

Evaluation of Cell Phone Induced Driver Behavior at a Type II Dilemma Zone

Ziaur Rahman, Diana Martinez, Nadia Martinez, Zirun Zhang, Arezoo Memarian, Sasanka Pulipati, Stephen P. Mattingly, Jay M. Rosenberger.

Accepted Manuscript Version

This is the unedited version of the article as it appeared upon acceptance by the journal. A final edited version of the article in the journal format will be made available soon.

As a service to authors and researchers we publish this version of the accepted manuscript (AM) as soon as possible after acceptance. Copyediting, typesetting, and review of the resulting proof will be undertaken on this manuscript before final publication of the Version of Record (VoR). Please note that during production and pre-press, errors may be discovered which could affect the content.

© 2018 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.

Publisher: Cogent OA

Journal: *Cogent Engineering*

DOI: <http://doi.org/10.1080/23311916.2018.1436927>



Evaluation of Cell Phone Induced Driver Behavior at a Type II Dilemma Zone

Ziaur Rahman¹, Diana Martinez², Nadia Martinez², Zirun Zhang², Arezoo Memarian¹, Sasanka Pulipati¹, Stephen P. Mattingly¹, Jay M. Rosenberger².

¹ Department of Civil Engineering, University of Texas at Arlington, Arlington, TX

² Department of Industrial Engineering, University of Texas at Arlington, Arlington, TX

1. Introduction

Cell phone usage creates a cognitive burden on the driving task and may jeopardize the safety of drivers, passengers, and other road users by reducing driving performance. In 2013, the Centers for Disease Control and Prevention (CDC, 2013) reported that about 69% of the total drivers of the United States (US) talk on their cell phone and 31% email or read and send text messages while driving. A 2014 report by the National Highway Traffic Safety Administration (NHTSA) found that approximately 3179 fatal crashes and 431,000 injury related crashes occurred due to distracted drivers (NHTSA, 2016). In addition, distracted drivers pose an additional threat to others when they approach an intersection. At a signalized intersection, these distracted drivers often face a decision-making challenge of whether to stop or go at the onset of the yellow indication. An incorrect decision in a dilemma zone can result in a rear end or right-angle collision depending on the type of error (Hurwitz et al., 2012). According to the 2014 Fatality Analysis Reporting System (FARS), 44,858 vehicles were involved in 29,989 fatal crashes with approximately ten percent occurring at an intersection (FARS, 2016). Hence, a comprehensive study of driver decision making at a dilemma zone while distracted by cell phone may identify opportunities for safety and operational improvements.

1.1. Distracted Drivers

A cellular phone, once used only for call receiving or call dialing, has now become an essential device for each person to maintain his or her everyday life. With the improvement of modern technology, cell phone usage is not just limited to dialing and receiving calls by a handheld (HH), a headset (HS), or a hands-free (HF) device; rather, smart phones have created opportunities for users to be socially active while on the go. A cell phone distracts a driver by visually, physically, cognitively, and audibly impairing them. Drivers become visually impaired when they look away from the roadway to see who is calling, physically impaired when they dial a cell phone number using a handheld device, and cognitively and audibly burdened when they engage in a conversation. Thus, call receiving, call dialing, texting, chatting, or even a simple conversation can increase the chances of decision impairment in dilemma zones (Mazzaze et al., 2004; Schreiner et al., 2004; Tornros et al., 2005; Lissy et al., 2000; Patten et al., 2004; Consiglio et al., 2003; and Hosking et al., 2006). Several research studies have specifically focused on the decreasing driver performance, which increases the probability of crashes. Caird and Scialfa (2005) show in their research that drivers using a cell phone respond to a sudden event almost one fourth of a second later than undistracted drivers. Their research also shows that if the time to take emergency action goes beyond one and half seconds, the fatality risk increases from 6.6% to 100%. A study by Bogle (2001) shows that drivers make double or triple the number of errors in driving tasks when distracted by cell phones. These findings appear consistent with the findings of Redelmeier and Tibshirani (1997). Bellavance (2005), Violanti and Marshall (1995), Sagberg (2001), and Rakauskas (2004), which show that drivers distracted by cell phone use experience a higher crash risk than undistracted drivers. Researchers also consider the role that different cell phone interfaces may have on driving performance. A study by Brace et al. (2007) examines the effects of *hands-free (HF)* and *handheld (HH)* cell phone use on driving performance. Their research indicates that using a cell phone while driving distracts a driver visually, physically, and/or cognitively, which increases the crash risk four fold. Alm and Nilsson (1994), Bogle (2001), Cain (1999), and Strayers and Johnston (2001) address cognitive versus physical demand and observe a different risk associated with HH and HF devices. Recent research (Mazzae et al., 2004;

Schreiner et al., 2004; Tornros and Bolling, 2005) also confirms that dialing either an HF or HH cell phone can have serious consequences on driving performance. Schreiner et al. (2004) examine the effects of dialing tasks using HH and HF phones on the ability to detect forward and peripheral events. They reveal that reaction times to visual events increase when using a HH device. Strayer et al. (2001) also find that cell phone users react slower, have longer following distance, and take longer to recover to following speed. In another study, Mazzae et al. (2004) investigate the effects of wireless phone interfaces on both phone tasks and driving performance. They use driving simulator data and conclude that the HH interface proves to be the most difficult task to perform while driving, followed by the *headset (HS)* and HF interfaces. Strayer et al. (2006) find that the impairment associated with conversing on a cell phone while driving and driving under the influence of alcohol have the same impact. Patten et al. (2004) examine participants answering a phone in either HH or HF mode, but they do not distinguish between answering a phone call and holding a conversation. This study considers the cell phone interface type and its impact on drivers in a dilemma zone while controlling for the experimental effects of cell phone call order. Clearly, various studies (both field test and simulator based tests) have examined the behavioral change of distracted drivers while using a cell phone either HF or HH, but only a handful of them (Xiong et al., 2015 and Savolainen, 2016) consider HF, HH, and HS devices all together in their research. Though these recent studies use the same experimental data set used in this research, the other studies fail to control for treatment order. This study focuses on the impact of cell phone use driver decisions at the dilemma zone and considers the cell phone as well as driver and vehicle characteristics when constructing the final model.

