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Effects of road infrastructure and traffic complexity in speed adaptation behaviour of distracted drivers

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ABSTRACT

The use of mobile phones while driving remains a major human factors issue in the transport system. A significant safety concern is that driving while distracted by a mobile phone potentially modifies the driving speed leading to conflicts with other road users and consequently increases crash risk. However, the lack of systematic knowledge of the mechanisms involved in speed adaptation of distracted drivers constrains the explanation and modelling of the extent of this phenomenon. The objective of this study was to investigate speed adaptation of distracted drivers under varying road infrastructure and traffic complexity conditions. The CARRS-Q Advanced Driving Simulator was used to test participants on a simulated road with different traffic conditions, such as free flow traffic along straight roads, driving in urbanized areas, and driving in heavy traffic along suburban roads. Thirty-two licensed young drivers drove the simulator under three phone conditions: baseline (no phone conversation), hands-free and handheld phone conversations. To understand the relationships between distraction, road infrastructure and traffic complexity, speed adaptation calculated as the deviation of driving speed from the posted speed limit was modelled using a decision tree. The identified groups of road infrastructure and traffic characteristics from the decision tree were then modelled with a Generalized Linear Mixed Model (GLMM) with repeated measures to develop inferences about speed adaptation behaviour of distracted drivers. The GLMM also included driver characteristics and secondary task demands as predictors of speed adaptation. Results indicated that complex road environments like urbanization, car-following situations along suburban roads, and curved road alignment significantly influenced speed adaptation behaviour. Distracted drivers selected a lower speed while driving along a curved road or during car-following situations, but speed adaptation was negligible in the presence of high visual cutter, indicating the prioritization of the driving task over the secondary task. Additionally, drivers who scored high on self-reported safe attitudes towards mobile phone usage, and who reported prior involvement in a road traffic crash, selected a lower driving speed in the distracted condition than in the baseline. The results aid in understanding how driving task demands influence speed adaptation of distracted drivers under various road infrastructure and traffic complexity conditions.

1. Introduction

Distracted driving is a major human factors issue in transport safety (Dingus et al., 2016; Pless and Pless, 2014; Haque et al., 2016b). An important finding in studies on mobile phone distracted driving is that drivers regulate their behaviour to compensate for inattention. Previous research suggests that while engaging in a dual task, drivers sometimes prioritize the driving task over use of the mobile phone through different mechanisms, such as reducing speech production (Becic et al., 2010), reducing eyes-off-the-forward roadway times (Hickman and Hanowski, 2012), reducing distraction proneness (Tivesten and Dozza, 2014), decreasing driving speeds (Wandtner et al., 2016; Young and Lenné, 2010; Oviedo-Trespalacios et al., 2017), and pulling over to the side

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of road (Zhou and Wang, 2016). A comprehensive review on self-regulation of mobile phone distracted drivers is available in Young (2015). In addition, theoretical models of compensatory behaviour need to be validated with empirical data. The lack of knowledge on the mechanisms and effect of the behavioural adaptation process prevents us from identifying countermeasures that can potentially reduce crash risk, enable road safety assessment of innovations in mobile phone systems, and provide a calibration of traffic and human factors models to predict and monitor driving performance.

Recent advocacy for broad approaches in road safety has emphasized the need to conduct system analyses and evolve from a driver-centric approach to a human-machine system approach (Oviedo-Trespalacios et al., 2016) and, more broadly, a socio-technical system approach (Young and Salmon, 2015). Utilising these approaches, it can be shown that systemic outputs of mobile phone distracted driving are influenced by the driving environment. Furthermore, research in mobile phone distracted driving has reported a wide range of behavioural adaptation behaviours that occur depending on the situation, e.g. drivers conversing on a mobile phone avoid overtaking slower vehicles (Charlton, 2009) or changing lanes (Cooper et al., 2009), and distracted drivers on winding roads decrease their speed (Tractinsky et al., 2013).

While prior research has recognized a variety of compensatory strategies in mobile phone distracted drivers, comparatively little is known about the mechanisms and moderators of this behavioural process. The lack of knowledge of the influence of traffic environment complexity in the behavioural adaptation processes of distracted drivers has led to the role of road environmental features being defined in an intuitive fashion. Young and Regan (2008) developed a successful theoretical model of behavioural adaptation that explains that behavioural adaptation depends on driver characteristics, secondary task demand, and driving task demand. The driving task demands are said to be influenced by traffic conditions, weather, road design, and occupants among many other factors. Unfortunately, the extent of this environmental impact on behavioural adaptation of distracted drivers is unknown, and the impact of the road environment complexity on driving behaviour of distracted drivers represents a distinct research gap.

This paper seeks to examine behavioural adaptation of drivers under different traffic and environmental complexity while engaged in mobile phone conversations. Tactical or strategical adaptation (e.g. long pauses or pulling over) to the distraction task is beyond the scope of this study. Traffic and environmental complexity here means the group of road features that change the inherent difficulty within the given driving situation that a distracted driver is facing. Knowing environmental predictors of speed behavioural adaptation could help understand mechanisms through which mobile phone usage results in safety-critical events, and how interventions could be developed to decrease the incidence of decisions by drivers to engage in distractive tasks like mobile phone conversations and texting.

