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Influence of bicyclist presence on driver performance during automated vehicle take-over requests

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ABSTRACT

One proposed benefit of automated vehicles (AVs) is their potential to mitigate the occurrence of serious crashes due to human error or poor decision making while driving. However, there are still many concerns associated with the use of SAE Level 3 AVs, which require intervention by a human driver after a take-over request (TOR). These concerns intensify when vulnerable road users, such as bicyclists, are introduced to the driving environment. The objective of this research was to investigate how human drivers of AVs interact with bicyclists during a right-turn maneuver after receiving a TOR. Changes in driver performance, including visual attention and crash avoidance behavior, were measured by using a high-fidelity driving simulator, with 43 participants each completing 18 right-turn maneuvers. Three independent variables were studied: the bicyclist's proximity to the intersection, the driver's proximity from the intersection when the TOR was received, and the driver's engagement in a distracting secondary task (a game on a tablet). In general, the results showed that the introduction of the secondary task led to decreased driver performance with respect to time-to-collision and the time that it took a driver to first identify the bicyclist on the roadway. When given more time to react before the intersection, drivers generally had safer interactions with the bicyclist.

1. Introduction

Over 94% of serious vehicle crashes are due to human error or poor decision making during driving (NHTSA, 2018). Driver-assistance systems and automated vehicles (AVs) seek to address some of these safety issues. Many currently used driver-assistance systems, such as collision warning and avoidance systems, lane-keeping systems, and adaptive cruise control, have been demonstrated to reduce the incidence of crashes and to improve driver safety (e.g., see Sayer, Bogard, Buonarosa, LeBlanc, Funkhouser, Bao, & Winkler, 2011). However, there are still many concerns with adding increasingly complex levels of automation to the driving environment.

The Society of Automotive Engineers (SAE) defines levels of automation on a scale from zero to five. Level 3 (L3: Conditional Automation), Level 4 (L4: High Automation), and Level 5 (L5: Full Automation) allow the AV system to monitor the environment. However, L3 and L4 have situations where the human driver controls the vehicle, providing numerous human behavior-related challenges for engineers. For example, at both levels, the driving task must be transitioned away from the AV to the human driver and, due to the limitations of AV systems, such transitioning could occur unexpectedly. In particular, under L3 automation, the driver could be required to take control of the vehicle at any moment.

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A report on Waymo AV disengagements listed 63 instances (over 352,000 miles of driving on California public roads) where a deactivation of the autonomous system occurred when a failure of the technology was detected or when the safe operation of the vehicle required the autonomous vehicle test driver disengage the autonomous mode and take immediate manual control of the vehicle (Waymo, , 2017). This low fraction of disengagements (0.2 per 1000 miles) was a fourth of the rate from 2015. However, 89% of disengagements occurred on urban (nonhighway) streets, highlighting the difficulty of these complex driving environments. In another example, a Mercedes-Benz AV tested solely on urban roads had more than 336 disengagements during 673 miles of driving, for a rate of nearly one disengagement every 2 miles (Mercedes-Benz, 2016). Given the potential for high disengagement rates and multiple transitions of control, it is important to understand the human behavioral aspects of automation.

1.1. AV and driving simulation

Laboratory driving simulators offer a safe and controlled environment to examine the human-related factors of driver behavior. Although some researchers have noted fidelity issues with certain simulation platforms (particularly fixed-base simulators) in addressing research questions (e.g., De Winter, Stanton, Price, & Mistry, 2016; Neubauer, Matthews, Saxby, & Langheim, 2010), many others have noted the important benefits of driving simulators (Bellem et al., 2017; Burnett, Harvey, & Donkor, 2017; Wang et al., 2010). Driving simulators have been specifically validated for evaluating research questions related to AV driving. Studies showed a strong correlation between L2 AVs and driving simulators with respect to driver comfort, driver performance during transitions of control, and on-road driver behavior (Bellem et al., 2017; Eriksson, Banks, & Stanton, 2017).

Numerous driving simulator studies have evaluated the potential for driver distraction and secondary task engagement when operating an AV. Although AVs are designed to lighten driver cognitive load, distraction and fatigue become prominent issues with increasing automation. Passive fatigue may result when the driver has a low cognitive load and does not have direct control over the driving task (Desmond & Hancock, 2001). With increasing vehicle automation, drivers are more likely to engage in secondary tasks and to look away from the road for extended periods (with no upper limit on how long they will look away from the road, even when they know automation could fail at any time) (Zeeb, Buchner, & Schrauf, 2015). This decreased driver vigilance leads to longer take-over times and less safe automated driving, as indicated by slower response times to critical events (Cunningham & Regan, 2015; Merat, Jamson, Lai, & Carsten, 2012).

1.2. Transitions of control

The importance of research into transitions of AV control cannot be overstated. If the automation of an AV fails unexpectedly, almost all drivers will crash. However, a timely warning in the form of a take-over request (TOR) will allow most drivers to avoid a collision (De Winter et al., 2016). A major issue associated with TORs is that drivers require time to reengage with the task of driving after a period of low cognitive load. Research by Louw et al. (2015) and Gold, Damböck, Lorenz, and Bengler (2013) found that driver reengagement may take as long as 5–7 s. In a driving simulation study in a highway environment, Merat et al. (2012) found that drivers took 30–40 s to stabilize their lateral position in response to a randomly occurring noncritical transition of control. Even when the transition was systematic and predictable, drivers still took nearly 10 s to stabilize their lateral position. Mok, Johns, Lee, Miller, Sirkin, Ive, and Ju (2015) studied the time to transition control in response to a road hazard (i.e., a construction zone on a curve). Five seconds before the road hazard was sufficient time for the driver to regain control of the vehicle, whereas 2 s was insufficient. Drivers felt most comfortable when the transition time between automated and manual driving was 8 s.

1.3. Multimodal conflicts

Bicyclists are extremely vulnerable in the roadway environment. In 2015, there were 840 deaths in the United States due to crashes between bicyclists and vehicles (FARS, 2017). One of the more prevalent types of vehicle-bicycle crashes is the right-hook (RH) crash, where a right-turning motorist strikes an adjacent, through-moving bicyclist (Fig. 1.1). In Oregon between 2007 and 2011, over 59% of all vehicle-bicycle crashes at signalized intersections were RH crashes (Hurwitz, Monsere, Jannat, Warner, & Razmpa, 2015). A major contributing factor to dangerous RH crash scenarios is a lack of situation awareness, with most drivers not identifying the bicyclist near the intersection (Jannat, 2014).

Numerous engineering treatments (e.g., signage, pavements markings, geometric designs) have been designed to increase the visibility of bicyclists at intersections. However, these treatments were created for drivers who are engaged in the driving task and aware of their surroundings. Such engagement and awareness may not be the case for many AV drivers, as demonstrated by a recent collision between a self-driving Uber and a pedestrian walking a bicycle across a street in Arizona (Griggs & Wakabayashi, 2018). Moreover, driving simulation studies of AVs, including those summarized in sections 1.1 and 1.2, have typically focused on highway driving. Despite the importance of potential interactions between L3 AVs and bicyclists, few simulation studies have been performed on urban streets or under other conditions where bicyclists are prevalent (Kyriakidis, Happee, & De Winter, 2015; Kyriakidis et al., 2017). Those studies that do exist typically only address the topic from the bicyclist's perspective.

