Final Report

Evaluation of Driver Behavior Influenced by Traffic Safety Messages from Roadside Units in Connected and Autonomous Systems

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16. Abstract

The safety of vulnerable road users (VRUs) at signalized intersections is a significant concern in urban traffic management. This study aims to enhance VRUs safety through the deployment of advanced communication and machine learning technologies. Using a Connected and Autonomous Vehicle (CAV) testbed, this research explores real-time communication between LiDAR sensors, Roadside Units (RSUs), On-Board Units (OBUs), and traffic controllers. This integration allows for the timely dissemination of safety messages and enables drivers to adjust their behavior to prevent potential crashes. The CAV testbed offers a controlled environment for studying these interactions, facilitating precise data collection and analysis.

By collecting driving data from 32 participants under three scenarios with two different sets of safety messages broadcasted by RSUs on the testbed, the study investigated the participants' driving behavior in interactions with pedestrians and bicyclists. The study utilized machine learning models, including Logistic Regression, Random Forest, and Support Vector Machine (SVM), to predict driver behavior under various scenarios. The SVM model demonstrated the highest accuracy, particularly in predicting lateral distance, with an accuracy rate of 0.88 in response to the "Keep to the Right Lane" message. Key findings emphasize the importance of factors such as driver demographics, experience, and familiarity with CAV technology in shaping responses to safety messages. Additionally, the male drivers showed significant adjustments in speed and acceleration, while female drivers exhibited a more consistent, cautious approach, with minimal changes in speed, acceleration, and lateral distance.

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Abstract

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Introduction

Enhancing the safety of VRUs, including pedestrians and cyclists, is a crucial aspect of urban traffic management [1-2]. This problem can be addressed by implementing advanced technologies and strategic planning to protect at-risk groups in urban environments [3]. Signalized intersections can be risky because of the interactions between vehicles and VRUs [4]. Pedestrians and bicyclists face chances of conflicts and crashes at these points due to their limited visibility and lack of protection compared to drivers [4-6]. One effective strategy involves using RSUs in CAV environments [7-8]. By sending out safety alerts as traffic safety messages, risks can be reduced and overall safety at intersections improved, thereby protecting VRUs [9]. RSUs can send real-time safety alerts and traffic safety messages to vehicles, significantly reducing the risks associated with intersections. By providing timely warnings and critical information, such as signal phase and timing, RSUs inform drivers so that they can make safer decisions, especially in areas with high pedestrian and cyclist activity [10-11]. This proactive approach not only mitigates potential conflicts/crashes but also fosters a safer and more efficient transportation environment.

In this study, a comprehensive CAV testbed was built near Morgan State University, encompassing a 3.6-mile loop with two signalized intersections. Each intersection is equipped with advanced sensing and communication technologies, including Light Detection and Ranging (LiDAR) sensors, Closed-Circuit Television (CCTV) cameras, RSUs, and smart traffic controllers capable of sending Signal Phasing and Timing (SPaT) messages. This report focuses on two types of safety messages, including pedestrian safety at the Cold Spring Ln - Hillen Rd intersection (the first intersection in the CAV testbed) and bicyclist safety at the E 33rd - Hillen Rd intersection (the second intersection in the CAV testbed). These locations were chosen based on their high pedestrian and bicycle traffic, with the former near major university buildings and the latter adjacent to recreational areas. Thirty-two (32) participants were invited to drive on the CAV testbed. Their personal vehicles were equipped with OBUs before driving through the testbed. The OBUs detected the geographic location of the vehicles and communicated with the LiDAR and RSU systems [12], which then broadcast the pre-configured safety messages adhering to the J2735 standard [13]. This standard outlines the necessary protocols for vehicular communication, ensuring interoperability and reliability of the transmitted messages. The safety messages were generated and verified by the USDOT's TIM message website [14], then the content of the messages was uploaded on the OBUs' dashboards.

Examining how drivers react to safety messages is vital for several reasons. By looking at changes in speed, acceleration, braking habits, and road positioning, the effectiveness of these messages in improving safety at congested intersections is gauged. This research provides valuable insights to develop better traffic management strategies and safety protocols. This study not only showcases the potential of CAV testbeds in boosting road safety but also highlights the critical role of targeted safety messages in protecting VRUs.

