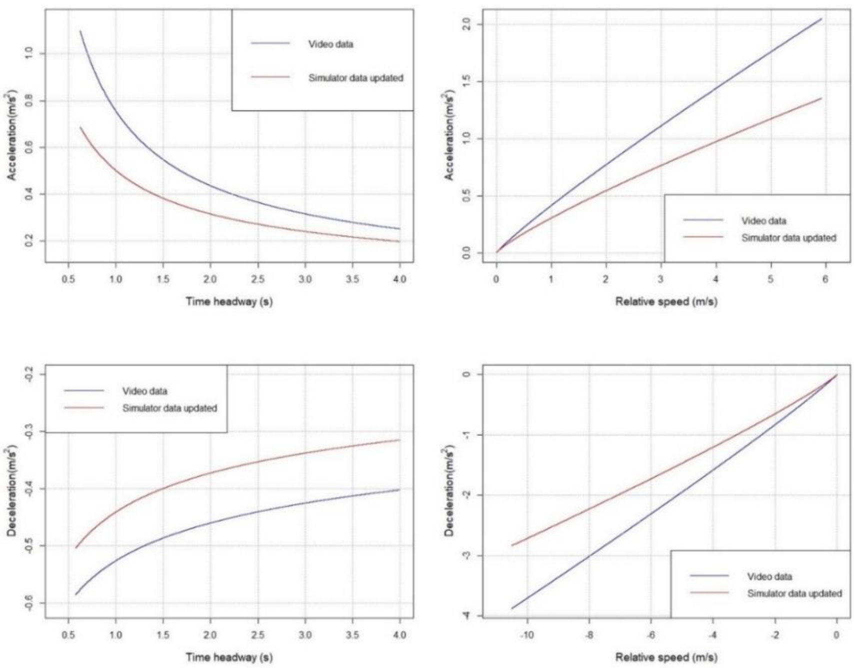

Figure 5.4: Sensitivity analysis after Bayesian updating

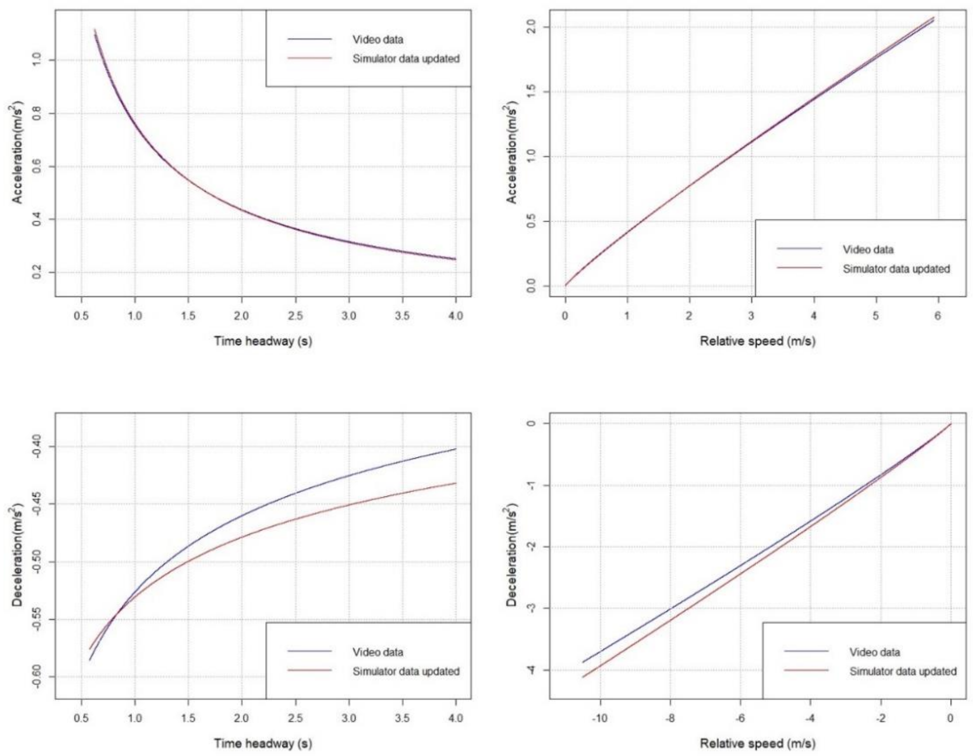

Figure 5.5: Sensitivity analysis after Combined Transfer Estimation

5.5.2 Joint estimation results

The differences between the two datasets are further investigated in the context of joint model estimation. In this approach, the car-following model is estimated combining simultaneously both data sources. Initially, the datasets have been considered as the same source and a single set of parameters have been estimated. The results of this model are not presented in the context of the present analysis, but its final log-likelihood value has been used for comparison purposes in Table 5.4. As a next step, a series of scale parameters are introduced to account for the differences between trajectory and simulator data. The scale parameters are applied to the sensitivity×stimulus terms, the standard deviation parameters and the reaction time parameters with the following formulation: ($\delta^{trajectory}+\delta^{simulator}\times$scale), where $\delta^{trajectory}$ is a dummy variable equal to 1 if the observation belongs to the trajectory dataset and $\delta^{simulator}$ is a dummy variable equal to 1 if the observation belongs to the driving simulator dataset. Six scale parameters are used in total. In essence, given that for every density function involved in the model specification (acceleration, deceleration and reaction time) a mean and a standard deviation component is estimated, each of the scale parameters is used to approximate the difference of the driving simulator data estimates with respect to the video trajectory data estimates. After incorporating the aforementioned scale specification in Equation 5.7, the acceleration/deceleration density function is given from Equation 5.23:

$$f\left(a_n^{cf,g}(t)|\tau_n\right)=\frac{1}{\sigma_{\varepsilon^{cf,g}}}\varphi\left(\frac{a_n^{cf,g}(t)\text{ - }s\left[X_n^{cf,g}(t\text{ - }\tau_n)\right]\times f\left[\Delta V_n(t\text{ - }\tau_n)\right]\left(\delta^{traj}+\theta^{\mu}\delta^{sim}\right)}{\sigma_{\varepsilon^{cf,g}}\left(\delta^{traj}+\theta^{\sigma}\delta^{sim}\right)}\right) \tag{5.23}$$

where θ^{μ} and θ^{σ} represent the scale parameters of mean and standard deviation respectively.

The parameter estimates of the model are presented in Table 5.4. Owing to the model specification, the t-ratio values of the scale parameters refer to the comparison with 1 rather than 0. All scale parameters, apart from reaction time standard deviation, are significantly different from 1. This result consists an additional indication to the tests applied in the previous section, that for joint estimation, the differences between the various data sources should be considered and captured.

Table 5.4: Parameter estimates of the joint model

Variable	Parameter estimate	Robust t-statistic
Reaction time distribution (Video trajectory data)		
μ_t	-0.3964	-16.45
σ_t	0.3264	65.20
Car-following acceleration		
Constant	0.7209	14.88
time headway (s)	0.5562	6.73
relative speed (m/s)	0.7801	15.10
σ^{acc}	0.7337	77.11
Car-following deceleration		
Constant	-0.5644	-12.01
time headway (s)	0.2584	2.77
relative speed (m/s)	0.8539	19.00
σ^{dec}	0.8008	74.95
Scale parameters		
Car-following acceleration mean	0.5435	-9.67 (1)
Car-following acceleration std. dev	0.4610	-27.90 (1)
Car-following deceleration mean	0.3052	-29.92 (1)
Car-following deceleration std. dev	0.8629	-2.61 (1)
Reaction time mean	-1.6500	-16.72 (1)
Reaction time std. dev	1.0908	0.23 (1)

LL: -22892.67
ρ^2: 0.19
Adj. ρ^2: 0.19
LR (compared to a joint model without scale parameters): 3024.48 (dof = 6)
LR (compared to Models 1 and 2 combined): 81.89 (dof = 4)

Towards this direction, the joint model is compared, using the likelihood ratio test, with (a) the joint model initially estimated without any scale parameters and (b) Models 1 & 2. Regarding the latter case, the log-likelihood of the joint model is compared with the sum of log-likelihood values of Models 1 and 2 with degrees of freedom equal to the sum of the parameters of the initial models minus the estimated parameters of the joint model. The null hypothesis is rejected in both comparisons revealing two different outcomes. At first, the joint model without accounting for scale differences, does not perform as well as the model including the scale parameters. This result is expected and consistent with all findings presented in the current analysis. The differences in driving behaviour between simulated and real road traffic driving affect model fit and need to be considered. On the other hand, the use of scale parameters does not manage to improve the model sufficiently, since the results of the likelihood ratio test with Models 1 & 2 show that the joint model does not perform equally to the two separate ones. As a brief conclusion, it should be mentioned that the use of scale parameters, in the suggested model specification, improves model fit but does not fully capture the differences between the different data sources and further approaches should be considered.

5.6 Conclusion

The current paper presents a detailed investigation of the applicability of car-following models estimated using driving simulator data to study real road traffic scenarios. This relates primarily to the transferability of model parameters estimated on data from simulator experiments and their suitability for representing driving behaviour in field traffic. While previous studies have conducted such transferability tests with simple models (that ignore heterogeneity in reaction time), a more advanced modelling approach was adopted which indicated that the differences become more pronounced when the model specifications are more complex.

The analysis is based on the comparison of car-following models estimated using driving simulator data collected at the University of Leeds Driving Simulator and the widely used I-80 trajectory dataset from the NGSIM project. Transferability between the two contexts has been primarily examined with basic approaches as the t-test of individual parameter equivalence and the TTS. The results of the initial transferability tests suggest that driving simulator data should be used with caution. For instance, the t-tests for individual parameter equivalence show that almost all parameters are not directly transferable, while also the mean reaction time is different in the simulated environment. Moreover, the sensitivity analysis, shows that in real life, drivers are more sensitive to changes in traffic conditions compared to simulated environments –

this can have crucial safety implications. As an example, the results indicate that drivers apply smaller deceleration rates in the simulated environment. Discrepancies like this may mislead to false interpretation of drivers' behaviour not only in terms road safety and crash investigation but also in microscopic modelling applications. The findings indicate that the parameters estimated from driving simulator data are not suitable for direct application in such models, which prompted us to investigate methods for improving transferability.

We have applied a series of techniques to improve the transferability of the simulator data, based on a) parameter updating and b) joint estimation that accounts for differences in scale. While Bayesian updating did not validate model transferability, the results of Combined Transfer Estimation have indicated that driving simulator data can be made transferable to real driving context, opening up new prospects for further research. The joint model estimation consists of several steps where specifications without and with parameters that would account for the differences in scale have been tested. The results of the joint model estimation reveal that there is a statistically significant difference in the scale of both acceleration and deceleration values of the two data sources. Moreover, this model performs significantly better compared to a model where a single vector of parameters has been considered for both datasets, without accounting for differences in scales. While the two separate models are always expected to outperform the joint model, our results indicate that the former performed significantly better and thus joint estimation did not adequately capture the differences between the two cases.

Considering all the above, within the framework of the present study, Combined Transfer Estimation is found to be the most efficient approach for improving the transferability of a car-following model estimated using driving simulator data to a field traffic context. It may be noted that given the secondary nature of the data, the traffic variables (speed, acceleration, space headway etc.) are significantly different between the two datasets, although there was an effort to use a road segment of the simulator data where these values were closer to the video trajectory data. Moreover, another limitation of the current work is related to the differences of the two samples that refer to drivers from different countries and thus, variations in driving behaviour may also be a result of cultural differences or differences in traffic flow and road geometry characteristics. For instance, Kusuma et al. (2017) and Papadimitriou & Choudhury (2017) estimated car-following models using video trajectory dataset collecting at a motorway weaving section at the M1 motorway in the UK. The latter study compared the UK data with the I-80 USA NGSIM data and differences were found not only in terms of number of lanes, or traffic flow but also the distributions of acceleration, speed and space headway varied. Given that these differences pose extra challenges in model transferability or joint estimation, our results are potentially on the conservative side and present an upper bound on issues of transferability. Further research is needed however, to compare the behaviour of drivers from the same country under similar driving conditions.

Based on the current findings, there is scope to extend the current study to other forms of car-following models e.g. the latent class GM (Koutsopoulos and Farah, 2012), IDM model (Treiber et al., 2000), Optimal Velocity model (Bando et al., 1995), as well as other driving behaviour models e.g. lane-change, passing etc.

In terms of practical use of the updating, although the proposed approach still requires actual road data for model updating, the framework makes it possible to combine human factors in the driving behaviour models and develop models for emerging technologies and/or risky scenarios (e.g. Paschalidis et al. 2019) without compromising the behavioural realism of the real world data. Thus, bridging the gap between simulated and real driving context enables researchers to utilize the best of both sources of data.

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CHAPTER 6: CONCLUSION

6.1 Summary

The overall aim of the thesis was to investigate the effects of drivers' characteristics in driving behaviour models with an explicit consideration of drivers' stress and the development of formulations to include this in mathematical models of driving behaviour. The research outcomes presented in the previous chapters have been based on a driving simulator experiment conducted using the University of Leeds Driving Simulator (UoLDS). Two different main scenarios were developed, including an urban and a motorway setting, where participants were intentionally subjected to stressful situations while their physiological responses were also observed at the same time. The main analysis has revolved around (a) investigating the general effects of drivers' characteristics on driving behaviour, (b) investigating the effects of contextual factors on driving behaviour, (c) incorporating stress in driving behaviour models and (d) investigating approaches to improve transferability of models estimated with driving simulator data to the real traffic context. The current section returns to these areas and presents how each of them has been addressed in this thesis.

6.1.1 The effects of drivers' characteristics on driving behaviour

The effects of individuals' characteristics on driving behaviour have been investigated to a lesser or greater extent in Chapters 2, 3 and 4 of the thesis. Among the significant relationships that have been found, many of them are related to gender and age, following the existing literature presented in Section 1.4. In particular, male and younger drivers have shown more "aggressive" behaviour to several of the scenarios of the urban setting, as presented in Chapter 2. The same chapter has also investigated the relationship of subjective measures (i.e. MDSI and personality questionnaires) with the observed behaviour. The personality traits of Anxiety and Excitement-seeking have been related to smaller and higher risky behaviour respectively. Some expected findings have also occurred regarding the reported driving style and the observed driving behaviour supporting findings from previous research (van Huysduynen et al., 2018). Despite the moderate strength of most associations, the incorporation of similar types of data in model specifications could result in more accurate representations of driving behaviour in future applications.

The effects of sociodemographic characteristics have been incorporated in both the gap-acceptance model and the car-following model of Chapters 3 and 4 respectively. Several significant effects have been found in these modelling contexts, showing that sociodemographic variables are an important component that should not be omitted from driving behaviour models. Moreover, model fit was always significantly improved after the inclusion of these variables. Significant driver characteristics in both models are age and driving frequency while some additional significant variables in Chapter 4 were gender and past accident involvement. It should be highlighted that the age groups between Chapter 2 and 3 considered different age ranges. The age ranges in Chapter 2 were based on literature findings however, in Chapter 3 a slightly different categorisation was applied, as it resulted in better model fit for the particular gap-acceptance scenario.

