I-STREET Initiative – Evaluation of Intelligent School Zone Beacon and Vehicle-Cyclist Detection and Warning System

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Final Report

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METRIC CONVERSION CHART

U.S. UNITS TO METRIC (SI) UNITS

LENGTH

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
in	Inches	25.4	millimeters	Mm
ft	Feet	0.305	meters	M
yd	Yards	0.914	meters	M
mi	Miles	1.61	kilometers	Km

METRIC (SI) UNITS TO U.S. UNITS

LENGTH

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
mm	millimeters	0.039	inches	In
m	Meters	3.28	feet	Ft
m	Meters	1.09	yards	Yd
km	kilometers	0.621	miles	Mi

TECHNICAL REPORT DOCUMENTATION PAGE

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16. Abstract

The main purpose of this study is to evaluate a smartphone-based app called "TravelSafely" developed by Temple/AI. This app has the capability to alert drivers if they exceed a given speed threshold in an active school zone or when they are approaching a cyclist and a collision is possible. We collected trajectory and eye tracking data from 50 participants. Each participant drove a circuit twice and, in each circuit, drive through 4 school zones and one staged cyclist. The driving subjects were randomized across three conditions: (1) Stealth/OFF condition (drivers did not receive any alerts), (2) Audio ON (drivers received audio alerts), and (3) Audio/Visual ON (drivers received both audio and visual alerts). Overall, the experimental study suggests that the availability of an app decreases the probability of speeding in school zones and increased visual scanning behavior. These could translate into improved situational awareness and increased safety in school zones. In the case of the bicyclist, the results showed a significant increase the probability of seeing the cyclist with the availability of the app when the bicyclist was not expected. This suggest the value of the app in improving safety in locations in which cyclists are generally not expected. It is useful to acknowledge that these results are based on a relatively small sample of valid data points. Therefore, future studies with larger samples are warranted.

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EXECUTIVE SUMMARY

The purpose of this study was to evaluate the performance of a technological solution that alerts drivers about the presence of vulnerable road users. The specific solution evaluated in this study is a smartphone-based app called "TravelSafely" developed by Temple/AI. This app has the capability to alert drivers if they exceed a given speed threshold in an active school zone. This vehicle-to-infrastructure (V2I) technology relies on intelligent school zone beacons, an infrastructure investment made by the City of Gainesville. The intelligent beacons broadcast the status of the school zone (active or not) which is in turn received by servers run by the service provider. The servers connect to a smartphone-based app that a vehicle driver may install on their smartphones. If their vehicle speed exceeds the internal threshold set in the app while within the school zone "geo fence", an alert is triggered. A secondary service provided by this same app is to provide alerts about bicyclists (irrespective of whether they are in the school zone or not). Based on the current vehicle location/speed and cyclist location, if the expected time to reach the cyclist location falls below an internal threshold, an alert is triggered on the smartphones of both the driver and the bicyclist. This system works only when both the driver and the bicyclist have the app open.

This study evaluated both school-zone and cyclist alert features using a naturalistic driving study in a driving circuit that integrated driving through school zones and road segments with a staged bicyclist. We collected trajectory and eye tracking data from 50 participants during this study. Each participant drove the circuit twice and, in each circuit, drive through 4 school zones and one staged cyclist (cyclist had the app turned on). The driving subjects were randomized across three conditions: (1) Stealth/OFF condition (drivers did not receive any alerts), (2) Audio ON (drivers received audio alerts), and (3) Audio/Visual ON (drivers received both audio and visual alerts).

The data were processed using a mix of manual and automated methods to derive several metrics that capture the safety effects of the app. The computed metrics broadly quantified driving speed and attention allocation. The impacts of the app were ascertained by comparing these metrics across the three experimental conditions.

The main findings of this study are summarized as follows:

- The probability of instantaneous speeds exceeding 20 miles/hour within school zones was less in Audio ON and Audio/Visual ON conditions compared to Stealth/OFF mode.
- The probability of the app triggering was less in Audio ON and Audio/Visual On conditions compared to Stealth/OFF mode.
- Drivers typically look at the school zone beacon while entering the school zone, even in Stealth/OFF condition. The exception is when the school zone beacon is overhead rather than roadside. The availability of the app was not found to systematically increase the likelihood of looking at the beacon. Looking at the beacon was considered as a proxy for situational awareness in school zones. However, there are several visual cues that could alert drivers to their presence in school zones.

- Drivers exhibited more medium and large saccades (measured without considering the turning of the head) in Audio ON and Audio/Visual ON condition compared to Stealth/OFF mode. This indicates that drivers exhibit more visual scanning behavior with the availability of the app (and the associated slowing down). This in turn could translate into improved situational awareness and improved traffic safety.
- Drivers were more likely to look at the cyclist in Audio ON and Audio/Visual On conditions compared to Stealth/OFF mode in their first trip. This suggests that the app did succeed in drawing attention of the driver to the cyclist. On their second trip, when drivers are familiar with the route (and were potentially expecting a cyclist), we find that there is a smaller difference between Stealth/OFF mode and Audio ON conditions. In contrast, drivers looked less at the cyclist in the Audio/Visual On condition relative to Stealth/OFF condition. The additional visual alert could be drawing the drivers' attention to the cell phone instead of the cyclist.

Overall, the experimental study suggests that the availability of an app decreases the probability of speeding in school zones. It did not alter the behavior of how drivers looked at the beacons but the analysis did show increased visual scanning behavior in the presence of the app. Together, the decreased speeding and increased scanning could translate into improved situational awareness and increased safety in school zones.

In the case of the bicyclist, the results showed a significant increase the probability of seeing the cyclist with the availability of the app when the bicyclist was not expected (trip 1). This suggest the value of the app in improving safety in locations in which cyclists are generally not expected. In contrast, when cyclists are expected (Trip 2), the app did not translate into significant increases in the probability of spotting the bicyclists as they were quite likely to be noticed even without the app. In this situation, having an audio-visual alert could have safety impactions as the gaze was drawn away from the cyclist to potentially the phone.

Even though this study represents a unique on-road eye-tracking effort to understand traffic safety, it is useful to acknowledge that the results are based on a relatively small sample of valid data points. We lost almost 30% of our data during our strict validity checks, particularly on the gaze data. Therefore, future studies with larger samples are warranted. Further, to our knowledge there are no attentional metrics that have been established as characteristic of safe driving in school zones or safe driving around cyclists. Examining whether changes in gaze and saccades will translate into fewer crashes, less severe crashes, or fewer near-misses is identified as an area of future work.

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ACRONYMS

FLHSMV	Florida Department of Highway Safety and Motor Vehicles
FDOT	Florida Department of Transportation
MUTCD	Manual on Uniform Traffic Control Devices
V2I	Vehicle to Infrastructure
IVIS	In-Vehicle Information System
PRC	Percent Road Center
AOI	Area of Interest
EEG	Electroencephalography
DSDS	Dynamic Speed Display Signs
ISA	Intelligent Speed Adaption
AI	Applied Information
UF	University of Florida
IRB	Institutional Review Board
T2	Transportation Technology Transfer
UFTI	University of Florida Transportation Institute
SMI	SensoMotoric
SSTP	Student Science Training Program
CSV	Comma-Separated Values

CHAPTER 1 INTRODUCTION

1.1 Background

In 2018, the Florida Department of Highway Safety and Motor Vehicles (FLHSMV) reported a 7.49% increase in the overall number of traffic crashes in Florida's roadways over the past three consecutive years 2015-2017. Crashes involving vulnerable users such as bicyclist and pedestrians have shown conflicting trends over the past years. The number of pedestrian crashes has increased 3.69%. On the contrary, bicyclist crashes have shown a 6.25% decrease during the past three years (FLHSMV, 2018). Although overall crashes have increased among drivers and pedestrians, the number of fatalities for driver, pedestrians, and bicyclist have shown reductions of 1.89%, 1.20%, and 8.57% respectively in Florida's roadways between the years 2016 to 2017. Overall, there is continued need to improve transportation safety. In particular, several stakeholders including school administrators, policymakers, law enforcement, and transportation professionals are interested in the safety of one of the most vulnerable users, the young pedestrians.

The Florida Department of Transportation (FDOT) has taken proactive measures to enhance safety in the vicinity of schools by establishing school speed zones in accordance with Florida Statue 316.1895. On July 1st, 2017, a revised and updated version of the Manual on Speed Zoning for Highways, Roads, and Streets in Florida was adopted for use by the State of Florida under Rule 14-15.012, F.A.C (FDOT, 2019). Updates have been made to the manual focused on overcoming the inconsistency in school zone signs that did not meet the Department standards or the Manual on Uniform Traffic Control Devices (MUTCD) requirements. In addition, a new chapter was created specifically for school zones which include the statewide requirement to install flashing beacons (S5-1) at all reduced speed school zones (El-Urfali, 2017).

In Florida, there are 3337 elementary, middle and high schools (Florida School Accountability Reports, 2019). Some of them could face a safety problem caused by vulnerable users (students) exposed to distracted drivers. A study conducted by Grabwski and Goodman (2009) in the U.S., showed that one in six drivers were distracted while driving in a school zone. This study was conducted across 20 middle schools in 15 states nationwide (Florida was not included in this study). Distractions can take attention away from the driving task and place the driver and other road users at an increased crash risk. A conservative estimate of glancing at a text message can cause a five-second distraction during which a vehicle driving 55 mph can traverse an entire length of football field (NHTSA, 2019). There can also be several other reasons including vision, obscuring vehicle, or bad weather that can affect the user's safety in school zones. Overall, it is imperative that drivers slow down and drive attentively in school zones.

In order to alert the drivers to speeding in a school zone, several approaches have emerged, including engineering, education, enforcement and emergency response. One technological solution that combines engineering with education uses GPS and cell phone technology to send an alert or warning message on the driver's cell phone if the driver of the vehicle does not reduce the speed of the vehicle in a school zone. We note that this technological intervention is relevant only for those road users that are carrying a smartphone with them.

1.2 Study Objectives

The main purpose of this study is to evaluate the performance of a technological solution that alerts drivers about the presence of vulnerable road users. A smartphone-based app called "TravelSafely" developed by Temple/AI has the capability to alert drivers if they exceed a given speed threshold in an active school zone. This vehicle-to-infrastructure (V2I) technology relies on intelligent school zone beacons, an infrastructure investment made by the City of Gainesville. The intelligent beacons broadcast the status of the school zone (active or not) which is in turn received by servers run by the service provider. The servers connect to a smartphone-based app that a vehicle driver may install on their smartphones. If their vehicle speed exceeds the internal threshold set in the app while within the school zone "geo fence", an alert is triggered. A secondary service provided by this same app is to provide alerts about bicyclists (irrespective of whether they are in the school zone or not). Based on the current vehicle location/speed and cyclist location, if the expected time to reach the cyclist location falls below an internal threshold, an alert is triggered on the smartphones of both the driver and the bicyclist. This system works only when both the driver and the bicyclist have the app open.

This study evaluated both school-zone and bicyclist alert features within the same app with greater emphasis on the former. Fifty subjects were recruited to drive in a circuit comprising four school zones under alternate experimental conditions (with the app-turned off, with only the audio alerts, and with audio and video alerts) and their driving behaviors (speed and gaze) were recorded. The heterogeneous data (video feeds, GPS trajectories, manually recorded logs, etc.) were integrated and analyzed and the safety implications of this technology were established. This report summarizes the overall study. Chapter 2 presents a brief synthesis of literature focusing on (1) safety studies using eye-tracking and (2) field studies of speed alerts. Chapter 3 describes the selection of school zones and the testing of the technology. Chapter 4 describes the experimental methodology. Chapter 5 presents the data analysis and results. Chapter 6 presents an overall summary of the work, states the major conclusions and identifies directions for future work.

CHAPTER 2 LITERATURE REVIEW

This chapter presents a synthesis of relevant literature. Section 2.1 presents an overview of safety studies that have used the eye tracking technology while Section 2.2 presents an overview of field studies of speed alerts on improving traffic safety. Section 2.3 presents an overall summary and identifies the unique positioning of this study.

2.1 Safety Studies Using Eye Tracking Technology

Eye tracking can be used to evaluate a driver's response to distractions or hazards and their interaction with in-vehicle information system (IVIS) technology, like pedestrian alert systems. Donmez et al. (2007) used this technology to identify distracted driving through eye movement glances towards an LCD touchscreen mounted within a driving simulator. Driving performance was evaluated through braking response to a car in front of the driver, and controlled steering through curves. The driver performed a text-matching task using the IVIS by scrolling through a list of options and selecting an answer. A driver feedback system that displayed a visual alert on the IVIS when their gaze had left the road for several seconds, to prevent distracted driving while performing the task was evaluated. The visual alert system successfully resulted in less time spent glancing at the display, and more time glancing at the roadway when compared to a control group. The evaluation quantified the distractions created by an IVIS, and showed it is possible to reduce this impact using additional visual alerts.

In a similar study, Rydström et al. (2009) reported a metric for how focused the driver was on the road within a driving simulator. Percent Road Center (PRC) computes the proportion of time gaze was fixated on the center of the road to understand the distribution of gaze during the task. The study used a selection task on an IVIS with an analog input knob that provided haptic feedback allowing the driver to keep their gaze on the road. Three levels of haptic feedback were evaluated, with and without visual feedback. Providing visual feedback resulted in more completed tasks and fewer errors when turning the knob, but significantly reduced PRC. No significant effects were found across different haptic responses in the presence of visual feedback, suggesting that intuitive haptic feedback cannot mitigate the impact of the IVIS on gaze allocation. The authors posit that visual input dominates additional haptic sensory information, further identifying distractions when using an IVIS while driving.

Kasneci et al. (2015) utilized eye tracking as a metric to evaluate driver response to various hazards within a driving simulator. Drivers would experience pedestrians appearing suddenly to cross the road, and near collisions with vehicles that attempt to merge into the driver's lane. The eye tracking data were then classified into fixations, saccades, and smooth pursuits in real time. A hazard was considered perceived by the driver if there was a fixation or smooth pursuit that overlapped with a bounding box drawn around the hazard, known as an Area of Interest (AOI). This metric was used to evaluate how well each driver performed and was later used to measure the performance of visually impaired individuals.

In a closely related study reported by Merenda et al. (2016), twenty-four drivers were put in pedestrian collision scenarios created in a driving simulator. Eye gaze behavior, braking performance, and user acceptance ratings were recorded. Three levels of pedestrian alert systems were tested: no alert, audio-only alert, audio-visual alert projected via an augmented reality see-through head-mounted display. Because this was a simulator study, the experimenters could control the time to collision for the pedestrian collision scenarios. Four levels of time to collision were created: 2s, 3s, 4s, and 5s. Though the simulated drive took place in an urban single lane setting, there were no other vehicles on the road. Gaze reaction time was defined as the time difference between the instant when the simulated pedestrian begins moving towards the road and the first fixation within the AOI around this pedestrian. Braking reaction time was defined as the time difference between the alert sounding and the brake pedal being inclined over 5 degrees. The authors reported no significant difference in gaze reaction time between the different alert types, though they found a significant difference in braking reaction time between no alert and audio and audio-visual alert. This lack of difference in gaze reaction time (despite a difference in braking reaction time) could be a result of the clean uncluttered scenario of the driving simulation.