2. Method

2.1. Participants

Thirty-two young drivers (18–26 years) were recruited to drive in a simulated urban/sub-urban road traffic environment. Recruitment of participants took place via e-mail, using newsgroups and social networks. All participants were required to have a valid driver license issued by a road authority in Australia. Table 1 describes the demographic characteristics of the drivers recruited for this experiment.

Table 1
Baseline demographic characteristics (n = 32).

Socio-demographic variables	N (%) [a]Mean (± *SD*)
Age (yrs.)	21.8 (±1.9)
Gender	
Male	16 (50)
Female	16 (50)
Years of driving experience	4.2 (±1.8)
Self-reported road crashes	
Yes	11 (34.4)
No	21 (65.6)
Frequency of mobile phone usage while driving (general use)	
At least 1 or 2 times per day	11 (34.4%)
At least 1 or 2 times per week	15 (46%)
At least 1 or 2 times per month	6 (18.8)
At least 1 or 2 times per year	0 (0.0%)
Never	0 (0.0%)
Safe attitude towards mobile phone usage[b]	
Strongly disagree, disagree and slightly disagree	1 (3.1)
Neither agree or disagree	2 (6.3)
Strongly agree, agree and slightly agree	29 (90.6)
Self-efficacy toward self-regulation[b]	
Neither agree or disagree	5 (15.6)
Strongly agree, agree and slightly agree	27 (84.4)

[a] Continuous variables (means and standard deviations are reported instead of numbers and percentages).
[b] Scale: (1) Strongly disagree – (7) Strongly agree.

2.2. Apparatus

The CARRS-Q Advanced Driving Simulator located at the Queensland University of Technology (QUT) was used in this study. This high fidelity simulator included a complete car with working controls and instruments on a 6°-of-freedom motion platform surrounded by three front-view projectors providing 180° high resolution field view to drivers. Wing mirrors and the rear view mirror were substituted by LCD monitors to simulate rear view mirror images. Road images and interactive traffic were generated at life size onto front-view projectors, wing mirrors and the rear view mirror at 60 Hz to provide a photorealistic virtual environment. The car used in this experiment was a complete Holden Commodore vehicle with automatic transmission. The simulator was also capable of producing realistic forces through the steering wheel to provide the realism of driving particularly during negotiating the horizontal curves. More information of the CARRS-Q Advanced Driving Simulator can be consulted in http://www.carrsq.qut.edu.au/publications/corporate/Simulator_fs.pdf or Haque and Washington (2015).

2.3. Experiment setup

Participants were invited to drive the CARRS-Q Advanced Driving Simulator after giving written informed consent. They also completed a questionnaire about demographic, attitudes and driving characteristics. The experiment included three randomly ordered driving routes and three randomly ordered experimental conditions (no distraction, handheld phone conversation, and hands-free conversation). All three driving routes had the same geometry and road layout but different route starting points and randomly located traffic events (e.g. interaction with a lead car, passing oncoming vehicles, interaction with pedestrians, etc.). The experimental conditions were counterbalanced to reduce learning effects.

The phone conversation dialogues used in this study were simple but cognitive in nature as they required the participants to provide an appropriate response after hearing a complete question (e.g., 'Jack left a dinner in his microwave for Jim to heat up when he returned home. Who was the dinner for?'), solving a verbal puzzle (e.g., 'Felix is darker than Alex. Who is lighter of the two?'), or solving a simple arithmetic problem (e.g., 'If three wine bottles cost 93 dollars, what is the cost of one wine bottle?'). These types of phone conversations required short term memory and processing of information, and thus increased the cognitive load of drivers. Conversation dialogues were modified from the conversations used by Burns et al. (2002). These dialogues were selected in order to ensure a consistent level of cognitive distraction among participating drivers. For experimental drives in phone conditions, the experimenter called the participant prior to the drive, and the primary task of the experimenter was to keep the participant engaged until the end of the drive and to not permit long pauses in conversation.

2.4. Simulated road scenarios

Seven road scenarios were simulated in the driving simulator with varying combinations of road marking, geometry, and road layout. Simulated roads were similar to the road network in Australia. These scenarios included a mixture of infrastructure and traffic complexity as illustrated in Table 2. Among these roads, there were two types of urbanization (urban or suburban), two types of traffic interaction (car following "fixed headway of 60 m" or free flow driving), three types of road geometry (straight road, mild bend along the road, and sharp bend along the road), and two types of adjacent traffic (the presence or absence of oncoming traffic along the opposite lane of two lane two-way undivided roads). Note that urban road environment here included a detailed simulation of the Central Business District (CBD) of Brisbane which has mostly grid type road configuration with the speed limit along these roads mostly 40 kph. The speed limits along suburban roads varied between 50 and 60 kph. A snapshot of each road traffic scenario is presented in Table 2. A representative length of 100 m was selected along each road segment to extract driving performance data. There were two main reasons for this type of data extraction. First, a selected segment should have uniform traffic and road geometry over its entire length to guarantee driving behaviour is observed against a particular type road infrastructure and traffic complexity. Second, segments must have enough separation from a previous (or future) change in the traffic conditions or road geometry in order to give drivers enough time to stabilise their driving and avoid possible transition effects.