1.2. Dilemma Zone

At a dilemma zone, drivers face the challenge of deciding to stop or go when the signal indication changes from green to yellow. The original *dilemma zone*, also known as a Type I dilemma zone (Figure 1) represents the portion of the roadway approach to an intersection where a driver may not stop comfortably nor safely reach the other side of the intersection before the phase changes. This type of dilemma assumes that drivers possess awareness of the variables (e.g. perception of distance from the stop line and speed) that define a dilemma zone. However, in the absence of knowledge of these variables, drivers tend to face a different dilemma when making the stop vs. go decision at the onset of the yellow indication. In this Type II dilemma zone (Figure 1), drivers must still decide whether to stop or go, but the dilemma remains due to their uncertainty associated with the variables that define the dilemma zone. Traffic engineers recognize the importance of mitigating the effect of the dilemma zone at a signalized intersection.

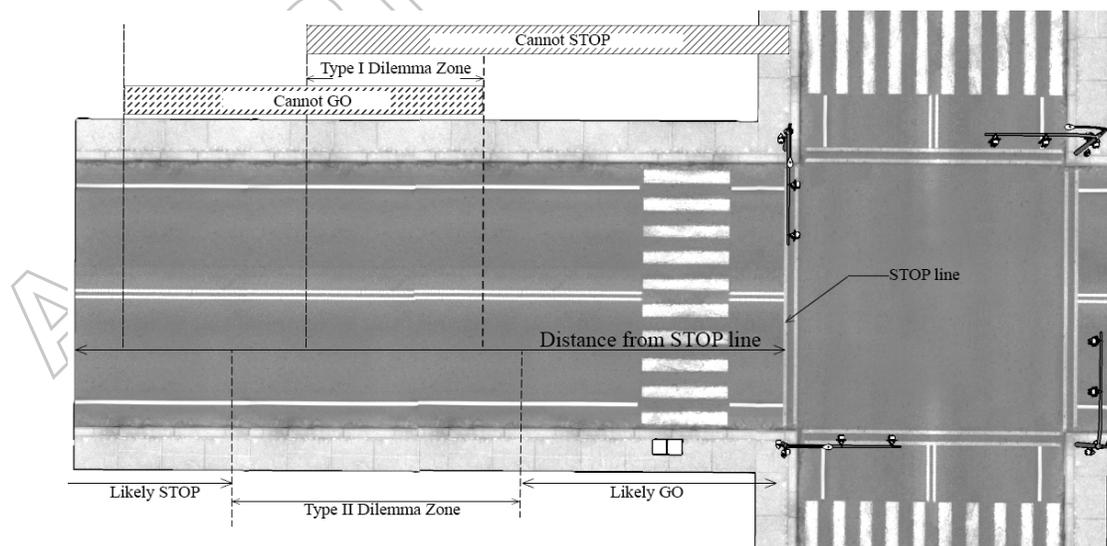


Figure 1. Definition of Different Dilemma Zones

The length and location of a dilemma zone may vary with the speed of the approaching vehicle, driver reaction time, vehicle acceleration and deceleration rates, vehicle distance from the intersection at the onset of the yellow indication and position in the traffic flow (Liu et al., 2007, Rakha et al., 2008; Elmitiny et al., 2010; Papaioannou, 2007). Two types of driver error in the dilemma zone pose significant safety risks. In the first case, a rear-end crash may result if a driver decides to stop when he or she should have proceeded. The other error, where a driver decides to proceed when he or she should have stopped, will result in a red light violation and possible right-angle collision (Hurwitz et al., 2012). The driver response to the dilemma zone makes a significant impact on intersection safety.

Several studies have used field data to evaluate drivers whereas several others use high-fidelity driving simulators. Elmitiny et al. (2010) shows that a vehicle's distance from the intersection at the onset of a yellow indication, operating speed, and the position in the traffic flow represent the most important predictors for both the stop vs. go decision and red-light running violation based on an analysis of 1292 drivers at an Orlando intersection. In a different approach, Liu et al. (2012) classify drivers into aggressive, conservative, and normal groups and apply an ordered-probit model on 1123 individual driver responses at six Maryland intersections. They consider many potential influential factors on driver behavior at a signalized intersection; the factors include vehicle characteristics and conditions, intersection layout, gradient, signal phasing sequence, cycle length, yellow signal duration and all red period, position in a platoon, vehicle speed, distance from the stop line, and driver characteristics. Their results show that a driver's age and gender, the difference between a vehicle's approaching speed and the average traffic flow speeds, and a vehicle's type and model characterize some major variables that define the dilemma zone distribution; these findings appear consistent with the results of Rakha et al. (2008). Drivers with a higher approach speed with respect to a posted speed limit remain more prone to face a dilemma zone at the onset of the yellow indication (Papaioannou, 2007). The decision at the dilemma zone also depends on the age of the participants. Caird et al. (2007) demonstrate that both young and older drivers appear less likely to run through the stop line when their time to the stop line is higher. On the other hand, Shinar and Compton (2004) and El-Shawarby (2008) show that young drivers appear more aggressive than adults at the onset of a yellow indication. Instead of trying to classify drivers based on their behavior, this paper recognizes that cell phone use multiplies the probability of crash occurrence at the onset of the yellow indication and assesses driver aggressiveness as one of many potential exogenous variables.

Some recent studies have considered the impact of cell phone use on driver decision-making in the dilemma zone. Savolainen (2016) compares several modeling frameworks such as pooled logit models, random parameter logit models, and latent class logit models for examining driver behavior. He uses the last two aforementioned models to mitigate the correlation of the decisions of participants and allows for the heterogeneity associated with them. Xiong et al. (2015) examine a stop vs. go situation along with fast go vs. slow go at the onset of the yellow indication by using General Linear Mixed models with a binomial distribution and logit link (mixed-effects logistic regression). Both of these previous approaches do not control for cell phone call order in their model estimation. Eluru and Yasmin (2015) use an econometric model to check the stop vs. go and success vs. failure decisions of participants and build distributions associated with different cell phone treatment types. Haque et al. (2015) use Classification and Regression Tree (CART) to consider the underlying heterogeneity of the variables to examine the stop vs. go driver behavior. This data mining approach seems to consider the interrelated heterogeneity of variables very easily and represent the independent variables properly. Their model development uses cross-validation, which can help limit the problems of overfitting the data on small data sets. However, with sufficient data, calibrating a CART model on a training data set and validating it on a separate testing data set reduces the likelihood of an overfit model. This study not only uses the CART modeling approach when examining stop vs. go behavior, but it also considers the controls for the experimental order of the phone calls (no call, incoming, and outgoing) and validates the models using a separate testing data set to show these models are not overfitting the data.

