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Safer driver responses at intersections with green signal countdown timers

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ABSTRACT

Traffic signal countdown timers (TSCTs) are innovative, practical, and cost effective technologies with the potential to improve safety at signalized intersections. The purpose of these devices is to assist motorists in decision-making at signalized intersections by providing them with real-time signal duration information. This study examines US driver responses in the presence of a green signal countdown timer (GSCT) and the implications those responses have on intersection safety. A driving simulator study was conducted to record driver responses to virtual GSCTs. Fifty-five participants (32 male and 23 female) responded to 1100 simulated traffic signals, half of which had GSCTs. A predictive model was developed and validated to estimate the change in driver's probability to stop at different distances from the stop line in the presence of a GSCT. The presence of a GSCT increased average driver stopping probability in the dilemma zone by 13.10%, while decreasing average driver deceleration rates by 1.50 ft/s^2. These results suggest that GSCTs may contribute to improved intersection safety in the US.

1. Introduction

1.1. TSCT operations

TSCTs are clocks that digitally display the time remaining for a particular signal indication, i.e., red, yellow, or green. They are implemented at intersections around the world to provide drivers with real-time information, the goal of which is to improve driver decision-making and vehicle control. Green signal countdown timers (GSCTs), which alert the driver to the onset of the yellow signal, are generally implemented to improve intersection safety and are the focus of this study.

TSCTs are primarily implemented at signalized intersections with fixed timing. Fixed-time signals allocate green time based on prior observation of vehicle volumes (turning movements, pedestrian volumes, etc.) and are not responsive to real-time demand. Alternatively, intersections with actuated signals utilize vehicle detection and additional timing parameters (minimum green, passage time, maximum green, etc.) so that the green time is allocated in response to calls for service. Typically, the final determination for an actuated signal is made 1 to 4 s (Tarnoff & Parsonson, 1981) before the indication changes (e.g., green to yellow, or red to green), providing a limited interval for the countdown. Therefore, application of the TSCT has the greatest potential for green, yellow, and red indications at fixed-time signals and for the predictable yellow change intervals at actuated signals.

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According to the Manual on Uniform Traffic Control Devices (MUTCD, 2009), it is not definitively known how many signalized intersections are currently operating in the US because no agency collects comprehensive numbers on them. However, it is estimated that there were 311,000 signalized intersections in the US in 2012 (National Transportation Operations Coalition (NTOC), 2012). Many of these signalized intersections are controlled by fixed-time signals, which are recommended in urban and downtown areas with high volumes of pedestrian traffic and where vehicle speed is low.

Fig. 1 illustrates the concept of operations for a TSCT. Chen, Zhao, and Hsu (2009) previously described its operation as follows, "The countdown time display panel is under the control of a countdown controller that runs in step with the signal controller. When a signal is counting down for a specific phase, the countdown control system shows the remaining time for that phase."

As illustrated in Fig. 1, the signal controller feeds the countdown controller with signal duration information, which then displays the information in the form of a GSCT.

1.2. GSCTs and safety

The expected safety benefits of GSCTs include reduced dilemma zone conflicts and reduced red light running at signalized intersections. In many conventional signal locations, the transition time from the green to the red indication is difficult for drivers to predict. This can cause drivers to get caught in the dilemma zone, in which the likelihood of making judgment errors is significantly higher.

There are two general types of dilemma zone: Type I and Type II, as shown in Fig. 2. A Type I dilemma zone corresponds to inadequate signal timing. This experiment focuses on driver behavior with respect to Type II dilemma zones. Moore and Hurwitz (2013) described a Type II dilemma zone as "the segment of roadway on the approach to a signalized intersection at which drivers have difficulty deciding whether to stop or proceed when presented with the circular yellow indication. The conflicts created in the Type II dilemma zone, or indecision zone, result in increased rear-end crashes caused by abrupt braking and in right-angle or left-turn head-on collisions caused by poor estimates of intersection clearance time."

A GSCT informs approaching drivers of the number of seconds of green remaining before the signal changes to yellow. This additional information can improve an approaching drivers' decision to stop or proceed through an intersection, minimizing Type II dilemma zone conflicts. However, prior research examining the safety benefits of GSCTs is inconsistent, showing both improved safety and diminished safety at various locations.

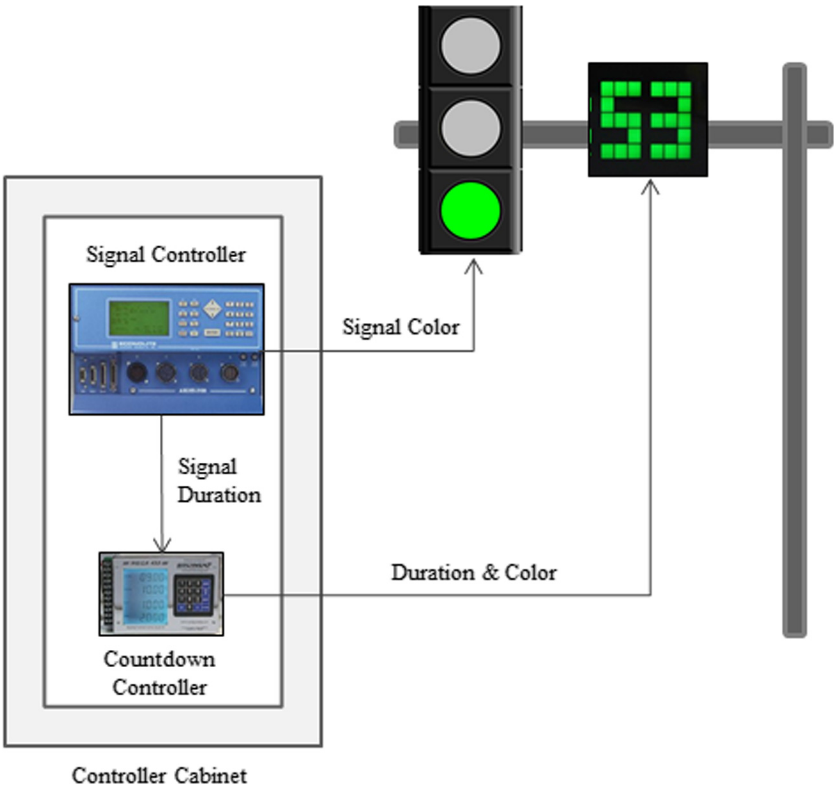

Fig. 1. Diagram of a TSCT that operates via signal and countdown controllers.