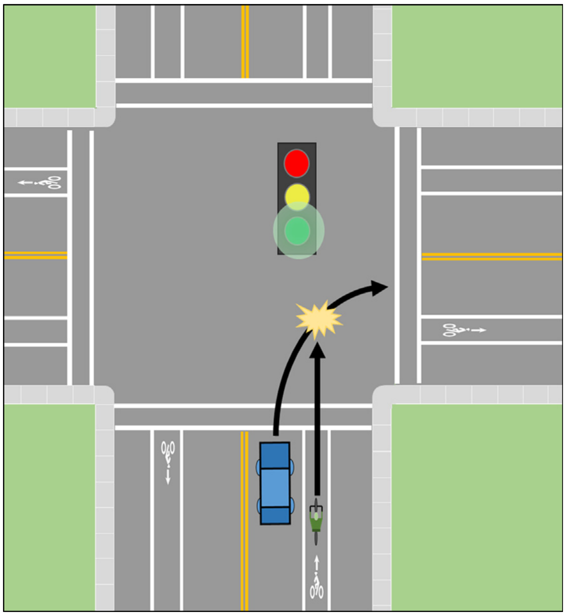

Fig. 1.1. Right-hook crash scenario.

With research on AVs and human behavior demonstrating reduced driving performance (e.g., Cunningham & Regan, 2015; Merat et al., 2012), AV transitions of control may be important factors in multimodal crashes and safety. However, more research is needed to quantify the safety implications of L3 AVs, especially in multimodal and urban environments. This research attempts to address some of these gaps in knowledge by using a driving simulator to evaluate drivers' visual attention and collision avoidance while operating an L3 AV.

2. Methodology

A driving simulation experiment was designed to evaluate driver performance related to a right-turning motorist's visual attention and crash avoidance behavior. This study was approved by the Oregon State University (OSU) Institutional Review Board (Study #8329). Two primary tools were used for this experiment: the OSU driving simulator and the Applied Science Laboratories (ASL) eye-tracking system.

2.1. OSU driving simulator

The full-scale OSU driving simulator is a high-fidelity motion-based simulator comprising a full 2009 Ford Fusion cab mounted above an electric pitch motion system capable of rotating ±4°. The pitch motion system allows for accurate representation of acceleration or deceleration (Swake et al., 2013). Three projectors are used to project a front view of 180° × 40°. An additional projector displays a rear image for the driver's center mirror. Two side mirrors have embedded LCD displays. Ambient sounds around and internal sounds inside the vehicle are modeled with a surround-sound system. The computer system includes a quad-core host running Realtime Technologies SimCreator Software (Version 3.2) with a 60-Hz graphics update rate. Fig. 2.1 shows views of the simulated environment created for this experiment from inside (left) and outside (right) the vehicle.

The driving simulator contains an AV software package, SimDriver V2, controlled by Java Script. Automation can be turned on by pushing a button on the vehicle's steering wheel or can be controlled through sensors coded in the virtual environment. The center of the vehicle's instrument panel contains an AV status display (2.5 in. high × 2.5 in. wide), which is clearly visible to the driver behind the steering wheel.

During the experiment, the vehicle dashboard showed four displays (Fig. 2.2) in the following order, indicating the different states of the AV: Manual Driving, Automation On, TOR, and Automation Off. All images, except for the TOR indication, were static. The TOR indication was a dynamic image designed to show hands grabbing the steering wheel with a countdown of 3 s. The TOR indication was accompanied by a beeping alert, based on NHTSA research on auditory alerts in vehicles (Singer, Lerner, Baldwin, & Traube, 2015). The alert beeped three times and then gave the following verbal guidance to the driver, depending on which direction they were expected to proceed: "Take control and continue straight," "Take control and turn left ahead," or "Take control and turn right ahead."

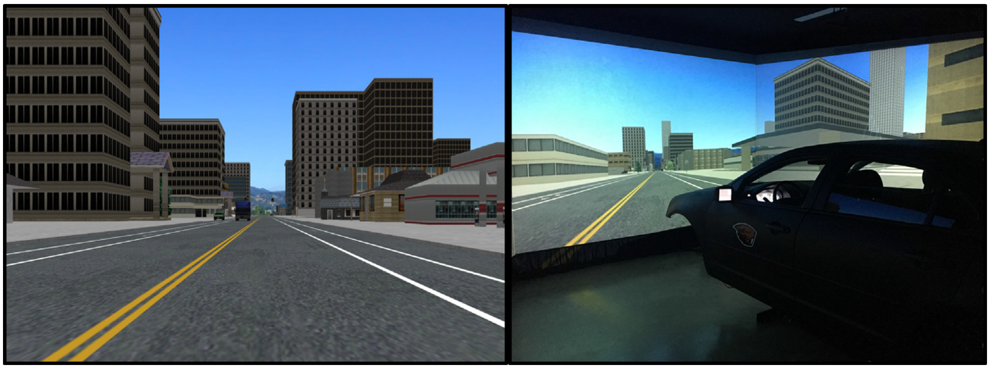

Fig. 2.1. Simulated environment in the OSU driving simulator, from the participant's perspective inside (left) and from outside (right) the vehicle.

Fig. 2.2. Central dashboard display (Manual, Automation On, TOR, and Automation Off).

2.1.1. Virtual environment

The environment was designed to replicate a typical urban roadway with a 30-mph speed limit. The roadway cross-section comprised two 11-foot travel lanes, two 6-foot bikes lanes, and two 7-foot parking lanes, one in each direction (Fig. 2.3). When present in the environment, a bicyclist traveled at a constant velocity of 16 mph. Higher bicyclist speeds are more difficult for drivers to project into the future and lead to more dangerous RH crash scenarios at signalized intersections (Jannat, 2014). Bicyclists and ambient traffic in the environment were coded manually, to ensure that each participant encountered the same number of vehicles and to limit the number of interactions or conflicts that each participant encountered. Before beginning the experimental drive, participants completed a 5-minute calibration drive to acclimate them to the

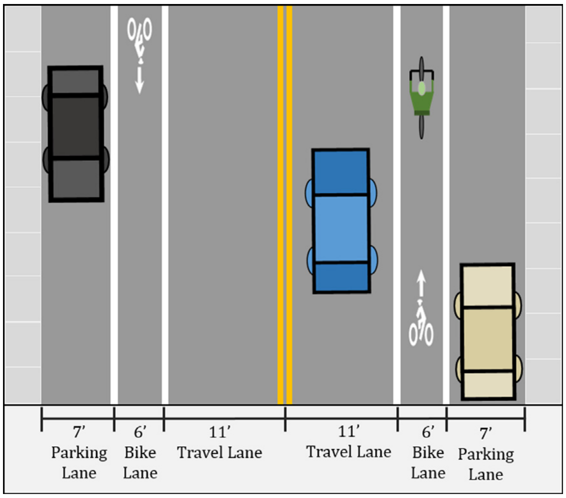

Fig. 2.3. Roadway cross section.

vehicle mechanics, the virtual environment of the simulator, and the AV characteristics, as well as to determine if they were prone to simulator sickness.

2.2. Eye tracker

In conjunction with the driving simulator, an eye-tracking system was used to record where participants were looking while driving in the simulator. Eye-tracking data were collected with the ASL Mobile Eye-XG platform, which allows the user unconstrained eye and head movements. A 30-Hz sampling rate was used, with an accuracy of 0.5–1.0°. Fixations occur when the gaze is directed towards a particular location and remains still for some period of time (Green et al., 2007; Fisher, Rizzo, & Caird, 2011). The ASL Mobile Eye-XG system records a fixation when the participant's eyes pause in a certain position for more than 100 ms.