2.5. Experimental protocol

Recruited participants were invited to the driving simulator laboratory at Queensland University of Technology (QUT). All participants were informed about potential risk of participation, and they signed a standardized informed consent form prior to participation. As part of this experiment, participants completed a questionnaire on socio-demographic characteristics and driving behaviour. Participants were briefed on the protocol of the experiment, with detailed instructions on how to operate the simulator vehicle. Participants took a practice drive and diagnosed for motion sickness before taking experimental drives. The practice drive included possible roads, signs, and vehicular and pedestrian traffic that the participant might encounter during the experimental drives. The participants were asked to drive for 10 min minimum, but they were allowed to drive as much as they wished to get comfortable with the simulator. They also practised phone conversations with a research officer. The research officer engaged in phone conversations was located in a different room so that she was not aware of the simulation progress. In experimental drives, participants drove three different driving routes for each mobile phone conditions (baseline, hands-free, and handheld). They used a Bluetooth headset for conversations in the hands-free condition, and put the mobile to their ear in the handheld condition. The order of experimental conditions was randomised across participants. Participants were instructed to drive as they normally would and to obey the posted speed limits. Participants were reimbursed with AUD $50 for their time upon completion of the experiment.

3. Data analysis techniques

3.1. Speed behavioural adaptation

The driving speed data was extracted from the simulator for each of the three driving conditions: baseline or no distraction, handheld phone conversation, and hands-free phone conversation. The speed adaptation in a particular phone condition was calculated based on deviation from the posted speed limit and the difference of their driving speed from the baseline (no phone) condition. Let SA_{ipt} be the speed adaptation of driver i in phone condition p at time interval t, S the selected driving speed at any time t, and S_L the posted speed limit. The speed adaptation for a phone condition is calculated by averaging for a range of time intervals as follows:

$$SA_{ipt} = \sum_{t=1}^{n} [(S - S_L)_{p=baseline} - (S - S_L)_{p=hands-free/handheld}]/n \tag{1}$$

Therefore, SA_{ipt} represents the difference in speed deviation from the speed limit between phone and baseline conditions.

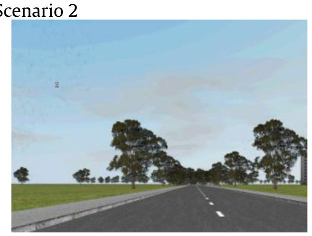
3.2. Statistical analysis

A two-step analysis approach was implemented in this study. First, to explore the underlying relationship between road traffic complexities and speed adaptation, a decision tree was developed. The purpose of this data mining using the decision tree is to identify the groups of road environmental features that generate similar types of speed adaptation. Secondly, a Generalized Linear Mixed Model (GLMM) with repeated measures was estimated to develop inference about the predictors of speed adaptation. Brief descriptions of these two methods are presented in the following paragraphs.

The decision tree was fitted following the CHAID (Chi-Squared Automatic Interaction Detection) exhaustive data mining algorithm developed by Kass (1980). The calibrated decision tree hierarchically identified mutually exclusive and exhaustive subgroups of road traffic complexities whose members share common characteristics that influence the speed adaptation of distracted drivers. The performance of exhaustive CHAID was also compared with representative community decision tree algorithms, including Classification and Regression Trees (CRT) and Quick, Unbiased, Efficient, Statistical Tree (QUEST). In addition, the fitness of the developed decision tree was tested by a cross-validation technique using 85% of random samples for model development and the remaining 15% for assessing model prediction capability. This cross validation procedure was repeated 10 times with different set of random samples.

Without requiring a specification on the functional form and assumption on the additivity of predictors, the decision tree was helpful in identifying the complex relationship between road traffic complexity and speed adaptation of distracted drivers. However, the developed decision tree was not capable of providing inferences about the predictors of speed adaptation. To circumvent this methodological shortcoming, the identified subgroups of road traffic complexity were converted into predictors and tested in a Generalized Linear Mixed Model (GLMM) with repeated measures.

Table 2
Simulated road scenarios in the driving simulation.

Scenario	Description	Road Infrastructure and Traffic Complexity			
		Urbanization	Presence of oncoming traffic	Traffic interaction (lead vehicle)	Road geometric configuration
Scenario 1 	Urban straight road (Speed limit 40 kph.)	Yes[a]	No	No	Straight road
Scenario 2 	Suburban straight road in free flow condition (Speed limit 60 kph.)	No	No	No	Straight road
Scenario 3 	Suburban straight road with a lead vehicle (Speed limit 60 kph.)	No	No	Yes	Straight road

Scenario 4 	Suburban curved road in free flow condition (Speed limit 60 kph.)	No	No	No	Sharp bend (r < 350m) along the road
Scenario 5 	Suburban curved road with oncoming traffic (Speed limit 60 kph.)	No	Yes	No	Sharp bend (r < 350m) along the road
Scenario 6 	Suburban curved road in free flow condition (Speed limit 60 kph.)	No	No	No	Mild bend (r > 350m) along the road
Scenario 7 	Suburban curved road with oncoming traffic (Speed limit 60 kph.)	No	Yes	No	Mild bend (r > 350m) along the road

[a] In the urban condition there were on average over 12 times as many buildings, oncoming vehicles and other highway furniture compared to the suburban condition.

