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Examining driver behavior at the onset of yellow in a traffic simulator environment: Comparisons between random parameters and latent class logit models

Peter T. Savolainen*

Department of Civil, Construction & Environmental Engineering, Iowa State University, 482A Town Engineering, Ames, IA 50011-3234, USA

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ABSTRACT

This study involves an examination of driver behavior at the onset of a yellow signal indication. Behavioral data were obtained from a driving simulator study that was conducted through the National Advanced Driving Simulator (NADS) laboratory at the University of Iowa. These data were drawn from a series of events during which study participants drove through a series of intersections where the traffic signals changed from the green to yellow phase. The resulting dataset provides potential insights into how driver behavior is affected by distracted driving through an experimental design that alternated handheld, headset, and hands-free cell phone use with "normal" baseline driving events. The results of the study show that male drivers ages 18–45 were more likely to stop. Participants were also more likely to stop as they became more familiar with the simulator environment. Cell phone use was found to some influence on driver behavior in this setting, though the effects varied significantly across individuals. The study also demonstrates two methodological approaches for dealing with unobserved heterogeneity across drivers. These include random parameters and latent class logit models, each of which analyze the data as a panel. The results show each method to provide significantly better fit than a pooled, fixed parameter model. Differences in terms of the context of these two approaches are discussed, providing important insights as to the differences between these modeling frameworks.

1. Introduction

Signalized intersections require high levels of driver attention and cognition in order to operate safely and efficiently. Drivers must often make quick decisions, particularly at the onset of the yellow signal phase. Driver errors under such circumstances are a principal factor contributing to intersection-involved crashes and fatalities. In 2012, a total of 4,602 vehicles were involved in fatal crashes at signalized intersections across the United States (NHTSA, 2013), highlighting the need for further efforts to reduce such collisions.

To this end, there has been substantive research into driver behavior at signalized intersections. Much of this research has focused on behavior within dilemma zones or indecision zones, where drivers must quickly determine whether they can safely clear an intersection at the onset of yellow (Köll et al., 2004; Gates et al., 2007; Papaioannou, 2007; Sharma et al., 2007; Elmitiny et al., 2009; Yan et al., 2009; Sharma et al., 2010; Burnett and Sharma, 2011; Zhixia and Heng, 2013; Abbas et al., 2014). These studies have examined how various site (e.g., signal timing, geometry), vehicle (e.g., vehicle type), and driver (e.g., age, gender) characteristics are associated with the decision to stop or proceed through the intersection at the onset of yellow. Deciding to proceed throught the intersection too late increases the risk of angel collisions due to red light running while stopping too soon increases the risk of rear-end collisions. This risk may be exacerbated due to driver distraction, which is becoming an increasing concern due to continuing increases in cell phone use among drivers (Russo et al., 2014).

Increased crash risks due to cell phone use have been a subject of research since 1997, when early work estimated a four-fold increase in crash risk (Redelmeier and Tibshirani, 1997). Subsequent research has shown cell phone use to increase response time and the frequency of traffic violations (Hancock et al., 2003; Patten et al., 2004; Strayer and Drews, 2004; Strayer et al., 2006). Ultimately, the National Highway Traffic Safety Administration (NHTSA) estimates that approximately 400 fatal crashes and 21,000 injury crashes per year involve drivers using a cell phone (NHTSA, 2013). These figures are likely to be conservative given under-

* Corresponding author. Fax: +1 515 294 2689.
E-mail address: pts@iastate.edu

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reporting of distracted driving among police-reported crash data (NHTSA, 2013), further emphasizing the critical nature of this issue.

The extant literature has included three general methods for assessing driver behavior during periods of cell phone use: on-road studies (Young et al., 2013; Klauer et al., 2014); field studies in controlled environments (Hancock et al., 2003; Owens et al., 2011); and driving simulator studies (Strayer et al., 2003; Strayer and Drews, 2004; Beede and Kass, 2006; Strayer et al., 2006; Kass et al., 2007; Strayer and Drews, 2007; Crisler et al., 2008; Charlton, 2009). Several of these studies focused specifically on the effects of cell phone use at signalized intersections (Hancock et al., 2003; Beede and Kass, 2006; Cooper and Strayer, 2008; Horrey et al., 2008; Young et al., 2013).