6.1.2 The effects of traffic conditions and time pressure on driving behaviour

The effects of traffic conditions and time pressure have been mainly investigated in Chapter 2, where the overall behaviour of participants in the two main settings is presented. The motorway scenario has involved a variety of traffic conditions and time pressure levels which had a substantial impact on observed behaviour. In particular, drivers' behaviour have been approximated in terms of speed, acceleration, lane-change/lane-choice, car-following and pedal depression. In many cases, significant differences have been observed across the different motorway sections, as a result of the traffic conditions and time pressure. For instance, (following the notation of Chapter 2), although time pressure have been applied both in segments M3 and M5, average speed is higher in the latter, as the former area has been a part of the "aggressive" surrounding traffic scenario, resulting in safety concerns. Also, average speed was lower in the last segment (M6), potentially because of participants' awareness regarding the upcoming pull over manoeuvre at the next intersection. Similar outcomes have also emerged regarding the lane-change behaviour. More specifically, the highest lane-change rate has been observed in the M4 segment potentially because of participants' efforts to manoeuvre through slow traffic. Moreover, the lane-change rate has been higher at the last segments, compared to the earlier ones, possibly because of the presence of time pressure. The effects of time pressure have been also investigated in the urban setting. In this scenario, participants have completed most of the tasks significantly faster, also applying higher speeds.

The effects of time pressure have been also included within a modelling framework in Chapter 3. In particular, the presence of time pressure increases the probability to accept a gap. It should be mentioned that, regarding this outcome, there might be confounding (or learning) effects, as time pressure was always applied at the second intersection, but these are likely to be minimal given the experimental design and the time difference between the two intersections. Moreover, similar issues have been reported to other similar work (see Rendon-Velez et al., 2016 for example). The effects of traffic conditions have been also investigated in Chapter 4, in the context of car-following. In this chapter, three different car-following models have been initially estimated for different segments of the motorway. The parameter estimates of these models (and the models overall) have been compared in terms of equivalence and the results showed significant differences in all cases. This outcome consists an additional indication that traffic conditions have a considerable impact of driving behaviour.

6.1.3 The incorporation of stress in driving behaviour models

One of the explicit aims of the current study has been the incorporation of stress in driving behaviour models. Work related to this research question has been presented in Chapters 3 and 4. The former chapter, focuses on the estimation of a gap-acceptance model. The modelling approach has been based on choice modelling techniques and the specification corresponds to an error component mixed logit model. Before presenting the final proposed model, a series of other models have been estimated, starting from a model including exclusively traffic-related variables and gradually adding variables. In each step, the added variables correspond to a different element of the driving behaviour task, namely, sociodemographic characteristics, contextual factors (time pressure in that case) and ultimately stress. In all cases, the newly added variables have had a significant contribution in the performance of the model showing that the omission of variables not related directly to traffic conditions may result in misrepresentations of driving behaviour. Moreover, increases in physiological responses have been associated with a higher probability of accepting a gap. With respect to these findings, one might argue that the effects of drivers' characteristics and other unobserved factors have been already being considered to some extent in existing driving behaviour models, in the form of disturbance terms (as e.g. in Toledo, 2003). This statement however, is only partially true as in the proposed gap-acceptance model of Chapter 3, the effect of the non-related to traffic variables has been significant on the top of a normally distributed error term that was included in the specification and was significant as well.

The incorporation of stress in driving behaviour models is further investigated in Chapter 4 in a car-following model example. The approach is different compared to

Chapter 3 as stress has been considered in a continuous task as car-following, rather than a discrete one, as gap-acceptance has been treated. This model has also extended the incorporation of stress, compared to existing approaches. For instance, Tarabay (2018) included stress in a model for traffic light violation which can be considered a more discrete case of driving behaviour. The incorporation of physiological responses for car-following has been also different, in terms of specification, compared to the model presented in Chapter 3. In the latter, physiological responses have been directly included in the utility functions however, in the car-following model stress has been considered as a latent variable that influences both acceleration-deceleration decisions and physiological responses simultaneously. Significant and positive effects of stress have been found on acceleration decisions however no significant outcomes have occurred regarding deceleration. An additional novelty of the current model specification has been the introduction of a latent variable while at the same time, heterogeneity in driving behaviour has been captured both at the inter (reaction time) and at the intra-individual (stress) level, following examples from the choice modelling practice (Hess and Train, 2011).

6.1.4 The transferability of driving simulator data to the real driving context

The models presented in Chapters 3 and 4 have shown some promising results regarding the possibility of incorporating stress and other drivers' characteristics in driving behaviour models. However, there have been some concerns regarding the validity of driving simulator data for the estimation of driving behaviour models. This issue has been investigated in Chapter 5 through the estimation of a car-following model based on driving simulator and video trajectory data. The results show that most of the parameters between the two models differ significantly and they are not transferable. However, after the application of parameter updating techniques, the two models do not significantly differ. Thus, there is an indication that parameters of models estimated with driving simulator data can be potentially used for microsimulation applications after some recalibration based on parameters estimated from a model that is based on real traffic data. In this chapter, the presented analysis has extended previous similar work (Papadimitriou and Choudhury, 2017) with a more flexible model specification and suggested techniques to improve transferability.

6.2 Progress made in achieving the research objectives

The previous section has presented a summary of the findings with respect to each of the main research objectives expressed in the introductory chapter of the thesis. The current section, returns to the same objectives and presents the overall progress made in each of them and the issues that still remain to be answered or resolved, including limitations of each approach.

O.1: Investigate in which way and what extent individual character traits and stress affect driving behaviour.

The analysis conducted in the thesis has provided answers to all the components of this question, to some extent. Sociodemographic characteristics have been incorporated as explanatory variables in the models of Chapters 3 and 4, showing some significant relationships. Moreover, physiological responses have been tested both as direct and indicators of a latent variable, in order to investigate the effects of stress levels on driving behaviour. However, their effect can still be tested in other forms of driving behaviour models (e.g. lane-change, overtaking etc) as further explained in Section 6.4. Similarly, the thesis does not present any models that incorporate the effects of personality and other traits, although some associations with observed behaviour were found in Chapter 2. Thus, the models presented in Chapters 3 and 4 (and additional models as well) can be augmented with variables derived from those indicators of individuals' traits.

O.2: Investigate how traffic conditions and contextual factors such as time pressure affect driving behaviour and how they are linked to stress levels.

The analysis in all Chapters 2, 3 and 4, has shown that driving behaviour is influenced by the traffic conditions and time pressure. This finding has been an outcome of both explanatory analysis and modelling techniques and resulted in a series of expected outcomes (e.g. higher probability of gap-acceptance under time pressure etc.). These chapters further have highlighted the need of incorporating the effects of contextual factors in driving behaviour models. However, issues as the absence of counterbalancing between the two main scenarios and the fixed order of scenarios and time pressure in each main scenario should be acknowledged. Furthermore, it is worth testing these effects with additional models e.g. gap-acceptance in lane-change behaviour might be affected under time pressure and drivers accept shorter gaps.

O.3: Investigate approaches to incorporate stress levels in driving behaviour models in order to obtain more behaviourally representative results.

Chapters 3 and 4 have suggested two different modelling approaches in terms of incorporating the effects of stress in the specification of driving behaviour models that resulted in some statistically significant results. The first approach has used variables derived from physiological responses as explanatory variables directly in the model specification while in the second, physiological responses have been used as indicators of a latent variable that represented stress. These two chapters revolve in essence around the main research objective of the thesis and the findings can pave the way for additional research on this topic. An interesting future approach (following the latent variable specification presented in Chapter 4) could be the expansion of the latent variable as a series of explanatory variable or the development of a dynamic model where past stress levels influence the current.

O.4: Investigate in which way behaviour in the simulator environment compares to a real life and whether models estimated with simulator data are transferable to the field traffic context.

Similarly to previous work, direct transferability of a car-following model, estimated with simulator data, to real traffic data has not been established in the current research work. This can be a result of the different nature of the two environments, including behavioural realism issues for the driving simulator, however, the examined cases have had further differences that may have led to this finding and have been acknowledged in Chapter 5 (e.g. different number of lanes, different countries etc.). While the initial lack of transferability is not novel, the application of the Combined Transfer Estimation parameter updating technique made it possible to significantly improve transferability. This matter needs to be further investigated with respect to remaining issues to be solved (e.g. the introduction of scale parameters needs to be improved and the influence of the number of observations of each data source needs to be mitigated).

6.3 Contributions to knowledge and practice

The analysis conducted in the thesis has resulted in a series of outcomes with respect to driving behaviour models and driving behaviour overall. These can be summarised as following:

- Individual characteristics significantly affect driving behaviour: In Chapter 1, the limitations of existing driving behaviour models are listed. Among them is the lack of drivers' individual characteristics, for the majority of the existing models. The models presented in Chapter 3 and 4, have included these variables in the specification resulting in significant parameter estimates. These results stress the need for the incorporation of these variables in driving behaviour models. The findings provide mathematical support to earlier discussions in the human factors literature and show how models of driving behaviour can go beyond purely "mechanical" approaches.
- Contextual factors significantly influence driving behaviour: As shown in Chapters 2 and 3, time pressure has significantly influenced driving behaviour. Similarly, most of the parameter estimates of the car-following models, presented in Chapter 4, have not been equivalent for different motorway segments. Thus, it may be concluded that contextual factors can significantly alter driving behaviour. The changes in driving behaviour should be considered in traffic microsimulation to improve the behavioural realism and predictive capability of these models.
- The incorporation of stress levels in driving behaviour models: The effects of stress have been included in the model specifications presented in Chapters 3 and 4 via drivers' physiological responses. The latter case, has extended the traditional GM model accounting for inter-intra heterogeneity showing that driving behaviour models need to account for both types of variation in driving behaviour and more complex specifications can be investigated in the future. Moreover, in both the aforementioned cases, stress has had an effect towards a more aggressive driving style. Although this finding requires further investigation, it enables the thinking for potential in-vehicle interventions that will exploit advancements in sensor technologies towards the improvement of road safety. In a recent study, (Pavlovskaya et al., 2017) a positive relationship between accident proneness and physiological responses is also reported indicating the need for additional research.
- Transferability improvement from driving simulator to real traffic context: The thesis has contributed in improving transferability of car-following models estimated with driving simulator data to approximate estimates of

models using real traffic data. Although this issue has been just tested on a single pair of datasets, it still consists an indication that behavioural validity issues, which may arise owing to the simulated nature of the data, are not an insurmountable obstacle, if the results are treated with caution. Among the tested approaches, joint model estimation has not significantly improved transferability. However, the application of the parameter updating technique of Combined Transfer Estimation showed that transferability from a driving simulator context to real traffic is feasible.

6.4 Future research directions

The work presented in the current thesis is only a first step towards the incorporation of drivers' characteristics in driving behaviour modelling. The significant associations that have been found, require further investigation which can be summarised in further analysis with respect to additional data, driving tasks and modelling approaches. The suggested future research directions are discussed in the current section.

First, although the relationship of physiological responses with the simulator scenarios have been investigated in Chapter 2, only a few significant associations have been found. However, results became more significant when shorter time windows were considered (as e.g. in Chapters 3 and 4). The latter has been investigated in a gap-acceptance and a car-following task, however, more scenarios are still available to be investigated following the same approach. These include specific tasks such as e.g. the overtaking scenario in the urban task but also more continuous tasks such as e.g. lane-change behaviour in the motorway task. Apart from the incorporation of physiological responses in these models, sociodemographic characteristics and trait-related data can be included in the models.

Another important factor of the current research has been the presence of time pressure. Its effects have been investigated generally in Chapter 2 and have also been included in the model specification presented in Chapter 3 supporting existing findings (Cœugnet et al., 2013; Rendon-Velez et al., 2016). However, it has not been used in the car-following model in Chapter 4. A next step could be to for example use the time pressure state as a shift to the sensitivity component of the GM car-following model. The same approach can also be applied in a lane-change model following for example the specification of Choudhury (2007). For instance, under time pressure, drivers may be willing to accept shorter gaps thus, this behaviour should be considered in the gap-acceptance part of the lane change-model.

The car-following models used in Chapters 4 and 5 are based on the stimulus-response framework, as it has been widely used in the existing literature and considered as an appropriate starting point. However, this approach is not necessarily the most accurate as it has specific limitations (e.g. drivers are assumed to accelerate when relative speed is positive) and also its principles may not be followed in a simulator environment. Therefore, additional and more flexible specifications can be tested to this end e.g. the latent class car-following model of Koutsopoulos and Farah (2012). Regarding the car-following model specification, aspects related to model identification and efficiency in estimation speed, when extra heterogeneity is added, can be also investigated, but these research directions extend the scope of the current thesis as they represent a more technical aspect of the models rather than enhancing behavioural insights.

The issue of model transferability has been investigated via the simulator data and one database of video trajectory data. Although the Combined Transfer Estimation approach has significantly improved transferability, the results presented in Chapter 5 are highly dependent on these specific data sets. Thus, it would be desirable to further investigate this issue by adding data sources. Moreover, the same can be also applied to the lane-changing context and even to a joint car-following and lane-change model.

Finally, it should be mentioned that the aim of the present research has been related to the improvement of driving behaviour models in terms of behavioural representativeness, with an ultimate goal to be used in microscopic simulation. Therefore, the estimated models should be validated in the future in order to investigate whether they produce realistic traffic conditions.

6.5 Concluding remarks

The current thesis focused mainly on the investigation of stress in driving behaviour models but also on the effects of driving characteristics in driving behaviour, generally. The results have been based on a driving simulator experiment conducted at the University of Leeds Driving Simulator. The issue of stress in driving behaviour models has been addressed to some extent, in terms of model specification in a gap-acceptance and car-following modelling context, while some significant associations occurred in the aforementioned models. Moreover, transferability issues have been investigated. Overall, findings indicate that stress and drivers' characteristics can significantly influence driving behaviour and thus should be considered in the respective models. However, for real life applications, it is suggested that the extent of these effects should be treated with caution and ideally rescaled based on real traffic observations.

6.6 References

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APPENDIX A: APPENDIX TO CHAPTER 2

A.1 Questionnaire surveys

Part A: General driving style

First, we would like to ask about your general driving style. There is a list of statements below concerning specific driving behaviours. Please read each statement carefully and indicate, on the following 6-point scale, to what extent the statement describes you.

