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Autonomous vehicles (AVs) may have the potential to mitigate a significant proportion of serious crashes which are due to human error or poor decision making behind the wheel. However, there are still many concerns associated with SAE Level 3 AVs that require intervention by a human driver after a take-over request (TOR). This concern intensifies when vulnerable road users such as bicyclists are introduced to the driving environment. The objective of this research was to investigate how human drivers interact with bicyclists during a right-turn maneuver after receiving a TOR. Changes in driver performance, including visual attention and crash avoidance, were measured using a high-fidelity driving simulator. Forty-three participants each completed 18 right-turn maneuvers. The time to react between the TOR and the intersection and bicyclist position on the approach to the intersection were varied. A distracting secondary task on a tablet was also introduced. In general, the results show the secondary task led to decreased driver performance with respect to time-to-collision and the time 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.

Influence of Bicyclist Presence on Driver Performance during Autonomous Vehicle Take-Over Requests

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Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Kayla Fleskes, Author

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1. INTRODUCTION

Over 94 percent of serious crashes are due to human error or poor decision making behind the wheel (NHTSA 2018). Driver assistance systems and autonomous vehicles (AVs) seek to address some of the safety issues caused by human drivers. Many of the driver assistance systems that are in current use, such as collision warning and avoidance systems, lane keeping systems (LKS), and adaptive cruise control (ACC) have been shown to help drivers avoid crashes and improve driver safety (for example, see Sayer et al. 2011).

However, there are still many concerns with adding increasingly complex levels of automation in the driving environment. One major concern is how AV will interact with multimodal traffic in urban environments. Bicyclists are extremely vulnerable in the roadway environment, with 840 deaths occurring in the U.S. in 2015 (FARS 2018). Experts in human factors and AVs are apprehensive about the interactions that will occur between AVs and bicyclists, and believe that more research is needed in this area (Kyriakidis et al. 2015).

Currently, 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 (Figure 1.1). For example, in Oregon between 2007 and 2011, over 59% of the total vehicle-bicycle crashes at signalized intersections were RH crashes (Hurwitz et al. 2015). In a simulator study involving 41 participants, it was found that one of the major contributing factors to dangerous RH crash scenarios was a lack of situational awareness (SA), with the majority of participants not identifying the bicyclist near the intersection (Jannat 2014).

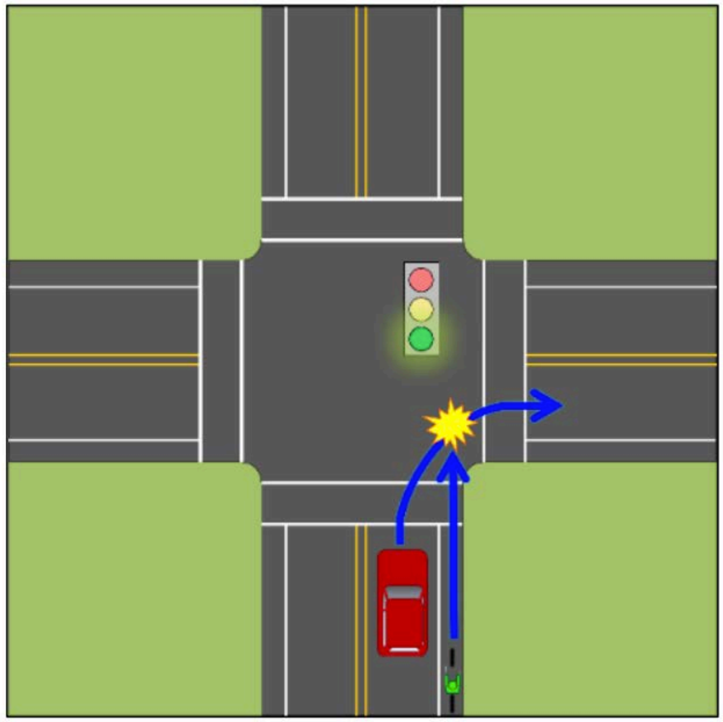


Figure 1.1 Right-hook crash during the latter green phase at a signalized intersection (Warner 2015)

While numerous engineering treatments have been designed to make bicyclists more visible at intersections (such as signage, pavements markings, and geometric design), these were created for drivers that are engaged in the driving task and aware of their surroundings, which may not be the case for many drivers of AVs. This was demonstrated by a recent collision between a self-driving Uber and a pedestrian walking a bicycle across the street in Arizona (Griggs and Wakabayashi 2018).

2. LITERATURE REVIEW

To help identify the human factors challenges associated with AVs, a comprehensive literature review was conducted on the current state of the research. While significant work has been published in the AV realm, very little of it has focused on the impact to pedestrian and bicyclist safety. This chapter pulls together the relevant work on AVs and bicyclist safety.

2.1. Levels of Automation

A discussion of AVs cannot take place without first classifying the different levels of automation. In this sense, hierarchical models of automation become extremely important. Traditionally in the literature, there are three main systems that can be used to classify autonomous vehicles: German Federal Highway Transportation Institute (BASt), National Highway Traffic Safety Administration (NHTSA) and Society of Automotive Engineers (SAE) (Gasser and Westhoff 2012; NHTSA 2013; SAE 2016). The U.S. Department of Transportation's guidance document "Federal Automated Vehicles Policy" states that manufacturers should ensure that their vehicles conform to SAE J3016 automation levels (NHTSA 2016). NHTSA's website on automated vehicles also references the SAE automation levels and therefore, the SAE classification system will be adopted for this research (NHTSA 2018).

SAE defines levels of automation on a scale from zero to five. The zero state includes no automation. Level 1 (L1: Driver Assistance) and Level 2 (L2: Partial Automation) require humans to monitor the driving environment while Level 3 (L3: Conditional Automation), Level 4 (L4: High Automation) and Level 5 (L5: Full Automation) allows for the AV system to monitor the environment (Figure 2.1). However, L3 and L4 provide numerous human factors challenges for engineers. At these levels, there will be need to transition control of the driving task from the AV back to the human, potentially on many unforeseen occasions or in specific locations, due to the limitation of the AV system. This can be difficult for numerous reasons, which will be discussed further in following sections.

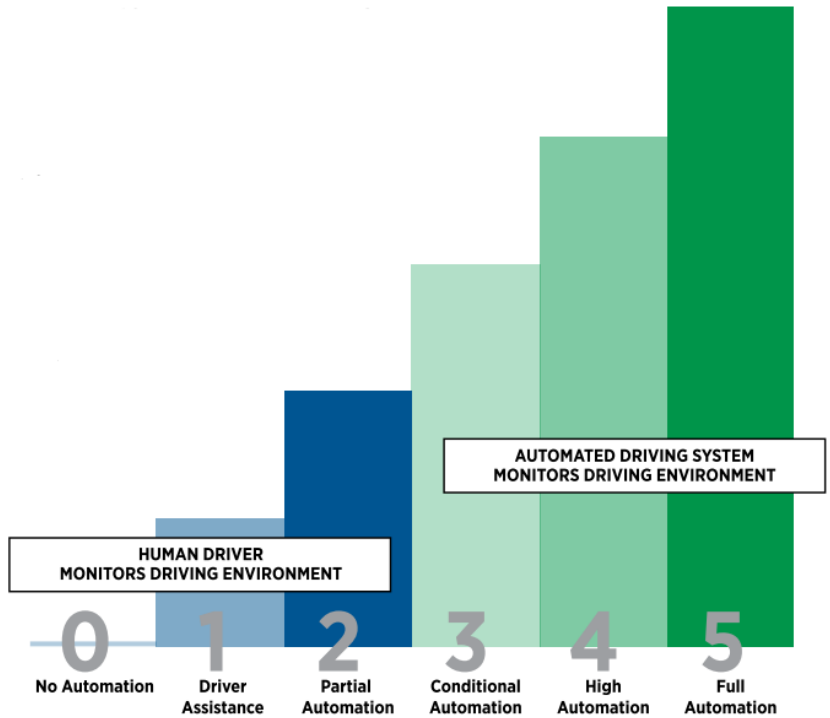


Figure 2.1 SAE levels of automation (SAE 2016)

In the U.S., there are numerous manufacturers pursuing AV technology deployment. In California, a state with a more robust regulatory system in place for public testing of autonomous vehicles, there were 47 manufacturers licensed to test autonomous vehicles as of December 2017 (California DMV 2017). Based on the disengagement reports submitted by these private companies in 2017, many of the vehicles that are being tested appear to classify as L3 automation.

One famous example of automation is the Waymo (Google) AV. In 2017, Waymo reported 63 disengagements of the automation on public roads in California out of over 352,000 miles of driving (Waymo 2017). This represents just 0.2 disengagements per thousand miles, only a fourth of the rate from 2015. However, of those 64 disengagements in 2017, the vast majority (57) occurred on urban streets, highlighting the difficulty of these complex driving environments. A Mercedes-Benz vehicle that was tested on public roads in California faced similar issues in 2016. All of the vehicle's 673 miles of driving was completed on urban streets (no highway driving), with over 336 disengagements, for a rate of nearly one disengagement every two miles (Mercedes-Benz, 2016).

With the potential for high rates of disengagements and transitions of control, it is important to understand the human factors aspects associated with automation.

2.2. Human Factors Issues with Automation

While L5 automation may bring about numerous safety and efficiency advantages to our surface transportation system, there are many human factors-related challenges associated with AV implementation, especially L3 and L4 automation. In a study of attitudes towards automation in the US, UK, and Australia (N=1533), safety was a concern for over 75% of respondents (Schoettle and Sivak 2014).

One way to examine human factors and driver behavior in a safe and controlled environment is through driving simulation in a laboratory setting. While some researchers note fidelity issues with certain simulation platforms, particularly fixed-base simulators in addressing certain types of research questions (e.g. De Winter et al. 2016; Neubauer et al. 2010), many others note the important benefits that simulation provides (Bellem et al. 2017; Burnett et al. 2017; Wang et al. 2010).

Specifically, driving simulation has been validated for evaluating research questions related to AV driving. For example, Bellem et al. (2017) found that moving-base driving simulators could be a useful tool to evaluate driving comfort in AVs. Driving simulation has also been shown to be an appropriate method for studying AV transitions of control. Eriksson et al. (2017) found strong positive correlations in driver behavior when comparing non-critical transitions of control in a driving simulator with on-road driver performance in a L2 autonomous vehicle. No significant differences were found between the two with regards to workload, driver performance, or perceived usefulness and satisfaction of the systems, indicating that driving simulation can be a reliable tool when evaluating AV capabilities.

Previous research has utilized driving simulation to evaluate AV safety. With regards to safety, two related concerns with L3 AVs include driver distraction and transitions of control.

2.2.1. Driver Distraction and Secondary Task Engagement

AVs are designed to lighten the cognitive load on drivers as the level of automation increases. However, driver distraction and fatigue become more prominent issues with increasing automation. When the driver has a low cognitive load and does not have direct control over the driving task, passive fatigue may result (Desmond and Hancock 2001). Increased vehicle automation has been demonstrated to reduce driver vigilance, as indicated by slower responses to critical events (Cunningham and Regan 2015).