This study builds upon the existing research literature by assessing driver behavior at the onset of yellow in a traffic simulator environment. The research was conducted as a part of the Transportation Data Competition, which was sponsored by the Transportation Research Board (TRB) Statistical Methods Committee in conjunction with the 2014 TRB Annual Meeting. This competition was aimed at evaluating the appropriateness of various data analytic methodologies for assessing driver behavioral data under such a setting. Several important analytical contributions are provided. First, the results demonstrate significant correlation in the behavior of study participants and unobserved heterogeneity across participants. Failure to account for such concerns may lead to inefficient or biased parameter estimates, providing motivation for two methodological alternatives, which are compared as a part of this study. The results provide insights into those factors affecting driver decisions at the onset of yellow, in addition to highlighting the importance of these methodological considerations.

2. Data and empirical setting

The analysis dataset was made available through the 2014 Transportation Research Board (TRB) Data Competition. This dataset originated from a wireless urban arterial study conducted through the National Advanced Driving Simulator (NADS) at the University of Iowa during the summer of 2004 (Ohlhauser et al., 2011). Simulated drives were performed on the NADS-1, a high-fidelity driving simulator that provided a 360-degree field of view, 13-degree freedom-of-motion, interactive traffic, and actual vehicle cabs. The NADS-1 provides data on vehicle position, velocity, and acceleration at rates of up to 240 Hz.

The participants in this study were required to have a valid driver license and details of the recruitment, screening, and compensation protocol have been detailed elsewhere (Marshall et al., 2010). The intent of the study was to examine the effects of wireless telephone use on driving performance among three age groups. During the study, each participant completed three “drives”. Each drive included three “segments” and each segment involve one rural area and one urban area. Five controlled intersections were encountered during each segment, with two of these intersections involving the onset of a yellow traffic signal indication during the driver’s approach. In total, each driver encountered 18 decision points at yellow onset. Hereafter, each of these decision point sequences is referred to as an event.

During each segment, the participants were randomly assigned one of three cell phone interfaces:

1. Handheld
2. Headset
3. Hands-free

Within each segment, drivers participated in one of three tasks:

1. Baseline —normal driving conditions (i.e., no phone conversation)
2. Outgoing— outgoing call (driver dialing out on phone)
3. Incoming— incoming call (driver answering phone)

The sequences of the baseline events, as well as those involving incoming and outgoing calls, were randomized within each driving segment. All yellow light events occurred while the participant was engaged in the conversation phase of the call. Given these potential sources of driver distraction, the principal focus of this study was to ascertain the effects of wireless telephone use on driver behavior. Specifically, this research examined differences in behavior when drivers encounter a yellow traffic signal indication while approaching a signalized intersection. The initial dataset included information from 1,157 scenarios in which a participant encountered a yellow signal indication while approaching a signalized intersection. These data were drawn from 49 study participants. Training data, which were collected during familiarization runs, were discarded from the analysis dataset. Instances of missing data for relevant variables, as well as cases where values of such variables were infeasible, were also discarded. The final dataset was comprised of 865 runs, details of which are presented in Table 1.

Table 1
Descriptive statistics for analysis dataset.

Variable	Min.	Max.	Mean	Std. Dev.
Young age (18–25 years)	0	1	0.37	0.48
Middle age (30–45 years)	0	1	0.35	0.48
Old age (50–60 years)	0	1	0.28	0.45
Male	0	1	0.53	0.50
Female	0	1	0.47	0.50
Driving event 1	0	1	0.34	0.47
Driving event 2	0	1	0.34	0.47
Driving event 3	0	1	0.33	0.47
Baseline condition	0	1	0.34	0.47
Handheld incoming call	0	1	0.11	0.31
Handheld outgoing call	0	1	0.11	0.32
Headset incoming call	0	1	0.11	0.31
Headset outgoing call	0	1	0.11	0.31
Hands-free incoming call	0	1	0.11	0.32
Hands-free outgoing call	0	1	0.11	0.31
Velocity at onset of yellow (mi/h)	24.6	53.9	42.6	5.0
Distance from stop line at onset of yellow (ft)	109.9	284.7	204.1	33.4
Time to stop line at onset of yellow (s)	2.48	3.81	3.27	0.38
Yellow duration (s)	2.78	4.38	3.84	0.41

The 49 study participants were approximately uniformly distributed among by gender and age group. There were fewer drivers among the oldest age cohort (ages 50–60) and slightly more male drivers than females. Vehicle speeds at the onset of yellow varied from varied from 24.6 to 53.9 mi/h. While speed limit information was not provided as a part of the dataset, the mean speed of 42.6 mi/h suggests a speed limit of approximately 40 mph. The distance of a vehicle at the onset of yellow ranged from 109.0 to 284.7 ft. Considering speed and distance, the expected time to the stop line ranged from 2.48 to 3.81 s. As per the details of the data competition, the duration of the yellow interval was programmed for a constant 4.00 s. However, the dataset showed values ranging from 2.78 to 4.38 s.