1. Not at all, 2. Very little, 3. Little, 4. Moderate, 5. Much, 6. Very much

I often do relaxing activities while driving	1	2	3	4	5	6
I often purposely tailgate other drivers	1	2	3	4	5	6
I often blow my horn or 'flash' the car in front as a way of expressing my frustration.	1	2	3	4	5	6
I feel I have control over driving	1	2	3	4	5	6
I often drive through traffic lights that have just turned red.	1	2	3	4	5	6
I usually enjoy the sensation of driving on the limit (dangerously)	1	2	3	4	5	6
On a clear freeway, I usually drive at or a little below the speed limit	1	2	3	4	5	6
While driving I try to relax myself	1	2	3	4	5	6
When I am in a traffic jam and the lane next to mine starts to move, I try to move into that lane as soon as possible	1	2	3	4	5	6
Driving usually makes me feel frustrated	1	2	3	4	5	6
I often daydream to pass the time while driving	1	2	3	4	5	6
I often swear at other drivers	1	2	3	4	5	6
When a traffic light turns green and the car in front of me doesn't get going, I just wait for a while until it moves	1	2	3	4	5	6

I drive cautiously	1	2	3	4	5	6
Sometimes lost in thought or distracted, I fail to notice someone waiting at a zebra crossing/pedestrian	1	2	3	4	5	6
In a traffic jam, I think about ways to get through the traffic faster	1	2	3	4	5	6
When a traffic light turns green and the car in front of me doesn't get going immediately, I try to urge the driver to move on	1	2	3	4	5	6
At an intersection where I have to give right-of-way to oncoming traffic, I simply wait patiently for cross-traffic to pass	1	2	3	4	5	6
When someone tries to skirt in front of me on the road I drive in an assertive way in order to prevent it	1	2	3	4	5	6
I often fix my hair and/or makeup while driving	1	2	3	4	5	6
I am often distracted or preoccupied, and suddenly realize that the vehicle ahead has slowed down, and I have to slam on the brakes to avoid a collision	1	2	3	4	5	6
I like to take risks while driving	1	2	3	4	5	6
I base my behaviour on the motto "better safe than sorry"	1	2	3	4	5	6
I like the thrill of flirting with death and disaster	1	2	3	4	5	6
It worries me when driving in bad weather	1	2	3	4	5	6
I often meditate while driving	1	2	3	4	5	6
Lost in thoughts I often forget that my lights are on full beam until flashed by another motorist	1	2	3	4	5	6
When someone does something on the road that annoys me, I flash them with the high beams	1	2	3	4	5	6
I get a thrill out of breaking the law	1	2	3	4	5	6
I often misjudge the speed of an oncoming vehicle when passing	1	2	3	4	5	6
I feel nervous while driving	1	2	3	4	5	6
I get impatient during rush hour	1	2	3	4	5	6

I feel distressed while driving	1	2	3	4	5	6
I often intend to switch on the windscreen wipers, but switch on the lights instead, or vice versa	1	2	3	4	5	6
I often attempt to drive away from traffic lights in third gear (or on the neutral mode in automatic car)	1	2	3	4	5	6
I often plan my route badly, so that I hit traffic that I could have avoided	1	2	3	4	5	6
I often use muscle relaxation techniques while driving	1	2	3	4	5	6
I plan long journeys in advance	1	2	3	4	5	6
I often nearly (or actually) hit something due to Misjudging my gap in a parking lot	1	2	3	4	5	6
I feel comfortable while driving	1	2	3	4	5	6
I am always ready to react to unexpected manoeuvres by other drivers	1	2	3	4	5	6
I tend to drive cautiously	1	2	3	4	5	6
I often honk my horn at others	1	2	3	4	5	6
I usually enjoy the excitement of dangerous driving	1	2	3	4	5	6

Part B: General personality

We would now like to know more about your general personality. There is a list of statements below that may (or not) describe yourself. Please read them carefully and indicate, on the following 6-point scale, your level of agreement with each one of them.

1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Somewhat agree, 5. Agree, 6. Strongly Agree

Personally, I:						
Act wild and crazy.	1	2	3	4	5	6
Adapt easily to new situations.	1	2	3	4	5	6
Am afraid of many things.	1	2	3	4	5	6
Am calm even in tense situations.	1	2	3	4	5	6
Am not easily annoyed.	1	2	3	4	5	6
Am not easily bothered by things.	1	2	3	4	5	6
Am not easily disturbed by events.	1	2	3	4	5	6
Am often in a bad mood.	1	2	3	4	5	6
Am relaxed most of the time.	1	2	3	4	5	6
Become overwhelmed by events.	1	2	3	4	5	6
Can handle complex problems.	1	2	3	4	5	6
Can't make up my mind.	1	2	3	4	5	6
Dislike loud music.	1	2	3	4	5	6
Don't worry about things that have already happened.	1	2	3	4	5	6
Enjoy being part of a loud crowd.	1	2	3	4	5	6
Enjoy being reckless.	1	2	3	4	5	6

Fear for the worst.	1	2	3	4	5	6
Feel that I'm unable to deal with things.	1	2	3	4	5	6
Get angry easily.	1	2	3	4	5	6
Get caught up in my problems.	1	2	3	4	5	6
Get irritated easily.	1	2	3	4	5	6
Get overwhelmed by emotions.	1	2	3	4	5	6
Get stressed out easily.	1	2	3	4	5	6
Get upset easily.	1	2	3	4	5	6
Keep my cool.	1	2	3	4	5	6
Know how to cope.	1	2	3	4	5	6
Lose my temper.	1	2	3	4	5	6
Love action.	1	2	3	4	5	6
Love excitement.	1	2	3	4	5	6
Panic easily.	1	2	3	4	5	6
Rarely complain.	1	2	3	4	5	6
Rarely get irritated.	1	2	3	4	5	6
Readily overcome setbacks.	1	2	3	4	5	6
Remain calm under pressure.	1	2	3	4	5	6
Seek adventure.	1	2	3	4	5	6
Seek danger.	1	2	3	4	5	6
Seldom get mad.	1	2	3	4	5	6
Willing to try anything once.	1	2	3	4	5	6
Worry about things.	1	2	3	4	5	6
Would never go hang gliding or bungee jumping.	1	2	3	4	5	6

Participant's post driving survey

Urban/rural run

	Event: First encountering with slow moving vehicle						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: First long lasting red traffic light						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Car violates priority and crosses the intersection						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: First traffic light change from green to yellow						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: First intersection crossing at rural road						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Second encountering with slow moving vehicle						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Second long lasting red traffic light						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Second traffic light change from green to yellow						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Second intersection crossing at rural road						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Final right turn manoeuvre						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

Overall stress level of the urban/rural run	1	2	3	4	5	6

Motorway run

	Event: First minutes of driving on the motorway until the first junction						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Surrounding vehicles execute dangerous manoeuvres						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Surrounding vehicles executing dangerous manoeuvres under time pressure situation						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Driving under slow moving traffic without time pressure						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Driving during slow moving traffic under time pressure						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

	Event: Driving under time pressure towards the end of the motorway session						Specific emotion(s)	
Stress level	1	2	3	4	5	6		
							Anxiety	
							Anger	
							Fear	
							Other:	

Overall stress level of the motorway run	1	2	3	4	5	6

Driving simulator experience

1. Please evaluate the realism of the driving simulator urban session compared to real-life driving experience:

Not realistic at all	1	2	3	4	Very realistic

2. Please evaluate the realism of the driving simulator motorway session compared to real-life driving experience:

Not realistic at all	1	2	3	4	Very realistic

3. Please indicate how close was your driving performance at the simulator compared to real-life driving:

Not at all	1	2	3	4	Very close to real life

4. Did you feel any type of motion sickness that might affected your driving performance?

□ Yes □ No

5. Is there any other comment that you would like to add regarding the driving simulator experiment? (optional)

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A.2 Results

Table A.1: Heart rate analysis

		Raw HR data				Normalised HR data			
		Mean	Std. Deviation	Test statistics		Mean	Std. Deviation	Test statistics	
Overtaking	NTP	81.70	13.53	F	2.313	-0.04	0.75	Z	-1.536
	TP	79.92	12.07	p-value	0.136	-0.26	0.74	p-value	0.125
				η^2	0.055				
Red traffic light long	NTP	84.10	19.81	Z	-2.676	0.12	0.76	Z	-2.715
	TP	79.68	15.46	p-value	0.007	-0.26	0.66	p-value	0.007
Red traffic light long (red to leave)	NTP	84.62	21.08	Z	-2.909	0.16	0.81	Z	-3.129
	TP	79.60	15.84	p-value	0.004	-0.28	0.72	p-value	0.002
Amber dilemma (scenario)	NTP	83.36	18.84	Z	-1.315	0.02	1.21	Z	-1.432
	TP	78.99	12.41	p-value	0.188	-0.36	0.94	p-value	0.152
Amber dilemma (junction)	NTP	83.42	18.84	Z	-1.315	0.03	1.26	Z	-1.367
	TP	79.14	12.50	p-value	0.188	-0.35	0.95	p-value	0.172
Gap-acceptance (scenario)	NTP	82.83	14.82	Z	-0.149	0.05	0.66	F	0.0347
	TP	83.51	17.96	p-value	0.882	-0.06	0.94	p	0.559
								η^2	0.009
Gap-acceptance (junction)	NTP	82.36	15.18	Z	-0.006	-0.03	0.67	F	0.136
	TP	83.59	19.82	p-value	0.995	-0.10	1.03	p	0.714
								η^2	0.003
Free driving	NTP	83.44	18.56	Z	-2.456	0.02	0.81	F	5.497
	TP	78.38	12.18	p-value	0.014	-0.40	0.78	p	0.024
								η^2	0.121

Table A.2: SC - CDA analysis

		SCRs frequency				SCRs mean amplitude				SCRs mean amplitude - normalised			
		Mean	Std. Deviation	Test statistics		Mean	Std. Deviation	Test statistics		Mean	Std. Deviation	Test statistics	
Overtaking	NTP	15.28	17.05	Z	-0.624	0.032	0.044	Z	-0.607	3.715	2.011	Z	-0.299
	TP	17.45	17.86	p-value	0.533	0.041	0.058	p-value	0.544	3.523	2.181	p-value	0.765
Red traffic light long	NTP	17.63	18.54	Z	-1.848	0.038	0.038	Z	-0.792	4.061	1.725	Z	-0.551
	TP	21.10	18.80	p-value	0.065	0.049	0.058	p-value	0.428	4.143	1.771	p-value	0.582
Red traffic light long (red to leave)	NTP	17.22	19.82	Z	-1.456	0.037	0.043	Z	-1.441	3.880	1.973	Z	-1.29
	TP	20.19	19.52	p-value	0.145	0.049	0.067	p-value	0.150	4.099	1.746	p-value	0.197
Amber dilemma (scenario)	NTP	19.45	22.29	Z	-0.789	0.030	0.049	Z	-0.811	2.963	2.438	Z	-0.357
	TP	16.78	21.67	p-value	0.430	0.038	0.065	p-value	0.417	2.913	2.522	p-value	0.721
Amber dilemma (junction)	NTP	22.99	33.63	Z	-1.737	0.032	0.076	Z	-0.438	2.132	2.651	Z	-1.055
	TP	14.90	26.64	p-value	0.082	0.025	0.052	p-value	0.661	1.475	2.342	p-value	0.291
Gap-acceptance (scenario)	NTP	18.18	17.70	Z	-0.911	0.038	0.049	Z	-1.98	3.773	2.039	Z	-1.524
	TP	16.98	16.46	p-value	0.362	0.031	0.046	p-value	0.048	3.596	2.090	p-value	0.128
Gap-acceptance (junction)	NTP	17.63	19.69	Z	-0.898	0.034	0.052	Z	-1.65	3.270	2.275	Z	-1.342
	TP	15.33	17.13	p-value	0.369	0.027	0.046	p-value	0.099	2.904	2.388	p-value	0.180
Free driving	NTP	16.45	18.65	Z	-1.385	0.040	0.049	Z	-0.138	4.088	1.734	Z	-0.109
	TP	19.74	18.55	p-value	0.166	0.043	0.067	p-value	0.890	4.182	1.604	p-value	0.913

Table A.3: SC - TTP analysis

		SCRs frequency				SCRs mean amplitude				SCRs mean amplitude normalised			
		Mean	Std. Deviation	Test statistics		Mean	Std. Deviation	Test statistics		Mean	Std. Deviatio n	Test statistics	
Overtaking	NTP	5.36	6.68	Z	-0.413	0.051	0.054	Z	-0.022	4.222	1.613	Z	-0.326
	TP	5.80	6.66	p-value	0.679	0.050	0.062	p-value	0.983	4.127	1.763	p-value	0.744
Red traffic light long	NTP	5.18	6.78	Z	-0.173	0.040	0.052	Z	-1.32	3.720	2.021	Z	-0.55
	TP	5.57	6.38	p-value	0.863	0.058	0.084	p-value	0.187	3.790	2.068	p-value	0.582
Red traffic light long (red to leave)	NTP	6.00	7.77	Z	-0.615	0.043	0.085	Z	-0.159	2.847	2.463	Z	-0.114
	TP	7.53	10.17	p-value	0.539	0.039	0.069	p-value	0.873	2.617	2.482	p-value	0.909
Amber dilemma (scenario)	NTP	5.20	13.76	Z	-0.357	0.008	0.030	Z	-0.459	0.716	1.775	Z	-0.459
	TP	6.69	16.83	p-value	0.721	0.011	0.032	p-value	0.646	0.740	1.822	p-value	0.646
Amber dilemma (junction)	NTP	6.68	7.27	Z	-2.255	0.055	0.072	Z	-0.703	4.021	1.874	Z	-0.95
	TP	5.29	5.98	p-value	0.024	0.048	0.066	p-value	0.482	3.762	2.247	p-value	0.342
Gap-acceptance (scenario)	NTP	6.43	8.57	Z	-0.641	0.044	0.066	Z	-1.718	3.394	2.246	Z	-1.667
	TP	5.83	8.54	p-value	0.521	0.035	0.063	p-value	0.086	2.861	2.481	p-value	0.096
Gap-acceptance (junction)	NTP	5.31	5.98	Z	-2.11	0.046	0.047	Z	-1.82	4.106	1.761	Z	-1.472
	TP	6.54	7.07	p-value	0.035	0.056	0.055	p-value	0.069	4.274	1.642	p-value	0.141
Free driving	NTP	5.51	6.80	Z	-1.445	0.048	0.063	Z	-1.257	4.012	1.919	Z	-1.241
	TP	6.65	7.53	p-value	0.148	0.056	0.065	p-value	0.209	3.949	2.003	p-value	0.215

Table A.4: Sociodemographic characteristics associations with the overtaking scenario

		Overtaking manoeuvre NTP	Overtaking manoeuvre TP	Time to overtake NTP	Time to overtake TP	Left lane min headw. NTP	Left lane min headw. TP	Right lane min headw. TP	Right lane min headw. NTP	Max speed during overtake TP	Max speed during overtake NTP
Gender	Z	-2.928	-2.904	-0.183	-1.750	-0.365	-0.700	-2.008	-1.260	-0.548	-1.820
	p-value	0.003	0.004	0.855	0.080	0.715	0.484	0.045	0.208	0.584	0.069
Age	Z	-1.907	-3.182	-1.826	-1.643	-0.730	-2.008	0.000	-0.730	-0.183	-0.639
	p-value	0.056	0.001	0.068	0.100	0.465	0.045	1.000	0.465	0.855	0.523
Frequency of driving	KW	4.051	4.395	2.819	0.471	2.829	6.576	2.076	3.563	1.914	6.995
	p-value	0.256	0.222	0.420	0.925	0.419	0.087	0.557	0.313	0.590	0.072
Miles per year	KW	0.465	4.265	3.233	6.180	1.762	0.441	1.033	1.274	3.471	2.782
	p-value	0.926	0.234	0.357	0.103	0.623	0.932	0.793	0.735	0.324	0.426
Driving experience	Z	-0.111	-2.002	-0.447	-0.516	-1.597	-1.872	-0.192	-0.194	-0.192	-0.839
	p-value	0.912	0.045	0.655	0.606	0.110	0.061	0.848	0.846	0.848	0.401
Minor accident involvement	Z	-0.045	-0.322	-0.730	-1.095	-0.365	-0.639	-1.278	-0.274	-0.548	-0.548
	p-value	0.964	0.748	0.465	0.273	0.715	0.523	0.201	0.784	0.584	0.584
Major accident involvement	Z	-0.401	-0.792	-0.372	-0.913	-0.868	-1.552	-0.868	-0.456	-1.364	-1.917
	p-value	0.688	0.428	0.710	0.361	0.385	0.121	0.385	0.648	0.172	0.055
Ticket for speeding	Z	-0.527	-0.887	-0.234	-1.714	-0.856	-0.894	-1.012	-1.789	-1.012	-0.522
	p-value	0.598	0.375	0.815	0.086	0.392	0.371	0.312	0.074	0.312	0.602
Life stress	KW	2.089	1.235	4.474	2.189	1.669	0.005	6.707	2.305	0.495	1.505
	p-value	0.352	0.539	0.107	0.335	0.434	0.998	0.035	0.316	0.781	0.471

