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

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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.

Keywords: skin-conductance, heart rate, blood volume pulse, stress measurement

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 focus 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.

2. Data

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 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.

Figure 1: The University of Leeds Driving Simulator

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

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.

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 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 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.

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 urban task and σ is its standard deviation.

Blood pressure (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 1:

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

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 2:

$$\mathrm{FAD_{X\,norm}} = \frac{\mathrm{FAD_X} - \mathrm{FAD_{X\,min}}}{\mathrm{FAD_{X\,max}} - \mathrm{FAD_{X\,min}}} \tag{2}$$

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.

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 1.

Table 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 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. All other observations were excluded from the data. Table 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 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

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 3.1)
- Car-following model with sociodemographic variables (but no latent stress variable) (Section 3.2)
- Car-following model with latent stress variable (but no sociodemographic variables) (Section 3.3)
- Car-following model with both sociodemographic and latent stress variables (Section 3.4)

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 3):

$$a_n(t)|\tau_n = \alpha \frac{V_n(t)^{\beta}}{\Delta X_n(t)^{\gamma}} \Delta V_n(t - \tau_n) \qquad (3)$$

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):

$$a_n^g(t)|\tau_n = s\,[X_n^g(t - \tau_n)] \times f\,[\Delta V_n(t - \tau_n)] + \varepsilon_n^g(t) \tag{4}$$

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 5 and 6):

$$s[X_n^g(t - \tau_n)] = \alpha^g \frac{1}{\Delta T_n(t)^{\gamma^g}} \tag{5}$$

$$f\,[\Delta V_n(t - \tau_n)] = \Delta V_n(t - \tau_n)^{\lambda^g} \tag{6}$$

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 7):

$$\varphi(\tau_n) = \begin{cases} \dfrac{\dfrac{1}{\tau_n \sigma_\tau}\varphi\left(\dfrac{\ln(\tau_n) - \mu_\tau}{\sigma_\tau}\right)}{\Phi\left(\dfrac{\ln(\tau^{max}) - \mu_\tau}{\sigma_\tau}\right) - \Phi\left(\dfrac{\ln(\tau^{min}) - \mu_\tau}{\sigma_\tau}\right)} & \text{if } \tau^{min} < \tau_n \leq \tau^{max} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

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 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 8):

$$\varphi\left(a_n^g(t)|\tau_n\right)=\frac{1}{\sigma_{\varepsilon^g}}\varphi\left(\frac{a_n^g(t)-s[X_n^g(t-\tau_n)]\times f[\Delta V_n(t-\tau_n)]}{\sigma_{\varepsilon^g}}\right) \tag{8}$$

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

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 9):

$$\varphi(a_n(t)|\tau_n)=\varphi(a_n^{acc}(t)|\tau_n)^{\delta[\Delta V_n(t-\tau_n)]}\varphi\left(a_n^{dec}(t)|\tau_n\right)^{(1-\delta[\Delta V_n(t-\tau_n)])} \tag{9}$$

where:

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

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 10):

$$\varphi(a_n(1),a_n(2),\ldots,a_n(T_n)|\tau_n)=\prod_{t=1}^{T_n}\varphi(a_n(t)\,|\tau_n) \tag{10}$$

The unconditional form of the distribution above is (Equation 11):

$$\varphi\left(a_n(1),a_n(2),\ldots,a_n(T_n)\right)=\int_{\tau^{min}}^{\tau^{max}}\varphi(a_n(1),a_n(2),\ldots,a_n(T_n)|\tau_n)\,\varphi(\tau_n)d\tau \tag{11}$$

At the final step, the model is estimated by maximizing the log-likelihood function of the acceleration observations (Equation 12):

$$LL=\sum_{n=1}^{N}\ln\left[\varphi\left(a_n(1),a_n(2),\ldots,a_n(T_n)\right)\right] \tag{12}$$

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 6 is extended to (Equation 13):

$$f\left[\Delta V_n(t-\tau_n)\right]=\Delta V_n(t-\tau_n)^{\lambda^g+\beta^g Z_n} \tag{13}$$

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 3.1.

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).

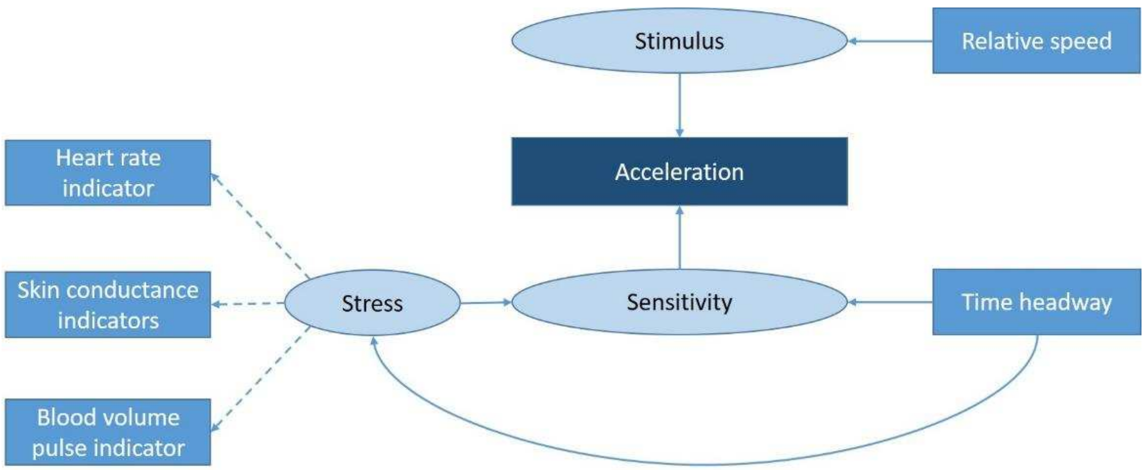

Figure 3: Example of the proposed car-following framework incorporating stress

The new latent variable model (presented in Figure 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 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 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 14-16):

Structural equations:

$$Stress_n(t)= \xi Y_n(t) + \eta_n(t), \qquad \eta_n(t)=N\sim(0,1) \tag{14}$$

$$a_n^g(t)|\tau_n = \{s[X_n^g(t)]+ \theta^g\ Stress_n(t)\}\times\ f\ [\Delta V_n(t-\tau_n)] + \varepsilon_n^g(t) \tag{15}$$