3. Statistical methods

A driver decision of whether to stop when encountering a yellow indication at a signalized intersection is a dichotomous (i.e., yes/no) variable. Such data are well suited for analysis by discrete outcome models, such binary logit or probit models. Binary outcome models allow for an examination of the driver behavioral process and how the decision of whether to stop or proceed throught an intersection is related to factors such as driver demographic characteristics, sources of driver distraction (i.e., cell phone use), and details of each driving simulator event (e.g., time of yellow onset, speed, etc.). There are several examples where logit models (Gates et al., 2007; Papaioannou, 2007; Rakha et al., 2008) or probit models (Liu et al., 2012; Sharma et al., 2011) have been used to assess the stop/go decision at signalized intersections.

3.1. Logit model

Under a logit model, the driver's decision as to whether or not to stop at the onset of yellow is specified as a linear function of covariates (represented as $\boldsymbol{S}_{\text{ij}}$):

$$\boldsymbol{S}_{\text{ij}} = \boldsymbol{x}'_{\text{ij}}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{\text{ij}}, \tag{1}$$

where $\boldsymbol{\beta}$ is a vector of estimable parameters, x_{ij} is a vector of explanatory variables (e.g., driver, vehicle, and simulation characteristics) associated with driver i and simulator event j, and $\boldsymbol{\varepsilon}_{\text{ij}}$ is an error term, which is assumed to follow a Generalized Extreme Value (GEV) Type I distribution. Given these definitions, the probability (P_{ij}) of driver i stopping during event j is defined as:

$$P_{\text{ij}} = \frac{\text{EXP}\left(\boldsymbol{x}'_{\text{ij}}\boldsymbol{\beta}\right)}{1 + \text{EXP}\left(\boldsymbol{x}'_{\text{ij}}\boldsymbol{\beta}\right)} \tag{2}.$$

The logit model is estimated using standard maximum likelihood procedures. However, within the context of this study, there are important methodological concerns that arise with respect to the estimation of a standard logitmodel. First, given that the same 49 participants are observed multiple (up to 18) times, it is reasonable to expect correlation in the decisions made by the same individuals across simulator events. Failure to account for this correlation will generally result in biased standard errors for the resulting parameter estimates. To mitigate this concern, the 49 participants are treated as a panel, with parameter estimates constrained to be equal for each individual and allowed to vary across individuals.

A related concern is the potential impact of unobserved heterogeneity, which arises from the fact that each individual may exhibit unique characteristics that make them more (or less) prone to stop (or proceed through) at the onset of yellow. This heterogeneity may also result in biased or inefficient parameter estimates. To address such concerns, the use of more flexible models is warranted as demonstrated by recent research in this area (Lavrenz et al., 2014). Within the context of this study, two alternatives are considered to account for heterogeneity across individuals: (2)

(1) a random parameter model, which accommodates heterogeneity across study participants by allowing parameters to vary over individuals based upon a specific parametric distribution; and
(2) a latent class model, which allows for heterogeneity across individuals without imposing any parametric assumptions as to the underlying distribution of this heterogeneity.

3.2. Random parameter logit model

The logit model assumes that the error terms $\left(\varepsilon_{\text{ij}}\right)$ are independently and identically distributed (IID) across observations. From an analytical standpoint, this is potentially problematic as the sample includes repeated observations of the same 49 individuals. As it is expected that these drivers may exhibit similar behaviors (i.e., drivers may be more or less prone to stop or go when encountering the yellow signal indication), this may result in correlation, violating the IID assumption. This concern can be relaxed by introducing a driver-specific parameter vector and allowing $\boldsymbol{\beta}_{\text{i}}$ to vary across individuals as shown in Eq. (3).

$$\boldsymbol{S}_{\text{ij}} = \boldsymbol{x}'_{\text{ij}}\boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_{\text{ij}} \tag{3}$$

By allowing the constant term to vary across drivers, the model is able to capture heterogeneity due to unobserved factors that are common to each study participant. This heterogeneity among drivers is assumed to follow one of several parameteric distributions (e.g., normal, lognormal, triangular, etc.) and is reflective of those unobserved factors (e.g., driving style, risk propensity, etc.) that may influence driver behavior and the decision-making process. This random constant term essentially partitions the variance into two components: a normally distributed error term with zero mean, which varies across drivers; and the generalized extreme value (GEV) error term described previously.

