Investigating the Impact of Buffer Time on Driving Behavior in Autonomous Intersections

by

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THESIS ABSTRACT

With the emergence of Autonomous Vehicles and the advancements in smart systems, autonomous traffic management continues to gain more attention in the modern transport networks. The introduction of autonomous vehicles into the real world, however, requires the use of control algorithms that can handle different road scenarios. One such practical scenario is Intersection Management (IM), which enables autonomous vehicles to enter an intersection from various directions simultaneously without collision. Prior research studied various factors affecting the quality and duration of taking over the control of autonomous vehicles when a system boundary is reached and the driver is out of the loop. However, no study investigated the effect of buffer time on the quality and duration of autonomous vehicle take-over when a system failure occurs just prior to an intersection. The objective of this study is to examine the impact of buffer time on driving behavior in terms of duration and quality of take-overs before, during, and after Take-Over Request (TOR) upon a system failure in level-3 autonomous vehicles prior to intersections while the driver is involved in a secondary task. To achieve this objective, a driving simulation environment with an autonomous intersection manager was set up, and 13 young drivers were asked to take-over the control of simulated autonomous vehicles, which were programmed to randomly fail either 3 or 7 seconds prior to intersections. The results indicated that buffer time has a statistically significant impact on the timing of taking control of autonomous vehicles. However, it does not have a statistically significant effect on how fast the driver returns to the driving position, or the quality of the take-overs in terms of breaking pattern and keeping the vehicle straight in its designated lane.

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1. Introduction

With the rise of technological advancement, the use of autonomous machines that are independent of the human being is no longer a fictional, but a factual phenomena that is soon finding its way into the real world. Technological advancement in artificial intelligence and Intelligent Transportation Systems (ITS) point to a future in which vehicles will handle a significant portion of the driving tasks themselves with little to no human control. The primary focus of ITS according to Au et al., is the integration of modern technology with vehicles and transportation infrastructure to enhance the efficiency, safety, and cost of transportation [1]. Developing fully autonomous vehicles will play a vital role in reducing the unnecessary rise in government budget due to transportation cost and traffic collisions. The autonomous driver agent will calculate distances and velocities accurately, monitor its surroundings and react instantly to situations that would be difficult for humans to maneuver.

Currently, various versions of autonomous vehicles are being tested in various cities within the US and around the world. The range of autonomous vehicles is defined on a five level continuum by the National Highway Traffic Safety Administration with different autonomy functionalities implemented at different levels [2].

At level 0, the lowest end of the continuum, the vehicle has no automation, and at level 4, the highest end of the continuum, the vehicle has full automation, where the driver is not expected to monitor the roadway under any condition. At level 2, the vehicle takes the responsibility of some main driving functionalities while sharing authority over some other tasks with the driver, and the driver is expected to continuously monitor the roadway and take-over control immediately as needed.

At level 3, the vehicle is able to take full responsibility over the control of the vehicle, and the driver is allowed to be free of roadway monitoring and to focus on the traffic, but expected to be ready to take-over control upon warning, called Take-Over-Request (OTR) [1]. This warning request is prompted when a system boundary (under certain traffic and environmental conditions such as high traffic density, accident on the road, roadway construction, ambiguous environment, a stationary obstacle on the road, an animal jumping in front of the vehicle, etc.) is reached or system failure occurs (due to software or hardware issues including sensor or actuator issues), upon which the driver is expected to take-over the control of the vehicle [3]–[5]. The driver is provided with certain transition or buffer-time following a TOR before taking-over the manual control of the vehicle.

1.1. Autonomous Intersection Management

Semi-Automatic Intersection Management (SemiAIM) intersection control systems [1] are created to accommodate various vehicle types to utilize reservation request protocols (RCP) at intersections. Upon receiving a reservation request from the vehicle agent, FCFS simulates the trajectory of the approaching vehicle based on the parameters of the request. If the requesting vehicle occupies a reservation that is already made by another semi-autonomous vehicle or by a human-driven vehicle, then the policy rejects the reservation request; otherwise, it accepts the request and reserves the space for the time and duration for the vehicle [1]. The manager then communicates to the driver agent by sending a confirmation message. This system, therefore, helps identify whether it is safe to allow a vehicle to cross the intersection or not.

RCPs in SemiAIMs are implemented by Intersection Managers (IMs) to help vehicles process traffic data and communicate with the control system using a speed control device in all vehicles. When a vehicle approaches an intersection, it makes a space-time reservation with an IM which simultaneously receives information about the vehicle’s size, speed, and lane. With this, IM calculates the trajectory of vehicles involved, verifies possible conflicts, decides whether to accept or reject the offer and suggest alternatives. Vehicles with accepted reservations enter the intersection. Use of IMs for traffic navigation helps vehicles interpret and respond to traffic to enter an intersection easily from various directions without collisions [1].

SemiAIM systems have been reported to produce smaller delays in intersections compared to conventional intersections with vehicles driven by humans. On average, vehicles passing every 3 seconds at conventional traffic signals encounter about 5-second delay, whereas SemiAIM systems reduce this to less than a second [1] for a more efficient and safer traffic for all vehicles.

1.2. Problem Statement and Research Questions

Since the driver is free to pay attention to other tasks at the time of the TOR, the he/she will not be aware of the traffic situation or will be out of the loop when a TOR is prompted. The driver’s out-of-loop status coupled with visual and/or cognitive distraction with a secondary task leads to deterioration in the driving performance as it will impact the duration and quality of the driver’s take-over [6], [7].

The take-over in autonomous vehicles has been investigated by prior research work to identify the main factors and their impact. However, the impact of buffer-time in intersections has not been addressed yet. This study investigates the impact of buffer-time of TOR (3 and 7 seconds) on the duration and quality of take-overs when a system failure in a level-3 autonomous vehicle occurs just prior to intersections while the driver is involved in a secondary task and is out-of-the loop. The objective of this work is to answer the following research questions:

- Will shorter buffer-time of TOR (3 seconds compared to 7 seconds) lead to less take-over time?
- Will shorter buffer-time of TOR (3 seconds compared to 7 seconds) decrease take-over quality?

2. Literature Review

Factors affecting take-over time and quality when a TOR is initiated while the driver is involved in a secondary task and is out-of-the-loop have been studied by researchers. These factor included type and nature of secondary tasks, traffic density, buffer-time, visual information prompted for the TOR, and TOR modality [6].