Literature Review

The integration of CAV technologies has garnered significant attention for its potential to improve road safety, especially for VRUs [1-2]. Ensuring the safety of VRUs, especially at signalized intersections, is a critical aspect of modern traffic management [2, 15]. Signalized intersections are often high-risk areas where pedestrians and bicyclists are most likely to be involved in traffic crashes. Advanced technologies such as LiDAR, radar, and CCTV play a key role in monitoring and safeguarding VRUs by providing real-time data on their presence and movements [16-17]. Integrating these technologies with real-time Signal Phasing and Timing (SPaT) data enhances the safety of VRUs at signalized intersections as well [18].

The effectiveness of safety messages, broadcasted via Vehicle-to-Everything (V2X) communication, becomes evident when considering their potential to enhance driver awareness and prompt safer behaviors. Communication between RSUs and OBUs allows for the timely delivery of these messages, alerting drivers to potential hazards and encouraging cautious driving [19]. This integrated approach not only assists in mitigating risks at intersections but also promotes a more responsive and adaptive traffic environment.

This research builds on these principles by exploring how safety messages impact driver behavior and evaluating a CAV testbed designed to improve road safety at Morgan State University. The testbed includes LiDAR sensors provide high-resolution mapping and object detection, then enhancing vehicle safety [20-21]. The CCTV cameras aid in traffic monitoring and situational awareness [22]. The RSU plays a key role in vehicle-to-infrastructure (V2I) communication, providing timely information regarding road conditions and broadcasting Basic Safety Messages (BSMs) that reduce the likelihood of crashes [23]. The CAV testbed also benefitted from a smart traffic signal controller that facilitated the seamless transmission and reception of SPaT data between the LiDAR sensors, RSUs, and OBUs [24]. The real-time transmission of SPaT data enhances the safety of VRUs by providing connected vehicles with timely information [25]. The purposes and benefits of this CAV testbed include safety evaluation, technological integration, data collection and analysis, and informing policy and standards development.

This research fills several gaps identified in the existing literature. While previous studies have explored various aspects of CAV technology, few have specifically focused on the impact of real-time safety messages on driver behavior in a CAV testbed environment. The existing literature on vehicle safety technologies, such as the studies by Chowdhury et al. [24] and Zhao [26], have primarily focused on individual components like LiDAR and CCTV for vehicle safety and traffic monitoring. However, these studies have not extensively explored the integration of these technologies with safety messaging in a comprehensive CAV testbed, particularly in the context of influencing driver behavior and enhancing the safety of VRUs. Our research addresses these gaps by utilizing a fully integrated CAV testbed at Morgan State University, combining LiDAR, CCTV, RSUs, and smart traffic controllers. The findings demonstrate the effectiveness of the safety messages in improving the safety of VRUs. In addition to advancing current understanding of CAV technology, this study also offers practical recommendations for traffic engineers and safety experts, emphasizing the importance of integrated transportation solutions in modern urban environments.

Methodology

The research utilized datasets collected from Morgan State University's CAV testbed. Figure 1 depicts Morgan State University's testbed.

Figure 1 Morgan State University's CAV testbed

Data was collected from 32 participants through a pre-survey that gathered detailed demographic, socio-economic, and driving background information. The survey also assessed their knowledge and use of CAV technology, familiarity with CAV testbeds, reliance on real-time traffic data, and awareness of vehicle connectivity and autonomy. Participants were informed about the CAV testbed and route but were not told about the safety messages they would receive, enhancing the validity of the data and ensuring a realistic assessment of driving behavior.

The pre-survey revealed that 80.6% of participants were male and 19.4% were female. Among all participants, 44.4% were aged 18-25 years, 30.6% were aged 26-35 years, 19.4% were aged 36-45 years, and 5.6% were aged 46-55 years, respectively. Additionally, the survey indicated that 52.8% of participants identified as Black or African American, 36.1% as White, 5.6% as Asian, and 5.6% as belonging to other ethnicities. In terms of educational status, 52.8% were graduate students, 27.8% were undergraduate students, 16.7% were postgraduate students, and 2.8% had a high school education or less.

After completing the pre-survey, participants were directed to drive on the CAV testbed, where they encountered three distinct scenarios. The first scenario acted as a baseline, with no safety messages being sent. This allowed for the observation of participants' usual driving behaviors under normal conditions and provided a reference point for evaluating the impact of the following scenarios.

