The Effects of Cellular Phone Usage on Driver Decisions at Signalized Intersections

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1.   INTRODUCTION

The term "dilemma zone" is generally used to describe the dilemma where approaching drivers must determine whether to stop or proceed through an intersection when a traffic signal changes from green to yellow (Gates *et al.*, 2010). The zone is defined in either time or space, and deterministic design values are used initially; however, both the length and the location of a dilemma zone may vary with the speed of the approaching vehicle, driver reaction time, and vehicle acceleration and deceleration rates (Liu *et al.*, 2006). Both types of driver error in the dilemma zone pose significant safety risks. In the first case, a rear-end crashes 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 crash. These safety concerns make the study of dilemma zones critical.

Within the dilemma zone some values can be determined empirically based on the driver speed such as the minimum safe stopping distance and critical crossing distance, which is the maximum distance from the stop bar where proceeding through the intersection is safe. Others, such as the perception-reaction time (PRT) may be measured; however, the perception-reaction time is only easily measured when the driver decides to stop. A more comprehensive assessment of perception-reaction time requires a driving simulator experiment paired with neuroscience. This study instead focuses directly on the driver decision-making and the propensity to make "correct" and "legal" choices.

Several studies have used to field data to evaluate the driver decision-making at intersections. Elmitiny *et al.* (2009) discovers that a vehicle's distance from the intersection at the onset of a yellow light, operating speed, and the position in the traffic flow are the most important predictors for both the stop/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: 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 stop line, and driver characteristics.   The results indicate that critical factors include the difference between a vehicle's approaching speed and the average traffic flow speeds, a driver's gender, age, talking over cell phone or not, and a vehicle's type and model. Instead of trying to classify drivers, this paper uses driving simulator data to assess the impact of cell phone use on driver behavior at intersections and considers driver aggressiveness as one of many potential exogenous variables.

Previous research indicates that cell phone usage should impact driver decisions. In fact, epidemiological evidence suggests that the impairment associated with conversing on a cell phone while driving and driving under the influence of alcohol have the same impact (Strayer *et al.* 2006). Strayer *et al.* use driving simulator data and find that cell phone users are slower to react, have longer following distance, and take a longer time to recover to following speed. Shah *et al.* (2010) support these findings and conclude that cell phone use produces prolonged reaction time. In another study, Mazzae *et al.* (2004) investigate the effects of wireless phone interface type on phone task performance and driving performance. They use driving simulator data and conclude that the handheld interface proves to be the most difficult task to perform while driving followed by the headset and hands free interfaces. While this paper does not focus on reaction time, it does investigate the potential impact of cell phone use on driver decision-making.

While driving simulator data is critical for developing controlled experiments, some previous studies have noted some concerns related to data quality and realism. According to Green (2005), removing the risk of death may cause driving simulator data to be biased. Lee *et al.* (2002) compares

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driving simulator data with corresponding data from a test track for the braking profile of drivers in last-minute braking situations; they find that the two data sets do not match exactly. In particular, drivers in the simulator appear less affected by the braking instructions. The exact impact on the driving simulator data likely varies based on the experiment and should be considered when evaluating results.

2.   CASE STUDY DESCIRPTION

The objective of this paper is to identify differences in driver behavior in a dilemma zone while distracted as well as to determine the factors that affect the driver's behavior. The data set comes from an experiment conducted at the University of Iowa National Advanced Driving Simulator (NADS). Participants from different age groups (young: 18-25yr; middle: 30-45yr; and old: 50-60yr) are exposed to driving through a signalized intersection while receiving a phone call (incoming or outgoing) or without receiving a phone call (baseline). The traffic signal changes from green to yellow to red to green again.

The experiment is structured to elicit a response from drivers. In the experimental design, the indication changes from green to yellow based on the vehicle's speed when the vehicle is either 3.0 or 3.75 seconds from the stop bar. In the 3.0 second case, the experiment expects to elicit a pass maneuver while in the 3.75 second case the experiment expects to elicit a stop maneuver. In the final experiment, these times do not occur consistently, and must be redefined.

Four models are developed in this paper for three different response variables. The first model considers whether the driver makes a legal maneuver. Two models predict whether the driver decides to pass through the intersection instead of stopping. The first model is a stepwise logistic regression model, while the second model uses a classification and regression tree. The final model considers whether the driver correctly follows the elicited maneuver or incorrectly contradicts it.