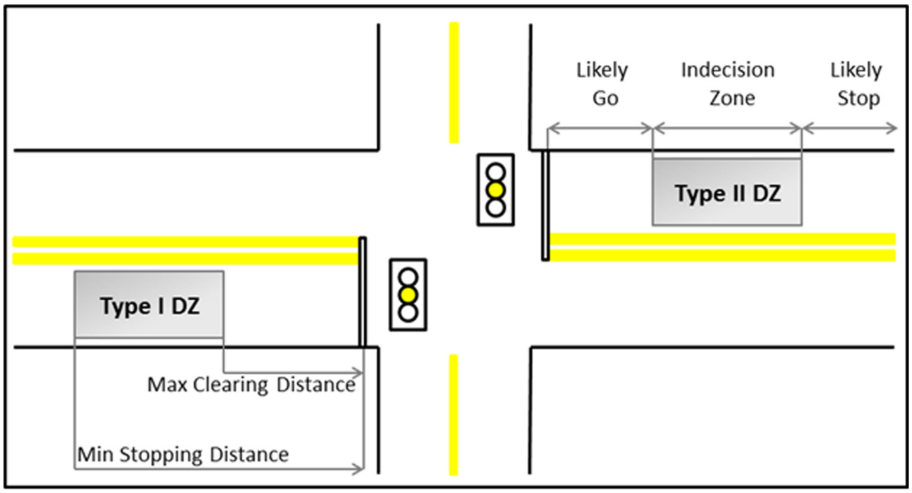

Fig. 2. Type-I and type-II DZ (Hurwitz, Knodler, and Nyquist (2011)).

1.3. Improved intersection safety due to GSCTs

GSCTs may reduce red light running behavior, a predominant safety concern at signalized intersections. Several studies conducted internationally show that GSCTs may improve intersection safety.

Yu and Shi (2015) developed a numerical model to predict driver following behavior in response to GSCTs using field data collected from one intersection with a GSCT near Jinan, China. Based on their model, the researchers concluded that GSCTs helped drivers make better-informed stopping decisions and that the GSCT reduced the number of cars running the intersection.

Ni and Li (2014) investigated the impact of GSCTs at four intersections along an arterial in Suzhou, China. Two of these intersections included GSCTs and two did not. From field observations, the researchers determined that while the GSCTs minimized safety prior to the yellow indication by increasing "risky following behavior", GSCTs minimized indecision and reduced rear-end collisions in the yellow interval. The authors concluded that GSCTs "are recommended to be cautiously installed", although noted this should be supplemented with safe driving education.

Kidwai, Karim, and Ibrahim (2005) observed drivers at two signalized intersections, one with and one without a TSCT, in Kuala Lumpur, Malaysia. Researchers found that average red light running was 37.1% with the TSCT and 66.2% at the traditional intersection, suggesting that the presence of a TSCT may reduce red light running violations.

In a before-and-after study conducted in Singapore, Lum and Halim (2006) found that GSCTs reduce red light running at signalized intersections. Lum and Halim observed a 65% decrease in red light running 1.5 months after installing the GSCT. However, the frequency of red light running behavior reached pre-installation levels after six months. This suggests that novelty may account for some or all of the impact of the GSCT studied for this population.

1.4. Deterioration of intersection safety due to GSCTs

Studies have shown that GSCTs can induce aggressive driving behavior, decreasing intersection safety. A detailed study conducted by Chen, Chang, Chang, and Lai (2007) showed that GSCTs had negative effects on intersection safety in Taiwan. TSCTs were installed at 187 intersections in one of three configurations (GSCT, RSCT, or both GSCT and RSCT). One year of pre- and post-installation crash data was collected and analyzed between 2003 and 2006. The intersections with only a GSCT had twice the number of reported crashes and a 33% increase in the number of injuries. Places where GSCTs were installed along with RSCTs observed a 19% increase in crashes. In a similar study, Chiou and Chang (2010) found that GSCTs made drivers more aggressive, extended the dilemma zone by 28 meters, and increased the frequency of rear-end crashes at the termination of the green phase.

Ma, Liu, and Yang (2010) examined the performance of GSCTs in Shanghai, China. Compared to a traditional intersection, the study found that at intersections with GSCTs, drivers crossed the stop line at higher speeds. Due to this phenomenon, GSCTs increased the likelihood of crashes in the intersection at the onset of the yellow change interval.

Long, Han, and Yang (2011) examined the effects of TSCTs on driver behavior during the yellow change interval at four urban signalized intersections in China. A strong correlation was found between the presence of TSCTs and red light running violations. The study found that TSCTs increased the probability that a driver entered an intersection during the later portions of the yellow, and sometimes red, indications.

