Implementation and Performance Evaluation of In-vehicle Highway Back-of-Queue Alerting System Using the Driving Simulator

Zhengming Zhang, Dan Shen, Renran Tian, Lingxi Li, Yaobin Chen, Jim Sturdevant, and Ed Cox

Abstract— **This paper proposes a prototype in-vehicle highway back-of-queue alerting system that is based on an Android-based smartphone app, which is capable of delivering warning information to on-road drivers approaching traffic queues. To evaluate the effectiveness of this alerting system, subjects were recruited to participate in the designed test scenarios on a driving simulator. The test scenarios include three warning types (no alerts, roadside alerts, and in-vehicle auditory alerts), three driver states (normal, distracted, and drowsy), and two weather conditions (sunny and foggy). Driver responses related to vehicle dynamics data were collected and analyzed. The results indicate that on average, the drowsy state decreases the minimum time-to-collision by 1.6 seconds compared to the normal state. In-vehicle auditory alerts can effectively increase the driving safety across different combinations of situations (driver states and weather conditions), while roadside alerts perform better than no alerts.**

I. INTRODUCTION

There is an increasingly highway congestion due to the substantial increase in automobile production, which leads to a higher collision rate compared to un-congested traffic conditions [1] [2]. Many factors can contribute to the traffic congestion, such as adverse conditions, holiday travels, traffic accidents, among others. Thus, it is quite difficult to accurately estimate the time, location, and length of traffic queues because of unpredictable traffic volumes and fluctuations. Since highway congestion typically results in slow or stopped traffic at various locations on highways, back-of-queue (BoQ) crashes are the main reasons for fatalities, which accounts for nearly 13% of all fatal accidents [2]. Furthermore, various factors including driver's driving state (e.g., distracted, drowsy, fatigue) and low visibility may contribute to the BoQ collisions when highway congestion happens.

To avoid and alleviate accidents and possible casualties, common advanced driver assistance systems (ADAS) have been developed and equipped on some production vehicles. The role of these safety systems is mainly to detect the potential risks and trigger warning signals to the driver. Existing ADAS features, such as adaptive cruise control (ACC), lane departure warning (LDW), and road departure mitigation system (RDMS), are less effective in the above-mentioned BoQ scenarios. On one hand, the advanced on-board sensors and powerful computation resources can accomplish the tasks of detecting potential crashes and applying braking assistance to mitigate/avoid the crashes if necessary. On the other hand, these functions may also increase the driving risk. In some emergency cases, some drivers may also find impossible to take over the control authority of the computer. To better overcome the disadvantages of ADAS in highway congestion scenarios, many researchers have designed and evaluated BoQ warning systems, which has illustrated a great potential in improving driver's situational awareness and smoothing the transition between human and machine [3], [4]. However, there is no systematic and comprehensive investigation on alert timing/frequency/location/modality, weather conditions, vehicle dynamics, driver state, and the corresponding driver responses from after receiving a warning, which can affect the effectiveness of the in-vehicle highway BoQ alerting system significantly [5].

Meanwhile, the Indiana Department of Transportation (INDOT) is able to collect traffic data using probe vehicle data acquired through freight, smartphones, in-vehicle GPS units, and differential GPS. Thus, highway congestion, queue locations, queue moving speed, and queue length can be monitored [6]. However, how to effectively disseminate the critical traffic information and potential hazards to road users still remains an open research question. Toward this direction, many research methods have been investigated that include road sign design, development of traffic monitoring systems, and BoQ warning systems, which all contribute to avoid and/or alleviate the potential BoQ crashes by enhancing driver's situational awareness.

More and more BoQ alerting systems have been explored and studied in recent years. By utilizing the historical highway traffic data, some representative highway BoQ scenarios were established with assistance from GIS/Map databases [7]. Authors in [8] proposed an in-vehicle BoQ warning system that can issue the warning to drivers on highways approaching traffic queues. The preliminary results also illustrated the effectiveness of applying the BoQ warning systems on highways. A new method for developing a prototype BoQ alerting system based on probe vehicle data was demonstrated in [9], where the speed differences among adjacent road segments were calculated and applied

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to identify the slow traffic queues. In [10], the authors evaluated the effectiveness of queue alerting systems on highway work zones using the software for traffic simulation. In [11], the authors studied the issue of how to understand the driver's responses to a variety of traffic dynamic information under different scenarios. The objective was to evaluate the warning effects and variable speed limits (VSLs). Some case studies also highlighted the results of deployment of the BoQ warning system. The Texas Department of Transportation (TxDOT) proposed an intelligent transportation system in work zones on Interstate 35. The series of projects spanned around 96 miles through a rural stretch of Central Texas [10].