Table A.5: Sociodemographic characteristics associations with the red traffic light scenario

		Mean speed NTP	Mean speed TP	Max speed NTP	Max speed TP	End speed NTP	End speed TP	Mean acceler. TP	Mean acceler. NTP	Max acceler. NTP	Max acceler. TP
Gender	Z	-0.575	-2.353	0.000	-2.248	-0.392	-2.196	-2.092	-0.941	-1.909	-2.536
	p-value	0.565	0.019	1.000	0.025	0.695	0.028	0.036	0.347	0.056	0.011
Age	Z	-2.997	-2.337	-2.282	-2.117	-1.787	-2.007	-1.650	-0.412	-0.962	-1.622
	p-value	0.003	0.019	0.022	0.034	0.074	0.045	0.099	0.680	0.336	0.105
Frequency of driving	KW	0.577	0.660	3.081	0.294	2.593	1.861	1.614	2.785	4.288	0.792
	p-value	0.902	0.883	0.379	0.961	0.459	0.602	0.656	0.426	0.232	0.851
Miles per year	KW	2.198	3.234	3.383	4.074	3.255	4.200	3.188	1.093	3.296	1.902
	p-value	0.532	0.357	0.336	0.254	0.354	0.241	0.363	0.779	0.348	0.593
Driving experience	Z	-0.235	-0.183	-0.678	-0.078	-0.417	-0.391	-0.600	-1.148	-0.287	-0.130
	p-value	0.814	0.855	0.498	0.938	0.676	0.696	0.549	0.251	0.774	0.896
Minor accident involvement	Z	-1.033	-0.111	-1.512	-0.664	-1.217	0.000	-1.291	-0.553	-0.775	-0.848
	p-value	0.302	0.912	0.130	0.507	0.224	1.000	0.197	0.580	0.439	0.396
Major accident involvement	Z	-1.757	-1.626	-1.406	-1.142	-1.098	-1.098	-0.176	-0.659	-0.659	-0.747
	p-value	0.079	0.104	0.160	0.253	0.272	0.272	0.860	0.510	0.510	0.455
Ticket for speeding	Z	-2.148	-0.832	-1.594	-0.243	-1.213	-0.312	-0.277	-0.554	-2.044	-0.762
	p-value	0.032	0.406	0.111	0.808	0.225	0.755	0.782	0.579	0.041	0.446
Life stress	KW	1.033	1.376	0.063	0.407	0.330	0.537	0.200	0.571	3.340	5.211
	p-value	0.597	0.503	0.969	0.816	0.848	0.765	0.905	0.751	0.188	0.074

Table A.6: Sociodemographic characteristics associations with the amber dilemma scenario

		Stopped NTP	Stopped TP	End speed NTP	End speed TP
Gender	Z	-0.622	-1.195	-0.078	-2.013
	p-value	0.534	0.232	0.937	0.044
Age	Z	-0.527	-0.695	-2.364	-2.777
	p-value	0.598	0.487	0.018	0.005
Frequency of driving	KW	3.413	8.867	2.597	1.695
	p-value	0.332	0.031	0.458	0.638
Miles per year	KW	2.485	2.279	0.940	2.314
	p-value	0.478	0.517	0.816	0.510
Driving experience	Z	-0.480	-2.131	-0.861	-2.191
	p-value	0.631	0.033	0.389	0.028
Minor accident involvement	Z	-0.028	-0.861	-0.738	-0.148
	p-value	0.977	0.389	0.461	0.883
Major accident involvement	Z	-1.820	-1.068	-0.483	-0.527
	p-value	0.069	0.285	0.629	0.598
Ticket for speeding	Z	-0.213	-0.944	-1.525	-1.213
	p-value	0.832	0.345	0.127	0.225
Life stress	KW	0.296	0.425	0.129	1.466
	p-value	0.862	0.809	0.938	0.480

Table A.7: Sociodemographic characteristics associations with the gap-acceptance scenario

		Time to clear NTP	Time to clear TP	Junction to finish NTP	Junction to finish TP	Mean speed after junction NTP	Mean speed after junction TP	Max speed after junction NTP	Max speed after junction TP	Total scenario time NTP	Total scenario time TP
Gender	Z	-0.157	-0.784	-0.745	-2.275	-0.497	-2.275	-0.732	-2.431	-0.118	-1.203
	p-value	0.875	0.433	0.456	0.023	0.619	0.023	0.464	0.015	0.906	0.229
Age	Z	-0.357	-0.632	-2.323	-1.993	-2.062	-2.007	-1.540	-0.522	-0.577	-1.292
	p-value	0.721	0.527	0.020	0.046	0.039	0.045	0.124	0.601	0.564	0.196
Frequency of driving	KW	9.755	7.700	2.738	0.411	2.754	0.396	2.379	1.352	6.595	5.544
	p-value	0.021	0.053	0.434	0.938	0.431	0.941	0.497	0.717	0.086	0.136
Miles per year	KW	5.834	3.639	2.717	1.383	2.764	1.340	4.124	1.610	5.504	3.935
	p-value	0.120	0.303	0.437	0.710	0.429	0.720	0.248	0.657	0.138	0.269
Driving experience	Z	-1.409	-0.235	-0.104	-0.170	-0.130	-0.156	-0.026	-0.183	-1.252	-0.443
	p-value	0.159	0.814	0.917	0.865	0.896	0.876	0.979	0.855	0.211	0.657
Minor accident involvement	Z	-0.221	-1.143	-1.162	-1.107	-1.254	-1.107	-0.959	-1.955	-0.129	-1.475
	p-value	0.825	0.253	0.245	0.268	0.210	0.268	0.338	0.051	0.897	0.140
Major accident involvement	Z	-0.022	-0.132	-0.813	-0.088	-0.747	-0.088	-0.791	-0.527	-0.527	-0.044
	p-value	0.982	0.895	0.416	0.930	0.455	0.930	0.429	0.598	0.598	0.965
Ticket for speeding	Z	-1.421	-2.148	-0.797	-1.629	-0.832	-1.628	-0.277	-1.074	-1.455	-2.183
	p-value	0.155	0.032	0.425	0.103	0.406	0.103	0.782	0.283	0.146	0.029
Life stress	KW	0.079	0.013	0.335	1.210	0.321	1.210	2.679	1.224	0.229	0.203
	p-value	0.961	0.993	0.846	0.546	0.852	0.546	0.262	0.542	0.892	0.903

Table A.8: Sociodemographic characteristics associations with the free driving scenario

	Mean speed NTP	Mean speed TP	Max speed NTP	Max speed TP	% above 40mph NTP	% above 40mph TP	% above 60mph NTP	% above 60mph TP
Z	-1.072	-2.353	-1.490	-1.882	-1.099	-2.542	-1.076	-1.150
p-value	0.284	0.019	0.136	0.060	0.272	0.011	0.282	0.250
Z	-1.897	-1.732	-1.512	-1.210	-1.734	-1.810	-0.720	-0.701
p-value	0.058	0.083	0.131	0.226	0.083	0.070	0.471	0.483
KW	0.553	0.648	0.235	1.221	0.667	0.403	2.417	1.301
p-value	0.907	0.885	0.972	0.748	0.881	0.940	0.491	0.729
KW	8.166	5.371	7.882	5.429	7.308	2.923	3.333	6.132
p-value	0.043	0.147	0.049	0.143	0.063	0.404	0.343	0.105
Z	-0.678	-1.043	-0.574	-0.835	-0.888	-0.647	-0.976	-0.505
p-value	0.498	0.297	0.566	0.404	0.375	0.518	0.329	0.614
Z	-0.111	-0.443	-0.406	0.000	-0.222	-0.187	-0.414	-0.357
p-value	0.912	0.658	0.685	1.000	0.825	0.852	0.679	0.721
Z	-1.670	-0.659	-1.011	-0.615	-1.495	-1.224	-0.329	-0.773
p-value	0.095	0.510	0.312	0.538	0.135	0.221	0.742	0.440
Z	-1.178	-0.346	-0.970	-0.346	-1.006	-0.123	-2.204	-1.615
p-value	0.239	0.729	0.332	0.729	0.315	0.902	0.028	0.106
KW	1.428	0.347	0.412	0.366	2.003	0.635	5.833	2.889
p-value	0.490	0.841	0.814	0.833	0.367	0.728	0.054	0.236

Table A.9: Correlation matrix between personality factors and overtaking task

		Anxiety	Anger	Vulnerability	Excitement
Right lane min headway NTP	r	.551	0.404	0.319	-0.438
	p-value	0.041	0.152	0.266	0.117

Table A.10: Correlation matrix between personality factors and red light task

		Anxiety	Anger	Vulnerability	Excitement
Scenario mean speed NTP	r	-0.223	-0.017	-0.189	0.295
	p-value	0.161	0.914	0.236	0.061
Scenario mean speed TP	r	-0.140	0.021	-0.002	.360
	p-value	0.382	0.895	0.988	0.021
Scenario max speed NTP	r	-.345	-0.123	-0.281	0.119
	p-value	0.027	0.445	0.075	0.458
Scenario max speed TP	r	-0.288	-0.099	-0.093	0.252
	p-value	0.068	0.540	0.563	0.112
Scenario end speed NTP	r	-.340	-0.136	-0.257	0.131
	p-value	0.029	0.396	0.105	0.414
Scenario end speed TP	r	-0.283	-0.072	-0.075	0.238
	p-value	0.073	0.657	0.641	0.134
Max acceleration NTP	r	-0.192	-0.023	-0.064	.371
	p-value	0.230	0.886	0.693	0.017

Table A.11: Correlation matrix between personality factors and amber dilemma task

		Anxiety	Anger	Vulnerability	Excitement
Stopped TP	r	0.050	0.118	-0.004	-.337
	p-value	0.758	0.463	0.980	0.031
End speed TP	r	-0.209	-0.101	-0.013	.427
	p-value	0.191	0.530	0.937	0.005

Table A.12: Correlation matrix between personality factors and gap-acceptance task

		Anxiety	Anger	Vulnerability	Excitement
Junction to finish NTP	r	0.101	-0.061	0.087	-.445
	p-value	0.528	0.703	0.590	0.004
Junction to finish NTP	r	0.059	-0.087	0.070	-.442
	p-value	0.718	0.595	0.670	0.004
Mean speed after junction NTP	r	-0.170	0.023	-0.094	.489
	p-value	0.287	0.888	0.557	0.001
Mean speed after junction NTP	r	0.059	-0.087	0.070	-.442
	p-value	0.718	0.595	0.670	0.004
Max speed after junction NTP	r	-0.192	-0.041	-0.083	.360
	p-value	0.230	0.800	0.605	0.021
Max speed after junction NTP	r	-0.123	0.063	-0.103	.466
	p-value	0.451	0.698	0.528	0.002
Max speed after junction NTP	r	-.342	-0.071	-0.140	.426
	p-value	0.031	0.663	0.388	0.006

Table A.13: Correlation matrix between personality factors and free driving task

		Anxiety	Anger	Vulnerability	Excitement
Mean speed NTP	r	-0.215	0.107	-0.085	.374
	p-value	0.178	0.507	0.598	0.016
Mean speed TP	r	-.317	-0.055	-0.056	.324
	p-value	0.043	0.734	0.730	0.039
Max speed NTP	r	-0.256	-0.033	-0.094	0.283
	p-value	0.106	0.838	0.558	0.072
Max speed TP	r	-.316	-0.069	-0.067	0.307
	p-value	0.044	0.666	0.676	0.051
% above 60mph NTP	r	-0.260	-0.007	-0.093	.328
	p-value	0.100	0.967	0.561	0.036
% above 60mph TP	r	-.353	-0.081	-0.082	.414
	p-value	0.024	0.612	0.611	0.007

Table A.14: Correlation matrix between MDSI factors and the overtaking task

		Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Careful
Overtaking manoeuvre NTP	r	-0.191	-0.072	0.149	0.176	0.026	-0.064	-0.299	0.110
	p-value	0.233	0.653	0.352	0.271	0.870	0.689	0.058	0.495
Time to overtake NTP	r	-0.021	0.347	-0.153	-0.259	-.549	0.225	0.089	-0.239
	p-value	0.944	0.224	0.602	0.370	0.042	0.439	0.762	0.410

Table A.15: Correlation matrix between MDSI factors and the red traffic light task

		Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Careful
Scenario mean speed NTP	r	0.003	-0.250	.338	0.153	0.225	-0.101	-0.285	0.123
	p-value	0.987	0.115	0.031	0.339	0.157	0.530	0.071	0.442
Scenario mean speed TP	r	0.174	-0.126	0.302	.342	.319	0.110	-.407	-0.141
	p-value	0.276	0.431	0.055	0.029	0.042	0.492	0.008	0.380
Scenario max speed TP	r	0.170	-0.104	0.188	0.284	0.144	.309	-0.295	-0.154
	p-value	0.287	0.518	0.240	0.072	0.369	0.049	0.061	0.336
Scenario end speed TP	r	0.193	-0.097	0.201	0.300	0.131	0.267	-.338	-0.200
	p-value	0.226	0.547	0.208	0.057	0.414	0.091	0.031	0.209
Scenario mean acceleration NTP	r	0.120	0.000	-0.221	-0.031	0.069	0.266	0.168	-0.033
	p-value	0.456	1.000	0.165	0.849	0.670	0.093	0.294	0.840
Scenario mean acceleration TP	r	-0.006	-0.008	-0.027	0.077	-0.183	.344	0.057	-0.080
	p-value	0.968	0.958	0.866	0.630	0.252	0.028	0.721	0.621
Scenario max acceleration NTP	r	0.216	-0.114	0.275	0.035	0.192	0.003	-0.081	-0.083
	p-value	0.176	0.479	0.082	0.828	0.228	0.984	0.614	0.608
Scenario max acceleration TP	r	0.205	0.027	0.123	0.225	0.214	0.102	-0.281	-0.116
	p-value	0.199	0.869	0.443	0.157	0.179	0.526	0.075	0.470

Table A.16: Correlation matrix between MDSI factors and the amber dilemma task

		Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Careful
Stopped TP	r	-.351	-0.027	-0.224	0.216	-0.019	-0.114	0.121	.343
	p-value	0.025	0.867	0.160	0.174	0.905	0.478	0.452	0.028
End speed TP	r	.398	-0.127	.316	0.031	0.246	0.253	-.329	-.395
	p-value	0.010	0.427	0.044	0.850	0.121	0.110	0.036	0.011