1.5. Research questions

The objective of this research was to investigate whether TSCTs have the potential to improve traffic safety at signalized intersections in the United States. This is the first study of its kind conducted on a population of US drivers in a driving simulator. The study considers the following fundamental research question: does the presence of GSCTs eliminate or reduce Type II dilemma zone conflicts by increasing the probability of a driver's correct decision to stop or proceed at the end of the green phase? Two specific research hypotheses were developed to address this research question:

(1) H_0 – *There is no significant difference in the probability to stop functions at the onset of the yellow indication at signalized intersections with and without GSCT.*
(2) H_0 – *There is no difference in deceleration of the drivers who decide to stop at the onset of the yellow indication at signalized intersections with and without GSCT.*

2. Material and methods

2.1. OSU driving simulator

The Oregon State University (OSU) driving simulator consists of a fully functional full-size 2009 Ford Fusion cab mounted on an electric pitch motion system that allows for onset cues for acceleration and braking events. The cab is surrounded by screens where the simulated environment is projected. As shown in Fig. 3, three projectors project a 180 degree front view. A fourth projector displays the rear image for the driver's center mirror. Two side mirrors have embedded LCD displays that permit the driver to see both rear sides. The cab instrument includes a steering control loading system that accurately represents steering torques based on speed and steering angle. The computer system consists of a quad core host that runs the "SimCreator" Software (Realtime Technologies, Inc.). The data update rate for the graphics is 60 Hz. It is a high-fidelity simulator that can capture and output highly accurate performance data such as speed, position, brake, and acceleration.

The virtual test tracks were developed using Internet Scene Assembler (ISA) software, which permitted using Java Script-based sensors on the test tracks to change the signal and to display dynamic objects such as a GSCT based on the vehicle's presence. GSCT triggering sensors were placed at a distance upstream from the intersection. The GSCT was activated when the vehicle was at a desired time-to-stop-line (TTSL) upstream of the intersection. TTSL is the number of seconds it takes for a vehicle travelling at a certain speed to reach the stop line starting from the moment of the yellow onset. The GSCT always counted down the last ten seconds of the green indication.

TTSL was chosen as a predictor of driver's probability to stop as it accounts for both vehicle's speed and position and has been previously documented as a strong predictor of driver behavior (Chang, Messer, & Santiago, 1985; Bonneson & Zimmerman, 2004; Hurwitz et al., 2013). For example, a driver approaching a signalized intersection at 45 mph is more likely to stop on yellow if the TTSL = 5 s compared to the scenario when TTSL = 2 s (Bonneson & Zimmerman, 2004; Moore & Hurwitz, 2013). The following parameters were recorded at roughly 10 Hz (10 times a second) throughout the entire duration of the experiment:

- Signal Change – To correlate driver responses with respect to the change in signal or GSCT display.
- Instantaneous Speed – To identify changes in speed in response to the GSCT display.
- Instantaneous Position – To identify the location of the vehicle at the onset of the yellow signal.

(a) (b)

Fig. 3. OSU driving simulator (a) view of forward projection and cab and (b) view from inside the cab.

2.2. Test track configurations

This research experiment involved two types of TSCT (GSCTs and RSCTs). This manuscript focuses on the implications of the GSCT evaluation. The GSCT experiment was composed of ten different test scenarios; TTSL = 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, and 6.0 s. Meanwhile, the RSCT experiment included three test scenarios: 20, 40, and 60 s. Thus, a total of 13 test scenarios, presented at thirteen different intersections, were included in both types of test tracks, those with and without TSCTs. The length of each test track was close to 6.25 km, so each test subject was required to drive approximately 12.50 km in total combining the lengths of both test tracks.

Each scenario was assigned a number and a random number generator was used to arrive at a final scenario sequence. GSCT test scenarios were randomly located at 10 of 13 possible locations. This process of signal arrangement was used to create four test track configurations: A, B, C, and D. The random assignment of intersections with each level of independent variables and the counterbalancing of the four track configurations contributed to minimizing the confounding effects of the order of exposures or of an upcoming event. The speed limit was kept the same (35 mph) for the entire roadway to reduce variability due to speed. In all four test tracks, the roadway was divided with one lane going each direction. Fig. 4 provides an example.

2.3. Independent variables

Presence of GSCT was included in the model as a binary variable with two possible levels: present or not present. TTSL was included as a continuous variable, although it can also be counted as a categorical variable of ten levels. Only TTSLs from 1.5 to 6 s at 0.5 s increments were considered for the model, as past research shows that nearly 100% of drivers proceed through an intersection when presented the yellow signal at a distance of 2 s or less and stop at a distance of 6 s or more (Moore & Hurwitz, 2013). This range was also chosen to reduce the complexity of the experimental design. Subjects' age was included as a continuous variable, while gender, education, and driving experience were included as factors of multiple levels. Table 1 describes the type and levels of each variable considered in building the model.

The first two variables, presence of GSCT and TTSL, were purely controlled, while subjects' driving experience and education were purely observed. Subjects' age and gender were not purely observed in the sense that the subject pool was selected to be representative of the Oregon driving population. That is, male/female proportion and the age distribution of the sample were kept as reasonably close to the Oregon driving population as possible.

2.4. Dependent variable

A GSCT may mitigate drivers' difficulty in determining the correct response at the onset of the yellow indication while approaching a signalized intersection. Because Oregon uses a restrictive yellow law, drivers' probability to stop on a yellow