As automation increases, drivers are also more likely to engage in secondary tasks. In a driving simulator study, researchers demonstrated that drivers were more prone to engage in secondary tasks (such as reading, watching a movie, etc.) and to look away from the road for extended periods of time (Merat et al. 2012). This led to longer take over times and less safe autonomous driving, as measured by response time to critical events.

Zeeb et al. (2015) analyzed gaze behaviors of 89 participants in a moving base driving simulator study and found similar results. During the time-critical take-over requests, drivers with poor monitoring behavior reacted more slowly and more incorrectly than drivers who more regularly monitored the road. There also did not appear to be an upper limit for how long a driver is willing to look away from the road, even when drivers were informed that the automation could fail and require the drivers to take over control of the vehicle (Zeeb et al. 2015).

2.2.2. Transitions of Control

The importance of research into transitions of control cannot be understated. In a very public pilot of L3 technology, Uber began running AVs in the City of Pittsburg and the City of San Francisco in 2016. Within the first few days of the San Francisco pilot, there were reports of Uber AVs running red lights (Isaac & Wakabayashi 2017). This error was blamed on the vehicle's operator. Despite the specific training that the operator received to monitor the system and respond to a takeover request (TOR), there were still adverse events associated with this technology.

In the Schoettle and Sivak survey (2014), 26% of US respondents were "very concerned" about vehicle performance in unexpected situations, where a TOR might be necessary. There is strong evidence that if automation fails unexpectedly, almost all drivers will crash, but a timely warning allows most drivers to avoid collisions (De Winter et al. 2014).

One major issue associated with TORs is the time that it takes drivers to re-engage with the driving task after a period of low cognitive load. Preliminary research by Louw et al. (2015) and Gold et al. (2013) has shown that driver reengagement may take between 5 and 7 seconds. In a driving simulator study in a highway environment, Merat et al. (2014) demonstrated that for non-critical transitions, it takes drivers 30-40 seconds after the transition of control to stabilize their lateral position when the transition of control would occur randomly. Even when the transition was more systematic and predictable, it still took drivers nearly 10 seconds to stabilize their lateral position, based on the standard deviation of lateral position.

Mok et al. (2015) varied the transition of control time to a road hazard (a construction zone on a curve), finding that two seconds to the road hazard was not sufficient time for the driver to regain control of the vehicle and react. While five seconds was sufficient, drivers felt more comfortable when the transition time between autonomous driving and manual driving was longer, at eight seconds. While based on a relatively small sample size (10 participants for each transition time), these results give an example of the amount of time necessary for distracted drivers to react in an unstructured transition of control.

Miller et al. (2014) evaluated different levels of automation and measured the post transition reaction time after a pedestrian incursion onto the roadway. The authors found that steering was strongly associated with reaction time, with automated steering leading to significantly longer reaction times than other automations modes, including highly automated driving. The authors theorized this was due to a lack of drivers understanding of the limitations of automation.

Another driving simulator study evaluated driver performance where intervention was required more frequently. De Winter et al. (2016) introduced an automation failure rate of approximately every three minutes. They found that although automation lowered the physical and mental demand of the participants, drivers still seemed to be alert throughout the experiment, responding to critical events correctly. Drivers were much more frustrated with this level of automation than with other studies with a more consistently correct AV.

Simulator studies involving AVs, including the ones summarized in the sections above, have typically focused on highway driving, not urban streets where interactions with other road users, such as bicyclists, could be extremely dangerous. In interviews with twelve experts in the human factors field of automated driving, the experts emphasized the importance of additional research on the interaction of AVs with other road users as well as human behavior during automation transitions of control (Kyriakidis et al. 2017).

2.3. Multimodal Conflicts

One major concern with AVs are how these vehicles will interact with multimodal traffic in an urban environment. This concern was brought up by numerous human factors researchers in Kyriakidis et al. (2017). Despite the importance of these new, potential interactions between L3/L4 AV and bicyclists, few studies have considered this topic. The studies that do exist typically only address the topic from the point of view of the bicyclist.

For example, Blau (2018) conducted a stated preference survey of 767 respondents. In general, both cyclists and pedestrians preferred separated facilities but this preference was heightened in a future scenario that included AVs. Hagenzieker et al. (2016) showed bicyclists images of bicycle-vehicle interactions with manual and autonomous vehicles.

Bicyclists were asked whether they thought they would be noticed by the vehicles and the action they would take in each scenario. In general, bicyclists took a conservative approach, believing that they would not be seen by the AV any more than by a driver in a manually driven vehicle. However, this is not always the case. In a case study of WEpod AVs (small, low-speed shuttles), pedestrians and cyclists felt slightly more comfortable around these vehicles compared to traditional motor vehicles (Rodriguez et al. 2016). This comfort with the AVs was attributed to the WEpods maintaining a low speed (15 km/h) and the presence of a human driver behind the wheel monitoring the system. This trust in the combination of autonomous and human driving could become problematic if the human driver becomes distracted and is no longer ready to respond to pedestrians or bicyclists on the roadway.

With research on AVs and human behavior demonstrating reduced driving performance, autonomous driving transitions of control could become important factors in RH crashes at signalized intersections.

2.4. Research Questions

Based on our review of the literature, there are gaps in human factors research related to AVs, especially in multimodal, urban environments. To help address these gaps in knowledge, six research questions were identified during the literature review process. These questions guided the development of experimental procedures.

2.4.1. Collision Avoidance

Time-to-collision (TTC) is defined by Gettman et al. (2008) 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, vehicle-bicycle interactions with a TTC of two seconds or less is considered a conflict (Sayed et al. 2013). A driver's yielding behavior also plays an important role in collision avoidance. With this in mind, four research questions were proposed.

- Research Question 1 (RQ1): Is the driver's decision to yield to a bicyclist influenced by the proximity of the vehicle to the intersection at the time of a TOR?
- Research Question 2 (RQ2): Is the driver's decision to yield to the bicyclist influenced by driver involvement in a secondary task prior to a TOR at a signalized intersection?
- Research Question 3 (RQ3): Is TTC affected by driver involvement in a secondary task prior to a TOR at a signalized intersection?
- Research Question 4 (RQ4): Is TTC affected by the proximity of the vehicle to the intersection at the time of a TOR?

2.4.2. Visual Attention

The visual attention of motorists can provide direct evidence of whether a driver recognizes and anticipates a hazard, in most cases (Fisher et al. 2011). As such, visual attention will be measured to assess the following research questions.

- Research Question 5 (RQ5): Is the visual attention of a right-turning driver influenced by the proximity of the TOR to a signalized intersection?
- Research Question 6 (RQ6): Is the visual attention of a right-turning driver at a signalized intersection influenced by driver involvement in a secondary task prior to a TOR?

3. METHODOLOGY

This chapter describes the equipment and experimental design that were used to evaluate the research questions in the Oregon State University (OSU) driving simulator. The approach for this experiment is grounded in accepted practice (Fisher et al. 2011) and leverages unique research capabilities at OSU. Two primary tools were used for this experiment, the OSU driving simulator and the Applied Science Laboratories (ASL) eye-tracking system.

3.1. 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 vehicle cab is mounted on the pitch motion system with the driver's eye point located at the center of the viewing volume. The pitch motion system allows for accurate representation of acceleration or deceleration (Swake et al. 2013). Three liquid crystals on silicon projectors with a resolution of 1,400 × 1,050 are used to project a front view of 180° × 40°. These front screens measure 11 ft. × 7.5 ft. A digital light-processing projector is used to display a rear image for the driver’s center mirror. The two side mirrors have embedded LCD displays. The update rate for projected graphics is 60 Hz. Ambient sounds around and internal sounds in 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. The simulator software is capable of capturing and outputting accurate values for performance measures (speed, position, brake, and acceleration). Figure 3.1 shows views of the simulated environment created for this experiment from inside (left) and outside (right) the vehicle.

Figure 3.1 Simulated environment in the OSU driving simulator, from the participant's perspective inside (left) and from outside (right) the vehicle.

The full-scale driving simulator is controlled from the operator workstation. The full driving simulator is located in a separate room from the desktop development simulator and the full simulator operator workstation. This separation prevents participants in the vehicle from being affected by visual or audible events from researchers during the experiment.

3.1.1. Autonomous Displays and Controls

The driving simulator is updated with an AV software package controlled by Java Script, SimDriver V2. The automation is turned on and off through a button push on the steering wheel of the vehicle. It can also be controlled through sensors coded in the virtual environment.

The virtual dashboard of the vehicle was updated using Altia Design to accommodate the new SimDriver functionality. Figure 3.2 shows the dashboard displayed inside the vehicle. Four different displays (Figure 3.3) were added to the vehicle dashboard to indicate the four different states of the autonomous vehicle during the experiment: manual driving, automation on, TOR and automation off. The displays were shown in this order to participants throughout the experiment. All the images were static except for the TOR indication, which was a dynamic image designed to show hands grabbing towards the steering wheel with a countdown of three seconds.

Figure 3.2 Dashboard display

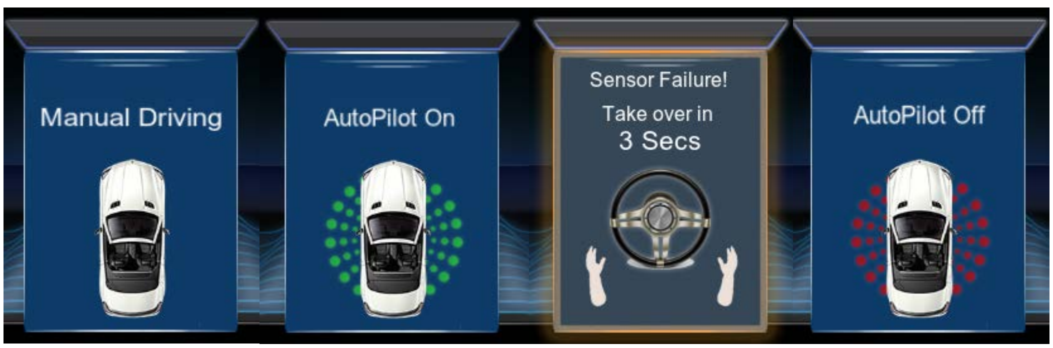


Figure 3.3 Central dashboard display (manual, automation on, TOR and automation off)

The TOR indication was accompanied by an alert sound following NHTSA research on auditory alerts in vehicles (Singer et al. 2015). The alert beeped three times before giving verbal guidance to the driver on how to proceed.

3.1.2. Virtual Environment

The virtual environment was developed by using Simulator software packages, including Internet Scene Assembler (ISA) (Version 2.0) and SimCreator. The simulated test tracks were developed in ISA by using Java Script-based sensors that controlled the motion of bicycles and ambient traffic. The environment was designed to replicate a typical urban roadway with a 30 mph speed limit. The roadway cross-section consisted of two 11-foot travel lanes, two 6-foot bikes lanes and two 7-foot parking lanes, one in each direction (Figure 3.4). When a bicyclist was present in the environment, the bicyclist always traveled at 16 mph. Higher bicyclist speeds are more difficult for drivers to project into the future and lead to more dangerous right-hook crash scenarios at signalized intersections (Jannat 2014).