Table A.17: Correlation matrix between MDSI factors and the gap-acceptance task

		Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Careful
Time to clear NTP	r	0.254	0.244	-.357	-0.205	-0.103	0.192	0.227	0.083
	p-value	0.109	0.125	0.022	0.199	0.521	0.230	0.153	0.604
Time to clear TP	r	0.082	0.179	-.464	-0.197	-0.183	0.164	0.294	0.085
	p-value	0.609	0.264	0.002	0.217	0.252	0.306	0.062	0.597
Junction to finish NTP	r	-0.240	0.069	-0.125	-.346	-.312	-0.285	0.268	0.128
	p-value	0.130	0.668	0.435	0.027	0.047	0.071	0.090	0.426
Junction to finish TP	r	-0.109	0.106	-.366	-0.290	-0.216	-0.214	.362	0.205
	p-value	0.496	0.508	0.019	0.066	0.174	0.178	0.020	0.198
Mean speed after junction NTP	r	0.216	-0.129	0.186	.328	.313	0.242	-0.254	-0.143
	p-value	0.175	0.420	0.245	0.036	0.047	0.127	0.110	0.373
Mean speed after junction TP	r	0.077	-0.140	.390	0.299	0.229	0.179	-.342	-0.212
	p-value	0.633	0.381	0.012	0.058	0.149	0.263	0.028	0.184
Max speed after junction NTP	r	0.247	-0.116	0.040	0.306	0.261	0.280	-0.179	-0.158
	p-value	0.120	0.469	0.804	0.051	0.100	0.077	0.262	0.324
Max speed after junction TP	r	0.080	-0.250	.476	0.259	0.241	0.219	-0.282	-0.263
	p-value	0.617	0.115	0.002	0.102	0.129	0.169	0.074	0.097
Total scenario time NTP	r	0.174	0.236	-.343	-0.287	-0.187	0.159	0.302	0.089
	p-value	0.276	0.137	0.028	0.069	0.243	0.319	0.055	0.581
Total scenario time TP	r	0.049	0.170	-.476	-0.248	-0.209	0.139	.349	0.114
	p-value	0.759	0.289	0.002	0.118	0.190	0.388	0.025	0.479

Table A.18: Correlation matrix between MDSI factors and the free driving task

		Dissociative	Anxious	Risky	Angry	High-velocity	Distress-reduction	Patient	Careful
Mean speed NTP	r	0.194	-0.122	.354	0.275	.543	.326	-.438	-.337
	p-value	0.224	0.449	0.023	0.082	0.000	0.037	0.004	0.031
Mean speed TP	r	0.253	-0.156	0.285	0.237	0.242	0.252	-.415	-.403
	p-value	0.110	0.330	0.071	0.136	0.128	0.111	0.007	0.009
Max speed NTP	r	0.249	-0.066	0.281	0.158	.451	0.256	-.310	-0.292
	p-value	0.117	0.680	0.076	0.323	0.003	0.106	0.049	0.064
Max speed TP	r	0.293	-0.132	0.293	0.177	0.249	0.280	-.390	-.412
	p-value	0.063	0.409	0.063	0.267	0.116	0.076	0.012	0.007
% above 40mph NTP	r	0.088	-0.041	0.156	.369	.396	0.270	-.418	-0.163
	p-value	0.585	0.798	0.330	0.018	0.010	0.088	0.007	0.308
% above 40mph TP	r	0.145	-0.073	0.210	0.275	0.226	0.209	-.391	-0.259
	p-value	0.364	0.649	0.187	0.082	0.156	0.190	0.011	0.102
% above 60mph NTP	r	0.247	-0.199	.416	0.000	.453	0.167	-0.212	-.376
	p-value	0.120	0.213	0.007	1.000	0.003	0.297	0.183	0.015
% above 60mph TP	r	0.210	-0.217	.322	0.087	0.247	0.195	-0.246	-.344
	p-value	0.187	0.174	0.040	0.590	0.119	0.223	0.121	0.028

Table A.19: Speed related variables repeated measures

Descriptive statistics			Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
Mean speed (m/s)	28.246	1.759	M1	-	-	-	-	-	-	-
				F	19.582					
	26.967	1.905	M2	p	0.000	-	-	-	-	-
				η^2	0.359					
				F	10.337	0.237				
	27.117	2.095	M3	p	0.003	0.629	-	-	-	-
				η^2	0.228	0.007				
	18.370	3.225	M4	Z	-5.232	-5.232	-5.232	-	-	-
				p	0.000	0.000	0.000			
	27.670	2.184	M5	Z	-1.273	-2.042	-1.430	-5.232	-	-
				p	0.203	0.041	0.153	0.000		
	25.940	3.323	M6	Z	-4.069	-1.609	-1.901	-4.682	-3.645	-
				p	0.000	0.109	0.057	0.000	0.000	
Maximum speed (m/s)	35.479	3.137	M1	-	-	-	-	-	-	-
				F	10.984					
	33.883	2.909	M2	p	0.002	-	-	-	-	-
				η^2	0.239					
				F	4.729	0.302				
	34.107	3.392	M3	p	0.037	0.586	-	-	-	-
				η^2	0.119	0.009				
				F	37.870	24.084	24.584			
	31.644	3.018	M4	p	0.000	0.000	0.000	-	-	-
				η^2	0.520	0.408	0.413			
				F	3.720	0.305	0.002	31.338		
	34.134	3.234	M5	p	0.062	0.585	0.964	0.000	-	-
				η^2	0.096	0.009	0.000	0.472		
				F	6.023	0.054	0.372	18.462	0.411	
	33.747	3.924	M6	p	0.019	0.818	0.546	0.000	0.526	-
				η^2	0.147	0.002	0.011	0.345	0.012	
% above speed limit	26.634	16.330	M1	-	-	-	-	-	-	-
	13.717	14.650	M2	Z	-3.931	-	-	-	-	-
				p	0.000					
	16.891	16.176	M3	Z	-3.284	-1.496	-	-	-	-
				p	0.001	0.135				
	3.798	8.075	M4	Z	-4.783	-3.861	-4.869	-	-	-
				p	0.000	0.000	0.000			
	19.486	18.944	M5	Z	-2.388	-1.671	-1.053	-4.697	-	-
				p	0.017	0.095	0.293	0.000		
	11.124	13.540	M6	Z	-3.915	-0.706	-2.385	-4.432	-3.243	-
				p	0.000	0.480	0.017	0.000	0.001	

Table A.20: Mean of positive and negative acceleration repeated measures

	Descriptive statistics			Repeated measures analysis						
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
	0.419	0.119	M1	-	-	-	-	-	-	-
				F	31.988					
	0.551	0.174	M2	p	0.000	-	-	-	-	-
				η^2	0.478					
				F	27.416	0.048				
Mean of positive acceleration (m/s^2)	0.558	0.175	M3	p	0.000	0.828	-	-	-	-
				η^2	0.439	0.048				
	0.456	0.151	M4	Z	-1.320	-2.812	-3.566	-	-	-
				p	0.187	0.005	0.000			
				F	0.173	21.155	23.739	-1.053 (Z)		
	0.428	0.157	M5	p	0.680	0.000	0.000	0.293	-	-
				η^2	0.005	0.377	0.405	-		
				F	4.615	4.760	5.252	-1.602 (Z)	2.799	
	0.483	0.162	M6	p	0.039	0.036	0.028	0.109	0.103	-
				η^2	0.117	0.120	0.130	-	0.074	
	-0.415	0.153	M1	-	-	-	-	-	-	-
	-0.525	0.212	M2	Z	-2.529	-	-	-	-	-
				p	0.011					
Mean of negative acceleration (m/s^2)	-0.503	0.190	M3	Z	-2.561	-0.063	-	-	-	-
				p	0.010	0.950				
	-0.416	0.129	M4	Z	-0.691	-2.561	-3.095	-	-	-
				p	0.489	0.010	0.002			
				F	0.820	-1.147 (Z)	-1.995 (Z)	-2.388 (Z)		
	-0.385	0.145	M5	p	0.371	0.251	0.046	0.017	-	-
				η^2	0.023	-	-	-		
	-0.489	0.246	M6	Z	-0.204	-1.760	-2.608	-1.414	-0.770	-
				p	0.838	0.078	0.009	0.157	0.441	

Table A. 21: Standard deviation of acceleration repeated measures

	Descriptive statistics			Repeated measures analysis						
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
	0.707	0.286	M1	-	-	-	-	-	-	-
				F	18.351					
	0.954	0.332	M2	p	0.000	-	-	-	-	-
				η^2	0.344					
				F	16.841	0.412				
Std. deviation of acceleration (m/s^2)	0.921	0.291	M3	p	0.000	0.525	-	-	-	-
				η^2	0.325	0.012				
	0.682	0.219	M4	Z	-6.76	-3.912	-3.943	-	-	-
				p	0.499	0.000	0.000			
				F	0.530	21.072	23.871	-0.471 (Z)		
	0.662	0.276	M5	p	0.472	0.000	0.000	0.637	-	-
				η^2	0.015	0.376	0.405	-		
				F	4.437	1.645	0.711	-2.608 (Z)	9.835	
	0.868	0.377	M6	p	0.042	0.208	0.405	0.009	0.003	-
				η^2	0.113	0.045	0.02	-	0.219	

Table A.22: Standard deviation of positive and negative acceleration repeated measures

Descriptive statistics				Repeated measures analysis						
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
	0.313	0.093	M1	-	-	-	-	-	-	-
				F	26.140					
	0.423	0.151	M2	p	0.000	-	-	-	-	-
				η^2	0.428					
Std. Dev. of positive acceleration (m/s^2)				F	22.624	0.116				
	0.413	0.128	M3	p	0.000	0.736	-	-	-	-
				η^2	0.393	0.003				
				F	1.765	13.449	15.907			
	0.334	0.090	M4	p	0.193	0.001	0.000	-	-	-
				η^2	0.048	0.278	0.312			
				F	0.482	14.211	12.539	0.353		
	0.324	0.090	M5	p	0.492	0.001	0.001	0.556	-	-
				η^2	0.014	0.289	0.264	0.010		
				F	20.119	0.492	1.115	12.895	16.777	
	0.448	0.173	M6	p	0.000	0.488	0.298	0.001	0.000	-
				η^2	0.365	0.014	0.031	0.269	0.324	
	0.736	0.409	M1	-	-	-	-	-	-	-
				F	11.923					
	1.048	0.477	M2	p	0.001	-	-	-	-	-
				η^2	0.254					
Std. Dev. of negative acceleration (m/s^2)				F	9.795	0.968				
	0.974	0.397	M3	p	0.004	0.332	-	-	-	-
				η^2	0.219	0.027				
	0.645	0.260	M4	Z	-1.241	-4.116	-3.802	-	-	-
				p	0.215	0.000	0.000			
				F	0.880	16.321	16.710	-0.079 (Z)		
	0.644	0.402	M5	p	0.355	0.000	0.000	0.937	-	-
				η^2	0.025	0.318	0.323	-		
				F	2.456	1.638	0.420	-2.796 (Z)	8.087	
	0.915	0.555	M6	p	0.126	0.209	0.521	0.005	0.007	-
				η^2	0.066	0.045	0.012	-	0.188	

Table A. 23: Lane-change frequency repeated measures

Descriptive statistics				Repeated measures analysis						
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
	1.266	0.725	M1	-	-	-	-	-	-	-
	1.112	0.877	M2	Z	-0.819	-	-	-	-	-
				p	0.413					
				F	1.122	-2.282 (Z)				
Lane-change frequency	1.452	1.111	M3	p	0.297	0.022	-	-	-	-
				η^2	0.031	-				
	2.311	1.480	M4	Z	-3.331	-4.078	-3.456	-	-	-
				p	0.001	0.000	0.001			
	1.520	1.336	M5	Z	-0.880	-1.921	-0.150	-3.784	-	-
				p	0.379	0.055	0.881	0.000		
	1.895	1.417	M6	Z	-2.592	-2.784	-1.335	-1.430	-1.982	-
				p	0.010	0.005	0.182	0.153	0.047	

Table A.24: Proportion spent on motorway lanes repeated measures

Measure	Descriptive statistics		Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
% spent in the leftmost lane	8.021	10.984	M1	-	-	-	-	-	-	-
	12.382	24.434	M2	Z	-0.689	-	-	-	-	-
				p	0.491					
	15.603	25.976	M3	Z	-0.832	-0.795	-	-	-	-
				p	0.405	0.426				
	21.173	23.832	M4	Z	-3.618	-2.684	-2.433	-	-	-
				p	0.000	0.007	0.015			
	15.925	23.967	M5	Z	-1.450	-0.990	-0.243	-1.697	-	-
				p	0.147	0.322	0.808	0.090		
	38.302	32.838	M6	Z	-4.684	-4.476	-4.160	-3.064	-4.128	-
				p	0.000	0.000	0.000	0.002	0.000	
% spent in the middle lane	49.979	23.490	M1	-	-	-	-	-	-	-
	32.072	24.894	M2	F	14.890	-	-	-	-	-
				p	0.000					
				η^2	0.298					
	37.987	24.764	M3	Z	-2.388	-1.325	-	-	-	-
				p	0.017	0.185				
	38.258	20.901	M4	F	5.570	2.656	-0.049 (Z)	-	-	-
				p	0.024	0.112	0.961			
				η^2	0.137	0.071	-			
	36.559	24.524	M5	F	8.91	0.821	-0.804 (Z)	0.105	-	-
				p	0.005	0.371	0.421	0.748		
				η^2	0.203	0.023	-	0.003		
	41.944	26.078	M6	F	2.533	3.651	-0.424 (Z)	0.61	1.197	-
				p	0.120	0.064	0.671	0.440	0.281	
				η^2	0.067	0.094	-	0.017	0.033	
% spent in the rightmost lane	41.89	27.77	M1	-	-	-	-	-	-	-
	55.37	32.34	M2	Z	-2.670	-	-	-	-	-
				p	0.008					
	46.25	31.60	M3	Z	-0.786	-1.916	-	-	-	-
				p	0.432	0.055				
	40.57	23.61	M4	F	0.061	-2.781 (Z)	-1.100 (Z)	-	-	-
				p	0.806	0.005	0.271			
				η^2	0.002	-	-			
	47.44	33.29	M5	Z	-0.710	-1.782	-0.355	-1.753	-	-
				p	0.478	0.081	0.722	0.080		
	19.65	22.62	M6	Z	-3.534	-4.727	-4.217	-4.085	-4.413	-
				p	0.000	0.000	0.000	0.000	0.000	

Table A.25: Headway related repeated measures

	Descriptive statistics		Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
Mean time headway (s)	3.410	1.144	M1	-	-	-	-	-	-	-
	2.743	0.917	M2	Z	-2.749	-	-	-	-	-
				p	0.006					
				F	19.126	-2.042 (Z)				
	2.393	0.650	M3	p	0.000	0.041	-	-	-	-
				η^2	0.353	-				
	4.191	2.099	M4	Z	-1.870	-3.346	-4.289	-	-	-
				p	0.062	0.001	0.000			
				F	15.346	-1.414 (Z)	0.638	-4.587 (Z)		
	2.524	0.700	M5	p	0.000	0.157	0.430	0.000	-	-
				η^2	0.305	-	0.018	-		
				F	4.434	-0.723 (Z)	6.198	-2.875 (Z)	3.925	
	2.865	0.909	M6	p	0.042	0.470	0.018	0.004	0.055	-
				η^2	0.112	-	0.150	-	0.101	
% spent at time headway < 1.5 secs	32.37	16.96	M1	-	-	-	-	-	-	-
				F	6.861					
	41.79	16.57	M2	p	0.013	-	-	-	-	-
				η^2	0.164					
				F	11.752	1.247				
	44.48	13.52	M3	p	0.002	0.272	-	-	-	-
				η^2	0.251	0.034				
				F	1.794	1.421	4.532			
	37.61	21.39	M4	p	0.189	0.241	0.040	-	-	-
				η^2	0.049	0.039	0.115			
				F	5.755	0.001	0.520	0.937		
	41.88	19.40	M5	p	0.022	0.979	0.476	0.340	-	-
				η^2	0.141	0.000	0.015	0.026		
				F	3.448	0.180	1.653	0.535	0.236	
	40.40	20.19	M6	p	0.072	0.674	0.207	0.469	0.630	-
				η^2	0.090	0.005	0.045	0.015	0.630	
Mean space headway (m)	100.654	34.282	M1	-	-	-	-	-	-	-
				F	19.309					
	71.263	19.652	M2	p	0.000	-	-	-	-	-
				η^2	0.356					
				F	32.131	4.915				
	63.369	14.585	M3	p	0.000	0.033	-	-	-	-
				η^2	0.479	0.123				
				F	1.798	3.503	9.070			
	87.303	45.693	M4	p	0.189	0.070	0.005	-	-	-
				η^2	0.049	0.091	0.206			
	72.538	24.194	M5	Z	-3.456	-0.079	-1.602	-1.163	-	-
				p	0.001	0.937	0.109	0.245		
	67.343	25.773	M6	Z	-4.258	-1.540	-0.581	-1.964	-1.430	-
				p	0.000	0.124	0.561	0.050	0.153	