3.   DATA PROCESSING

The initial data set contains 1,157 observations and 17 variables. Of these observations, the data set is reduced to 505 observations due to at least one of the following reasons: data familiarization (291 observations); values of -1 in multiple time frame events (4 observations); data contradictions where the time frame values indicate that the driver made the first stop beyond the stop line while distance values indicate that the driver stopped before the stop line (135 observations); short or long yellow lights outside of the 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 observations). Of the final 505 observations, 100 points are randomly selected for model validation purposes, and labeled as the *testing set*. The remaining 405 observations are labeled as the *training set*, and the total 505 observations are called the *total set*. The set of predictor variables that is used to build the models contains continuous and categorical variables of two or more levels, which are represented by dummy variables. The *elicit* variable is defined so that all observations with a "time to stop bar" greater than 3.375 seconds are "stop" and all others are classified as "pass." Three binary variables are defined for 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, if the "Minimum Acceleration After Acceleration Pedal Change" is less than the 10th percentile or if the "Maximum Acceleration After Acceleration Pedal Change" is greater than the 90th percentile.

In the final data set, the frequencies between the different group ages are 36.8% for young drivers, 30.3% for old drivers and 32.9% for middle aged drivers. 44.4% are females while 55.6% are males. The call types are incoming (I), baseline (B), outgoing (O), and the treatment orders are; IBO (16.0% of the observations), IOB (14.9%), OBI (17.8%), OIB (14.9%), BIO (18.6%), and BOI (17.8%). The cell phone devices include handheld (HH), headset (HS), and hands-free (HF). These devices combined with the call are: IHH (11.1%), IHS (12.9%), IHF (11.9%), OHH (13.1%), OHS (10.3%), OHF (10.5%), and B (30.3%). The velocity (vel) is a continuous variable that ranges from 25.21 and 52.65 mph. The acceleration pedal (accel) presented a change of direction due to depression (28.1%) and release (71.9%). Based on the aggressiveness level variables previously defined, 7.3% of the drivers are considered aggressive based on the speed (speed), 11.9% based on deceleration (dec), and 10.1% based on acceleration (acc). Finally, 41.6% of the drivers has an elicited pass maneuver (elicit).

4. MODELING AND ANALYSIS

This section describes four models for driver behavior in a dilemma zone while distracted. The responses are: legal vs. illegal maneuver, pass vs. stop driver decision, and correct vs. incorrect decision. For each of these responses, the statistical software SAS is used for generating the logistic regression models 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. In addition, a Classification and Regression Tree (CART) model is used as another tool to study the pass vs. stop driver decision response.

4.1 Legal vs. Illegal Pass Maneuver

This model defines legal and illegal stop and pass maneuvers. In this model, a *legal pass* occurs when the driver passes the stop bar during a green or yellow traffic light. Three database values are used to define this state: "First Stop Frame" = -1, "Distance from Stop Line" = 9999, and the frame when the vehicle crosses the stop bar has a green or yellow indication, which is determined based on the frame times given for the traffic signal changes ("Green to Yellow," "Yellow to Red," and "Red to Green. Correspondingly, an *illegal pass* occurs when the driver passes during a red light, which is based on the same three database values: "First Stop Frame" = -1, "Distance from Stop Line" = 9999, and the frame when the vehicle crosses the stop bar has a red indication.

This model only considers the passes from the previously defined set of observations. This new subset is 108 observations, which has 59% legal passes (y=1) and 41% illegal passes (y=0). In the final model, all estimated parameters have a small p-value (p-value <0.2), which indicates that they are likely to be significant parameters. The legal vs. illegal pass model is:

$$\hat{y} = -0.3990 + 1.1069 * IBO + 1.7979 * OIB + 2.4881 * OHF \qquad (1)$$

For all of the logistic regression models, the probability that an observation is either legal or illegal is defined by the following equation:

$$E(y) = \frac{1}{1 + e^{-(\hat{y})}} \qquad (2)$$

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. After controlling for these effects, the overall tendency (~60%) is to engage in illegal behavior when a pass maneuver occurs; however, many drivers opt out of the pass maneuver and simply stop. This overall tendency includes the no phone call as well as most phone scenarios; however, the outgoing hands free phone call has a positive impact on performing a legal maneuver.