In Scenario 2, static safety messages were broadcasted at two intersections to enhance driver awareness. These messages, while not reflecting active roadway conditions, aimed to improve general driver caution. At the Cold Spring Ln - Hillen Rd intersection, the message "Pedestrian signal, please caution, stay in lane" informed drivers of likely pedestrian crossings near the university. Similarly, at the E 33rd - Hillen Rd intersection, the message "Bicyclists on roadway, please cross intersection with care" warned drivers about potential cyclists on the road. In Scenario 3, static messages targeting specific road conditions were introduced. For instance, "reduce your speed" was broadcasted near the Morgan Bridge to prevent pedestrian crashes, while "keep to the right lane" at E 33rd - Hillen Rd helped accommodate bike lanes and enforce speed limits. These predefined messages promoted safer interactions with pedestrians and cyclists by encouraging cautious driving, even if they did not react to real-time conditions. The safety messages were broadcasted at random intervals. The random broadcasting prevents biases or expectations among participants, ensuring their reactions were genuine and reflective of natural responses to unexpected stimuli. The random broadcasting provided a thorough assessment of how messages perform under different conditions. Thus, it provides valuable insights into driver reactions to unforeseen alerts. Based on this variability, participants are fully prepared to face unexpected messages on the testbed, thus validating the practical utility of the safety messages.

After completing the three driving scenarios on the CAV testbed, participants were asked to fill out a post-survey questionnaire. This survey aimed to gather feedback on their overall experience and their perceptions of the safety messages received during the test drive.

The design of scenarios 2 and 3 was carefully planned to assess specific safety situations in line with industry standards, particularly the J2735 standard [27]. Scenario 2 and 3 featured messages followed J2735 guideline to ensure they met safety protocols for protecting VRUs. Adhering to these standards was essential for maintaining the study’s integrity and ensuring reliable results, as variations in message content or timing could impact participants' perceptions and responses. Proper placement of RSUs and precise timing of message broadcasts were critical for effective communication and minimizing delays.

A tablet connected with the OBU was used to provide participants with essential real-time information during their drive on the CAV testbed. The tablet provided SPaT information, showing the transition between green, yellow, and red signal phases at each intersection, along with the remaining time before these changes. Participants received specific Traveler Information Messages (TIMs) broadcast at intersections, delivering timely safety alerts like pedestrian crossings and bike lane information, all in line with the J2735 standard. Figure 2 illustrates the tablet's interface and the real-time communication between the OBU, RSU, signal controller, and LiDAR on the CAV testbed.

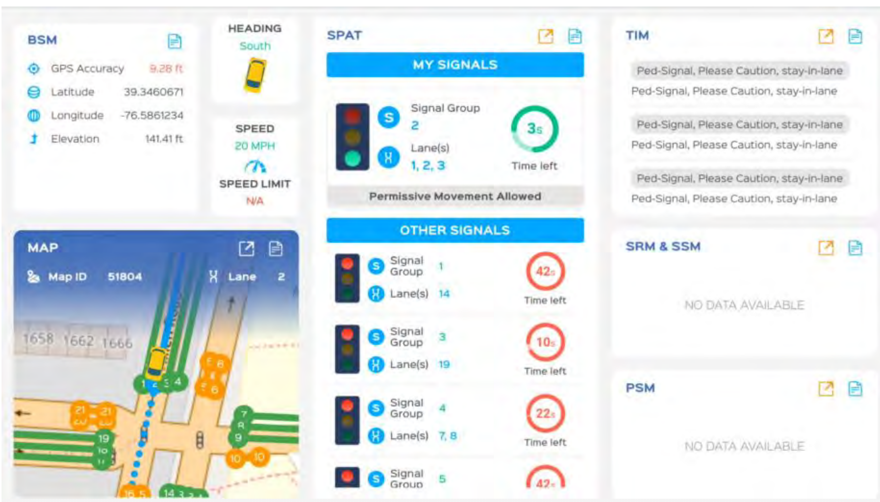

Figure 2 Real-Time Communication and Tablet View on the CAV Testbed

The tablet collected key datasets every 0.1 seconds for each participant, including speed, road elevation, acceleration, and latitude and longitude. Speed and acceleration data show how vehicles respond to safety messages, while road elevation reflect visibility and braking distances. Latitude and longitude offer precise location data, aiding in the analysis of specific roadway conditions and identifying VRU crash hotspots. The data was collected as hashed datasets. To decode this information, Wireshark software [28] and the USDOT decoder [14] were used. The agreement between the data decoded by Wireshark and the USDOT website highlights the reliability of the collected datasets. This consistency ensures that the safety analysis is based on accurate and verifiable data.