Measurement equations:

$$I_{k,n}(t)=\beta_{I_k} + \zeta_{I_k}\ Stress_n(t) + u_{k,n}(t) \qquad u_{k,n}(t) = N\sim(0,\sigma_{I_k}^2) \tag{16}$$

where: $Stress_n(t)$, 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 17):

$$\varphi\left(I_{k,n}(t)\right)=\frac{1}{\sigma_{I_k}}\varphi\left(\frac{I_{k,n}(t) - \zeta_{I_k}\ Stress_n(t)}{\sigma_{I_k}}\right) \tag{17}$$

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 18:

$$L\left(I_{k,n}(t)|\ \zeta_{I_k},Stress_n(t),\sigma_{I_k},t\right) = \prod_{k=1}^{K} \varphi\left(I_{k,n}(t)\right) \tag{18}$$

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 19:

$$LL= \sum_{n=1}^{N} \ln \left[\int_{\tau_{min}}^{\tau_{max}} \left(\prod_{t=1}^{T} \left(\int_{\eta} \varphi(\alpha_n(t)) \, L\left(I_{k,n}(t) | \, \zeta_{I_k}, Stress_n(t), \sigma_{I_k}, t\right) \, \varphi(\eta) d\eta \right) \right) \varphi(\tau) d\tau \right] \quad (19)$$

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 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 20 to 22) have been tested and compared with the proposed model specification.

$$a_n^g(t) = s[X_n^g(t)] \times f\left[\Delta V_n(t-\tau_n)\right] + \theta^g \, Stress_n(t) + \varepsilon_n^g(t) \quad (20)$$

$$a_n^g(t) = (\alpha^g + \theta^g \, Stress_n(t)) \frac{1}{\Delta T_n(t)^{\gamma^g}} \times f\left[\Delta V_n(t-\tau_n)\right] + \varepsilon_n^g(t) \quad (21)$$

$$a_n^g(t) = \alpha^g \frac{1}{\Delta X_n(t)^{\gamma^g + \theta^g \, Stress_n(t)}} \times f\left[\Delta V_n(t-\tau_n)\right] + \varepsilon_n^g(t) \quad (22)$$

Each variant presented above represents different approximations regarding the effects of stress on car-following behaviour. For instance, Equation 20 assumes that stress has an overall shift on acceleration values, Equations 21 and 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 4.3) and thus were not selected as the recommended specifications.

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 3.2 while the rest of the process remains the same as in Section 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. 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 4.1). 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 3. These can be summarised to the base car-following models without sociodemographic variables (Section 4.1), car-following models with sociodemographic variables, but no latent stress variable (Section 4.2), car-following models with latent stress variable, but no sociodemographic variables (Section 4.3) and car-following models with both sociodemographic and latent stress variables (Section 4.4). The final equations, including the parameter estimates for all models, are presented in Appendix A.

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 3.1. The parameter estimates are presented in Table 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 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) 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 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 23):

$$t_{diff,k} = \frac{\beta_{1,k} - \beta_{2,k}}{\sqrt{\left(\frac{\beta_{1,k}}{t_{1,k}}\right)^2 + \left(\frac{\beta_{2,k}}{t_{2,k}}\right)^2}} \tag{23}$$

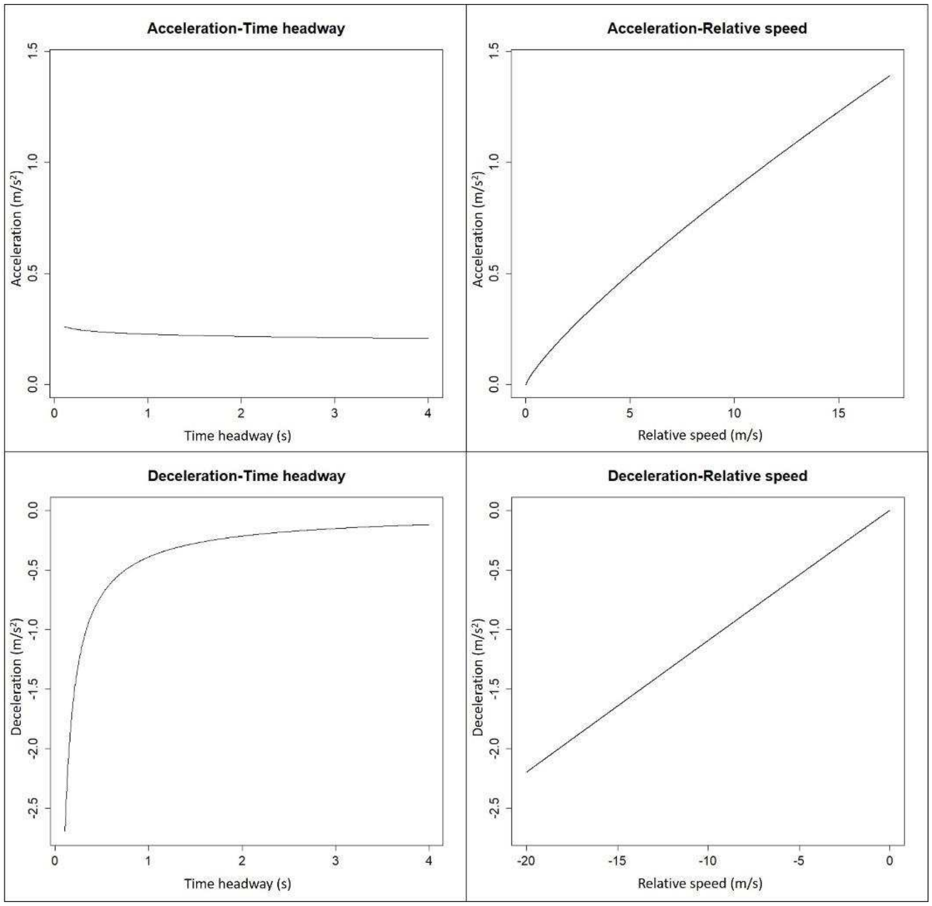

Figure 4: Sensitivity plots of the "Aggressive drivers" car-following model

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 3.