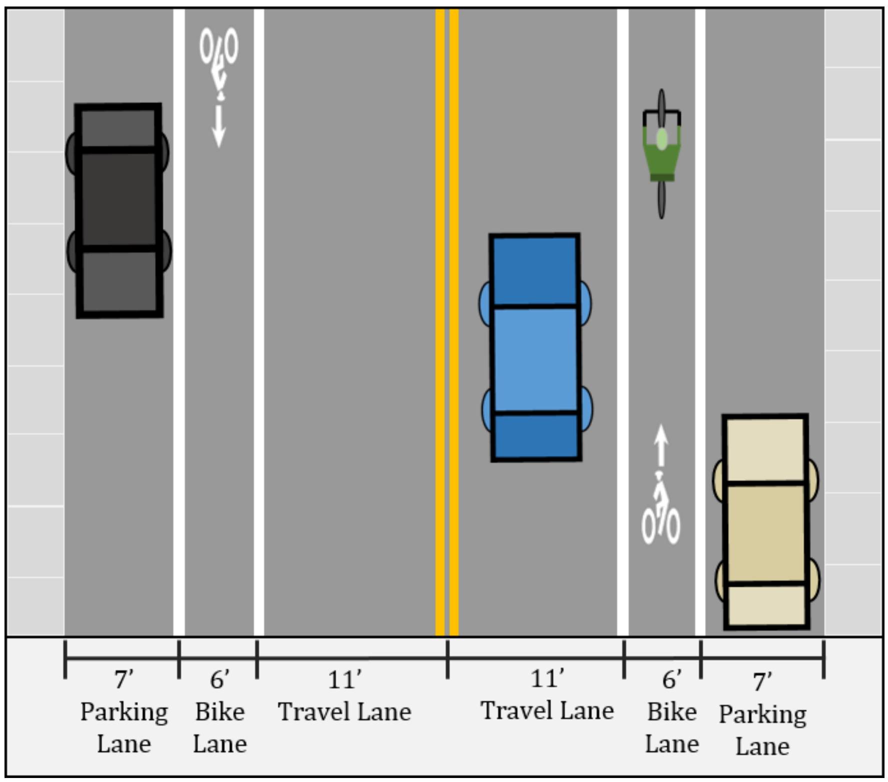


Figure 3.4 Roadway cross section

3.2. <u>Eye Tracker</u>

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 (Figure 3.5), which allows the user unconstrained eye and head movements. A 30-Hz sampling rate was used, with an accuracy of 0.5–1.0°. The participant's gaze was calculated based on the correlation between the participant's pupil position and the reflection of three infrared lights on the eyeball. Eye movement consists of fixations and saccades. Fixations occur when the gaze is directed towards a particular location and remains still for some period of time (Green 2007; Fisher et al. 2011). Saccades occur when the eye moves between fixations.

The ASL Mobile Eye-XG system records a fixation when the participant's eyes pause in a certain position for more than 100 milliseconds. Quick movements to another position (saccades) are not recorded directly but are calculated based on the dwell time between fixations. Total dwell times are recorded by the equipment as the sum of the time of fixations and saccades consecutively recorded within an area of interest (AOI).

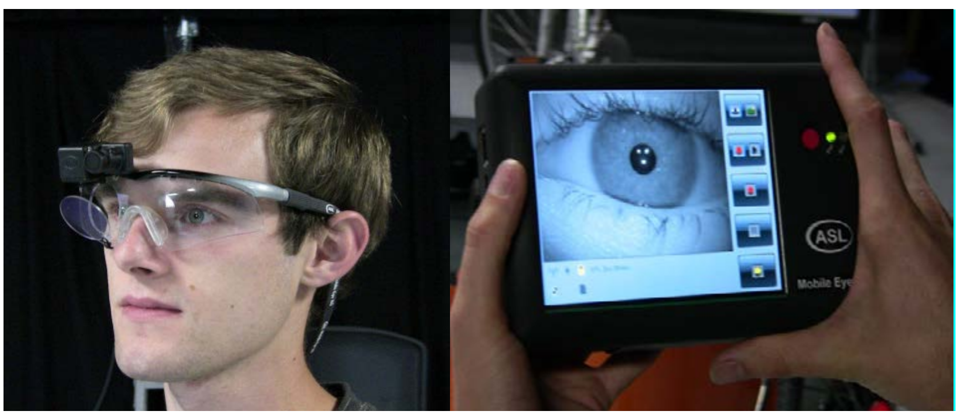


Figure 3.5 OSU researcher demonstrating the Mobile Eye XG glasses (left) and Mobile Recording Unit (right).

3.3. <u>Independent Variables</u>

Three independent variables were included in the experiment: presence and location of bicycle, secondary task engagement, and TOR proximity. These variables were selected by the research team to address the research questions.

The location and presence of the bicyclist was varied to induce interactions with the vehicle at signalized intersections, based on a total of five alpha and beta tests by the research team. A bicyclist was placed either relatively closer or farther from the intersection, to intentionally induce a more or less difficult yield or go decision by the driver.

The second independent variable was whether participants were engaged in a secondary task or not. The task was both a motor and cognitive task, specifically a bubble game developed by Rokni et al. (2017). The task involves popping a bubble of a particular color on a touch screen device mounted in the cab of the vehicle (Figure 3.6). The task was intentionally designed to be difficult and to keep drivers engaged in the game.

Figure 3.6 OSU researcher demonstrating the bubble game mounted in the vehicle cab

The final independent variable was the TOR proximity to the intersection. The TOR was presented to the driver either 5s, 10s, or 15s upstream of the stop line on the approach to intersection.

3.4. Factorial Design

A factorial design was chosen for this experiment to enable exploration of all three independent variables separately. The factorial design for the three variables, each with two or three levels, resulted in the inclusion of 18 scenarios, which were presented within subjects. Table 3.1 summarizes the independent variables and their associated levels in the factorial design.

Table 3.1 Experimental variables and levels

VARIABLE	ABBREVIATION	CATEGORY	LEVEL DESCRIPTION
Relative Bicycle Position	B	Discrete	No bicycle
			Bicycle closer to stop line
			Bicycle farther from stop line
TOR Proximity	TOR	Discrete	5 seconds from stop line
			10 seconds from stop line
			15 seconds from stop line
Secondary Task	Game	Dichotomous (Categorical)	No secondary task
			Playing the bubble game

The starting position of the bicyclist was varied based on the TOR proximity so the bicyclist would only become visible to the driver 10 seconds ahead of a TOR. The starting positions shown in Figure 3.7 were chosen to keep the bicyclist on the same trajectory relative to the vehicle, regardless of when the driver received the TOR. Prior to 10 seconds before the TOR, the bicyclist was stationary behind a parked vehicle and obscured from the view of the driver. The bicyclist closer to the intersection was positioned 20 meters ahead of the bicyclist farther from the intersection.

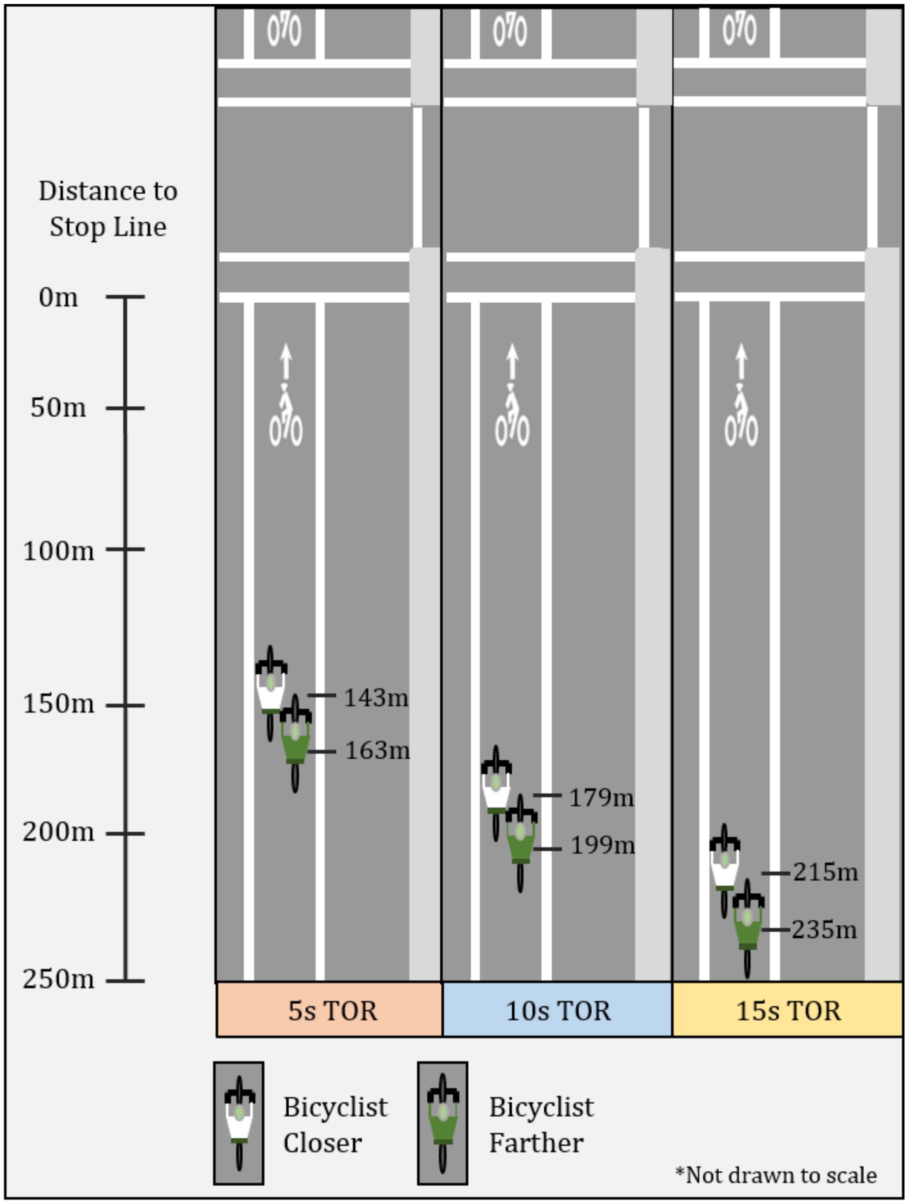


Figure 3.7 Bicycle starting position based on TOR proximity

The within-subject design provides advantages of greater statistical power and reduced error variance associated with individual differences (Cobb 1998). However, one fundamental disadvantage of the within-subject design is the existence of "practice effects," caused by practice, experience, and growing familiarity with procedures as participants move through the sequence of conditions. To control for practice effects, the order of the presentation of scenarios to participants needs to be randomized or counterbalanced

(Girden 1992). To control for the practice or carryover effect, the order of the scenarios was counterbalanced. Four different track layouts were developed and presented in random order to each participant. Randomized, partial counterbalancing was chosen due to its simplicity and flexibility in terms of statistical analysis and number of required participants. Each track had four or five scenarios, each with a different level of independent variables which was randomly assigned.

Table 3.2 presents the configuration layout for each of the 18 scenarios that were presented to participants, in a randomized order, across four tracks. Figure 3.8 shows an example grid layout as presented to the drivers. Extra intersections and left turns were introduced to the track layout so that participants would not anticipated the scenarios at intersections. The scenarios were separated by 45-90 seconds of driving.