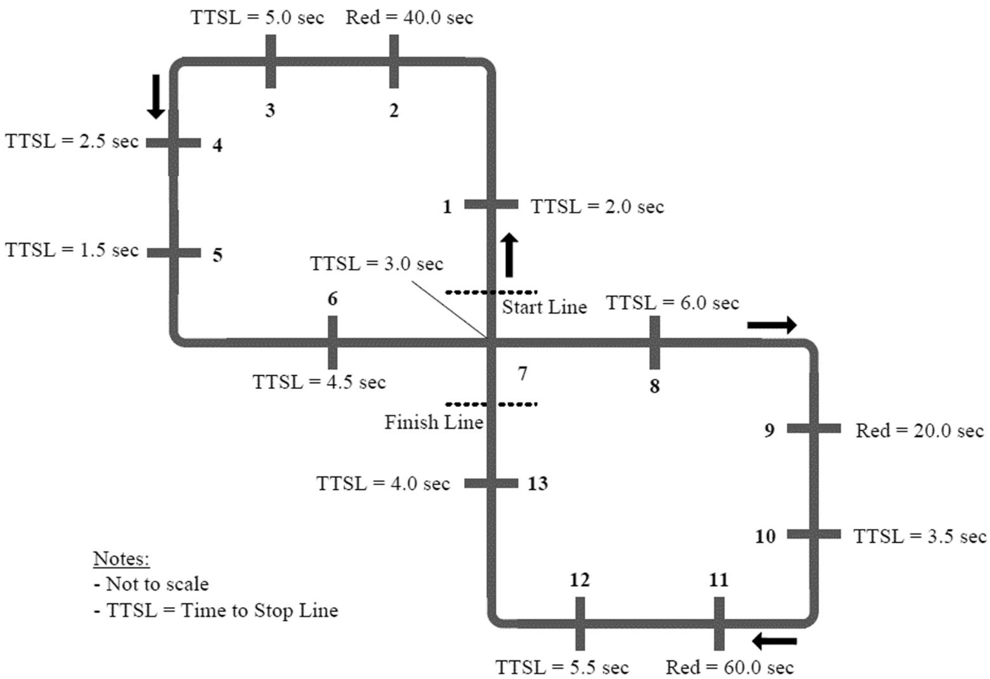

Fig. 4. Example test track with RSCTs (Red) and GSCTs (TTSL).

Table 1
Levels of independent variables.

Name of the variable	Category	Levels
Presence of the GSCT	Binary	1, and 0 (present or absent)
TTSL (s)	Continuous	1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, and 6.0 s
Age	Continuous	Continuous (18 to 78 years)
Gender	Binary	M (Male), and F (Female)
Driving Experience	Categorical	Five levels as indicated in Table 4.2 (1 through 5)
Education	Categorical	Seven levels as indicated in Table 4.2 (1 through 7)

signal is likely to increase in the presence of a GSCT. If true, this would suggest that GSCTs are effective in mitigating Type II dilemma zone conflicts. Therefore, the probability to stop function was established as the variable of interest in this experiment. Drivers' stop-or-go decision was coded as a binary variable (i.e., categorical variable of two levels) in the mathematical model to estimate the probability to stop for a given combination of explanatory variables.

In the driving simulator, vehicle speed, acceleration, and signal state data were collected from ten intersection scenarios. Java script based sensors were used to continuously monitor drivers position and speed to calculate the TTSL and change the signal state from green to yellow when the vehicle was at a desired distance (e.g., TTSL = 3.0 s) from the stop line. The final driver decision to stop or go was extracted from the simulator data output files.

2.5. Experimental procedure

The experimental procedure can be described in six sequential steps:

- Step 1: Upon arrival in the laboratory, an IRB approved informed consent document was presented and explained to the subject.
- Step 2: Subject demographics were collected through an online survey.
- Step 3: Subjects performed a calibration drive including roads, signalized intersections, and adjacent land use similar to that of the experiment lasting approximately 4 min in duration. The purpose of the drive was to acclimate the driver to the operational characteristics of the simulator and to assess the likelihood of simulator sickness.
- Step 4: The experimental drive without GSCT was administered. The authors did not perform a "crossover" design where the order of exposure to different treatments varies between subjects. In a crossover design, a significant time gap should exist between exposures to different treatments to "wash out" the carryover effect and remove statistical bias (Stufken & Hedayet, 2003). Testing each subject at two different times with considerable time gap was not a viable option for this study. However, the instantaneous speeds (measured at a distance upstream of the intersections where no effect of GSCTs should exist) from the control and the treatment scenarios were examined to confirm that subjects' usual driving behavior did not differ between the two scenarios.
- Step 5: Subjects were provided instructions regarding the meaning of GSCTs. The instructions included a one-page handout with pictures and text as well as verbal instructions from a researcher. This procedure of instructing drivers on the new traffic signal devices was consistent with previous driving simulator-based research (Knodler, Noyce, Kacir, & Gardner, 2005). Following this, an experimental drive with the GSCTs was conducted.
- Step 6: A follow-up online survey was conducted to evaluate the subject's comprehension of and preferences for GSCTs.

2.6. Test subjects

Subjects were recruited for the experiment through subject archives, email list serves, and flyers posted on the OSU campus and in the surrounding community. Demographic information was collected with an online survey administered after the informed consent process was completed. Sixty-seven subjects participated in the simulator study. Approximately 18% (7 female and 5 male) of subjects reported simulation sickness at various stages of the experiment. All responses recorded from the subjects who exhibited simulator sickness were excluded from the data analysis. Thus, the final data set was composed of 55 test subjects; 32 male (58% of total) and 23 female (42% of total). The average age of subjects was approximately 36 years with a range of 19 to 73 years.

3. Results

3.1. Data exploration

Driver decision to stop or go through the intersection on the yellow interval was recorded 10 times for "with GSCT" and "without GSCT" scenarios for each subject. That is, each test subject was observed interacting with 20 intersections that were included in the model. Thus, the final data set consisted of 1100 intersection interactions from 55 test subjects. Driver demographics were also considered.

For data visualization, a boxplot (Fig. 5) was constructed to display the association of the two principal predictors of interest with the response variable. Visual inspection of Fig. 5 provides preliminary evidence that the presence of GSCT influenced drivers' stop/go decisions at the onset of the yellow indication. For example, the median TTSL for drivers who chose to proceed through the intersection was 2.5 s in absence of the GSCT, whereas it was 2.0 s when a GSCT was present. Similarly, the median TTSL for drivers who chose to stop was 5 s and 4.5 s in absence and in presence of GSCT respectively. Drivers were more likely to stop at a distance closer to the intersection when a GSCT was present.