Table 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				

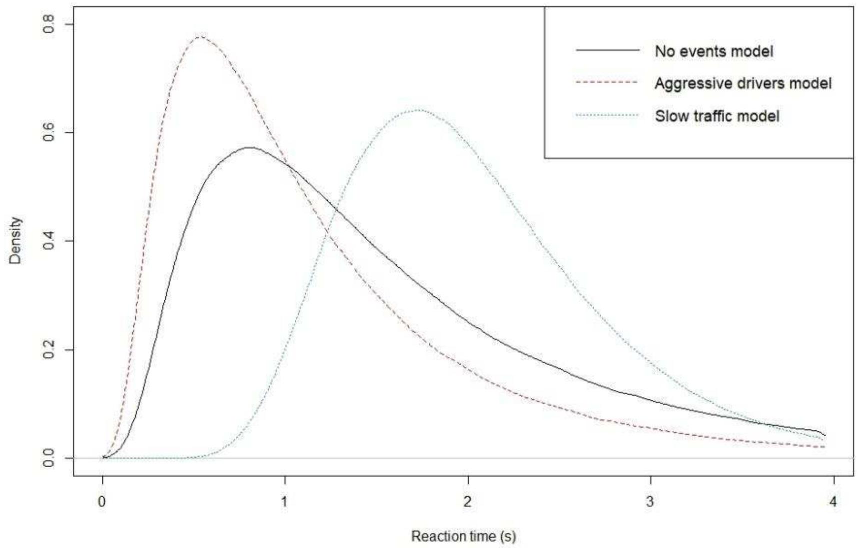

Figure 5 Reaction time distributions of the car-following models

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 affect 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, the models were also compared pairwise, in terms of total fit, with the likelihood ratio test. For each pair, the total sum of LL (unrestricted model) was compared with the LL value of a model estimated using the same data but a single set of parameters only for both components (restricted model). The two models were then compared using the likelihood ratio test with degrees of freedom equal to the difference in estimated parameters. 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.

4.2. 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 3.2. The parameter estimates are presented in Table 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.

Table 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	

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.

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.

4.3. Car-following models with latent stress variable

Following the suggested methodological framework from Section 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 15 are presented in Table 5. The estimates of the other specifications (Equations 20-22) 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 only on the HR indicator of "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 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 4.1, 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 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 6 to 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.

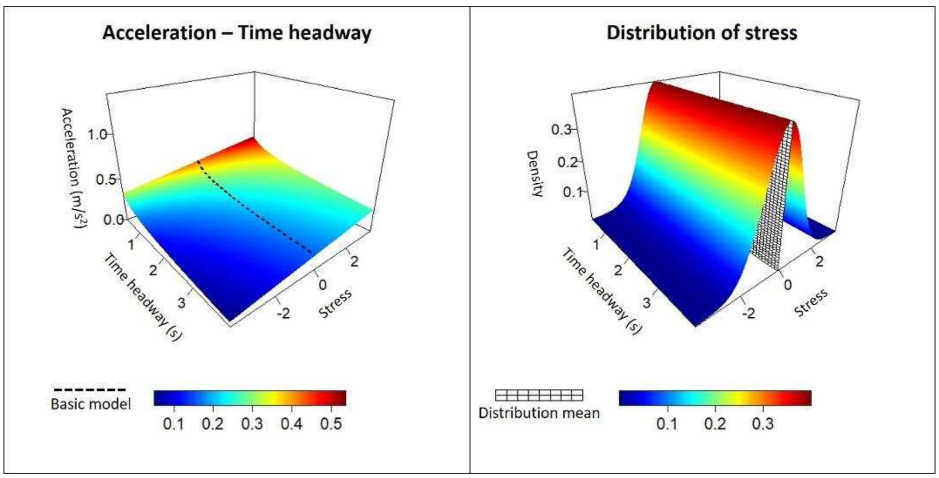

Figure 6: Time headway sensitivity analysis of the "No events" latent variable model

Regarding the derived acceleration patterns per se, Figure 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, 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 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 7 where the sensitivity plot of 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 higher upper range of acceleration compared to the base model (though with lower probabilities, owing to the distribution assumption of stress).

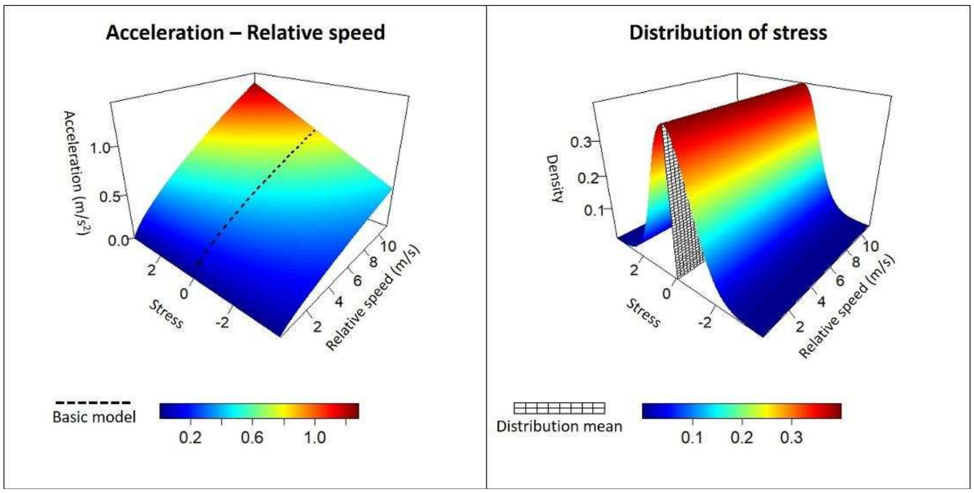

Figure 7: Relative speed sensitivity analysis of the “No events” latent variable model

The outcomes presented regarding the “No events” model also extend to the “Aggressive drivers” model, as congruous patterns are observed (Figure 8 and 9) and all the acceleration trends are in line with expectations. Moreover, Figure 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 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.