Table 3.2 Track layout

SCENARIO	BICYCLE (B)	TOR PROXIMITY (TOR)	SECONDARY TASK (ST)
		Track 1	
1	Farther	10 s	Yes
2	None	5 s	No
3	Farther	15 s	Yes
4	Farther	5 s	Yes
		Track 2	
5	None	15 s	Yes
6	None	10 s	Yes
7	Farther	5 s	No
8	Closer	10 s	Yes
9	Farther	10 s	No
		Track 3	
10	Closer	15 s	No
11	Farther	15 s	No
12	Closer	10 s	No
13	Closer	5 s	Yes
14	None	10 s	No
		Track 4	
15	Closer	15 s	Yes
16	Closer	5 s	No
17	None	15 s	No
18	None	5 s	Yes

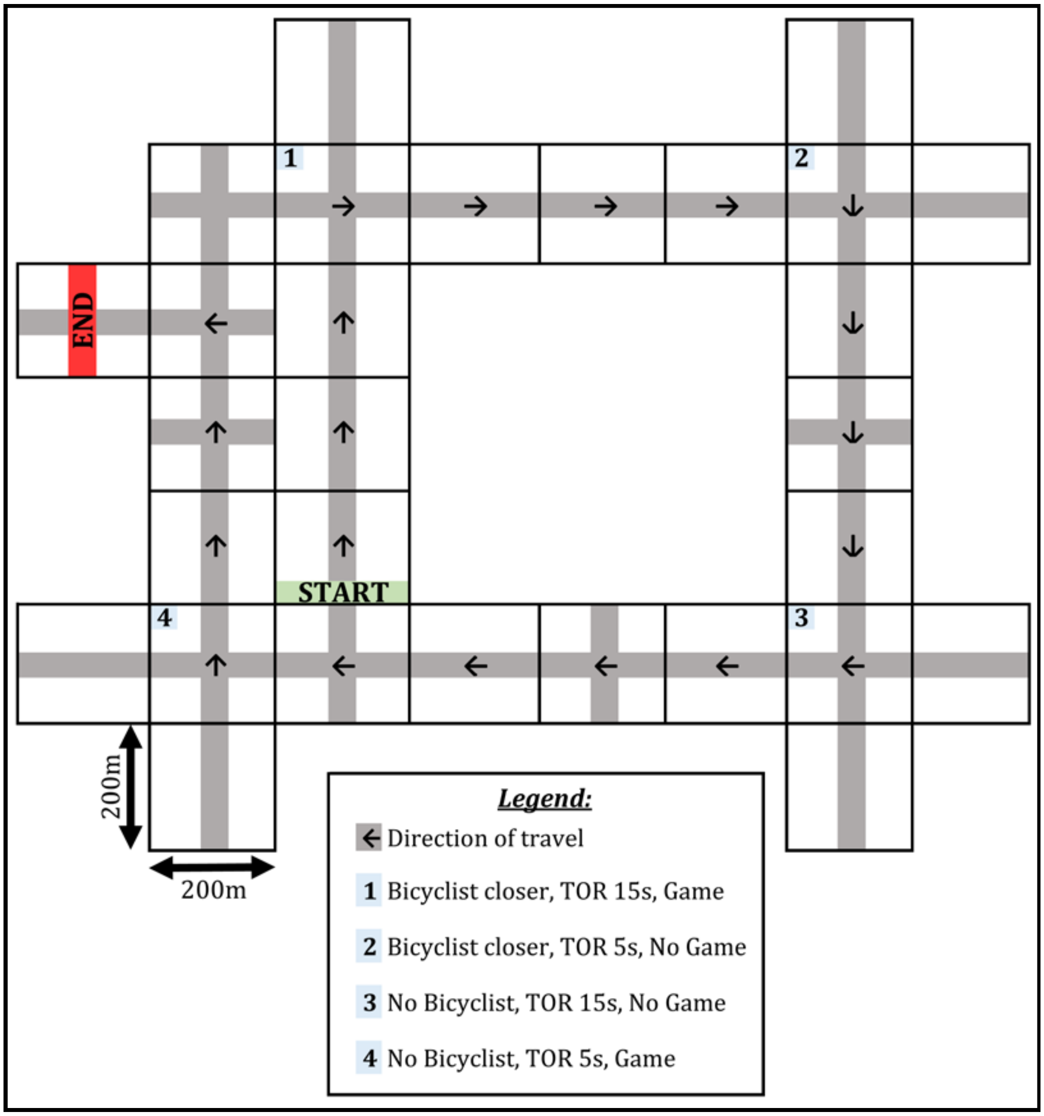


Figure 3.8 Layout for grid 4

3.5. Experimental Protocol

This section describes the step-by-step procedures of the driving simulator study, as conducted for each individual participant. This study was approved by the Oregon State University Institutional Review Board (Study #8329).

3.5.1. Recruitment

A total of 46 participants, primarily from the communities around Corvallis, OR were recruited for the driving simulator study. The population of interest was licensed drivers; therefore, only drivers with driving licensure and at least 1 year of driving experience were recruited for the experiment. Participants were required to not wear glasses or have poor vision, to be physically and mentally capable of legally operating a vehicle, and to be deemed competent to provide written, informed consent. Participants were recruited through flyers posted around campus and the surrounding community and through emails sent to different campus organizations and email listservs. Although it was expected that many participants would be Oregon State University students, an effort was made to incorporate participants of all ages within the specified range of 18 to 75 years.

3.5.2. Informed Consent

When the test participant arrived at the laboratory, they received an informed consent document, which described the reasoning behind the study, the importance of participation, and the risks and benefits of the test for the participant. The researcher discussed the document and the overall idea of the experiment with the participant. The participant was informed that they could stop the experiment at any time for any reason and still receive full compensation ($10 cash) for participating in an experimental trial. To avoid biasing the experiment, participants were not told the specific research hypotheses.

3.5.3. Prescreening Survey

Participants were administered a prescreening survey on their demographics (i.e., age, gender, ethnicity, driving experience, highest level of education, and prior experience with driving simulators) and questions in the following areas:

- Vision – Good vision was crucial for this experiment. Participants were asked if they used corrective glasses or contact lenses while driving. Their abilities to see the driving environment clearly and to read visual instructions (displayed on the screen) to stop driving were confirmed.
- Simulator sickness – Participants with previous driving simulation experience were asked about any simulator sickness that they experienced. If they had previously experienced simulator sickness, they were encouraged not to participate in the experiment.
- Motion sickness – Participants were surveyed about any kind of motion sickness they had experienced in the past. If an individual had a strong tendency towards any kind of motion sickness, they were encouraged not to participate in the experiment.

3.5.4. Calibration Drive

After completing the prescreening survey, participants performed a 5-minute calibration drive. The overall purpose of this drive was to acclimate participants to the mechanics of the vehicle and the virtual reality of the simulator, and to determine if they were prone to simulator sickness. Once seated in the vehicle for the test drive, participants were allowed to adjust the seat, rearview mirror, and steering wheel to maximize comfort and performance while driving. They were instructed to drive and follow all traffic laws as they normally would. Participants were instructed on how to turn the automation on and off and the meaning of the dashboard displays that they might see during the experiment.

According to Zhao et al. (2015), effective calibration drives introduce the participant to three primary roadway characteristics in the simulator environment: horizontal curves, acceleration and deceleration on a stretch of roadway, and turning at intersections. The calibration drive included elements that the drivers would encounter during the experimental drives, with the exception of the bicyclists at an intersections.

3.5.5. Eye Tracking Calibration

After the calibration drive was completed, researchers equipped participants with a head-mounted eye tracker. Participants were directed to look at different locations on a calibration image projected on the forward screen of the driving simulator (Figure 3.9).

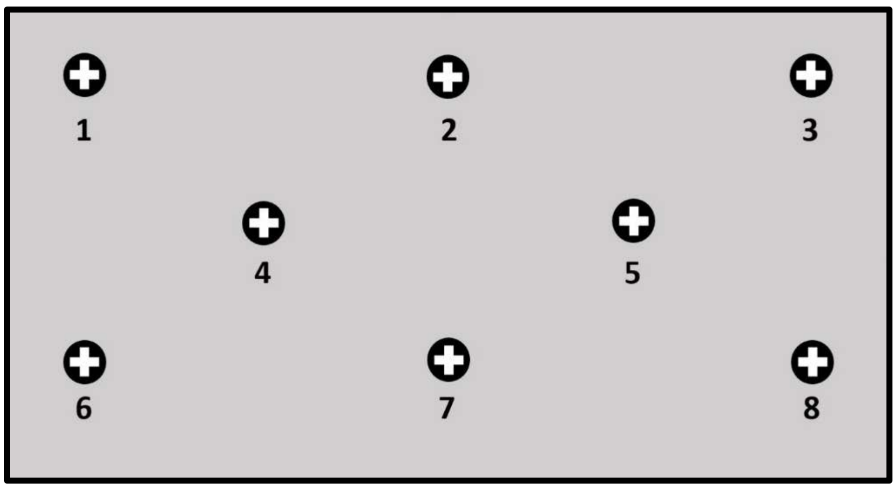


Figure 3.9 Eye tracking calibration screen

3.5.6. Experimental Drive

After the motorist's eyes were calibrated to the driving simulator screens, they were given brief instructions about the test environment and the tasks that they were required to perform. The experiment was divided into four tracks. At the completion of each experimental drive, the researcher instructed the participant to stop the vehicle and ascertained whether the participant was experiencing simulator sickness. The virtual driving course (four tracks) was designed to take 30 minutes to complete.

3.5.7. Post-Drive Survey

Following the experimental drives, participants answered a post-drive survey. The survey included questions on the participant's experience and their attitude towards automation after the experimental drives.

4. RESULTS

This chapter presents the results of the simulator experiment. This includes a description of participant demographics, results from the analysis of visual attention and results discussing the TTC between the vehicles and the bicyclists.

4.1. Participant Demographics

In total, 46 individuals (23 women, 22 men, 1 prefer 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.

The age of participants ranged from 18 to 74 years (M_{age} = 30.7, SD_{age} = 15.11). Table 4.1 summarizes additional self-reported demographic data of the analyzed dataset.

Table 4.1 Participant demographic information

Question	Possible Responses	Number of Participants	Percentage of Participants
How many years have you been licensed?	1–5 years	16	37%
	6–10 years	9	21%
	11–15 years	5	12%
	16–20 years	3	7%
	More than 20 years	10	23%
How often do you drive in a week?	1 time per week	9	21%
	2–4 times per week	12	28%
	5–10 times per week	12	28%
	More than 10 times per week	10	23%
How many miles did you drive last year?	0–5,000 miles	14	33%
	5,000–10,000 miles	10	23%
	10,000–15,000 miles	3	7%
	15,000–20,000 miles	14	33%
	More than 20,000 miles	2	4%
What corrective lenses do you wear while driving?	Glasses[1]	0	0%
	Contacts	14	33%
	None	29	67%
Do you experience motion sickness?	Yes	5	12%
	No	38	88%

[1]Recruitment materials stated that wearing glasses was an exclusionary criterion.

4.2. Crash Avoidance Results

Driver performance in L3 autonomous systems will play a major role in the safety of these vehicles. One measure of performance is the crash avoidance behavior of drivers, which can including driver's yielding behavior and a driver's TTC with a bicyclist. The following section discusses driver performance with respect to crash avoidance.