Other than the aforementioned research works on BoQ alerting systems, commercially available applications on smartphones, such as OpenStreet Maps, Google Maps, and Apple Maps all have features of illustrating traffic conditions, such as Transit (showing public transportation networks), traffic information (showing real-time traffic information), and the status of congestion (green for no traffic delay, orange for medium amount of traffic delay, and heavy traffic delay) [12], [13], [14]. However, these applications have not implemented the BoQ warnings to drivers.

The above research works illustrated feasible ways to design the BoQ warning systems and deliver alerting messages to drivers. However, none of these papers have conducted systematic studies on the integrated effects of BoQ alerts timing/modality/frequency, driver states, driver responses, vehicle dynamics, and weather conditions after obtaining the warning information. Meanwhile, the driving simulator has been used for evaluating ADAS system functions or other safety devices frequently in recent years due to its high-fidelity and efficiency. Therefore, it is necessary to understand the effectiveness of the designed BoQ alerting system with multiple variables through the driving simulator study.

In this paper, we propose an in-vehicle highway BoQ alerting system to send alerting messages to drivers approaching traffic queues on highways using a driving simulator. The prototype system has been developed using an Android-based smartphone app. The app can receive commands from the web server and trigger BoQ alerts to subjects on the driving simulator. A web server is designed to provide the simulated notification upon request. A new alerting notification will be generated by adjusting the customized parameters with different sounds and contents by visiting this web server. The main contributions of the paper are summarized as follows:

- A set of traffic scenarios were designed for subject testing, with different alerting types, different driving states, and different weather conditions.
- Statistical analysis was performed to compare the performance of the proposed in-vehicle auditory alert with no alert and roadside traffic sign alert using the vehicle dynamics data from the driving simulator.
- Results showed that the driver states and type of alerts are two influential factors of driving safety, while no interactions between them were found.

II. Methodology

A. Experiment Design and Hypotheses

We recruited 40 subjects to participate in two different sub-experiments (Fig. 1). In the first experiment, we used a mixed design (containing both between-subjects and within-subjects designs) to examine the effects of driver states (drowsy, distracted, and normal), type of alerts (in-vehicle auditory alert, roadside traffic sign alert, and no alert), and their interaction. A subject in task 1 experienced all three different driver states and one type of alert. We used the between-subjects design on the driver states because of the difficulty for a subject to be drowsy multiple times during an experiment session. In task 2, we applied the within-subjects design to both types of alert and visibility conditions (fog and clear).

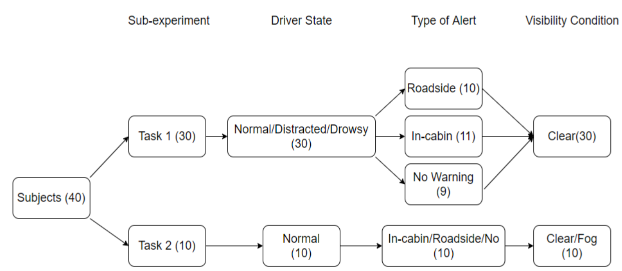

Fig. 1. Design of Experiment (the number in parenthesis represents the number of participants in the corresponding test condition.)

The in-vehicle auditory alert is a female-voiced warning: "Slow down! Traffic queue is ahead," followed by a hazardous beeping. We mounted a smartphone in the front of the co-pilot seat to deliver the in-vehicle auditory alert. A roadside traffic sign is shown in Fig. 3. Both in-vehicle auditory alert and the roadside traffic sign alert are triggered or placed exactly one mile away from the traffic queue. Also, we showed subjects both alerts to make them familiar with the alerts. To control the driver states, we adopted two strategies for distracted and drowsy states, respectively. To induce a distracted state, we asked subjects to involve in a secondary task, the 1-back task [15], after starting the driving simulator test. The main idea of the 1-back task is to simulate the distracted state, such as chatting and answering the phone while driving via constantly repeating a random number. One researcher plays a pre-recorded sequence of numbers (20 numbers per minute), and the subject needs to repeat the previous number at the time he/she listens to the current one. We did not require any specific accuracy, but we ask them to do their best. Overall, most of the subjects had an over 90% of accuracy. We induced the drowsy state naturally and measured the drowsiness through the Karolinska sleepiness scale (KSS) [16]. Before starting the drowsy test, we assigned the subject to a preparation test, where the simulator track is an endless circle with no buildings. We showed the subject the KSS and gained the initial score, and asked the subject to be sleepy as best as one can while driving. We measured the subject's KSS score every 6 minutes until they achieved the seventh sleepiness score. Once the subject attains the level of sleepiness, we start the drowsy state simulator test immediately. Due to the uncertainty of side effects of drowsiness and inducing time, we arrange the drowsy test as the last test.