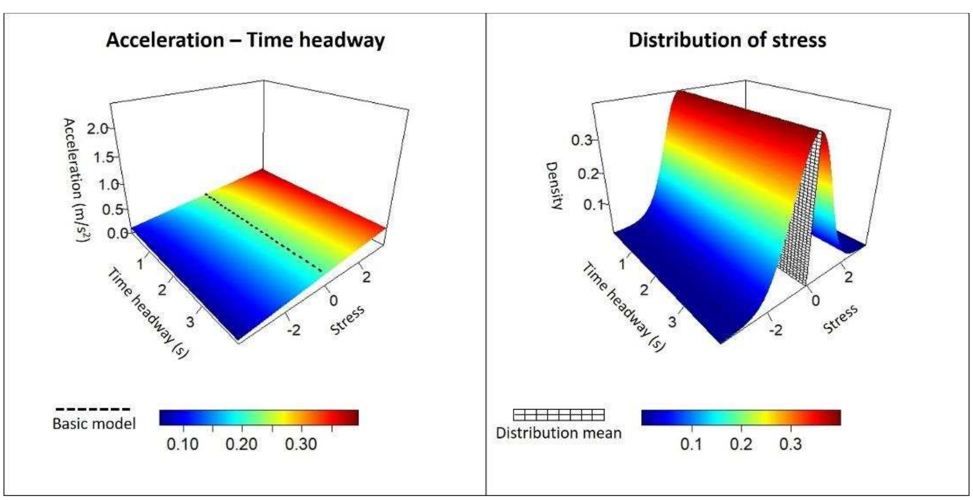

Figure 8: Time headway sensitivity analysis of the “Aggressive drivers” latent variable model

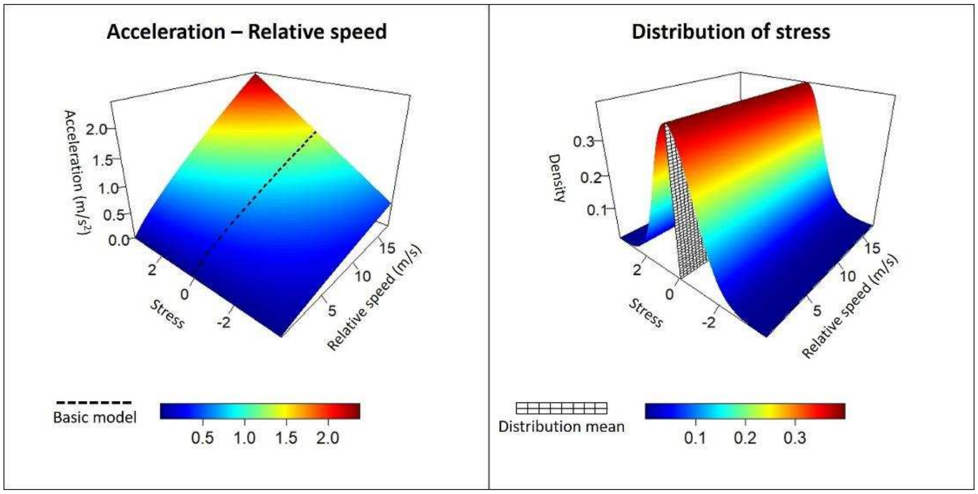

Figure 9: Relative speed sensitivity analysis of the "Aggressive drivers" latent variable model

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. 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 3.2 and 3.3. The parameter estimates are outlined in Table 6.

Similar to the models presented in Section 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 C. They show similar trends to those illustrated in Figures 6-9.

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.

Table 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	

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.

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 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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Appendix A

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

A.1.1 No events model

Acceleration regime

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

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

Deceleration regime

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

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

A.1.2 Aggressive drivers model

Acceleration regime

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

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

Deceleration regime

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

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

A.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

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

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

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

A.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

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

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

A.2.2 Aggressive drivers model

Acceleration regime

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

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

Deceleration regime

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

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

A.2.3 Slow traffic model

Acceleration regime

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

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

Deceleration regime

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

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

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

A.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

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

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

A.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

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

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

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

A.4.1 No events model

$$Stress_n(t) = -0.041 \times \Delta T_n + \eta_n(t)$$
$$\eta_n(t) \sim N(0,\ 1^2)$$

Acceleration regime

$$a_n^{cf,acc}(t) = \left[0.188 \frac{1}{\Delta T_n(t)^{0.394}} + 0.016 \times Stress_n(t)\right] |\Delta V_n(t-\tau_n)|^{0.956-0.188\times Female-0.008\times Age+0.171\times Frequency} + \varepsilon_n^{cf,acc}(t)$$
$$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.446^2)$$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.099 \frac{1}{\Delta T_n(t)^{1.800}} |\Delta V_n(t - \tau_n)|^{1.696+0.502\times Female-1.050\times Accident-0.387\times Frequency} + \varepsilon_n^{cf,acc}(t)$$
$$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.727^2)$$

A.4.2 Aggressive drivers model

$$Stress_n(t) = -0.036 \times \Delta T_n + \eta_n(t)$$
$$\eta_n(t) \sim N(0,\ 1^2)$$

Acceleration regime

$$a_n^{cf,acc}(t) = \left[0.137 \frac{1}{\Delta T_n(t)^{0.033}} + 0.023 \times Stress_n(t)\right] |\Delta V_n(t - \tau_n)|^{0.827} + \varepsilon_n^{cf,acc}(t)$$
$$\varepsilon_n^{cf,acc}(t) \sim N(0,\ 0.633^2)$$

Deceleration regime

$$a_n^{cf,dec}(t) = -0.163 \frac{1}{\Delta T_n(t)^{0.907}} |\Delta V_n(t - \tau_n)|^{0.955+0.290\times Female} + \varepsilon_n^{cf,acc}(t)$$
$$\varepsilon_n^{cf,dec}(t) \sim N(0,\ 0.979^2)$$

Appendix B

B.1 Base "No events" model sensitivity analysis considering sociodemographic characteristics