The set of messages was strategically utilized in locations with higher crash risks involving pedestrians and cyclists to assess how drivers responded to these instructions. Speed reduction is particularly important, as lower speeds can significantly lessen the severity of conflicts and crashes. allowing more time for drivers to react. Advising drivers to stay in the right lane prevents dangerous lane changes and reduces conflicts with VRUs. Figure 3 illustrates the specific locations within the CAV testbed where these messages were broadcasted.

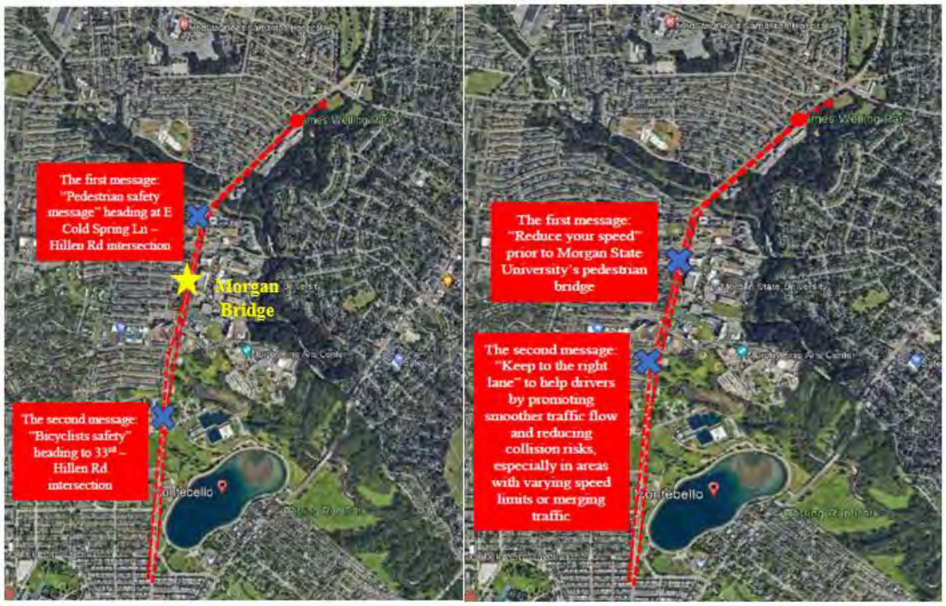

Figure 3 Locations of Message Broadcasts on the CAV Testbed In Scenario #2 (Left Figure) and in Scenario #3 (Right Figure)

To analyze driver behavior in response to safety messages being broadcasted within the CAV testbed, it is essential to select effective machine learning models to accurately interpret the dataset. This section highlights suitable models that are designed to capture the relationships between independent variables (such as demographics and driving behaviors) and dependent outcomes (such as changes in speed, acceleration, and lateral distance). In order to establish meaningful relationships between the dependent and independent variables, Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM) models were evaluated. The machine learning models focused on a critical 20-second window following the receipt of the safety message to ensure efficient and relevant results. The purpose of this time frame is to allow participants to process the information they have received, analyze the content of the message, and then make an informed decision based on the information they have received. In Python, several robust machine learning libraries provide efficient algorithms for implementing LR, RF, and SVM models. Scikit-learn is a widely used library offering straightforward implementations of these algorithms. The report utilized the Scikit-learn library to develop machine learning models.

Results

The analysis of driver behavior before and after receiving safety messages was conducted over a 20-second period [29, 30] both prior to and following message reception.

The 20-second window was chosen to allow drivers enough time to process, understand, and respond to the safety messages, capturing both cognitive and behavioral reactions. Shorter intervals, like 10 or 15 seconds, might not allow sufficient time for drivers to fully process and adjust their behavior based on the message. By using a 20-second interval, the analysis encompasses the complete process of receiving the message, reflecting on its content, and making necessary adjustments in driving behavior. This method accounts for varying response times among drivers, including those who may need more time to react. The focus of the analysis was on changes in speed, acceleration, and lateral distance relative to the road's curbs. Examining these factors during a 20-second interval reveals how drivers adjust their behavior in response to the safety messages. Tables 1 and 2 illustrate the changes in speed and acceleration observed before and after receiving the safety messages, respectively.