Since each subject experiences multiple times of BoQ scenarios, we designed a pseud-queue to reduce the learning effect. During each test, there are none to two waves of slow vehicles placed on the track based on the track's length. When the subject's vehicle arrives at certain checkpoints, the driving simulator generates a wave of slow vehicles ahead to simulate the potential BoQ situation. When the subject approaches the slow vehicles, the slow vehicles in the same lane as the subject's vehicle will change lanes to allow the subject to overtake. In addition to the pseud-queue, we prepared three different length tracks with similar configurations (including driveway, roadside building, etc.) Even though the length of the track is different, we restrict the tracks after alerts (last one mile) to be the same in order to make tracks comparable.

We designed some general driving guidelines to control the macroscopic driving behavior: 1) Subjects need to maintain in the middle lane for the entire test. 2) Subjects cannot overtake the front vehicle by switching lanes. 3) Subjects should maintain at 65 miles per hour if applicable. 4) Subjects should place their safety as the first priority when driving. The first three guidelines control their general driving behavior, while the last one allows them to demonstrate their true driving behavior when encountering BoQ scenarios.

For the above experiment design, the ultimate goal is to test the hypotheses below:

1) Both in-vehicle auditory alert and roadside traffic sign alert can improve the safety of the ego vehicle compared with no alert.
2) Drowsy state jeopardizes the ego vehicle's safety the most, distracted states jeopardizes the safety less than the drowsy state, and the normal state's safety is the baseline.
3) There are interaction effects of driver states and types of alerts, such as the higher effect of in-vehicle auditory alerts when the driver is drowsy.
4) Worse visibility condition (e.g., foggy) decreases driver safety compared with normal visibility condition (e.g., clear).
5) There are interaction effects of visibility conditions and types of alerts, such as the higher effect of in-vehicle auditory alerts when the visibility condition is foggy.

B. Data Collection Hardware

The obtained data from this study are mainly from two sources. One is a driving simulator that collects the vehicle dynamics data such as driving position, driving speed, and driving acceleration. The other source is the Driver State Sensing (DSS) which acquires the subjects' drowsiness data. Fig. 2 below demonstrates the DriveSafety DS-600c high-fidelity driving simulator in the Transportation and Autonomous Systems Institute (TASI) at Indiana University-Purdue University Indianapolis (IUPUI).

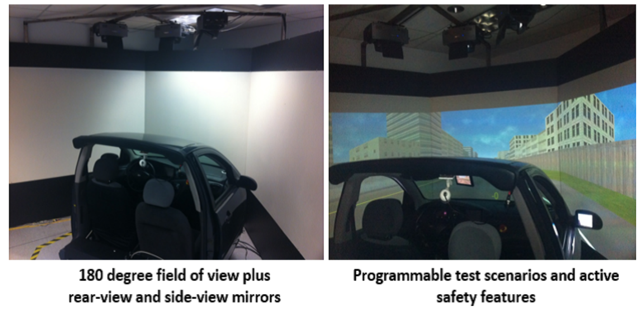

Fig. 2. The DriveSafety high-fidelity driving simulator.

The driving simulator has rear-view and side-view mirrors and can accomplish longitudinal motion cues (5 inches) and variable pitch angle (+/-2.5 degrees). A partial vehicle cabin is instrumented with standard driver controls, full-width front interior, position/time triggering, and active instrumentation. The driving simulator is also available to set/assign different signs/visual signals at different roadside locations [8]. For the roadside BoQ alert, as can be seen in Fig. 3, a roadside traffic sign with the text "Be Prepared to Stop" is designed in the driving simulator to mimic the actual roadside mobile signs implemented by INDOT where a large message board is carried by a roadside assistance truck [8].