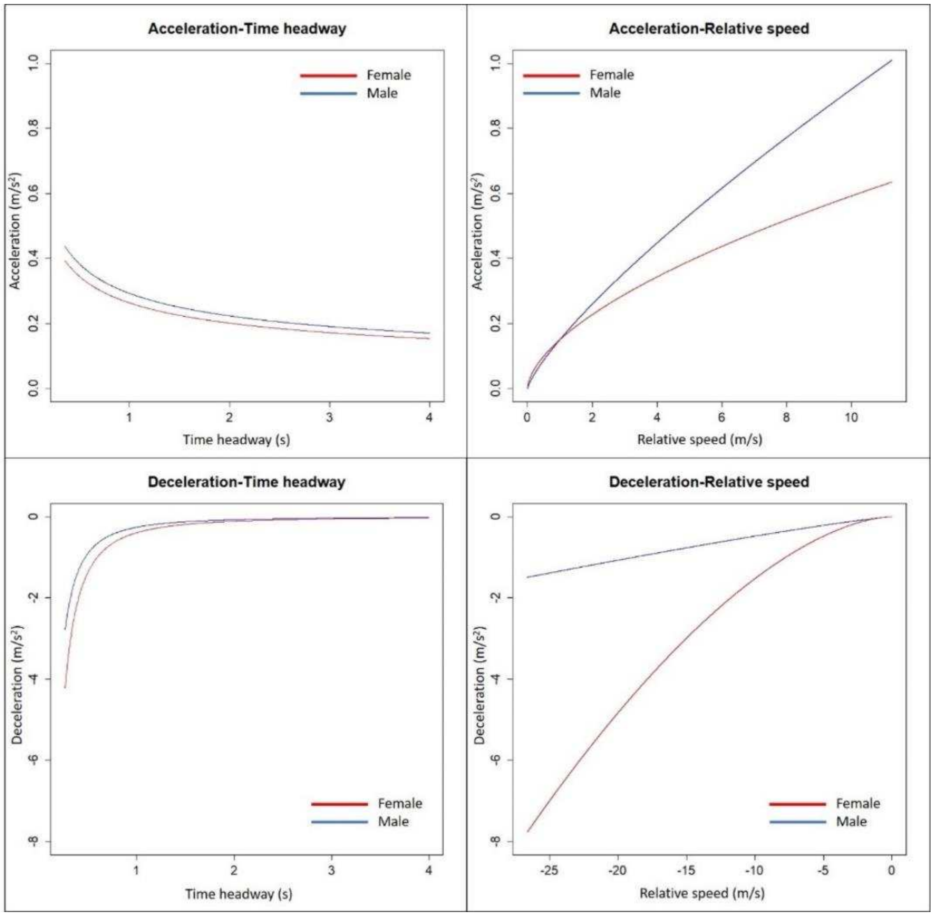

Figure B.1: Gender sensitivity analysis

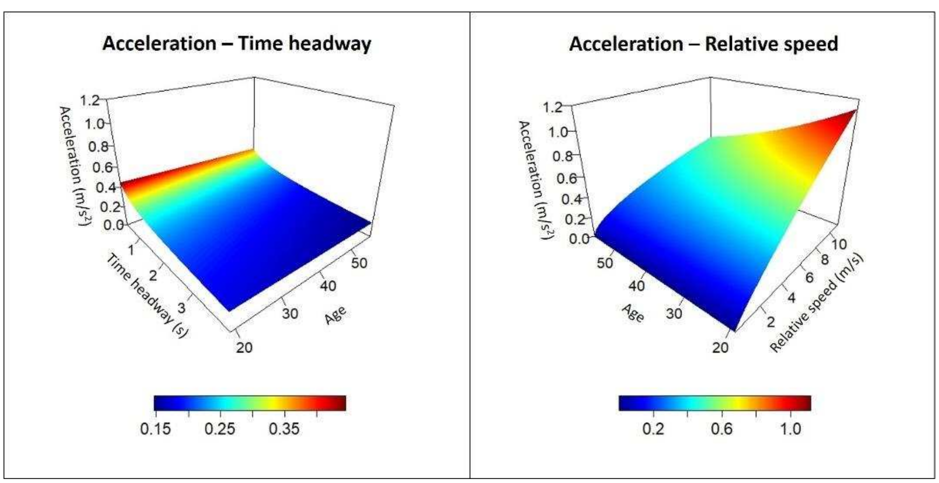

Figure B.2: Age sensitivity analysis

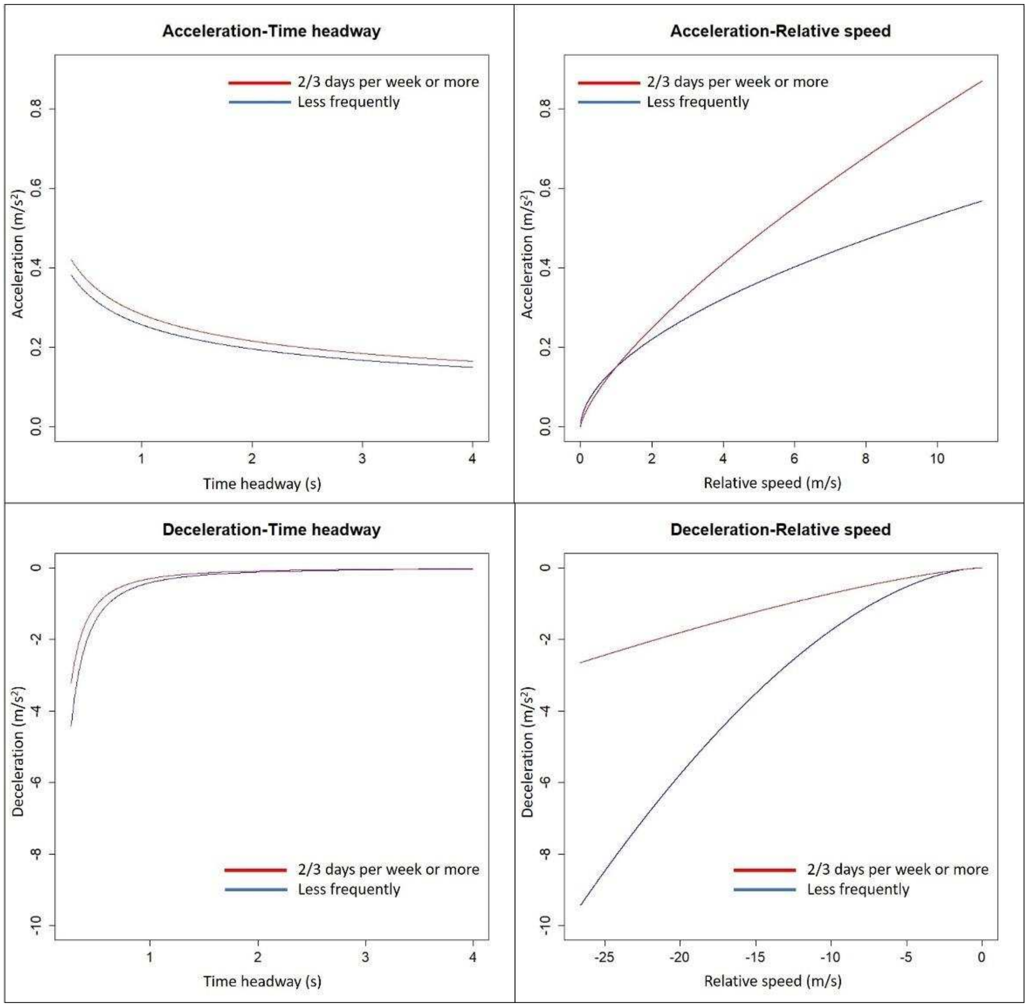

Figure B.3: Driving frequency sensitivity analysis

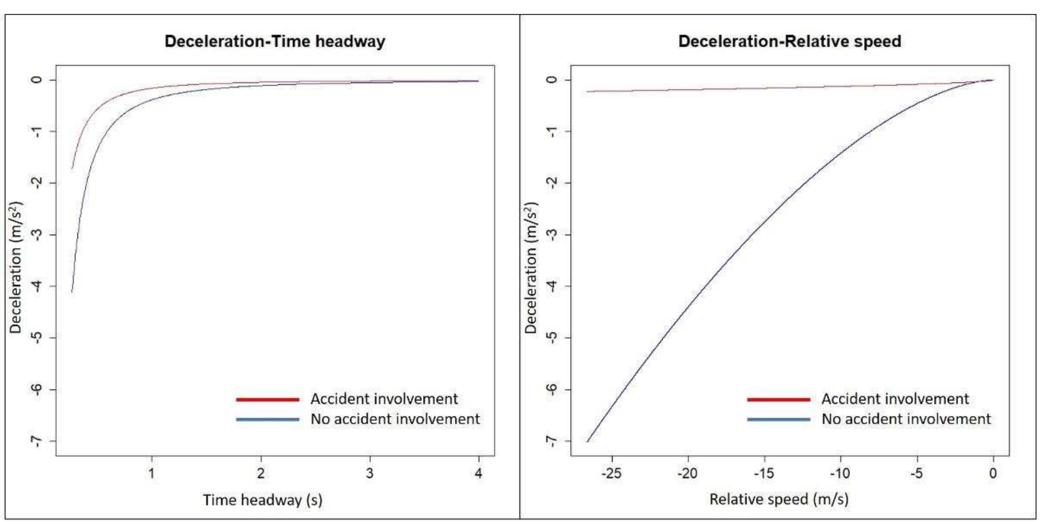