In addition, driver characteristics, phone condition, and secondary task experience were used as predictors of speed adaptation. Let's say SA_{ij} represents the speed adaptation of participant i along road segment j, and μ_{ij} is the corresponding mean. The model structure of the GLMM for the speed adaptation can be expressed as follows:

$$g(\mu_{ij}) = \alpha + \mathbf{X}'_i\boldsymbol{\beta} + \mathbf{Y}'_i\boldsymbol{\gamma} + \mathbf{Z}'_j\boldsymbol{\lambda} \tag{3}$$

where g is the link function with Gaussian link, $\boldsymbol{X}_i$ is a vector of attributes for driver characteristics and secondary task experience (i.e. age, gender, years of driving experience, frequency of mobile phone usage, safe attitude towards mobile phone usage, self-efficacy towards self-regulation), $\boldsymbol{Y}_i$ represents phone conditions (i.e. handheld or hands-free phone conversations), and $\boldsymbol{Z}_j$ is a vector of attributes for road infrastructure and traffic complexity including those derived from the decision tree. α, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\lambda}$ are estimable parameters. Parameters (such as β) in the GLMM are estimated as follows (Wang and Abdel-Aty (2006)):

$$S(\beta) = \sum_{i=1}^{k} \frac{\partial \mu'_i}{\partial \beta} V_i^{-1}(SA_i - \mu_i(\beta)) = 0 \tag{2}$$

where V_i is an estimator of the covariance matrix of SA_i specified as $V_i = \phi {A_i}^{1/2} R_i(\rho) {A_i}^{1/2}$. In the covariance matrix, A_i is a $n_i \times n_i$ diagonal matrix with $v(\mu_{ij})$ as the j^{th} diagonal element. V_i can be different from one driver to another, but it is common to specify the same form for all drivers. $R_i(\rho)$ is a $n_i \times n_i$ working correlation matrix specified by the vector parameter ρ. An exchangeable working correlation that makes constant correlations between any two observations within a driver is specified as:

$$Corr(SA_{ij}, SA_{il})\{\begin{matrix} 1 & j = l \\ \rho & j \neq l \end{matrix} e.g. R_{4x4} = \begin{bmatrix} 1 & \rho & \rho & \rho \\ \rho & 1 & \rho & \rho \\ \rho & \rho & 1 & \rho \\ \rho & \rho & \rho & 1 \end{bmatrix} \tag{5}$$

Detailed expressions for estimating ρ's are available in Liang and Zeger (1986), and the suitability of this approach for modelling driving performance of distracted drivers has been tested before by Haque et al. (2016a). The goodness of fit of the above model was tested using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

4. Results

4.1. Descriptive statistical analysis

Prior to developing speed adaptation models, a descriptive statistical analysis was performed to compare speed adaptation behaviour of distracted drivers across mobile phone conditions and road traffic complexity. Table 3 presents the summarized data and associated *t-test* results. It appears that the maximum speed adaptation (about 5.77 kph) occurred along a suburban road during car-following. A similar magnitude of speed adaptation (about 5.03 kph) occurred along a road with a sharp bend during handheld phone conversation. Statistical differences in speed adaptation by mobile phone conditions were tested using *t-tests* after Bonferroni correction for multiple comparisons. The difference in speed adaptation between handheld and hands-free phone conditions was not statistically significant except one out of seven road traffic scenarios. A slight difference between two phone conditions was only observed for driving along a road in an urban area, indicating that drivers distracted by handheld phone conversations adapt their speed less than in the hands-free phone condition.

Potential differences in speed variability were examined using paired sample *t*-tests. However, no differences were observed between the baseline and distracted conditions ($p > 0.05$).

4.2. Decision tree analysis

A decision tree was constructed to explain variability in speed adaptation behaviour of distracted drivers. The risk estimate of this model with our data was 31.5, and the cross-validation risk estimate was 32.4, which were the lowest values for all the algorithms tested. A total of five variables were included as possible explanatory variables in the decision tree, including urbanization (urban or suburban), traffic interaction (car-following or free flow driving), road geometric configuration (straight road, mild bend (r > 350m) along the road, or sharp bend (r < 350m) along the road), the presence of adjacent traffic (the presence or absence of oncoming traffic along the opposite lane of two lane two-way undivided roads), and mobile phone conditions (handheld or hands-free phone conversations). No maximum tree depth was set for the decision tree, but the significance values for splitting nodes and merging categories were set as 5%.

Fig. 1 presents the developed decision tree for the speed adaptation behaviour of distracted drivers. The final model structure identifies three splitting variables, including urbanization, traffic interaction, and road geometric configuration. The presence of an urban environment represents the highest information gain and is therefore at the top of the tree. Speed adaptation in the urbanized environment is about −0.45 kph, while the speed adaptation along suburban roads is about 3.13 kph.

Traffic interaction splits the speed adaptation along suburban roads into two groups. Speed adaptation in car-following situation is about 5.08 kph, indicating that distracted drivers select an average 5.08 kph lower speed during car-following situation along suburban roads. In the free-flow condition, the average driving speed of distracted drivers is about 2.75 kph lower than for the baseline condition.

Road geometric condition was the third level variable in the decision tree, which further splits speed adaptation in free flow driving condition along suburban roads. Results indicate that speed adaptation along straight road segment or roads with mild curve is about 1.91 kph, while speed adaptation along roads with sharp bend is about 4.01 kph.

It appears that road traffic complexity can be grouped into four homogeneous groups following the complementary and exclusive branches of the decision tree for the speed adaptation behaviour of distracted drivers. They are urbanized environment (includes scenario 1), car-following along suburban roads (includes scenario 3), driving along straight or mildly curved roads in free flow conditions (includes scenarios 2, 6, and 7), and driving along suburban road with a sharp bend (includes scenarios 4 and 5). These four groups were converted into four mutually independent and exclusive indicator variables following the procedure in Haque et al. (2016a) and tested in the GLMM model to develop inferences about speed adaptation behaviour.

