JOURNAL OF INTELLIGENT TRANSPORTATION SYSTEMS
2016, VOL. 0, NO. 0, 1–11
http://dx.doi.org/10.1080/15472450.2016.1198699

Taylor & Francis
Taylor & Francis Group

Measuring the safety impact of road infrastructure systems on driver behavior: Vehicle instrumentation and real world driving experiment

Justin Schorr, Samer H. Hamdar, and Claire Silverstein

Department of Civil and Environmental Engineering, Traffic and Networks Research Laboratory, George Washington University, Ashburn, VA, USA

ABSTRACT

Featured in this pilot experimental study is the construction and design of an instrumented vehicle that is able to capture vehicle trajectory data with an extremely high level of accuracy and time resolution. Once constructed and properly instrumented, the various data collection systems were integrated with one another and a driving experiment was conducted on northern Virginia roadways with 18 participants taking part in the study. Trajectory data were collected for each of the drivers as they traversed a predefined loop of four roadway segments with varying numbers of lanes and varying shoulder widths. Data collected from the experiment were then used to calibrate the parameters of the prospect theory car-following model through a genetic algorithm calibration procedure. Once all model parameters were successfully calibrated, significance testing was carried out to determine the impacts that the varying roadway infrastructure had on driving behavior. Results indicated that there were significant changes in behavior when comparing one lane roadways to their two lane counterparts—specifically in cases where the roadway featured a wide shoulder. Additional testing was conducted to ensure that there was no variation based on gender, as nine study participants were female and nine were male. The successfulness of this first study conducted with the newly constructed instrumented vehicle creates the opportunity for a variety of additional studies to be conducted in the future.

ARTICLE HISTORY
Received 4 November 2014
Revised 17 June 2015
Accepted 2 April 2016

KEYWORDS
car-following models; driver behavior; genetic algorithm calibration; on-road experiment; vehicle instrumentation

Introduction

Roadway infrastructure impacts driving behavior, which, in turn, has significant implications when analyzing vehicle-to-vehicle interactions and assessing macroscopic transportation network performance. The main question of interest is: How does the road surrounding environment impact the aggressive (risk attitudes) driving behavior from a traffic flow theory perspective? In order to address this question, the objective of this research is to conduct a real-world driving experiment featuring a vehicle instrumented to collect trajectory, location, and vehicle diagnostic data. Data from this experiment are then utilized to explicitly formulate the structure of the relationship between various car-following model parameters and one of the geometric features (shoulder width/number of lanes) shown to be significant in previous studies (Hamdar & Schorr, 2013).

Motivation and contribution

If total collisions are considered a surrogate measure for safety, the motivation for the examination of the different factors leading to unsafe driving conditions is highlighted by the 5,615,000 collisions that occurred on United States roadways in 2012 (an increase from the previous 3 years) (NHTSA, 2014). Additionally, these collisions resulted in 33,561 fatalities (an increase from the previous 2 years), and when considering vehicles miles traveled (VMT) as a measure of congestion—the problem is exacerbated as the total VMT in 2012 was 2,969 billion, producing a fatality rate of 1.13 fatalities per 100 million vehicle miles traveled (both the total VMT and the fatality rate have increased over the previous 2 years) (NHTSA, 2014). What becomes clear is that roadways are trending in a direction that is both less safe and increasingly congested. Various methods of vehicle instrumentation have been utilized over the past 40 years in an effort to gain additional insights into the factors that contribute to decreased safety on roadways (Lenne, 2013). New technologies allow for faster and more accurate data collection methods, which allow for a more detailed examination of driver behavior. It is up to research practitioners to demonstrate the capabilities of new data collection methods and to identify the

CONTACT Justin Schorr justin11@gwmail.gwu.edu Department of Civil and Environmental Engineering, Center for Intelligent Systems Research, Traffic and Networks Research Laboratory, The George Washington University, Exploration Hall, 20101 Academic Way, Ashburn, VA 20147, USA.
Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/gits.
This paper was originally submitted to the "Celebrating 50 Years of Traffic Flow Theory" conference held during August 2014 in Portland, Oregon. The paper was peer reviewed following the guidelines of the *Journal of Intelligent Transportation Systems*.

potential applications in terms of safety, congestion, and driver behavior (among others).

Objectives

The main objective of this study is to demonstrate how data collected by a highly accurate instrumented vehicle can be used to enrich our understanding of the impact that changes in roadway geometry have on driving behavior. To realize this main goal, the specific objectives of this study are as follows:

- Construct an instrumented vehicle such that trajectory and headway data can be collected at a high time resolution and subsequently synced together.
- Design a real-world driving experiment utilizing the instrumented vehicle on roadway segments with varying geometric characteristics.
- Calibrate the parameters of the prospect theory model using the data gathered from the driving experiment.
- Determine the impacts that specific roadway geometric characteristics have on driving behavior through statistical analysis of calibrated model parameters.

Background

While data-driven approaches (predominately focused around the modeling and evaluation of collision data) are commonplace in the transportation research community, new and affordable technologies have led to advancements in the collection of real-time driving data. The quantification of driving behavior in real time is an important advancement in the assessment of roadway safety—allowing for new insights through a variety of different methodologies and their subsequent applications. Three main approaches are used for the collection of real-time data: driver simulators, naturalistic studies, and instrumented vehicles, all of which have an associated set of pros and cons.

Driver simulators have been used extensively in a wide range of applications including (but not limited to) assessment of driver distraction (Young et. al, 2013), the performance of active safety and information systems (Liu & Wen, 2004; Ma, Smith, & Fontaine, 2015), and the evaluation of impaired drivers (Akerstedt, Peters, Anund, & Kecklund, 2005), as well as those with certain medical conditions (Frittelli et al., 2009). Driver simulators are particularly useful as they allow for simulated driving experiences to be conducted in a safe and controlled environment where various scenarios (including complicated and high-risk environments) can be created and held constant for all participants in a given study (Bifulco, Pariota, Galante, & Fiorentino, 2012). However, the obvious drawback to these studies is that they do not take place on actual roadways and are unable to capture the natural interactions that occur between drivers in the real-world environment (Carston, Kircher, & Jamson, 2013). As such, on-road data collection methods such as naturalistic studies and instrumented vehicles are becoming increasingly popular in order to better understand road safety crash risks and risk factors (Lenne, 2013).