Figure B.4: Accident involvement sensitivity analysis

B.2 Base “Aggressive drivers” model sensitivity analysis considering sociodemographic characteristics

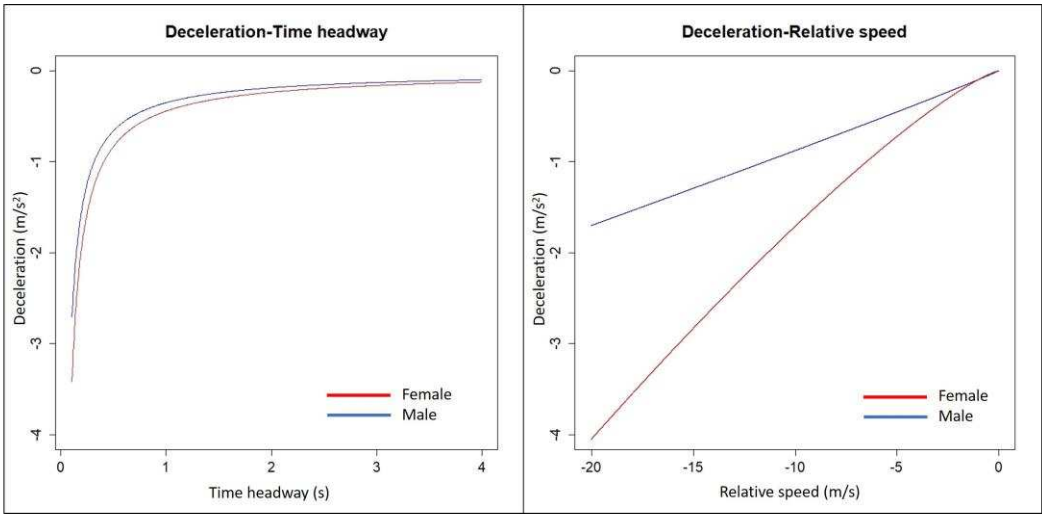

Figure B.5: Gender sensitivity analysis

A.3 Base “Slow traffic” model sensitivity analysis considering sociodemographic characteristics