2.3. Independent variables

A factorial design was chosen for this experiment to enable exploration of all three independent variables separately. Table 2.1 summarizes the independent variables and their associated levels in the factorial design. The experiment included three independent variables: TOR proximity, relative bicycle position, and secondary task engagement.

TOR proximity was defined by the vehicle position when the TOR was presented to the driver (TOR length remained constant at 3 s). TOR proximity was 5, 10, or 15 s upstream of the stop line on the approach to the intersection.

Relative bicycle position was varied, based on five alpha and beta tests performed by the research team, to induce interactions between the bicycle and vehicle at signalized intersections. A bicyclist was placed relatively closer or farther from the stop line on the approach to the intersection, to intentionally induce different yielding or overtaking decisions by the driver. The starting position of the bicyclist was varied based on the TOR proximity, such that the bicyclist only became visible to the driver 10 s ahead of a TOR. Starting positions were chosen to keep the bicyclist on the same trajectory relative to the vehicle, regardless of when the driver received the TOR (Fig. 2.4). Prior to 10 s before the TOR, the bicyclist was stationary behind a parked vehicle and obscured from the driver's view. The bicyclist closer to the intersection was positioned 20 m ahead of the bicyclist farther from the intersection. Additional bicyclists were coded into the simulation outside the tested scenarios, so that drivers would not predict an interaction with a bicyclist.

The final independent variable was participant engagement in a secondary (motor and cognitive) task. The task was a game developed by Rokni, Tapiro, Parmet, and Oron-Gilad (2017), which involves popping a bubble of a particular color on a touch-screen device mounted in the cab of the vehicle (Fig. 2.5). The task was intentionally designed to be difficult and to engage drivers. *Playing games is one anticipated secondary task that the promise of automation will bring and, as such, is a reasonable secondary task to study.*

The factorial design resulted in the inclusion of 18 scenarios, which were presented within subjects. Twelve of those scenarios included bicycles. To control for practice or carryover effects, the scenario order was partially counterbalanced by utilizing four different tracks, each ranging in length from approximately 3 to 7 min, depending on the driver's speed and track length. Each track had four or five right-turn scenarios, with randomly assigned variables. Extra intersections and left turns were introduced to the track layout so that participants would not anticipate the scenarios at intersections. Scenarios were separated by 45–90 s of driving in automated mode.

2.4. Dependent variables

Three dependent variables were measured and evaluated through this work. These dependent variables were position data from the vehicle and bicyclist (used in time-to-collision measurements), the driver's yielding behavior (whether a driver chose to yield to the bicyclist at the intersection), and fixation data from the eye-tracking software.

Table 2.1
Experimental variables and levels.

Variable	Category	Abbreviation	Level description
Relative Bicycle Position	Discrete	No Bike	No bicycle
		Bike Closer	Bicycle closer to stop line
		Bike Farther	Bicycle farther from stop line
TOR Proximity	Discrete	5 s TOR	TOR received 5 s from stop line
		10 s TOR	TOR received 10 s from stop line
		15 s TOR	TOR received 15 s from stop line
Secondary Task	Dichotomous (Categorical)	No Game	No secondary task
		Game	Playing the bubble game

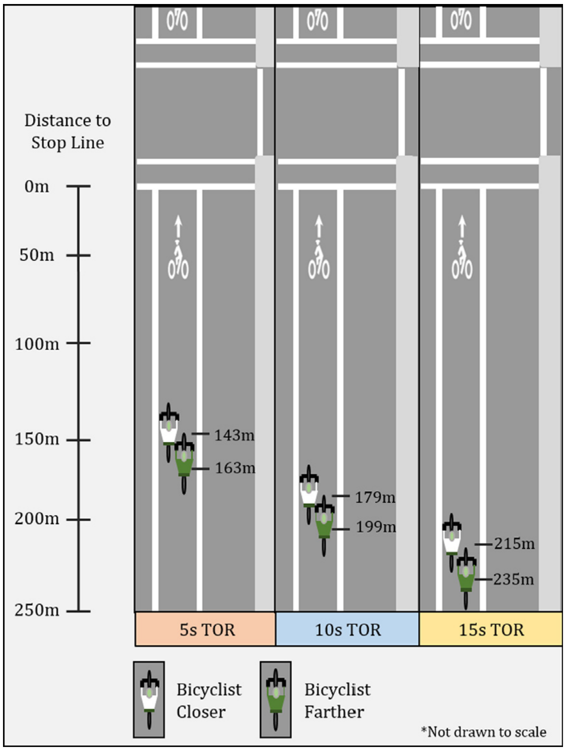

Fig. 2.4. Bicycle starting position based on TOR proximity.

Fig. 2.5. OSU researcher demonstrating the bubble game mounted in the vehicle cab.

2.5. Experimental protocol

Participants were recruited through flyers posted around Corvallis, Oregon and through emails sent to different campus organizations and email listservs. At the start of the experiment, participants were asked to provide informed consent and answer a prescreening survey to ensure that they were licensed to drive a motor vehicle for more than 1 year, had good vision, and were not prone to simulator sickness. The prescreening survey also included demographic questions (i.e., age, gender, ethnicity, driving experience, highest level of education, and prior experience with driving simulators). After completing the prescreening survey, participants were introduced to the driving simulator controls. The AV functions and displays were explained. Participants then completed an approximately 5-min calibration drive. After the experimental drives, which took approximately 30 min to complete, participants answered a postdrive survey, which included questions on their experience and their attitude towards automation after the experimental drive.

2.6. Participant demographics

A total of 46 participants, (23 women, 22 men, 1 preferred not to answer) participated in the simulator study. Only 6.5% of participants (3 women) reported simulator sickness and did not complete the experiment. All responses recorded from participants who reported simulator sickness were excluded from the analyzed dataset. Although it was expected that many participants would be OSU students, an effort was made to incorporate participants of all ages within the specified range of 18–75 years. The age of participants ranged from 18 to 74 years (M_{age} = 30.7, SD_{age} = 15.11).

3. Results

Two measures of driver performance were evaluated: collision avoidance behavior and visual attention. The collision avoidance behavior of drivers was evaluated based on a driver's yielding behavior and time-to-collision (TTC) with a bicyclist. Visual attention was evaluated based on the driver's total fixation duration (TFD) on the bicyclist and the driver's first fixation on the bicyclist in the roadway.

3.1. Collision avoidance results

To conceptualize the collision avoidance behavior of participants, three time-space diagrams were created, one for each TOR scenario (Figs. 3.1–3.3). Trajectories were recorded from the centroid of a participant. Trajectories on the plots represent two different vehicle-bicyclist interactions. Each plot shows two cases, developed based on collected position data: (1) a case where a participant yielded to a bicyclist, and the bicyclist was farther from the intersection, and (2) a case where a participant did not yield to a bicyclist, and the bicyclist was closer to the intersection.

Several important pieces of information can be obtained from these figures. The figures highlight when the bicyclist first began to move in each TOR scenario, and they demonstrate that the bicyclists remained on a constant trajectory regardless of the movement of the vehicle. The figures illustrate how long a driver had to decide whether or not to yield to the bicyclist, and they show the relative position between the driver and the bicyclist at any given time. Finally, the three plots highlight the different yielding behaviors of participants: for example, some participants accelerated past the bicyclist, whereas others braked to yield to the bicyclist. In the first two yielding cases, the drivers braked before passing the bicyclist; in the third case, the driver identified that the bicyclist was behind them and stopped to yield to the bicyclist.