For example, [8] investigated the effects of a secondary task on the timing and quality of takeover performance, and found that the secondary task the drivers were involved in during TOR had no statistically significant impact on the quality and timing of take-overs. [4], [7] explored the influence of traffic density on drivers' take-over performance, and reported that higher traffic density was shown to negatively affect take over performance. [4] reported poorer takeover performance with a high traffic density of approximately 30 vehicles per kilometer in the neighboring lane. [7] examined the effect of different traffic densities on the take-over process, and reported that drivers' behaviors are negatively affected by high traffic density during a TOR in terms of mean take-over times, time to collision, longitudinal accelerations, and number of collisions occurred.

[8] explored the effect of buffer-time on take-over performance, and reported that with shorter buffer-time (5 seconds as compared to 7 seconds), the subjects come to a decision more quickly, reacting faster, but the quality is generally worse since gazes in mirrors and shoulder checks decrease, the accelerations increase, and the brake is used excessively with a high collision risk. [9] studied whether a short buffer-time of four seconds is sufficient for drivers to recognize the subtle cues that may indicate a potentially hazardous situation after they have been out-of-the-loop while not driving, and found that the drivers need at least 7 seconds to locate other vehicles properly in a novel traffic scene.

[10] studied the effect of the amount of visual information given to the drivers at the time of TOR on how quickly they were able to resume manual control, and found that less information lead to slower take-over times. However, there was no statistically significant effect on drivers' timing of collision avoidance maneuver. The results suggested that take-over time and quality of collision avoidance response appear to be largely independent of visual information provided for TOR, and while long take-over time did not predict collision outcome, kinematically late TOR did.

[5] investigated the effects of TOR modality (auditory, vibrotactile, and auditory-vibrotactile) on drivers' responses (i.e., steering, braking, and lane change). The study reported that auditory-vibrotactile led to significantly faster steer-touch times than the other two TOR modality (auditory or vibrotactile). The results also showed that there was no statistically significant difference between TOR modalities on brake times and lane change times.

2.1. Missing Work

Although the aforementioned studies looked into factors affecting the quality and duration of take-overs including the effects of various buffer-times, no prior study looked into the effects of buffer time when a TOR is prompted just prior to an intersection. Previous research studied TOR prompts occurring in road sections where there is less needed to communicate and/or interact with other drivers in order to avoid accidents.

A system failure prior to an intersection would be a grave issue because approaching an intersection is considered to be a multi-task situation where the driver needs to interact with other drivers while attempting to take-over control of the vehicle [11]. The rate of accidents at intersections was reported to be high as a result of the increased traffic-related information, signs, and lights the driver is expected to pay attention to, comprehend, and process prior to intersections as compared to other parts of the roads.

When TOR occurs right before an intersection, the situation would be hazardous and life threatening, and the possibility of a fatal crash would be at a maximum. Intersections are dynamic traffic situations [11] and common traffic zones for accidents [12], and they require multi-tasking (vehicle control and interactions with other drivers) and higher attention of drivers. When approaching an intersection, drivers need to both manage and anticipate interactions with other road users, and keep control of the vehicle [11].

Intersections are dangerous road sections representing a traffic situation and complexity that have not been studied to see how TOR time affects the quality and duration of take-overs. Therefore, it is paramount to examine safe buffer-time prior to intersections, which is the objective of this experimental study.

3. Experimental Setup

3.1. GMOST

The study was conducted using multi-player driving simulator, called GMOST. The simulator is built on a 3 by 3 miles terrain. The terrain is populated by traffic roads, signs, residential areas, office buildings, trees, and other environmental objects that simulate real traffic environment. The roads were acquired from Esayroads3d, which was imported from the Unity Terrain Tools website. Some of them have 2 lanes with 25 mph speed limit while others have 4 lanes and 45 mph speed limit. Traffic signals and stop signs at intersections were eliminated, and replaced by intersection managers. About 50 to 120 autonomous vehicles were developed and integrated into the simulation. They were spawned at various points in the environment with random destinations. Four autonomous vehicles are spawned at once and spawning of these vehicles continuous at a frequency of 30 seconds until a threshold is reached, then spawning stops. When the vehicles reach their destinations, they are rerouted to new destinations. Routing is based on A^* path search algorithm [36]. A* path search package was imported from Unity assets store, and it uses waypoints to search the shortest path to destinations. The script in the package was modified to set up reasonable speeds for this game. The traffic density was set to be high where the vehicles are spaced at 100 m from each other with a 4-second gap [11] in all directions. Autonomy of the vehicles is turned off when the 'driver' either presses the brake pedal more than 10% depression or steers to deviate by 2 degrees. Also, the autonomy could be turned on and off by pressing a button on the steering wheel.

The intersection manager works on a first-come first-serve basis depending on the approaching vehicle's speed and distance to the collider at the intersection. The traffic lights and stop signs were not used to control the intersections. Instead, Unity game object colliders were placed at each intersection to create an independent intersection manager that detects the order of the vehicles and makes decisions about the orders of passes. The intersection manager stores the intersection name and ID, and it consists of different software modules that are responsible for coordinating the traffic, detecting passing vehicles, and communicating with vehicles. Each intersection manager has a border area to monitor. To enhance safety, the intersection manager was programmed to handle two scenarios. The first scenario is when there is no driver involved~~,~~ where the intersection manager adds the vehicles to a queue and allows them to pass one by one as a normal passing situation. The second scenario is when both vehicles, with and without a driver, approach the intersection to make a pass. In this case, the vehicle with a driver is added as a special case to the intersection manager and warning messages are sent to the other AI agents within the intersection. The first vehicle to arrive has the priority to pass without stopping at the intersection while the other vehicles wait for who is next in the queue to pass. When the driver manually disengages the automation, he/she will have to take full control of driving the vehicle and follow the intersection manager's instructions, which would be either pass or stop.

All AI Agents including the driver vehicles have a ray-cast feature that is mounted on their vehicles to monitor any pedestrians crossing the road and to detect AI vehicles speed, distance, and direction. This feature helps to avoid accidents by making some space between vehicles to be more realistic. The ray-cast can be adjusted as required based on the length of the detection line. When an autonomous vehicle fails and becomes manual for its driver to take control, the existence of this manual vehicle is detected, and a visual message is presented on its dashboard to inform the driver about its order of turn to proceed. Therefore, the first agent or driver projected to arrive at the intersection is given the priority to proceed at the intersection. The others wait until it is their turn to proceed.

Right angle intersections were created in GMOST, which were situated at approximately every half a mile within the environment. The intersection manager informs the vehicles of their turn (proceed or stop) via a visual color reflected on their dashboard about 155 meters prior to intersections.