2. Contribution

Cell phone use appears to multiply the risks associated with dilemma zone driver behavior, and very few studies have investigated this relationship comprehensively. This paper uses a different methodology than previous studies. This methodology considers three different behavioral reactions (i.e. stop vs. go, legal vs. illegal, and expected vs. unexpected) using logistic regression and using a nonparametric CART approach that considers the interrelated heterogeneity of variables when examining the stop vs. go behavior. As opposed to other studies, this paper's methodology controls for experimental treatment order and shows that it is significant and cannot be ignored. Finally, the methodology divides the data set into training and testing sets to validate the results and ensure that the estimated models do not overfit the data. By controlling for demographics, driver behavior, and experimental design, the research team isolates the impact of cell phones under different use scenarios. While the logistic regression models focus on the overall impact of the variables, the CART model develops subpopulations based on the variables' impact. The first model out of the four considers whether the driver makes a legal or illegal maneuver. The next two models predict whether the driver decides to go through the intersection instead of stopping. The final model considers whether the driver performs an experimentally elicited expected maneuver or contradicts it by performing an unexpected maneuver. These models provide similar results; however, their descriptions of the influential factors differ.

3. Data Source and Description

3.1. Driving Simulator

Examining cell phone induced driver behavior at the onset of the yellow indication at a dilemma zone requires a huge set of data with multiple explanatory variables. Running an experiment in the real world is not only costly and infeasible but also not safe for participants. The National Advanced Driving Simulator (NADS) at the University of Iowa provides an ideal mechanism for conducting this kind of experiment in a simulated environment. NADS-1 at this research facility is the world's 2nd largest high fidelity driving simulator, and it can create a realistic reproduction of motion cues for sustained acceleration and braking maneuver, movement across multiple lanes of traffic, and interaction with varying road surfaces (NADS, 2016). This 24-ft dome shaped NADS-1 simulator can house an actual vehicle cab, which not only provides 360° horizontal and 40° vertical angle of view for the driver but also is equipped with 13-degree-of-freedom motion. A combination of these factors ensures the closest experience to driving an actual vehicle. Some of the results of output variables are recorded at rates up to 240 Hz. The analysis data set originated from a study conducted by NADS and was made available in 2014 by the Transportation Research Board (TRB) Data Competition Committee (Statistical Methods ABJ80).

3.2. Participants

A total of 49 participants took part in the experiment. The experiment is structured in such a way that participants of different age groups and genders drive through a signalized intersection. The three different age groups defined for the experiment are *young (18-25 years old)*, *middle aged (30-45 years old)*, and *old (50-60 years old)*.

3.3. Simulation Experiment

All 49 participants had to complete four drives; the first drive familiarized the participant with the driving simulator environment. The remaining three drives represent the experiment and included three segments and two intersections. As a result, each participant encountered six intersections. On each of their drives, participants were randomly assigned to a HH, HF, or HS cell phone interface, and a sequence of *baseline* (no call), *incoming call*, and *outgoing call* (denoted BOI, BIO, OBI, OIB, IOB, and IBO).

During different phases, a signalized intersection presents a green, yellow, or red indication. NADS designed the experiment so that the signal indication changes from green to yellow based on the vehicle's speed when the front of the vehicle is either 3.0 or 3.75 seconds from the stop bar. The light remains yellow for 4.0 seconds. However, within the data, the yellow time ranges from 2.78 to 4.38 seconds because of observed deviations in the simulator. Later, the light transitions to red for another 5.0 seconds. Ambient traffic remains unchanged for all scenarios. After removal of several redundant data,

the initial data set contains 1157 observations and 17 variables where each row represents data for one yellow event. A summary of all these variables and their brief description with category examples are given in Appendix A, while a detailed data description can be accessed by going to the following website (<http://trbstats.weebly.com/2014-trb-data-competition.html>).

4. Data Processing

4.1. Cleaning

The Data Competition Committee recommends omitting 291 of the initial 1157 observations, because they represent practice runs, which reduces the data set to 866 observations. According to Safer Street L.A. (Beeber, J. 2011), the upper 85th percentile of traffic on a 35 mph street will drive at 45 mph, and so a yellow time of only 3.6 seconds is almost one second shorter than the 4.3 seconds required for stopping a vehicle at the stop line. Based on this definition, the 866 observations have some data points that have short or long yellow times. The research team also notes that out of the 866 observations in the final data set, some data observations show contradictory values in terms of representing the specific point where the vehicle stopped with respect to the stop line. Hence, a total of 361 of these observations are omitted from further analysis (Table 1).

Table 1. Explanation for Reduced Data Set

	Description	Omitted Observations	Remaining Observations
1	Initial data provided by 2014 TRB Data Contest Committee		1157
2	2014 TRB Data Contest Committee recommends omitting data because of familiarization	291	866
3	Data contradictions where the time frame values indicate that the driver made the first stop beyond the stop line while the distance values indicate that the driver stopped before the stop line	135	731
4	Short or long yellow lights outside of a 3.9-to-4.1-second range, which is considered to encompass the yellow times similar to the expected yellow time of 4.0 seconds	222	509
5	Erroneous data for values of -1 in multiple time frame events	4	505

Even though the data set is reduced to 505 observations (*total set*) from 866 observations, the distributions of the variables and treatment orders remain similar as shown in Table 2. In the final data set (*total set*), the frequencies among different age groups are 36.8% for young drivers, 30.3% for old drivers, and 32.9% for middle-aged drivers. On the other hand, among the participants almost 44.4% are females while 55.6% are males. These percentage ratios remain very similar as in initial 866 observations. In addition, the driving attributes are also similar. The range of velocity (*vel*), which is a continuous variable, remains similar between the initial set and the final data set; velocity originally ranges from 24.61 to 53.95 mph and the range changes to 25.21 to 52.65 mph, in the final data set.