While allowing the constant term to vary is able to capture differences across study participants, the model still implicitly assumes the covariates have consistent effects across participants. This introduces a second concern as there is also likely to be heterogeneity in terms of the effects of these covariates. This heterogeneity is also reflective of unobserved characteristics of the driver or simulator setting, which are not able to be captured by the model. To accommodate such variability, all parameters are allowed to vary across individuals, though the parameters maintain the same value for each participant. Since the resulting model formulation does not have a closed form solution, simulated maximum likelihood methods are used to estimate the random parameters model shown in Eq. (4):

$$P_{\text{ij}} = \int_x \frac{\text{EXP}\left(\boldsymbol{x}'_{\text{ij}}\boldsymbol{\beta}_{\text{i}}\right)}{1 + \text{EXP}\left(\boldsymbol{x}'_{\text{ij}}\boldsymbol{\beta}_{\text{i}}\right)} f\left(\boldsymbol{\beta}|\boldsymbol{\phi}\right) d\boldsymbol{\beta}, \tag{4}$$

where $(\boldsymbol{\beta_i}|\boldsymbol{\phi})$ is the density function of $\boldsymbol{\beta}$ with $\boldsymbol{\phi}$ referring to a vector of parameters of the density function (mean and variance), and all other terms as previously defined. Under this approach, logit probabilities are approximated by drawing values of $\boldsymbol{\beta_i}$ from f($\boldsymbol{\beta_i}|\boldsymbol{\phi}$) for given values of $\boldsymbol{\phi}$. Halton draws have been demonstrated as an efficient alternative to random draws in prior research (Halton, 1960; Bhat, 2003; Train, 2003). For the purposes of this study, 200 Halton draws are utilized as a part of model estimation as recommended in prior studies (Bhat, 2003). In this study, a normal distribution is assumed for the functional form of the parameter density functions. For further details on the random parameters (also referred to as the mixed logit) model, readers are referred elsewhere (Greene and Hensher, 2003).

3.3. Latent class logit model

In contrast to the random parameters model, an alternate means to accommodate unobserved heterogeneity among study participants is through the use of a latent class model. Both the random parameter and latent class models assume that driver behavior depends on additional factors beyond those that are directly observable (e.g., driver characteristics, details of each simulation event). However, the latent class models do not make any assumptions as to the form of this underlying heterogeneity. Instead, latent class models assume individuals are implicitly sorted into a series of Q classes, with the classification unknown (i.e., unobserved) for a particular individual. It is assumed that parameters have identical effects within these classes, but different effects between classes. The prior probability for class q and driver i follows the form of a logit model:

$$H_{\text{iq}} = \frac{\exp\left(\boldsymbol{z}^{i}_{i}\boldsymbol{\theta_q}\right)}{\sum_{q=1}^{Q}\exp\left(\boldsymbol{z}'_{i}\boldsymbol{\theta_q}\right)}, q = 1, \ldots, Q, \boldsymbol{\theta}_{\text{q}} = \boldsymbol{0}, \tag{5}$$

where $z_i$denotes a set of characteristics that are associated with class membership. To ensure the model can be identified, the Qth parameter vector is arbitrarily normalized to zero. The likelihood for participant i is the expectation over all classes of the class-specific contributions:

$$P_i = \sum_{q=1}^{Q} H_{iq} P_{i|q} \quad (6).$$

The log-likelihood function, which can be solved through maximum likelihood procedures, is:

$$\ln L = \sum_{i=1}^{N} \ln P_i = \sum_{i=1}^{N} \ln \left[\sum_{q=1}^{Q} H_{iq} \left(\prod_{t=1}^{T_i} P_{it|q} \right) \right] \quad (7).$$

An analytical consideration is how many classes should be considered. General practice is to 'test down' by decreasing the value of Q and using likelihood ratio tests. Using this approach, Q was ultimately set equal to two for the latent class model estimated as a part of this study. Increasing to more than two classes resulted in model instability and convergence issues.