The physical equipment used for the simulator consists of a metal frame (Volair Sim Cockpit Chasis) to mount three LCD screens (LG 29” IPS LED FHD 21:9 UltraWide FreeSync Monitor), driver seat, and steering wheel as well as gas and brake pedals (Logitech G920 Driving Force). The front and side views of the environment were presented through three mounted LCD screens (Figure 1). The middle LCD screen represents the front windshield and dashboard. The dashboard has a directional arrow, the text messaging window, visual info for the order of pass, speedometer, and a visual TOR warning for system failure. With three LCD screens, the ‘driver’ has 180 degrees field of view. A rearview mirror was placed to provide rear visibility, and side mirrors were implemented to show side views. Road noise and engine noise were played back via speakers.

Figure 1: The physical equipment used for the simulator

3.2. Text Messaging as a Secondary Task

A text messaging system as a secondary task was designed and implemented into GMOST. Texting was chosen as the secondary task because texting while driving has been reported to have the most negative impact on driving performance as it involves all three type of distractions: cognitive, manual, and visual [37], [38]. With more frequent and longer glances off-the-road as well as at least one-hand off the wheel, texting while driving has the greatest probability of leading to an accident [39]. National Safety Council research indicates that cell phone use and texting while driving cause at least 28 percent of all traffic accidents in the USA [40]. This is a specially greater concern for young and inexperienced drivers (generally defined in this context as novices) because texting while driving is widespread among high school and college students ranging between 15-24 year-olds in age, over 70% of whom text while driving [38], [41], [42].

Text messages as secondary tasks in the form of questions were sent to the participating drivers and presented in a 200 by 400 pixels screen on the far right of the dashboard at the bottom right corner of the front-view, below the windshield. A total of 60 Distractive Messages (DM) inquiring responses were developed, and digitally stored. The system is designed to send one of these randomly selected messages with a 4-seconds time-gap in between the messages responded and received. The driver is expected to select one of the four multiple choices to each DM. To read and answer these DMs, the driver has to take his/her eyes off the road to be able to respond to messages.

3.3. System Failure and Buffer-time

Participants were instructed that they would need to take-over control of the vehicle if a sudden system failure occurs. For each participant, approximately 15 number of system failures occurred, and these failures occur when the autonomous vehicle is 7 seconds, or 3 seconds away from an intersection depending on the speed of the autonomous vehicle when the TOR occurs. 7and 3 seconds were chosen as two different buffer-times based on prior research. In prior research, it was found that 7-second buffer-time needed by drivers to locate other vehicles properly in a novel traffic scene [43], 4 seconds are too short and 6 seconds are sufficient [9], novice drivers need at least 8 seconds to become fully situational aware and take control of an autonomous vehicle after being out of loop [44], and older and more experienced drivers were reported to be in need of 6 seconds to become fully situationally aware and take control of an autonomous vehicle [45]. Therefore, there is no agreed upon buffer-time in literature for an optimal TOR in general, and no research has been done to investigate different buffer-times when autonomous vehicles fail prior to intersections.

3.4. Take-over Request (TOR)

In this study, two types of take-over request (TOR) modality were given; auditory and visual. The auditory TOR consisted of double high-pitched beeps (240 ms beeps of 2800 Hz with a 100 ms interval in between) according to guidelines of NHTSA for crash warnings [5], [46] and Visual TOR was given by a warning message on a red background with 'SYSTEM FAILURE!' text printed on it and presented on the instrument panel. The sounds were produced from left and right speakers located on both sides of the simulators.

3.5. Participants

13 drivers (10 male and 3 female aged 20–38 years) participated in this experimental study. They all had normal vision and valid state driver's licenses for at least 3 year(s). The autonomous vehicles had system failures randomly occurring at either 7 or 3 seconds before some intersections. Therefore, all participants received random instances of two buffer-times; 7 seconds (7SG), 3 seconds (3SG), and again randomly no system failure (NFG). Each participant receives an approximate number of 7 seconds (7SG), 3 seconds (3SG), and no system failure (NFG).

4. Experimental Procedures

The study took place in two days, where 13 sessions were conducted and each session lasted for one hour. The participants drove 25 minutes in each session. At the beginning of each session, participants were given instructions regarding the purpose of the experiment, and provided with a brief training about GMOST including the autonomous vehicle with its dashboard, speedometer, text-messaging system, the traffic, TORs, and intersection manager indicating the right of way for the autonomous vehicle. Participants were also trained on how to control the steering wheel and accelerator and brake pedals when the autonomous system fails.

Participants were seated in the simulator, where they were able adjust the seat and steering wheels. Then, the participants were asked to ride the autonomous vehicle for 3 minutes to be familiar with it, and drive from point A to point B, which were designed to take about 25 minutes to drive.

Participants were told that the autonomous vehicle functions perfectly, they do not need to monitor the roadway, and they are encouraged to engage in the secondary task, reading and responding to the text-messages. A text-message was presented to them every 4 seconds.

The participants were told that they can manually disengage the automation by steering, braking, or pressing a button on the steering wheel. Participants were instructed that when a TOR is provided, they have to take the steering wheel with both hands and follow the instructions of the intersection manager, which would be either pass or stop. If they were not given the right of way, participants were asked to press the brake to stop at the intersection, and then proceed when provided with a green light on the dashboard indicating that they are given the right of the way.

If they were given the right of the way after the TOR occurred when they got closer to the intersection, they were asked to take control of the wheel as well as the gas pedal as to continue driving the autonomous vehicle and pass the intersection at or closer to the speed prior to the TORs. They were asked to drive the vehicle as if they are in real traffic.

4.1. Data Collection

4.1.1. Take-over Time

Two measures were taken to calculate take-over time, which are first-contact-time and take-control-time. First-Contact-Time (FCT) is the time in milliseconds between TOR and hands-on steering wheel, press on the brake or gas pedal, which is considered a measure of motor readiness [6]. FCT is the time between the TOR and the moment when the hands steer the wheel by greater than 1 degree [5] or the brake or gas pedal is pressed to more than 0% [5], whichever comes first indicating how long it takes the driver to return to a driving position. During automated driving, the steering wheel does not move, and an absolute steering of 1 degree is the minimum value that can be reliably attributed to human input [5]. Similar to the steer touch reaction time, brake or gas pedal depression greater than 0% represents the initial movement of the brake or gas pedal [5]. If the autonomous vehicle is given the right of the way through a green light as reflected on the dashboard, pressing on the gas pedal would be a reasonable behavior to keep the vehicle at a steady speed until it is time to slow down for a smooth transition towards the intended lane at the intersection.