Naturalistic approaches utilize unobtrusive methods (typically in participants' own vehicles) to collect data in real traffic conditions (Lenne, 2013). Again, the applications of naturalistic studies are vast, including (but not limited to) the examination of risks to heavy vehicle operators through the use of data acquisition systems, internal and external cameras, and daily activity registers (Soccolich et al., 2013); assessment of heavy vehicle operator response to a forward collision warning system through the use of gaze monitoring and brake pedal position (Wege, Will, & Victor, 2013); examination of older driver engagement in secondary activities at intersections through the use of a video camera system as well as a vehicle diagnostic logging system (Charlton, Catchlove, Scully, Koppel, & Newstead, 2013); analysis of rapid deceleration events for older drivers through the use of a custom driver monitor system that featured a two-axis accelerometer (Keay et al., 2013); and impacts of a forward distance warning system on car driving performance through the Australian Transport Accident Commission's SafeCar project (Young et al., 2007). Naturalistic studies allow for the collection of large amounts of data (in terms of both the number of participants and the number of trips made) over an extended period of time. Furthermore, the instruments used to collect data are unobtrusive (Heuer et al., 2010), and these types of studies do not require a researcher to be present in the vehicle during data collection (the collection of these "baseline" data is intended to reflect "normal driving"; Carsten et al., 2013). However, practical and analytical challenges can impact naturalistic studies, as data sets are large and complicated, often requiring the processing of hundreds or even thousands of hours of vehicle-based and video data (Lenne, 2013). Additionally, since no variables are controlled by the researcher, causal conclusions cannot be drawn from naturalistic driving studies (Carsten et al., 2013).

Similar to naturalistic studies, field operational tests (FOT) are long-range studies and again involve some sort of instrumentation. In these studies objective data on situation and behavior are collected through an automated process and subjective data are usually collected manually or electronically (Carsten et al., 2013). These studies have been used to make a variety of observations on driving behavior, including the evaluation of the safety impacts associated with adaptive cruise control (Rakha, Hankey, Patterson, & Van Aerde, 2001). In addition to the studies mentioned to this point, controlled on-road studies involving instrumented vehicles offer opportunities for unique data collection through the use of multiple methods (Lenne, 2013). These controlled on-road studies are defined by their reliance on a predetermined route in order to identify differences in performance and behavior under varying driving conditions (Carsten et al., 2013). Furthermore, from a behavior perspective, field studies utilizing instrumented vehicles are frequently regarded as the ultimate validation stage for assessing behavioral models, safety measures, and improved road infrastructure design (Santos, Merat, Mouta, Brookhuis, & De Waard, 2005), as well as addressing their adoption. Still, the potential drawbacks of these controlled on-road studies must be mentioned, as the studies do not collect data over a long time period (Lenne, 2013) and many require a researcher to be present in the vehicle (potentially impacting the driver's behavior) (Lenne, 2013; Carsten et al., 2013). With that being said, these types of studies are well suited to address research questions that are independent of exposure and that utilize independent factors that are stable over shorter periods of time (such as age and personality), and are excellent tools in the early stages of system development and FOT design (one example of this being a situation where drivers' headway is impacted, and thus the need for additional sensors [such as LIDAR sensors] is required; Carsten et al., 2013). Examples of studies utilizing this type of instrumented vehicle data collection include examination of the number and nature of errors committed by drivers in distracted and undistracted states (Young, Salmon, & Cornelissen, 2013), analysis of the situational awareness of both novice and experienced drivers at rail crossings (Salmon, Lenné, Young, & Walker, 2013), and evaluation of an intersection violation warning system (Neale, Perez, Lee, & Doerzaph, 2007; Brewer, Koopmann, & Najm, 2011). In addition, instrumented vehicles have been used in driver training through the benchmarking of experienced drivers (Underwood, 2013).

In addition to the behavioral applications mentioned already, driver simulators, field studies, and instrumented vehicles can allow for collection of trajectory data in order to assess and calibrate car-following models. Car-following models describe the behavior of the following vehicle as a function of the lead vehicle's trajectory, allowing for estimation or prediction of the following vehicle's trajectory in response to the actions of the lead vehicle (Soria, Elefteriadou, & Kondyli, 2014). Driver simulator experiments have been conducted to evaluate car-following behavior under both normal and evacuation scenarios (Xu, Kuan Yang, Hua Zhao, & Jie Li, 2012), and field tests have been conducted using loop detector data to determine distance gaps under different congestion regimes (Dijker, Bovy, & Vermijs, 1998). While these types of studies are most certainly useful in understanding car-following behavior, instrumented vehicles allow for more detailed data collection and thus have been used frequently in both data collection and calibration efforts (Soria et al., 2014).

Examples of instrumented vehicles being used for data collection and the assessment of driver behavior variability in car-following include two studies by Brackstone, Sultan, and McDonald (2002, 2009), where headways for drivers following the instrumented vehicle were recorded in the first study, and then the research was extended (in the second study) to study the factors that influence the decision-making process of car following. While the drivers in Brackstone's studies knew they were part of an experiment, Kim et al. (2007) used an instrumented vehicle equipped with an infrared sensor, a differential global positioning system (DGPS) inertial distance measuring instrument, a vehicle computer, and a digital video camera to measure the position, speed, and acceleration (as well as demographic information collected from the video recordings) of the following vehicles, whose drivers were unaware that they were being monitored as part of the study. In an effort to quantify driver reaction times, Ma and Andreasson (2006) equipped a vehicle developed by Volvo Technologies with a GPS system, an on-board computer, two LIDAR sensors (facing front and rear), and cameras corresponding to the sensors. The study was conducted on Stockholm, Sweden, roadways, and the "follow-the-leader" behaviors of random vehicles behind the instrumented vehicle were observed.