Table 1 Percentage Changes in Speed in Scenarios 2 and 3 by Participant Gender

Scenario	Message Content	Interval: 20 Seconds Before to The Message Receiving Point							
		Speed				Acceleration			
		Male – increase (%)	Male – Decrease (%)	Female – increase (%)	Female – Decrease (%)	Male – increase (%)	Male – Decrease (%)	Female – increase (%)	Female – Decrease (%)
#2	Pedestrians Safety Message	25	46.9	6.3	21.9	31.3	50	6.3	12.5
	Bicyclists Safety Message	40.6	40.6	12.5	6.3	46.9	34.4	9.4	9.3
#3	Reduce Your Speed	37.5	43.8	6.3	12.5	40.6	40.6	9.4	9.4
	Keep to the Right Lane	50	31.3	9.4	9.4	53.1	28.1	9.4	9.4

Table 2 Percentage Changes in Acceleration in Scenarios 2 and 3 by Participant Gender

Scenario	Message Content	Interval: The Message Receiving Point and 20 Seconds Afterward							
		Speed				Acceleration			
		Male – increase (%)	Male – Decrease (%)	Female – increase (%)	Female – Decrease (%)	Male – increase (%)	Male – Decrease (%)	Female – increase (%)	Female – Decrease (%)
#2	Pedestrians Safety Message	50	31.3	3.1	15.6	43.8	37.5	3.1	15.6
	Bicyclists Safety Message	15.6	65.6	9.4	9.4	15.6	65.6	12.5	6.3
#3	Reduce Your Speed	21.9	59.4	12.5	6.3	21.9	59.4	6.3	12.5
	Keep to the Right Lane	28.1	53.1	6.3	12.5	28.1	53.1	6.3	12.5

As shown in Table 1, in scenario #2, after the RSUs broadcasted the pedestrian safety message at the E Cold Spring Ln – Hillen Rd intersection (the first intersection of the CAV testbed) and the bicyclist safety message at the E 33rd - Hillen Rd intersection (the second intersection of the CAV testbed), a significant percentage of males exhibited a reduction in speed (46.9%) and acceleration (50%). The results highlighted a notable behavioral response to the pedestrian safety message. This suggests drivers are slowing down to ensure pedestrian safety at the intersection. The smaller reduction in speed for females indicates that they may already drive more cautiously or respond differently to such messages.

Despite the presence of protected bike lanes before and after the intersection, a high percentage of males exhibited increases in speed (40.6%) and acceleration (46.9%) following the broadcast of bicycle safety messages near the E 33rd and Hillen Rd intersection. These varied responses are likely due to the need to overtake or safely navigate around cyclists. This suggests that some drivers may speed up to avoid sudden stops, maintaining a smoother traffic flow and ensuring safety for both drivers and cyclists.

In scenario #3, broadcasting speed reduction and lane-keeping messages at both intersections on the CAV testbed was associated with a high percentage of speed reduction among males (43.8%). This means a strong compliance with the speed reduction message. Additionally, the significant percentages of males increasing speed (50%) and males increasing acceleration (53.1%) suggest drivers are accelerating to merge into the right lane smoothly. This behavior is aimed at maintaining orderly traffic flow and reducing the risk of collisions by adhering to the lane-keeping instruction.

The analysis reveals effective message communication, as evidenced by high percentages of speed and acceleration reduction, particularly among males, indicating prompt and safety-oriented speed adjustments. Increased speeds and acceleration in response to lane-keeping messages demonstrate active compliance with lane guidance, reducing congestion and side-swipe risks. Additionally, the observed gender-based response variability, with males making more aggressive adjustments and females showing more cautious behavior, highlights differing driving behaviors and risk perceptions.

During the next interval, which includes the safety message and the subsequent 20 seconds, the following results were observed:

In scenario #2, the high percentage of males increasing speed (50%) and increasing acceleration (43.8%) following the pedestrian safety message at E Cold Spring Ln - Hillen Rd intersection indicates a significant behavioral change post-message reception, likely to maintain or regain desired speeds after initially slowing down. The low percentages for females in both speed and acceleration changes suggest a more conservative approach, maintaining their initial cautious behavior.

The bicyclist safety message at E 33rd - Hillen Rd intersection was followed by high percentages of males decreasing speed (65.6%) and acceleration (65.6%), suggesting that participants took greater caution when approaching cyclists. Females exhibit lower percentages in both categories, indicating a more balanced response to the message without significant speed or acceleration changes.