Take-Control-Time (TCT) is the time in milliseconds between TOR and the first measurable brake/gas pedal or steering wheel response to the situation [8], which is defined by 10% for brake/gas pedal position or 2° for steering wheel angle [4], [6]. TCT was recorded based on whether the autonomous vehicle was directed to stop or given the right of way to proceed into the intended lane at the intersection by the intersection manager. If the vehicle was given the right of way, then TCT was calculated as the time in milliseconds between TOR and first measurable press (10% or greater) on gas pedal or steering wheel movement (greater than 2 degrees). If the vehicle was directed to stop at the intersection, TCT was calculated as the time in milliseconds between TOR and first measurable press (10% or greater) on the brake pedal. As soon as the driver's input exceeds one of these thresholds, it is considered to be an overt maneuver and recorded as TCT [4].

4.1.2. Take-Over Quality

Take-over quality was calculated via **Maximum Longitudinal Deceleration (MLD)** and the standard deviation of lateral position (SDLP). Maximum Longitudinal Deceleration (MLD) MLD was used to figure out how well the driver decelerated when coming to a stop at the intersection or slowing down for a smooth transition at the intersection to the intended lane; quickly and abruptly, smoothly, or fluctuated braking. An expected and careful driving behavior would be decelerating smoothly, releasing the gas pedal, letting the vehicle roll, and pressing the brake pedal gently to come to a standstill at the stop line if the vehicle was directed to stop or to slow down for a smooth transition at the intersection if the right of way was given as compared to risky driving behavior that would be continuing driving at high speed through the intersection or braking harshly at the end with a strong deceleration for a shorter period of time to stop [37]. Better take-over quality behavior to safely control the vehicle would be exhibiting smoother velocities.

MLD was calculated by measuring maximum deceleration m/ s2 (time to stabilize the vehicle) [4] as the driver's braking velocity behavior starting with TCT leading to the intersection. To calculate MLD, the interval, which is the difference in distance from the time when the vehicle starts to decelerate (x_0) until the vehicle stops decelerating (x_1). Then, the deceleration, as seen in the formula below, is calculated by dividing the interval by the difference-in-time between the time the participant first starts decelerating until the participant stops decelerating.

$$\textbf{Deceleration} = \frac{\boldsymbol{interval}}{\boldsymbol{t}^{\ \ \mathbf{2}}}$$

The mean of all decelerations for both buffer-times (3 and 7 seconds) was taken to calculate the MLD. The higher the MLD, the faster the break and the harder the breaking pattern. Any deceleration less than a second is ignored due to not being indicative of a stop or braking pattern.

Standard Deviation of Lateral Position (SDLP): is a measure of keeping the vehicle within the allocated lane, and it is considered to be a sensitive parameter for vehicle control and traffic safety [48]. Therefore, SDLP in this study is used as another indicator of good driving behavior. The lateral position is calculated using horizontal and vertical coordinates, indicating the center of the lane the vehicle is in as well as the position of the vehicle. After the perfect driving line is calculated, and the vehicle's position is determined, the closest distance to the line is calculated representing the lateral position of the vehicle. The standard deviation of all the lateral position measurements indicates how much the driver swerved. The higher the number, the more the vehicle deviates from the lane.

SDLP is calculated a little differently depending on whether the vehicle is given the right of way, and the direction the vehicle takes at the intersection. There are three scenarios when the vehicle is given the right of way; straight through an intersection, making a right turn, or making a left turn.

a. SDLP when Making Turn:

Making a turn in the intersection requires the driver to exhibit more sensitive control over the vehicle through the intersection. Right and left turns are measured in the same way. The take-over quality when making a turn will be judged based on the steering data which ranges from -1 to 1 indicating the wheel being turned all the way to the left at -1 or all the way to the right at 1. A perfect turn is approximated as a cosine wave, indicating that the turn started slowly, the wheel is then rapidly adjusted to a peek, then returned back in a similar way when the turn is complete. A perfect cosine wave was approximated for each turn and the participants turn was evaluated against it using a common curve fitting method known as Root Mean Square fit. This gives an error measurement indicating the difference from a perfect turn. A single error measurement was calculated for each turn and this error represents the turn smoothness. The mean and standard deviation of the smoothness was calculated for each participant so it can be compared across the different fail times. This idea follows a similar idea from [49] where once the data was collected a regression analysis was used to identify the influence of the curve radius on the SDLP to determine what size ramp would be the best.

SDLP when the vehicle makes a left and right turn is calculated by looking at the smoothness in the steering data. For this, an optimal turn is defined, then each turn is compared against it to find the error for each turn. The lower the error, the smoother the turn. A perfect turn will be defined as a cosine wave, turning the wheel slowly at the start, then more rapidly until the max, and then back in the same way. Understeering and oversteering are indicated in the error as it further deviates from the cosine curve as the participant is correcting and turning the wheel. To find the turns to compare against, the start of the turn, the peak of the turn and the duration are found. Then, using cosine interpolation a cosine wave is found from the initial point to the peak, then back from the peak turn amount to straight again. This gives the estimated perfect turn that is used to calculate error for the turn. To calculate error, the Root Mean Square Error is used as follows:

$$\text{Error} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}}$$

b. SDLP when Straight Through:

SDLP is the most indicative of having control over the vehicle when going straight through the intersection. A higher SDLP indicates lower quality take-over (the driver did not stay straight and may have gone outside of the lane often) as opposed to lower SDLP indicating higher quality take-over. To calculate SDLP, 3 main pieces of information are considered: the vehicle's location, the coordinates of the perfect path, and the distance from the vehicle to the perfect path. The lateral position was calculated for each point of data in the drive, then the standard deviation of the lateral position data was taken as an indicator of how well the participant have control over the vehicle and stays within the indicated lane.

The driving data is submitted from GMOST via POST requests to a nodejs server where the data is processed and stored in a to a mongoDB database. Data is processed and visualized via a web interface (Figure 2).