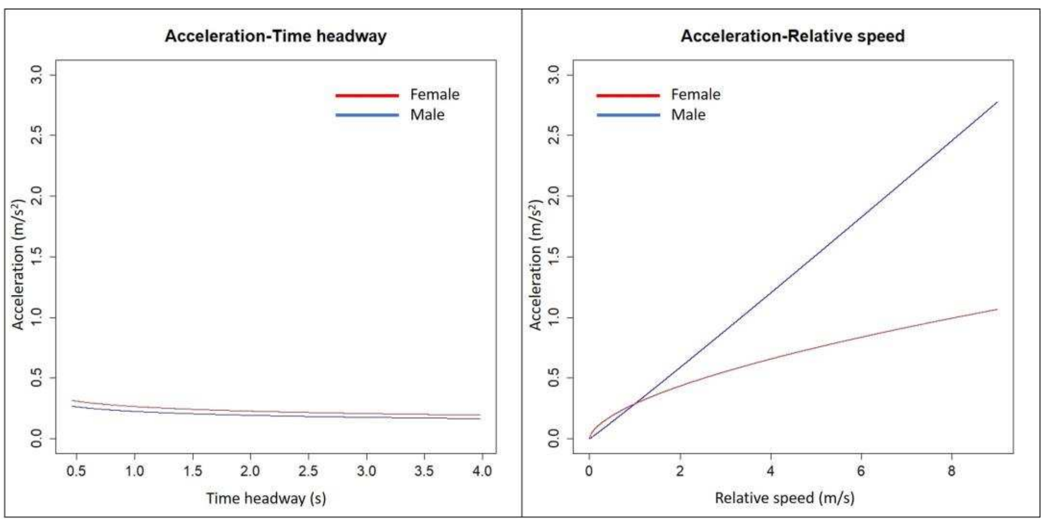

Figure B.6: Gender sensitivity analysis

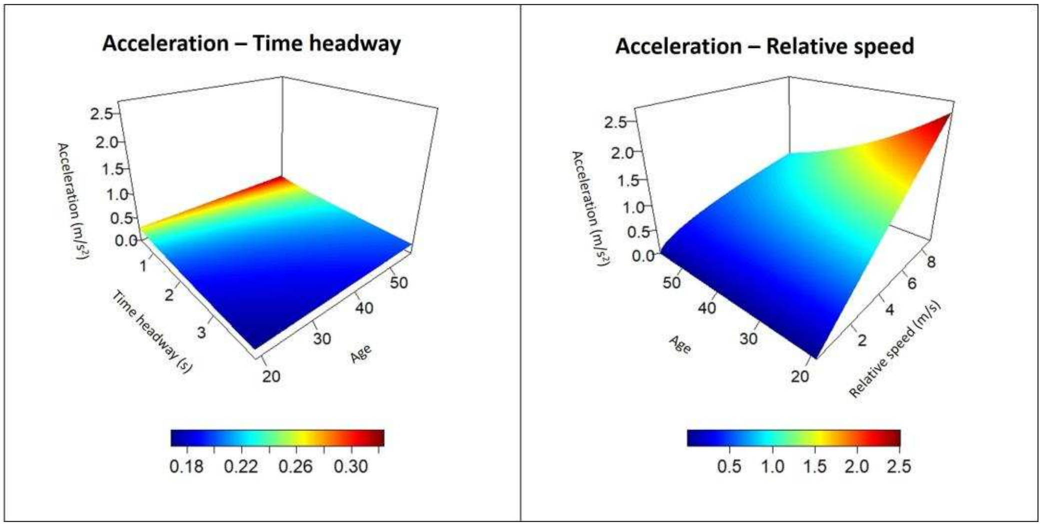

Figure B.7: Age sensitivity analysis

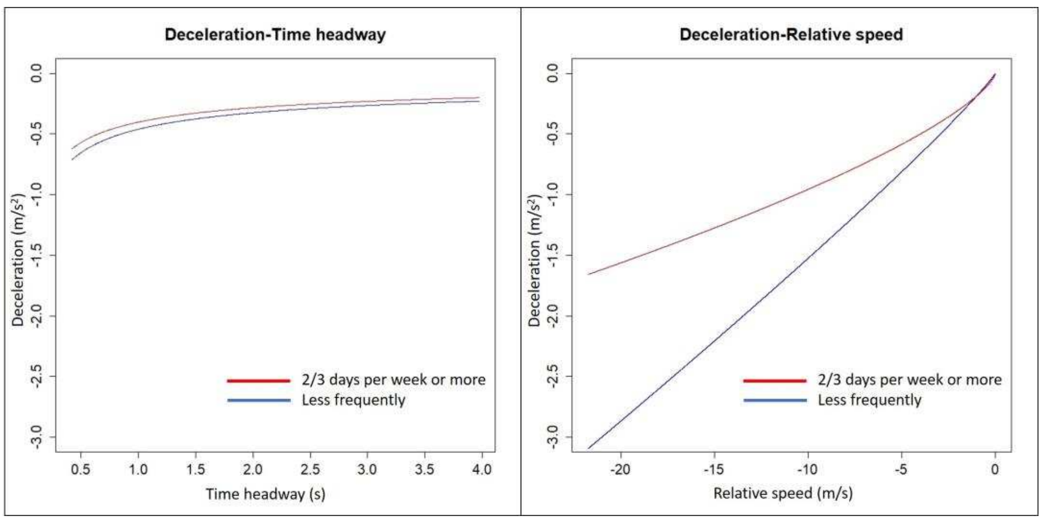

Figure B.8: Driving frequency sensitivity analysis

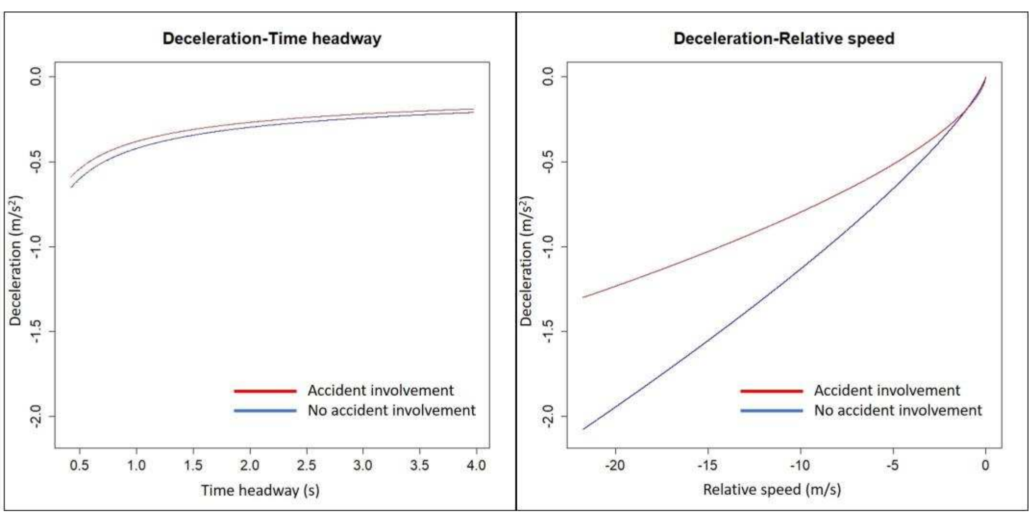

Figure B.9: Accident involvement sensitivity analysis

Appendix C

C.1 Latent variable "No events" model sensitivity analysis considering sociodemographic characteristics