The Hosmer and Lemeshow probability test (Hosmer *et al*., 2013), which is based on a Chi-squared goodness-of-fit test, is considered for assessing the fit of the estimated logistic regression model. For this case, the p-value is 0.999, which provides a strong implication that the null hypothesis cannot be rejected, and thus, the model fits. However, the coefficient of determination R^2 of this model is 16.1%.

4.2 Pass vs. Stop Driver Decision

4.2.1 Logistic Regression Model

The stepwise logistic regression pass vs. stop model is built with the training set, and further validated with the testing set. The dependent variable of this model 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, this model has as a response variable of two possible values: pass (1) or stop (0). The training set contains 101 pass observations. The pass vs. stop logistic regression model is presented in the following equation:

$$\hat{y} = -0.0772 + 0.5986 * ageO - 0.5864 * gender - 0.6187 * OBI - 0.7618 * IOB - 0.5563 * IHH$$

$$-0.3432*accel - 1.7277*dec - 1.8369*acc - 1.2863*elicit \qquad (4)$$

In the final model, most estimated parameters have a p-value around 0.10 or smaller, which indicates that they are likely to be significant parameters. The most significant variables are *elicit* and *acc* p-values 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.

Contrary to the legal vs. illegal pass model, the pass vs. stop model does not show a significant tendency of drivers to perform either maneuver. In order to examine the effects of different variables, the estimated logistic probabilities are computed by using Equations (2) and (4). When holding the rest of the predictive variables at a fixed value, two treatment orders still have an impact. Like the previous model, this indicates that the experiment is impacting the driver decisions; however, the significant treatments differ from the first model. The treatments' impacts appear similar to some other variables and increase the probability of stopping by 85% or 115%. The experiment's effort to elicit a response does not appear to have the intended effect. When the experiment elicits a "pass" maneuver, the drivers are 262% more likely to actually stop instead. This behavior likely indicates that the drivers are driving more cautiously because they know their behavior is being observed in an experiment; however, there may be an overall tendency to drive more cautiously because cell phones are being used. The aggressive driver variables support this finding of overall conservative behavior because aggressive accelerating drivers and aggressive decelerating drivers both appear more likely to stop, 530% and 460%. On the other hand, one cell phone variable, incoming hand held, supports the overall conservatism due to cell phone use because previous research (Mazzae *et al*., 2004) has found hand held phones have the most significant impact of cell phones on driving performance. In the pass vs. stop model, the incoming hand held phone calls make drivers 75% more likely to stop. Beyond the impacts of these other variables, old drivers appear 82% more likely to complete a pass maneuver. Female drivers on the other hand appear more conservative and 80% more likely to stop. Finally, when a driver significantly reduces the accelerator pedal, he or she appears about 40% more likely to stop.

The value of the Hosmer and Lemeshow goodness-of-fit statistic computed from these frequencies is 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-R^2 (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, passed or stopped). This model is validated using a Hosmer and Lemeshow test on the testing data; the test yields a goodness-of-fit statistic of 10.9 with 9 degrees of freedom and a p-value of 0.29, and suggests that the model presented above has a good fit. The Tjur-R^2 value for the testing data set is 0.40.