4. Results and discussion

4.1. Preliminary investigation

During the course of the analysis, a variety of methodological issues were identified, which are briefly summarized prior to presenting the final analysis results. The extant research literature has shown that several factors tend to have substantive impacts on driver stop/go decisions when encountering a yellow signal indication. These include:

- Vehicle speed at the onset of yellow—Higher vehicle speeds at the onset of yellow reduce the time available for reaction and braking by the driver. Consequently, vehicles tend to proceed through the intersection more frequently when speeds are higher (Bonneson and Son, 2003; Gates et al., 2012).
- Distance from stop line at the onset of yellow—The further a vehicle is from the stop line at the onset of yellow, the greater the time (distance) available for a stopping maneuver. Consequently, vehicles are more likely to stop at greater distances from the stop line (Bonneson and Son, 2003; Gates et al., 2012).
- Yellow duration—Shorter yellow intervals have been found to increase the likelihood of drivers proceeding through the intersection. While not necessarily intuitive, it is hypothesized that this effect is potentially due to several factors (Bonneson and Zimmerman, 2004; Bonneson and Son, 2003; Gates et al., 2007). First, drivers may be less averse to the risk of red light running at locations where the crossing distances are smaller (and thus yellow durations are shorter). Secondly, this finding may reflect locations with insufficient yellow intervals.

The first two factors (speed and distance) essentially reflect the fact that driver decisions are based on the approximate time to the stop line at the onset of yellow. The details of the data competition state that the traffic signal would generally change to yellow at one of two pre-determined timings, either 3.00 or 3.75 s. prior to arrival at the stop bar. The prior was intended to elicit a "go" response while the latter was intended to elicit a "stop". On a related note, the light was to remain yellow for a constant 4.00 s. However, there was significant inconsistency in this area. Fig. 1 illustrates the relationships between yellow duration and the pre-determined timings, as well as whether the associated drivers stopped or not.

While the data competition instructions suggest there should be two explicit conditions, it appears there are at least three. First, there is a very large group of data points around a 3.00-s yellow time, nearly all of which involved drivers going through the yellow light. It is possible that these are largely instances where the yellow time was truncated once those vehicles traversed the intersection, though there are instances of vehicles stopping at yellow times of 3.00 s or even less. It should also be noted that there are no instances where the yellow time was truncated below 3.50 s when the pre-determined timing of 3.75 s was utilized. Finally, there were two additional subgroups of data points that show yellow duration to increase linearly with the time to stop line. These groups are evidenced by the linear scatter plots, which show yellow durations that are approximately 0.25 or 1.25 s greater than the time to stop.

The net effect of these issues is that utilizing yellow duration in the analysis presents severe confounds, which serve to: (a) introduce a spurious relationship between the stop/go decision and the yellow interval; and (b) confound the effects of other factors, such as the time to stop bar, as well as demographic characteristics and other event data. Consequently, yellow duration was not included in the analyses.

4.2. Model results

Table 2 presents the final results from three discrete outcome models estimated as a part of this study: a pooled, fixed parameter logit model; a random parameters panel data logit model; and a latent class panel data logit model. Parameter estimates and standard errors are included, with statistically significant variables indicated by asterisks. For the random parameter models, the standard deviation is provided for those parameter estimates that were found to vary across individuals.

To aid in interpreting the quantitative impacts of these factors, Table 3 provides marginal effects for each model. For binary indicator variables, these values indicate the change (increase or decrease) in the probability that a driver will stop at the onset of yellow (as compared to the baseline category). For example, male drivers ages 18–25 and 30–45 were significantly more likely to stop as compared to the other age groups. Older males (ages 50–60) were 9.34–10.88 percent less likely to stop when considering the results of the random parameters and latent class models. For continuous variables, such as time to the stop bar, the marginal effects represent the percent increase in the probability of stopping associated with a one-unit (one-second in this case) increase in the covariate.

4.3. Comparison of analytical frameworks

Visual inspection of the results shows that the sign/direction of effects was consistent across each of the analytical frameworks. However, there are significant differences with respect to the magnitude of these effects. These differences reflect differences in terms of the underlying assumptions for each model. For example, the simplest form of the logit model is not able to account for correlation in behavior among the same drivers. Consequently, the standard errors are biased downward, which tends to over-state the statistical significance of the parameter estimates.

It is also important to note the implications that arise based upon the underlying assumptions between the random parameters and latent class models. First, both models indicate there is significant correlation in behavior among the same study participants (and significant variability across participants).