4.3. Generalized linear mixed model (GLMM) results

The repeated measures GLMM described in equation 2 was estimated to identify significant predictors of speed adaptation of distracted drivers. As the difference in speed adaptation was not statistically significant, and mobile phone condition was not a significant node in the decision tree, speed adaptations across phone conditions were averaged and included as the dependent variable in GLMM. In addition to road infrastructure/traffic complexity identified by the decision tree, driver personal characteristics such as age, gender, driving experience, psychological resources like self-efficacy and attitudes towards mobile phone use, and secondary task experience were used as predictors of speed adaptation in the GLMM. The parsimonious model was derived using the Akaike information Criterion (AIC) and Schwarz's Bayesian Criterion (SBC).

Table 3
Estimations speed adaptation behaviour by scenario, road infrastructure, traffic complexity and interface type.

Condition	Handheld Mean (SD)	Hands-free Mean (SD)	p-value	Combined interface[†] Mean (SD)
Scenario 1: Urbanised straight road	−1.77 (5.14)	0.87 (4.15)	0.003[*]	−0.45 (4.05)
Scenario 2: Suburban straight road in free flow condition	0.86 (5.03)	1.27 (4.42)	0.627	1.07 (4.09)
Scenario 3: Suburban straight road with leading traffic	5.77 (8.03)	4.39 (6.92)	0.326	5.08 (6.4)
Scenario 4: Suburban curved road (r < 350m) in free flow condition	5.03 (5.16)	4.34 (5.06)	0.486	4.69 (4.31)
Scenario 5: Suburban curved road (Curve r < 350m) with oncoming traffic	4.28 (5.95)	2.39 (6.43)	0.059	3.33 (5.56)
Scenario 6: Suburban curved road (r > 350m) in free flow condition	1.33 (5.2)	2.11 (4.89)	0.313	1.72 (4.57)
Scenario 7: Suburban curved road (r > 350m) with oncoming traffic	3.68 (4.76)	2.21 (6.22)	0.307	2.94 (3.83)

[*] Significant differences in speed adaptation between handheld and hands-free interface after Bonferroni correction for multiple comparisons (p < 0.007).
[†] Average speed adaptation during handheld and hands-free conversation by condition.

AIC and SBC values of the final model were 708.42 and 719.46, respectively.

The significant variables estimated by the GLMM are reported in Table 4. Significant variables in the parsimonious model were *road traffic complexity*, *driver age*, *self-reported prior involvement in a crash*, *driving experience*, and *attitude towards mobile phone usage*. Driver gender, self-efficacy towards self-regulation, and the frequency of mobile phone usage while driving were not significant predictors in the GLMM for speed adaptation.

Among the four categories of road traffic complexity, driving along straight or mildly curved roads in free flow conditions was used as the reference or base category. Compared to the base category, the speed adaptation of distracted drivers is about 3.17 kph higher during car-following along suburban roads, about 2.10 kph higher while driving along roads with a sharp bend, and about 2.36 kph lower during driving through at urbanized road environment.

Among the driver demographics, speed adaptation increases by about 0.83 kph with each year increase in driver age. Drivers who self-reported having been involved in a traffic crash during previous three years are found to adapt their speed more in distracted conditions. Years of driving experience is a negative predictor of speed adaptation. Distracted drivers are found to select about 0.88 kph faster speed for every additional year of driving experience. Among the psychological variables, *attitude towards mobile phone use* is a significant predictor, indicating that drivers who believe that mobile phone conversations impair driving performance appear to reduce their speed more in distracted condition for every additional point on the Likert scale response ((1) Strongly disagree – (7) Strongly agree).

5. Discussion and conclusions

Using a simulator experiment in an advanced driving simulator, this study examined the impact of road infrastructure and traffic complexity on the speed adaptation of mobile phone distracted drivers. By applying a combined decision tree and GLM model, this study identifies that drivers modify their speed behaviour under the presence of certain types of road infrastructure and traffic complexity, including car-following situations along suburban roads, roads with a sharp bend, and urbanized road environments. After controlling for driver characteristics and unobserved specific heterogeneity, the study shows that, under presence of car following interaction, drivers selected the lowest speed compared to the rest of the road characteristics and traffic complexity included in this study. Overall, the findings seem to support the theoretical model of Young and Regan (2013) in which driving behaviour adaptation of distracted drivers is postulated to be a function of driving task demands and driver characteristics.

In most examples of road traffic complexity tested in this study, the difference in speed adaptation was not significantly different across handheld and hands-free phone conditions. Earlier research has also reported similar lack of differences in driving performance (e.g. safety-critical events, reaction time and lane keeping) (Horrey and Wickens, 2006; Fitch et al., 2014; Fitch et al., 2013) or slightly differences in speed (Caird et al., 2008) between hands-free and handheld phone conditions. These may suggest that the adaptation processes of mobile phone distracted drivers are by and large explained by interactions with the road traffic environment rather than the variations in hands-free and handheld phone conditions. In addition, given the fact that speed adaptation was not consistent throughout driving, it may imply that the "speed reductions" are not solely explained by the presence of dual-tasking, and there might be some influence of personal characteristics (e.g., experience or decision making processes).