Once data from instrumented vehicles are collected, the next step in evaluating car-following models is the calibration stage. One such study was conducted by Panwai and Dia (2005), who evaluated AIMSUN, PARAMICS, and VISSIM models using instrumented vehicle data collected in Stuttgart, Germany. In this case, the instrumented vehicle was equipped with radars to record the differences in speed and headway between the instrumented vehicle and the vehicle immediately in front of it (Manstetten, Krautter, & Schwab, 1997). Similarly, Punzo and Simonelli (2005) examined Newell's model, the Gipps model, an intelligent driver model, and the MITSIM model though the use of trajectory data recorded from four instrumented vehicles. Here, the four vehicles were all instrumented with GPS devices and Global Navigation Satellite System receivers (GLONASS) to record vehicle spacing data and drove in a platoon on both urban and "Sextraurban" roadways in Naples, Italy (Punzo, Formisano, & Torrieri, 2005). One final example of a study focused around car-following model calibration

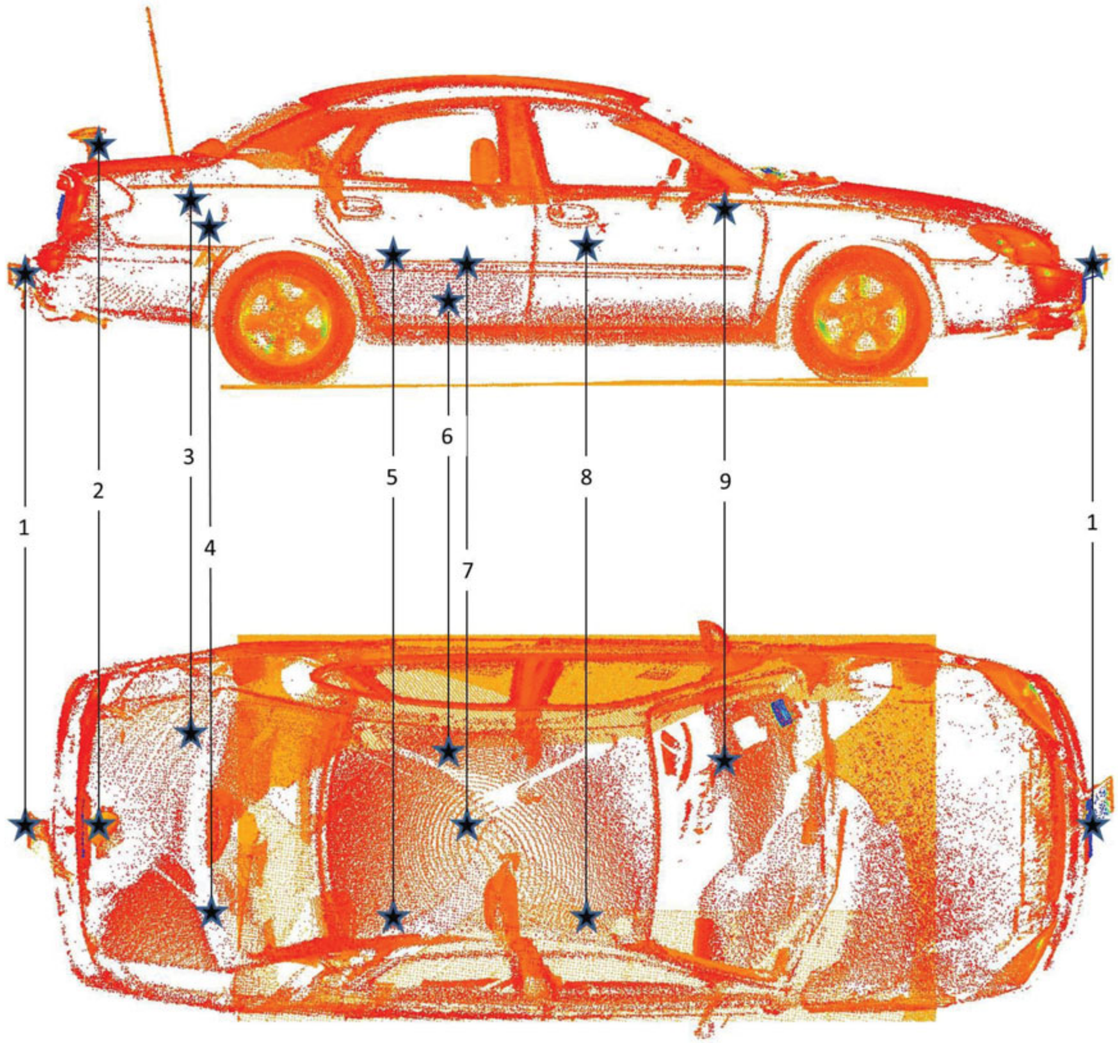

Figure 1. Vehicle instrumentation.

using data from instrumented vehicles was conducted by Soria et al. (2014). Here, a Honda Pilot sports utility vehicle (SUV) was equipped with four wide-coverage digital cameras, a Honeywell mobile digital recorder, a GPS system, and a laptop to record geographical position, speed, spacing, left–right turn signal activation, video clips, and audio recordings. The instrumented vehicle was positioned as the follower and only the front camera was used to determine the spacing between the leader and the follower (Soria et al., 2014). The authors then used the data obtained from the instrumented vehicle to calibrate the Gipps model, the Pitt model, the MITSIM model, and the modified Pitt model.

Research methodology

Vehicle instrumentation

The instrumented vehicle used for data collection in this experiment is comprised of three systems working in unison: a LIDAR system, a DGPS system, and an on-board diagnostics (OBD) monitoring system. Data from all three systems are received by an in-vehicle laptop, which generates a local time stamp for synchronization purposes. A schematic for the vehicle instrumentation (overlaid on a laser scan of the actual vehicle) is provided in Figure 1; Table 1 then lists the various components.

Table 1. Vehicle instrumentation key.

Instruments		
Number	Instrument name	Data collected
1	Lidar sensors (2)	Trajectory data
2	DGPS antenna	Vehicle position data
3	External computing unit	
4	Sync box	
5	Ethernet switch	
6	DGPS receiver	Vehicle position data
7	Power box	
8	Laptop	
9	On-board diagnostics logger	Vehicle diagnostic data

Experimental setup

The driving experiment in this study allows for observation of moment-by-moment local interactions among drivers, and measures drivers' preferred traffic measures with known attributes (gender, age, and attitude). Furthermore, experimental set-up involves testing one of the exogenous geometric factors shown to impact safety. For this pilot study, the authors have selected shoulder width and the number of lanes as the test variables, and a driving experiment was conducted in an interrupted flow scenario. In order to combat the potential impact that other geometric factors may have on experimental results, the selected roadway segments were all at least 1 mile in length and featured changes in both vertical and horizontal alignment. Figure 2 displays a GoogleEarth image of the northern Virginia roadway segments selected for this experiment generated by the differential GPS data recorded during experimentation. The black line in the figure is the actual DGPS path traveled by a study participant, and the base stations zdc11910 and lwx11910 (used to increase the accuracy of the DGPS recordings) are seen in the top left and bottom center of the figure. Additionally, each of the four segments is highlighted in the figure where the red lines mark the start and/or end point of a segment. Segment 1 is a two-lane roadway with a wide shoulder, segment 2 is a one-lane roadway with a wide shoulder, segment 3 is a two lane roadway with a narrow shoulder, and segment 4 is a one-lane roadway with a narrow shoulder.