In the random random parameters model, this correlation is indicated by the statistically significant standard deviation for the constant term. In addition, the random parameter model also indicates there is significant variability in the behavior of females in the middle age group (ages 30–45). This suggests there may be impor-

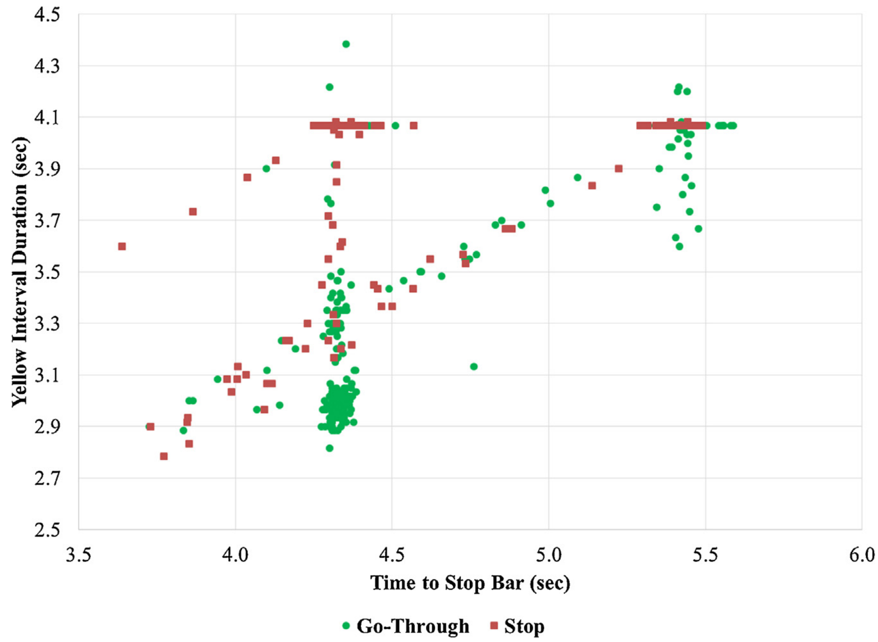

Fig. 1. Yellow interval duration versus time to stop line.

Table 2
Parameter estimates for various model formulations.

Variable	Pooled logit model	Random parameter logit model	Latent class logit model	
			Class I	Class II
Constant	−0.218 (0.657)	−0.159 (1.005)	1.085 (1.026)	−3.557 (1.432)
Std. Dev.		1.592 (0.234)[c]		
Male age 50–60	−0.827 (0.247)[c]	−1.714 (0.322)[b]	−1.530 (0.402)[c]	−1.683 (0.717)[b]
Female age 18–25	−0.510 (0.241)[b]	−1.033 (0.828)	−1.230 (0.398)[c]	−1.127 (0.595)
Female age 30–45	−0.686 (0.247)[c]	−1.464 (1.072)	−0.852 (0.436)[a]	−0.941 (0.500)[a]
Std. Dev.		3.183 (1.356)[b]		
Female age 50–60	−0.383 (0.276)	−1.021 (0.817)	−0.846 (0.463)[a]	−0.126 (0.542)
Driving event 1	−0.468 (0.177)[c]	−0.802 (0.247)[c]	−0.837 (0.281)	−0.802 (0.416)[a]
Driving event 2	−0.161 (0.180)	−0.325 (0.246)	−0.524 (0.289)[a]	0.032 (0.368)
Time to stop (Baseline)	0.415 (0.194)[b]	0.680 (0.255)[c]	0.567 (0.297)[a]	0.785 (0.425)[a]
Time to stop (Handheld)	0.446 (0.196)[b]	0.718 (0.259)[c]	0.570 (0.302)[a]	0.924 (0.425)[b]
Time to stop (Headset)	0.391 (0.197)[b]	0.616 (0.259)[c]	0.434 (0.300)	0.965 ((0.429)[b]
Time to stop (Hands-free)	0.455 (0.198)[b]	0.737 (0.258)[c]	0.528 (0.303)[a]	1.035 (0.423)[b]
Class probabilities			0.693 (0.066)[c]	0.307 (0.066)[c]
Initial log-likelihood	−599.57	−599.57	−599.57	
Constant-only log-likelihood	−567.25	−567.25	−567.25	
Final log-likelihood	−549.87	−424.92	−423.06	
McFadden rho-squared	0.083	0.291	0.294	

Note: Tabular values indicate parameter estimates (standard errors) for each model.
[a] Statistically significant at $\alpha = 0.10$.
[b] Statistically significant at $\alpha = 0.05$.
[c] Statistically significant at $\alpha = 0.01$.

Table 3
Marginal effects for predictor variables by model formulation.