A difference in speed adaptation between handheld and hands-free conditions was only observed in the urban road environment. Handheld conversations were associated with a speed increment of 1.77 kph, while hands-free conversations were associated with a speed decrement of about 0.87 kph. This might be due to the misperception of risk about phone conditions among drivers in which hands-free phone conversations are often perceived as the "safer" option (Huth and Brusque, 2014). In contrast, an Australian study conducted by Horberry et al. (2006) reported that increased environmental complexity (visual clutter) does not trigger speed changes. As there is a difference between these two phone conditions, there may be two possible explanations for this difference in the urban road environment: (*i*) handheld mobile phone use is not legally permitted in Australia and participants in this study are likely to have little or no experience using a handheld mobile phone in a highly urbanised area such as Brisbane CBD which means that they have not developed a response based on their driving experience, or (*ii*) the proprioceptive sensory feedback coming from the participant's hand and arm are likely to cause a larger impairment in scenarios where the visual workload is more demanding.

Distracted drivers adapt their speed 2.4 kph less on urban than suburban roads with similar road geometry and traffic. A recent naturalistic study in Germany also reported that distracted drivers adapt their speed 1.6 kph less in urban than suburban roads (Metz et al., 2015). These results may imply that drivers engaged in a secondary task on a road with low hazards may engage more actively in the secondary task. Larger engagement in the secondary task could result in larger speed adaptation. Recent research has shown that drivers prefer to engage in a secondary task in less demanding situations (Wandtner et al., 2016).

In suburban areas, distracted drivers reduce their speed by 3.5 kph in car-following situations compared to free flow driving. Previous research also reported that traffic interactions such as heavy traffic and windy roads lead drivers distracted by mobile phone tasks selecting a lower driving speed compared to the non-distracted condition (Tractinsky et al., 2013). Using naturalistic data, Fitch et al. (2014) argued that speed decrease in high traffic conditions may be due to vehicle to vehicle interactions, not necessarily a consequence of mobile phone usage. In this study, vehicle

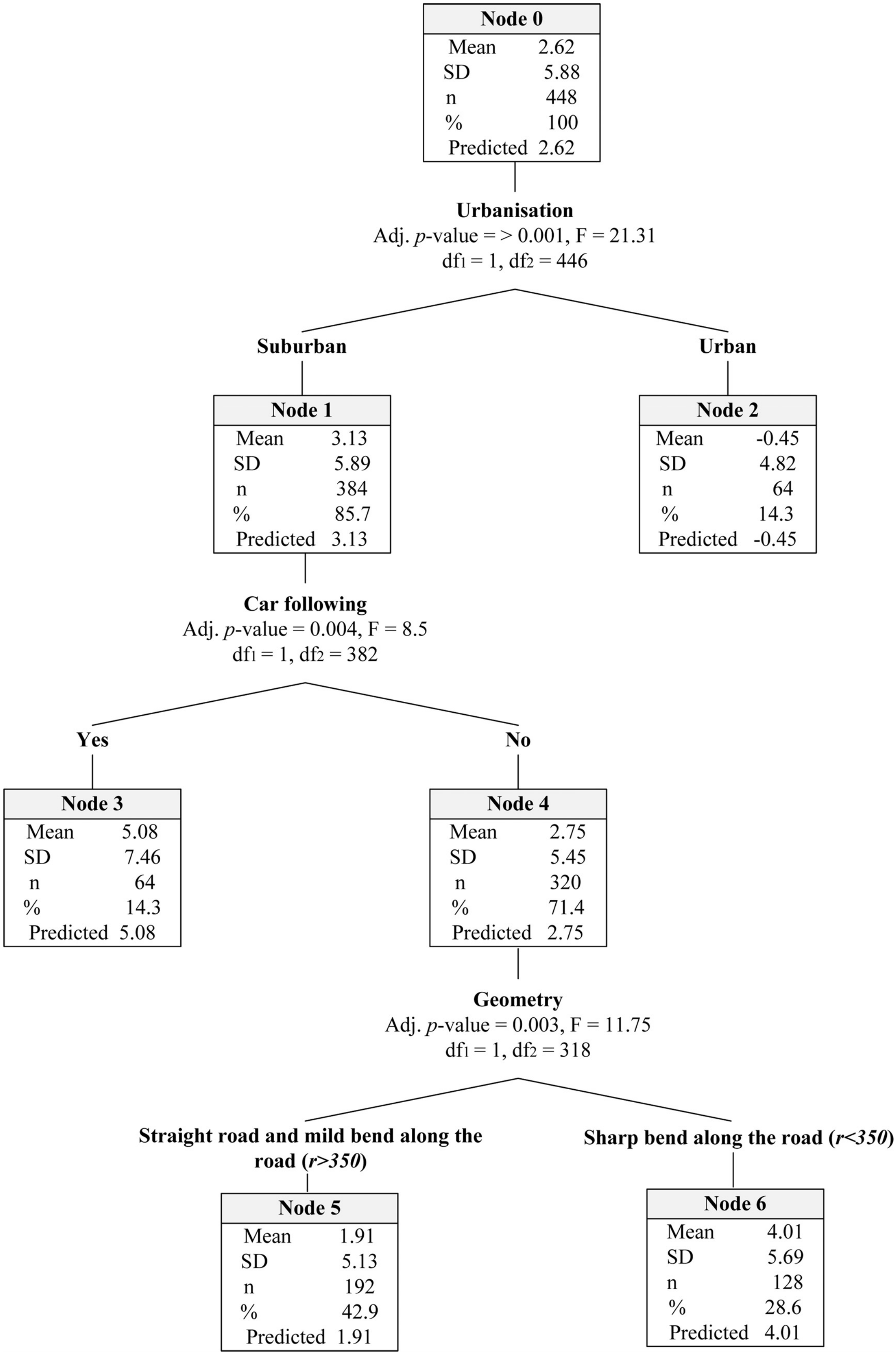


Fig. 1. Decision tree of speed adaptation.

to vehicle interaction was controlled, with the lead vehicle in the car-following scenario programmed to keep a constant headway of 60 m from the driven car. Therefore, the corresponding speed reduction by distracted drivers may be explained by the presence of traffic, possibly serving as a trigger for behavioural adaptation of distracted drivers.