Shinohara et al. (2017) investigated differences in eye tracking patterns between Japanese and US participants viewing simulations of automated driving through San Francisco and Osaka. The goal of this study was to inform culture-specific models of driver attention and situational awareness for cooperation between human drivers and automated vehicles. Fifty-one participants in the US and forty-seven participants in Japan were eye tracked in a lab setting and then completed a situation awareness questionnaire. There were significant differences in mean and total fixation time with US participants having longer fixations. Area of interest analysis revealed that Japanese participants tended to look longer on foreground objects.

Chuang et al. (2017) employed electroencephalography (EEG) recordings to find out why the effectiveness of auditory notifications differed between student volunteers in a lab environment and professional truck drivers in a driving simulator. Thirty participants were recruited to the study and asked to respond if they heard a target notification and to ignore if they heard a distractor sound. This study found that professional truck drivers were both slower and less sensitive to target notifications than students. Simultaneously there were differences in EEG activity of both groups suggesting that different demographics process notifications differently.

Palazzi et al. (2018) collect eye-tracking data from eight drivers in a variety of real-world conditions. They explore driver gaze behavior at different times of the day (morning, evening, night), weather conditions (sunny, rainy, cloudy), and in different environments (urban, expressway, and rural). Their data collection is similar to our work in that they collect real-world eye tracking data from general populations, however they focus on modeling and predicting gaze behavior based on visual input from a Garmin VirbX camera mounted on the roof of the vehicle. They also provide definitions to classify sequences of eye movements as task relevant actions, inattentive phases, subjective actions, and data resulting from errors in eye tracking data. The data collected in their study is used to train a Convolutional Neural Network auto-encoder that can predict saliency maps from inputs of RGB video frames, optical flow, and associated semantic segmentations. They concluded that driver speed impacted the concentration of gaze points towards the center of the road, as more visual information must be integrated within the same time period and requires more concentration with less exploration.

2.2 Field Studies of Speed Alerts on Improving Traffic Safety

Simpson (2008) evaluated the effectiveness of placing flashing beacons on school zone speed limit signs to improve speed compliance in school zones. A sample of 15 school zones equipped with flashing beacons and 15 comparison school zones without flashers were selected throughout North Carolina. Flashers had been installed at each school zone for at least 3 years. Speed data were collected at each site for the entire morning (7:00 a.m. to 9:45 a.m.) and afternoon (1:45 p.m. to 4:15 p.m.) during school times. They also collected around 100-speed samples or 1 hour of data in the morning and afternoon during non-school time hours. Simpson studied the percentage of vehicles exceeding the speed limit, average speed, 85th percentile speed and pace speed for both conditions. The study results showed no significant difference in vehicle speeds between the flasher and non-flasher locations during school time hours. Although a minimal decrease in vehicle speeds and in the percentage of vehicles exceeding the speed limit was found in sites with flashing beacons, the average speeds for all sites were over 5 mph above the school-time speed limit, with the 85th percentile speeds exceeding the speed limit by 12 mph. Even though a decrease in speed was found from non-school time hours to school-time hours at both conditions, the speed reductions were not enough to be in compliance with the posted speed limit.

Ullman and Rose (2005) studied the effects of the dynamic speed display signs (DSDS) in three school zones in Texas. The purpose of the study was to evaluate the effectiveness of DSDS in permanent applications in seven locations statewide (assigned by the Texas Department of Transportation) where speeds needed to be reduced. Three locations of the school zones had a range of roadway and speed conditions that promoted drivers to speed. A total of 13,584 speeds were measured at the seven locations. The study results for the school zones showed a statistically significant reduction in speeds that were maintained months after the installation of the DSDS. The results showed that DSDS was more effective when used in conjunction with school zone speed limits. This caused a reduction of 1 to 4 mph, reducing the 85th percentile of motorists who exceed the posted speed limit and increased the number of vehicles who followed the posted speed limit even when the school zone was not active.

Other innovative technological solutions have been tested to reduce speeding in the school zones and other speed-restricted areas. Paine et.al (2007) reviewed research findings on intelligent speed adaptation (ISA) and evaluated an onboard speed advisory system that alerts drivers when the speed limit is exceeded. Although this study analyzed only 25 trials conducted in 14 different countries except for the U.S., it provides a great background of the evolution of technological solutions that have taken place to assess the problem of speeding in restricted areas. The authors indicated that extensive trials of “passive” (systems alert the driver with audio or visual warning when the speed its exceeded, allowing the driver to make a choice on what action should be taken) ISA throughout the world have proven to significantly reduce incidents and reduce speeds in restricted areas. In order to be effective, the ISA technology needs the active support of government by providing accurate digital maps of speed limits, giving incentives, and promoting this technology.

2.3 Summary

In summary, safety studies using eye tracking technology have been primarily done using a driving simulator. None of these have specifically looked at driving behavior in school zones. However, these studies do provide insights on defining AOIs, trends in gaze distributions at increased driving speeds, and deriving performance measures for attention based on fixations.

Field studies on speeding alerts have primarily focused on speed-reduction as the performance measure to evaluate the effectiveness of the strategy. In the context of school-zones, the effects of flashing beacons and DSDS were evaluated but these are not in-vehicle technologies. Past field studies have not used eye tracking and the associated performance measures that could be generated as additional ways of evaluating the effectiveness of speeding alert technologies.

The overall literature synthesis highlights that this study is unique in its approach of using eye-tracking (in addition to speed measurements) in a field study to evaluate the safety benefits of in-vehicle speeding alert apps.

CHAPTER 3 SCHOOL ZONE SELECTION AND TECHNOLOGY TESTING

This chapter first presents an overview of the procedure used to finalize a subset of school zones that were to be used for testing. Next, we present a discussion about the process of testing the technology with the involvement of the vendor, both in general, and specifically for the school-zones chosen for the experiments.

3.1 School Zone Selection and Beacon Activation

School zone beacons in Gainesville, Florida are of two types: 1) those that are controlled by the Trafficware controllers at the adjacent intersection (if the school zone beacons are in the fiber-line path from the controller) and 2) those that are in neighborhoods (generally farther away from other major signalized intersections) and controlled by the AI/Glance system. Only the latter can communicate with the TravelSafely app, and as a result, we worked with these beacons. An example of such a beacon located at NE 15th Street is shown in **Figure 1**. This is referred to as "Beacon 4.1" in this experimental study.

Figure 1 Intelligent school beacon on NE 15th St. controlled by the AI/Glance system (Beacon 4.1 in this study)

We coordinated with the City of Gainesville, FDOT, and Temple/AI to determine a driving circuit within 5 miles of the UF campus that had intelligent school beacons available for activation. The selection criteria for the school zones / beacons considered in the study included

1) potential for speeding, 2) proximity to each other so that the full driving circuit can be completed during the active school-zone times (often about 1.5 hours), and 3) ability to satisfy IRB requirements for safe conduct of experiment.

The University of Florida East Campus (2046 NE Waldo Rd., Gainesville, FL, 32609) was chosen to be the starting point of the study to allow participants to park, meet the researcher at the UF Transportation Technology Transfer (T2) Center to receive a brief description of the study, address any questions they may have had, and sign the study consent. This visitor's parking at the UF East Campus was used as a safe area to help participants become acclimated to the vehicle and the study technologies before initiating the study. This location satisfied the IRB safety criteria required for conducting naturalistic driving studies.

The finalized driving circuit makes a 5.7-mile loop that covers four school zones and one bicyclist staging area as shown in **Figure 2**. The beacons that are coded as *school zone dot beacon number* (e.g., Beacon 4.1 and 4.2) refer to those school zones where there are beacons both at the start and end of the school zone. **Table 1** identifies the location of individual school beacons of interest presented in the map in **Figure 2.** Other specifications (distances between beacons, bicyclist staging area, etc.) about the study route are described in **Table 2**. The five school zone beacons were activated by Temple/AI.

Initially, three potential locations were considered as bicyclist stations to measure the effectiveness of the app. Two of these locations were also recommended by Temple/AI as they were high-speed roads with enough room to safely "stage" the cyclist (who will be a member of the research team) on the sidewalk. The research team finally decided on one station (Indicated in **Figure 2** and **Tables 1** and **2**) that included road facilities that enhance the cyclist's safety, i.e., a bike lane and a wide sidewalk. This location additionally provided the research team easy access to drop/pick up the cyclist. The chosen station was on NE 39thAvenue (FL 222). This road segment is away from local school zones, traffic lights, and other control factors that can affect a driver's operating speed. The speed limit in FL 222 is 45 mph.

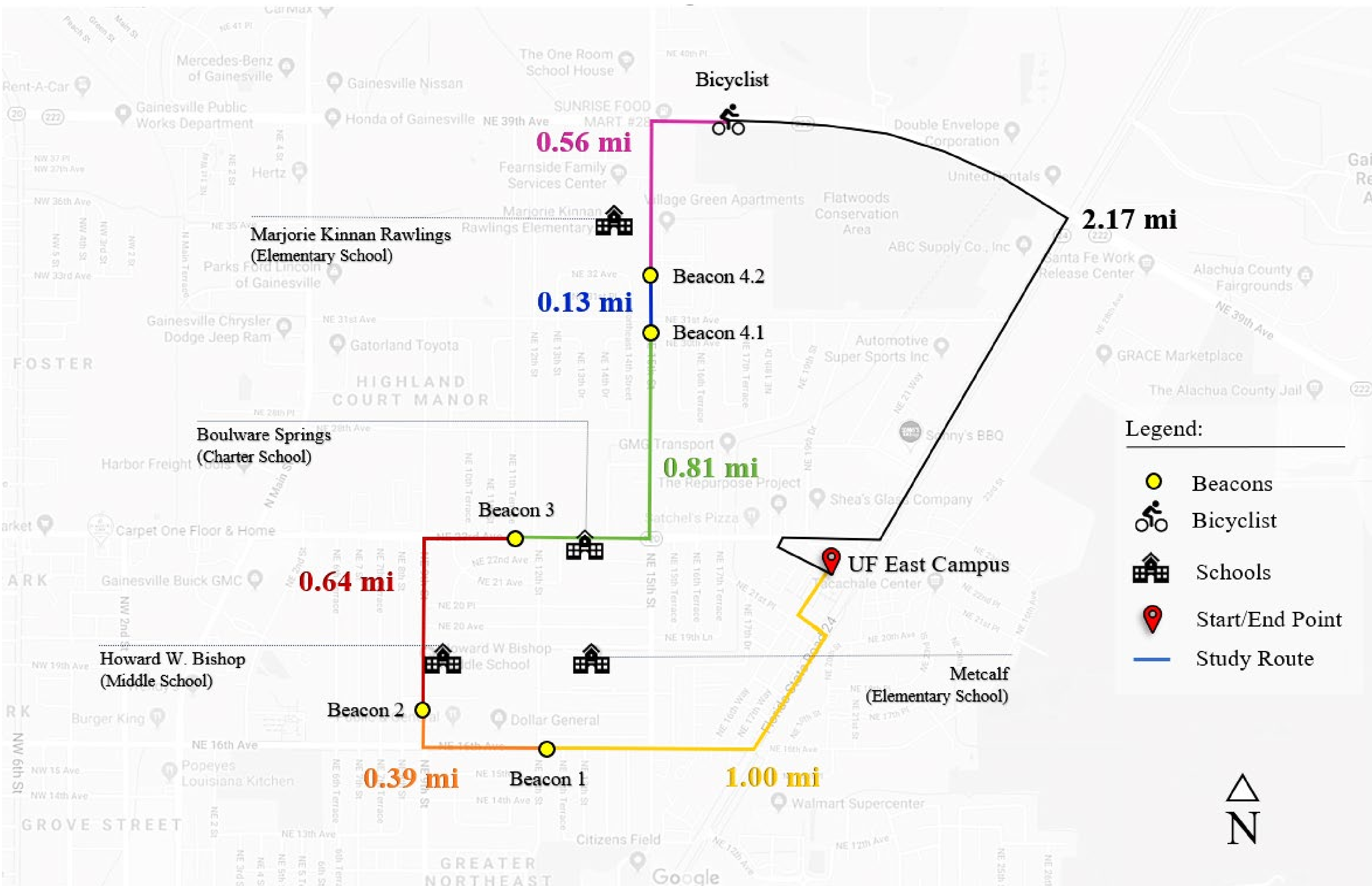

Figure 2 Final driving circuit and study landmarks

Table 1 Bicyclist and studied school zones with beacon locations and status

Beacon ID	Status	Associated School	Latitude	Longitude	Notes
1	Active	Metcalf Elementary School	29°39'59.70"N	82°18'34.86"W	-
2	Active	Howard W. Bishop Middle School	29°40'4.54"N	82°18'52.95"W	-
3	Active	Boulware Springs Charter School	29°40'25.65"N	82°18'39.36"W	Crossing guard (NE 12th St. & NE 23rd Ave.)
4.1*	Active	Marjorie Kinnan Rawlings Elementary School	29°40'51.13"N	82°18'20.65"W	Crossing guard (15th St. & 31st Ave.)
4.2	Active		29°40'58.09"N	82°18'20.74"W	-
Bicyclist	Active	-	29°41'17.71"N	82°18'10.57"W	NE 39TH Ave (FL-222)

**The geographic location of Marjorie Kinnan Rawlings Elementary School is at the end of a long straight road segment where drivers tend to speed. As a result, two school zone flashing signs are placed on NE 15th street to alert drivers of the presence of a school zone.*

Table 2 Tabulated distance specifications of the study route

Route Color	Map Locations	*Distances between points (mi)
■ (yellow)	UF East Campus – Beacon 1	1.00
■ (orange)	Beacon 1 – Beacon 2	0.39
■ (red)	Beacon 2 – Beacon 3	0.64
■ (green)	Beacon 3 – Beacon 4.1	0.81
■ (blue)	Beacon 4.1 – Beacon 4.2	0.13
■ (pink)	Beacon 4.2 – Bicyclist	0.56
■ (black)	Bicyclist – UF East Campus	1.22

**Distances were measured on Google Earth, using the path tool to measure the distance between key points along the study route.*

3.2 Technology Testing and Setting App Thresholds

Temple/AI conducted an in-person visit to Gainesville on January 8th, 2019 to evaluate proposed school zones and cyclist locations and to finalize the internal thresholds for the app functionality. In addition, there were regular conference calls between the Temple/AI representatives and UF team. Based on the information provided by engineers from Temple/AI, the internal TravelSafely app thresholds were designed to trigger under the following conditions:

- **School Zones**: The alert triggered if the driver was operating the vehicle 5 mph above the speed limit. This excess speed threshold can be altered by changing parameters in Temple/AI's algorithm. The speed limit in the four shortlisted school zones was 15 mph. Therefore, alerts were set to be triggered if subjects were driving at 20 mph or higher.
- **Cyclist**: The alert triggered if the vehicle was operating at a speed of 15 mph or higher and the app identified a cyclist near the study vehicle using the TravelSafely app. If the cyclist did not have the app activated, no alerts were triggered. The alert had both an audio and a visual component. Both components triggered simultaneously 10 seconds before the vehicle passed the cyclist. **Figure 3** presents the alert criteria schematically. These criteria were established by Temple/AI prior this research study and the UF research team was not involved in the design of the collision alert algorithm that decides when the alert will be triggered.