Table 2. Distribution of Variables and Treatment Orders

	Variables	Initial Set: 866 observations	Total Set: 505 observations
		Total (%)	Total (%)
Explanatory variables	Young age (18-25 years)	322 (37.2)	186 (36.8)
	Middle age (30-45 years)	303 (35.0)	166 (32.9)
	Older age (50-60 years)	241 (27.8)	153 (30.3)
	Male	459 (53.0)	281 (56.0)
	Female	407 (47.0)	224 (44.0)
Treatment order	BOI	139 (16.1)	90 (17.8)
	BIO	146 (16.9)	94 (18.6)
	IOB	145 (16.7)	75 (14.9)
	IBO	147 (17.0)	81 (16.0)
	OBI	142 (16.4)	90 (17.8)
	OIB	147 (17.0)	75 (14.9)
Cell Phone Device Treatment	Baseline	295 (34.1)	153 (30.3)
	Incoming HH	96 (11.1)	56 (11.1)
	Incoming HF	98 (11.3)	60 (11.9)
	Incoming HS	92 (10.6)	65 (12.9)
	Outgoing HH	98 (11.3)	66 (13.1)
	Outgoing HF	96 (11.1)	53 (10.5)
	Outgoing HS	91 (10.5)	52 (10.3)

4.2. Variables Encoding

The study builds four models with different response variables such as stop vs. go, expected vs. unexpected decision, and legal vs. illegal through movement with a set of candidate predictor variables. The set of predictor variables include continuous and categorical variables of two or more levels, which are represented by a set of binary two-level categorical variables. In addition to the predictor variables defined in the original data set and given in Appendix A, the research team defines four other binary predictor variables. Three of these predictor variables represent three possible types of driver aggressiveness; the subject is considered an aggressive driver if the “overall velocity at green to yellow” is greater than the 90th percentile (referred to as *speed*), if the “minimum acceleration after acceleration pedal change” is less than the 10th percentile (*dec*), or if the “maximum acceleration after acceleration pedal change” is greater than the 90th percentile (*acc*). Based on these definitions, the study classifies 7.3% of the drivers as aggressive based on the speed (*speed*), 11.9% based on deceleration (*dec*), and 10.1% based on acceleration (*acc*). The fourth predictor variable, *elicit*, is defined to be “stop” for observations in which the “time to stop bar” of the yellow signal is greater than 3.375 seconds; otherwise the elicit variable is classified as “go.”

4.3. Data Sets

From the final 505 observations (*total set*), 100 are randomly selected for model validation purposes and labeled as the *testing set*. The remaining 405 observations are labeled as the *training set*. Of the 505 observations in the total data set, more than 81% of the responses are legal stops or legal goes. Therefore, the *total set* does not have enough balance between the legal and illegal through movements to develop an accurate model. As an alternative, the study considers a data set with only the legal and illegal through movement cases. This data set (*through movement set*) includes 108 observations, of which 59% are legal (represented by 1) and 41% are illegal (0).

5. Modeling and Analysis

Four models are developed to assess driver behavior in a dilemma zone while distracted. The response variables considered in this study are: legal vs. illegal through movements (Model 1), stop vs. go driver decision (Models 2 & 3), and expected vs. unexpected decision (Model 4). For each of these responses, the statistical software SAS is used for generating logistic regression models (Models 1, 2 & 4) with the PROC LOGISTIC function including a stepwise selection where a significance level of 0.3 is required to allow a variable into the model, and a significance level of 0.35 is required for a variable to stay in the model. For all of the logistic regression models, the probability that an observation is true (i.e. legal, go, or expected) is defined by the following equation:

$$P_i = \frac{1}{1 + e^{-y_i}}, \quad \text{where } y_i = \beta x_i + \beta_0, \quad \text{for } i = 1 \Leftarrow n \quad (1)$$

where n is the number of observations, and y_i is a utility function of the binary dependent response variable, which takes the independent predictor variables x_i . Here, β is a vector of regression coefficients of the utility function, and P_i is the probability that the response is true.

The legal vs. illegal through movement of drivers crossing a stop bar is considered for Model 1, and the *through movement set* is used for modeling. The other three models in this research use the *total set*. In Model 2, a stepwise logistic regression stop vs. go model is built with the training set, and further validated with the testing set. The dependent variable of Model 2 is defined based on the “first stop frame” variable, which has a frame number if the vehicle stopped, and a value of -1 if the vehicle did not stop. Therefore, Model 2 has as a response variable: stop (0) or go (1). The training set contains 101 go observations.

In addition to the logistic regression models, the study uses a Classification and Regression Tree (CART) model (Model 3) as another tool to study the stop vs. go driver decision response. CART (Hastie et al., 2001) uses decision trees to map observations to conclusions. This data mining strategy considers the stop vs. go driver decision response (Model 3) using the *classregtree* function from Matlab Statistics Toolbox on the training set. CART is a binary recursive partitioning methodology. A parent node is split exactly into two child nodes, and if required, each child node will act as a parent node and split again. Instead of attempting to decide whether a given node is terminal or not, CART proceeds by growing trees until it is not possible to grow them any further. A common technique among the first generation of tree classifiers is to continue splitting nodes (growing the tree) until some goodness-of-split criterion fails to be met. CART determines the best tree by testing for error rates or costs. The authors apply a constraint requiring that at least twelve observations be on a terminal leaf node. This ensures an ample number of observations at the terminal node, which reduces the chances of overfitting the data. The probability of a response variable being 1 within each leaf of a tree is the relative frequency of the response variable being 1 in the training data. Consequently, the probabilities within the leaves of the tree are considered conditional or posterior probabilities based upon the tree logic.

A stepwise logistic regression model is performed to investigate the probability of a driver making the expected decision based on the elicited maneuver (Model 4). The expected vs. unexpected response variable is defined based on the driver’s decision (dependent variable in the previous model) and the elicit variable. If the driver’s decision matches with the elicited maneuver, the decision is expected (1); otherwise, it is unexpected (0). In the training set, 174 observations are expected decisions. The following subsections describe the model formulation and validation process along with brief discussion on the hypothesis and results.

5.1. Legal vs. Illegal Through Movement

A legal through movement occurs when the driver crosses the stop bar during a green or yellow indication, and on the other hand, an illegal through movement occurs when the driver crosses during a red indication. Model 1 is developed for predicting legal and illegal through movements, which considers IBO and OIB treatment orders and outgoing HF device. The function for Model 1 is given by

$$\hat{y} = -0.3990 + 1.1069 * IBO + 1.7979 * OIB + 2.4881 * OHF \tag{2}$$

(0.157) (0.031) (0.004) (0.022)

The p-values for the variables are shown in the parentheses.