Table 4
Generalized Linear Mixed Model (GLMM) estimates of speed adaptation of distracted drivers.

Parameter	Coefficient	SE	t-statistic	p-value	95% CI
Road Infrastructure/Traffic Complexity					
Straight suburban road and mild bend (r > 350) along the suburban road	—[a]	—[a]	—[a]	—[a]	—[a]
Car following along the suburban road	3.17	1.21	2.61	0.010[*]	[0.76, 5.57]
Sharp bend (r < 350) along the suburban road	2.1	0.83	2.50	0.014[*]	[0.44, 3.76]
Straight urban road	−2.36	0.85	−2.80	0.006[**]	[−4.02, −0.69]
Self-reported collision					
No	—[a]	—[a]	—[a]	—[a]	—[a]
Yes	2.26	0.81	2.78	0.006[**]	[0.65, 3.86]
Age (years)	0.83	0.28	2.926	0.004[**]	[0.27, 1.39]
Safe attitude towards mobile phone usage[b]	1.96	0.41	4.70	<0.001[***]	[1.13, 2.78]
Driving experience (years)	−0.88	0.33	−2.63	0.01[*]	[−1.54, −0.21]
Intercept	−24.53	6.68	−3.66	<0.001[***]	[−37.77, −11.29]
Number of observations	128				
ρ	0.17				
AIC	715.072				
BIC	725.874				

[a] Reference category.
[b] Scale: (1) Strongly disagree – (7) Strongly agree.
[*] P < 0.05.
[**] P < 0.01.
[***] P < 0.001.

Among the road geometric conditions, distracted drivers are found to adapt their speed more while driving through a sharp bend compared to straight roads or mildly curved roads. Curves with a radius less than 350 m are usually more complex and drivers tend to reduce their speed from the speed limit (Schurr et al., 2002). The reductions in speed along curved roads with a radius less than 350 m are more acute for distracted drivers, implying that the mobile phone distraction is additive to the effect of the natural complexity of road infrastructure (Oviedo-Trespalacios et al., 2015).

Personal characteristics like driver age, driving experience, self-reported prior involvement in a traffic crash, and safe attitude towards mobile phone use are significant predictors of speed adaptation in the distracted condition. This agrees with Young and Regan (2013)'s theoretical model in which driver characteristics are postulated as moderators of driving behaviour adaptation in a distracted condition. The findings from this study provide further support that the speed reduction observed among distracted drivers may be part of a decision making process that privileges road safety, but this assertion needs to be carefully examined. To examine the differential effect of age on driving speed, speed adaptation of distracted drivers across the categories of traffic complexity are plotted against driver age using the estimates of GLMM. As shown in Fig. 2, speed adaptation decreases with driver age with older young-drivers (i.e. closer to the sample upper limit of 26 years) exhibiting lower speed adaptation than younger drivers (i.e. closer to 18 years). Given the restricted range of ages, starting from the age of first licensure (18), it is possible that this result reflects the effect of driving experience rather than age, or some combination of age and experience. Years of driving experience, on the other hand, was a negative predictor of speed adaptation. This suggests that experienced drivers might have better preparation to cope with the extra load from the mobile phone task and that they simply do not need to adapt. Finally, frequency of mobile phone usage was not associated with speed adaptation. This finding supports previous research reporting the lack of association between driver's distractibility and performance (Farah et al., 2015). Further research is required to arrive at a better understanding of these factors.

This study suggests that road and traffic complexity plays an important role in the decision making process of distracted drivers in speed adaptation. This research will serve as a base for future studies in the area of self-regulation. Funkhouser and Sayer (2012) argued that the lack of knowledge on how drivers self-regulate means it is difficult to make accurate estimates of risk and, therefore, to predict crashes. This may also limit the development of countermeasures and increase the uncertainty in traffic models. A proper understanding of vehicle dynamics could potentially support system-wide technological countermeasures, e.g. vehicles providing warning alerts to drivers to be more attentive to the driving task. Likewise, it is necessary to understand whether those drivers who do not self-regulate have an increased risk of collision (particularly in hands-free conversation which is legal in Australia) as interventions could target this group of drivers. Finally, it is important to note that distracted drivers reducing their speed may sound like a favourable adaptation in terms of safety but it may lead to other types of crash risk because of other drivers performing aggressive overtaking manoeuvres to pass the slow moving vehicle. Additionally, it could have consequences for traffic flow that may impact the overall performance of the transport system.