4.2.1. Time-Space Diagrams

To help conceptualize the crash avoidance behavior of participants, three time-space diagrams were created, one for each TOR scenario (Figure 4.1, Figure 4.2, and Figure 4.3). The trajectories were recorded from the centroid of the user. For each plot, a case where a participant yielded and a case where a participant did not yield to the bicyclist was considered. The figures help highlight the time when the bicyclists first begins to move for the different TOR scenarios and show the difference in distance between the two bicycle conditions. The figures also demonstrate the time the driver has to make the decision to yield or go, and the relative position between the driver and bicyclist at a given time. As noted previously, the starting positions of the bicyclists were adjusted so that the bicyclists were only visible to the participants for 10s before the TOR, allowing for the same amount of time for the driver to identify the bicyclist before the TOR across all scenarios.

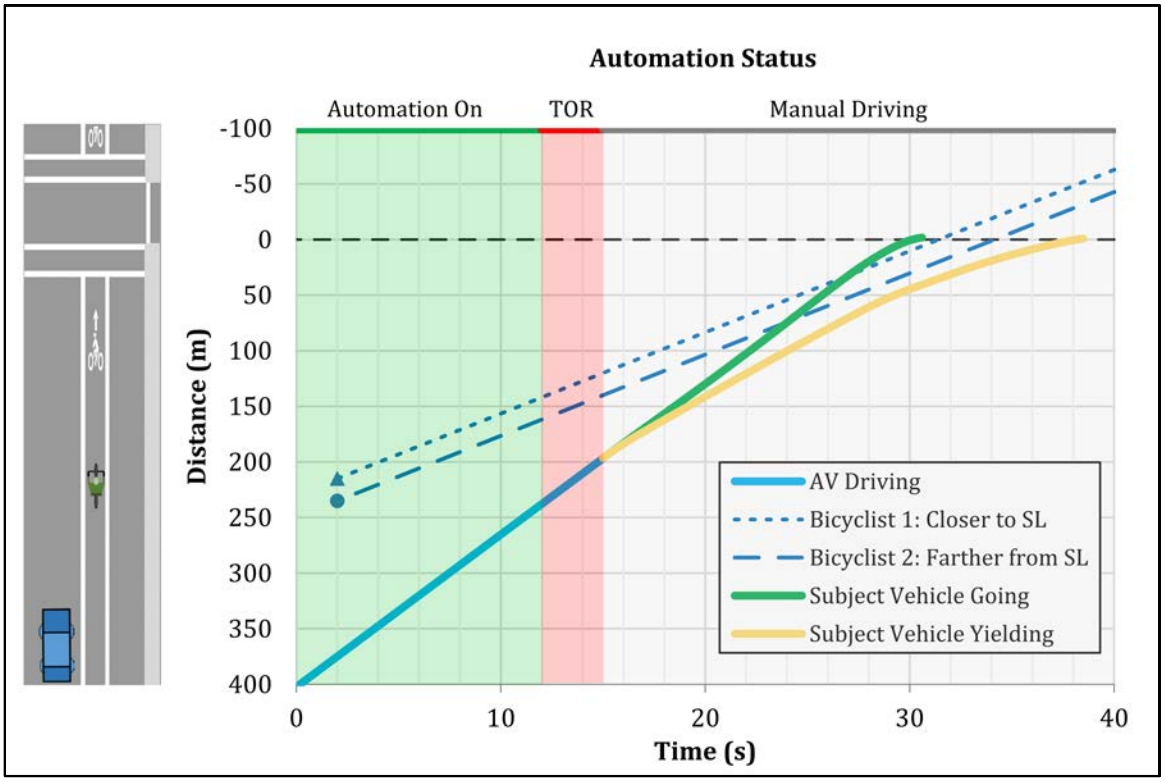


Figure 4.1 Example time-space diagram for 15 s TOR

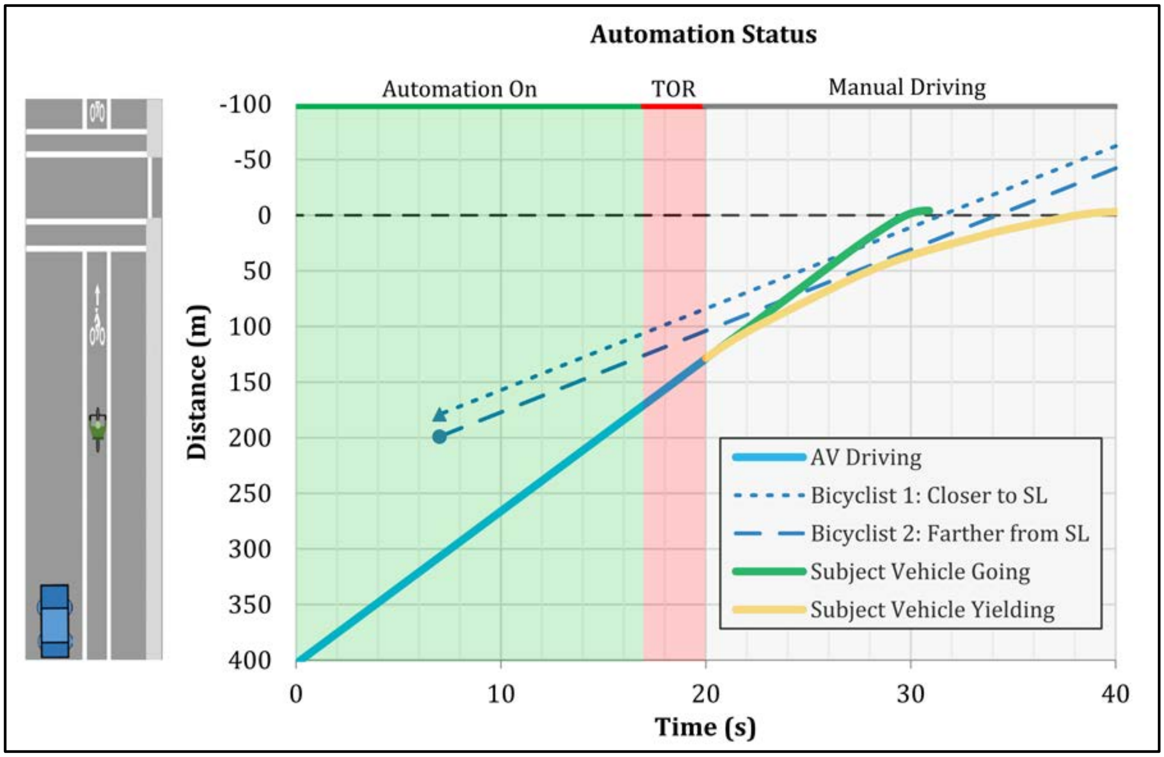


Figure 4.2 Example time-space diagram for 10 s TOR

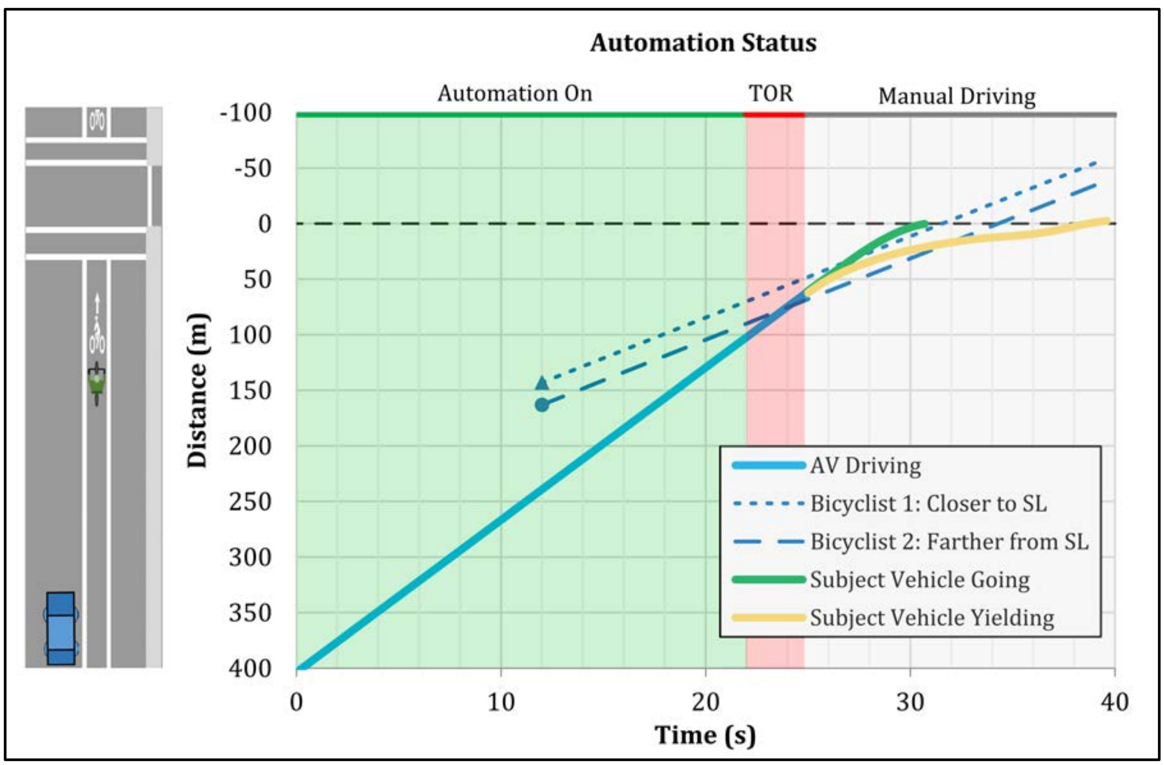


Figure 4.3 Example time-space diagram for 5 s TOR

The three plots highlight the different yielding behavior of different participants, with some accelerating past the bicyclist and others braking to yield to the bicyclist. In the first two yielding cases, the drivers brake before passing the bicyclist, while in the third case, the driver identifies that the bicyclist is behind them and stops to yield to the bicyclist.

4.2.2. Yielding Behavior

Across all 516 cases in the experiment (43 participants by 12 scenarios where a bicyclist was present), drivers yielded to the bicyclist in 284 instances (56% of cases). Figure 4.4 shows the number of yielding cases disaggregated by each level of independent variable. Unsurprisingly, the majority of yielding cases occurred when the bicyclist was relatively closer to the intersection than farther from the intersection (n=210 versus n=74). There were also more yielding events for the 15 second TOR condition than the 10 second or 5 second (n=105, n=94, n=85, respectively). The yielding events were evenly split with respect to the secondary task, with participants yielding n=142 times for the game and no game conditions.