3.2. Model selection: generalized linear mixed model

The experiment was designed to develop a probability to stop function with reasonable predictive power. The dependent variable to be modeled from the data was a binary response (stop/go on yellow) from the drivers. For a continuous response variable, a linear regression model is generally sufficient (Ramsey & Schafer, 2013). However, classical statistical procedures often fail to deal with non-normal data such as counts or proportions, like the driver response in this experiment. In addition, the data included a random effect from the subjects. One effective and flexible approach to analyze non-normal data when random effects are present is called a Generalized Linear Mixed Model (GLMM), which accounts for both the fixed effects and the random effects in the response. The variables included in the model listed in Table 1 described all potential sources of variations which were assumed to have fixed effects. A random effect was also included to account for the inherent differences among subjects.

The entire data set was randomly split in half for developing the model with one half and cross-validating the model with the second half. To divide the data, the responses from males and females of different age groups were placed into separate bins, and then the first half was picked randomly from each bin (Table 2). The age groups were defined based on the crash statistics of Oregon drivers involved in injury or fatal crashes (Oregon Department of Transportation (ODOT), 2013). However, only drivers 18 years of age or older were included in the study and test subjects over age 65 were combined into one group due to comparatively lower participation rates. The final age categories are as follows: 18 to 24, 25 to 34, 35 to 44, 44 to 54, 55 to 64, and 65+. There was a slight overrepresentation of subjects in the 18 to 24 and 25 to 34 categories. However, the sample was deemed representative of the Oregon driver population using a Chi-Squared Goodness-of-fit test (χ-squared = 0.289, df = 5, p-value = 0.998).

A GLMM with a random intercept was considered the best suited model for this experiment. The full model (Eq. (1)) that included all explanatory variables is as follows:

$$Logit(p) \sim (1|Subject) + GSCT + TTSL + Age + Gender + Edu + DExp \quad (1)$$

where

p = Probability that a driver will stop at the onset of yellow,
$(1|Subject)$ = Random effect of subjects,
$GSCT$ = Presence of GSCT; 1 if present, and 0 otherwise,
$TTSL$ = Time to stop line in seconds (1.5 through 6.0 with 0.5 s increment),
Age = Subject's age in years,
$Gender$ = Subject's gender; factor with two levels,

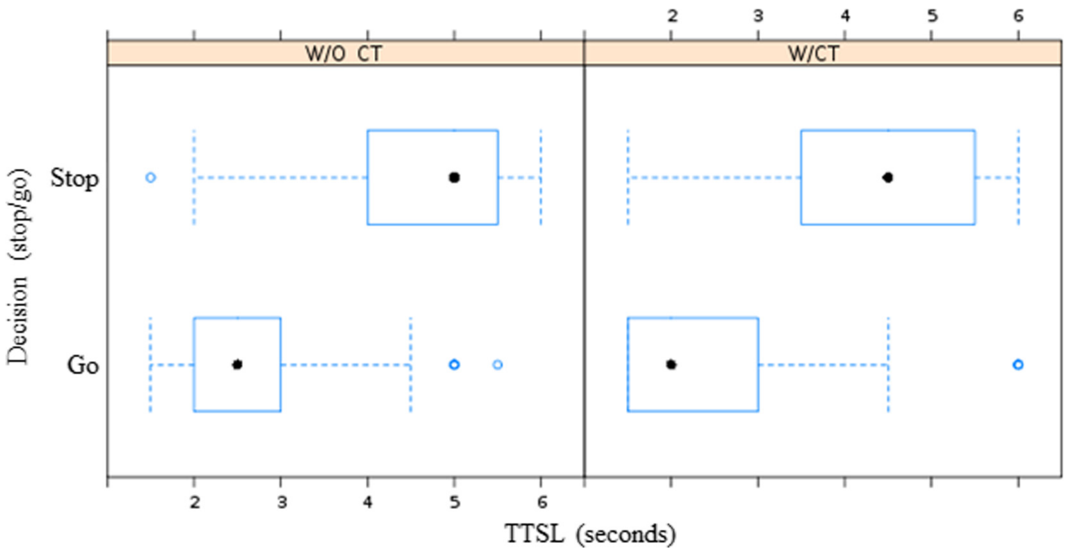

Fig. 5. Boxplot of driver's stopping decision data.

Table 2
Splitting data for model development and cross-validation.

	Column1 Age Group1	Column2 Age Group2	Column3 Age Group3	Sample
# of Males (total data set)	M1	M2	M3	...so on
# of Females (total data set)	F1	F2	F3	
Data for Model (Randomly picked)	(M1/2) + (F1/2)	(M2/2) + (F2/2)	(M3/2) + (F3/2)	∑(Column N) (N = 1, 2,... Number of age groups)
Total				55/2 ≈ 28 subjects

Table 3
Model selection of GSCT experiment.

Iteration	Model	AIC	Significant predictors	Comments
1	***Logit (p) ~ (1|Subject) + GSCT + TTSL + Age + Gender + Edu + DExp***	413.3	GSCT, and TTSL	GLMM (Full model with random effect)
2	***Logit (p) ~ (1|Subject) + GSCT + TTSL***	405.4	GSCT, and TTSL	GLMM (Reduced model with random effect)
3	***Logit (p) ~ GSCT + TTSL***	–	GSCT, and TTSL	GLM (Reduced Model without random effect) final model

Edu = Subject's education; factor with seven levels,
DExp = Subject's driving experience; factor with five levels.

The full model was taken as the starting point for arriving at the final model. As shown in Table 3, the next iteration of the model included the random effect, but excluded the non-significant fixed predictors (based on *p*-values). The AIC value for this first version of the reduced model (405.4) was compared to that of the full model (413.3) and was found to be very similar. This suggested that the removal of statistically non-significant predictors did not result in significant loss of the prediction power.

In the first iteration it was observed whether the random effect included in the model was indeed meaningful. One way of explaining this was to observe the summary statistics for the random effect from the GLMM, which showed that the variance in the response due to the random effect was very close to zero ($1.029e^{-05}$). This suggests that the variation in the response was not sourced from the random effect of the predictor. As such, the random effect of subjects was removed in the third iteration. Exclusion of the random effect from the model resulted in a Generalized Linear Model (GLM), or logistic regression model (LRM). Thus, the final model (Eq. (2)) was a GLM with two predictors; one binary (GSCT) and one continuous (TTSL). Final Model:

$$Logit(p) \sim GSCT + TTSL \tag{2}$$

It can be noticed in Eq. (2) drivers' age was found statistically non-significant. This suggests that drivers' stopping behavior on the circular yellow indication cannot be explained by their age.