Fig. 3. Roadside traffic sign alert in the driving simulator.

C. Driving Scenario Design

Three components are integrated in the driving simulator, namely, HyperDrive, Vection, and Dashboard, respectively. HyperDrive is the software for system preparation and scenario creation. Vection is the software for running the simulation after creating test scenarios. Dashboard is the tool that interfaces with the HyperDrive and Vection. The overall structure of the driving simulator can be found in [8].

To simulate the highway BoQ alerting system with real driving conditions on Interstate highway I-465, several test scenarios were created in the driving simulator, where we can build the test environment with roadway networks and controlled entities. Entities were also used to determine objects in the environment, such as vehicles or road signs. As described in [8], the simulated I-465 is a ring road of

Indianapolis with a length of around 52.79 miles (84.46 km). The test environment of both the internal view and external view of DS-600 is demonstrated in Fig. 4. Furthermore, several key variables that are collected after every simulation are depicted in Table I.

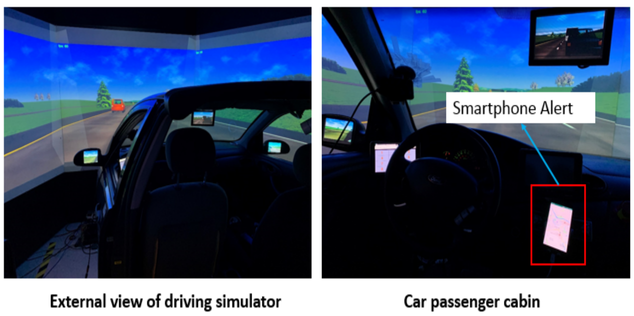

Fig. 4. Actual test conditions using the driving simulator.

TABLE I
KEY VARIABLES COLLECTED AFTER SIMULATION.

Key Variable Name	Unit
Longitudinal or Lateral Acceleration	m/s^2
Crash or not	0 or 1 (binary)
Crash Speed	m/s
Brake Pressure	0 – 100%
Steering Angle	degree
Vehicle Location	m

To eliminate the learning effects from the subjects and the predictability of the coming scenarios, three different road segments were designed and assigned from the overall I-465 route to subjects randomly with the lengths of 5 miles, 6 miles, and 7 miles, respectively. To make sure that all test scenarios are similar besides several controlled variables (alert types, driver states, and weather conditions), these test road segments were established based on the following rules:

1) All road segments are on the highway suburban areas.
2) There are three lanes along the driving direction and three lanes on the opposite way.
3) The curves included in the simulation are relatively large ($\geq$ 1,000 meters).
4) Subjects have a good view range and enough time when approaching the queue in the end of each test.
5) All queues are static at the end of each scenario.
6) The visibility in the simulated foggy condition is the same in three different road segments.

Meanwhile, both roadside sign alert and the in-vehicle auditory alert are placed and triggered at about 1 mile upstream of the BoQ. The in-vehicle auditory alert is delivered through the smartphone installed on the cluster of the driving simulator vehicle cabin (shown on the right of Fig. 4). Note that subjects may get increasingly familiar with the scenarios and slow down the vehicle when encountering slower traffic. To avoid such learning effects, we placed one or two waves of the slow traffic (not slow enough to be at the BoQ) randomly during each test scenario. Thus, it is much more difficult for the subjects to estimate the final traffic queue positions. To better demonstrate and summarize the test scenarios while experiments, some key designs were shown in Fig. 5.

D. Participants and Procedures

There is a total of 40 (24 male, 16 female) recruited subjects. Most subjects (33) aged in the range of 20-30, where the average age of all subjects were 25.51 (STD = 7.19). 30 subjects were assigned to Task 1 and 10 subjects were assigned to Task 2. All recruited subjects were screened initially to satisfy the research needs, such as having normal hearing, no virtual reality sickness, and holding a valid driver's license. We asked the subjects in Task 2 not to consume any product with caffeine within 24 hours before the actual testing. Before subject testing, we explained the use of the driving simulator and 1-back task, respectively. There is a 2-minute break between each test, and a more extended break is rendered if request. Due to the uncertainty of inducing sleepiness, there is no uniform completion time, but the average completion time for a test scenarios is about one and a half hours.