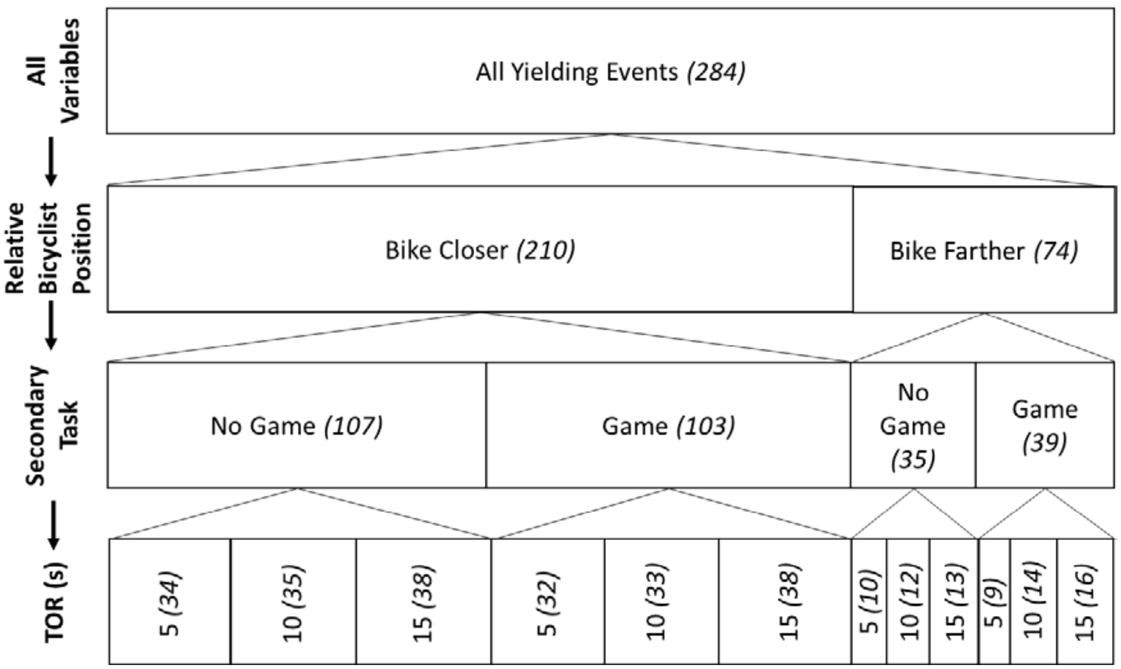


Figure 4.4 Yielding events by independent variables

The decision to yield or go at the intersection is a binary choice which can be modeled by a linear probability model. Since each participant completed all 12 right-turn scenarios where a bicyclist was present, this dataset can be considered a panel dataset. Panel data requires replication of the same units over time (Wooldridge 2016). A fixed-effects linear probability model was created using Stata to help determine the effect that the independent variables had on a driver's decision to yield or go at the intersection. Fixed-effects better estimate the effect of individual variables when all other variables remain constant and is widely used for panel data analysis (Wooldridge 2016). Using a fixed-effects model helps control for the omitted variable bias and data were clustered by participant to account for individual differences between drivers. As shown in Table 4.2, there is a significant effect of the relative bicyclist position ($t = -9.23, P < 0.001$) and a TOR of 5 seconds ($t = -9.23, P = 0.003$) on the probability of a driver yielding to the bicyclist.

Table 4.2 Fixed-effects linear probability model on a driver's yielding decision

Variable	Category	Coefficient	Standard Error	t	*P*
Yield (Dependent Var.): (1 if the driver yields to the bicyclist, 0 otherwise)	-	-	-	-	-
Relative Bicycle Position: (1 if bike is farther from the stop line, 0 if bike is closer)	-	-.5233	.0567	-9.23*	< 0.001
Secondary Task: (1 if playing the game, 0 if not playing the game)	-	-.0039	.0204	-0.19	0.851
TOR: (2 if TOR is 5s	TOR=2	-.1163	.0367	-3.17*	0.003
1 if TOR is 10s	TOR=1	-.0523	.0318	-1.64	0.108
0 if TOR is 15s)					
				R^2 (within subjects)	0.4174
				Number of Obs.	516
				Number of Groups	43
				Obs. Per Group	12

* Statistically significant at 95% confidence interval

As the TOR proximity decreases from 15 seconds to 5 seconds or 10 seconds, there is a decreased probability in yielding. A TOR occurring 5 seconds from the stop line decreases the probability that a driver will yield by 11.6% compared to the 15-second condition. As the bicyclist goes from relatively closer to the stop line to relatively farther from the stop line, the probability that a driver will yield to the bicyclist decreases by 52.3%.

4.2.3. TTC Calculation

To further investigate the effect of the independent variables on the collision avoidance behavior of the drivers, a time-to-collision (TTC) value was calculated for each of the 226 observations where a driver did not yield to the bicyclist at the intersection. SAE J2944 (2015) defers to the methodology presented by van der Horst (1990) when calculating TTC. For a right–angle approach, van der Horst calculates the TTC considering velocity using the following equations:

$$TTC = \frac{d_2}{v_2}, \text{ if } \frac{d_1}{v_1} < \frac{d_2}{v_2} < \frac{d_1+l_1+w_2}{v_1} \quad \textbf{Equation 4.1}$$

$$TTC = \frac{d_1}{v_1}, \text{ if } \frac{d_2}{v_2} < \frac{d_1}{v_1} < \frac{d_2+l_2+w_1}{v_2} \quad \textbf{Equation 4.2}$$

where,

d_1, d_2 = distances from the front of vehicles 1 and 2, respectively, to the area of the intersection

l_1, l_2, w_1, w_2 = the lengths and widths of vehicles 1 and 2, respectively

v_1, v_2 = vehicle speeds

For the case of the right-hook crash scenario where the subject vehicle turns in front of the bicyclist, this procedure can be simplified, as described in Hurwitz (2015).

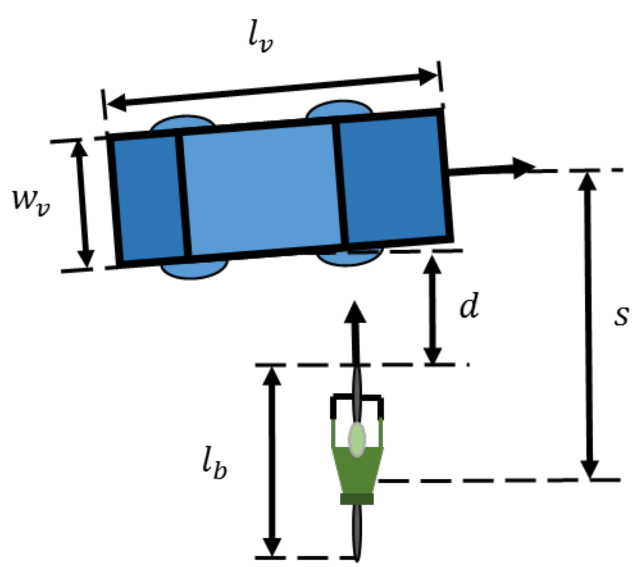


Figure 4.5 TTC calculation for RH crash scenario (Hurwitz 2015)

Since the location of the bicycle and vehicle centroids were recorded in the driving simulator, distances between the vehicle and the bicyclist were calculated from their centroids using the following equations (Hurwitz 2015):

$$TTC = \frac{d}{v_b},$$ **Equation 4.3**

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

where,

$v_b, v_v, =$ velocity of bicycle and subject vehicle, respectively (for this experiment, the bicyclist travelled at a constant velocity of 16mph, or 7.15m/s)

w_v = width of the 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

4.2.4. TTC Results

In total, there were 516 right-turn maneuvers in the presence of a bicyclist (43 participants by 12 intersections with bicyclists present). Two hundred twenty six of those right-turn maneuvers resulted in the subject vehicle turning in front of the bicyclist and not yielding at the intersection. Table 4.3 shows the minimum TTC measurements for each of the 226 maneuvers. More interactions occurred when the bicyclist was farther from the stop line compared to the closer condition (79.7% versus 20.3%). The number of interactions with the bicyclist was about equally split among participants who were not playing the bubble game (n=114) and those who were (n=113).

Table 4.3 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 SL (46)	Game (25)	5	2	2	3	3	10
		10	3	3	2	1	10
		15	0	0	1	4	5
	No Game (21)	5	1	1	5	2	9
		10	0	0	1	7	8
		15	0	0	1	3	4
Farther from SL (181)	Game (88)	5	0	1	0	33	34
		10	0	0	1	26	27
		15	0	0	0	27	27
	No Game (93)	5	0	0	0	33	33
		10	0	0	0	30	30
		15	0	0	0	30	30
Total			6	7	14	199	226

The boxplots below indicate the three independent variables (TOR, relative bicycle position, secondary task) appear to have some influence on TTC (Figure 4.6). There is a very obvious difference in means between the two bicycle conditions ($M_{Closer} = 1.81\ s$, $SD_{Closer} = 0.785\ s$; $M_{Farther} = 4.28\ s,\ SD_{Farther} = 0.911\ s$). While the mean does not appear to be different between the five second ($M_{5s} = 3.45\ s,\ SD_{5s} = 1.255\ s$) and ten second ($M_{10s} = 3.65\ s,\ SD_{10s} = 1.373\ s$) TOR conditions, there is a visible difference between the 15 second condition ($M_{15s} = 4.35\ s,\ SD_{15s} = 1.217\ s$). Finally, there appears to be a slight difference between the secondary task conditions ($M_{Game} = 3.58\ s,\ SD_{Game} = 1.425\ s$; $M_{No\ Game} = 3.97\ s,\ SD_{No\ Game} = 1.209\ s$).

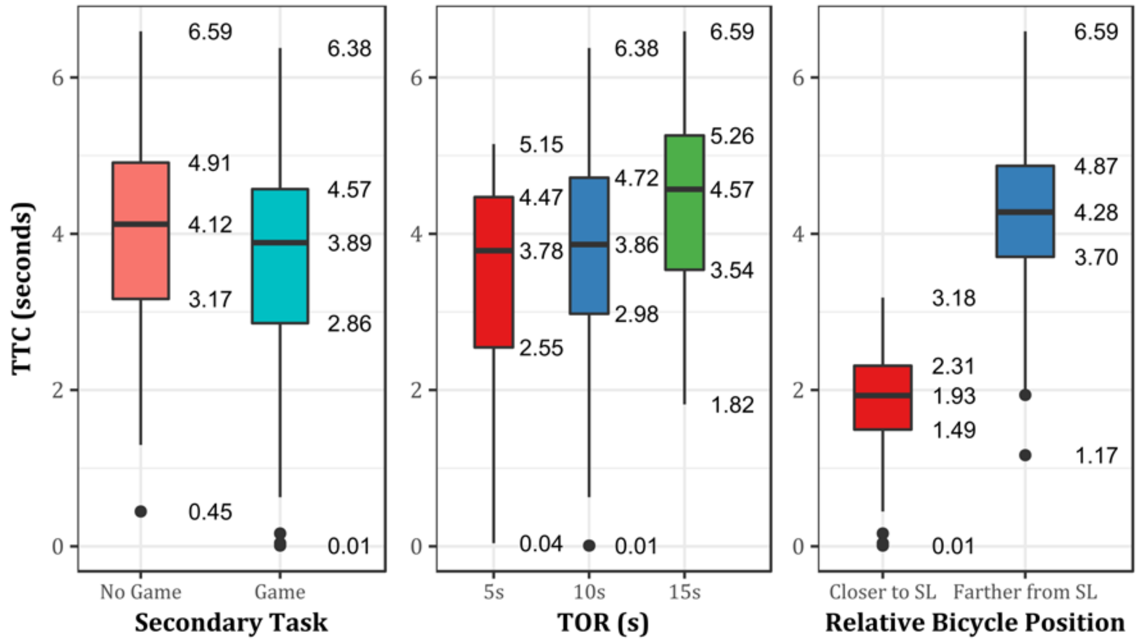


Figure 4.6 Boxplots of independent variables and TTC

Repeated measures analysis of variance (ANOVA) is typically used to analyzed data when each participant is exposed to all possible combinations of independent variables, resulting in multiple measurements for each participant (Ramsey and Schafer 2013). However, there were numerous zero values for the TTC measurements across participants which represented the case where a participant yielded to the bicyclist. Unbalanced data such as this can be problematic for repeated measures ANOVA. To still account for the effect of multiple measurements across individual participants, ANOVA tests were performed using subjects as a blocking factor (Ramsey and Schafer 2013). Relative bicycle position, TOR proximity, and secondary task are the within-subject factors and TTC is the dependent variable. The results are shown in Table 4.4.