The treatment orders IBO and OIB, and the outgoing call with a hands-free phone increase the probability of a driver performing a legal maneuver. The treatment orders' significance indicates that the experiment has some impact on behavior. Based on the coefficients of each independent variable of Model 1, the probability of each observation is calculated. This calculation indicates that there is an overall tendency (~60%) to engage in illegal behavior when a through movement occurs, but many drivers opt out of the go maneuver and simply stop. This overall tendency is true for most of the phone scenarios, although the outgoing hands-free phone call has a positive impact on performing a legal maneuver. Table 3 shows the odds ratios of the parameters. Once again, the results from Table 3 indicate that the outgoing hands-free phone call has a more significant effect on driver behavior than treatment order.

Table 3 Odds Ratio for Legal vs Illegal Through Movement (Model 1)

Odds Ratio Estimates			
Treatment	Point Estimate	95% Wald Confidence Limits	
IBO	3.025	1.106	8.272
OIB	6.037	1.778	20.494
OHF	12.038	1.439	100.728

The study uses the Hosmer and Lemeshow probability test (see Hosmer et al. (2013) for complete details), which is based on a Chi-squared test ($\chi^2=0.0028$, DF=2) as a goodness-of-fit test. After segmenting the model results into probability clusters, the observed probabilities do not appear significantly different from the expected probabilities and have a p-value of 0.999. In addition, three tests of the model significance are in Table 4. The coefficient of determination, R², of Model 1 is 16.1%.

Table 4 Hypothesis Test for Legal vs Illegal Through Movement (Model 1)

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	p-value
Likelihood Ratio	18.98	3	0.0003
Score	16.69	3	0.0008
Wald	14.39	3	0.0024

5.2. Stop vs. Go Driver Decision

5.2.1. Logistic Regression Model

Model 2 has as a response variable of two possible values: stop (0) or go (1). The function of the stop vs. go logistic regression model is presented in the following equation:

$$\hat{y} = -0.0772 + 0.5986 * ageO - 0.5864 * gender - 0.6187 * OBI - 0.7618 * IOB - 0.5563 * IHH - 0.3432 * accel - 1.7277 * dec - 1.8369 * acc - 1.2863 * elicit \tag{3}$$

(0.0239) (0.0994) (0.0761) (0.1056) (0.2327)
 (0.2297) (0.0234) (0.0028) (<0.0001)

Most estimated parameters have a p-value of 0.10 or smaller, which indicates that they are likely to be significant parameters. The most significant variables are *elicit* and *acc* which have p-values of <

0.0001 and 0.0028, respectively, while the least significant parameters, *accel* and *IHH*, have p-values between 0.22 and 0.24. This is also clear from estimated Odds ratio presented in Table 5.

Table 5 Odds Ratio for Stop vs. Go Maneuver

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence	
		Limits	
ageO	1.820	1.089	3.041
Gender	0.556	0.332	0.932
OBI	0.539	0.266	1.091
IOB	0.467	0.209	1.042
IHH	0.573	0.228	1.440
Accel	0.710	0.408	1.234
Dec	0.178	0.040	0.799
Acc	0.159	0.036	0.698
Elicit	0.276	0.153	0.500

The value of the goodness-of-fit statistic computed by the Hosmer and Lemeshow probability test is $\chi^2=10.7$, and the corresponding p-value computed from the chi-squared distribution with 8 degrees of freedom is 0.22. The p-value is not significant, so the null hypothesis that the model fits cannot be rejected, which indicates the model seems to fit well. The coefficient of determination Tjur-R² (Tjur, 2009) value for this model is 0.38, which is computed by obtaining the difference between the mean of the predicted probabilities of an event (i.e., the two categories of the response variable, stop or go).

Using the testing data, Model 3 is validated with a Hosmer and Lemeshow test. The test yields a goodness-of-fit statistic of $\chi^2=10.9$ with 9 degrees of freedom and a p-value of 0.29, which suggests that the model presented above has a good fit. The Tjur- R² value for the testing data set is 0.40, which is greater than that of the training set, suggesting that the model is not overfitting the data.

5.2.2. Classification and Regression Tree Model

CART (Hastie *et al.*, 2001) uses decision trees to map observations to conclusions. The decision tree and posterior probabilities from the CART model are illustrated in Figure 2. The splitting variables are: elicit, ageO, acc, gender, and treatments OIB and BIO.

Given the estimated probability distribution from the tree model, a driver is highly probable to stop when he or she is supposed to go (probability = 0.8916). If drivers are supposed to stop, many factors affect the probability of making the decision to go. For example, given they are asked to stop, old male drivers have a higher probability of going than stopping (probability = 0.6818). Given that a driver is not aggressive based on the acceleration in the top 10 percent and the driver is not in the old age group, treatment order such as OIB and IBO affect the probability of going significantly. A chi-square goodness of fit test is conducted and yields a goodness-of-fit statistic of 2.5 with 6 degrees of freedom and a p-value

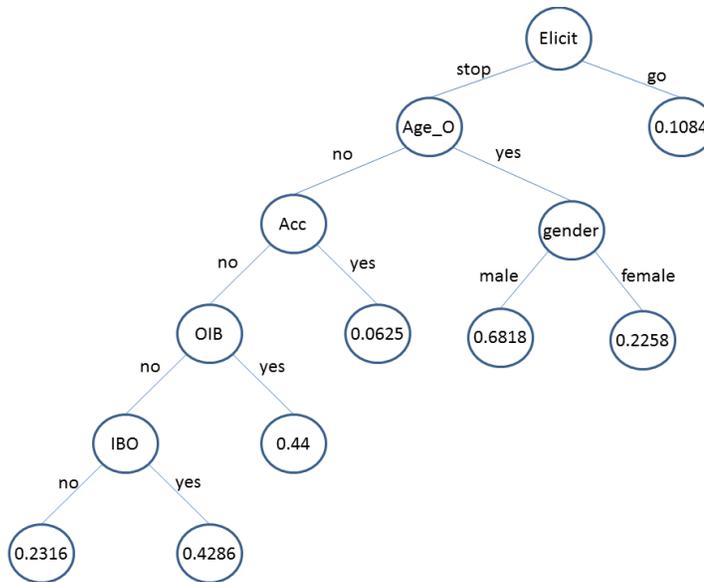


Figure 2 Decision tree model for probability of “go” for Model 3.

of 0.87. Therefore, the null hypothesis cannot be rejected, and it can be concluded that the posterior probability distribution of the decision tree model is a good fit. The R^2 value of this decision tree model is calculated from the posterior probabilities using the Tjur- R^2 mentioned previously. These values are 0.49 for the training set and 0.49 for the testing set, which suggests that the model does not overfit the data. This model generates a better fit and produces similar conclusions as the logistic regression models. However, the cell phone use is notably absent from this model. This supports the conclusion that the drivers’ behaviors are impacted by being observed in an experiment.