Variable	Marginal effects by model formulation		
	Pooled logit model	Random parameter logit model	Latent class logit model
Female age 18–25	−3.78	−7.85	−5.26
Female age 30–45	−4.92	−4.38	−5.05
Female age 50–60	−1.59	−1.72	−3.10
Male age 50– 60	−6.31	−10.88	−9.34
Driving event 1	−6.71	−9.8	−7.10
Driving event 2	−1.89	−2.86	−2.41
Time to stop (Baseline)	+17.02	+16.93	+20.01
Time to stop (Handheld)	+11.28	+11.26	+13.59
Time to stop (Headset)	+10.35	+9.94	+13.44
Time to stop (Hands-free)	+11.36	+11.25	+14.19

Values indicate change in probability of stopping for 1-unit change in predictor.

tant differences specific to this age group that are not accounted for by the variables in the dataset, which may reflect general differences in driving style for example.

The parameter estimates from the latent class model also show distinctive differences between study participants. This model demonstrates that there are two distinctive classes of drivers based upon their collective behaviors at the onset of the yellow signal indication.

While many of the parameters were similar between the two classes, substantive differences are reflected in terms of the important unobserved characteristics that are common to these drivers (as indicated by the significant differences in the constant terms between the two classes), as well as in the relative sensitivity of these drivers based upon their time to the stop bar and cell phone use status. Drivers in Class I, who comprised of 69.3 percent of the sample, were more likely to stop overall, but tended to be less sensitive to their time to the stop bar. There was little difference in terms of the effects of cell phone use among this class of participants. In contrast, participants in Class II were less likely to stop. Interestingly, drivers became more sensitive to their time to the stop bar when they were using one of the various cell phone types. This is in significant contrast to the other model formulations, which demonstrated little effect of cell phone use overall.

Drivers also tended to show differences in terms of their familiarization process with the simulator as the probability of stopping was lower during both the first and second driving events (as compared to the third) for participants in Class I. Those in Class II only exhibited a significantly lower stopping rate during the first driving event.

When examining the goodness of fit between the alternate modeling frameworks, the standard (pooled, fixed parameter) logit model has significantly poorer fit than the random parameters and latent class models (p-value <0.01). However, there is little difference in terms of the fit between the two models that account for unobserved heterogeneity. This suggests that strong consideration should be given as to which framework is most appropriate on a theoretical basis.

The random parameters model identifies those parameters that exhibit heterogeneity across individuals. In doing so, a parametric distribution must be assumed for this heterogeneity. Consistent with empirical research, the normal distribution was found to provide the best fit, but there is not a strong theoretical justification for this or any other specific distribution.

In contrast, the latent class model segments these individuals into classes, each of which exhibits its own unique set of parameters. Unfortunately, actual class membership cannot be observed as the model only allows for an estimation of the probability of a specific individual belonging to either class. It should also be noted that no covariates were identified that could distinguish between the two latent classes. Consequently, the probability of belonging to either class was fixed. In settings where significant predictors for class membership can be identified, latent class models may provide additional insights of interest.

4.4. Practical implications of results

The following is a brief practical summary of model results:

- Demographic characteristics—Young (age 18–25) and middle age (age 30–45) male drivers were the most likely to stop among the study participants. Stopping rates were marginally lower among older (age 50–60) females and significantly lower among young females, middle age females, and older males. Collectively, these findings may reflect either inherent differences in driving behavior or the fact that certain types of drivers are more easily acclimated to the driving simulator environment.
- Drive number—Related to the prior point, drivers were more likely to stop on their second or third visit/drive than the first. The probability of stopping was 6.7–9.8 percent lower during the first drive (as compared to the third) and 1.9–2.9 percent lower during the second drive. This finding may reflect either an anticipatory effect, wherein drivers are expecting a signal change, or higher levels of comfort as the participants have become accustomed to the simulator.
- Cell phone use—Consistent with expectations, there appears to be some evidence of distraction due to cell phone use. Significant differences were not observed between incoming and outgoing calls. However, Fig. 2 illustrates trends in the probability of stopping with respect to the time to the stop bar for the baseline condition, as well as each of the three cell phone conditions. Interestingly, drivers were more likely to stop when using the handheld phone and hands-free devices and less likely to stop when using the headset. As discussed previously, the latent class model showed that one class of drivers did not show any clear consistency in terms of the effects of cell phones. However, the other class of participants was shown to be increasingly sensitive to time to the stop bar. This may suggest that distraction is causing these drivers to overreact and brake more rapidly at the onset of yellow. Further research is warranted to better understand the reasons for these differences.