E. Data Pre-processing

To take advantage of the data from both the driving simulator and the DSS, the combined data need to be pre-processed before being analyzed. Since two sets of data were captured from different computers, the most important step of data pre-processing is to synchronize them. The need for time synchronization arises from the need to process sequential data collected from different sensors at different sampling rates. To match the driving simulator data to the DSS data, each frame of the DSS data was time-stamped at the rate of 40, and the UNIX timestamp was recorded as part of the saved data. Similarly, each frame of driving simulator data was also timestamped with the rate of 60. We developed software programs to synchronize the data such that the list of the indices in the driving simulator data can be generated and used for extracting the synchronized data with the DSS data. Finally, the pre-processed data has nine key variables for each test scenario, including time, left eye open status, right eye open status, velocity, steering wheel angle, acceleration, braking ratio, position X, and position Y.

F. Metrics Selection

We selected three widely-used metrics as the indicator of safety, which are the minimum time-to-collision (mTTC), maximum braking (mBraking), and maximum steering angle (mSteer). mTTC measures the time to collision under the current speed, and either a high speed of the vehicle or a short distance away from the incident might cause a small mTTC, which is considered dangerous. Maximum braking is very similar to maximum deceleration, which causes driving discomfort for the driver and may lead to safety concerns on surrounding vehicles. The maximum steering

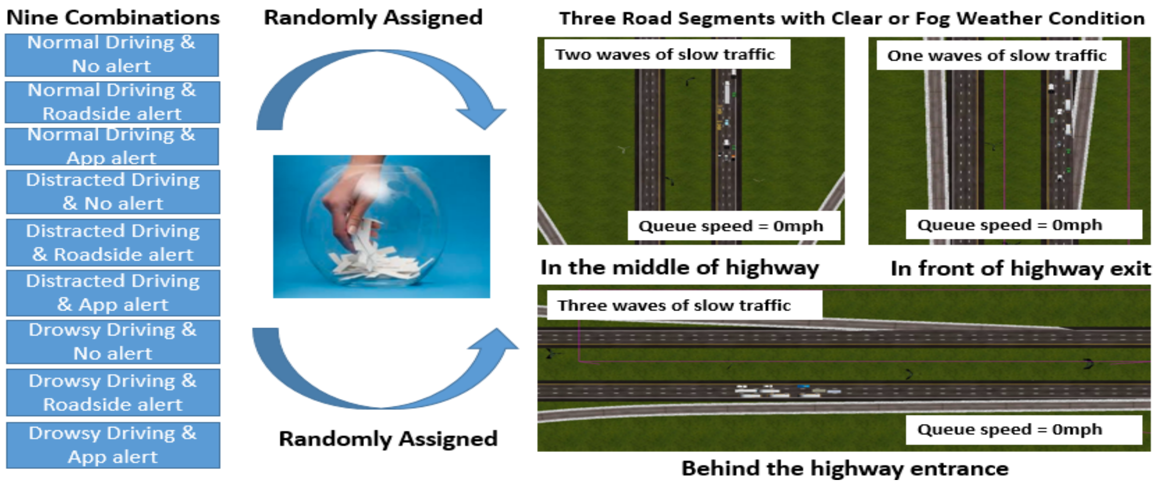

Fig. 5. Some key scenario designs in the driving simulator.

angle is an indicator of vehicle stabilization. In addition to the above-mentioned metrics, we also considered the remaining distance (RD) to the traffic queues when mTTC is triggered. Therefore, we have a remaining distance when the driver attains the maximum time-to-collision. A Larger RD indicates an earlier engagement to prevent the crash. Note the mTTC and mBraking are calculated for the last one mile of the speed profile (after the alert is issued). The mSteering is calculated for the last half mile (where the highway is straight).

III. Results

We first performed the analysis of variance (ANOVA) to examine whether the effect of a potential independent variable is statistically significant ($\alpha < .05$). If it is, we then use Tukey's HSD test to make pairwise comparisons between each level of the independent variable. Standard assumptions for the models are used and checked. This section is composed of the results of two tasks, respectively.

A. Task 1

In Task 1, the control variables are driver states and type of alerts. For each alert type (no alert, roadside traffic sign alert, and in-vehicle alert), there are 11, 10, and 9 subjects with three different driver states, respectively. Therefore, there are 90 data points. We first studied the effects of two types of BoQ alerts on driving safety. When mTTC is the dependent variable, ANOVA results indicate the effect of this type of alert is significant (F = 9.78, p-value $<$ .001), which means that there is a different within-group variation of mTTC between each group. We further applied post-hoc test. The mean comparisons of in-vehicle and roadside alert (mean difference = -1.3251, p-value = .001) and in-vehicle and no alert (mean difference = -1.6516, p-value $<$ .006) are significant, which means the in-vehicle auditory alert improve the mTTC by 1.3 and 1.7 seconds when compared with roadside alert and no warning, respectively. In other words, drivers with in-vehicle auditory alerts averagely have more than one second to perform maneuvers than roadside traffic signs and no alerts (Fig. 6).