For the experiment, 18 drivers (nine males and nine females between the ages of 20 and 33 years) drove the instrumented vehicle through all four roadway segments. Drivers were instructed to behave as they would normally, with the exception that they were not permitted to pass the lead vehicle at any point during the test run. While it would be impossible to conduct all test runs in identical traffic conditions, a no-passing restriction was imposed by instructing drivers to imagine that, when on the two lane segments, there was a stream of vehicles next to them such that they could not pass the lead vehicle. This restriction was imposed as to try to create a similar traffic flow scenario for all study participants and to eliminate data collection problems associated with free-flowing vehicles (no leader). The lead vehicle was operated by an author of this study and speed was varied (±7 mph from the posted speed limit) on as consistent a basis as possible (given the surrounding traffic conditions), at approximately the same locations throughout each of the four segments.

Modeling and calibration

Drivers evaluate their acceleration choice options based on the resulting potential gains and losses. Prospect theory (Kahneman & Tversky, 1979) has been used to model this decision-making process (Hamdar, Treiber, Mahmassani, & Kesting, 2008). Here, drivers frame the stimulus where different utilities are assigned to different acceleration choices considering different weights for gains and losses, and then "edit" the choices based on a prospect index calculated in the same way as expected utility are calculated. The prospect theory value function is formulated as:

$$U_{PT}\left(a_n\right) = \frac{\left[w_m + (1 - w_m)\left(\tanh\left(\frac{a_n}{a_0}\right) + 1\right)\right]}{2} \times \left[\frac{\left(\frac{a_n}{a_0}\right)}{1 + \left(\frac{a_n}{a_0}\right)^2}\right]^{\gamma} \quad (1)$$

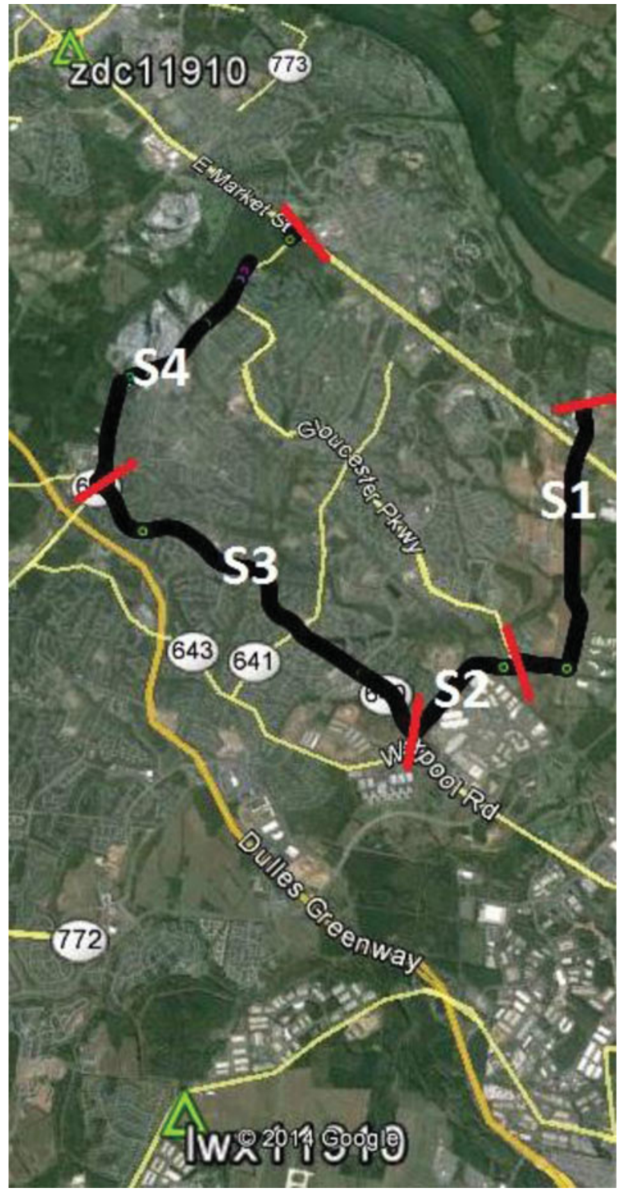

Figure 2. Roadway segments used in this pilot study. Roadway segment image is courtesy of GoogleEarth, retrieved July 23, 2014.

where U_{PT} is the acceleration value function, a_0 is the normalization parameter, $\gamma > 0$ is a sensitivity exponent indicating how sensitive a driver is towards gains or losses in travel times (i.e., speeds), and w_m is the relative weight of losses compared to the gains. Here, a driver choosing a_n as his or her desired acceleration will gain U_{PT} unless he or she is involved in a rear-end collision. The value of a_0 is set as a constant equal to 1 m/s^2. This non-varied model parameter indicates the subjective scale of the acceleration: accelerations $|\dot{v}_{\mathrm{int}}| < a_0$ are considered to be "near the reference point," leading to increased sensitivity. In other words, this parameter may be considered as the scaling unit of the acceleration to be used inside exponentials or noninteger powers requiring dimensionless arguments (i.e., Eq. (1)). Furthermore, a crash seriousness term $k(v, \Delta v)$ is used to calculate the disutility resulting from a crash as follows:

$$U(a_n) = \left(1 - p_{n,i}\right) U_{PT}(a_n) - \mathrm{p}_{\mathrm{n,i}} w_c \mathrm{k}(v, \Delta v) \qquad (2)$$

where $p_{n,i}$ is the subjective probability of driver i in vehicle n being involved in a crash at the end of a car-following duration; $p_{n,i}$ is approximated by a normal distribution given that drivers are assumed to estimate the future speed $v_{n-1}(t + \Delta t)$ of vehicle $n - 1$ to be normally distributed with a mean equal to the current speed $v_{n-1}(t)$ and a standard deviation of $\alpha * v_{n-1}(t)$ (α is a velocity uncertainty parameter); $U_{PT}(a_n)$ is derived from Eq. 1; and w_c is a crash weighting function which is lower for drivers willing to take a higher risk. The value of $k(v,\Delta v)$ is set equal to 1 for simplicity since the model estimations are only based on velocity. Regarding w_c, a higher w_c corresponds to conservative individuals while a lower value corresponds to drivers willing to take a higher risk; this parameter is the subjective weighing factor associated with a collision-related loss (i.e., collision weight). A more elaborate explanation of the model parameters may be found in Hamdar, Mahmassani, and Treiber (2015).