5.3. Expected vs. Unexpected Driver Decision

A stepwise logistic regression model is used to investigate the probability of a driver making the expected decision based on the elicited maneuver (Model 4). The expected vs. unexpected logistic regression model is presented in the following equation:

$$\hat{y} = 0.7865 - 0.8456 * ageO + 0.7418 * BIO - 0.5296 * OIB - 0.3724 * IBO + 0.4406 * accel + 0.5482 * acc - 2.9871 * elicit$$

(0.0013)
(0.0059)
(0.2127)
(0.0891)
(0.0857)
(4)

(0.1482)
(<0.0001)

Equation 4 shows in parenthesis that all estimated parameters have small p-values (p-value <0.2), which indicates that they are likely to be significant parameters. Based on the coefficients of each independent variable of Model 4, the probability of each record is calculated. This calculation indicates an overall tendency (~69%) to make an expected decision (1: probabilities greater than 0.5), while the rest indicates an unexpected decision (0: probabilities less than 0.5).

Like the previous models, the experimental treatment order appears to have an impact on driver decision-making. When no call occurs during the first run, drivers seem more likely to make expected decisions. Most significantly, the *elicit* variable is the strongest indicator of making an unexpected choice where the drivers elicited to go are almost twenty times more likely to be unexpected and stop. Driver aggression with respect to acceleration suggests a greater probability (73%) of making the expected choice. Similarly, changing the accelerator pedal also indicates a higher probability (55%) of making an expected choice. Older drivers appear to be 133% more likely to make unexpected decisions. While the

other age groups may have coped with phone usage, older drivers may be significantly distracted. However, as a separate variable, cell phone use does not appear to be significant in influencing a driver's ability to make an expected or unexpected decision.

The value of the Hosmer-Lemeshow goodness of-fit-statistic for the training data set is 2.6, and the corresponding p-value with 8 degrees of freedom is 0.96, which indicates that the model fits well. The coefficient of discrimination Tjur-R² value of Model 5 is 0.52. For the testing set, the value of the Hosmer and Lemeshow goodness-of-fit statistic is 4.8, and the corresponding p-value with 9 degrees of freedom is 0.78. The Tjur- R² value for the testing data set is also 0.52, which demonstrates that the model does not overfit the training data.

6. Conclusions

The purpose of this study is to identify differences in driver behavior in a dilemma zone while distracted by cellular phone calls. The database and experimental data appear to have significant weaknesses. The data and experiment need more careful control to improve the quality of the final conclusions. Some potential confounding effects such as other vehicles on the road and platoon location are not clearly defined nor provided. Overall volume may also impact behavior.

Three different response variables are defined: *legal vs. illegal* through movement (Model 1), *stop vs. go* driver decision (Models 2 & 3), and *expected vs. unexpected* decision (Model 4). Statistical Analysis (Logistic Regression Models) suggest that the impact of cell phone use (treatment order) appears relatively inconclusive with the outgoing hands-free device appearing to have the most significant impact on performing a legal maneuver (Model 1). Overall, the drivers appear to be behaving conservatively; this is likely due to being observed. All models except the *legal vs. illegal* through movement model appear to support this conclusion. While the *legal vs. illegal* through movement models do not directly support this finding, they do not contradict it either. Instead, they offer further insight into the driver behavior. Overall, the drivers tend to stop (Models 2 & 3). However, when they decide to go, they tend to make the wrong choice and run the red light. Only one cell phone experimental case, the outgoing hands-free call, appears to mitigate this effect (Model 1). Contrary to likely expectations, Model 4 shows that aggressive drivers when defined based on acceleration tend to make expected decisions and appear more likely to stop when elicited to do so. The logistic regression model (Model 2) and the CART model (Model 3) on stop vs go driver decision show that older drivers appear to be particularly negatively impacted by this experiment. Based on the stop vs. go models, old drivers appear more likely to go, in particular when they are elicited to stop, which presents a particularly risky mistake. When most drivers behave conservatively, the old drivers appear less likely to make expected decisions. While cell phone usage rarely appears to be significant in any of the models, the outgoing hands-free treatment appears to significantly mitigate the likelihood of performing an illegal maneuver (Model 1). This represents a potential opportunity for adjusting future policy and technological advancements to improve intersection safety.

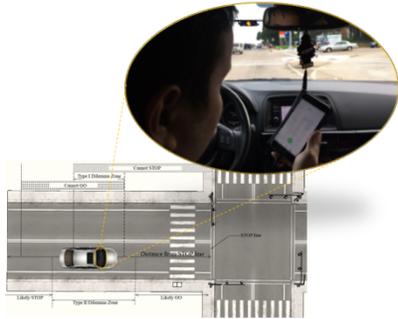
Acknowledgement

The authors are grateful to the Transportation Research Board (TRB) Data Competition Committee-Statistical Methods (ABJ80) for data providing and creating a great opportunity for the students to take part in 2014 Data Contest. The authors are also grateful to USDOT-National Highway and Transportation Safety Association for funding the wireless urban arterial project conducted at the University of Iowa-The National Advanced Driving Simulator. Special Thanks to Professor Linda Ng. Boyle, Dr. Matthew Karlaftis and Susan Chrysler for creating and undertaking this opportunity.