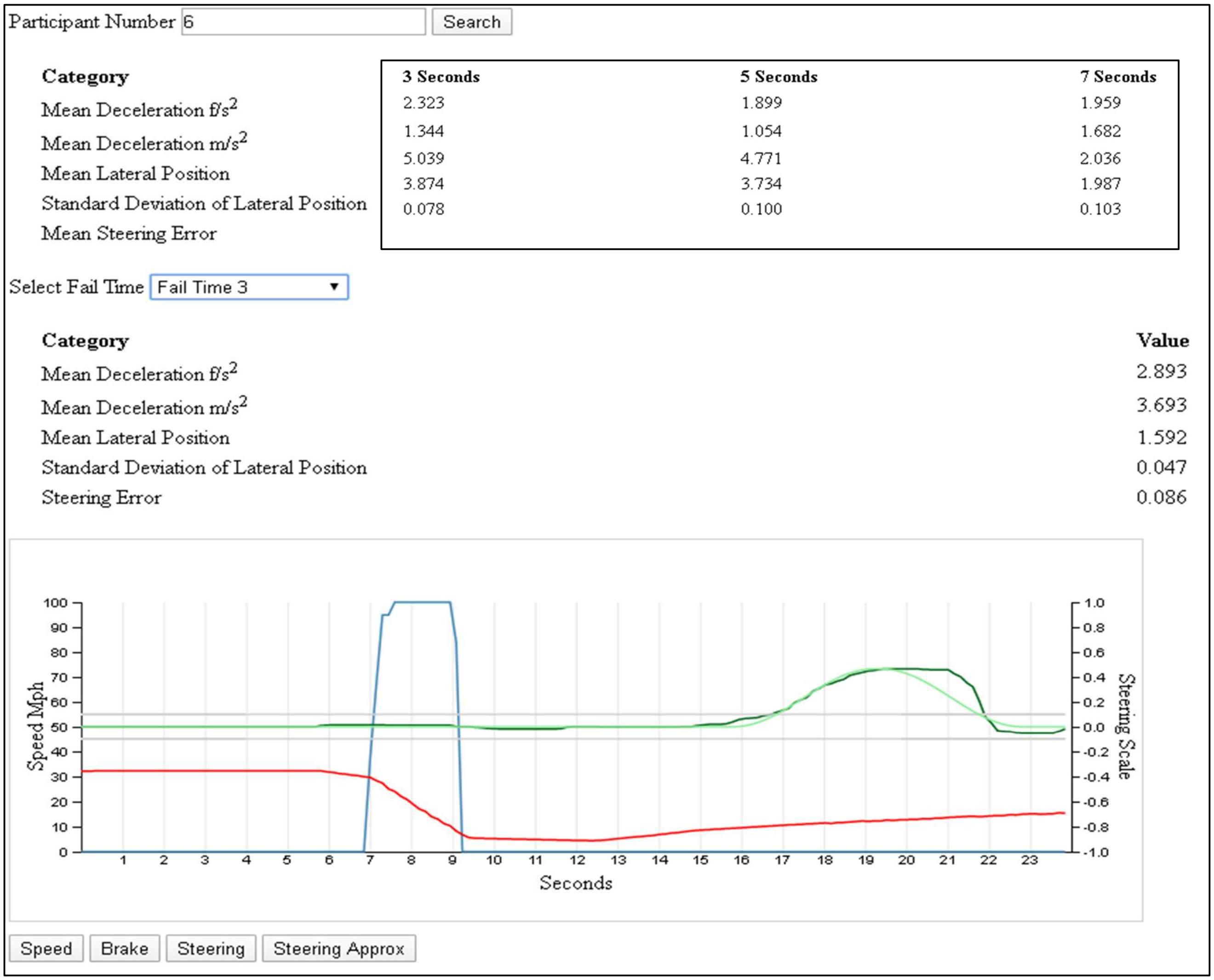

Figure 2: The web interface for looking up participant data and viewing individual fail times

4.2. Data Analysis

In this study, we compared two groups (independent variables), 7 seconds (7SG) and 3 seconds (3SG), on two constructs, which is the driving behavior in terms of duration and quality of take-overs. To analyze the effect of buffer-time on driving behavior, we conducted MANOVA analyses for the duration of take-overs and quality of take-overs. This method was chosen because the experiment will affect all dependent variables separately and in combinations with each other, the dependent variables share a common conceptual meaning from different dimensions, and it will be possible to account for the interaction of the dependent variables with each other for each construct. The level of significance (alpha) was set at .05 level. Pillia's T was used to determine overall multivariate significance of dependent variables on the groups.

Driving Behavior:

Duration of take-over is measured by FCT and TCT, and quality of take-over is measured by MLD and SDLP, which are four dependent variables related to driving behavior. One MANOVA analysis was ran with two independent (7SG and 3SG) and four dependent variables (FCT, TCT, MLD & SDLP), and two more MANOVA were run; one for the duration and another for the quality of take-overs. MANOVA was used to compare the groups on each dependent variable individually as well as all of them together as one single construct. The scoring of driving behavior data was done by the same raters using the same rubric. For all MANOVA and ANOVA, the significance was set to .05.

5. Results & Discussions

The purpose of this study is to examine the effects of buffer-time on driving-behavior in terms of duration and quality of take-overs in a level-3 autonomous vehicle when a system failure occurs before an intersection while the driver is involved in a secondary task and is out-of-loop. Table 1 shows the mean and standard deviation values for FCT and TCT measuring the duration of take-overs, and the mean and standard deviation values for MLD and SDLP measuring the quality of take-overs by all participants across both groups (3SG and 7SG).

First-Contact Time (FCT) measured drivers' motor readiness, indicating how ready the driver is to return to a driving position. As seen in Table 1, FCTs, in milliseconds, were lower with participants in 7SG than participants in 3SG. This indicates participants in 7SG were quicker to return to a driving position than the ones in 3SG. Take-Control-Time (TCT) is the time it takes for drivers to take control of the autonomous vehicle after a system failure. As seen in Table 1, participants in 3SG had lower TCT values than participants in 7SG, indicating a faster response in taking control of the autonomous vehicle than participants in 7SG.

When the means for both FCT and TCT were compared, while participants in 7SG were faster to return to a driving position, participants in 3SG were faster to take control of the vehicle. This could be because the participants in 3SG were closer to the intersection at the time of the TOR (3 seconds), prompting an urgency in them to quickly take control of the vehicle before the vehicle reaches the intersection uncontrolled. In the same way, participants in 7SG were slower in taking control of the vehicle because they felt there was sufficient time and distance to the intersection, and there was no need to hurry in controlling the vehicle.

Maximum Longitudinal Decelerations (MLDs) were calculated to measure how well the driver decelerated. The lower is the MLD value, the higher quality or smoother is the deceleration. As seen in Table 1, participants in 7SG had a lower MLD than the ones in 3SG. As expected, **participants in 3SG had harder break patterns with higher MLD values indicating lower deceleration quality**. This could be because participants in 7SG with sufficient time and distance to the intersection were able to break smoother than participants in 3SG.