In scenario #3, the high percentage of males decreasing speed (59.4%) and acceleration (59.4%) after receiving speed reduction messages indicates strong compliance with the broadcast. Females show a lower response in both categories, maintaining a steadier driving pattern. Additionally, high percentages of males decreasing speed (53.1%) and acceleration (53.1%) in response to the “keep to the right lane” message suggest that drivers are adhering to the lane guidance and slowing down to merge smoothly into the right lane. Females, again, show less drastic changes, indicating a more conservative driving style.

When comparing the interval from 20 seconds before broadcast to the interval from 20 seconds after the broadcast, several key differences emerge.

- Pedestrian Safety Message: Initially, 46.9% of males decreased speed, but post-message, this dropped to 31.3%, while 50% increased speed to return to or maintain desired speeds. Females maintained a cautious approach throughout with minimal changes in speed or acceleration.
- Bicyclist Safety Message: Initially, 40.6% of males increased speed and 40.6% decreased it. Post-message, a significant 65.6% decreased both speed and acceleration, indicating a cautious approach to avoid potential collisions with cyclists. Females showed low percentages in both intervals, indicating a consistent cautious approach.
- Reduce Your Speed Message: Initially, 43.8% of males decreased speed and 40.6% decreased acceleration. Post-message, these figures increased to 59.4%, demonstrating continued compliance with the speed reduction instruction. Females remained relatively unchanged, showing steady behavior.
- Keep to the Right Lane Message: Initially, 50% of males increased speed and 53.1% increased acceleration to merge smoothly. Post-message, 53.1% decreased speed and acceleration, suggesting adjustments to lane changes. Females again showed minimal changes, indicating consistent cautious driving.

The trajectory of each vehicle was comprehensively analyzed to determine how the driver veered toward the right or left curbs of the road. Each vehicle in the study was equipped with an OBU that used a built-in Global Positioning System (GPS) receiver to collect geographic coordinates. The GPS receiver determines the vehicle’s position by communicating with at least four satellites, calculating latitude and longitude based on precise timing signals. This process allows the OBU to track the vehicle's trajectory in real-time. GPS accuracy typically ranges from 9.8 to 32.8 feet (or 3 to 10 meters), depending on factors like satellite geometry, signal obstructions from buildings or trees, atmospheric conditions, and the quality of the GPS receiver.

Before receiving safety messages, participants’ driving trajectories showed typical behavior, often including slight veers toward the right or left curb. After receiving the messages, significant adjustments in driving behavior were observed. Changes in speed and acceleration, as seen through trajectory analysis, highlight the drivers’ responses to the safety messages. Drivers' tendency to adjust their path to accommodate cyclists or to enhance pedestrian safety indicates an increased awareness and adherence to the conveyed safety protocols. This immediate adjustment demonstrates the drivers’ ability to react to real-time information and mitigate potential risks effectively. Table 3 illustrates the changes in lateral distance (shifts toward the right or left curbs) observed among male and female participants in scenarios #2 and #3.

Table 3 Lateral Distance Changes (Tilting Toward Right or Left Curbs) Among Male and Female Participants in Scenarios #2 and #3

Scenario	Message Content	Lateral Distance			
		Male – Tilt to the right curb (%)	**Male – Tilt to the left curb (%)**	**Female – Tilt to the right curb (%)**	**Female – Tilt to the left curb (%)**
#2	Pedestrians Safety Message	59.4	21.9	15.6	3.1
	Bicyclists Safety Message	28.1	53.1	3.1	15.7
#3	Reduce Your Speed	71.9	9.4	9.4	9.3
	Keep to the Right Lane	71.9	9.4	15.6	3.1

The trajectory analysis under scenarios #2 and #3 provides insight into how participants responded to traffic safety messages by adjusting their lateral positions on the road. The key findings from Table 3 are as follows:

- High Compliance with Lane-Keeping and Speed Reduction Messages: A significant proportion of participants, especially males, adhered to the "keep to the right lane" and "reduce your speed" messages, as evidenced by 71.9% tilting to the right curb for both messages.
- Cautious Driving Behavior Among Females: Female participants consistently displayed lower percentages of tilting to either curb, indicating a steady and cautious driving approach. This contrasts with the more aggressive adjustments observed among males, highlighting gender-based differences in response to traffic safety messages.
- Impact of Environmental Factors: The location of Morgan State University's campus buildings and bike lanes significantly influenced driver behavior. High pedestrian activity at E Cold Spring Ln - Hillen Rd led to substantial right tilting, while the presence of bike lanes before E 33rd - Hillen Rd prompted drivers to move left, ensuring cyclist safety.