Table A.26: Pedal depression repeated measures

Descriptive statistics			Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
Std. deviation acceleration pedal depression	9.861	3.358	M1	-	-	-	-	-	-	-
	12.039	4.171	M2	Z	-3.189	-	-	-	-	-
				p	0.001					
	12.297	5.039	M3	Z	-3.331	-0.393	-	-	-	-
				p	0.001	0.694				
	9.096	3.702	M4	Z	-2.325	-4.116	-4.336	-	-	-
				p	0.020	0.000	0.000			
	10.630	3.917	M5	F	-1.430 (Z)	5.664	-2.718 (Z)	-2.608 (Z)	-	-
				p	0.153	0.023	0.007	0.009		
				η^2	-	0.139	-	-		
	11.417	5.431	M6	Z	-1.948	-1.100	-1.932	-3.692	-1.304	-
				p	0.051	0.271	0.053	0.000	0.192	
Std. deviation of braking	12.795	7.902	M1	-	-	-	-	-	-	-
	17.623	10.188	M2	Z	-2.419	-	-	-	-	-
				p	0.016					
	16.572	9.151	M3	Z	-2.152	-0.251	-	-	-	-
				p	0.031	0.802				
	10.989	3.463	M4	F	1.961	-3.598 (Z)	-3.425 (Z)	-	-	-
				p	0.170	0.000	0.001			
				η^2	0.053	-	-			
	10.304	7.138	M5	F	2.047	-3.425 (Z)	-3.771 (Z)	0.362	-	-
				p	0.161	0.001	0.000	0.551		
				η^2	0.055	-	-	0.010		
	26.464	31.737	M6	Z	-2.671	-1.838	-2.152	-3.488	-3.755	-
				p	0.008	0.066	0.031	0.000	0.000	

Table A.27: Heart rate repeated measures

Descriptive statistics			Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
HR mean (bpm)	82.069	18.804	M1	-	-	-	-	-	-	-
	81.766	17.949	M2	Z	-0.314	-	-	-	-	-
				p	0.753					
	80.345	11.831	M3	Z	-0.487	-0.016	-	-	-	-
				p	0.626	0.987				
	77.268	11.038	M4	Z	-2.247	-1.571	-2.262	-	-	-
				p	0.025	0.116	0.024			
	79.815	12.594	M5	Z	-0.283	-0.644	-0.204	-2.090	-	-
				p	0.777	0.519	0.838	0.037		
	82.822	16.408	M6	Z	-0.063	-0.707	-0.236	-1.995	-1.100	-
				p	0.950	0.480	0.814	0.046	0.271	

Table A.27: Heart rate repeated measures (continued)

Descriptive statistics			Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
HR mean normalised	0.013	0.542	M1	-	-	-	-	-	-	-
	0.02	0.589	M2	Z	-0.189	-	-	-	-	-
				p	0.850					
	-0.044	0.458	M3	Z	-0.424	-0.283	-	-	-	-
				p	0.671	0.777				
	-0.289	0.383	M4	Z	-2.199	-1.728	-2.451	-	-	-
				p	0.028	0.084	0.014			
	0.034	0.66	M5	Z	-1.110	-0.613	-0.408	-2.545	-	-
				p	0.912	0.540	0.683	0.011		
	0.055	0.671	M6	Z	-0.126	-0.408	-0.440	-1.901	-0.754	-
				p	0.900	0.683	0.660	0.057	0.451	

Table A.28: Skin conductance – CDA repeated measures

Descriptive statistics			Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
SCRs frequency (CDA)	12.717	13.937	M1	-	-	-	-	-	-	-
	11.961	13.402	M2	Z	-1.103	-	-	-	-	-
				p	0.270					
	14.638	15.925	M3	Z	-0.864	-1.409	-	-	-	-
				p	0.388	0.159				
	15.307	14.889	M4	Z	-1.051	-1.785	-0.157	-	-	-
				p	0.293	0.074	0.875			
	14.847	15.798	M5	Z	-1.462	-1.409	-0.295	-0.459	-	-
				p	0.144	0.159	0.768	0.647		
	15.635	15.69	M6	Z	-1.257	-1.867	-1.048	-0.060	-0.331	-
				p	0.209	0.062	0.295	0.952	0.741	
SCRs mean (CDA - µS)	0.038	0.058	M1	-	-	-	-	-	-	-
	0.032	0.038	M2	Z	-0.983	-	-	-	-	-
				p	0.326					
	0.03	0.025	M3	Z	-0.204	-0.033	-	-	-	-
				p	0.838	0.974				
	0.033	0.034	M4	Z	-0.539	-1.147	-0.063	-	-	-
				p	0.590	0.252	0.950			
	0.035	0.049	M5	Z	-0.692	-0.393	-0.164	-0.246	-	-
				p	0.489	0.694	0.870	0.806		
	0.042	0.057	M6	Z	-1.633	-1.949	-1.425	-1.154	-2.296	-
				p	0.103	0.051	0.154	0.248	0.022	

Table A.28: Skin conductance – CDA repeated measures (continued)

Descriptive statistics			Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
SCRs normalised mean (CDA)	4.02	1.84	M1	-	-	-	-	-	-	-
	4.333	1.354	M2	Z	-0.419	-	-	-	-	-
				p	0.675					
	4.347	1.365	M3	Z	-0.487	-0.098	-	-	-	-
				p	0.626	0.922				
	4.539	1.164	M4	Z	-0.727	-0.852	-0.299	-	-	-
				p	0.467	0.394	0.765			
	4.151	1.716	M5	Z	-0.436	-0.049	-0.131	-0.328	-	-
				p	0.663	0.961	0.896	0.743		
	4.359	1.604	M6	Z	-1.017	-1.294	-1.081	-0.778	-1.188	-
				p	0.309	0.196	0.280	0.437	0.235	

Table A. 29: Skin conductance – TTP repeated measures

Descriptive statistics			Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
SCRs frequency (TTP)	4.394	6.864	M1	-	-	-	-	-	-	-
	4.194	4.472	M2	Z	-0.213	-	-	-	-	-
				p	0.831					
	4.831	5.411	M3	Z	-0.950	-1.032	-	-	-	-
				p	0.342	0.302				
	4.806	4.472	M4	Z	-1.671	-1.115	-0.049	-	-	-
				p	0.095	0.265	0.961			
	5.036	6.918	M5	Z	-1.622	-1.294	-0.246	-0.927	-	-
				p	0.105	0.196	0.806	0.354		
	4.745	5.084	M6	Z	-0.999	-0.613	-0.426	-0.901	-0.131	-
				p	0.318	0.540	0.670	0.368	0.896	
SCRs mean (TTP - µS)	0.048	0.054	M1	-	-	-	-	-	-	-
	0.046	0.056	M2	Z	-0.999	-	-	-	-	-
				p	0.318					
	0.043	0.046	M3	Z	-0.164	-0.36	-	-	-	-
				p	0.870	0.719				
	0.044	0.048	M4	Z	-0.131	-0.707	-0.409	-	-	-
				p	0.896	0.480	0.682			
	0.045	0.057	M5	Z	-0.098	0.000	-0.426	-0.110	-	-
				p	0.922	1.000	0.670	0.912		
	0.056	0.066	M6	Z	-2.047	-2.137	-1.425	-2.080	-2.604	-
				p	0.041	0.033	0.154	0.038	0.009	

Table A.29: Skin conductance – TTP repeated measures (continued)

Descriptive statistics			Repeated measures analysis							
	Mean	Std. Deviation			M1	M2	M3	M4	M5	M6
	4.302	1.569	M1	-	-	-	-	-	-	-
	4.51	1.159	M2	Z	-0.770	-	-	-	-	-
				p	0.441					
SCRs normalised mean (TTP)	4.273	1.557	M3	Z	-0.115	-0.229	-	-	-	-
				p	0.909	0.819				
	4.689	0.895	M4	Z	-0.573	-0.676	-0.147	-	-	-
				p	0.566	0.499	0.883			
	4.296	1.578	M5	Z	-0.197	-0.328	-0.36	-0.628	-	-
				p	0.844	0.743	0.719	0.530		
	4.542	1.44	M6	Z	-1.261	-1.870	-1.851	-0.999	2.031	-
				p	0.207	0.062	0.064	0.318	0.042	

Table A.30: Correlation matrix of physiological responses with the motorway variables

		hr	hr_z	cda sum	cda sum_z	cda mean_z5	cda sum_z5	ttp freq	ttp mean	ttp sum	ttp sum_z	ttp mean_z5	ttp sum_z5
Mean speed	r	0.088	.146	-0.056	0.126	-0.028	-.182	0.007	0.061	-0.046	.151	-0.015	-.140
	p	0.200	0.031	0.412	0.081	0.682	0.007	0.915	0.376	0.499	0.033	0.822	0.039
Maximum speed	r	.144	0.081	-0.074	0.049	0.103	-0.051	0.000	0.107	-0.048	0.138	0.123	-0.094
	p	0.034	0.238	0.278	0.496	0.130	0.460	0.998	0.119	0.485	0.053	0.071	0.169
% above speed limit	r	0.072	0.052	-0.079	0.040	.134	-0.084	0.013	0.049	-0.075	0.066	.147	-0.086
	p	0.290	0.444	0.250	0.576	0.050	0.221	0.845	0.478	0.274	0.357	0.030	0.207
Std. deviation of acceleration	r	.162	0.109	-0.004	.177	0.120	0.001	-0.010	.165	0.062	.259	.159	-0.040
	p	0.017	0.109	0.952	0.014	0.078	0.989	0.882	0.015	0.368	0.000	0.020	0.556
Total lane changed	r	0.055	-0.035	0.059	0.005	0.077	0.112	0.097	-0.008	0.107	0.000	0.061	.138
	p	0.417	0.609	0.385	0.945	0.258	0.100	0.157	0.906	0.117	0.998	0.372	0.042
% spent in the leftmost lane	r	-0.080	-0.013	0.131	0.070	0.032	0.054	.145	-0.014	.142	-0.064	-0.005	.182
	p	0.243	0.852	0.054	0.334	0.636	0.428	0.033	0.834	0.037	0.373	0.942	0.007
% spent in the middle lane	r	-0.098	0.070	-0.090	0.036	-.185	-0.111	-0.094	-.135	-0.098	0.000	-.170	-0.117
	p	0.151	0.305	0.188	0.617	0.006	0.105	0.168	0.048	0.152	0.995	0.012	0.085
% spent in the rightmost lane	r	.146	-0.047	-0.039	-0.090	0.121	0.043	-0.048	0.122	-0.042	0.054	.141	-0.061
	p	0.032	0.491	0.568	0.215	0.075	0.527	0.482	0.075	0.538	0.447	0.039	0.375
Mean of positive acceleration	r	0.085	0.016	-0.022	.161	0.132	-0.010	-0.034	0.123	0.039	.270	.165	-0.059
	p	0.215	0.815	0.745	0.025	0.053	0.886	0.615	0.072	0.565	0.000	0.015	0.386
Mean of negative acceleration	r	-.213	-0.092	0.003	-.193	-0.128	0.005	0.010	-.169	-0.066	-.274	-.150	0.044
	p	0.002	0.177	0.961	0.007	0.061	0.945	0.883	0.013	0.336	0.000	0.027	0.523
Std. Dev. of positive acceleration	r	0.057	0.065	0.059	0.205	0.131	0.033	-0.008	0.133	0.081	0.27	0.184	-0.016
	p	0.402	0.345	0.389	0.004	0.054	0.634	0.912	0.05	0.233	0.000	0.007	0.814
Std. Dev. of negative acceleration	r	0.179	0.13	-0.023	0.15	0.096	-0.007	-0.008	0.148	0.041	0.222	0.132	-0.037
	p	0.008	0.056	0.736	0.037	0.162	0.919	0.908	0.029	0.553	0.002	0.053	0.586
Std. deviation acceleration pedal depression	r	0.054	0.051	-0.081	0.198	0.136	-0.071	-0.095	0.057	-0.048	0.271	0.167	-0.143
	p	0.431	0.453	0.235	0.006	0.046	0.297	0.166	0.404	0.482	0.000	0.014	0.035
Std. deviation of braking	r	0.109	0.155	-0.038	0.121	0.082	0.000	-0.03	0.053	-0.009	0.165	0.132	-0.049
	p	0.111	0.023	0.582	0.094	0.228	0.995	0.663	0.435	0.891	0.021	0.053	0.478

APPENDIX B: APPENDIX TO CHAPTER 4

B.1 Base car-following models (no sociodemographic variables) equations

B.1.1 No events model

Acceleration regime

$$a_n^{cf,acc}(t) = 0.193 \frac{1}{\Delta T_n(t)^{0.400}} \left|\Delta V_n(t - \tau_n)\right|^{0.707} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.447^2)$$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.219 \frac{1}{\Delta T_n(t)^{1.192}} \left|\Delta V_n(t - \tau_n)\right|^{0.786} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.770^2)$$

B.1.2 Aggressive drivers model

Acceleration regime

$$a_n^{cf,acc}(t) = 0.139 \frac{1}{\Delta T_n(t)^{0.063}} \left|\Delta V_n(t - \tau_n)\right|^{0.818} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.634^2)$$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.174 \frac{1}{\Delta T_n(t)^{0.857}} \left|\Delta V_n(t - \tau_n)\right|^{1.009} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.985^2)$$

B.1.3 Slow traffic model

Acceleration regime

$$a_n^{cf,acc}(t) = 0.347 \frac{1}{\Delta T_n(t)^{0.275}} |\Delta V_n(t - \tau_n)|^{0.674} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.337^2)$$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.255 \frac{1}{\Delta T_n(t)^{0.486}} |\Delta V_n(t - \tau_n)|^{0.709} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.694^2)$$

B.2 Car-following models with sociodemographic variables (no latent stress variable)

B.2.1 No events model

Acceleration regime

$$a_n^{cf,acc}(t) = 0.190 \frac{1}{\Delta T_n(t)^{0.389}} |\Delta V_n(t - \tau_n)|^{0.942-0.192\times Female-0.008\times Age+0.176\times Frequency} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.447^2)$$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.100 \frac{1}{\Delta T_n(t)^{1.801}} |\Delta V_n(t - \tau_n)|^{1.695+0.503\times Female-1.050\times Accident-0.387\times Frequency} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.727^2)$$