6. Limitations and future research

Some important limitations must be considered while interpreting the results of this study. First, this research only considered operational control of distracted drivers; strategic and tactical behavioural adaptations need to be examined in order to get a complete picture of the impacts of behavioural adaptation due to mobile phone distraction. In this experiment, drivers did not have the opportunity to disengage or strategically select where to start the secondary task. Research has confirmed that before starting a secondary task, drivers are able to develop a situational model to manage the dual-tasking (Metz et al., 2011). A well-designed future experiment should provide for tactical behavioural adaptation to understand the overall impact of compensatory strategies (see Kircher et al. (2016)).

Second, the generalization of these findings must take into account that simulator studies are sometimes questioned in relation to their resemblance to real world driving and vehicle motion. Nevertheless, the driving simulator used in this research is a high fidelity simulator with a motion platform with six degrees of freedom that can move and twist in three dimensions. This simulator has been successful in developing traffic flow models that performed better than previous models in explaining real world driving data (Saifuzzaman et al., 2015). Other researchers (e.g. Charlton (2009) and Meuleners and Fraser (2015)) have also

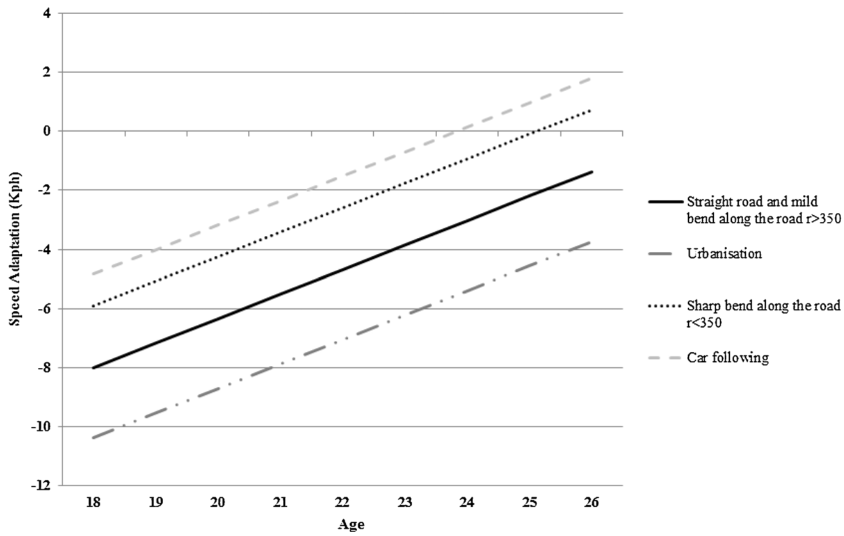


Fig. 2. Speed adaptation of distracted drivers as a function of road infrastructure/traffic complexity and age.

demonstrated the relative validity of driving simulators compared to real world driving. Nevertheless, even the most sophisticated driving simulators do not provide all of the visual, vestibular, and proprioceptive changes that occur when driving in certain speed, which is particularly important for this research. Although driving simulators are advantageous tools for studying human factors, naturalistic settings are necessary in future research.

Third, although the urban scenario of this study included an exact and detailed simulation of Brisbane CBD, the lack of traffic interactions (e.g. presence of pedestrians along sidewalk, oncoming traffic, etc.) might not completely represent the experience of driving in Brisbane CBD area or a typical urban scenario. Therefore, care should be taken in utilising the results of this study given that the virtual environment/animation may lack of the richness of the traffic system in Australia and generalisation may be too inaccurate. Future experimental studies should consider this limitation.

Fourth, an artificial type of conversation dialogues was used in this study mainly to ensure a consistent level of cognitive distraction among participants. The artificiality of the conversations may limit generalization of the observed speed adaptation behaviour. Differences in conversation may produce different levels of speed adaptation. The research to date has shown that contentious conversation increases work load (Lansdown and Stephens, 2013). On the other hand, changes in driving behaviours have been found to be consistent across different levels of difficulty in mobile phone conversations (Rakauskas et al., 2004). Nevertheless, without a systematic definition of complexity, it is difficult to confirm if resource allocation while driving is more sensitive to the initial engagement of attention than the conversation it-self. This merits further investigation.

Fifth, the small sample size and the relatively young sample may limit the degree to which the findings of this study can be generalized to the overall driver population. Also, road and traffic features included in this study are limited and rather simple. Despite these limitations, this research serves as a starting point to be used in distracted driving research (and of particularly importance for young drivers who are a high-risk group for distracted driving (Scott-Parker and Oviedo-Trespalacios, 2017)). In future studies, larger sample sizes and more naturalistic/diverse scenarios are necessary to rigorously determine the speed regulation behaviour of distracted drivers. In general, future research should replicate these findings to better determine the robustness of these effects.

Sixth, participation in this study was voluntary. This could have produced selection bias, meaning that perhaps the 'safest' young drivers may have been interested to voluntarily participate in the research, while the 'riskiest' young drivers were not. Future research should seek to recruit a larger sample with a better mix of safe/risky and experienced/inexperienced drivers to better understand the effects of driver factors on speed adaptation.

Nevertheless, future research must consider using mobile phone tasks that include a variety of activities such as texting, navigating, answering, and taking pictures/selfies. Previous research has confirmed that different tasks may change self-regulatory strategies and tactical behaviour in different ways (Kaber et al., 2012). The results of this study, which only examined the effects of mobile phone conversations, should be confirmed or compared with other mobile phone tasks. It should also be noted that mobile phone conversations require other support tasks (e.g. dialling, answering, monitoring the battery or reaching for the phone) which could be studied for a fuller understanding of mobile phone distraction and driver behavioural adaptation.

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