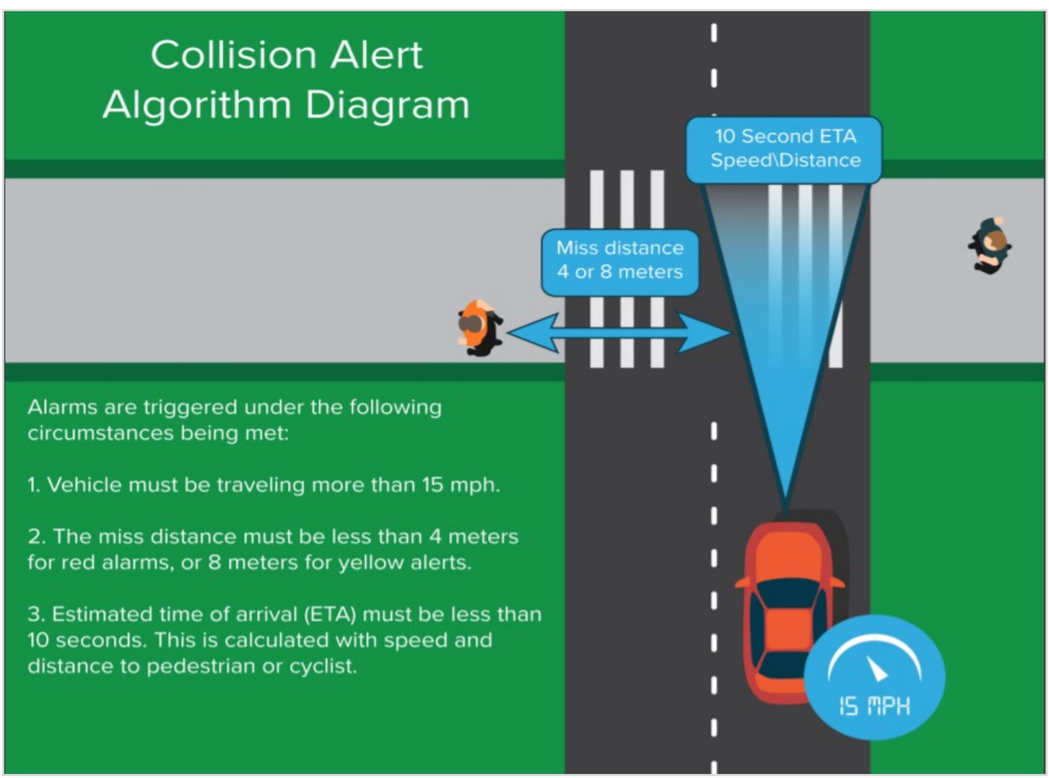

Figure 3 TravelSafely collision alert criteria (Source: Temple/AI)

Temple/AI did site visits to demonstrate the functionality of the TravelSafely app. UF did field testing with Temple/AI representatives as well as independently to determine if the alerts triggered as expected. Technical challenges faced included mismatches in versions of the TravelSafely app and the Android operating system running on the study staff phones and the versions used by Temple/AI for debugging on their end. Some beacons of interest also had to be reactivated, as they did not work during some test runs. Independent student testing of vehicle-to-cyclist communication was not successful. To improve the results with the cyclist alert, Temple/AI recommended, that the cyclist turn the app "On" right before the driver approaches its staging location. Leaving the app "On" for long periods of inactivity (stationary staging) causes a drift in the GPS data, explaining why past tests failed to trigger an alert. Overall, all challenges were addressed via meetings between graduate research assistants, senior project team members, and engineers and senior leadership at Temple/AI.

During the field test on the chosen route, the cyclist and school zone alerts triggered as expected. Screenshots in **Figure 4** were captured during the field tests with Temple/AI.

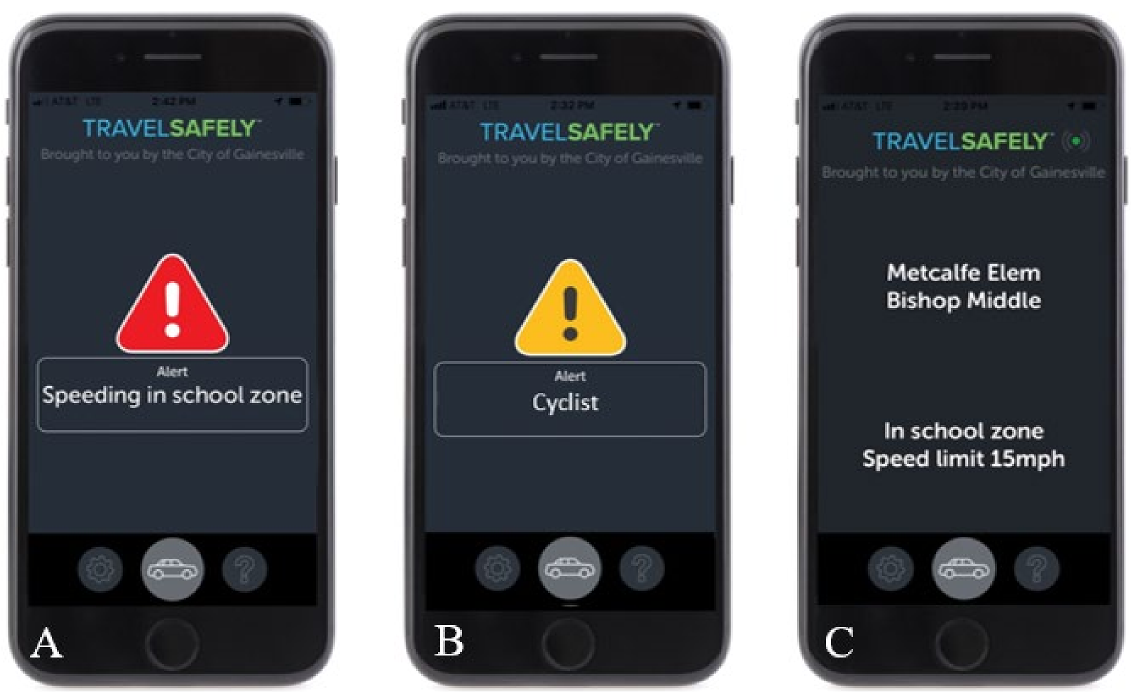

Figure 4 TravelSafely' screenshots captured during field testing in the finalized corridor show the alerts being triggered as expected: A) when entering a school zone above the speed limit, B) when there is a cyclist in the vicinity, and C) when approaching a speed limit

As a final field test independent of Temple/AI representatives, a graduate research assistant drove the UFTI instrumented vehicle (2004 Honda Pilot) on the driving circuit during afternoon school zone times. A second graduate research assistant in the passenger seat of the vehicle took notes on whether the alert was triggered. Specifically, the focus was on the two scenarios relevant to the objectives of the study: 1) when approaching school zones with speeds above the speed limit and 2) when there were cyclists in the vicinity. Study staff posed as cyclists at the bicyclist staging areas to test the effectiveness of the app. This test also provided the research team estimates of the total run time of the experiment per participant to further fine-tune the study logistics such as transporting the cyclist to his/her location, etc.

3.3 Summary

A 5.7-mile study route was chosen covering school zones in which the app could work, ensuring safety requirements of the study and practical considerations of a reasonable experiment run time. Five beacons were activated by Temple/AI. The study team performed experiments to ensure that the technology worked in the chosen corridor. Issues were resolved via meetings with Temple/AI.

CHAPTER 4 EXPERIMENTAL METHODOLOGY

Based on the literature reviewed, school zones selected, and technology testing, UF researchers finalized a study protocol and obtained IRB approval. The rest of this chapter (1) describes the equipment used, (2) provides an overview of the key steps in the study protocol, and (3) describes the recruitment of the subjects and experimental conditions for data collection.

4.1 Equipment

4.1.1 Motor Vehicle

Participants drove the University of Florida Transportation Institute (UFTI) instrumented vehicle, a 2004 Honda Pilot shown in **Figure 5A**, along the designated road circuit. Before starting the data collection process, UF Motor Pool and a Honda dealer inspected the vehicle and to guarantee that the vehicle was operating in optimal condition. The UF Insurance Office updated the coverages for auto liability to cover the participants in case of any collisions. The UFTI vehicle is instrumented with several cameras but these were not used in this study as video data were collected using eye-tracking devices.

4.1.2 Smartphone/Mobile App

The TravelSafely app was installed on an Android phone (Model: A502DL) provided by the UFTI (as shown in **Figure 5B**). A data plan was purchased for use with this phone. The study participants did not have to use their own cell phones so that they did not have to install apps on their phone and use their own data plans. Further, this approach prevents any interruptions caused by unexpected phone calls/text messages to the participants' phones during the study.

To provide a secondary track of the vehicle speeds (TravelSafety also tracks vehicle speed) a GPS tracker app called "iMove" was used to record the vehicle trajectory and speed during the study. To avoid the GPS tracker app interrupting the functionalities of the TravelSafely app, the "iMove" app was launched on the student researcher's personal smartphone at the beginning of each trip. Subjects were not aware of the GPS tracker app as this was primarily to be used to validate the GPS data from TravelSafely.

4.1.3 Eye Tracking

Eye tracking data were collected via a SensoMotoric (SMI) ETG head-mounted glasses based mobile eye tracker, as shown in **Figure 5C**. This equipment reports up to 60Hz gaze data and the camera feed from the scene camera on the glasses. This allows the experimenter to overlay gaze data on the scene camera view and observe what the participating driver was looking at.

A B C

Figure 5 Apparatus and equipment used in the study: A) UFTI instrumented vehicle (2004 Honda Pilot), B) UFTI's smartphone - Alcatel TCL android phone (Model: A502DL), and C) SMI ETG 2 head-mounted glasses.

4.2 Key Steps in the Study Protocol

Participants were asked to report to the visitor's parking lot of the UF East Campus as shown in **Figure 6**. The researchers escorted them to the study vehicle, read the consent form to them, and explained to the participants their role in the study and offered them time to ask any questions they may have about the study. The researcher showed them the study route on a printed map so they had a better understanding of where they will be driving. They were told that simple verbal navigation guidance will be provided by the researcher during the study. Before signing the consent (approved by the IRB) the researcher confirmed the subject's valid driver's license by doing a visual inspection of the expiration date. All the study participants showed a valid driver's license.

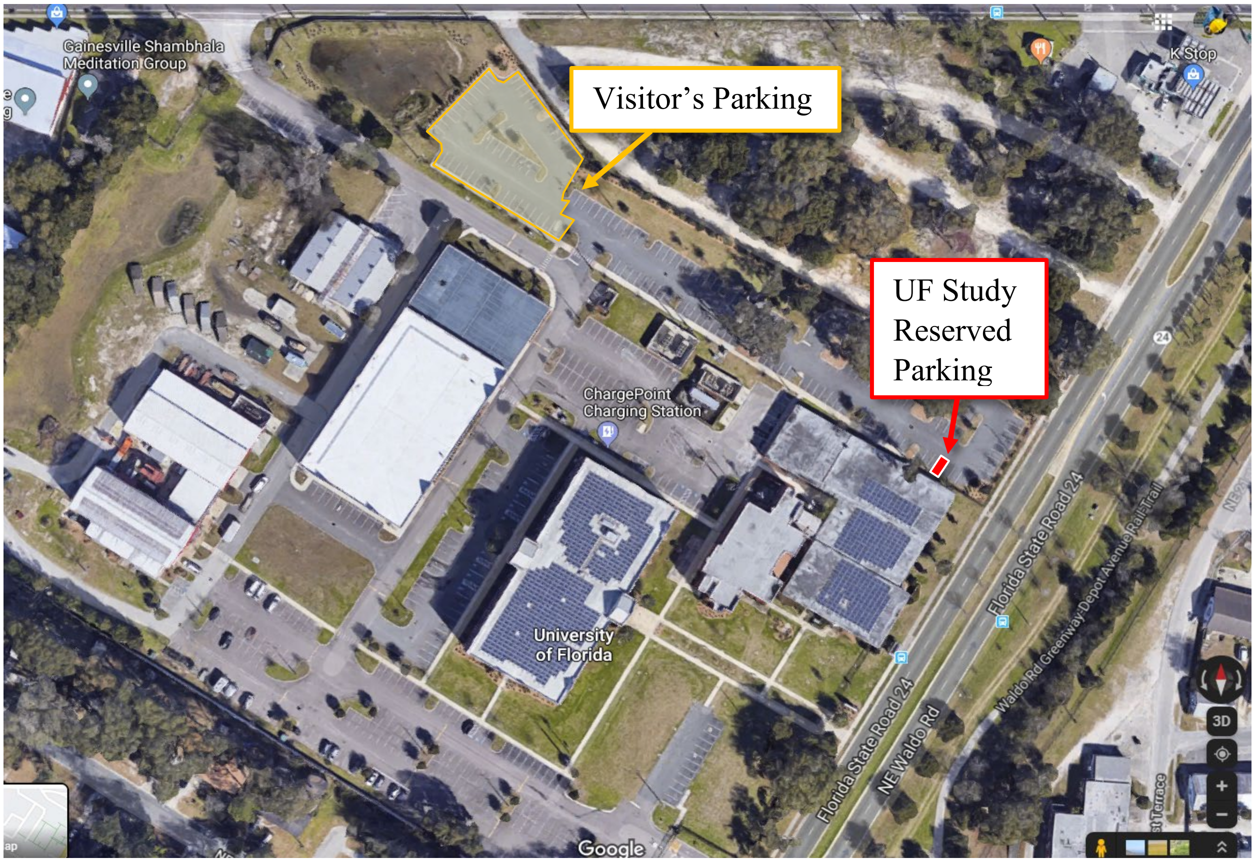

Figure 6 UF East campus visitor's parking (Yellow) and UF Study Reserved Parking (Red)

After signing the consent, participants drove around the parking lot until they felt comfortable with the vehicle (the "warm up" period). Once this warmup period was over, they were asked to return to the initial parking spot, (identified by traffic cones) to be fitted the head-mounted eye tracker. They were shown how their pupils were tracked through the cameras embedded in the eye tracking glasses.