3.1.1. Yielding behavior

Across all 516 cases in the experiment (43 participants in 12 scenarios where a bicyclist was present), drivers yielded to the bicyclist in 284 instances (56% of cases). Unsurprisingly, most cases of yielding occurred when the bicyclist was relatively

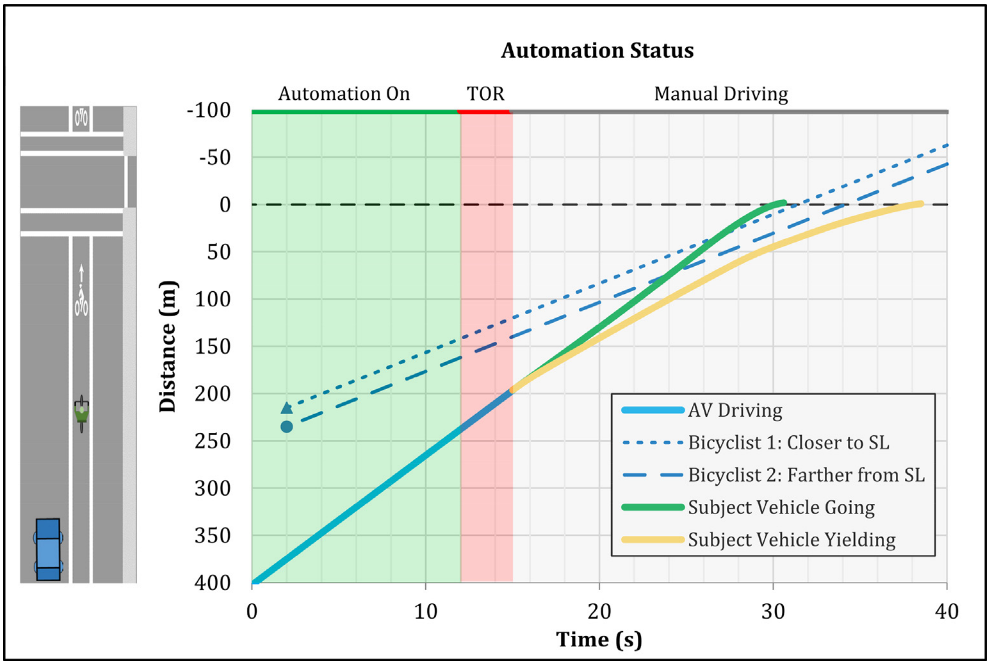

Fig. 3.1. Example time-space diagram for 15 s TOR.

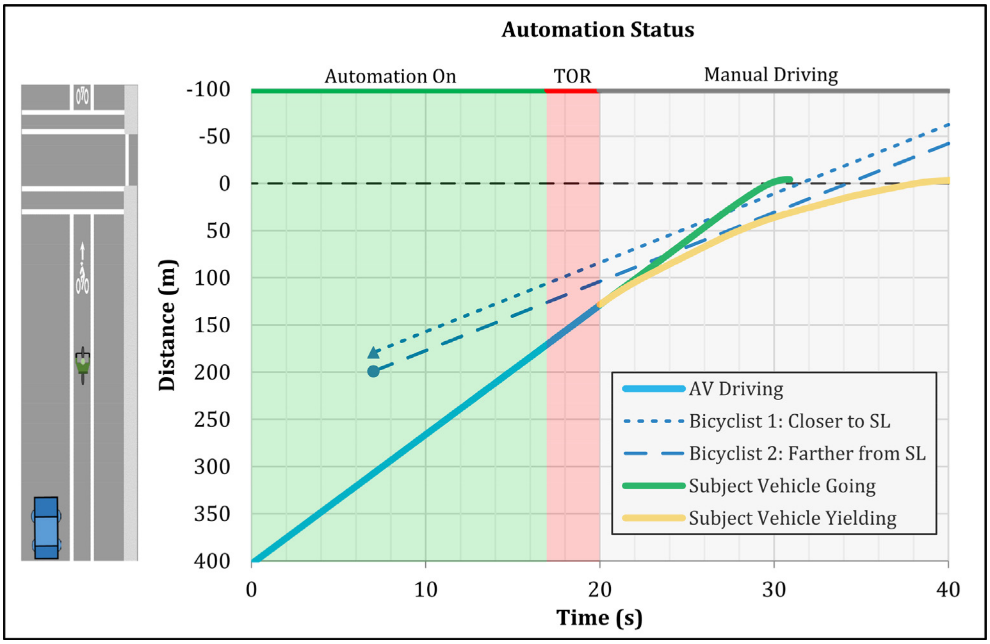

Fig. 3.2. Example time-space diagram for 10 s TOR.

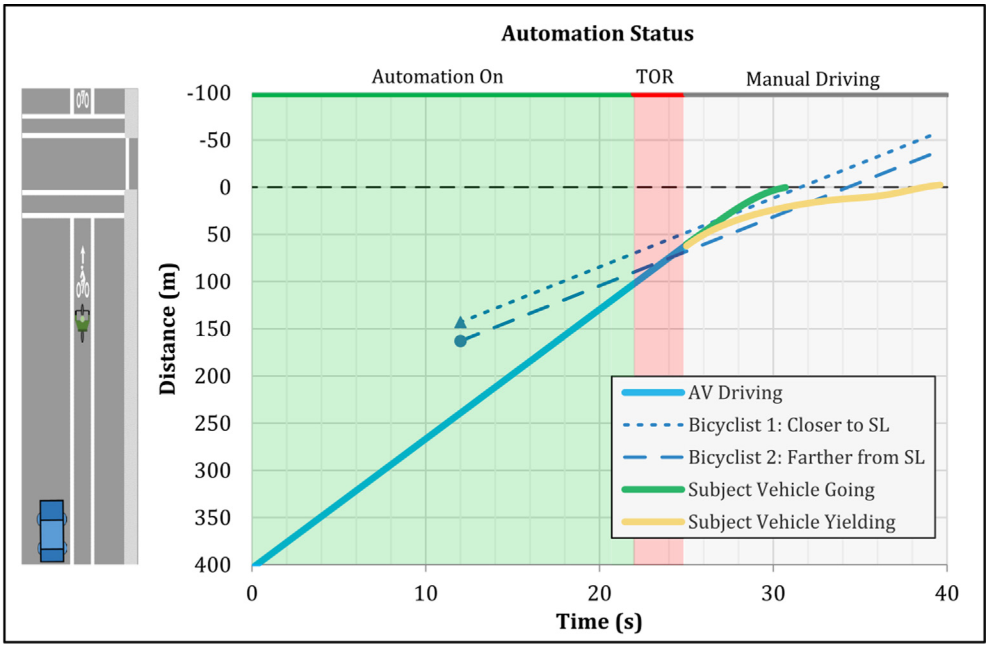

Fig. 3.3. Example time-space diagram for 5 s TOR.

closer to the intersection (n = 210). There were more yielding events when the TOR was received at 15 s from the stop line (n = 105) compared to the 10-s (n = 94) and 5-s (n = 85) TOR conditions. Yielding events were evenly split with respect to secondary task, with participants yielding 142 times for the game and no-game conditions.