Additionally, a logistic functional form given here is employed to reveal the stochastic nature of acceleration choice:

$$f(a_n) = \left\{ \frac{e^{(\beta_{PT} \times U(a_n))}}{\int_{a_{min}}^{a_{max}} e^{(\beta_{PT} \times U(a'))} da'}, \; a_{min} \le a_n \le a_{max} \right. \qquad (3)$$

where β_{PT} is the sensitivity of choice to the total utility and $f(a_n)$ is the probability density function. The physical meanings of the estimated parameters given in the fourth section are listed Table 2.

These safety parameters are all estimated from the experimental data using 1–3 presented in the preceding and the calibration method defined next using Eq. 4.

Trajectory data recorded by the instrumented vehicle (velocity, acceleration and space headway) at a resolution of 0.1 s is used to calibrate the model just presented.

Table 2. Physical meanings of estimated parameters.

Parameter	Description
Γ	Driver sensitivity of gains or losses (in travel times)
w_m	Driver's relative weight of losses compared to gains (risk aversion)
w_c	Crash weighting function
B	Driver sensitivity to surrounding environment (impatience)
α	Driver uncertainty of leading vehicle's velocity

Since headway data were not always recorded at the same time resolution as the vehicle motion data, values were interpolated based on the change in vehicle velocity between recorded headway values. Calibration was then performed on a segment-by-segment basis for each driver using a genetic algorithm procedure. Genetic algorithm calibration falls under the umbrella of artificial intelligence systems—an evolving field of research that has definite applications in the transportation research community, including the calibration of car-following models (Colombaroni & Fusco, 2013). Defining the architecture of the genetic algorithm calibration procedure (Hamdar, 2009), the fitness function takes the following form:

$$F_{mix}\left[v^{sim}\right] = \sqrt{\frac{1}{\left|v^{data}\right|} \frac{\left(v^{sim} - v^{data}\right)^2}{\left|v^{data}\right|}} \qquad (4)$$

where v^{sim} is the experimental data (time series), v^{data} is the empirical data (time series), and $\langle . \rangle$ is the temporal average of a time series of duration ΔT. The fitness function has a mixed form, as it considers both the relative error (sensitive to differences at individual time steps) and the absolute error (sensitive to differences in the time series as a whole). Furthermore, chromosomes represent sets of the target calibration parameters, and at each chromosome generation, fitness is determined by the mixed error function just shown (greedy selection is used to select the parameters with the 10 best fitness scores). Chromosomes are then generated from these parents and then recombined to generate children, with a crossover point chosen through random selection, and (excluding the chromosome with the single best fitness score) genes are mutated (random selection) with a probability and rate of 10%. Initially, a fixed number of generations are evaluated, and the process is terminated when the fitness score drops below 10% or there is no improvement for 20 consecutive chromosome generations.

Results and discussion

Calibration results and significance testing

Table 3 displays the descriptive statistics for the calibration results. This includes the average and standard deviation values for the calibration parameter, velocity, and

Table 3. Descriptive statistics for all segments.

Segment	Stat	Vel (m/s)	Space (m)	Head (s)	ψ	γ	Wm	Wc	Tmax	α	β	Tcorr	RT (s)	Vel error
1	Avg	15.18	33.03	2.21	5.97	0.73	3.66	89833	5.26	0.21	6.33	17.83	0.63	0.173
	Dev	1.60	7.94	0.66	3.73	0.62	2.18	23796	1.57	0.09	3.39	5.23	0.73	0.074
2	Avg	13.99	33.09	2.41	5.40	1.09	2.83	97944	4.83	0.11	7.08	20.39	0.36	0.100
	Dev	1.07	13.12	1.14	4.90	0.72	1.98	16913	2.07	0.06	2.81	4.02	0.36	0.056
3	Avg	14.71	30.52	2.10	5.64	0.63	4.11	95000	5.16	0.19	5.60	20.83	0.72	0.169
	Dev	1.14	6.99	0.55	4.50	0.46	2.24	25752	0.91	0.06	2.90	4.59	0.53	0.072
4	Avg	15.70	29.69	1.90	4.27	0.71	3.94	100778	5.67	0.13	6.63	20.22	0.62	0.137
	Dev	1.50	7.46	0.48	3.91	0.58	2.46	19283	1.72	0.06	3.03	3.81	0.47	0.059

Table 4. Descriptive statistics for number of lanes.

Lanes	Stat	Vel (m/s)	Space (m)	Head (s)	ψ	γ	Wm	Wc	Tmax	α	β	Tcorr	RT (s)	Vel error
1	Avg	14.84	31.39	2.16	4.83	0.90	3.39	99361	5.25	0.12	6.86	20.31	0.49	0.119
2	Avg	14.95	31.77	2.15	5.81	0.68	3.88	92417	5.21	0.20	5.96	19.33	0.68	0.171

Table 5. Descriptive statistics for shoulder widths.

Shoulder	Stat	Vel (m/s)	Space (m)	Head (s)	ψ	γ	Wm	Wc	Tmax	α	β	Tcorr	RT (s)	Vel error
Wide	Avg	14.58	33.06	2.31	5.68	0.91	3.25	93889	5.05	0.16	6.71	19.11	0.49	0.137
Narrow	Avg	15.21	30.10	2.00	4.96	0.67	4.02	97889	5.42	0.16	6.11	20.53	0.67	0.153

Table 6. Descriptive statistics for males and females.

Gender	Stat	Vel (m/s)	Space (m)	Head (s)	ψ	γ	Wm	Wc	Tmax	α	β	Tcorr	RT(s)	Vel error
Female	Avg	15.01	27.00	1.82	5.48	0.62	3.49	94861	5.25	0.14	6.68	20.06	0.653	0.143
Male	Avg	14.78	36.16	2.49	5.16	0.96	3.78	96917	5.21	0.18	6.14	19.58	0.514	0.147

space and time headways for each segment. Additionally, these descriptive statistics are provided for geometric characteristics (number of lanes and shoulder width) and gender in Tables 4, 5, and 6, respectively.