Table 4.4 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 x Secondary Task	1	0.84	0.361
Relative Bicycle Position x TOR	2	0.46	0.635
Secondary Task x TOR	2	2.37	0.097
Relative Bicycle Position x Secondary Task x TOR	2	0.52	0.597
Error	180		

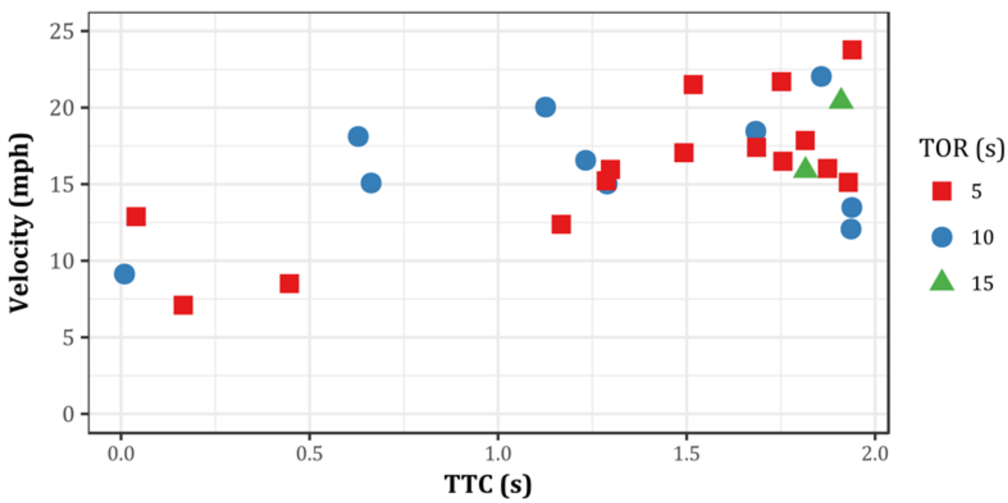
Note: *F* denotes *F* statistic; *df* denotes degrees of freedom.
* Statistically significant at 95% confidence interval

By using Tukey corrected post-hoc tests for pairwise comparison of the main effect of relative bicycle position, it was found that regardless of the TOR proximity and secondary task, on average participants had a larger TTC value when the bicyclist was farther from the stop line (P < 0.001). Pairwise comparisons for the main effect of secondary task also showed that regardless of the relative bicycle position and TOR proximity, participants playing the game had a smaller TTC value (P = 0.001). There was not a significant difference between the 5 second and 10 second TOR conditions, but there was a difference between the 15 second condition and the two other TOR conditions, with drivers having a larger TTC value in the 15 second condition (P=0.002, P=0.0021).

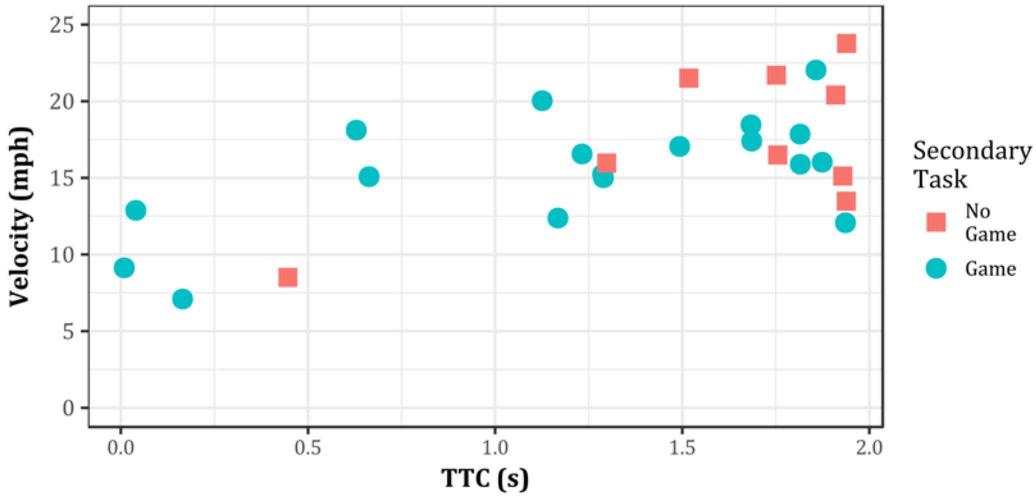
4.2.5. Potential Crash Severity

While TTC alone cannot identify the potential crash severity, it can be combined with other data, such as velocity to indicate how severe a potential crash may be. Small reductions in velocity can make a large impact on bicyclist safety. For example, the risk of death nearly doubles when a pedestrian is struck by a vehicle going 20 mph compared to 25 mph (Tefft 2013).

To understand potential crash severity, interactions with a low TTC were identified (Table 4.3) and paired with velocity. A threshold of two seconds or less was used for this analysis based on work by Sayed et al. (2013). These higher-risk TTC values are plotted in Figure 4.7. The relative bicycle position was not plotted for the low TTC values since only two events occurred when the bicyclist was farther from the intersection. The remaining cases are all from the bicyclist relatively closer to the intersection.



(a)



(b)

Figure 4.7 Velocity and TTC for (a) TOR and (b) secondary task

The majority of higher-risk scenarios occurred when the participants were distracted by playing the game (n=18) or when the TOR occurred with five seconds upstream of the stop line (n=15) (Table 4.5). Interactions with the bicyclist farther from the stop line typically had higher TTC values, with only two interactions of two seconds or less (compared to the closer bicyclist, with 25 interactions with a TTC of two seconds or less). When the TOR occurred five seconds upstream of the stop line, there were more interactions with a TTC of two seconds or less (n=15) compared to the 10 second (n=10) or 15 second (n=2) conditions. There were two collisions with the bicyclist during the experiment, both of which occurred when the bicyclist was closer to the stop line and the participant was distracted by the secondary task. In general, as mean velocity decreased across the levels of independent variables, the mean TTC decreased (Table 4.5).

Table 4.5 Descriptive statistics when minimum TTC < 2 secs

Variables	Level	n	Mean (SD) Velocity (mph)	Mean (SD) TTC (s)
Relative Bicycle Position	Bike Closer	25	16.43 (4.13)	1.326 (0.635)
	Bike Farther	2	12.23 (0.22)	1.552 (0.543)
TOR (s)	5	15	16.02 (4.55)	1.518 (0.634)
	10	10	16.00 (3.86)	1.236 (0.649)
	15	2	18.15 (3.19)	1.863 (0.067)
Secondary Task	No Game	9	17.44 (4.84)	1.609 (0.488)
	Game	18	15.46 (3.69)	1.209 (0.651)

4.3. <u>Visual Attention Results</u>

Visual attention data were gathered and reduced from the ASL Mobile Eye XG for the 34 participants with complete eye-tracking data. There were an additional five participants with partial eye-tracking data due to the participant accidentally adjusting the glasses and ruining the calibration. The remaining four participants could not be calibrated for eye-tracking.

4.3.1. Total Fixation Duration (TFD)

For each right turn scenario, the number and length of participants' fixation on various areas of interest (AOIs) were recorded. Total fixation duration (TFD) was generated by averaging all participant's fixations in each scenario for each AOI. A TFD of zero indicates that the participant did not fixate at that particular AOI during that scenario. A higher TFD indicates greater interest in the bicyclist, suggesting a higher potential for distraction, which can be useful for comparing the distraction potential of different variables (Poole and Ball 2005). TFD measurements help determine whether a driver identified critical elements in the visual scene (Reyes and Lee 2008).

A fixation was recorded on the bicyclist if the participant fixated on the bicyclist when it was ahead of the vehicle or when the bicyclist was visible in the rear view or side view mirrors. The sum of these fixations across each scenario indicates the TFD for the bicyclist (Figure 4.8).

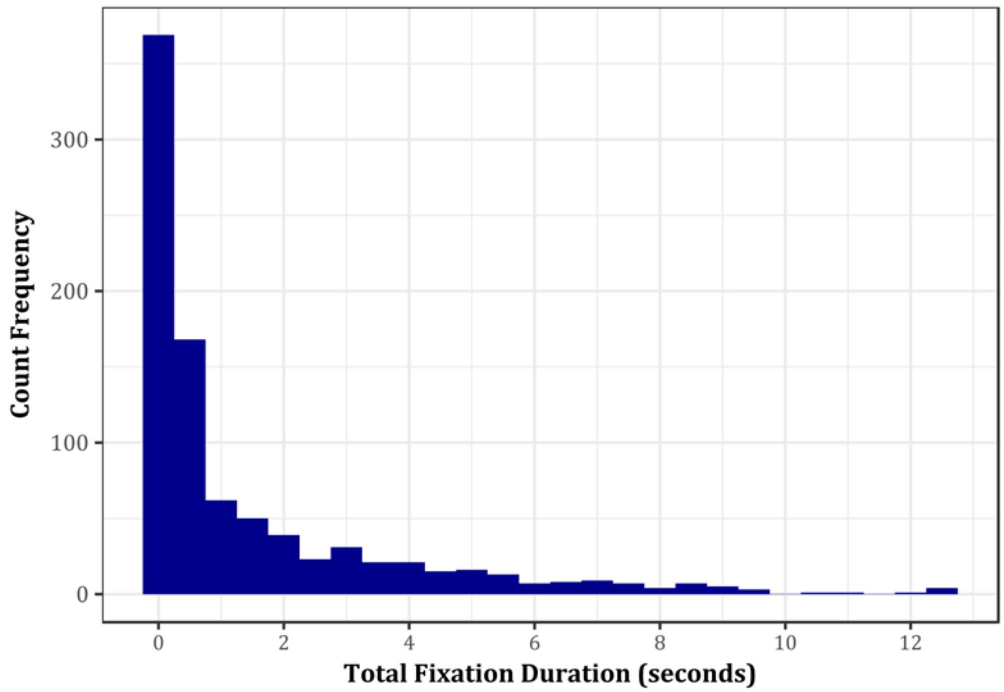


Figure 4.8 Histogram of TFD on the bicyclist

Each participant is exposed to all possible combinations of independent variables, resulting in multiple measurements for each participant. A repeated-measures ANOVA test was conducted to determine whether the total fixation duration differed between scenarios. Since the Mauchly's sphericity assumption was not met, the Huynh-Feldt adjusted p-values are reported (Abdi 2010). Table 4.6 shown the repeated-measures ANOVA results.