References

1. CDC. (2013, March 14). *CDC Press Release*. Retrieved from CDC: https://www.cdc.gov/media/releases/2013/p0314_driving_mobile_device_use.html
2. NHTSA. (2016). Retrieved from <http://www-nrd.nhtsa.dot.gov/Pubs/812260.pdf>
3. Hurwitz, D.S., Wang, H., Knodler Jr., M.A., Ni, D., Moore, D., 2012. Fuzzy sets to describe driver behavior in the dilemma zone of high-speed signalized intersections. *Transp. Res. Part F: Traffic Psychol. Behav.* 15 (2), 132–143.
4. FARS. (2016). *Fatality Analysis Reporting System*. Washington: NHTSA.
5. Mazzae, E. N., Ranney, T. A., and Watson, G. S., Hand-held or Hands-free? The Effects of Wireless Phone Interface Type on Phone Task Performance and Driver Preference. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 48, 2004, pp. 2218-2222.
6. Törnros, J., Bolling, A. Mobile phone use – effects of conversation on mental workload and driving speed in rural and urban environments. *Transp. Res. Part F: Traffic Psychol. Behav.* 2006. 9 (4), 298–306. doi:<http://dx.doi.org/10.1016/j.trf.2006.01.008>.
7. Lissy, K. S., Cohen, J. T., Park, M. Y., and Graham, J. D., Cellular Phone Use While Driving: Risks and Benefits. 2000.
8. Patten, C., Kircher, A., Östlund, J., and Nilsson, L., 2004. “Using mobile telephones: Cognitive workload and attention resource allocation.” *Accid. Anal. Prev.*, 36(3), pp. 341–350.
9. Consiglio, W., Driscoll, P., Witte, M., Berg, W.P., 2003. Effect of cellular telephone conversations and other potential interference on reaction time in a braking response. *Accid. Anal. Prev.* 35 (4), 495–500. doi:[http://dx.doi.org/10.1016/S0001-4575\(02\)00027-1](http://dx.doi.org/10.1016/S0001-4575(02)00027-1).
10. Hosking, S., Young, K., & Regan, M. (2006). The Effects of Text Messaging on Young Novice Driver Performance. Report funded by The National Roads and Motorists' Association (NRMA) Motoring and Services and NRMA Insurance.
11. Caird, J.K., Chisholm, S., Edwards, C.J., Creaser, J.I., 2007. The effect of yellow light onset time on older and younger drivers' perception response time (PRT) and intersection behavior. *Transp. Res. Part F: Traffic Psychol. Behav.* 10 (5), 383–396.
12. Bogle, K. (2001). Effect of Car Phone use on Cognitive Ability and Driving Performance. Classen School of Advanced Studies, Oklahoma City, Oklahoma.
13. Redelmeier, D., Tibshirani, R., 1997. Association between cellular-telephone calls and motor vehicle collisions. *N. Engl. J. Med.* 336 (7), 453–458.
14. Bellavance, F. (2005). Linking Data from Different Sources to Estimate the Risk of Collision When Using a Cell Phone While Driving. Paper Presented at the International Conference on Distracted Driving, Toronto, Canada.
15. Violanti, J. and Marshall, J. (1996). Cellular Phones and Traffic Accidents: An Epidemiological Approach. *Accident Analysis and Prevention.* 28(2): 265-270.
16. Sagberg, F. (2001). Accident Risk of Car Drivers During Mobile Telephone Use. *International Journal of Vehicle Design.* 26(1): 57-69.
17. Rakauskas, M.E., Gugerty, L.J., Ward, N.J., 2004. Effects of naturalistic cell phone conversations on driving performance. *J. Saf. Res.* 35 (4), 453–464. doi:<http://dx.doi.org/10.1016/j.jsr.2004.06.003>.
18. Brace, C. L., Young, K. L., and Regan, M. A. Analysis of the literature: The use of mobile phones while driving. *Analysis*, 37 (2007), pp. 261–265
19. Alm, H. & Nilsson, L. (1994). Changes in driver behavior as a function of handsfree mobile phones – A simulator study. *Accident Analysis and Prevention.* 26(4):441-451.

20. Cain, A., & Burris, M. (1999). Investigation of the use of mobile phones while driving. Center for Urban Transportation Research, College of Engineering, University of South Florida.
21. Strayer, D. & Johnston, W. (2001). Driven To Distraction: Dual-Task Studies of Simulated Driving and Conversing on a Cellular Telephone. *Psychological Science*. 12(6):462-466.
22. Törnros, J., Bolling, A., 2006. Mobile phone use – effects of conversation on mental workload and driving speed in rural and urban environments. *Transp. Res. Part F: Traffic Psychol. Behav.* 9 (4), 298–306. doi:<http://dx.doi.org/10.1016/j.trf.2006.01.008>.
23. Strayer, D.L., Johnston, W.A., 2001. Driven to distraction: Dual-task studies of simulated driving and conversing on a cellular telephone. *Psychol. Sci.* 12 (6), 462–466.
24. Savolainen, P.T., Examining driver behavior at the onset of yellow in a traffic simulator environment: Comparisons between random parameters and latent class logit models. *Accid. Anal. Prev.* (2016), <http://dx.doi.org/10.1016/j.aap.2016.01.006>.
25. Xiong, H. Narayanaswamy, P., Bao, S., Flannagan, C., and Sayer, J. How do drivers behave during indecision zone maneuvers? *Accident Analysis and Prevention*. (2015), <http://dx.doi.org/10.1016/j.aap.2015.04.023>
26. Strayer, D. L., Drews, A., and Crouch, D. J., A Comparison of the Cell Phone Driver and the Drunk Driver. *Journal of Human Factors*, vol. 48, no. 2, 2006, pp. 381–391.
27. Liu, Y., Chang, G.-L., Tao, R., Hicks, T., Tabacek, E., 2007. Empirical observations of dynamic dilemma zones at signalized intersections. *Transp. Res. Rec.: J. Transp. Res. Board* 2035, 122–133.
28. Rakha, H., Amer, A., El-Shawarby, I., 2008. Modeling driver behavior within a signalized intersection approach decision-dilemma zone. *Transp. Res. Rec.: J. Transp. Res. Board* 2069 (1), 16–25.
29. Elmitiny, N., Yan, X., Radwan, E., Russo, C., Nashar, D., 2010. Classification analysis of driver's stop/go decision and red-light running violation. *Accid. Anal. Prev.* 42 (1), 101–111.
30. Papaioannou, P., 2007. Driver behaviour, dilemma zone and safety effects at urban signalised intersections in Greece. *Accid. Anal. Prev.* 39 (1), 147–158.
31. Hurwitz, D.S., Wang, H., Knodler Jr., M.A., Ni, D., Moore, D., 2012. Fuzzy sets to describe driver behavior in the dilemma zone of high-speed signalized intersections. *Transp. Res. Part F: Traffic Psychol. Behav.* 15 (2), 132–143.
32. Liu, Y., Chang, G., Yu, J., 2012. Empirical study of driver responses during the yellow signal phase at six Maryland intersections. *J. Transp. Eng.* 138, 31–42.
33. Caird, J.K., Chisholm, S., Edwards, C.J., Creaser, J.I., 2007. The effect of yellow light onset time on older and younger drivers' perception response time (PRT) and intersection behavior. *Transp. Res. Part F: Traffic Psychol. Behav.* 10, 383–396.
34. Shinar, D., Compton, R., 2004. Aggressive driving: an observational study of driver, vehicle, and situational variables. *Accid. Anal. Prev.* 36, 429–437.
35. El-Shawarby, I., Amer, A., Rakha, H., 2008. Driver stopping behavior on high-speed signalized intersection approaches. *Transp. Res. Rec.: J. Transp. Res. Board* 2056 (1), 60–69.
36. Eluru, N., Yasmin, S., Disentangling the influence of cell phone usage in the dilemma zone: An econometric approach. *Accid. Anal. Prev.* (2015), <http://dx.doi.org/10.1016/j.aap.2015.11.036>
37. Haque, M.M., et al., Decisions and actions of distracted drivers at the onset of yellow lights. *Accid. Anal. Prev.* (2015), <http://dx.doi.org/10.1016/j.aap.2015.03.042>
38. NADS. (2016, June). Retrieved from https://www.nads-sc.uiowa.edu/sim_nads1.php
39. Beeber, J., Maximizing Safety At Signalized Intersections Through Increased Yellow And All-Red Signal Phases. *Safer Streets L. A. March*, 2011. Retrieved from <http://saferstreetsla.org/signal-timing/>
40. Hastie, T., Tibshirani, R., Friedman, J. H., *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer Verlag, New York, 2001.
41. Hosmer, Lemeshow, Stanley, Sturdivant, and Rodney, X., *Applied Logistic Regression*. Wiley. 2013.
42. Hastie, T., Friedman, J. H., Huang, H., Tibshirani, R., & SpringerLink (Online service). (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd; 2. ed.). New York: Springer. doi:10.1007/978-0-387-84858-7