Standard Deviation of Lateral Positions (SDLPs) were calculated to measure how well the drivers kept the vehicle straight within their allocated lanes. The lower is the value, the better is the take-over quality. As seen on Table 1, although the mean values are almost equal, participants in **3SG had a slightly lower mean SDLP score than participants in 7SG,** indicating a little straighter pattern for participants in 3SG than participants in 7SG. This was not expected. The participants in 7SG would be expected to have a straighter lateral driving pattern with better mean SDLP value than participants in 3SG. This could be contributed by the fact that as the length of the drive gets longer, it may be more difficult to keep the vehicle at the same level of straightness, which could be easier in short distances. Therefore, the straightness value of the lateral position of the vehicle may be impacted by the distance the participants drove after the TORs.

Table 1: Means and Std. Deviations for Duration (FCT & TCT) and Quality (MLD & SDLP) of Take-Overs

Groups	MFCT	SFCT	MTCT	STCT	MMLD	SMLD	MSDLP	SSDLP	N
3SG	2572.69	1250.67	6115.97	4608.08	2.65	2.48	1.49	2.13	119
7SG	2314.81	1308.30	8775.93	7662.19	2.50	1.67	1.50	1.94	81

Note. MFCT: Means of First-contact time; STCT: Standard Deviation of Take-control time; MMLD: Means of Maximum longitudinal deceleration; SSDLP: Standard Deviations of Standard deviation of lateral position

In sum, based on the descriptive statistics, participants in 7SG were faster to return to driving position and had a better breaking behavior than participants in 3SG. On the other hand, participants in 3SG were faster to take control of the vehicle, and had a slightly better behavior in keeping the vehicle straight within the allocated lane.

A multivariate analysis of variance was conducted to assess if the two groups (7SG and 3SG) were different on the duration (TCT and FCT) and quality (MLD and SDLP) of take-overs when considered together. The box's test of equality of covariance matrices showed that observed covariance matrices of the dependent variables are not equal across groups (sig. .000). The population variances for the groups as well as the population covariance matrices for the dependent variables are considered to be equal if the group sizes are approximately equal as calculated by largest/smallest < 1.5 [39, p. 220], which, in this current study, is 1.47 (119/81). Therefore, the homogeneity of variance assumption is considered to be met.

As seen in Table 2, the multivariate analysis showed a significant difference between groups when all four dependent variables considered together (Pillai's T = .051, F = 2.6, p=.037, multivariate eta squared = .051). It should be noted that the power was .724, that is, the chance of rejecting the null hypothesis was 72% when in fact the null hypothesis should have been rejected. This result suggests that participants in the two groups (3SG, 7SG) were statistically significantly different when the quality and duration of take-overs considered together. Examination of the coefficients for the linear combinations distinguishing the two groups indicated that FCT (Eta squared = .042, p = .003) contributed statistically significantly to distinguish the two groups while TCT (Eta squared = .01, p = .162), MLD (Eta squared = .001, p = .638) and SDLP (Eta squared = .000, p = .958) did not.

Table 2: Comparison of Mean Values of FCT, TCT, MLD, and SDLP across Groups

Groups	Value	F	Sig. (alpha=.05)	Partial Eta Squared	Observed Power
Pillai's T	.051	2.6	.037	.051	.724

Note. FCT: First-contact time; TCT: Take-control time; MLD: Maximum longitudinal deceleration; SDLP: Standard deviation of lateral position

P < .05

Two additional multivariate analysis of variances were conducted to assess if the two groups were different on the duration of take overs (TCT and FCT considered together), as well as on the quality of take-overs (MLD and SDLP considered together). As seen in Table 3, the multivariate analysis showed a statistically significant difference between groups on the duration of the take-overs (Pillai's T = .05, F = 5.18, p=.006, multivariate eta squared = .05). However, there was no statistically significant difference between the groups on the quality of take-overs (Pillai's T = .001, F = .11, p=.896, multivariate eta squared = .067). These results suggest that groups were statistically significantly different on the duration of the take-overs while they were not statistically significantly different on the quality of the take-overs.

Table 3: Comparison of the Mean Values of FCT and TCT across Groups

Groups	Value	F	Sig. (alp.=.05)	Partial Eta Squared	Observed Power
Duration (TCT & FCT) - Pillai's T	.05	5.18	.006	.05	.824
Quality (MLD & SDLP) - Pillai's T	.001	.11	.896	.001	.067

Note. FCT: First-contact time; TCT: Take-control time

P < .05

To find out how much each dependent variable (FCT and TCT) contributes to the difference in the duration of take-overs, follow up one-way ANOVAs were conducted. The result of the analysis indicated that FCT was statistically significantly different between 7SG and 3SG groups. Post hoc test with LSD showed that participants in 7SG took control of the vehicle statistically significantly slower than the participants in 3SG (F = 8.76; Sig. = .003; Eta squared = .042).

Other than FCT, there was no statistically significant difference on any of the other dependent variables as seen on Table 4: TCT (F = 1.974; Sig. = .162; Eta squared = .010), MLD (F = .222; Sig = .638; Eta squared = .001), and SDLP (F = .003; Sig. = .958; Eta squared = .000). The eta squares are telling us that only 4.2%, 1%, .1%, and 0% of the variability in the TCT, FCT, MLD, and SDLP values, respectively, for a participant is attributed to group membership (3SG and

7SG). This means the group membership does not define the change in the TCT, MLD, or SDLP values.

Table 4. Independent One-way ANOVA on FCT, TCT, MLD, and SDLP Dependent Variables

Dependent Variable	F	Sig.	Partial Eta Squared
First Contact Time (FCT)	8.767	.003	.042
Take Control Time (TCT)	1.974	.162	.010
Mean Longitudinal Deceleration (MLD)	.222	.638	.001
Standard Deviation of Lateral Position (SDLP)	.003	.958	.000

Computed using alpha = .05

These results showed that the driver behaved statistically significantly differently in terms of the combination of the duration and quality of take-over when the TOR is prompted early (7 seconds) as compared to when the TOR is prompted late (3 seconds) due to a system failure in a level 3 autonomous vehicle prior to intersections. The results also suggest that duration of the take-over was statistically significantly different when the TOR is prompted early than when it is prompted late. The driver is statistically significantly slower to take control of the autonomous vehicle when the TOR is prompted 7 seconds prior to intersections than when the TOR is prompted 3 seconds prior to intersections. The buffer-time does not make difference in the quality of take-overs in terms of breaking and lateral lane-keeping patterns, and well as the pace of returning to a driving position after a TOR upon a system failure in a level-3 autonomous vehicle prior to intersections.