The eye tracking calibration process was next. During the calibration process, subjects were asked to stare at four focal points (**Figure 7**) for several seconds in order to conduct eye tracking calibration.

- **Focal Point 1**, Top number at the light pole: Participants were asked to stare at the tip of the "1", (the top number at the light pole) for a few seconds as shown in **Figure 7A**.
- **Focal Point 2**, Bottom number at the light pole: Participants were asked to stare at the bottom of the "5", (the bottom number at the light pole) for a few seconds as shown in **Figure 7B**.
- **Focal Point 3**, Doorknob: Study subjects were asked to stare at the doorknob located to their left side as shown in **Figure 7C**.
- **Focal Point 4**, Black box: Subjects were asked to stare at the Ethernet port (Black box) located on the car's dashboard for a few seconds as shown in **Figure 7D**.

This process provides data to determine later on whether the eye tracking for the particular subject was generally accurate or not. In **Figure 7**, (which was generated based on post processing of data after the experiments were complete) the blue dots represent where the subjects should be looking at and the orange dots represent where the "gaze" of the respondent was based on the eye tracker data. If the two-colored dots are close, then it can be concluded that the eye tracking data are accurate and can be used for further analysis. Further details on this analysis including the development of thresholds for determining when the dots are "close" are presented in Chapter 5.

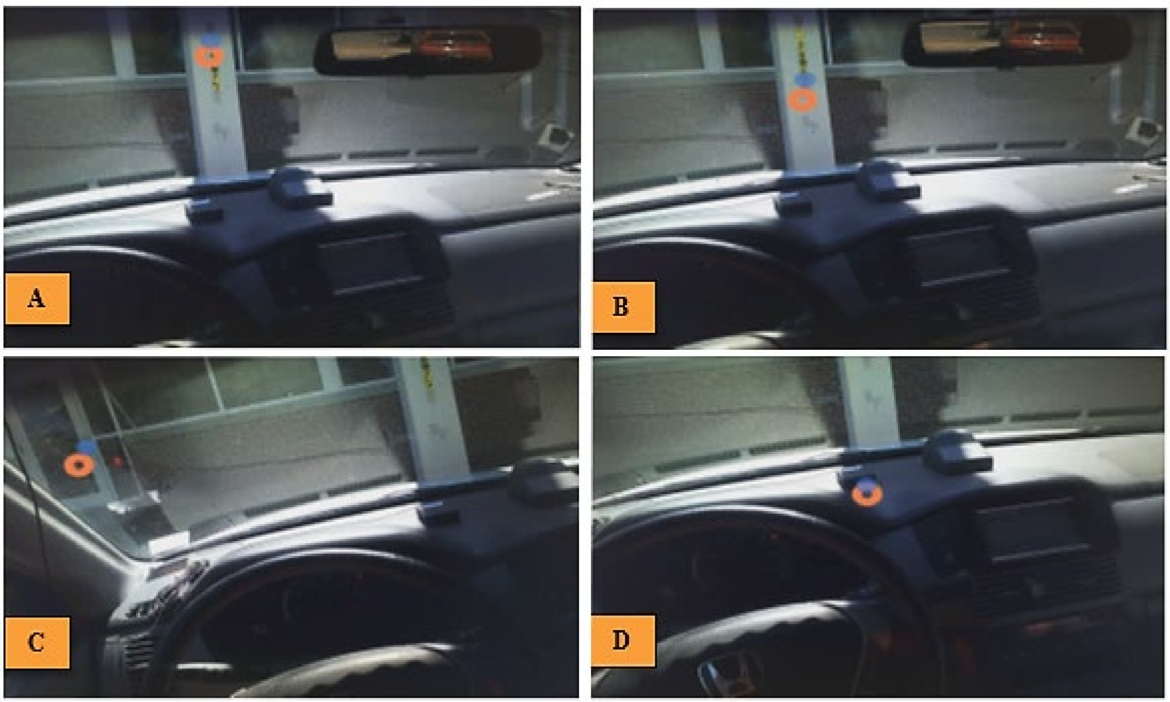

Figure 7 Eye tracking calibration process – Focal points

After completing the calibration process, participants were notified that during the drive the researcher will not engage in any conversation with the exception of providing driving directions. The participants were shown the overall driving circuit prior to the drive so that they had a general idea of their path. Further, they were also advised to stay in the right lane, as most turns in their route were right turns (the one exception was the left turn on to NE 15th St. from 23rd Ave.). In case the subjects had any question or concerns, they could talk with the researcher at any point of the study. Once participants were ready to start the circuit, the experimenter sat in the rear seat (behind the front passenger seat), activated the GPS tracking device (iMove app) and started the study. The TravelSafely app was launched on the Android phone five minutes prior to the start of the study.

The subjects could have been in one of three conditions (stealth mode, audio alert only, or audio and visual alerts; further discussions in next section). The drivers were blind to their condition and so they did not know whether the app would alert them or not.

Study subjects did two rounds of the driving circuit. During each circuit, the researcher seated in the back annotated in a log sheet all the events that happened during each trip. The data logged included (1) presence of pedestrians or cyclist in the surroundings, (2) crossing guards, (3) status of the traffic lights at the time of arrival (Green or Red), (4) if the TravelSafely alert triggered during schools zones, how many times it triggered, (5) approximate speed of drivers when entering the school zones, and (6) the presence of other factors such as traffic, busses, police cars, and emergency vehicles. An example travel log from Participant 1, Trip 1 is shown in **Figure 8**. The area highlighted with the red square shows that the experimenter has noted that the traffic signal prior to the first school zone was red when the participant arrived there, there was one speeding alert when driving through the school zone, and there was no crossing guard at this location.

After completing the first circuit, the participants returned to the same parking lot where they initiated the study to complete a second calibration. They were asked to look at the same targets one more time before removing the eye tracking glasses. The purpose of this second calibration was for the researcher to compare the initial and final calibration and determine whether any gaze shift had occurred along the study route.

After the two trips were completed, they returned to the parking lot and completed the after-study survey on the researcher's laptop. This survey focused on their driving experience and their experience with the TravelSafely app in case of those in the non-stealth conditions. Once the survey was completed, participants received their compensation ($75 gift card). The researcher in the car provided an overview of how the data collected would be analyzed and addressed any other questions or concerns from the respondents.

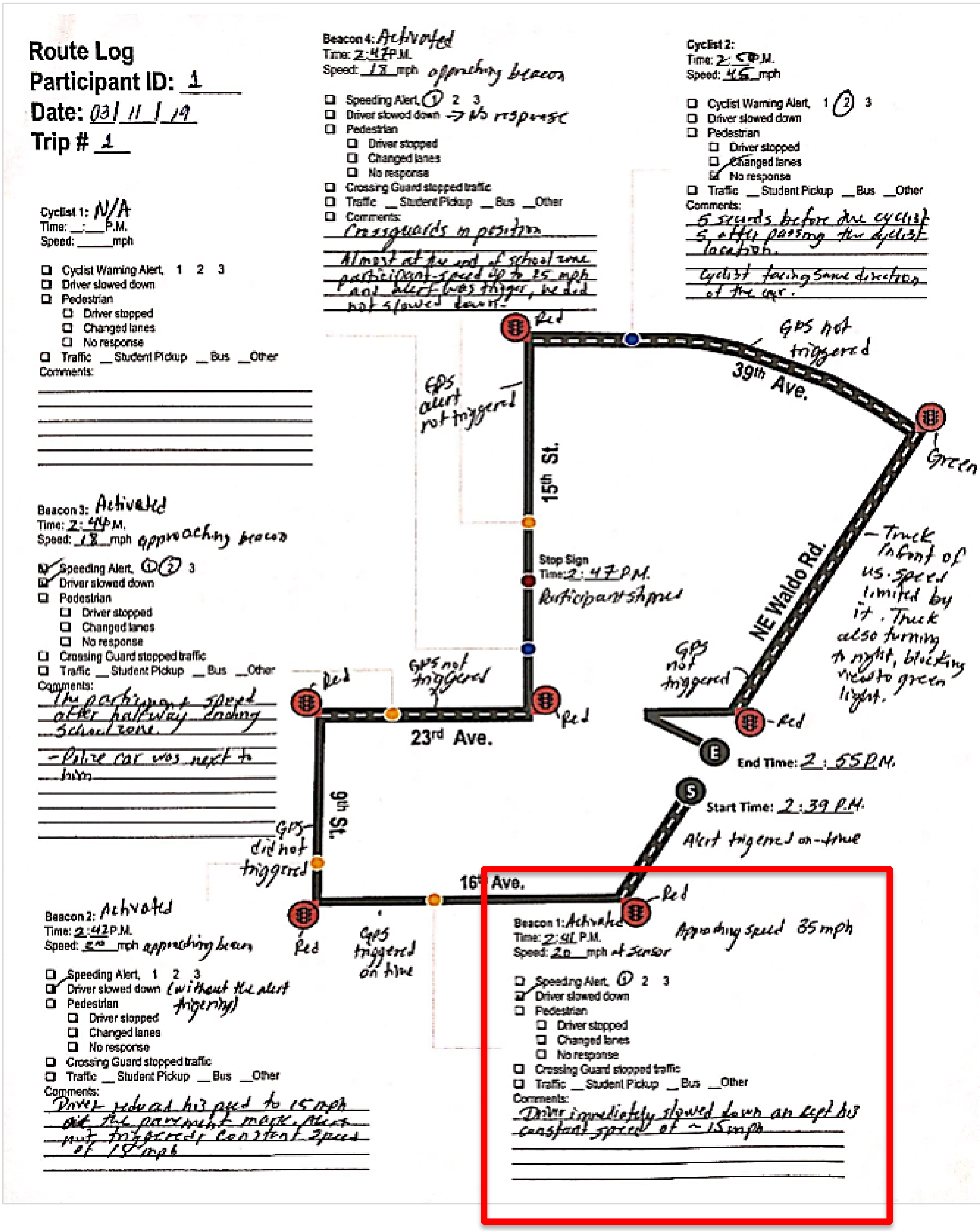

Figure 8 Data log for Participant 1, Trip 1

4.3 Recruitment of Participants and Data Collection

The study participants were recruited through advertisement emails, flyers, and word of mouth. Drivers 18 years of age or older with a valid driver's license, not wearing eyeglasses (participants could wear contact lenses if needed), owning a smartphone, and willing to drive using a cellular app (TravelSafely) were deemed eligible to participate. Qualifying participants were notified by email with the available dates to participate in the study. The principal investigator then sent them a calendar invitation as proof of their enrollment to the study. Participants were enrolled in the study in the order they indicated their availability (first come first serve) until we reached our total sample size (50 participants). The participants were blind to their assigned condition.

Fifty drivers participated in the experiment during the months of March, April, and May of 2019. The study time for each participant was about 1.5 hours including consent, practice/familiarization, calibration, driving, and debrief. The study team offered participant slots in the morning (8:15 am – 9:45 am) and afternoon (2:15 pm – 3:45 pm) active school zone times, during the weekdays (Monday-Friday). Out of the 50 participants who agreed to participate in the study, only one person did not show up the day of the study. As there were multiple people on the waitlist for participating in the study, another participant was scheduled.

The subjects were assigned to one of three conditions:

- **Stealth Mode.** In this condition, the TravelSafely app was on and the audio was muted. The phone was placed in the center console away from the sight of the driver so that they could not see any visual alerts that may pop up. Data from subjects in this condition provide baseline estimates of travel behavior in the absence of alerts.
- **Audio Alert Only.** In this condition, the TravelSafely app was on, the phone volume is set to maximum so that any audio alerts can be clearly heard by the driver. The phone was placed in the center console away from the sight of the driver so that they could not see any visual alerts that may pop up. Data from subjects in this condition provide estimates of travel behavior in the presence of only audio alerts.
- **Audio Visual Alerts.** In this condition, the TravelSafely app was on, the phone volume is set to maximum so that any audio alerts can be clearly heard by the driver. The phone was mounted to the windshield above and slightly to the left of the steering wheel within the sight of the driver so that they could easily see any visual alerts that may pop up. Data from subjects in this condition provide estimates of travel behavior in the presence of audio and visual alerts.

The subjects were blind to their assigned condition. **Table 3** provides an overview of subjects by condition and dates of data collection. **Table 4** provides a demographics distribution of the participants recruited for the study.

Table 3 Subjects by Condition and Dates of Engagement

Condition	**Participant IDs**	**Scenario Creation**	**Dates of Engagement**
Stealth Mode	11-20, 36-40, 46-50	Phone audio muted, Phone placed in center console out of sight.	April 11 to April 23, May 9 to May 16, May 22 to May 30
Audio Alert Only	1-10, 31-35, 41-45	Phone audio at maximum volume. Phone placed in center console out of sight.	March 11 to April 10, May 7 to May 9, May 17 to May 22
Audio-Visual Alert	21-30	Phone audio at maximum volume. Phone mounted to the windshield above and slightly to the left of the steering wheel.	April 24 to May 6

Table 4 Demographics distribution of participants

<table>
<tr><th colspan="6">Ethnicity</th></tr>
<tr><td>White</td><td>Black/African American</td><td>Hispanic/Latin American</td><td>Asian/Pacific Islander</td><td>Native American</td><td>Other</td></tr>
<tr><td>36%</td><td>30%</td><td>14%</td><td>8%</td><td>4%</td><td>8%</td></tr>
<tr><th colspan="3">Gender</th><th colspan="3">Age Range</th></tr>
<tr><td>Male</td><td colspan="2">Female</td><td>18-25 years old</td><td colspan="2">26 and above</td></tr>
<tr><td>36%</td><td colspan="2">64%</td><td>48%</td><td colspan="2">52%</td></tr>
</table>

CHAPTER 5 DATA ANALYSIS

The fundamental objective of this study is to examine the safety benefits of the school-zone speeding alert app. This can be determined based on (1) travel speeds (does the app reduce the probability of speeding in school zones) and (2) situational awareness (does the app improve the awareness of the driver about their presence in a school zone setting). The secondary focus of this study is examining the safety benefits of the cyclist alert app. This can be done by examining the situational awareness of the driver (does the app increase the likelihood of the driver noticing the cyclist).

This chapter describes the data analysis process employed to derive the required metrics from the variety of data collected. The results from the analysis are then presented and discussed. Given the complexity of the overall analysis procedure, this is presented as a flowchart in **Figure 9**. The variety of data collected by the study (video, Gaze, GPS, manual logs, etc.) are identified in the far left and the metrics of intersect (following from discussions in the previous paragraph) are presented in the far right (probability distribution of speeds, number of times app triggered, etc). The intermediate processing steps could be broadly broken down into (1) validation/cleaning of raw gaze and GPS data and (2) the processing of cleaned gaze/GPS data for deriving the metrics of interest.