Figure 4 illustrates the locations of the right and left curbs at both intersections, as well as the bike lane at the E 33rd and Hillen Road intersection.

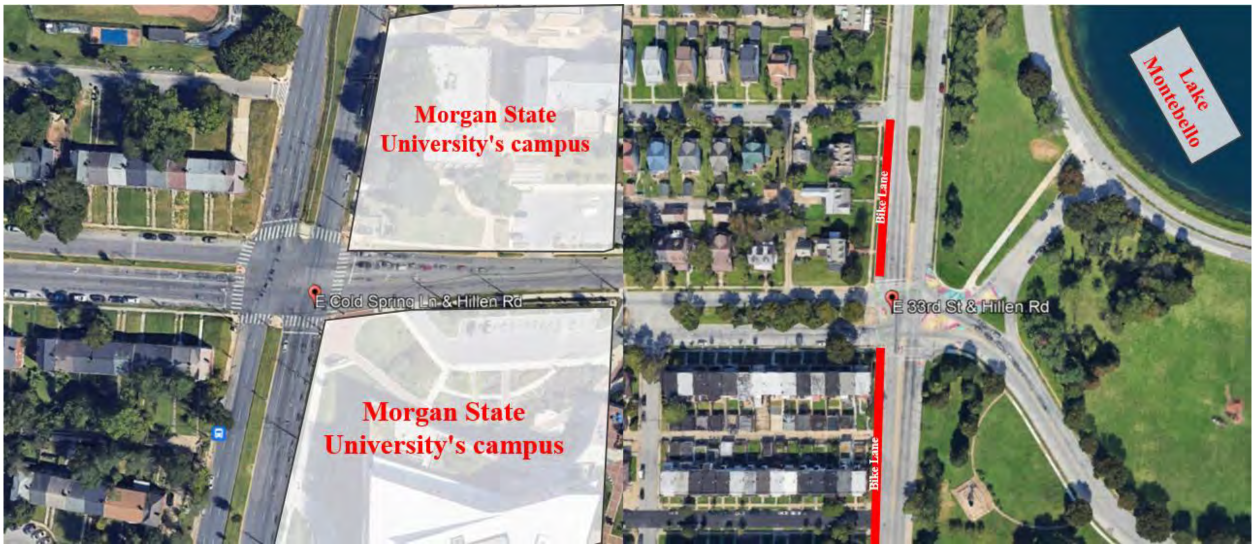

Figure 4 Positions of Left and Right Curbs at E Cold Spring Ln - Hillen Rd (Left Figure) and E 33rd St - Hillen Rd (Right Figure) Intersections

Machine Learning Models Analysis

The study investigated behavioral aspects to understand how factors like gender, age, ethnicity, education level, driving experience, familiarity with CAV technology, and use of in-vehicle driver alerts relate to participants' driving performance in terms of speed changes, acceleration variations, and lateral distance adjustments.

Gender can influence driving behavior due to various psychological and cultural factors. Age is also a factor, as younger and older drivers may have different reflexes and comfort levels with technology, leading to different responses to safety messages. Older drivers, for example, are often more cautious but less quick to adapt to new technologies. Ethnicity and education can shape driving habits and attitudes toward safety, with cultural norms and levels of awareness about technologies. A driver's experience and familiarity with CAV technology can further affect how well they understand and respond to the safety messages. As a result of repeated interaction with warning systems, familiarity and comfort with the technology may improve, thereby improving reaction times and decision-making accuracy during critical moments. In addition, these warnings can help drivers gain a better understanding of the capabilities and limitations of the system, thereby promoting a more safe and informed driving style. Table 4 illustrates the highly correlated independent variables identified by machine learning models, the training models used, and the accuracy rates of the developed models.