The summary output and the coefficients of the final model (Eq. (2)) are given in detail in Table 4. Certain aspects of the result are worth noting. First, all three coefficients of the model are significant (*p*-value <0.001). Second, small deviance residuals (median = 0.161) shows that the response is predicted well enough by the model when the predictors are included.

To be able to numerically calculate the probability to drivers' stop function, the final model was transformed from a logit to a probability (Eq. (3)). The transformation is as follows:

Table 4
Final model summary.

Model summary:				
Formula: *Stopped ~ GSCT + TTSL*, family = "binomial"				
Deviance Residuals:				
Min	1Q	Median	3Q	Max
−3.2846	−0.4402	0.1610	0.5090	2.5966
Coefficients:				
	Estimate	Std. error	z-value	p-value
(Intercept)	−5.90	0.514	−11.459	<0.001
GSCT	1.05	0.263	3.997	<0.001
TTSL	1.71	0.138	12.332	<0.001

Number of Observations: 560.
Number of Groups: 28.

$$Logit(p) = log\left(\frac{p}{1-p}\right) = a + bx + cy$$
$$\text{Or, } p = \frac{1}{1 + e^{-(a+bx+cy)}} \tag{3}$$

where

p = Probability that a driver will stop at the onset of yellow,
a, b, c = Coefficients of the predictors in the final model,
x, y = The two predictors, GSCT and TTSL.

The final probability model (Eq. (4)) was derived by plugging in the values of the coefficients a, b, and c in Eq. (3), which is as follows:

$$p = \frac{1}{1 + e^{-(-5.90+1.05*GSCT+1.71*TTSL)}} \tag{4}$$

3.3. Model validation

Validation of the model developed for this study involved cross-validating the model with half of the data set and comparing calculated stopping probabilities with other TTSL-based FL models.

3.3.1. Cross-validation of the model

Data regarding the presence of GSCT and TTSL from the second half of the data (27 drivers) were input into the model, and a probability to stop on yellow was calculated for each subject interaction with the signal. The following algorithm (Eq. (5)) was applied to identify the conditions of stopping before the intersection and continuing through the intersection:

$$Stopped_{predict} = \begin{cases} yes, & p \geqslant 0.5 \\ no, & p < 0.5 \end{cases} \tag{5}$$

where

$Stopped_{predict}$ = Predicted behavior of the driver at the intersection (stop/go through the intersection on yellow indication).
p = Calculated probability to stop before intersection using Eq. (4).

The calculated values of drivers' stopping probability were compared to the actual observed behavior of the 27 drivers, and the predictive power of this model was estimated (Table 5).

As shown in Table 4, the mathematical model developed in this study correctly predicted the behavior for the remaining 27 test subjects with an accuracy of 88.7%. In a similar study, Moore and Hurwitz (2013) were able to correctly predict driver's stopping behavior with an accuracy of 90% with their TTSL-based FL model.

3.3.2. Comparison of probability to stop models

It was anticipated that the LRMs developed from the two scenarios (i.e., with and without GSCT) should yield different probability distributions. A comparison between the current model (LRM) for the "with GSCT" scenario and Moore and Hurwitz's FL model should be significantly different. However, the probability distribution of the current model for the "without GSCT" scenario should be very similar to the FL model.

At the onset of the yellow indication, drivers are presented with the difficult task of assessing their speed and position with respect to a downstream intersection, and deciding whether to go or stop. Past research shows FL is capable of predicting the outcome of drivers' decision making in the Type II dilemma zone (Moore & Huwitz, 2013; Rakha, El-Shawarby, & Setti, 2007). In order to validate the model developed in this study, it was compared with both Moore and Hurwitz (2013) and Rakha's (2007) TTSL-based FL model. The probability to stop function was first calculated for the 10 TTSLs using both the LRM model and the FL model developed by past research. The calculated values of probability to stop are depicted in Fig. 6, which compares the performance of the model developed for this study with Moore and Hurwitz's (2013) and Rakha's (2007) models. The blue and red lines represent the probability to stop functions in the presence and absence of GSCTs, calculated from the model developed for this study. The green line represents the probability to stop function derived from the FL model (Moore & Huwitz, 2013). Visual inspection suggests that the probability to stop at a certain value of TTSL in the presence of GSCT was higher than that calculated with the FL model. A similar comparison of the probabilities calculated from the W/O GSCT_LRM and Moore and Hurwitz's FL model (which are essentially the same cases) would result in smaller differences.

The probability distribution from w/o GSCT_LRM and w/o GSCT_FL (Moore & Huwitz, 2013) models were compared through a non-parametric goodness-of-fit test (two-sample Kolmogorov-Smirnov test), which indicates no statistically significant difference.

Table 5
Prediction Accuracy of the Final LRM Model.

		Predicted		% Correct
		Stop	Go	
Observed	Stop	295	32	90.2%
	Go	29	184	86.4%
			Total	88.7%

3.4. Model comparison to real-world observations

3.4.1. Probability to stop

This study's research objective was to quantify the benefit of using a GSCT in terms of improvement in drivers' probability to stop at an intersection, i.e., the vertical separations between the blue[1] and the red lines in Fig. 6 of the previous section. The difference in probabilities (Δp) were calculated from the derived model and are shown in Fig. 7. Values of Δp are positive for TTSL cases, suggesting the presence of GSCT always increases a driver's probability to stop on a yellow indication.