6. Conclusions

The data collected and analyzed in this experimental study showed that buffer-time (3 and 7 seconds) had a statistically significant impact on the combination of duration and quality of taking-over the control of level 3 autonomous vehicle upon a system failure before an intersection. The data showed that, the driver takes over the control of the vehicle statistically significantly faster when the TOR is given 3-seconds prior to an intersection as compared to when the TOR is given 7 seconds prior to an intersection. This could be explained by the urgency the driver may have felt in controlling the vehicle when the vehicle is closer to an intersection upon a TOR. The same level of urgency to control the vehicle may not have been felt by the driver when the TOR is given 7 seconds prior to the intersection with a longer distance and time to the intersection. This result is congruent with the research study by [8], who reported that the subjects come to a decision more quickly and react faster with shorter buffer-time (5 seconds as compared to 7 seconds).

However, the buffer-time did not have statistically significant effect on how fast the driver returns to the driving position, or the quality of the take-overs in terms of breaking pattern and keeping the vehicle straight in its designated lane. This means, the take-contact time, quality of deceleration and quality of keeping the vehicle straight are not affected by buffer-time, whether the TOR is prompted early (7 seconds) or late (3 seconds). This result contradicts the finding by [8], who reported that the quality of take-overs in terms of braking suffers with shorter buffer-time (5 seconds as compared to 7 seconds).

APPENDIX A

Youngstown
STATE UNIVERSITY

One University Plaza, Youngstown, Ohio 44555
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September 24, 2019

Dr. Abdurrahman Arslanyilmaz, Principal Investigator
Dr. John Sullins, Co-investigator
Mr. Salman M L Matouq, Co-investigator
Mr. Jake Mauk, Co-investigator
Department of Computer Systems and Informational Science
UNIVERSITY

RE: IRB Protocol Number: 014-2020
Title: Driver Readiness to Take Control of Autonomous Vehicles

Dear Dr. Arslanyilmaz, et. al.:

The Institutional Review Board of Youngstown State University has reviewed the above mentioned Protocol via expedited review and determined that it meets the criteria of an expedited protocol, Category #7. Therefore, I am pleased to inform you that your project has been fully approved for one year. You must submit a Continuing Review Form and have your project approved by September 23, 2020, if your project continues beyond one year.

Any changes in your research activity should be promptly reported to the Institutional Review Board and may not be initiated without IRB approval except where necessary to eliminate hazard to human subjects. Any unanticipated problems involving risks to subjects should also be promptly reported to the IRB. Best wishes in the conduct of your study.

Sincerely,

Dr. Severine Van Slambrouck
Director, Office of Research Services, Compliance and Initiatives
Authorized Institutional Official

SVS:cc

c: Dr. Coskun Bayrak, Chair
Department of Computer Science and Information Systems

REFERENCES

[1] Dresner, Kurt, and Peter Stone. "A Multiagent Approach to Autonomous Intersection Management." *Journal of Artificial Intelligence Research*, vol. 31, 2008, pp. 591-656.

[2] “Preliminary Statement of Policy Concerning Automated Vehicles,” National Highway Traffic Safety Administration, 2013.

[3] M. Walch, K. Lange, M. Baumann, and M. Weber, “Autonomous Driving: Investigating the Feasibility of Car-driver Handover Assistance,” in *Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, New York, NY, USA, 2015, pp. 11–18, doi: 10.1145/2799250.2799268.

[4] C. Gold, M. Körber, D. Lechner, and K. Bengler, “Taking Over Control From Highly Automated Vehicles in Complex Traffic Situations: The Role of Traffic Density,” *Hum. Factors J. Hum. Factors Ergon. Soc.*, vol. 58, no. 4, pp. 642–652, Jun. 2016, doi: 10.1177/0018720816634226.

[5] S. Petermeijer, P. Bazilinskyy, K. Bengler, and J. de Winter, “Take-over again: Investigating multimodal and directional TORs to get the driver back into the loop,” *Appl. Ergon.*, vol. 62, pp. 204–215, Jul. 2017, doi: 10.1016/j.apergo.2017.02.023.

[6] K. Zeeb, A. Buchner, and M. Schrauf, “What determines the take-over time? An integrated model approach of driver take-over after automated driving,” *Accid. Anal. Prev.*, vol. 78, pp. 212–221, May 2015, doi: 10.1016/j.aap.2015.02.023.

[7] J. Radlmayr, C. Gold, L. Lorenz, M. Farid, and K. Bengler, “How traffic situations and non-driving related tasks affect the take-over quality in highly automated driving,” 2014, doi: 10.1177/1541931214581434.

[8] C. Gold, D. Damböck, L. Lorenz, and K. Bengler, “‘Take over!’ How long does it take to get the driver back into the loop?,” 2016.

[9] W. Vlakveld, N. van Nes, J. de Bruin, L. Vissers, and M. van der Kroft, “Situation awareness increases when drivers have more time to take over the wheel in a Level 3 automated car: A simulator study,” *Transp. Res. Part F Psychol. Behav.*, vol. 58, pp. 917–929, Oct. 2018, doi: 10.1016/j.trf.2018.07.025.

[10] T. Louw, G. Markkula, E. Boer, R. Madigan, O. Carsten, and N. Merat, “Coming back into the loop: Drivers’ perceptual-motor performance in critical events after automated driving,” *Accid. Anal. Prev.*, vol. 108, pp. 9–18, 01 2017, doi: 10.1016/j.aap.2017.08.011.

[11] S. Lemonnier, R. Brémond, and T. Baccino, “Gaze behavior when approaching an intersection: Dwell time distribution and comparison with a quantitative prediction,” *Transp. Res. Part F Psychol. Behav.*, vol. 35, pp. 60–74, Nov. 2015, doi: 10.1016/j.trf.2015.10.015.

[12] A. S. Al-Ghamdi, “Using logistic regression to estimate the influence of accident factors on accident severity,” *Accid. Anal. Prev.*, vol. 34, no. 6, pp. 729–741, Jan. 2002, doi: 10.1016/S0001-4575(01)00073-2.

[13] J. R. Treat *et al.*, “Tri-level study of the causes of traffic accidents: final report. Executive summary,” Institute for Reserch in Public Safety, Bloomington, IL, DOT HS 805 099, May 1979.

[14] F. Shic, “Computational methods for eye-tracking analysis: Applications to autism,” ProQuest Information & Learning, US, 2009.

[15] T. Busjahn, C. Schulte, and A. Busjahn, “Analysis of code reading to gain more Insight in program comprehension,” in *Proceedings of the 11th Koli Calling International Conference on Computing Education Research (Koli Calling ’11)*, Koli, Finland, Nov. 2011, pp. 1–9, doi: 10.1145/2094131.2094133.