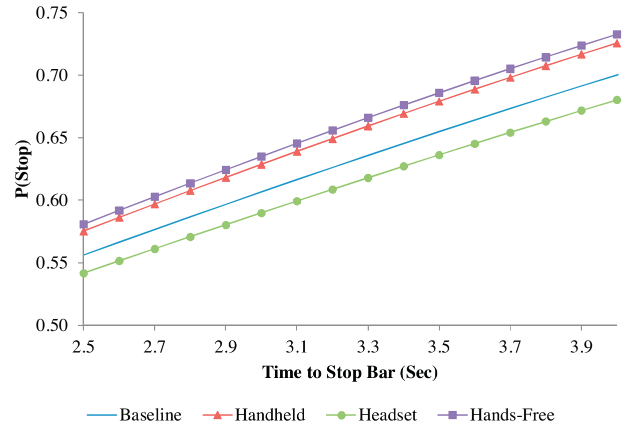

Fig. 2. Probability of stopping versus time to stop bar by cell phone use.

5. Conclusions

This study compared several modeling frameworks for examining driver behavior at the onset of a yellow signal indication. Behavioral data were obtained from a driving simulator study that was conducted through the National Advanced Driving Simulator (NADS) laboratory at the University of Iowa. These data were drawn from a series of events during which study participants used the simulator to traverse an intersection as a traffic signal changed from the green to yellow phase. The resulting dataset provides potential insights into how driver behavior is affected by distracted driving through an experimental design that alternated cell phone use with "normal" baseline driving events.

The results of the study show that the probability of stopping is highest among younger male drivers. It is unclear whether these effects are due to differences in physiology, driving behavior, or familiarity and comfort in a simulated driving environment. Drivers tended to stop more frequently as they became more familiar with the driving environment, which provides some support for the latter explanation. Interestingly, cell phone use was not found to exhibit consistent influences on driver behavior, though some of the participants did appear to be affected by this potential distraction. Ultimately, it is unclear how closely these simulator results would reflect naturalistic driving data.

There were several potentially important pieces of information that were not available in the simulator study dataset, which would shed further insight into stop-and-go decisions, including the following:

- Roadway information—While the intersection characteristics were presumably similar throughout the trial runs, information was not available as to speed limit (assumed to be 40–45 mph), intersection width, and other geometric factors that may impact drivers.
- Study participant characteristics—Only age and gender were available for each driver, leaving the potential for a diverse range of factors that could influence differences between individuals. Driving experience, physical health, and familiarity with use of cell phones and video games/simulator environments would all help to explain individual-level differences.
- Efficacy of simulation—As in all simulator studies, there is some uncertainty with respect to how transferable these results would be to an actual driving environment. While certain characteristics, such as reaction times, would seem well-suited to a virtual environment, this dataset showed higher than expected deceleration rates to demonstrate one example of how these results may vary from actual driving experience.
- Data irregularities—Some of the data issues discussed previously, such as the discrepancies with yellow intervals, may have introduced confounds that prohibited the ability to identify important relationships in the data.

Beyond the practical results noted above, this study also provided important insights as to two approaches for dealing with unobserved heterogeneity. Initially, a logistic regression (i.e., logit) model was estimated, which has been the most widely applied method for empirical studies in this area. However, given that the study involved panel data where multiple driving events were observed for the same 49 drivers, correlation in behavior among drivers and unobserved heterogeneity across drivers introduce methodological concerns for the logit model. To address these concerns, random parameter and latent class logit models were also estimated.

Ultimately, the results showed each of these alternate modeling frameworks to outperform the pooled fixed parameter logit model. The goodness-of-fit was quite similar between the random parameter and latent class models. While the random parameters model can be compared directly to a pooled logit model using standard statistical tests, a choice between the random parameter and latent class models relies largely upon theoretical considerations.

Moving forward, discrete outcome models present a promising avenue for the analysis of driver behavioral data at signalized intersections. Such models can be used for predictive performance, which is an important consideration given continuing advances in connected vehicle technologies that introduce a need to develop predictive algorithms that can aid in reducing the frequency of crashes due to cell phone use and other distractions. It is important to recognize that various alternative frameworks are also available for predictive purposes, such as artificial neural networks, including the multilayer perceptron and radial basis functions. For modeling complex non-linear behavior, machine learning has also emerged as a powerful alternative to parametric models. Ultimately, subsequent research is warranted to further examine the benefits of these approaches in terms of predictive capability and practical interpretability.

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