As stated earlier, in real world driving, the dilemma zone is generally located between TTSL 2.5 s to 5.5 s (Bonnenson et al., 2002). However, this range may vary among intersections. For this study, a range of 2 to 4.5 s was considered based on observed driver stop/go decision making. Consequently, the area under the curve between a TTSL equal to 2 and 4.5 s was divided by the difference in TTSL (4.5–2.0 = 2.5 s) to estimate the overall increase in stopping probability resulting from the presence of a GSCT. The overall increase in stopping probability due to GSCTs was 13.10%. That is, the presence of a GSCT is expected to increase a driver's probability to stop in the dilemma zone by 13.10%.

3.4.2. Validation of deceleration rates

Average deceleration rates for each subject approaching an intersection were computed by dividing the instantaneous speed (at the moment the brake was first applied) with the time taken to come to a complete stop. Fig. 8 shows the cumulative distribution of the observed decelerations for scenarios with and without GSCT. Observed deceleration rates were higher in the absence of the GSCT: the mean deceleration rate with GSCT was 10.69 ft/s^2 (95% confidence interval: 11.35 and 10.03 ft/s^2) and 9.19 ft/s^2 (95% confidence interval: 8.51 and 9.95 ft/s^2) without. The difference between the means was found to be statistically significant based on a two-way *t*-test (p-value = 0.016).

The deceleration rate for the "without GSCT" case is comparable to commonly accepted deceleration rates. For example, the ITE recommended value of deceleration rate for computing a change interval is 10 ft/s^2 (Institute of Transportation Engineers (ITE), 1999), close to that of the "without GSCT" case. Fig. 9 compares deceleration rates calculated through past research with that calculated in this study. As shown, the deceleration rates observed from this simulator study (without GSCT) were consistent with previous field research. Therefore, the driving behavior of test participants observed in the simulation lab was not widely different from previously observed real-world driving behavior.

4. Discussion

4.1. Study limitations

GSCTs are implemented internationally at predominantly pre-timed signals. GSCTs are typically not used for actuated signals because current vehicle detection mechanisms and signal control algorithms for actuated systems permit the precise estimation of time remaining for a signal only a few seconds before phase termination. This characteristic has widely been described as the most significant limitation to applying GSCTs in actuated traffic signal systems (Chen et al., 2009). Therefore, this research studied driver behavior in presence of GSCTs exclusively at pre-timed traffic signals. As defined earlier, the Type-II dilemma zone occurs due to driver indecision and can potentially occur at any intersection regardless of the signal control type. A large number of intersections are located on busy city streets with a potentially high frequency of dilemma zone conflicts. A significant portion of these signals run under fixed-time control, where GSCT implementation is expected to immediately reduce the risk of both red light running and rear-end crashes. However, rural high-speed intersections running under fully actuated control are outside the scope of GSCT until a reliable prediction algorithm for signal change is developed.

In addition to the speed and driver demographic factors addressed in this research, there are other factors that can potentially influence drivers' stop/go decision in the dilemma zone. Signal timing and coordination, intersection geometry, vehicle type and characteristics, weather conditions, regional driving practices, and enforcement have also been found to influence driver behavior at the onset of the circular yellow indication (NCHRP, 2012).

To simplify the experimental design and reduce the potential for simulator sickness, left-turns were excluded from the study design. Although GSCTs have been implemented for left-turn movements, limiting the scope of this study to through

[1] For interpretation of color in Fig. 4, the reader is referred to the web version of this article.

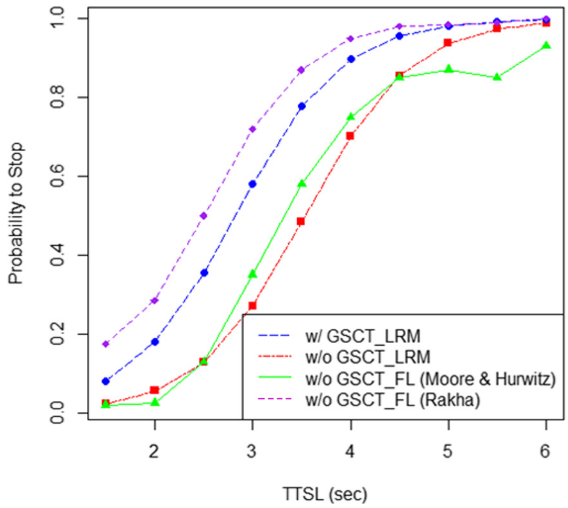

Fig. 6. Comparison between the LRM and previous FL Model.

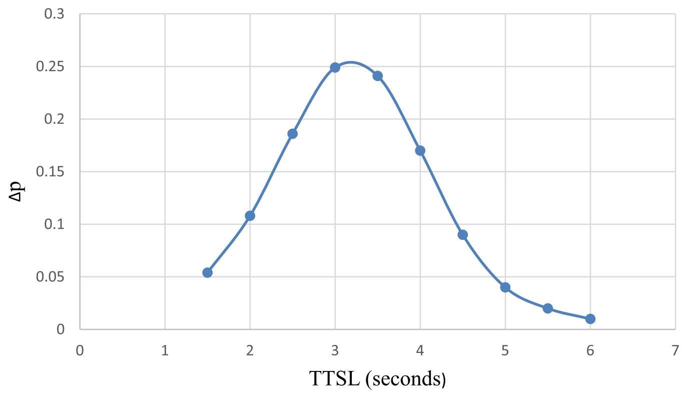

Fig. 7. Difference in driver's stopping probabilities (Δp) with TTSL.

movements enabled the researchers to focus on the effectiveness of GSCTs while minimizing the risk of simulator sickness for participating drivers.

Because GSCTs do not exist in the US, it was necessary to perform a driving simulator experiment and no field validation was possible. However, when possible, data for non-GSCT cases were cross-validated with field data. Results were similar, substantiating the validity of driving simulation. Further, drivers' stopping behavior at traffic signals, perception reaction time, and deceleration rates have previously been validated in the OSU driving simulator (Moore & Hurwitz, 2013).