The decision to yield or go at the intersection is a binary choice that can be modeled by a linear probability model. Each participant completed all 12 right-turn scenarios where a bicyclist was present; therefore, the dataset can be considered to be a panel dataset. Panel data require replication of the same units over time (Wooldridge, 2016). A fixed-effects linear probability model was created using Stata to determine the effect that the independent variables had on a driver's decision to yield or go at the intersection. Widely used for panel data analysis, fixed-effects models can be used to estimate the effect of individual variables when all other variables remain constant (Wooldridge, 2016). Using a fixed-effects model helps control for omitted variable bias. Data were clustered by participant to account for individual differences between drivers. Bicyclist proximity to the intersection ($t = -9.23,\ P < 0.001$) and a 5-s TOR ($t = -9.23,\ P = 0.003$) had significant effects on the probability of a driver yielding to the bicyclist (Table 3.1).

As TOR proximity decreased from 15 s to 5 or 10 s, the probability of yielding decreased. A TOR at 5 s from the stop line decreased the probability that a driver would yield by 11.6% compared to the 15-s condition. As bicyclist proximity from the intersection changed from closer to farther, the probability that a driver would yield decreased by 52.3%.

3.1.2. TTC calculation

To investigate the effect of the independent variables on the collision avoidance behavior of the drivers, the TTC value was calculated for each of the 226 observations where a driver did not yield to the bicyclist at the intersection. Gettman et al. (2008) defined TTC as the expected time for two vehicles to collide if they remain at their present speed and path. TTC is an important measure of the likelihood of a collision. Generally, a vehicle-bicycle interaction with a TTC of 2 s or less is considered a conflict (Sayed, Zaki, & Autey, 2013). SAE J2944 (2015) defers to the methodology presented by Van Der Horst (1990) when calculating TTC. For a RH crash scenario where the subject vehicle turns in front of the bicyclist, this procedure can be simplified, as described in Hurwitz et al. (2015).

Bicycle location and vehicle centroids were recorded in the driving simulator. Distances between the vehicle and bicyclist were calculated from their centroids by using the following equations (Hurwitz et al., 2015):

$$TTC = \frac{d}{v_b}, \tag{4.3}$$

$$d = s - \frac{w_v}{2} - \frac{l_b}{2}, \tag{4.4}$$

where

$v_b, v_v, =$ velocity of bicycle and subject vehicle, respectively (where the bicyclist traveled at a constant velocity of 16 mph, or 7.15 m/s)
$w_v =$ width of subject vehicle
$l_b, l_v, =$ length of bicycle and subject vehicle, respectively
$d =$ distance from middle point of the side of the car and front of the bicycle
$s =$ center-to-center distance between bicycle and car (Fig 3.4).

3.1.3. TTC results

In total, there were 516 right-turn maneuvers in the presence of a bicyclist (43 participants by 12 intersections with bicyclists present). Of these, 226 maneuvers resulted in an interaction between the subject vehicle and bicyclist (defined as the vehicle turning in front of the bicyclist and not yielding at the intersection). Table 3.2 shows the minimum TTC measurements for each of these 226 maneuvers. Comparing interactions by bicyclist location, more interactions occurred when the bicyclist was farther from rather than closer to the stop line (79.7% vs. 20.3%). The number of interactions with bicyclists was about equal among participants who were not playing the bubble game (n = 114) and those who were (n = 113). Two right-hook collisions were recorded.

Most of the higher-risk interactions (TTC $\leq$ 2 s) occurred when participants were distracted by the secondary task (n = 18) or when the TOR occurred within 5 s of the stop line (n = 15) (Table 3.2). Interactions with the bicyclist farther from the stop

Table 3.1
Fixed-effects linear probability model on a driver's yielding decision.

Variable	Category	Coefficient	Standard Error	t	*P*
Yield (Dependent Var.): (1 if driver yields to bicyclist, 0 otherwise)	–	–	–	–	–
Relative Bicycle Position: (1 if bike is farther from stop line, 0 if closer)	–	−0.5233	0.0567	−9.23*	<0.001
Secondary Task: (1 if playing game, 0 if not)	–	−0.0039	0.0204	−0.19	0.851
TOR:	TOR = 2	−0.1163	0.0367	−3.17*	0.003
(2 for 5 s TOR, 1 for 10 s TOR, 0 for 15 s TOR)	TOR = 1	−0.0523	0.0318	−1.64	0.108
			R^2(within subjects)		0.4174
			Number of Obs.		516
			Number of Groups		43
			Obs. Per Group		12

* Statistically significant at 95% confidence interval.

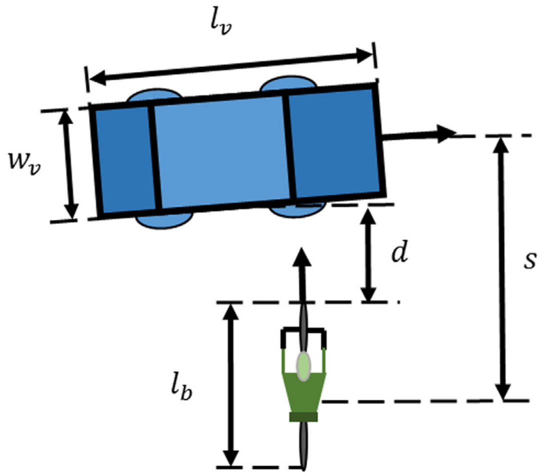

Fig. 3.4. TTC calculation for RH crash scenario (Hurwitz, 2015).

Table 3.2
TTC results.

Relative position of bicyclist	Secondary Task	TOR (s)	TTC (s)				Total
			0–0.99	1.0–1.5	1.51–2.0	2.0+	
Closer to stop line (46)	Game	5	2	2	3	3	10
	(25)	10	3	3	2	1	10
		15	0	0	1	4	5
	No Game	5	1	1	5	2	9
	(21)	10	0	0	1	7	8
		15	0	0	1	3	4
Farther from stop line (181)	Game	5	0	1	0	33	34
	(88)	10	0	0	1	26	27
		15	0	0	0	27	27
	No Game	5	0	0	0	33	33
	(93)	10	0	0	0	30	30
		15	0	0	0	30	30
Total			6	7	14	199	226

line typically had higher TTC values, with only two higher-risk interactions. By contrast, for bicyclists closer to the stop line, there were 25 higher-risk interactions. When the TOR occurred 5 s before the stop line, there were a greater number of higher-risk interactions (n = 15) compared to when the TOR occurred at 10 s (n = 10) or 15 s (n = 2) from the stop sign. Both vehicle-bicyclist collisions occurred when the bicyclist was closer to the stop line and the participant was distracted by the secondary task (see Fig. 3.4).

Fig. 3.5 demonstrates that the three independent variables had some influence on TTC. The strongest difference in mean TTC values was observed between the two bicycle positions ($M_{Closer} = 1.81$ s, $SD_{Closer} = 0.785$ s; $M_{Farther} = 4.28$ s, $SD_{Farther} = 0.911$ s). Mean TTC under the 15-s TOR condition ($M_{15s} = 4.35$ s, $SD_{15s} = 1.217$ s) was longer than the mean TTC values under the 5-s ($M_{5s} = 3.45$ s, $SD_{5s} = 1.255$ s) and 10-s ($M_{10s} = 3.65$ s, $SD_{10s} = 1.373$ s) TOR conditions. There was a slight difference in mean TTC values between secondary task conditions ($M_{Game} = 3.58$ s, $SD_{Game} = 1.425$ s; $M_{No\ Game} = 3.97$ s, $SD_{NoGame} = 1.209$ s).