B.2.2 Aggressive drivers model

Acceleration regime

$$a_n^{cf,acc}(t) = 0.139 \frac{1}{\Delta T_n(t)^{0.055}} \left|\Delta V_n(t - \tau_n)\right|^{0.815} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.634^2)$$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.163 \frac{1}{\Delta T_n(t)^{0.907}} \left|\Delta V_n(t - \tau_n)\right|^{0.950+0.289\times Female} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.979^2)$$

B.2.3 Slow traffic model

Acceleration regime

$$a_n^{cf,acc}(t) = 0.332 \frac{1}{\Delta T_n(t)^{0.223}} \left|\Delta V_n(t - \tau_n)\right|^{1.449-0.436\times Female-0.012\times Age} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.337^2)$$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.250 \frac{1}{\Delta T_n(t)^{0.504}} \left|\Delta V_n(t - \tau_n)\right|^{0.941-0.152\times Accident-0.203\times Frequency} + \varepsilon_n^{cf,acc}(t)$$

$$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.686^2)$$

B.3 Car-following models with latent stress variable (no sociodemographic variables)

B.3.1 No events model

$\text{Stress}_n(t) = -0.041 \times \Delta T_n + \eta_n(t)$

$\eta_n(t) \sim N(0,\ 1^2)$

Acceleration regime

$$a_n^{cf,acc}(t) = \left[0.190 \frac{1}{\Delta T_n(t)^{0.409}} + 0.018 \times \text{Stress}_n(t)\right] |\Delta V_n(t - \tau_n)|^{0.731} + \varepsilon_n^{cf,acc}(t)$$

$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.446^2)$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.219 \frac{1}{\Delta T_n(t)^{1.190}} |\Delta V_n(t - \tau_n)|^{0.787} + \varepsilon_n^{cf,acc}(t)$$

$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.770^2)$

B.3.2 Aggressive drivers model

$\text{Stress}_n(t) = -0.036 \times \Delta T_n + \eta_n(t)$

$\eta_n(t) \sim N(0,\ 1^2)$

Acceleration regime

$$a_n^{cf,acc}(t) = \left[0.137 \frac{1}{\Delta T_n(t)^{0.042}} + 0.023 \times \text{Stress}_n(t)\right] |\Delta V_n(t - \tau_n)|^{0.829} + \varepsilon_n^{cf,acc}(t)$$

$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.633^2)$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.173 \frac{1}{\Delta T_n(t)^{0.856}} |\Delta V_n(t - \tau_n)|^{1.011} + \varepsilon_n^{cf,acc}(t)$$

$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.985^2)$

B.4 Car-following models with both sociodemographic and latent stress variables

B.4.1 No events model

$\text{Stress}_n(t) = -0.041 \times \Delta T_n + \eta_n(t)$

$\eta_n(t) \sim N(0,\ 1^2)$

Acceleration regime

$a_n^{cf,acc}(t) = \left[0.188 \dfrac{1}{\Delta T_n(t)^{0.394}} + 0.016 \times \text{Stress}_n(t)\right] |\Delta V_n(t-\tau_n)|^{0.956-0.188\times\text{Female}-0.008\times\text{Age}+0.171\times\text{Frequency}} + \varepsilon_n^{cf,acc}(t)$

$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.446^2)$

Deceleration regime

$a_n^{cf,dec}(t) = -0.099 \dfrac{1}{\Delta T_n(t)^{1.800}} |\Delta V_n(t-\tau_n)|^{1.696+0.502\times\text{Female}-1.050\times\text{Accident}-0.387\times\text{Frequency}} + \varepsilon_n^{cf,acc}(t)$

$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.727^2)$

B.4.2 Aggressive drivers model

$\text{Stress}_n(t) = -0.036 \times \Delta T_n + \eta_n(t)$

$\eta_n(t) \sim N(0,\ 1^2)$

Acceleration regime

$a_n^{cf,acc}(t) = \left[0.137 \dfrac{1}{\Delta T_n(t)^{0.033}} + 0.023 \times \text{Stress}_n(t)\right] |\Delta V_n(t - \tau_n)|^{0.827} + \varepsilon_n^{cf,acc}(t)$

$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.633^2)$

Deceleration regime

$a_n^{cf,dec}(t) = -0.163 \dfrac{1}{\Delta T_n(t)^{0.907}} |\Delta V_n(t - \tau_n)|^{0.955+0.290\times\text{Female}} + \varepsilon_n^{cf,acc}(t)$

$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.979^2)$

B.5 Base “No events” model sensitivity analysis considering sociodemographic characteristics

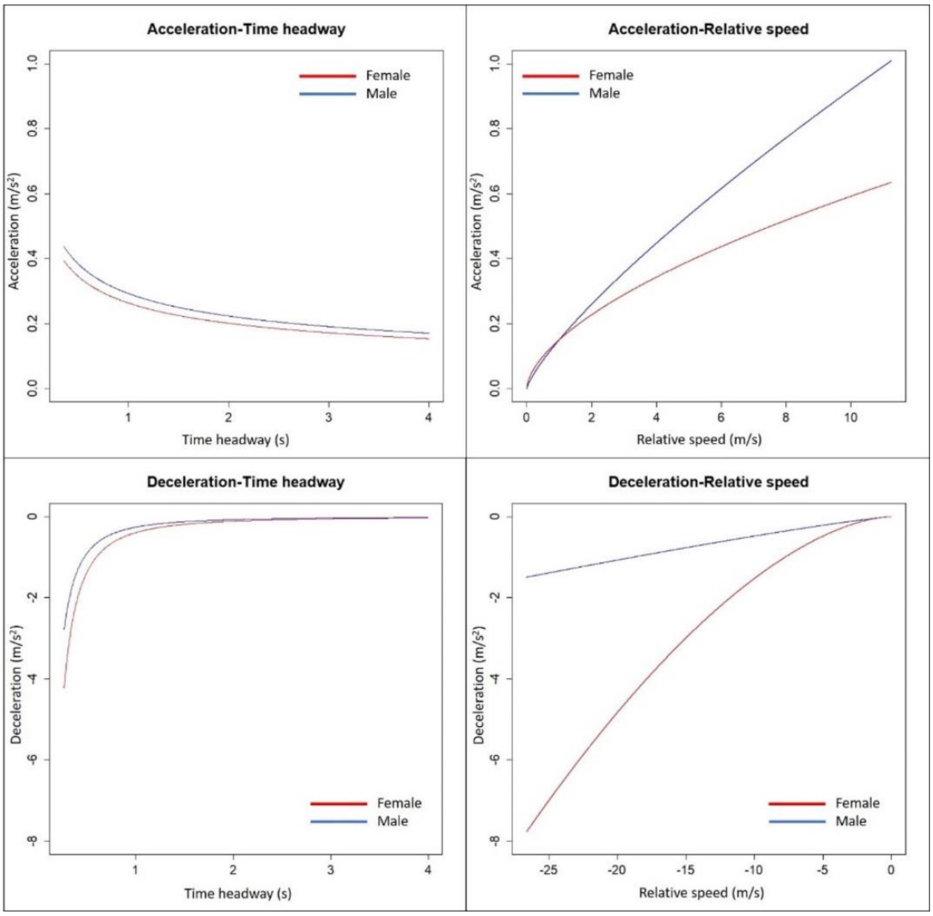

Figure B.1 Gender sensitivity analysis

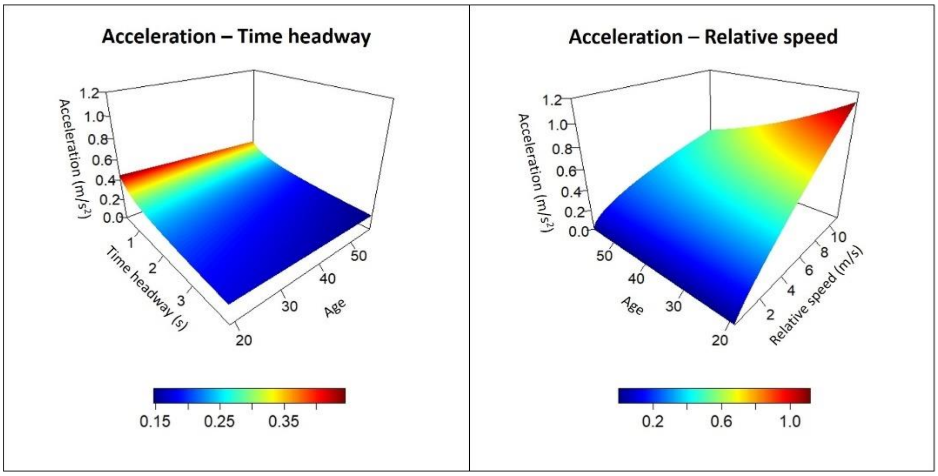

Figure B.2 Age sensitivity analysis

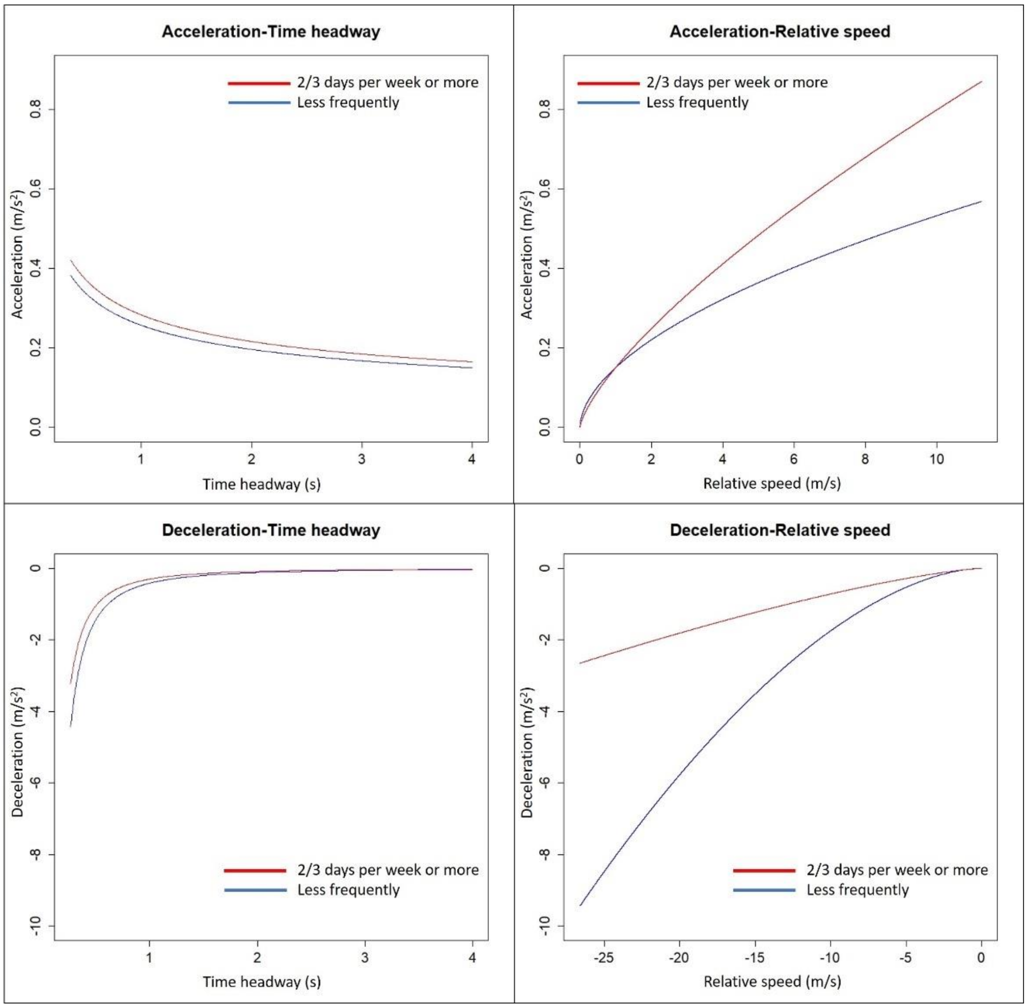

Figure B.3 Driving frequency sensitivity analysis

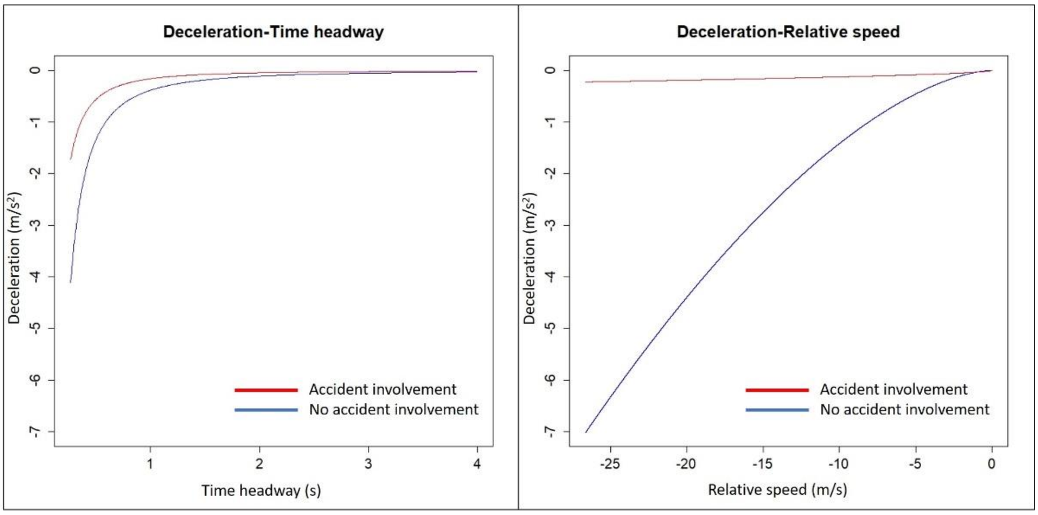

Figure B.4 Accident involvement sensitivity analysis

B.6 Base “Aggressive drivers” model sensitivity analysis considering sociodemographic characteristics

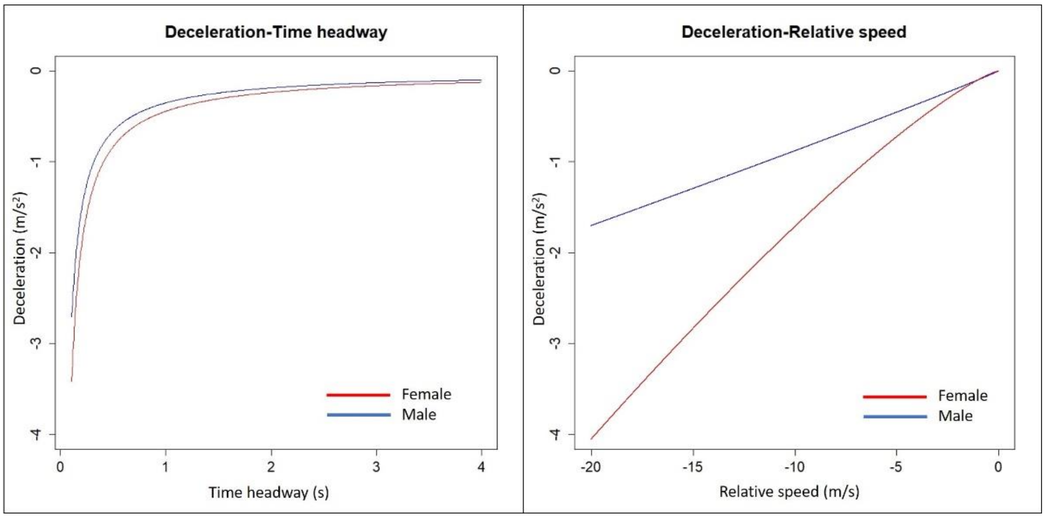

Figure B.5 Gender sensitivity analysis

B.7 Base “Slow traffic” model sensitivity analysis considering sociodemographic characteristics