4.2.2   Classification and Regression Tree Model

CART (Hastie *et al*., 2001) uses decision trees to map observations to conclusions. This data mining strategy is employed to model the pass vs. stop driver decision response using the *classregtree* function from Matlab Statistics Toolbox on the training set. A constraint is applied indicating that at least 12 observations are to be on a terminal leaf. The posterior probabilities on each leaf are the frequency from the training data. The decision tree and posterior probabilities are illustrated in Figure 1. 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 pass (probability = 0.1084). If drivers are supposed to stop, many factors affect the probability of making the decision to pass. For example, given they are asked to stop, old male drivers have a higher probability of passing than stopping (probability = 0.6818). Treatment order such as OIB and IBO affect the probability of passing significantly given that the level of aggressiveness based on the acceleration is not in the top 10 percent and the driver is not in the old age group. 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 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. This model generates a better fit and produces similar conclusions to the logistic regression model; 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.
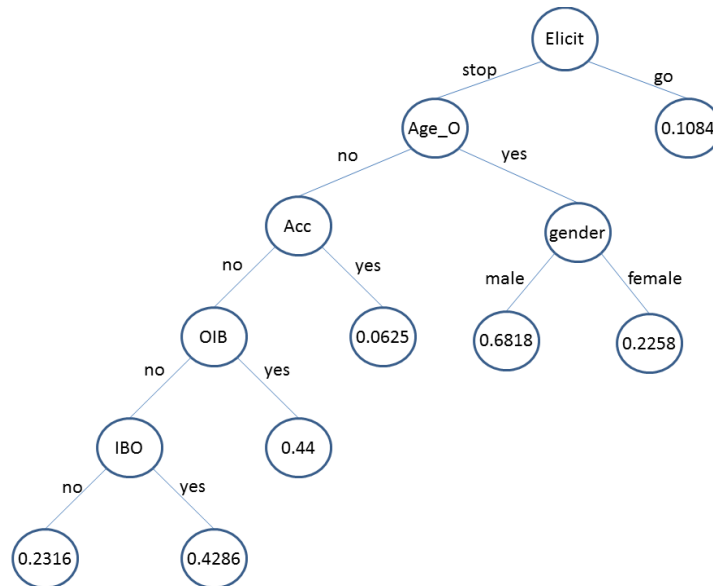
Figure 1. Decision tree model for probability of "pass"

4.3. Correct vs. Incorrect Model

A stepwise logistic regression model is developed to predict the probability of a driver making the correct decision based on the elicited maneuver. The correct vs. incorrect 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 correct (y=1); otherwise, it is incorrect (y=0). In the training set, 174 observations are correct decisions. In the final model, all estimated parameters have a small p-value (p-value <0.2), which indicates that they are likely to be significant parameters. The correct vs. incorrect logistic regression model is presented in the following equation:

$$\hat{y} = 0.7865 - 0.8456*ageO + 0.7418*BIO - 0.5296*OIB - 0.3724*IBO + 0.4406*accel$$
$$+0.5482*acc - 2.9871*elicit \tag{5}$$

The model indicates that there is an overall tendency (~69%) to make a correct choice. Like the previous models, the experimental treatment order appears to have had an impact on driver decision-making; however, in this case there appears to be a valuable conclusion. When there is no call during the first run, drivers are more likely to do what they are supposed to do. Most significantly, the *elicit* variable is the strongest indicator of making an incorrect choice where the drivers elicited to pass are almost twenty times more likely to be incorrect and stop. Driver aggression with respect to acceleration indicates a greater probability (73%) of making the correct choice. Similarly, changing the accelerator pedal also indicates a higher probability (55%) of making a correct choice. Older drivers appear to be 133% more likely to make incorrect 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 a correct or incorrect decision.

The value of the Hosmer-Lemeshow goodness of-fit-statistic 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-R^2 value of this model is 0.52. For the testing set, the value of the Hosmer and

Lemeshow goodness-of-fit statistic is 4.819, and the corresponding p-value with 9 degrees of freedom is 0.78. The Tjur- R^2 value for the testing data set is also 0.52.

5. 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 are not clearly defined nor provided. Overall volume may also impact behavior.

Three different response variables are defined: *legal* vs. *illegal* pass maneuver, *pass vs. stop* driver decision, and *correct vs. incorrect decision*. A stepwise logistic regression model is created for each of these responses as well as a classification and regression tree model for the *pass vs. stop* driver decision. Overall, the drivers appear to be behaving conservatively; this is likely due to being observed. All models except the *legal* vs. *illegal pass* model appear to support this conclusion. While the *legal* vs. *illegal pass* model does not directly support this finding it does not contradict it either. Instead, it offers further insight into the driver behavior. Overall, the drivers tend to stop; however, when they decide to pass, 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. Contrary to likely expectations, aggressive drivers when defined based on acceleration tend to make correct decisions and appear more likely to stop when elicited to do so. Older drivers appear to particularly negatively impacted by this experiment. Based on the pass vs. stop models, old drivers appear more likely to pass, in particular when they are elicited to stop, which presents a particularly risky mistake. While most drivers behave conservatively, the old drivers appear less likely to make correct decisions and engage to potentially dangerous errors. The impact of cell phone use appears relatively inconclusive with single variables appearing in only two of the models.

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