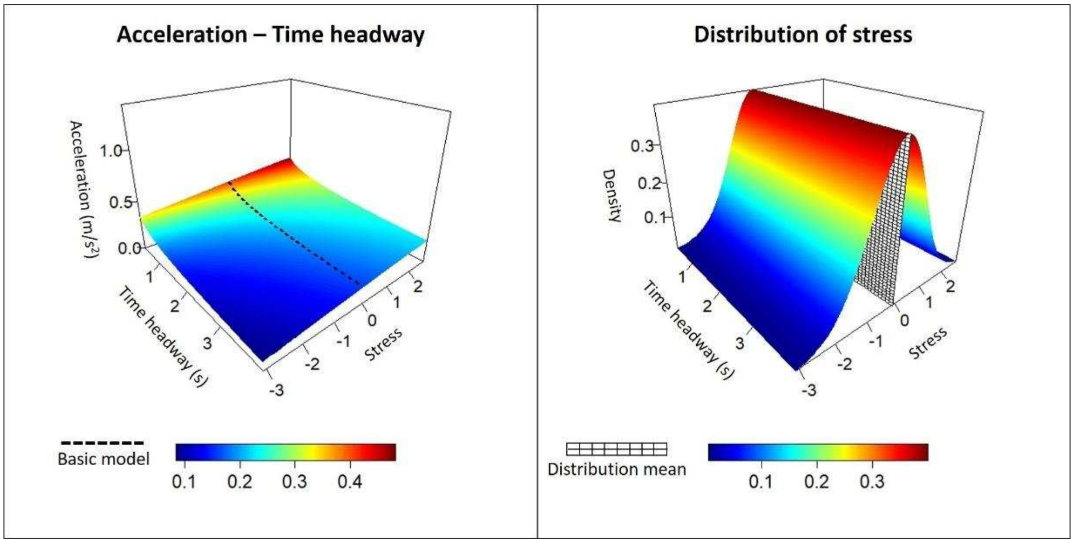

Figure C.1: Time headway sensitivity analysis

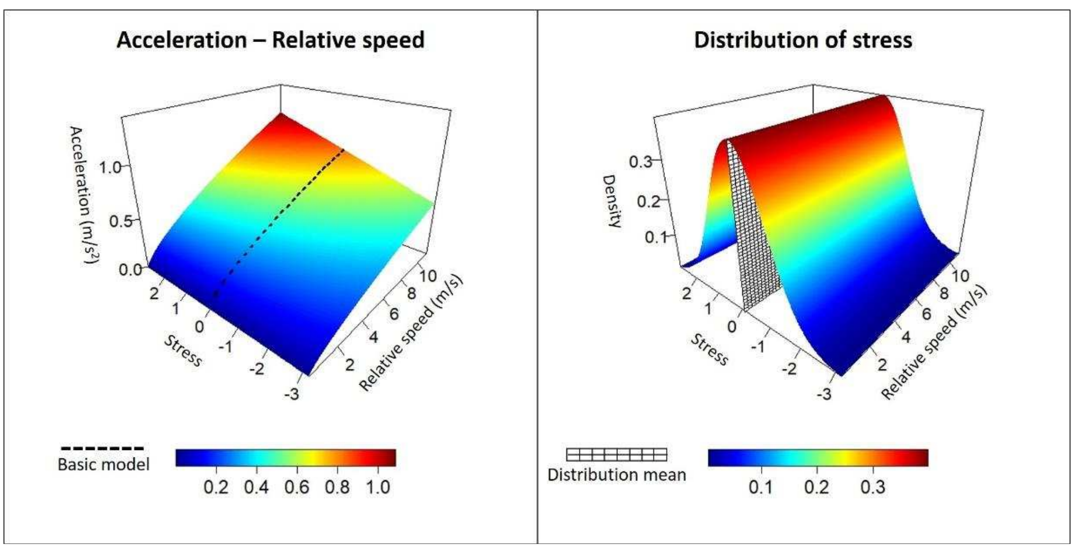

Figure C.2: Relative speed sensitivity analysis

C.2 Latent variable "Aggressive drivers" model sensitivity analysis considering sociodemographic characteristics

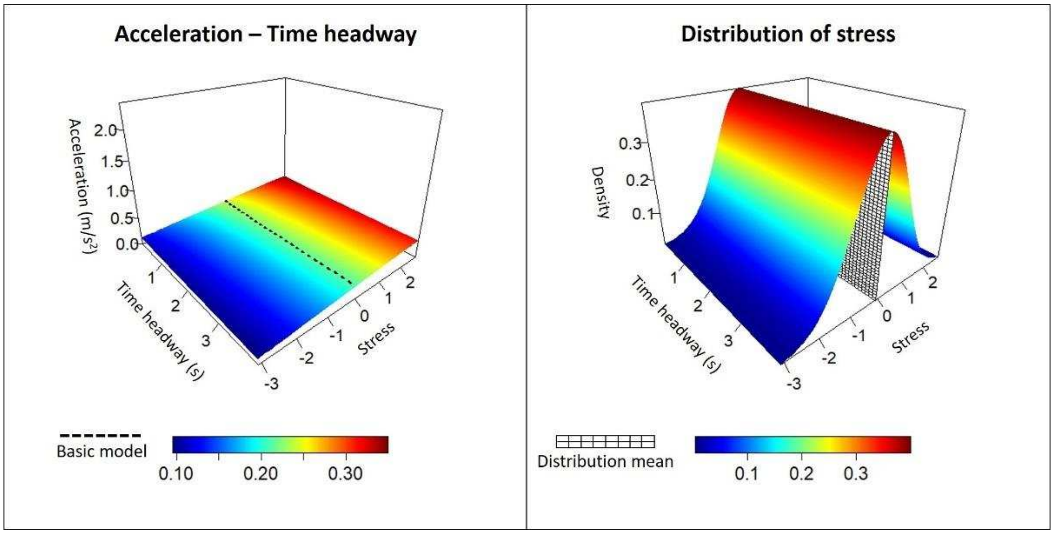

Figure C.3: Time headway sensitivity analysis

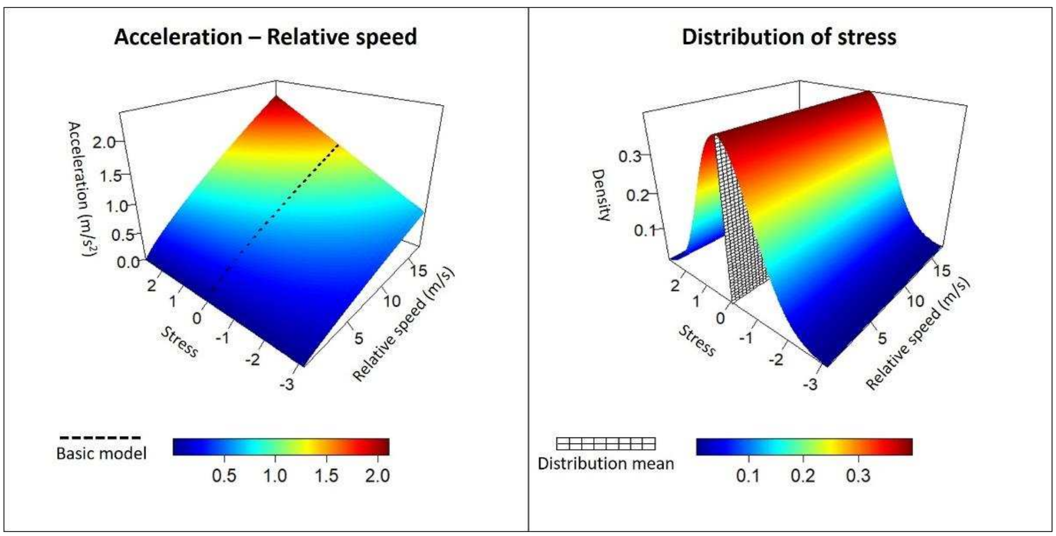

Figure C.4: Relative speed sensitivity analysis