It is useful to highlight that a mix of manual, semi-automated, and automated methods was used in the data assembly as indicated in the flowchart. The data analysis team comprised three doctoral level students, three master's degree students, and five undergraduate students. A high school student also participated in project activities over summer via the University of Florida Student Science Training Program (SSTP) program. The annotation of the AOIs was by far the most time/labor intensive step (as also highlighted in the flow chart).

The rest of this chapter is organized as follows. Section 5.1 presents an overview of the different input data streams. Section 5.2 describes the validation of eye-tracking data; Section 5.3 describes the validation of GPS data and Section 5.4 describes the overall valid data used for further analysis. Section 5.5 presents speed-based metrics and Section 5.6 presents gaze-based metrics.

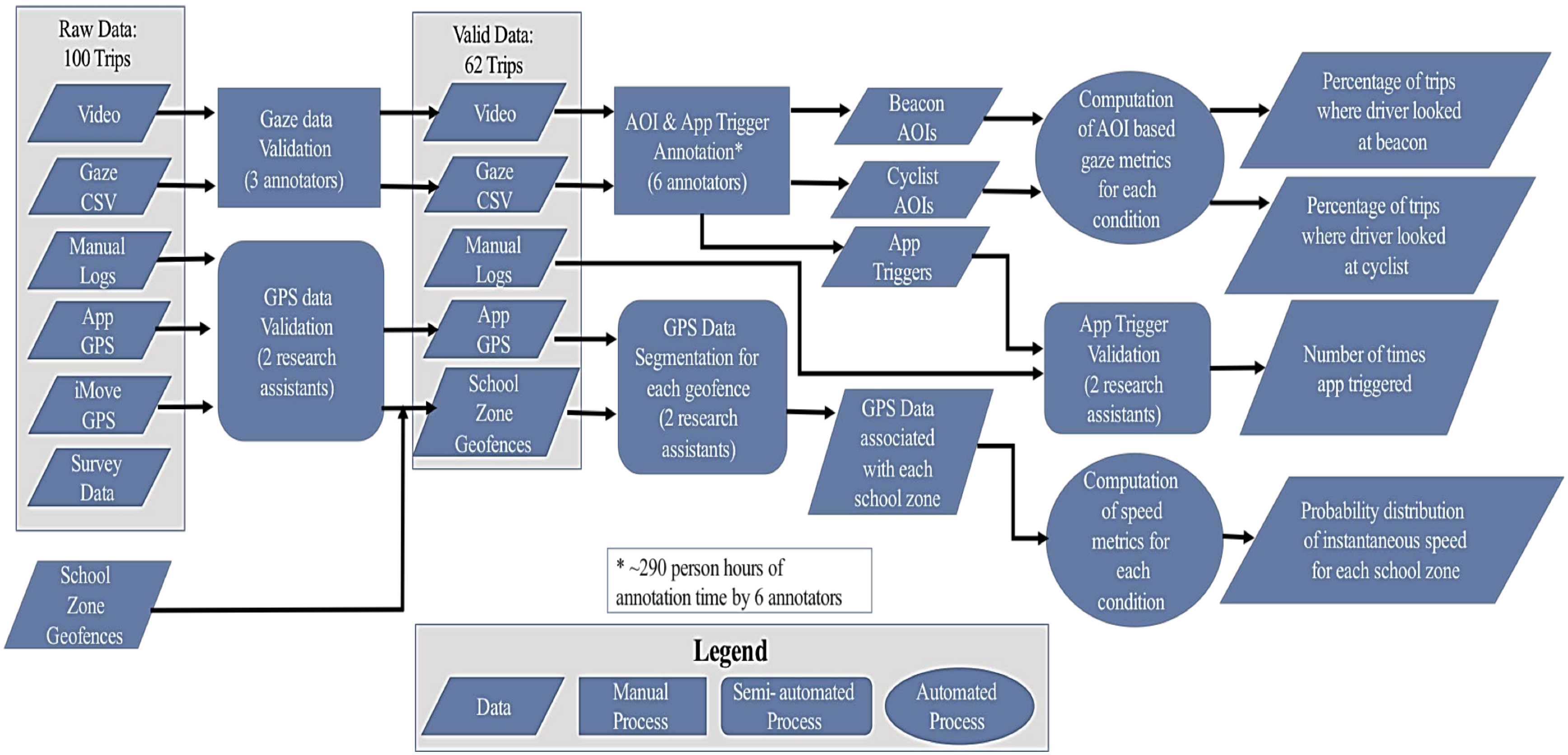

Figure 9 Flowchart representing the data analysis framework

5.1 Overview of Data Collected

5.1.1 Eye Tracking Data

Eye tracking data were collected via a SensoMotoric ETG head mounted mobile eye tracker. This equipment reports up to 120Hz gaze data (CSV format) and the camera feed (video format) from the scene camera on the glasses. This allows the experimenter to overlay gaze data on the scene camera view and observe what the participating driver was looking at.

5.1.2 TravelSafely/ GPS Data

The parent company, AI, extracted the vehicle trajectory data specifically for the experimental runs made for this study and provided these to the research team at University of Florida. It is useful to note that UF does not have access to data generated by other users of the app who were not part of our experimental study. The data were first transferred to the I-Street testbed data repository and, subsequently, extracted for analysis. This data file primarily includes the position and velocity of the UFTI vehicle when used for the experiments with the app turned on. This data stream, however, does not include information on whether or not the app triggered. As already discussed, we also collected trajectory data using the iMove app installed on the researcher's phone. These data were used to validate the TravelSafety trajectory data.

5.1.3 Manual Travel Logs

The manual travel logs are the hand-written logs of each trip recorded by the experimenter. A key detail from these logs is information on whether the alert was triggered for each school zone, and how many times the alert was triggered. The researcher riding in the back seat of the vehicle used a clipboard and pen to complete the travel log for each trip. An example travel log from Participant 1, Trip 1 was shown in **Figure 8**. Similar observations were made for each school zone and each participant. The location within the school zone where the app triggered and the exact time of the trigger could not be manually recorded.

5.1.4 After Study Survey

A survey collected feedback from the participants to help UF researchers elicit attitudes and preferences for safety in the local school zones. Questions included demographics of the participant such as age, gender, ethnicity, driving experience, type of vehicle and the number of days they drive per week. Additionally, the participant was also asked for feedback on the TravelSafely app such as whether it assists in driving and whether they would recommend it. Simple descriptive statistics from these responses are summarized in **Appendix A**.

5.2 Validation of Eye Tracking Data

The glasses-based SMI eye tracker uses optical eye tracking technology that estimates gaze location by tracking the location of the human user's pupil with an infra-red camera. The location of the pupil is mapped to the scene camera using a 3D model of the eye (Hansen, 2009). This mapping depends on an eye tracking calibration procedure for accuracy. The number of points used for calibration and the field of view spanned by the calibration targets influence the accuracy of gaze estimation. There is a trade-off between the number of points used in the calibration procedure and the time needed for setup before starting data collection.

The most common source of error in gaze estimation occurs if the eye tracking glasses shift position on the user's head, for example, if the user scratches behind their ear. During our experiment, we are unable to monitor eye tracking accuracy or interrupt the task for a recalibration in case of such an occurrence. As a result, we perform an eye tracking validation at the beginning and end of each trip and discard trials where gaze estimation error exceeds a pre-determined threshold.

3.3.1 Procedure

Participants performed an eye tracking calibration before their trip using the numbers on the light pole in front of them when the experimental vehicle was parked (described in Chapter 4). The accuracy of this calibration was estimated by instructing the participant to look at four targets (two numbers painted on the light pole, a doorknob to the left of the participant, and a black box within the vehicle). The researcher viewed the current gaze point in real time as it was streamed to the data recorded unit attached to the eye tracker. If the researcher was satisfied with the gaze estimates, the experiment would proceed. Else the participant would be re-calibrated. After the participant finished their trip and parked the experiment vehicle, the researcher asked them to perform another calibration accuracy check. The participant was asked to look at the same targets as before.

At the time of data analysis, annotators used the following procedure to assess gaze estimation error at the end of each trip:

1. In the eye tracking data processing software, fast forward the gaze replay till the end of each trip was reached.
2. For each target point in the calibration procedure, determine if the gaze error is below the threshold for that target. If yes, gaze on this target is considered accurate.
3. If at least 2 of 3 targets are marked as having accurate gaze estimates, the eye tracking data for this trip is marked as valid.

Appendix B contains the equations used to map pixels from the scene camera to degrees of visual angle. The thresholds for gaze data validity were set as follows:

- **Targets 1 and 2, Painted numbers on the light pole:** If the distance between the gaze point and the specified number was greater than the width of the pole, then the data was considered invalid. The threshold for this distance was approximately 93 pixels, or 4.4 degrees visual angle.
- **Target 3, Doorknob:** If the distance between the gaze point and the doorknob was more than the width of the door, then the data for the trip was rated as invalid. The width of the door is approximately 107 pixels, or 5.1 degrees visual angle.

- **Target 4, Black box**: If the distance between the gaze point and the target was more than the width of the black box, then the data for the trip was rated as invalid. The pixel length of the black box is approximately 72 pixels, or 3.4 degrees visual angle.

3.3.2 Inter Annotator Consistency Checks

As the determination of gaze validity depends on the skill of the student research assistant, we used the following procedure to resolve individual differences between students performing the annotations: Two undergraduate annotators check each trip for gaze data validity. If there was a disagreement between the annotators for a particular trip, a final annotator (graduate student) would examine the gaze data for that trip. The validation process was performed again, along with an additional validation of accuracy at the point in time where the driver passed the staged cyclist. If gaze estimates were considered accurate by the final annotator, the gaze data for the trip was marked as valid. The final annotator checked several ad-hoc targets in this case, including rearview mirror, the cyclist, the speedometer, and the phone (if visible).

Table 5 shows the percentage of trips that each annotator considered valid. Annotator 1 and 2 judged 67% and 68% of the trips as having valid gaze data respectively. Cohen's kappa was used to measure inter-annotator reliability between Annotator 1 and 2. As this value was 0.5670, it falls within the range of "moderate agreement" for the kappa statistic (McHugh, 2012). The annotators disagreed on 19 trips, which were then re-examined by the final annotator. After this re-examination, 69% of the trips were marked as having valid gaze data.

Table 5 Gaze validity results from each annotator

Method	**Valid Trip 1**	**Valid Trip 2**	**Overall Valid**
Annotator 1	68%	66%	67%
Annotator 2	64%	72%	68%
Final Annotator	72%	66%	69%

In total, 69% of the trips were marked as having valid eye tracking data associated with them. When broken down by condition, the validity check resulted in 27 valid trips in the OFF condition, 27 valid trips for Audio ON, and 15 valid trips for Audio/Visual ON. When broken down by participant, 7 participants had 0 valid trips after this process; 17 participants had 1 valid trip; 26 participants had 2 trips. Because the experiment had included both morning and afternoon active school zone times, the total data comprised 32 morning trips and 68 afternoon trips. After the gaze data validation procedure, 20 morning trips and 49 afternoon trips were retained. In other words, 37.5% of the morning trip data and 28.0% of the afternoon data were removed from analysis as the associated gaze data was not valid.

5.3 Validation of GPS Data

The vehicle trajectory database provided to the research team contained all the trajectories of all the participants/trips in one large datafile. First, GPS data files were extracted for each of the 50 participants based on the manual travel logs that logged the participant's trip number, trip date, and trip start- and end- times. In restructuring the AI raw data into the 50 participants, it was observed that there were some data points outside the trip duration. This was largely due to the TravelSafely app being turned on before the trip and being turned off a while after a trip was completed. Therefore, the data points recorded outside the start and end time of the trip were discarded. Next, the total number of data points recorded for each trip were calculated. Given the start- and end- times of the trip and the data recording frequency of the app, we also know the total number of data points expected if all data were perfectly recorded. If the number of actual points were less than one-half of the number of expected points for the trip, this trip was tagged as invalid from the GPS data perspective. Out of the 100 trips only 8 were determined as unusable using the above metric.

The trajectory data contained the day and times of the study period in addition to the longitude, latitude and speed of each participant along the study route. The timestamps provided had a four-hour shift from the Eastern Time (US). The speeds were recorded in km/h and were converted to mph. The trajectory data form the AI app were compared against the trajectory data locally collected using the iMove app. Speed-location profiles form both sources were mostly similar (see **Figure 10**). As the AI app provided data at a higher frequency, we decided to use the trajectory information from this source for all further analysis.

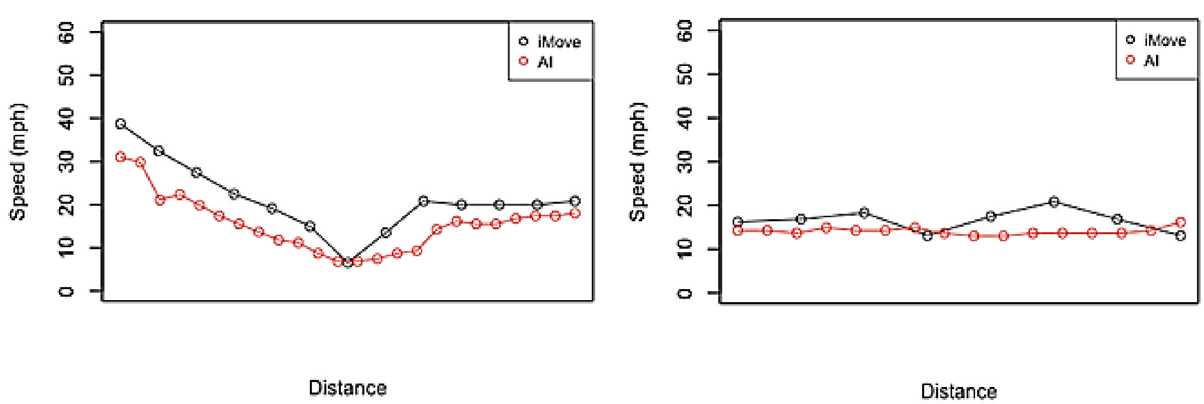

Figure 10 Comparison between the iMove speed data and AI speed data for S06 (Trip 2) in School Zone 1(left) and School Zone 3 (right)

5.4 Valid Sample of Data for Further Analysis

In total, 50 drivers participated in the experiment across all three conditions. Each driver completed two trips, and as a result, eye tracking data and GPS trajectory data for a total of 100 trips were available. GPS data were valid for 92% of the trips. Eye tracking data were valid for 69% of the trips. **Table 6** shows the number of valid trips for each validity criterion: gaze validity only, GPS validity only, and both valid. For all subsequent data processing, only those trips that had both valid GPS and eye tracking data were used, i.e. 23 trips for the stealth mode, 24 trips for the Audio ON condition and 15 trips for the audio-visual on condition.