[16] M. K. Eckstein, B. Guerra-Carrillo, A. T. Miller Singley, and S. A. Bunge, “Beyond eye gaze: What else can eyetracking reveal about cognition and cognitive development?,” *Dev. Cogn. Neurosci.*, vol. 25, pp. 69–91, 2017, doi: 10.1016/j.dcn.2016.11.001.

[17] M. E. Crosby and J. Stelovsky, “Subject differences in the reading of computer algorithms,” in *Proceedings of the Third International Conference on Human-Computer Interaction on Designing and Using Human-Computer Interfaces and Knowledge Based Systems (2nd ed.)*, Boston, Massachusetts, USA, 1989.

[18] A. Arslanyilmaz and J. Sullins, “Multi-player online simulated driving game to improve hazard perception,” *Transp. Res. Part F Psychol. Behav.*, 2018, doi: 10.1016/j.trf.2018.02.015.

[19] S. Papavlasopoulou, K. Sharma, and M. Giannakos, “How do you feel about learning to code? Investigating the effect of children’s attitudes towards coding using eye-tracking,” *Int. J. Child-Comput. Interact.*, vol. 17, pp. 50–60, Sep. 2018, doi: 10.1016/j.ijcci.2018.01.004.

[20] C. Hasse, D. Grasshoff, and C. Bruder, “How to measure monitoring performance of pilots and air traffic controllers,” in *Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA ’12)*, New York, NY, USA, 2012, pp. 409–412, doi: 10.1145/2168556.2168649.

[21] S. Eivazi, R. Bednarik, M. Tukiainen, M. Fraunberg, V. Leinonen, and J. Jääskeläinen, “Gaze behaviour of expert and novice microneurosurgeons differs during observations of tumor removal recordings,” in *Proceedings of the Symposium on Eye Tracking Research and Applications - ETRA ’12*, Santa Barbara, California, 2012, pp. 377–380, doi: 10.1145/2168556.2168641.

[22] G. Tien, M. S. Atkins, B. Zheng, and C. Swindells, “Measuring situation awareness of surgeons in laparoscopic training,” in *Proceedings of the 2010 Symposium on Eye-Tracking*

Research & Applications (ETRA '10), New York, NY, 01 2010, pp. 149–152, doi: 10.1145/1743666.1743703.

[23] Y. Guéhéneuc and P. T. Laigle, "TAUPE: Towards Understanding Program Comprehension," in *Proceedings of The Conference of the Center for Advanced Studies on Collaborative Research (CASCON'06*, 2006, pp. 16–19, doi: 10.1145/1188966.1188968.

[24] K. Sharma, P. Jermann, and P. Dillenbourg, "How students learn using MOOCs: An eye-tracking insight," in *Proceedings of the 2nd MOOC European Stakeholders Summit*, Lausanne, France, Feb. 2014.

[25] K. Sharma, P. Jermann, and P. Dillenbourg, "With-me-ness: A gaze-measure for students attention in," in *Proceedings of International Conference of the Learning Sciences*, Boulder, Colorado, USA, Jun. 2014.

[26] N. J. Nilsson, P. Hart, and B. Raphael, *A* search algorithm*. Menlo Park, California: Stanford Research Institute, 1968.

[27] D. A. Redelmeier and R. J. Tibshirani, "Association between cellular-telephone calls and motor vehicle collisions," *N. Engl. J. Med.*, no. 7, p. 453, 1997.

[28] C. S. Gauld, I. Lewis, and K. M. White, "Concealing their communication: Exploring psychosocial predictors of young drivers' intentions and engagement in concealed texting," *Accid. Anal. Prev.*, vol. 62, pp. 285–293, Jan. 2014, doi: 10.1016/j.aap.2013.10.016.

[29] Neil M. Issar *et al.*, "The link between texting and motor vehicle collision frequency in the orthopaedic trauma population," *J. Inj. Violence Res.*, no. 2, p. 95, 2013, doi: 10.5249/jivr.v5i2.330.

[30] NHTSA National Highway Traffic Safety Administration, "Driving distracted, stats and facts, driving and texting," U.S. Department of Transportation, Washington, DC, 2010.

[31] J. l. Cook and R. M. Jones, "Texting and accessing the web while driving: Traffic citations and crashes among young adult drivers," *Traffic Inj. Prev.*, vol. 12, no. 6, pp. 545–549, Dec. 2011, doi: 10.1080/15389588.2011.620999.

[32] M. A. Harrison, "College students' prevalence and perceptions of text messaging while driving," *Accid. Anal. Prev.*, vol. 43, no. 4, pp. 1516–1520, Jan. 2011, doi: 10.1016/j.aap.2011.03.003.

[33] Z. Lu, X. Coster, and J. de Winter, "How much time do drivers need to obtain situation awareness? A laboratory-based study of automated driving," *Appl. Ergon.*, vol. 60, pp. 293–304, Apr. 2017, doi: 10.1016/j.apergo.2016.12.003.

[34] S. Samuel, A. Borowsky, S. Zilberstein, and D. Fisher, "Minimum Time to Situation Awareness in Scenarios Involving Transfer of Control from an Automated Driving Suite," *Transp. Res. Rec.*, vol. 2602, no. 1, pp. 115–120, 2016.

[35] T. j. (1) Wright, S. (1) Samuel, S. (1) Zilberstein, A. (2) Borowsky, and D. l. (3) Fisher, “Experienced drivers are quicker to achieve situation awareness than inexperienced drivers in situations of transfer of control within a level 3 autonomous environment,” in *Proceedings of the Human Factors and Ergonomics Society*, 01 2016, pp. 270–273, doi: 10.1177/1541931213601062.

[36] Marvin. McCallum, J. L. Brown, C. M. Richard, J. L. Campbell, Battelle Center for Human Performance and Safety., and United States. National Highway Traffic Safety Administration., “Crash warning system interfaces,” 2007.

[37] H. Hooft van Huysduynen, J. Terken, and B. Eggen, “The relation between self-reported driving style and driving behaviour. A simulator study,” *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 56, pp. 245–255, Jul. 2018, doi: 10.1016/j.trf.2018.04.017.

[38] C. R. Huizinga *et al.*, “Evaluation of simulated driving in comparison to laboratory-based tests to assess the pharmacodynamics of alprazolam and alcohol:,” *J. Psychopharmacol. (Oxf.)*, Mar. 2019, doi: 10.1177/0269881119836198.

[39] K. A. Pituch and J. Stevens, *Applied multivariate statistics for the social sciences: analyses with SAS and IBM’s SPSS*, 6th edition. New York: Routledge/Taylor & Francis Group, 2016.