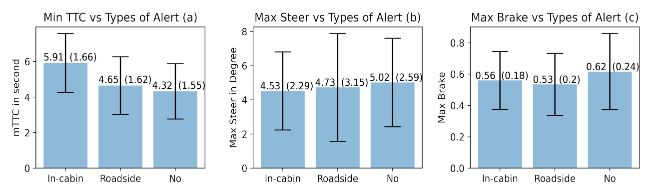

Fig. 6. Average mTTC (left), average mSteer (middle), and mBrake (right) for different types of alerts. The number in the parenthesis is the standard deviation of the samples.

In the model with either mSteer (F = 0.344, p-value = .71) or mBrake (F = 1.09, p-value = .34) as the independent variable, the effect of alert types is not significant. Therefore, the type of alert does not change the vehicles' stabilization and maximum braking. Note that mBrake is not necessarily the same as the maximum deceleration because mBrake does not measure the time length of braking. Pressing the braking pedal a longer time and a shorter time with the same force will result in completely different deceleration but the same mBrake. Fig. 6 shows that there is little difference in the average mBrake and mSteer across the groups.

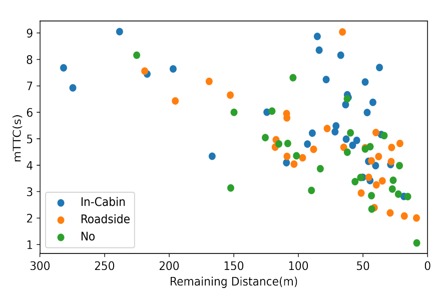

Fig. 7. Scatter plot of alert types.

Fig 7 demonstrates the last metric, remaining distance when attaining mTTC. The average RD for the in-vehicle auditory alert is 94.09 meters (STD = 70.76), which is 20 meters longer than roadside and no alert. Moreover, we can see the majority of green (no warning) and orange (roadside) points are located at the bottom-right corner, which is considered as the most dangerous situation (low TTC and remaining distance). The blue (in-vehicle) points are located across the top region, which indicated a relatively safe TTC with uniformly distributed RDs.

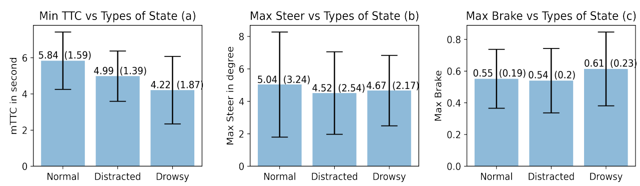

Fig. 8. Average mTTC (left), average mSteer (middle), and average mBrake (right) for different driver states. The number in the parenthesis is the standard deviation of the samples.

Then we studied the effect of driver state. When the dependent variable is mTTC, the ANOVA results indicate that the effect of driver state is significant (F = 8.11, p-value $<$ .001). The mean difference between drowsy and normal states (mean difference = 1.62, p-value = 0.001) is significant, while the other two comparisons are not. In other words, we found the drowsy state reduces the mTTC by 1.6 seconds when compared with the normal state (shown in Fig. 8). Again, when either the mBrake or mSteer is the dependent variable, the driver state's effect is not significant. Fig. 9 shows similar results, where the green (drowsy) and orange (distracted) points are located at the bottom right corner.

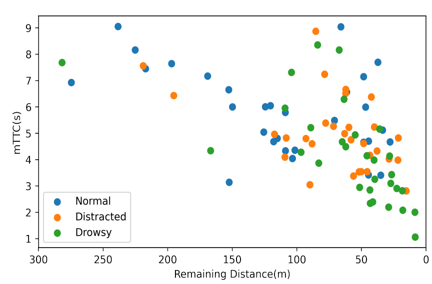

Fig. 9. Scatter plot of driver states.

Moreover, the effects of the interaction between driver states and type of alerts in all three models are not significant (mTTC: F = 1.06, p-value = .38; mBrake: F = 0.39, p-value = .88; mSteer: F = 0.74, p-value = .56). We conclude that there is no effect of the interaction between driver states and type of alerts.