Table 6 Number of valid trips after GPS and gaze validation across conditions

Condition	**Number of Trips**			
	Total Data	**Gaze Valid Data**	**GPS Valid Data**	**Gaze + GPS Valid Data**
Stealth/OFF Mode	39	27	35	23
Audio ON	41	27	38	24
Audio/Visual ON	20	15	19	15

5.5 Speed-based Metrics

Speed was the primary metric derived from the GPS trajectories. The study hypothesis is that the alerts provided by the app will slow down the drivers in school zones. From the overall trajectories of the drivers, the trajectories corresponding to movements within each school zone were extracted. The geofence coordinates of the school zones were not provided by AI. Therefore, we generated those coordinates by traversing the school zones using the iMoves GPS Tracker app.

Profiles of instantaneous speeds within school zone boundaries under alternate experimental conditions (stealth, Audio, and Audio-Visual) were generated. The profiles (**Figure 11)** indicate that the probability of higher instantaneous speeds (especially speeds higher than 20 mph) were higher in the stealth mode. With the availability of the app, the graphs shift left indicating a reduction in the probability of observing high instantaneous speeds in the school zones. **Figure 12** presents the same data but separately for each school zone. The trends for the individual school zones are similar to the overall trend indicated in **Figure 11**.

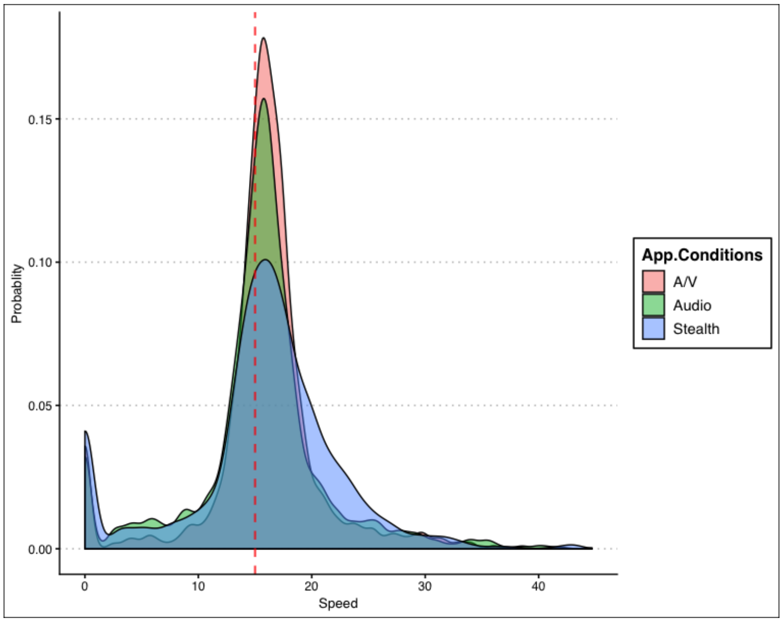

Figure 11 Comparison between the speed distribution for the Stealth/OFF, Audio ON, Audio/Visual ON conditions. (Dashed Red line indicated the School Zone Speed Limit i.e., 15 mph)

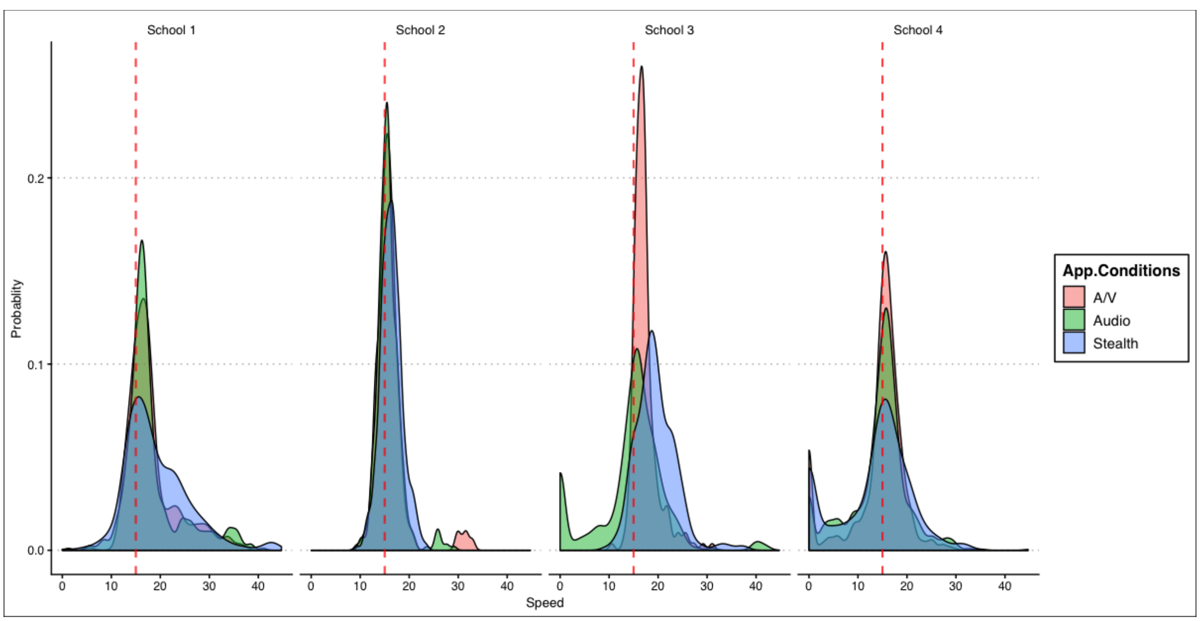

Figure 12 Comparison between the speed distribution for the Stealth/OFF, Audio ON, Audio/Visual ON conditions by School Zone. (Dashed Red line indicated the School Zone Speed Limit i.e., 15 mph)

Table 7 presents the probability of instantaneous speeds exceeding 20 mph at each school zone and under alternate experimental conditions. These were derived from the graphs in **Figure 12** (number of instances where speed exceeded 20mph as a fraction of the total number of instances). It is evident that the probabilities are the highest in the stealth mode with a reduction when the app was in use (in either the audio or audio-visual modes) suggesting that instances of speeding are reduced with the availability of the app.

Table 7 Probability of instantaneous speeds exceeding 20 mph

App Condition	School Zone 1	School Zone 2	School Zone 3	School Zone 4
Stealth/ OFF Mode	36%	6.06%	36%	14%
Audio ON	23%	4.6%	13.4%	11%
Audio/Visual ON	23%	1.1%	1%	6.4%

The TravelSafely app was designed to trigger an alert when the driver exceeds 20 mph in a school zone. Each instance of the app triggering was recorded in the manual logs (cross-validation of the manual entries against audio-video data from the eye-tracker recordings did indicate that the manual entries were made correctly). It is useful to recall that even in the Stealth/OFF condition when the participant did not see or hear the triggered alert, the researcher was able to log such an instance. Thus, the changes in speeding behavior can be measured in terms of the changes in the number of times the app triggers. Specifically, the proportion of instances in which the app triggers should be higher in the stealth mode (as the driver is not getting this feedback) compared to the audio-on and audio-visual on conditions.

Table 8 presents the number of school zones instances for which the app did and did not trigger, and the total number of instances (number of subjects in this condition * 2 trips/subject * 4 school zones/trip). Note that we are using 100% of the data collected in this analysis, as the app triggering is not impacted by availability of GPS or Gaze data. When in the stealth mode, the app triggered in over 50% of the instances of driving through the school zone which reduced to 38% in the case of audio-on condition and 46% in the audio-visual on condition.

Table *8* Percentage of App triggers in each condition

App Condition	**Number of Total Instances**	**Number of school zones instances in which the app did not trigger**	**Number of school zones instances in which the app triggered once or more**	**Percentage of times when App Triggered**
Stealth/OFF	160	76	84	52.5%
Audio ON	160	99	61	38.13%
Audio/Visual ON	80	43	37	46.25%

Thus, the analysis based on app-triggers also reinforces the result that the availability of the app alerts reduces instances of over-speeding in the school zones.

It is useful to note here that there are some inconsistencies between speeds recorded and apps triggering. Specifically, there were instances in which the app triggered in a school zone but the instantaneous speeds were never higher than 20 mph. There were also instances in which the speeds were over 20 mph, but the app did not trigger in the school zone. This could be, in part, because of latency between speed measurement and app triggers. As already indicated the current data stream recorded by AI does not include data on when and where apps triggered. Therefore, we are unable to perfectly match the location and time of app triggering to the instantaneous speeds.

5.6 Gaze-based Metrics

The SMI head mounted eye tracking glasses used in this experiment record the user's gaze at 60Hz. Raw gaze data is processed to extract fixations and saccades. Fixations refer to clusters of raw gaze points that are very close in space and time [Salvucci & Goldberg, 2000]. It is during fixations that information processing occurs. The fast movement of the eye from one fixation point to another is known as saccade. Information processing does not occur during saccades. In other words, if a raw gaze point falls within a school zone beacon AOI, we must ascertain that it is part of a fixation in order to count the beacon as having been looked at.

The SMI eye tracking data processing software, BeGaze, provides tools to process raw gaze points into fixations. Each fixation is defined by the 2D location, starting timestamp, duration (ms), and dispersion (pixels). Dispersion is calculated as

$$D = [(x) \ - min(x)] + [(y) \ - min(y)], \qquad (1)$$

where x and y represent the set of 2D points that comprise the fixation. The average value of x and y are used to compute the 2D fixation location. Duration is computed as the difference in timestamps between the last and first points in the fixation. BeGaze uses I-DT, a dispersion-based method, for fixation detection [Salvucci & Goldberg, 2000]. The method uses two parameters to generate fixations, a minimum duration and maximum dispersion. The minimum duration enforces that all clusters of points considered to be a fixation must span at least this much time and was defined as 80 ms. The maximum dispersion limits how far gaze points can be from each other while forming a fixation cluster and was defined as 100 pixels. To detect saccades BeGaze uses I-VT, a velocity-based method [Salvucci & Goldberg, 2000]. The method uses two parameters to generate saccades, a minimum duration and minimum peak velocity. Similar to fixation detection, the minimum duration defines the shortest possible saccade that will be detected and is defined as 22 ms. Sequences that were not labelled as fixations and had a maximum instantaneous velocity that exceeded 40 degrees per second were considered a saccade. All raw eye tracking data was processing through BeGaze to extract fixations and their corresponding time stamps.

Undergraduate research assistants marked a bounding box to demarcate an AOI for each active school zone beacon for each trip and each participant. **Figure 13** is a screenshot from the eye tracking data processing software. The screenshot shows the blue bounding box that represents the AOI for this school zone beacon and the orange circular marker that represents the participant's gaze. When the orange marker is inside the blue bounding box (see also previous discussion on "fixation"), the software counts this event as "the participant looked at the beacon". In the moment in time represented in **Figure 13**, the driver was looking at the road rather than the beacon. Annotating the bounding boxes is a tedious manual process which takes around 30 minutes per minute of eye tracking data. After this annotation, the process of computing the metrics is automatic. We first present the gaze metrics for school zone beacons and then present the gaze metrics for the cyclist.

Figure 13 Example of bounding box to demarcate an area of interest (AOI) for this school zone beacon. In this frame, the driver is looking at the road rather than the flashing beacon.

5.6.1 Driver Attention on School Zone Beacons

Our initial metric of interest is the percentage of the trips in which drivers looked at the flashing school-zone beacons. This is considered as a surrogate measure of situational awareness. It is useful to acknowledge that there is no established evidence on what drivers should be looking at for safely navigating school zones. Further, there are several things in the school zone that could cue the drivers to their situation. However, given that the app works based on the flashing beacon, we chose to examine whether the in-vehicle alert would increase the probability of the driver looking at the flashing beacon.

The computations for each school zone beacon and each trip are as follows: Raw gaze data, after being pre-processed, is converted into fixation locations. If a driver's fixation is inside the AOI for the current school zone beacon, their fixation count is incremented. As long as a driver's fixation count is greater than zero, that beacon is marked as being looked at for that trip. **Table 9** provides the percentage of trips where the driver looked at (i.e., fixated once or more) a school zone beacon for each condition in the study. In general, we find that drivers look at the flashing school zone beacons when they are located at the side of the road. In contrast, in School Zone 3, there is a much lower percentage of trips where the driver fixates on the beacon, which could be because this is the only beacon is located overhead and also because the approach speed was higher for this school zone than all others. There is no clear evidence from the table that the app systematically changed the way in which people looked at the flashing beacon. Even in the case of the school zone with the overhead beacon, it seems that drivers were potentially substituting the app for looking at the beacon as the %-looked-at reduced with the apps.

Table 9 Percentage of trips for GPS + Gaze Valid data where driver looked at beacon

Condition	**School Zone 1**	**School Zone 2**	**School Zone 3**	**School Zone 4.1**	**School Zone 4.2**	**Overall (Zones 1,2,4)**
Beacon location	Roadside	Roadside	Overhead	Roadside	Roadside	
Approaching Speed	35 mph	30 mph	40 mph	30 mph	30 mph	
Stealth/OFF Mode	52.17%	60.87%	30.43%	69.57%	73.91%	61.57%
Audio ON	62.50%	54.17%	25.00%	62.50%	79.17%	62.50%
Audio/Visual ON	60.00%	80.00%	13.33%	80.00%	86.67%	74.44%

5.6.2 Saccade Amplitude

Another way of using gaze-data to understand situational awareness is by examining the "scanning behavior". In this analysis we examine whether drivers were primarily looking at one place (straight ahead) or whether they were scanning the area. Saccades can be used for this purpose. Saccades are fast movements of the eye as people switch their attention from one region of interest to another. The angular distance that the eye travels during a saccade is termed saccade amplitude.

We computed the saccade amplitude of the drivers for three school zones (School Zones 1, 2 and 3). School Zone 4 had a four way stop within the school zone and as a result, drivers slowed to a stop and looked all four ways. Therefore, we did not consider this school zone in our analysis as the gaze behavior is expected to be quite different from those school zones where drivers are driving right through. For all the conditions, only the first trip was included for the measurements (considering processing times). The saccades were bucketed into small, medium and large amplitude saccades based on the thresholds: 2-10 visual angle degrees for small saccades, 10-30 visual angle degrees for medium saccades, and 30-70 visual angle degrees for large saccades respectively.

Table 10 shows the percentage of small, medium, and large saccades for the School Zones 1, 2 and 3. In School Zones 1 and 3, we see that there are more medium- and large- saccades in the conditions where the driver was being alerted by the app (Audio On, Audio/Visual On) compared to the Stealth/OFF mode, though not in School Zone 2. School Zones 1 and 3 had higher approach speed limits (35mph and 40 mph respectively) than the approach speed limit for School Zone 2 (30mph). From the instantaneous speed distributions in **Figure 13**, there is a clear left shift in the speed distribution in School Zones 1 and 3 when the app is on. Taken together, these observations suggest that driving speeds tend to be slower and drivers have an associated change in visual scanning behavior in such a way that they look around more. It may be expected that increased scanning (greater saccade amplitude) is correlated with more awareness and therefore has a positive impact on safety.