The parameters listed in the tables that are not previously defined are the reaction time (RT), driver's anticipation/maximum anticipation time horizon T_{max}, and correlation time of intra-driver variability T_{corr}. Parameter T_{corr} is calibrated once the acceleration distribution is known by using the Wiener Process (Mehdi, 1994).

In order to interpret the statistical significance of the change in calibration parameters based on number of lanes, shoulder width and gender, multiple multivariate analysis of variance (MANOVA) tests were conducted (using the SAS software). Results of the MANOVA test indicate whether or not you can reject the null hypothesis—the null hypothesis being that a certain exogenous characteristic has no statistically significant impact on the change in calibration parameters. For statistical significance and the rejection of the null hypothesis, the p value must be less than .05. Table 7 displays the MANOVA results for the impacts of number of lanes, shoulder width, and gender on the calibration parameters. In addition, the impact of changing segments is included at the top of this table to demonstrate that the null hypothesis can be rejected for the change in segments. If the null hypothesis could not be rejected for the changing segments as a whole, then there would be no statistical significance of the calibration results for this study.

From the table, it is clear that a change in the number of lanes has the most statistically significant impact

Table 7. General MANOVA testing.

Segment			
Statistic	Value	F Value	p Value
Wilks' lambda	0.484	1.84	0.0106
Pillai's trace	0.615	1.78	0.0146
Hotelling–Lawley trace	0.872	1.90	0.0094
Roy's greatest root	0.571	3.93	0.0005
Shoulder width statistic			
Wilks' lambda	0.784	1.90	0.0684
Pillai's trace	0.216	1.90	0.0684
Hotelling–Lawley trace	0.276	1.90	0.0684
Roy's greatest root	0.276	1.90	0.0684
Lanes statistic			
Wilks' lambda	0.688	3.13	0.0036
Pillai's trace	0.312	3.13	0.0036
Hotelling–Lawley trace	0.454	3.13	0.0036
Roy's greatest root	0.454	3.13	0.0036
Gender statistic			
Wilks' lambda	0.787	1.86	0.0745
Pillai's trace	0.213	1.86	0.0745
Hotelling–Lawley trace	0.271	1.86	0.0745
Roy's greatest root	0.271	1.86	0.0745

Table 8. MANOVA testing for changing number of lanes based on shoulder width.

No shoulder—Changing lanes			
Statistic	Value	*F* Value	*p* Value
Wilks' lambda	0.717	1.14	0.3704
Pillai's trace	0.283	1.14	0.3704
Hotelling–Lawley trace	0.395	1.14	0.3704
Roy's greatest root	0.395	1.14	0.3704
Wide shoulder—Changing lanes			
Statistic	Value	*F* Value	*p* Value
Wilks' lambda	0.555	2.31	0.0458
Pillai's trace	0.445	2.31	0.0458
Hotelling–Lawley trace	0.801	2.31	0.0458
Roy's greatest root	0.801	2.31	0.0458

on the change in the calibration parameters. With this in mind, the data set was separated based on shoulder width and a MANOVA test was again conducted for the number of lanes. These results are displayed in Table 8.

Here, it is clear that the null hypothesis cannot be rejected when considering a change in the number of lanes on roadways with narrow shoulders, but it can be rejected for a change in the number of lanes on roadways with wide shoulders.

Finally, to ensure that there was no statistically significant difference based on gender, a final MANOVA test was carried out for each segment using gender as the dependent variable. These results (Table 9) demonstrate that the null hypothesis cannot be rejected based on gender for any of the segments.

Table 9. MANOVA testing based on gender by segment.

Segment 1—Gender			
Statistic	Value	*F* Value	*p* Value
Wilks' lambda	0.364	1.56	0.2725
Pillai's trace	0.636	1.56	0.2725
Hotelling–Lawley trace	1.749	1.56	0.2725
Roy's greatest root	1.749	1.56	0.2725
Segment 2—Gender			
Statistic	Value	*F* Value	*p* Value
Wilks' lambda	0.235	2.90	0.0745
Pillai's trace	0.765	2.90	0.0745
Hotelling–Lawley trace	3.258	2.90	0.0745
Roy's greatest root	3.258	2.90	0.0745
Segment 3—Gender			
Statistic	Value	*F* Value	*p* Value
Wilks' lambda	0.372	1.50	0.2895
Pillai's trace	0.628	1.50	0.2895
Hotelling–Lawley trace	1.687	1.50	0.2895
Roy's greatest root	1.687	1.50	0.2895
Segment 4—Gender			
Statistic	Value	*F* Value	*p* Value
Wilks' lambda	0.466	1.02	0.4940
Pillai's trace	0.534	1.02	0.4940
Hotelling–Lawley trace	1.148	1.02	0.4940
Roy's greatest root	1.148	1.02	0.4940

Discussion of results and parameter explanation

Based on the significance testing conducted in the preceding, results from this pilot experimental study indicate that drivers change their behavior significantly on roadways with wide shoulders when there are a varying number of lanes. With this in mind it is important to interpret the parameter values from segments 1 and 2 (displayed earlier, in Table 3). Interpretation of the changes in the calibration parameters between these two segments requires an explanation of the "physical meaning" for each of the parameters individually. Beginning with the gamma parameter (γ), this can be thought of as a driver's sensitivity to perceived gains and losses. That is, if the value function of the Prospect Theory model generally has the form seen in Figure 3, increasing gamma would be indicative of an increase in the amplitude of the curve derived from Eq. 1.

Furthermore, the parameter w_m represents the relative weight a driver puts on losses as compared to gains. Increases in this parameter are therefore indicative of a driver who is "valuing" potential risks more than that of potential gains, that is, becoming more risk averse. Increasing the alpha parameter is indicative of a driver being more uncertain of the leader vehicle's velocity, and the beta parameter can be thought of as the drivers' sensitivity to the surrounding environment. Increasing the beta parameter could be indicative of a number of things, including a more experienced driver or one who has become impatient. The T_{max} parameter can be thought of as the anticipation of the driver, as increasing values indicate a driver that is thinking multiple steps ahead and decreasing values indicate a driver who has a myopic view and is thinking about what is occurring "in the moment."