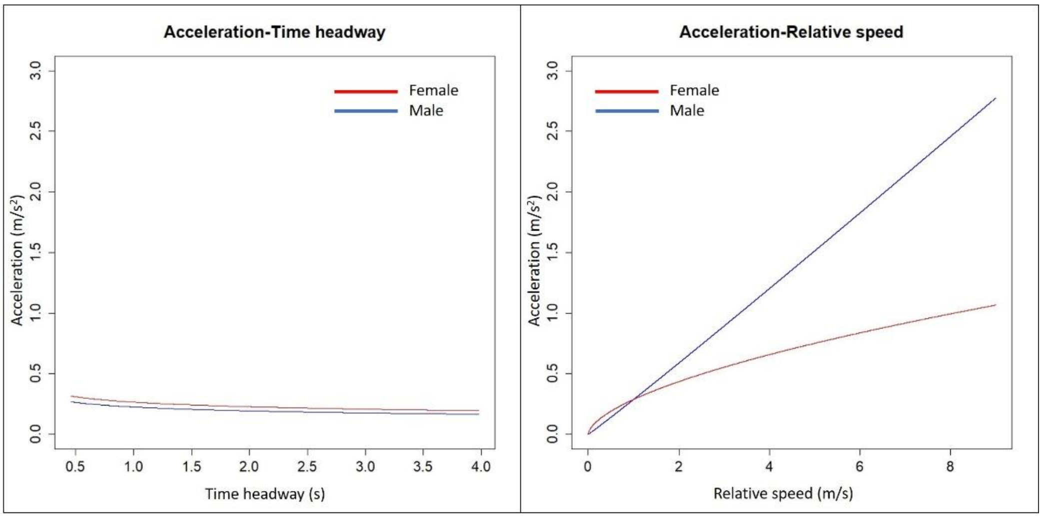

Figure B.6 Gender sensitivity analysis

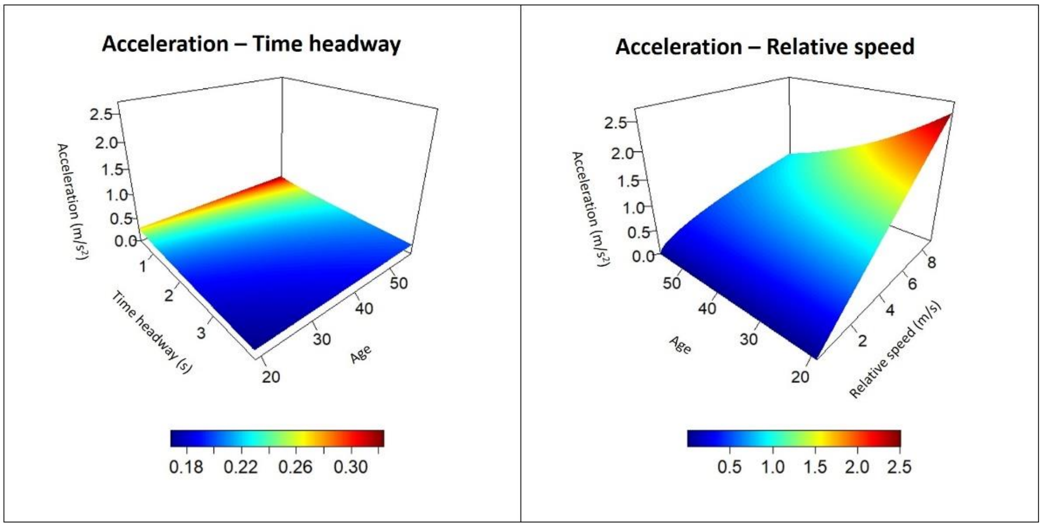

Figure B.7 Age sensitivity analysis

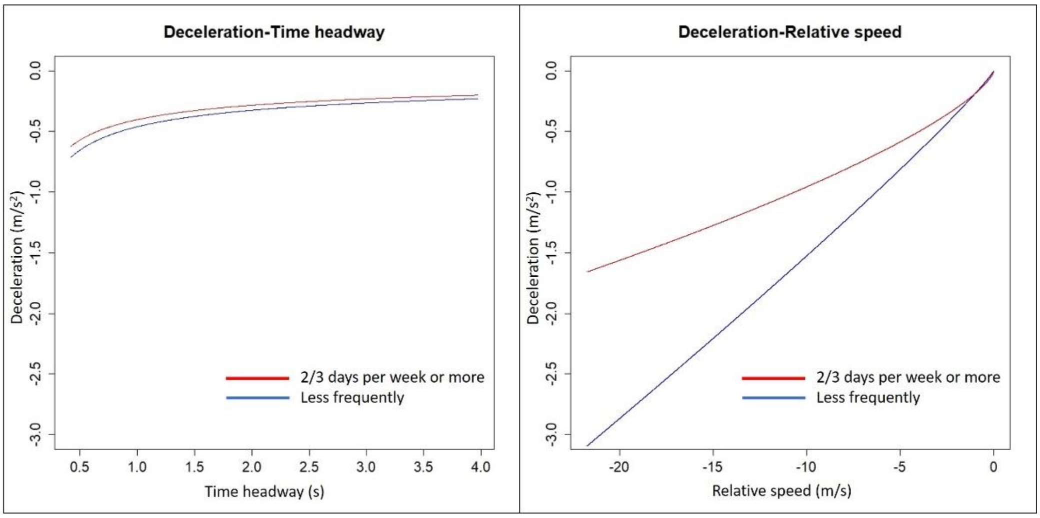

Figure B.8 Driving frequency sensitivity analysis

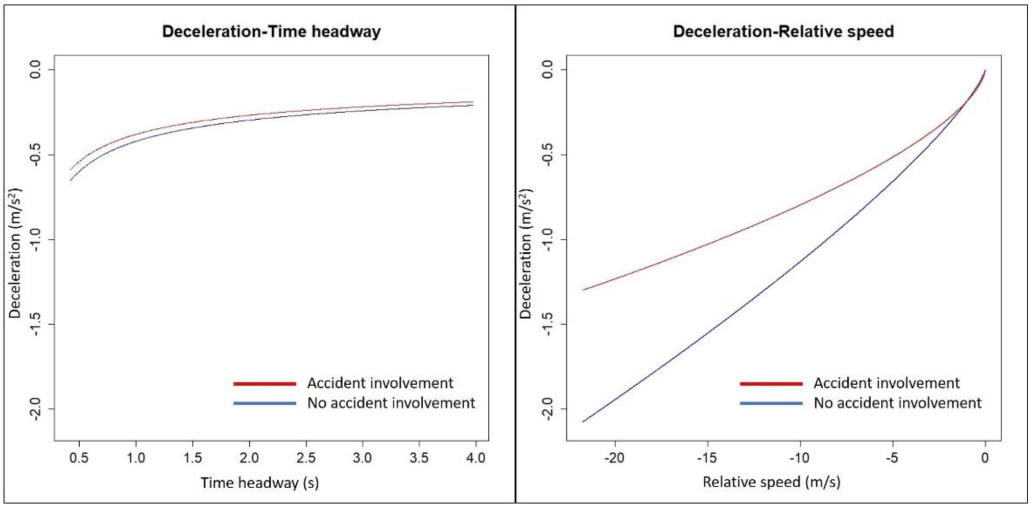

Figure B.9 Accident involvement sensitivity analysis

B.8 Latent variable "No events" model sensitivity analysis considering sociodemographic characteristics

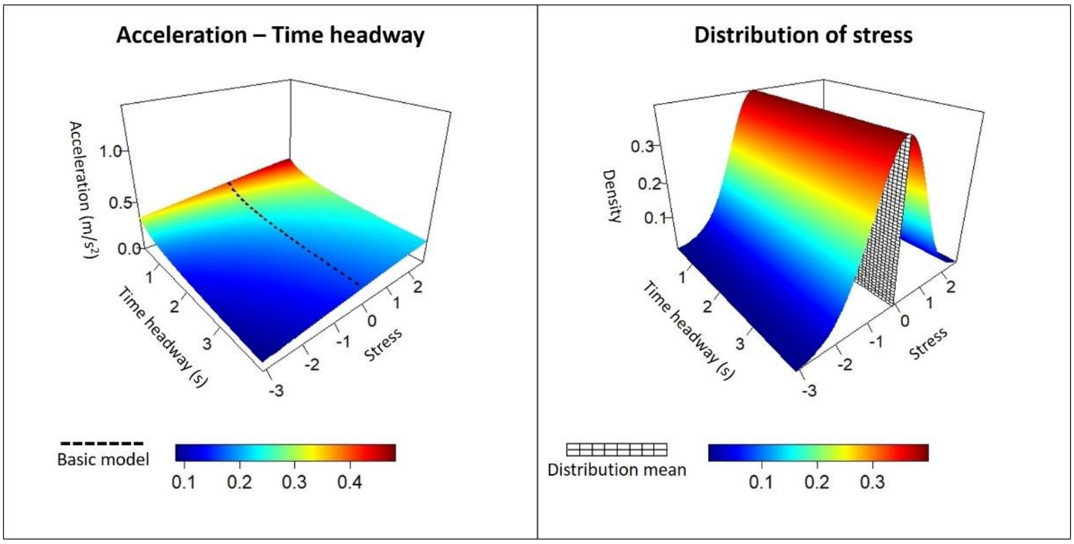

Figure B.10 Time headway sensitivity analysis

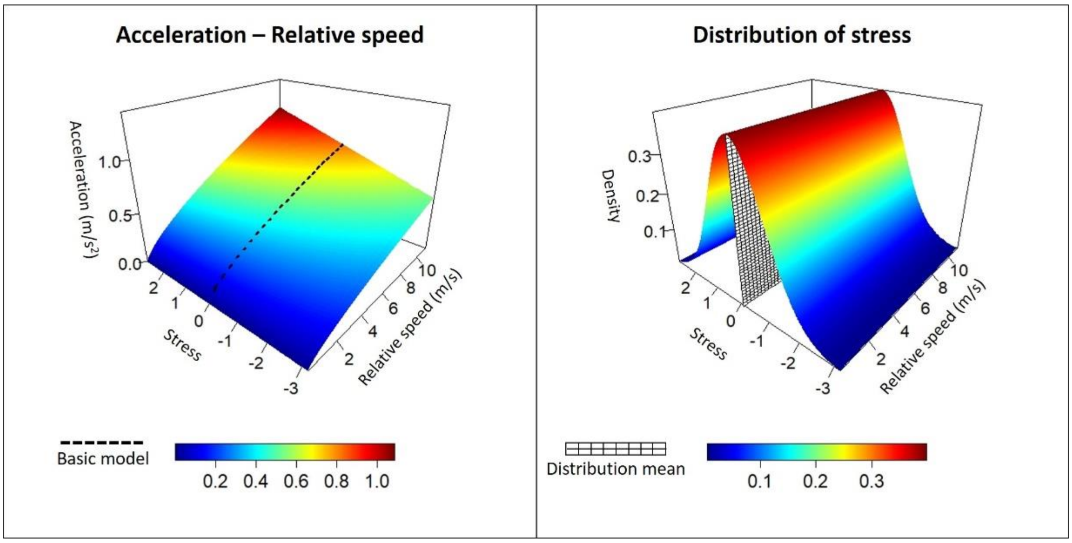

Figure B.11 Relative speed sensitivity analysis

B.9 Latent variable “Aggressive drivers” model sensitivity analysis considering sociodemographic characteristics

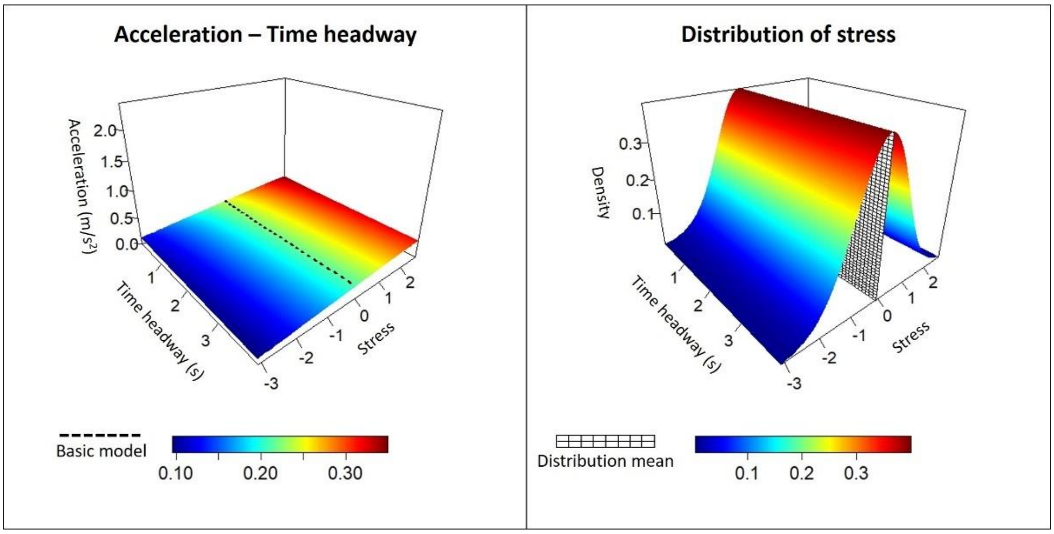

Figure B.12 Time headway sensitivity analysis

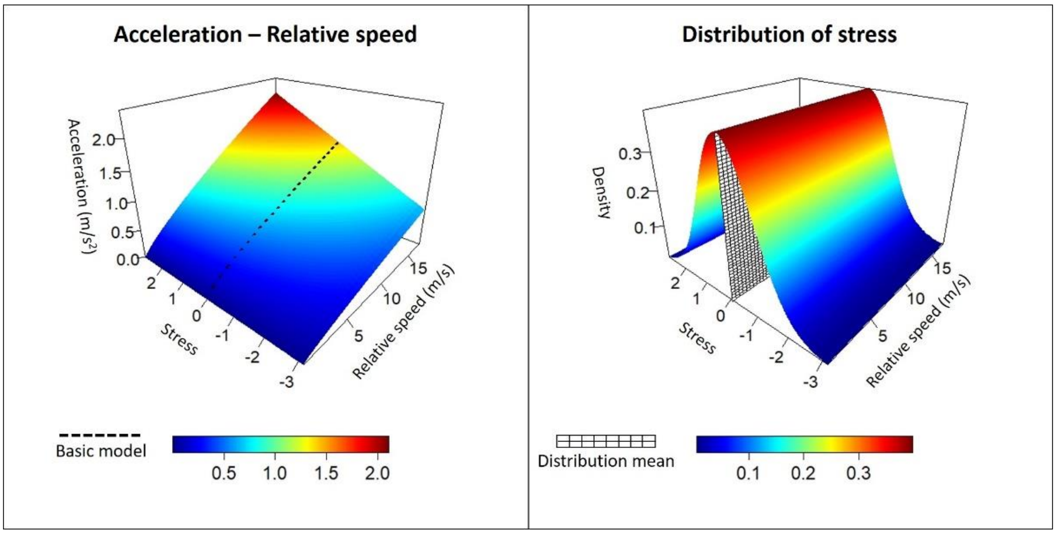

Figure B.13 Relative speed sensitivity analysis