When we qualitatively inspected the eye tracking data, we noticed that medium and large saccades involving drivers looking from one side of the road to the other, road sign to phone, beacon to speedometer as drivers enter school zone for example. Small saccades involve shifting focus of attention from the center of their lane to an oncoming vehicle that is in the opposite lane, looking from one parked car to the next in a row of cars, and small shifts within the center of their own driving lane. Further systematic coding is needed to fully characterize the automobile and roadside elements drivers looked at.

Table 10 Percentage of Small, Medium and Large saccades across each condition

App condition	Small	Medium	Large
School Zone 1 Trip 1			
Stealth/OFF Mode	68.87	29.42	1.71
Audio ON	60.75	35.84	3.41
Audio/Visual ON	57.43	38.61	3.96
School Zone 2 Trip 1			
Stealth/OFF Mode	67.99	29.75	2.26
Audio ON	67.02	30.87	2.11
Audio/Visual ON	70.42	28.99	0.59
School Zone 3 Trip 1			
Stealth/OFF Mode	65.35	32.52	2.12
Audio ON	60.11	35.73	4.16
Audio/Visual ON	60.73	37.17	2.09

It is important to note that measuring eye movement to capture shift in driver attention requires the assumption is that the head is stationary. In our study, the driver was able to move their head in a naturalistic manner and the eye tracker we used does not report head orientation. As a result, though we report saccade amplitudes, it should be noted that these amplitudes do not account for the head turning. This could be rectified in future with an experimental setup that included a dashboard camera that faced the driver or an eye tracker with an integrated inertial measurement unit.

5.6.3 Driver Attention on Cyclist

Unlike in the case of school zone alerts in which there are multiple cues, the cyclist alert app can be evaluated based on whether or not the app increased the probability of the driver seeing the cyclist triggering the alert.

The metric of interest is the percentage of trips in which the driver looked at the staged cyclist. The computations in this case are as follows: Raw gaze data, after being pre-processed, is converted into fixation locations. If a driver's fixation is inside the AOI for the cyclist, the fixation count is incremented. As long as a driver's fixation count is greater than zero, the cyclist is marked as being looked at for that trip. **Table 11** provides the percentage of trips where the driver looked at (i.e., fixated once or more) the cyclist for each condition in the study. We consider Trip 1 and Trip 2 separately because drivers were familiar with the driving circuit in Trip 2 and likely anticipated that there would be a cyclist coming up. This is reflected in the condition Stealth/OFF Mode, where the percentage of drivers who looked at the cyclist goes up to 45.45% in Trip 2, compared to 16.67% in Trip 1.

We focus on the differences across conditions for Trip 1. The findings indicate that the percentage of drivers who looked at the cyclist at least once or more was greater whenever the app was ON. However, Audio ON might be considered more effective than Audio/Visual ON, possibly because the alert itself drew the driver's attention away from the cyclist, thus bringing down the percentage of trips where the cyclist was looked at from 50% to 33%. This trend is seen in Trip 2 as well (50% in Audio ON versus 28% in Audio/Visual ON). Thus, the results suggest that the cyclist alter app is effective in drawing attention of the driver to the presence of the cyclist especially in situations in which the cyclist was not expected in the first place.

Table 11 Percentage of trips with GPS + Gaze Valid data where driver looked at cyclist

Condition	**Trip 1**	**Trip 2**
Cyclist location	Roadside, shortly after School Zone 4	Roadside, shortly after School Zone 4
Stealth/OFF Mode	16.67%	45.45%
Audio ON	50.00%	50.00%
Audio/Visual On	33.33%	28.57%

CHAPTER 6 SUMMARY AND CONCLUSIONS

The main purpose of this study was to evaluate the performance of a phone-based safety application that (1) alerts drivers when they speed in school zones (2) alerts drivers when they are near cyclists. The technology is aimed at improving safety for vulnerable road users. The specific solution evaluated in this study is a smartphone-based app called "TravelSafely" developed by Temple/AI. This app implements the capability to alert drivers if they exceed a pre-specified speed limit (such as 5 mph above the school zone speed limit) when intelligent school zone beacons are active (The city of Gainesville already had several such intelligent school zone beacons). A secondary service provided by this same app is to alert drivers about cyclists if the expected time to collision is below a certain threshold (irrespective of whether they are in the school zone or not). The cyclist alert works if the cyclist also has the TravelSafety app turned on.

This study evaluated both school-zone and cyclist alert features using a naturalistic driving study that used a driving circuit that integrated driving through school zones and road segments with a staged bicyclist. We collected trajectory and eye tracking data from 50 participants during this study. Each participant drove the circuit twice and, in each circuit, drive through 4 school zones and one staged cyclist (cyclist had the app turned on). The driving subjects were randomized across three conditions: (1) Stealth/OFF condition (drivers did not receive any alerts), (2) Audio ON (drivers received audio alerts), and (3) Audio/Visual ON (drivers received both audio and visual alerts).

The data were processed using a mix of manual and automated methods to derive several metrics that capture the safety effects of the app. The computed metrics broadly quantified driving speed and attention allocation. The impacts of the app were ascertained by comparing these metrics across the three experimental conditions.

The main findings of this study are summarized as follows:

- The probability of instantaneous speeds exceeding 20 miles/hour within school zones was less in Audio ON and Audio/Visual ON conditions compared to Stealth/OFF mode.
- The probability of the app triggering was less in Audio ON and Audio/Visual On conditions compared to Stealth/OFF mode.
- Drivers typically look at the school zone beacon while entering the school zone, even in Stealth/OFF condition. The exception is when the school zone beacon is overhead rather than roadside. The availability of the app was not found to systematically increase the likelihood of looking at the beacon. Looking at the beacon was considered as a proxy for situational awareness in school zones. However, there are several visual cues that could alert drivers to their presence in school zones.
- Drivers exhibited more medium and large saccades (measured without considering the turning of the head) in Audio ON and Audio/Visual ON condition compared to Stealth/OFF mode. This indicates that drivers exhibit more visual scanning behavior with the availability of the app (and the associated slowing down). This in turn could translate into improved situational awareness and improved traffic safety.

- Drivers were more likely to look at the cyclist in Audio ON and Audio/Visual On conditions compared to Stealth/OFF mode in their first trip. This suggests that the app did succeed in drawing attention of the driver to the cyclist. On their second trip, when drivers are familiar with the route (and were potentially expecting a cyclist), we find that there is a smaller difference between Stealth/OFF mode and Audio ON conditions. In contrast, drivers looked less at the cyclist in the Audio/Visual On condition relative to Stealth/OFF condition. The additional visual alert could be drawing the drivers' attention to the cell phone instead of the cyclist.

Overall, the experimental study suggests that the availability of an app decreases the probability of speeding in school zones. It did not alter the behavior of how drivers looked at the beacons but the analysis did show increased visual scanning behavior in the presence of the app. Together, the decreased speeding and increased scanning could translate into improved situational awareness and increased safety in school zones.

In the case of the bicyclist, the results showed a significant increase the probability of seeing the cyclist with the availability of the app when the bicyclist was not expected (trip 1). This suggest the value of the app in improving safety in locations in which cyclists are generally not expected. In contrast, when cyclists are expected (Trip 2), the app did not translate into significant increases in the probability of spotting the bicyclists as they were quite likely to be noticed even without the app. In this situation, having an audio-visual alert could have safety impactions as the gaze was drawn away from the cyclist to potentially the phone.

It is useful to acknowledge that these results are based on a relatively small sample of valid data points. We lost almost 30% of our data during our strict validity checks, particularly on the gaze data. In addition to performing similar experiments with larger sample sizes, the following are also identified as areas of future research.

- While the overall performance of the app was generally robust, we did notice discrepancies between speeds observed and apps triggered (app triggered when the speeds did not exceed 20 mph and app not triggering when the speeds did exceed 20 mph). This could be because of accuracy of GPS data, algorithms that trigger the alert, and/or latency issues. These could be addressed in future upgrades of the app.
- The school zone boundaries are generally staggered in the two directions (the point at which the driver sees end of school zone sign in one direction is not the same place at which the start school zone sign in painted in the roadway in the opposite direction). The app uses the school zone marking on the roadway to define the geo fence. This leads to false alerts when the driver starts accelerating after seeing the end of school zone sign but is still within the geo-fence established by the app. This can be rectified by modifying the school zone boundaries by direction and by using a higher resolution GPS which can give lane-level precision.
- The data stream recorded by Temple/AI did not include if and when the app triggered. Notes from the manual logs were used to determine if the app triggered. Availability of this information within the data stream that also contains the GPS traces will allow us to study changes in speeding behavior immediately after the alert is received.

- The data recorded in this study was from heterogeneous sources and the gaze data and GPS data were not synchronized. This precluded analyses such as how long it took drivers to slow down after they looked at school zone beacons or the cyclist.
- Finally, to our knowledge there are no attentional metrics that have been established as characteristic of safe driving in school zones or safe driving around cyclists. Examining whether changes in gaze and saccades will translate into fewer crashes, less severe crashes, or fewer near-misses is identified as an area of future work.

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APPENDIX A: Survey Responses

Fifty-eight percent (58%) of the respondents indicated that presence of school zones and speed limit signs "always" affected their driving behavior while 40% of the respondents indicated that it affected them "most of the time". Sixty-eight percent (68%) of the respondents indicated the flashing yellow light was "extremely effective" in changing their driving behavior in school zones while 24% felt it was "very effective". Only 4 of the 50 total respondents felt that the flashing yellow was only "moderately" or "slightly" effective. Overall, these indicate that there is already a good level of self-regulation of driving in school zones and the presence of flashing yellow is indeed perceived to be effective[1].

The respondents were asked to identify the factors that could affect the safety of vulnerable road users in school zones (multiple responses were allowed). The results are summarized in **Figure 15**. Visibility was indicated as the most important factor followed by speed limit. Pavement marking was the least important factor.

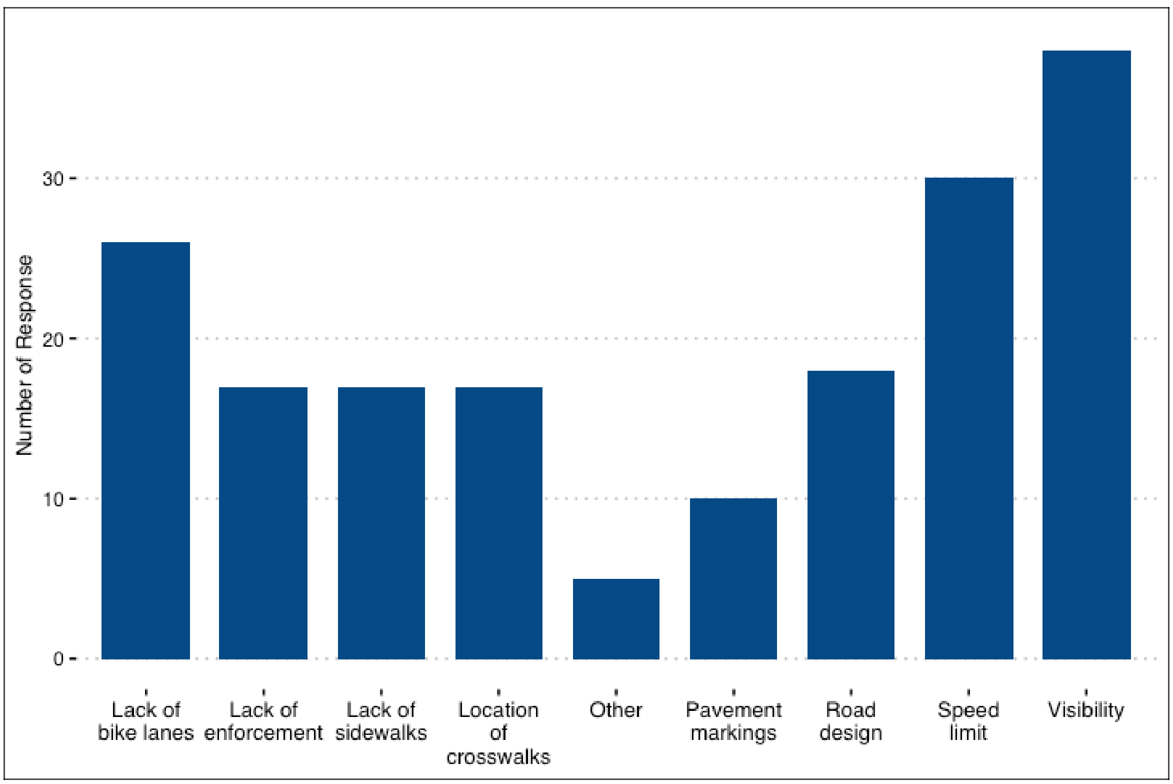

Figure 14 Distribution of Factors impacting the safety of vulnerable road users at school zones.

[1] We acknowledge that people can be expected to overstate "positive" behaviors in such stated-preference surveys and therefore the exact percentages should be used with caution. However, it is our expectation that the trends in the behavior (i.e., driving patterns of people are more likely to be impacted in school zones with flashing yellow than not) are still likely to hold.

The next set of questions which were related to the app were asked only to those in the "ON" condition as only these respondents experienced the app. Responses are available for only 19 subjects even though the total number of participants in the ON condition were 30 because of a glitch in the survey tool. A response to an initial question led to a misclassification of some participants and therefore the opinion questions did not pop up. This issue was rectified later on.