Repeated-measures analysis of variance (ANOVA) is typically used to analyze data when each participant is exposed to all possible combinations of independent variables, resulting in multiple measurements for each participant (Ramsey & Schafer, 2013). However, there were numerous cases where a participant yielded to the bicyclist, resulting in no TTC measurement. Such unbalanced data can be problematic for performing repeated-measures ANOVA. To analyze the unbalanced dataset while still accounting for the effect of multiple measurements across individual participants, ANOVA tests were performed using subjects as a blocking factor (Ramsey & Schafer, 2013). The results are shown in Table 3.3.

Pairwise comparisons of the main effect of each independent variable were analyzed by using Tukey-corrected post-hoc tests. Regardless of TOR proximity or secondary task, participants had larger mean TTC values when the bicyclist was farther from the stop line ($P < 0.001$). Regardless of bicycle position or TOR proximity, participants engaged in the secondary task had a smaller TTC value ($P = 0.001$). The 15-s TOR condition was associated with significantly larger mean TTC values compared to the 5- and 10-s conditions ($P = 0.002$, $P = 0.0021$).

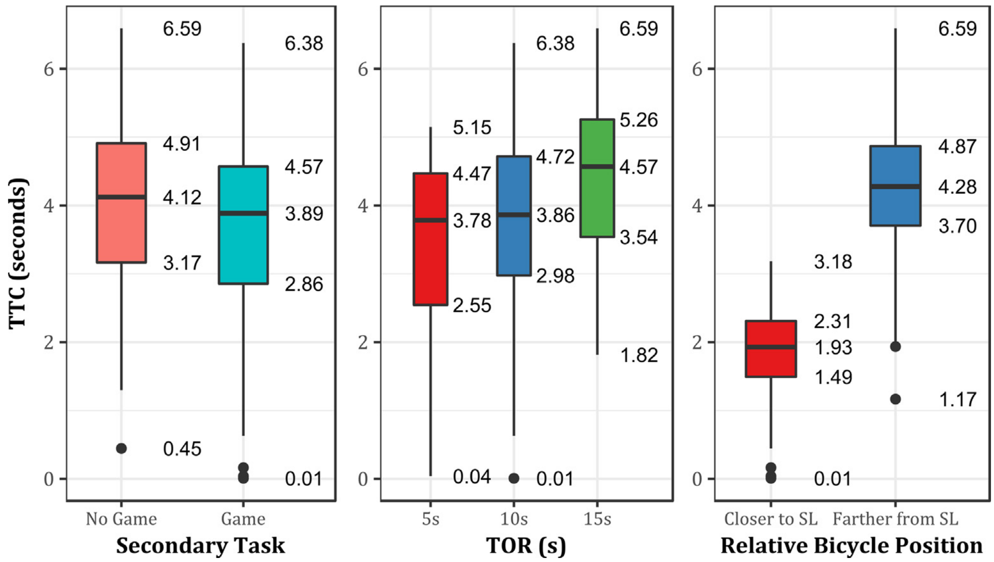

Fig. 3.5. Boxplots of independent variables and TTC.

Table 3.3
Blocking design ANOVA results on TTC (s).

Blocking Factor	*df*	*F*	*P*
Participant	40	6.07*	<0.001
Within-Subjects Factors	*df*	*F*	*P*
Relative Bicycle Position	1	315.87*	<0.001
Secondary Task	1	15.87*	<0.001
TOR	2	8.84*	<0.001
Relative Bicycle Position × Secondary Task	1	0.84	0.361
Relative Bicycle Position × TOR	2	0.46	0.635
Secondary Task × TOR	2	2.37	0.097
Relative Bicycle Position × Secondary Task × TOR	2	0.52	0.597
Error	180		

Note: *F* denotes *F* statistic; *df* denotes degrees of freedom.
* Statistically significant at 95% confidence interval.

3.2. Visual attention results

The visual attention of motorists can generally provide direct evidence of whether a driver recognizes and anticipates a hazard (Fisher et al., 2011). Visual attention data were gathered and reduced for the 34 participants with complete eye-tracking data. Five participants had partial eye-tracking data because the participant accidentally adjusted their glasses and ruined the calibration. Four participants could not be calibrated for eye-tracking.

3.2.1. Total Fixation Duration (TFD)

For each right-turn scenario, the number and length of participants' fixations on various areas of interest (AOIs) were recorded. AOIs were created for the bicyclist when it was ahead of the vehicle, behind the vehicle, or viewed through the rear-view or side-view mirrors. The TFD was generated by averaging all participant's fixations in each scenario for each AOI, with a TFD of zero indicating that the participant did not fixate on a particular AOI during that scenario. A higher TFD indicates greater interest in the AOI. TFD measurements can help determine whether a driver identifies critical elements in a visual scene (Reyes & Lee, 2008). A fixation on the bicyclist was recorded if the participant fixated on the bicyclist when it was ahead of the vehicle or visible in the rear-view or side-view mirrors. The sum of these fixations across each scenario indicates the TFD for the bicyclist.

A repeated-measures ANOVA test was conducted to determine whether the TFD differed between scenarios. As Mauchly's sphericity assumption was not met, Huynh-Feldt adjusted *P*-values are reported (Abdi, 2010). Table 3.4 shows the repeated-measures ANOVA results.

Bonferroni-corrected post-hoc tests were performed for pairwise comparisons of the main effect of each independent variable. Regardless of TOR proximity or secondary task, participants fixated on the bicyclist significantly longer on average

Table 3.4
Repeated-measures ANOVA results for TFD on the bicyclist (seconds).

Within-Subjects Factors	$F(\nu_1, \nu_2)$	P	η_p^2
Relative Bicycle Position	19.27 (1, 33)*	<0.001	0.369
Secondary Task	21.05 (1, 33)*	<0.001	0.389
TOR	40.21 (2, 66)*	<0.001	0.549
Relative Bicycle Position × Secondary Task	1.00 (1, 33)	0.325	0.029
Relative Bicycle Position × TOR	12.68 (2, 66)*	<0.001	0.278
Secondary Task × TOR	4.04 (2, 66)*	0.032	0.109
Relative Bicycle Position × Secondary Task × TOR	2.01 (2, 66)	0.142	0.057

Note: F denotes F statistic; ν_1 and ν_2 denote degrees of freedom; η_p^2 denotes partial eta squared.
* Statistically significant at 95% confidence interval.

when the bicyclist was closer to the stop line ($P < 0.001$). Regardless of the relative bicycle position or TOR proximity, participants engaged in the secondary task fixated on the bicycle significantly less frequently ($P < 0.001$). There was a significant difference among all TOR conditions ($P < 0.001$ for all comparisons), with drivers fixating on the bicyclist significantly longer as TOR proximity increased.

3.2.2. Time to first bicycle fixation

During scenarios with a bicyclist, the bicyclist was not visible to the participant until 10 s before the participant received a TOR. To determine when the participant first identified the bicyclist in the bike lane, the time to first bicycle fixation was calculated. A time of zero indicates that the participant identified the bicyclist immediately when it entered the roadway. Data were visualized as boxplots of time to first bicycle fixation, disaggregated by independent variables (Fig. 3.6). On average, participants who were engaged in the secondary task took about 4.5 s longer to identify the bicyclist on the roadway ($M_{Game} = 11.25$ s, $SD_{Game} = 5.88$ s; $M_{No\ Game} = 6.70$ s, $SD_{No\ Game} = 6.28$ s).