Table 4.6 Repeated-measures ANOVA results on TFD on the bicyclist (s)

Within-Subjects Factors	$F(v_1, v_2)$	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 x Secondary Task	1.00 (1, 33)	0.325	0.029
Relative Bicycle Position x TOR	12.68 (2, 66) *	< 0.001	0.278
Secondary Task x TOR	4.04 (2, 66)*	0.032	0.109
Relative Bicycle Position x Secondary Task x TOR	2.01 (2, 66)	0.142	0.057

Note: F denotes F statistic; v_1 and v_2 denote degrees of freedom; η_p^2 denotes partial eta squared.
* Statistically significant at 95% confidence interval

By using Bonferroni corrected post-hoc tests for pairwise comparison of the main effect of relative bicycle position, it was found that regardless of the TOR proximity and secondary task, on average participants fixated on the bicyclist significantly longer when the bicyclist was closer to the stop line (P < 0.001). Pairwise comparisons for the main effect of secondary task also showed that regardless of the relative bicycle position and TOR proximity, participants playing the game fixed on the bicycle significantly less (P < 0.001). There was a significant difference between all of the TOR conditions (P<0.001 for all comparisons), with drivers fixating on the bicyclist significantly longer as the TOR proximity increased.

4.3.2. Time to First Bicycle Fixation

During the scenarios where there was a bicyclist, the bicyclist remained stationary on the side of the road obscured behind a parked car until 10 seconds before the participant received a TOR. The bicyclist was not visible to the participant until that point in time. To determine whether there was an effect on how long it took the participant to identify the bicyclist entering the bike lane, the time to first bicycle fixation was calculated. A bicycle fixation was defined as the participant fixating on the bicycle when it was ahead of the vehicle or when the bicyclist was visible in the rear view or side view mirrors. A time to the first bicycle fixation of zero indicates that the participant identified the bicyclist when it first entered the roadway. Data were visualized as boxplots of time to first bicycle fixation disaggregated by the different levels of independent variables in Figure 4.9.

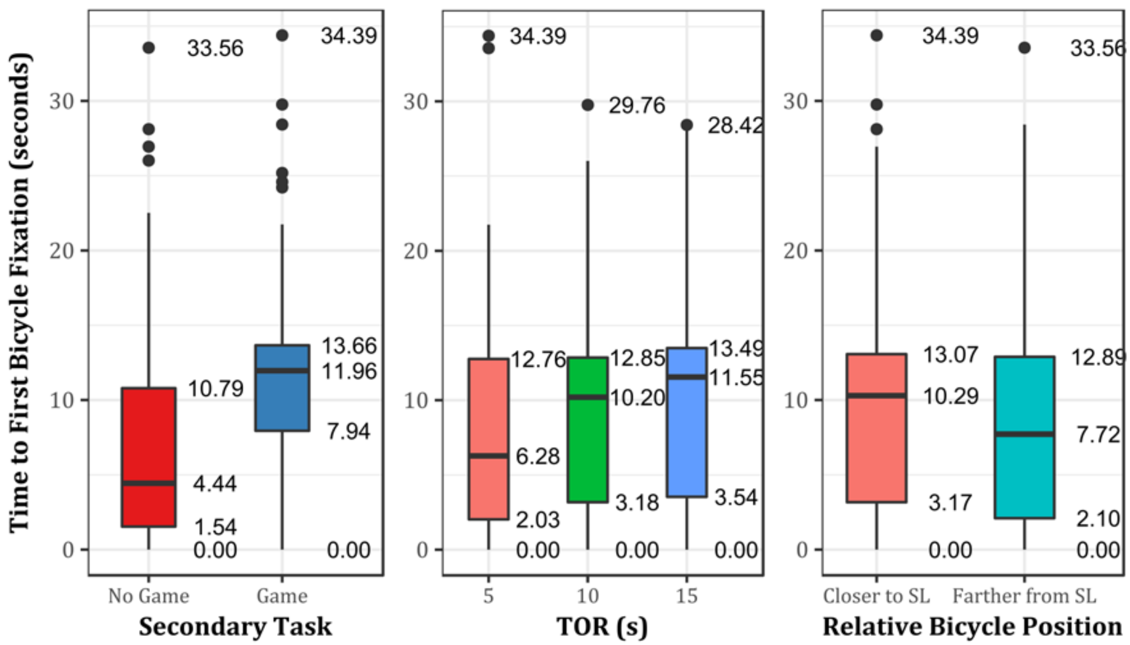


Figure 4.9 Time to first bicycle fixation

Despite participants being instructed to be prepared to take over control of the vehicle when requested, participants took approximately 4.5 seconds longer on average to identify the bicyclist on the roadway when they were playing the game ($M_{Game} = 11.25\ s$, $SD_{Game} = 5.88\ s$; $M_{No\ Game} = 6.70\ s$, $SD_{No\ Game} = 6.28\ s$).

There were 20 participants who identified and fixated on all 12 bicyclists throughout the experiment. A repeated-measures ANOVA test was conducted on the participants that fixated on all the bicyclists to determine whether the time to first bicycle fixation differed between scenarios. Pairwise comparisons were conducted to find the origin of the difference whenever a significant effect was observed. As shown in Table 4.7, relative bicycle position ($F(1,19) = 12.96, P = 0.002$), secondary task ($F(1,19) = 39.69, P < 0.001$), and TOR ($F(2,38) = 6.14, P = 0.005$) have significant main effects on the first time to fixation on the bicyclist. There was also a statistically significant interaction between the combined effects of relative bicycle position and secondary task on first time to fixation on the bicyclist ($F(1,19) = 5.80, P = 0.026$). In terms of independent variables, the change in TOR proximity had the highest effect on the first time to fixation on the bicyclist, with about 54% of within-subject variance being accounted for by this interaction.

Table 4.7 Repeated-measures ANOVA results on time of first bicycle fixation (s)

Within-Subjects Factors	$F(v_1, v_2)$	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 x Secondary Task	5.80 (1, 19)*	0.026	0.234
Relative Bicycle Position x TOR	0.59 (2, 38)	0.559	0.030
Secondary Task x TOR	1.24 (2, 38)	0.302	0.061
Relative Bicycle Position x Secondary Task x TOR	1.59 (2, 38)	0.218	0.077

Note: F denotes F statistic; v_1 and v_2 denote degrees of freedom; η_p^2 denotes partial eta squared.
* Statistically significant at 95% confidence interval

By using Bonferroni corrected post-hoc tests for pairwise comparison of the main effect of relative bicycle position, it was found that regardless of the TOR proximity and secondary task, on average participants fixated on the bicyclist significantly sooner when the bicyclist was farther from the stop line and started closer to the subject vehicle (P = 0.002). Pairwise comparisons for the main effect of secondary task also showed that regardless of the relative bicycle position and TOR proximity, participants playing the game fixed on the bicycle significantly later (P < 0.001). There was not a significant difference between the 5 second and 10 second TOR conditions, but there was a difference between the 15 second condition and the two other TOR conditions, with drivers fixating on the bicyclist significantly later in the 15 second condition (P=0.025, P=0.039).

5. CONCLUSIONS

This chapter presents study conclusions related to automation take over requests in the presence of bicyclists. Overall, there is a consistent narrative across the performance measures that the independent variables had an effect on the driving performance of participants. The first two sections of the chapter focuses on the conclusions related to the results of the experiment. The following sections discuss the limitations of the work as well as future research opportunities.

5.1. <u>Crash Avoidance Findings</u>

The results of this study 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. The primary findings based on the research are:

- *RQ1: Is the driver's decision to yield to a bicyclist influenced by the proximity of the vehicle to the intersection at the time of a TOR?* When all other variables are held constant, participants are 11.6% less likely to yield to the bicyclist when they are presented with a TOR five seconds from the intersection compared to when they are presented with a TOR 15 seconds from the intersection.
- *RQ2: Is the driver's decision to yield to the bicyclist influenced by driver involvement in a secondary task prior to a TOR at a signalized intersection?* There is no statistically significant differences in a driver's decision to yield at an intersection when a driver is involved in secondary task prior to a TOR.
- *RQ3: Is TTC affected by driver involvement in a secondary task prior to a TOR at a signalized intersection?* When drivers played a game while the car was driving in L3

automation, they had a statistically significant lower mean TTC, indicating a less safe interaction.

- *RQ4: Is TTC affected by the proximity of the vehicle to the intersection at the time of a TOR?* When drivers are given more time to respond at an intersection (i.e. 15 seconds instead of ten or five seconds), there is a statistically significant higher mean TTC between the vehicle and bicyclist. These higher TTC values represent safer interactions and lower likelihoods of collisions.

5.2. Visual Attention Findings

The results of this study indicate that there is a difference between how individual drivers identify the bicyclist after a TOR while driving in a L3 autonomous vehicle. The primary findings based on the research are:

- *RQ5: Is the visual attention of a right-turning driver influenced by the proximity of the TOR to a signalized intersection?* Drivers who received a TOR closer to the intersection identified the bicyclist earlier than drivers who received a TOR farther from the intersection. As the drivers received a TOR closer to the intersection, they were more likely to fixate on the bicyclist for a longer period of time.
- *RQ6: Is the visual attention of a right-turning driver at a signalized intersection influenced by driver involvement in a secondary task prior to a TOR?* There was a significant effect of driver involvement in a secondary task prior to a TOR on the visual attention of a driver. Drivers on average took longer to identify the bicyclist when they were playing a game prior to the TOR and fixated on the bicyclist significantly less.

5.3. Limitations

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. However, there are limitations associated with this work, including the following:

- Like most within-subject study designs, there is a limitation associated with possible fatigue and carryover effects, which can cause a participant's performance to degrade over the course of the experiment. The magnitude of these effects were limited by randomizing the presentation of grids to different participants and keeping the length of the drive brief.
- The number and levels of independent variables that were investigated were limited by the total drive time. In particular, only one secondary distracting task was introduced and there were only three different levels of the TOR time variable. In addition, the length of the TOR alert was kept constant at three seconds. There may be more variation in this alert time in real L3 vehicles based on the performance of the vehicle sensors. The geometry of the roadway was also kept constant throughout the experiment, with participants only experiencing one environment and roadway cross section.
- For many participants, this was their first experience driving an AV. Perhaps with more driving L3 AV experience, participants would exhibit different driving behavior.
- Although efforts were made to recruit a sample of drivers similar to the driving population in the State of Oregon, the final sample was skewed slightly younger.

5.4. <u>Future Work</u>

As mentioned in the literature review, this area of human factors research is relatively uninvestigated, yet is crucial for understanding the safety implications of L3 AVs in urban environments. A few suggestions for future work include:

- To address additional variation in independent variables, including different distracting tasks, increasing variation in TOR alerts, or increasing variation in bicyclist behavior. The secondary task could also be offered optionally instead of prescriptively to drivers in future studies to determine at what thresholds they would feel comfortable engaging in a secondary task.
- Driver perception of automation could be more fully investigated to determine if drivers would feel comfortable using this type of automation in their personal vehicle. This could include varying the time between scenarios as a variable to determine a threshold for the number of TOR that a driver would be willing to endure to achieve the benefits of using automation.
- Similar scenarios could be examined from the perspective of a bicyclist. Using driving simulation, a 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 human bicyclist.

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