ACCEPTED MANUSCRIPT

Appendix A
Initial data set variables with brief description

#	Variable	Definition [Category/Example]
1	Subj_001YM_	Subject 001 is a Young Male <i>Y: Young (18-25), M: Middle aged (30-45), Older (50-60)</i> <i>M: Male and F: Female</i>
2	Run_001YM_D1HH_T1BOI	Subject 001 is a young male whose Drive 1 (D1) was with handheld (HH) phone condition and Treatment (T1) was in the order of BOI: baseline, outgoing and incoming call <i>HH: HandHeld, HF: HandFree, HS: HeadSet</i> <i>B: Baseline, O: Outgoing call, I: Incoming call</i> <i>BOI, OBI and IOB</i>
3	Green to Yellow (frame number)	The video frame number when the traffic signal changed from green to yellow. <i>Example: Frame #1185302 indicates that the green to yellow change occurred at frame# 1185302 or $1185302/240\text{Hz} = 4938.8$ seconds into the drive</i>
4	Yellow to Red (frame number)	The frame number when the traffic signal changed from yellow to red <i>Example: $1186278/240 - 1185302/240 = 4$ seconds yellow</i>
5	Red to Green (frame number)	The frame number when the traffic signal changed from red to green <i>Example: $1187478/240 - 1186278/240 = 5$ seconds red</i>
6	Accel Pedal Changed 10%	The frame number for when the participant had an accelerator pedal change of greater than 10%
7	Accel Pedal Change Direction	Accelerated or not <i>-1: released and 1: depressed</i>
8	First Stop Frame	Frame number when vehicle first stops <i>Example: -1: didn't stop</i>
9	Dist from Stop Line	Distance from stop line <i>Example: "+" value: before line, "-" value: beyond line, and 9999: didn't stop</i>
10	Min Accel After Accel Pedal Change (ft/s ²)	Max deceleration between (row 5) and when driver goes past intersection.
11	Max Accel After Accel Pedal Change (ft/s ²)	Max acceleration between (row 5: 10% increase in Accel Pedal) and when driver goes past intersection.
12	Ov Vel at Green To Yellow (mph)	Participant's velocity when the light first turns from green to yellow
13	Ov Dist at Green to Yellow (feet)	Participant's distance from stop line when the light first turns from green to yellow
14	Ov Vel at Stop Line (mph)	Participant's velocity when they reached stop line
15	Frame at Stop Line	Frame # when participant reached stop line
16	Vel at Yellow to Red (mph)	Participant's velocity when the light goes from yellow to red
17	Event ID:	This is a number between 300 to 317 and is used to identify which run is B (baseline), O (outgoing), and I (incoming) <i>300-305: baseline, 306-311: outgoing, 312-317: incoming</i>

About the Author:

Ziaur Rahman is a Transportation Engineer graduated from the Civil Engineering Department of the University of Texas at Arlington (UTA). He holds an M.Eng. in Transportation Engineering from UTA. He has extensively collaborated on projects with the Transportation Research Center for Livable Communities and the North Central Texas Council of Government. His area of research interest includes transportation safety, transportation and public health, transportation and air quality, data mining, and statistical modeling and analysis.

Public Interest Statement:

Cell phone usage creates a cognitive burden on driving and may jeopardize the safety of drivers, passengers, and other road users, and few studies have investigated this relationship comprehensively. This research considers three different behavioral reactions in a dilemma zone, such as stop vs. go, legal vs. illegal, and expected vs. unexpected, and studies the interrelated heterogeneity of variables when examining the stop vs. go behavior. Unlike other studies in the literature, the research methodology here controls for experimental treatment order, which is shown to be significant. All models, except a legal vs. illegal through movement model, show that the drivers using cell phones appear to behave conservatively, which is likely due to being observed. In addition, using hands-free devices on outgoing calls appear to significantly mitigate the likelihood of performing an illegal maneuver. This represents a potential opportunity for adjusting future policy and technological advancements to improve intersection safety.