Twenty participants identified and fixated on all 12 bicyclists in the experiment. Repeated-measures ANOVA was conducted on the data from these 20 participants to determine whether the time to first bicycle fixation differed between scenarios. As shown in Table 3.5, relative bicycle position ($P = 0.002$), secondary task ($P < 0.001$), and TOR proximity ($P = 0.005$) had significant main effects on the time to first bicycle fixation. A statistically significant interaction was found between the combined effects of relative bicycle position and secondary task on the time to first bicycle fixation ($P = 0.026$). Among independent variables, the change in TOR proximity had the highest effect on the time to first bicycle fixation, accounting for about 55% of within-subject variance.

Bonferroni-corrected post-hoc tests for pairwise comparisons of the main effect of TOR proximity revealed that regardless of the bicyclist position or secondary task, there was a difference between the 15-s TOR condition and the two other TOR conditions. Drivers in the 15-s condition fixated on the bicyclist significantly later than in the other TOR conditions ($P = 0.025$, $P = 0.039$).

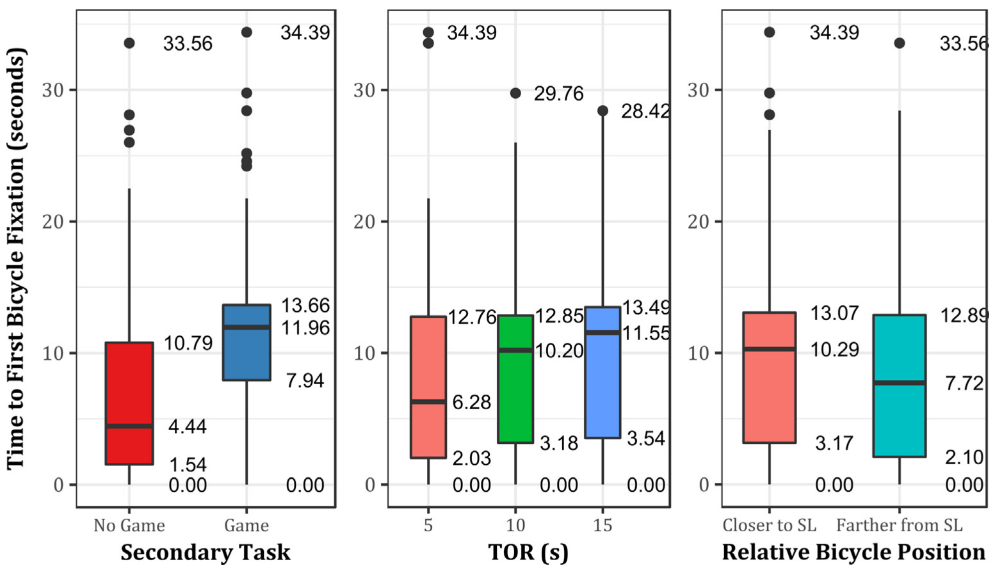

Fig. 3.6. Time to first bicycle fixation.

Table 3.5
Repeated-measures ANOVA results on time to first bicycle fixation (seconds).

Within-Subjects Factors	$F(\upsilon_1, \upsilon_2)$	P	η_p^2
Relative Bicycle Position	12.96 (1, 19)*	0.002	0.405
Secondary Task	39.68 (1, 19)*	<0.001	0.676
TOR	6.14 (2, 38)*	0.005	0.244
Relative Bicycle Position × Secondary Task	5.80 (1, 19)*	0.026	0.234
Relative Bicycle Position × TOR	0.59 (2, 38)	0.559	0.030
Secondary Task × TOR	1.24 (2, 38)	0.302	0.061
Relative Bicycle Position × Secondary Task × TOR	1.59 (2, 38)	0.218	0.077

Note: F denotes F statistic; υ_1 and υ_2 denote degrees of freedom; η_p^2 denotes partial eta squared.
* Statistically significant at 95% confidence interval.

4. Conclusions

The goal of this research was to investigate how human drivers of AVs interact with bicyclists during a right-turn maneuver after receiving a TOR. Changes in driver performance, including visual attention and crash avoidance behavior, were measured by using a high-fidelity driving simulator. Overall, the results across performance measures consistently showed that the independent variables had an effect on participant driving performance. These results indicate that there is a difference between how individual drivers avoid colliding with a bicyclist after receiving a TOR on the approach to an intersection.

When all other variables were held constant, participants were 11.6% less likely to yield to a bicyclist when presented with a TOR 5 s from an intersection compared to participants presented with a TOR 15 s from an intersection. Drivers who received a TOR farther from the intersection identified the bicyclist earlier and fixated on the bicyclist for longer compared to drivers who received a TOR closer to the intersection. When drivers were given more time to respond (i.e., TOR of 15 s vs. 10 or 5 s from the intersection), the mean TTC between the vehicle and bicyclist was significantly longer, indicating a safer vehicle-bicyclist interaction and a lower likelihood of collision. This research demonstrates that when given a 3-s TOR alert, drivers require between 10 and 15 s before an intersection to safely interact with a bicyclist and avoid a RH crash. Drivers who received a TOR farther from the intersection generally identified the bicyclist earlier and had safer interactions with the bicyclist, either choosing to yield or safely turning with ample space between the vehicle and bicyclist.

Driver involvement in a secondary task before receiving a TOR had a significant effect on the driver's visual attention. Drivers who were playing the game took longer to identify the bicyclist and fixated for a shorter time on the bicyclist. Drivers who played the game while the car was driving in L3 automation mode had significantly lower mean TTC values, indicating that the interactions were less safe. Although L3 AVs may not be marketed to consumers as a way to take their mind off the task of driving, it is inevitable that some drivers will attend to a secondary task in the AV. The results of this study demonstrate that such secondary task involvement increases the probability of having higher-risk interactions with bicyclists while turning right at an intersection.

Although this research provides valuable insight on the interaction of L3 automation and human drivers in close proximity to an intersection in the presence of a bicyclist, there are limitations associated with this work. Like most within-subject study designs, there are limitations associated with possible fatigue and carryover effects, which can cause a participant's performance to degrade during an experiment. The magnitude of these effects was limited by randomizing the presentation of grids to different participants and keeping the drive lengths brief. In addition, the number and levels of independent variables that were investigated were limited by the total drive time. In particular, the length of the TOR alert was kept constant at 3 s. There may be more variation in this alert time in real L3 vehicles. Furthermore, for many participants, this was their first experience driving an AV. Drivers with greater L3 AV experience would potentially exhibit different driving behavior.

This area of human factors research is relatively uninvestigated, yet is crucial for understanding the safety implications of L3 AVs in urban environments. Future studies should address additional variations in the independent variables, such as differences in the distracting tasks, TOR alerts, or bicyclist behavior. The secondary task could be offered optionally instead of prescriptively to drivers to determine the threshold at which they would feel comfortable engaging in a secondary task. Driver perception of automation could be more fully investigated, to determine whether drivers would feel comfortable using L3 automation in their personal vehicle. The time between scenarios could be varied to determine the threshold for the number of TORs that a driver would be willing to endure to achieve the benefits of automation. Finally, similar scenarios could be examined from the bicyclist's perspective. Using driving simulation, an L3 AV could be coded based on the real-world behavior collected through this study, or by using networked simulation pairing a human driver and a human bicyclist.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2019.06.007.

References

Abdi, H. (2010). The greenhouse-Geisser correction. In N. Salkind (Ed.). *Encyclopedia of research design* (Vol. 1, pp. 544–547). Thousand Oaks, CA: SAGE Publications.