B. Task 2

In Task 2, we control the visibility conditions and type of alerts. Since this task utilized between-subjects design (three types of alerts and two visibility conditions), there are 60 data points for 10 subjects. Again, we first examine the effect of the type of alerts. When mTTC is the dependent variable, the ANOVA results indicate the effect of type of alert is significant (F = 5.05, p-value = .009), which means different types of alerts have different mTTCs. Tukey HSD test found the mean differences between in-vehicle and no alert (mean difference = -1.25, p-value = 0.03) and in-vehicle and roadside alert (mean difference = -1.33, p-value = 0.02) are statistically significant, which is consistent with the results from Task 1. In other words, in-vehicle auditory alerts increase the mTTC by more than one second when compared with the roadside alert and no alert. When either mBrake (F = 1.05, p-value = 0.36) or mSteer (F = 1.00, p-value = 0.37) is the dependent variable, the effect of type of alerts is not significant. Although the effect of alert types is not significant on mBrake, Fig. 10 shows that the average mBrake of no alert is slightly higher than the roadside and in-vehicle alert. If the sample size is larger, the effect might be significant.

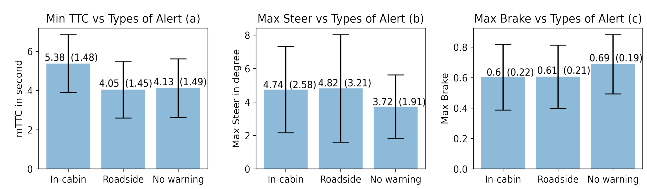

Fig. 10. Average mTTC (left), average mSteer (middle), and mBrake (right) for different types of alerts. The number in the parenthesis is the standard deviation of the sample.

Then, we examine the effect of the visibility condition. We found the effect of visibility condition is close to significant in the model of mTTC (F = 2.97, p-value = 0.09), but it is far from significant in the other models (mBrake: F = 1.81, p-value = 0.18; mSteer: F = 0.29, p-value = 0.60). The average scores of each metrics are showed in Fig. 11. In addition, Fig. 12 shows the orange points (foggy condition) are more concentrated in the bottom right corner, which means the distances attaining mTTC under foggy condition are shorter than the clear condition.

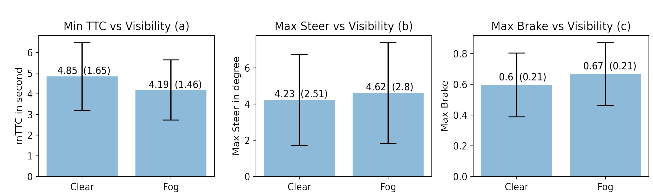

Fig. 11. Average mTTC (left), average mSteer (middle), and average mBrake (right) for different visibility conditions. The number in the parenthesis is the standard deviation of the samples.

IV. CONCLUSIONS

This paper implemented an in-vehicle highway BoQ alerting system based on an Android-based smartphone app.

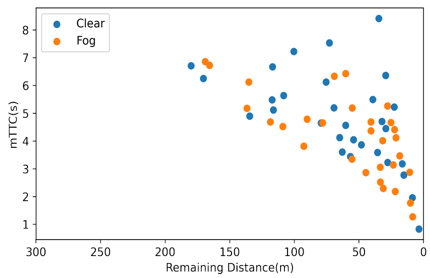

Fig. 12. Scatter plot of visibility conditions.

Then a mixed design (containing both between-subjects and within-subjects designs) to examine the effects of driver states, type of alerts, and visibility conditions was devised for assessing the effectiveness of the proposed alerting system. The data analysis on the collected data indicated the effectiveness of the in-vehicle auditory alert (Hypothesis 1). Hypothesis 2 was also supported by the results, where drivers in drowsy states perform the worst in the BoQ scenarios. Although the effect of visibility condition is not statistically significant, we found that the average difference between clear and foggy conditions is close to significant (Hypothesis 4). Both hypotheses of the interaction effect are not supported by the results, so we conclude that there is no interaction effect between the type of alerts and driver states/visibility conditions. One topic for future work is to evaluate the efficiency of multi-modal alerts instead of auditory-only alert. Another future topic is to collect and analyze how are the reaction times of drivers affected regarding the in-vehicle alert and the outside sign.

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