Looking at the changes in average calibrated values for these parameters between segments 1 and 2 we see that the one-lane segment (segment 2) features higher values for beta and gamma and lower values for alpha, T_{max}. and w_m. The combined impacts of increased gamma and decreased w_m demonstrate that not only is the driver putting less weight on perceived losses, but the driver is

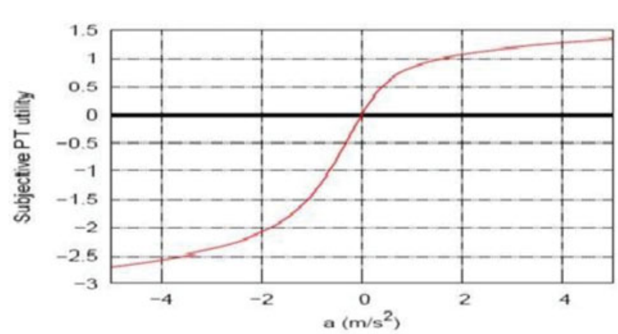

Figure 3. Prospect theory value function (Hamdar, 2009).

also increasing his or her sensitivity to perceived gains and losses. This result is further explained by an increase in the beta parameter, which, in combination with the impacts discussed earlier, seems to indicate that drivers became increasingly impatient during this segment of the experiment. Reaffirming this notion is the decrease in the value for T_{max}, which demonstrates that drivers are thinking more in the moment, rather than anticipating what maneuvers they may make in the future (which seems to indicate a growing level of frustration). Finally, the largest percentage decrease in any parameter value is seen in that of alpha, indicating that the driver is very certain of what the vehicle in front of him or her is doing, once again reaffirming the notion that drivers became increasingly impatient and frustrated while traversing this segment of the experiment.

In addition to the driving environment discussed in the preceding, significance testing indicated that drivers change their behavior when moving between one and two lane roadways in general. The most significant changes in terms of the individual calibration parameters are seen in alpha, beta, and gamma. Here we once again observe that drivers on one-lane roadways are much more certain of the lead vehicle's velocity (decreased alpha), become increasingly sensitive to their environment (or potentially increasingly impatient—increased beta), and become increasingly sensitive to perceived gains and losses (increased gamma—with a slight decrease in the risk aversion parameter w_m).

While the changes in calibration parameters were not statistically significant for shoulder width or gender, it is interesting to observe that drivers had a higher average velocity, lower space headway, and thus much lower time headway on roadways with narrow shoulders. That is, when shoulder width narrowed, drivers followed the lead vehicle much more closely. The same was true when comparing female drivers to male drivers, as female drivers had an average time headway that was nearly 0.7 s less than their male counterparts. These changes in average values were not observed when comparing one-lane to two-lane roadways, as the average velocity, spacing, and time headway were almost identical in this case.

Conclusions and future work

This pilot real-world study featured the construction of an instrumented vehicle that was able to successfully capture high-time-resolution trajectory data through the use of multiple instruments working in unison. Furthermore, a driving experiment was successfully conducted with 18 participants driving a predefined "loop" that featured four segments with varying number of lanes and shoulder widths. Data collected from the driving experiment were then effectively calibrated using a genetic algorithm calibration procedure. Finally, significance testing was conducted on the calibrated parameters for the prospect theory value function and results indicated that there were significant changes in driver behavior for varying number of lanes—specifically when the roadway featured a wide shoulder as opposed to a narrow one.

Research conducted in this study differentiated itself from that of previous studies not only with the combination of instruments that were used, but also in the accuracy and time resolution of the data that were collected. Further differentiating this study from previous works, the driving experiment that was conducted tested the differences in behavior based on changing roadway geometry and then used the collected trajectory data to successfully calibrate the parameters of the prospect theory car-following model.

Given that this was the first study for this instrumented vehicle, construction and data synchronization posed significant challenges that needed to be overcome before the actual driving experiment could take place. With these major obstacles out of the way, opportunity abounds for additional driving experiments to be conducted with a seemingly limitless potential for different types of experimental setups. Furthermore, the vehicle used in this study was constructed in such a manner that additional instruments can easily be integrated in the vehicle and instrumentation design, once again opening the door for a wide variety of future applications and testing.

Funding

This material is based upon work supported by the National Science Foundation under Grants No. 0927138 and No. 1351647. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

References

Akerstedt, T., Peters, B., Anund, A., & Kecklund, G. (2005). Impaired alertness and performance driving home from the night shift: a driving simulator study. *Journal of Sleep Research*, *14*(1), 17–20.

Bifulco, G. N., Pariota, L., Galante, F., & Fiorentino, A. (2012). Coupling instrumented vehicles and driving simulators: opportunities from the DRIVE IN2 project. *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference*, 1815–1820.

Brackstone, M., Sultan, B., & McDonald, M. (2002). Motorway driver behaviour: Studies on car following. *Transportation Research Part F: Traffic Psychology and Behaviour*, *5*(1), 31–46.

Brackstone, M., Waterson, B., & McDonald, M. (2009). Determinants of following headway in congested traffic. *Transportation Research Part F: Traffic Psychology and Behaviour*, *12*(2), 131–142.

Brewer, J., Koopmann, J., & Najm, W. G. (2011). *System capability assessment of cooperative intersection collision avoidance system for violations (CICAS-V)*, No. HS-811 499.

Carsten, O., Kircher, K., & Jamson, S. (2013). Vehicle-based studies of driving in the real world: The hard truth? *Accident Analysis & Prevention*, *58*, 162–174.

Charlton, J. L., Catchlove, M., Scully, M., Koppel, S., & Newstead, S. (2013). Older driver distraction: A naturalistic study of behaviour at intersections. *Accident Analysis & Prevention*, *58*, 271–278.

Colombaroni, C., & Fusco, G. (2013). Artificial neural network models for car following: Experimental analysis and calibration issues. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations (Special Issue)*, *18*(1), 5–16.

Dijker, T., Bovy, P., & Vermijs, R. (1998). Car-following under congested conditions: empirical findings. *Transportation Research Record*, *1644*, 20–28.

Frittelli, C., Borghetti, D., Iudice, G., Bonanni, E., Maestri, M., Tognoni, G., Pasquali, L., & Ludice, A. (2009). Effects of Alzheimer's disease and mild cognitive impairment on driving ability: A controlled clinical study by simulated driving test. *International Journal of Geriatric Psychiatry*, *24*(3), 232–238.

Hamdar, S., & Mahmassani, H. (2009). Life in the fast lane: Duration-based investigation of driver behavior differences across freeway lanes. *Transportation Research Record*, *2124*, 89–102.