Bellem, H., Klüver, M., Schrauf, M., Schöner, H. P., Hecht, H., & Krems, J. F. (2017). Can we study autonomous driving comfort in moving-base driving simulators? A validation study. *Human Factors, 59*(3), 442–456. https://doi.org/10.1177/0018720816682647.

Burnett, G., Harvey, C., & Donkor, R. (2017). *Simulators for transportation human factors: Research and practice* (1st ed.). London: CRC Press.

Cunningham, M., & Regan, M. A. (2015). Autonomous vehicles: Human factors issues and future research. *Australasian road safety conference*.

De Winter, J. C. F., Stanton, N. A., Price, J. S., & Mistry, H. (2016). The effects of driving with different levels of unreliable automation on self-reported workload and secondary task performance. *International Journal of Vehicle Design, 70*(4), 297–324.

Desmond, P. A., & Hancock, P. A. (2001). Active and passive fatigue states. In L. Erlbaum (Ed.), *Stress, workload and fatigue* (pp. 455–465). NJ: Mahwah.

Eriksson, A., Banks, V. A., & Stanton, N. A. (2017). Transition to manual: Comparing simulator with on-road control transitions. *Accident Analysis and Prevention, 102*, 227–234. https://doi.org/10.1016/j.aap.2017.03.011.

Fatality Analysis and Reporting System (FARS) (2017). FARS data tables: Summary.

Fisher, D., Rizzo, M., & Caird, J. (2011). *Handbook of driving simulation for engineering, medicine, and psychology*. Boca Raton: CRC Press.

Gettman, D., Pu, L., Sayed, T. and Shelby, S. Surrogate Safety Assessment Model and Validation: Final Report. PHWA-HRT-08-051. Federal Highway Adminstration, Washington D.C., June 2008.

Gold, C., Damböck, D., Lorenz, L., & Bengler, K. (2013). Take over! How long does it take to get the driver back into the loop? In *Proceedings of the human factors and ergonomics society* (pp. 1938–1942) https://doi.org/10.1177/1541931213571433.

Green, T. (2007). Where do drivers look while driving (and for how long)? In: R. E. Dewar & R. Olson (Eds.), *Human Factors in Traffic Safety* (2nd ed., pp. 57–82). Tucson, AZ: Lawyers and Judges Publishing.

Griggs, T., & Wakabayashi, D. (2018). *How a self-driving Uber killed a pedestrian in Arizona*. New York Times https://www.nytimes.com/interactive/2018/03/20/us/self-driving-uber-pedestrian-killed.html.

Hurwitz, D. S., Monsere, C. M., Jannat, M., Warner, J., & Razmpa, A. (2015). Towards effective design treatment for right turns at intersections with bicycle traffic.

Jannat, M. (2014). *Right-hook crash causality at signalized intersections*. Oregon: State University.

Kyriakidis, M., Happee, R., & De Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour, 32*, 127–140. https://doi.org/10.1016/j.trf.2015.04.014.

Louw, T., Kountouriotis, G., Carston, G., & Merat, N. (2015). Driver inattention during vehicle automation: How deos driver engagement affect resumption of control? In: *4th International Conference on Driver Distraction and Inattention (DDI2015)*. http://eprints.whiterose.ac.uk/91858/.

Merat, N., Jamson, A. H., Lai, F. C. H., & Carsten, O. (2012). Highly automated driving, secondary task performance, and driver state. *Human Factors, 54*(5), 762–771. https://doi.org/10.1177/0018720812442087.

Mercedes-Benz (2016). Disengagemnet of autonomous vehicle system. Retrieved from https://www.dmv.ca.gov/portal/wcm/connect/fdea0433-4935-414f-84a2-1e815e416964/MercedezBenz_disengage_report_2016.pdf?MOD=AJPERES.

Mok, B., Johns, M., Lee, K. J., Miller, D., Sirkin, D., Ive, P., & Ju, W. (2015). Emergency, automation off: unstructured transition timing for distracted drivers of automated vehicles. In *IEEE conference on intelligent transportation systems, proceedings, ITSC, 2015-October* (pp. 2458–2464). https://doi.org/10.1109/ITSC.2015.396.

National Highway Traffic Safety Administration (NHTSA) (2018). Automated vehicles for safety. Retrieved April 26, 2018, from https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety.

Neubauer, C., Matthews, G., Saxby, D., & Langheim, L. (2010). Simulator methodologies for investigating fatigue and stress in the automated vehicle. *Advances in Transportation Studies* (SPEC. ISSUE), 7–18. https://doi.org/10.4399/97888548416592.

Ramsey, F. L., & Schafer, D. W. (2013). *The statistical sleuth: A course in methods of data analysis* (3rd ed.). Boston, MA: Cengage Learning.

Reyes, M. L., & Lee, J. D. (2008). Effects of cognitive load presence and duration on driver eye movements and event detection performance. *Transportation Research Part F: Traffic Psychology and Behaviour, 11*(6), 391–402. https://doi.org/10.1016/j.trf.2008.03.004.

Rokni, D., Tapiro, H., Parmet, Y., & Oron-Gilad, T. (2017). Crossing the road while playing a mobile game app – effects of age, environmental load and game complexity 880–880. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 61*(1). https://doi.org/10.1177/1541931213601512.

Sayed, T., Zaki, M. H., & Autey, J. (2013). Automated safety diagnosis of vehicle-bicycle interactions using computer vision analysis. *Safety Science, 59*, 163–172. https://doi.org/10.1016/j.ssci.2013.05.009.

Sayer, J., Bogard, S. E., Buonarosa, M. L., LeBlanc, D. J., Funkhouser, D. S., Bao, S., ... Winkler, C. B. (2011). Integrated vehicle-based safety systems light-vehicle field operational test key findings report.

Singer, J., Lerner, N., Baldwin, C., & Traube, E. (2015). Auditory alerts in vehicles: effects of alert characteristics and ambient noise conditions on perceived meaning and detectability. *24th International technical conference on the enhanced safety of vehicles (ESV), Gothenburg, Sweden*.

Society of Automotive Engineers (SAE) (2015). Operational definitions of driving performance measures and statistics. Retrieved from https://saemobilus.sae.org/content/J2944_201506/.

Swake, J., Mafruhatal, J., Islam, M. and Hurwitz D.S., Driver response to phase termination at signalized intersections: Are driving simulator results valid? In: 7th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design, New York, 2013.

Van Der Horst, A. R. A. (1990). *A time-based analysis of road user behaviour in normal and critical encounters*. Delft: University of Technology.

Wang, Y., Mehler, B., Reimer, B., Lammers, V., D'Ambrosio, L. a., & Coughlin, J. F. (2010). The validity of driving simulation for assessing differences between in-vehicle informational interfaces: A comparison with field testing. *Ergonomics, 53*(3), 404–420. https://doi.org/10.1080/00140130903464358.

Waymo (2017). Disengagment report: Report on autonomous mode disengagments for Waymo self-driving vehicles in California. Retrieved from https://www.dmv.ca.gov/portal/wcm/connect/42aff875-7ab1-4115-a72a-97f6f24b23cc/Waymofull.pdf?MOD=AJPERES&CVID=.

Wooldridge, J. M. (2016). *Introductory econometrics* (6th ed.). Mason, OH: South-Western Cengage Learning.

Zeeb, K., Buchner, A., & Schrauf, M. (2015). What determines the take-over time? An integrated model approach of driver take-over after automated driving. *Accident; Analysis and Prevention, 78*, 212–221. https://doi.org/10.1016/j.aap.2015.02.023.