4.2. Interpretation of results

A probabilistic model was developed to quantify the safety benefits of GSCTs using the change in drivers' stopping probability in response to a yellow indication while in the dilemma zone. Due to the binary nature of the outcome (stop/go through the intersection), and repeated measurement from single test subjects, a GLMM was fitted initially. While driver demographics were considered in the initial model, none appeared to be significant predictors of stopping behavior. In addition, the random effect of the subject was found to be incapable of explaining the variability in stopping probability. Thus, the final model was reduced to fit a GLM. This work delivers a final model that is capable of predicting drivers' stopping probability with a prediction accuracy of 88.7%.

An effort was made to quantify the safety improvement due to the presence of GSCTs by using the model. An overall increase in driver's probability to stop in the dilemma zone was predicted. The improvement was found most prominent for TTSL measurements equal to 3.0 and 3.5 s, representing an approximately 25% improvement in the probability to stop.

The average deceleration rates recorded in absence of a GSCT were consistent with previous research, substantiating the validity of driving simulation in this study. Deceleration rates decreased in the presence of a GSCT, indicating a possible

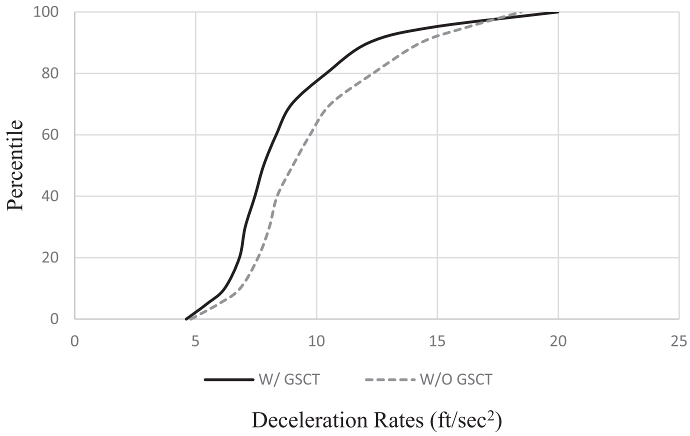

Fig. 8. Cumulative deceleration rates – with and without GSCT.

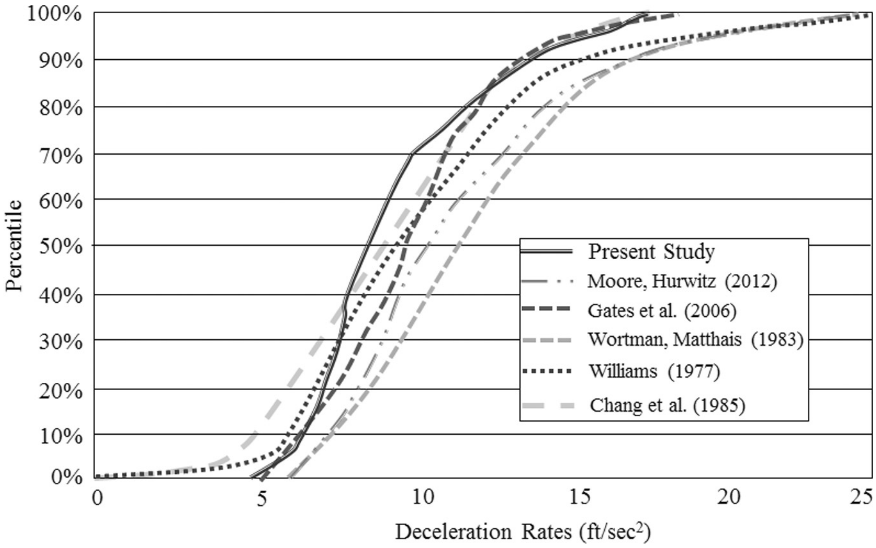

Fig. 9. Comparison of cumulative deceleration rates.

safety improvement. The study found a statistically significant (p-value = 0.016) reduction in the mean deceleration rate (1.5 ft/s^2) due to the presence of GSCTs.

A special case of the model developed in this work can be created by setting the value of GSCT to zero in Eq. (4). The resulting model can be applied to predict driver stopping probability for different TTSL cases. This is essentially the same model developed by the Moore and Hurwitz (2013) TTSL-based FL model, meaning it should yield similar results. Therefore, as a validation effort, the predicted probabilities calculated from the two models were compared by a two-sample Kolmogorov-Smirnov test. No evidence of significant difference (p-value = 0.759) was detected.

The discussion presented in this section forms the basis of the author's conclusion that a reasonable validation effort was made to consolidate the findings of this work. As such, this research contributes to the body of knowledge on the safety implications of GSCT at signalized intersection.

5. Conclusion

It is concluded that the implementation of GSCTs at signalized intersections may significantly improve driver stopping behavior in response to the onset of the circular yellow indication.

This study is the first to examine the behavior of US drivers in response to vehicular countdown timers in a driving simulator environment. It included a representative sample of the population of licensed Oregon drivers based on gender, age, and driving experience. Although, the study was conducted in a simulated environment, the findings add to the body of knowledge on the behavior of US drivers. A long-term field study involving multiple cities with different demography is suggested for comprehensive knowledge on the real-world safety benefits suggested by the surrogate safety measures documented in this study. The major contribution of this study include the provision of preliminary evidence and a predictive model supporting the benefit of applying GSCTs at signalized intersections in the US. However, the scopes of inference for the developed models were limited due to the scope of the experiments and subject recruitment. These limitations form the basis of recommendations for future work, including:

- A larger sample size has the potential of eliminating unexpected bias on the response variable. Older age groups were slightly under-represented in the sample.
- Expanding the driving simulation studies to include RSCT, YSCT, other TSCT display configurations, and other intersection types. Additional evidence will strengthen the case for the use of these devices.
- Although reasonable validation efforts were made in this work, studying driver responses to TSCT in the field is critical if they are to be considered for adoption at any scale in the United States.

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