Hamdar, S. H., Mahmassani, H. S., & Treiber, M. (2015). From behavioral psychology to acceleration modeling: Calibration, validation, and exploration of drivers' cognitive and safety parameters in a risk-taking environment. *Transportation Research Part B: Methodological*, *78*, 32–53.

Hamdar, S. H., & Schorr, J. (2013). Interrupted versus uninterrupted flow: A safety propensity index for driver behavior. *Accident Analysis & Prevention*, *55*, 22–33.

Hamdar, S., Treiber, M., Mahmassani, H., & Kesting, A. (2008). Modeling driver behavior as sequential risk-taking task. *Transportation Research Record: Journal of the Transportation Research Board*, *2088*, 208–217.

Heuer, S., Chamadiya, B., Gharbi, A., Kunze, C., & Wagner, M. (2010, November). Unobtrusive in-vehicle biosignal instrumentation for advanced driver assistance and active safety. *Biomedical Engineering and Sciences (IECBES), 2010 IEEE EMBS Conference*, 252–256.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, *47*(2): 263–291.

Keay, L., Munoz, B., Duncan, D. D., Hahn, D., Baldwin, K., Turano, K. A., Munro, C. A., Bandeen-Roche, K., & West, S. K. (2013). Older drivers and rapid deceleration events: Salisbury Eye Evaluation Driving Study. *Accident Analysis & Prevention*, *58*, 279–285.

Kim, T., Lovell, D., & Park, Y. (2007). Empirical analysis of underlying mechanisms and variability in car-following behavior. *Transportation Research Record: Journal of the Transportation Research Board*, 1999; http://dx.doi.org/10.3141/1999-18

Lenne, M. G. (2013). The contribution of on-road studies of road user behaviour to improving road safety. *Accident Analysis and Prevention*, *58*, 158–161.

Liu, Y. C., & Wen, M. H. (2004). Comparison of head-up display (HUD) vs. head-down display (HDD): driving performance of commercial vehicle operators in Taiwan. *International Journal of Human–Computer Studies*, *61*(5), 679–697.

Ma, J., Smith, B. L., & Fontaine, M. D. (2015). Comparison of in-vehicle auditory public traffic information with roadside dynamic message signs. *Journal of Intelligent Transportation Systems: Technology Planning and Operations*, *20*(3), 244–254.

Ma, X., & Andréasson, I. (2006). Estimation of driver reaction time from car-following data: Application in evaluation of general motor-type model. *Transportation Research Record: Journal of the Transportation Research Board*, *1965*, 130–141.

Manstetten, D., Krautter, W., & Schwab, T. (1997). *Traffic simulation supporting urban control system development*. Mobility for Everyone 4th World Congress on Intelligent Transport Systems, 21–24 October 1997, Berlin, Germany (paper no. 2055).

Mehdi, J. (1994). *Stochastic processes* (2nd ed.). New Dehli, India: New Age International (P) Limited Publishers.

Neale, V. L., Perez, M. A., Lee, S. E., & Doerzaph, Z. R. (2007). Investigation of driver-infrastructure and driver-vehicle interfaces for an intersection violation warning system. *Journal of Intelligent Transportation Systems*, *11*(3), 133–142.

NHTSA. (2014). *Traffic safety facts: 2012 occupant protection*. Washington, DC: U.S. Department of Transportation, National Highway Traffic Safety Administration: 2014. Publication no. DOT-HS-811–892.

Panwai, S., & Dia, H. (2005). Comparative evaluation of microscopic car-following behavior. *IEEE Transactions on Intelligent Transportation Systems*, *6*(3), 314–325.

Punzo, V., & Simonelli, F. (2005). Analysis and comparison of microscopic traffic flow models with real traffic microscopic data. *Transportation Research Record*, *1934*, 53–63.

Punzo, V., Formisano, D., & Torrieri, V. (2005). Part 1: Traffic flow theory and car following: Nonstationary kalman filter for estimation of accurate and consistent car-following data. *Transportation Research Record*, *1934*, 1–12.

Rakha, H., Hankey, J., Patterson, A., & Van Aerde, M. (2001). Field evaluation of safety impacts of adaptive cruise control. *Journal of Intelligent Transportation Systems*, *6*(3), 225–259.

Salmon, P. M., Lenné, M. G., Young, K. L., & Walker, G. H. (2013). An on-road network analysis-based approach to studying driver situation awareness at rail level crossings. *Accident Analysis & Prevention*, *58*, 195–205.

Santos, J., Merat, N., Mouta, S., Brookhuis, K., & De Waard, D. (2005). The interaction between driving and in-vehicle information systems: Comparison of results from laboratory, simulator and real-world studies. *Transportation Research Part F: Traffic Psychology and Behaviour*, *8*(2), 135–146.

Soccolich, S. A., Blanco, M., Hanowski, R. J., Olson, R. L., Morgan, J. F., Guo, F., & Wu, S. C. (2013). An analysis of driving and working hour on commercial motor vehicle driver safety using naturalistic data collection. *Accident Analysis & Prevention*, *58*, 249–258.

Soria, I., Elefteriadou, L., & Kondyli, A. (2014). Assessment of car-following models by driver type and under different traffic, weather conditions using data from an instrumented vehicle. *Simulation Modelling Practice and Theory*, *40*, 208–220.

Wege, C., Will, S., & Victor, T. (2013). Eye movement and brake reactions to real world brake-capacity forward collision warnings—A naturalistic driving study. *Accident Analysis & Prevention*, *58*, 259–270.

Xu, Z., Kuan Yang, X., Hua Zhao, X., & Jie Li, L. (2012). Differences in driving characteristics between normal and emergency situations and model of car-following behavior. *Journal of Transportation Engineering*, *138*(11), 1303–1313.

Young, K. L., Regan, M. A., Triggs, T. J., Tomasevic, N., Stephan, K., & Mitsopoulos, E. (2007). Impact on Car Driving Performance of a Following Distance Warning System: Findings from the Australian Transport Accident Commission SafeCar Project. *Journal of Intelligent Transportation Systems*, *11*(3), 121–131.

Young, K. L., Salmon, P. M., & Cornelissen, M. (2013). Distraction-induced driving error: An on-road examination of the errors made by distracted and undistracted drivers. *Accident Analysis & Prevention*, *58*, 218–225.