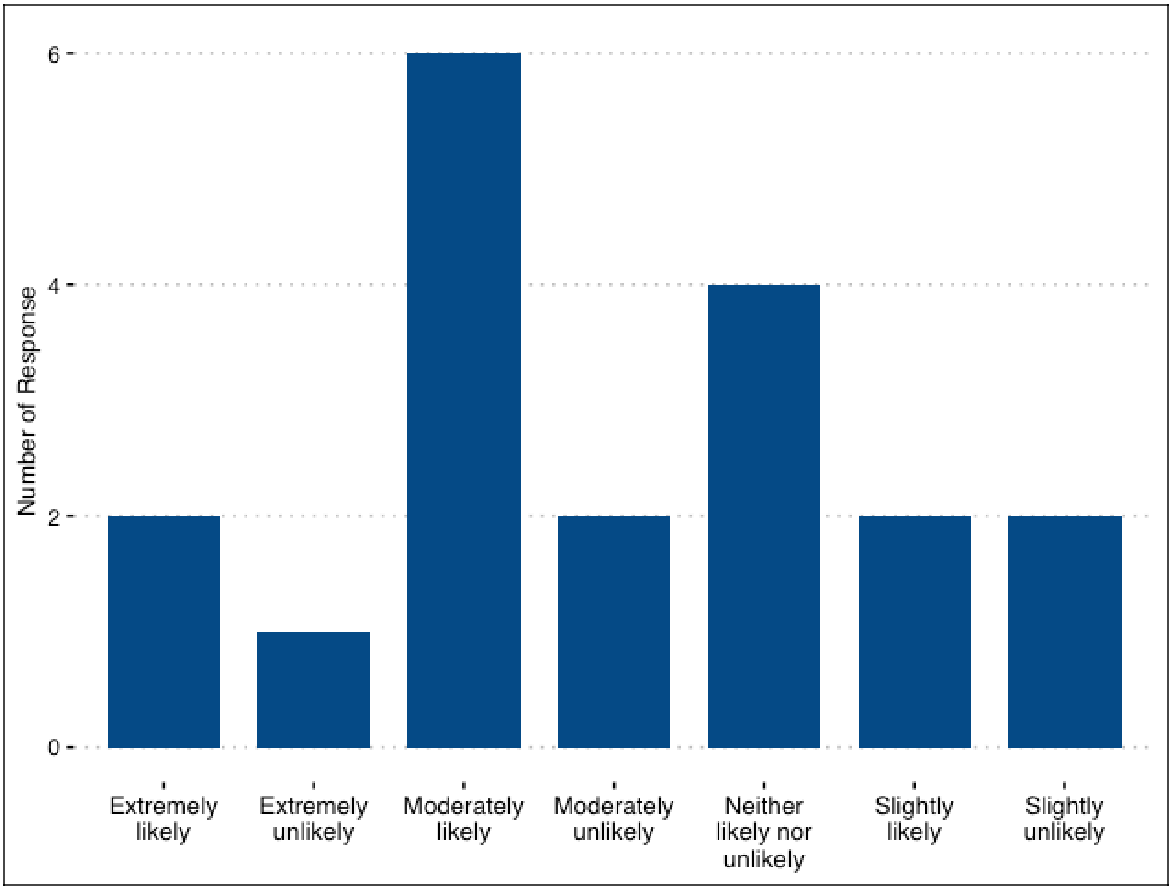

Figure 15 Distribution of responses to the question "How likely are you to use the TravelSafely app while driving"

Practically all of the 19 respondents indicated that the app had a "positive" influence on their driving behavior through the school zones. About 63% felt that the app made them a better driver in the school zones. However, these general positive feelings about the app did not translate into a high likelihood of app use. Specifically, the responses to the question "How likely are you to use TravelSafely while driving" are indicated in **Figure 16** and the responses to the question "How likely are you to recommend the Travel Safely app to others" are indicated in **Figure 17**. In talking informally with the participants, we found that they felt that not enough people are using it and thus they did not feel it was worthwhile installing another app on their phone.

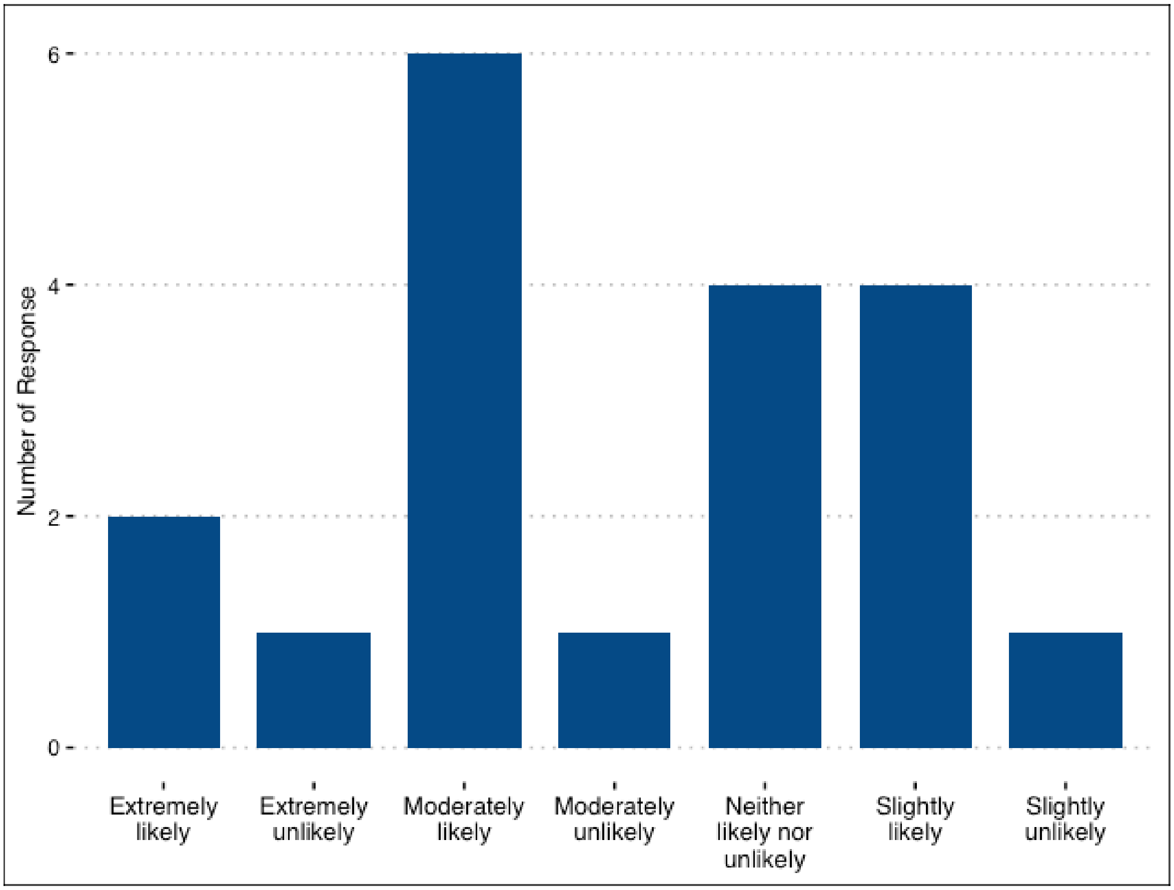

Figure 16 Distribution of responses to the question "How likely are you to recommend the TravelSafely app to others"

76% of the respondents were between the ages of 20 and 30. 64% of the survey respondents were female. 46% of the respondents owned a vehicle and 70% of the respondents owned a regular sedan. 50% of the respondents reported driving 7 days a week while only 8% reported driving 3 days or less. The ethnicity distribution is shown in **Figure 18**.

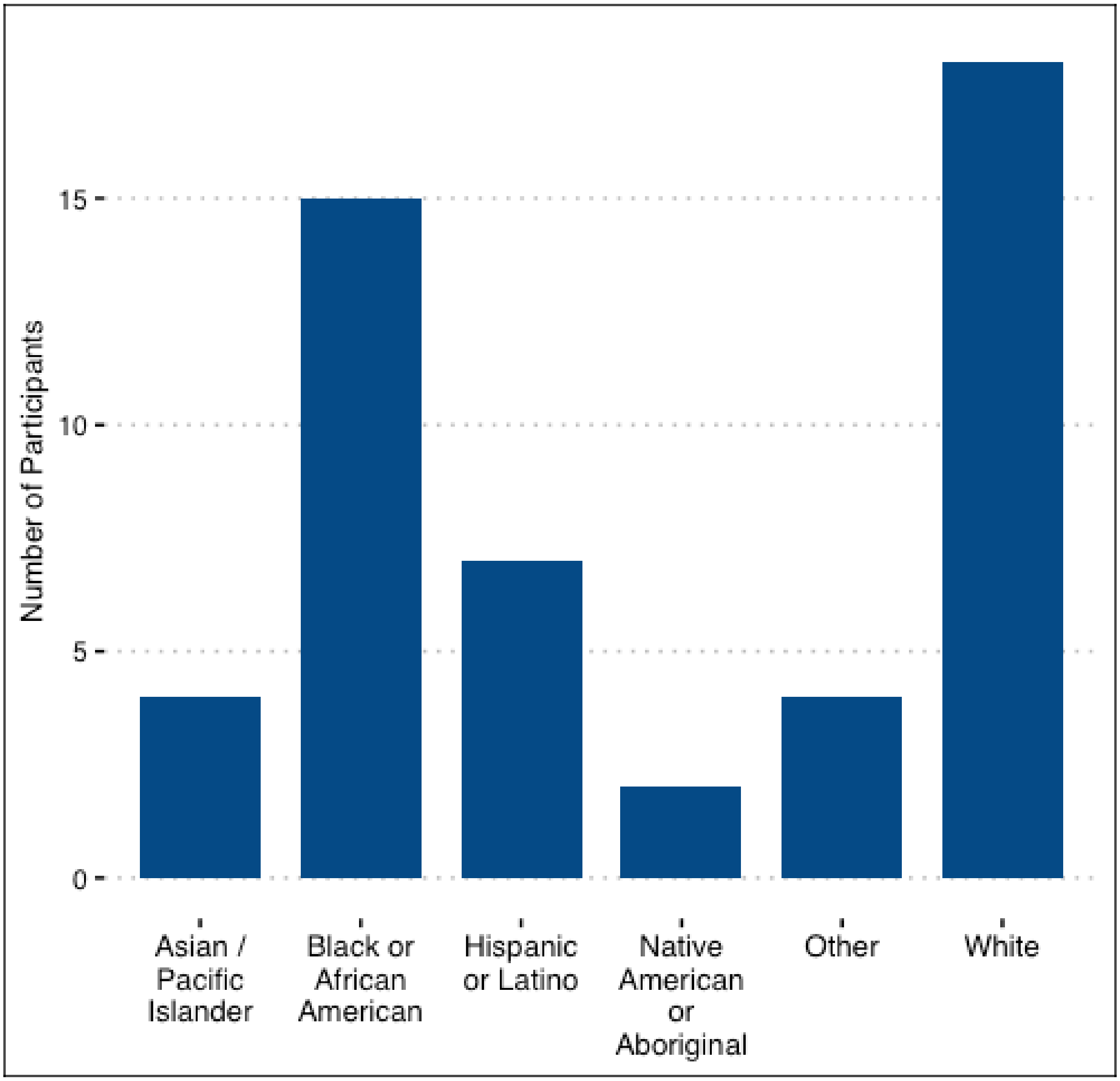

Figure 17 Distribution of ethnicity of the subjects.

Over 75% of the survey respondents had 6-15 years of driving experience (**Figure 19**)

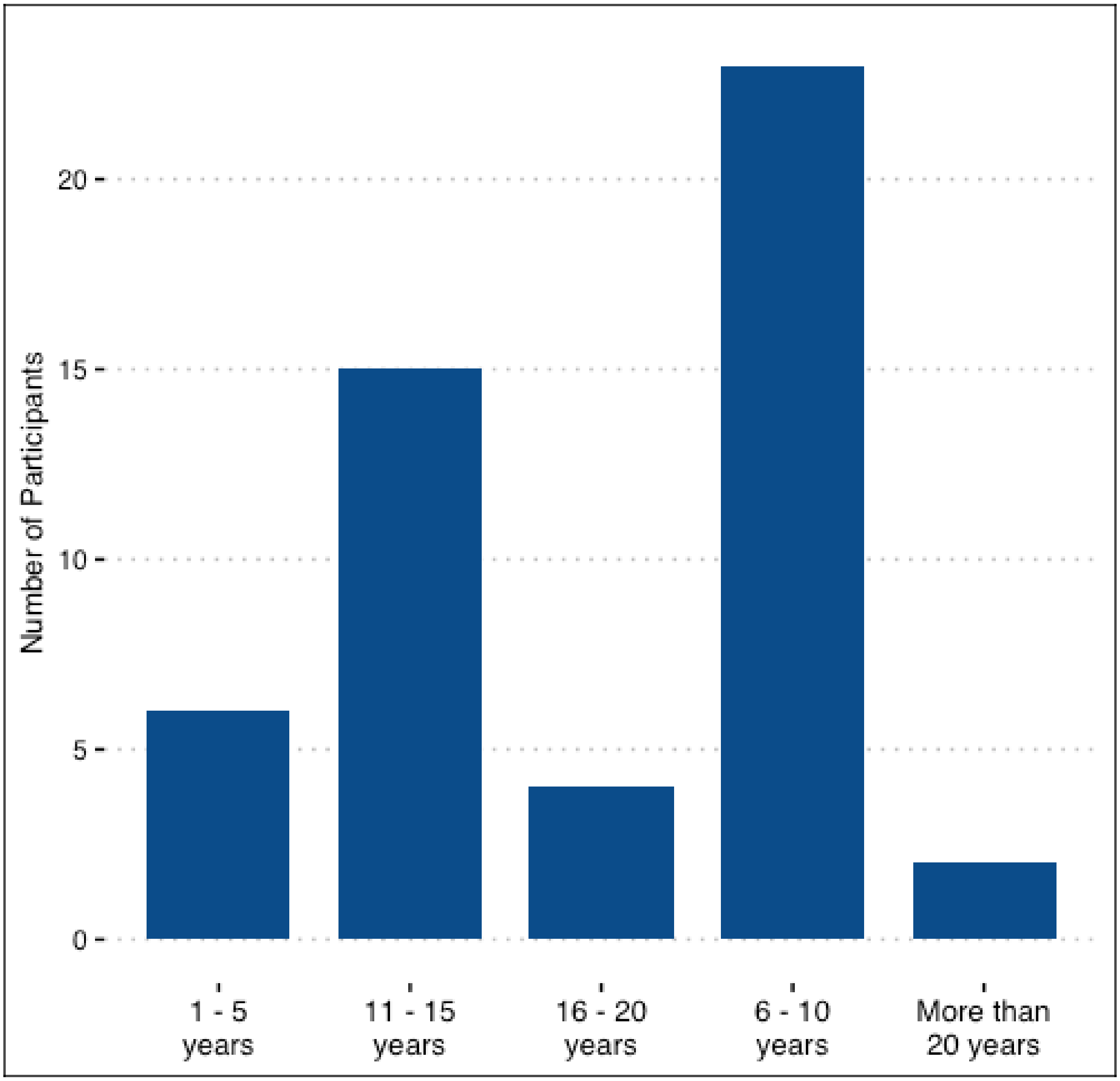

Figure 18 Distribution of driving experience of the subjects.

APPENDIX B: Pixels Per Visual Degree Computation

Pixels per degree of visual angle is used to convert distances measured in screen space of the scene camera from pixels into that of visual angle. We compute the pixels per degree by first computing the length of the diagonal from the one corner of the scene camera to the opposite corner. This is computed in pixels using the width and height of the scene camera image in pixels. Using the Pythagorean Theorem the diagonal for a 1280 pixels by 960 pixels rectangle is

$$c_{pix} = \sqrt{(1280^2 + 960^2)} = \sqrt{(2560000)} = 1600 pixels.$$

The field of view for the SMI ETG2 glasses is provided in the spec sheet as 60 degrees horizontally, and 46 degrees vertically. This is then used to compute the length of the of the diagonal in degrees

$$c_{deg} = \sqrt{(60^2 + 46^2)} = \sqrt{(5716)} = 75.6^\circ.$$

We then compute the number of pixels per degree as

$$1600\ pixels/75.6^\circ \ = 21.164\ pixels/^\circ.$$