Table 4 Machine Learning Models Results

Scenario	Message Content	Dependent Variables	Independent Variables – The Result of Correlation Matrices	Training Models	Accuracy Rate- The best model
#2	Pedestrians Safety Message	Speed	Familiarity with CAV, Ethnicity, Driving Experience	LR	0.78
		Acceleration	Familiarity with CAV, Ethnicity, Driving Experience	LR	0.783
		Lateral Distance	Familiarity with CAV, Ethnicity, Driving Experience	SVM	0.8
	Bicyclists Safety Message	Speed	Gender, Age Ethnicity	RF	0.785
		Acceleration	Gender, Age Ethnicity	RF	0.692
		Lateral Distance	Gender, Age Ethnicity	LR	0.683
#3	Reduce Your Speed	Speed	Gender, Age, Ethnicity	SVM	0.717
		Acceleration	Gender, Age, Ethnicity	SVM	0.719
		Lateral Distance	Gender, Age, Ethnicity	SVM	0.817
	Keep to the Right Lane	Speed	Education status, Driving experience, Familiarity with CAV	SVM	0.775
		Acceleration	Education status, Driving experience, Familiarity with CAV	SVM	0.783
		Lateral Distance	Education status, Driving experience, Familiarity with CAV	SVM	0.88

It is important to note that LR is valuable for its simplicity and effectiveness in binary classification tasks. RF provides robust predictions even when the data contains noise or missing values. RF is also selected due to its robustness in handling large numbers of input features and preventing overfitting through ensemble learning. SVM is advantageous for its capacity to find optimal hyperplanes that maximize the margin between classes, and it offers strong performance in scenarios where the data is not linearly separable. In contrast, other models such as deep learning networks, while powerful, may require larger datasets and more computational resources, and they often lack the interpretability needed for practical application and policymaking in traffic safety analysis. The report therefore concentrated on LR, RF, and SVM models.

The results shown in Table 4 demonstrated that gender, age, ethnicity, education status, driving experience, and familiarity with CAV technology all significantly contribute to how drivers adjust their speed, acceleration, and lateral position when receiving safety messages. These findings highlight the complexity of driver behavior and the necessity for personalized safety interventions that consider diverse characteristics. The results highlighted that:

The LR model showed strong performance in predicting speed and acceleration, with accuracy rates of 0.78 and 0.783, respectively. These results suggest that the independent variables of familiarity with CAV technology, ethnicity, and driving experience are significant predictors of how drivers adjust their speed and acceleration in response to pedestrian safety messages. The SVM model demonstrated the highest accuracy in predicting lateral distance (0.80) and this indicates its ability to capture subtle changes in vehicle positioning along the CAV testbed.

For bicyclist safety, the Random Forest (RF) model achieved the highest accuracy in predicting vehicle speed, with a score of 0.785. Upon further analysis, gender emerged as the most predictive variable, showing a strong correlation with variations in driver speed when cyclists were present. The reason likely is due to distinct risk perception and decision-making patterns between male and female drivers. While age showed a moderate association, particularly in the older demographic, its impact on driving behavior was more pronounced in scenarios involving speed regulation. Hereupon, it suggests that older drivers tend to adopt more cautious driving strategies in proximity to cyclists. The RF model's lower accuracy in predicting vehicle acceleration (0.692) suggests that other unmodeled variables, such as environmental factors or driver familiarity with the area, may contribute to acceleration behavior. In addition, the Logistic Regression (LR) model achieved an accuracy of 0.683 for predicting lateral distance, indicating that while it provides reasonable insight into how drivers position their vehicles relative to cyclists, gender again played a significant role in determining lateral spacing. Age, particularly among older drivers, was also found to be influential in both models, supporting the hypothesis that age-related factors, such as reaction times and cautious driving tendencies, affect driver behavior in these contexts.

In scenario #3, after receiving messages such as "reduce your speed" and "keep to the right lane", the SVM model consistently outperformed others across all dependent variables. The high accuracy rates indicate that the independent variables—ethnicity, gender, age, education status, driving experience, and familiarity with CAV technology—are crucial in shaping how drivers interpret and respond to these messages.

Figures 5 to 8 illustrate the confusion matrices for the optimal models under the messages for pedestrian safety, bicyclist safety, "reduce your speed," and "keep to the right lane," respectively. The goal of using confusion matrices in machine learning models is to provide a detailed breakdown of the model's performance, beyond just overall accuracy. A confusion matrix allows not only the number of correct predictions to be seen but also the types of errors the model is making. Specifically, it shows the number of true positives, true negatives, false positives, and false negatives. This information is essential for identifying the limitations of a model. For instance, in predicting driver behavior, it is essential to determine whether the model is more susceptible to false positives (incorrectly predicting risky behavior) or false negatives (failing to detect actual risky behavior). This distinction is essential because each type of error has significant implications for safety outcomes. False positives can lead to unnecessary interventions or alerts, which may cause driver confusion or distraction. Conversely, false negatives can result in missed warnings for genuinely risky behaviors, potentially failing to prevent crashes.

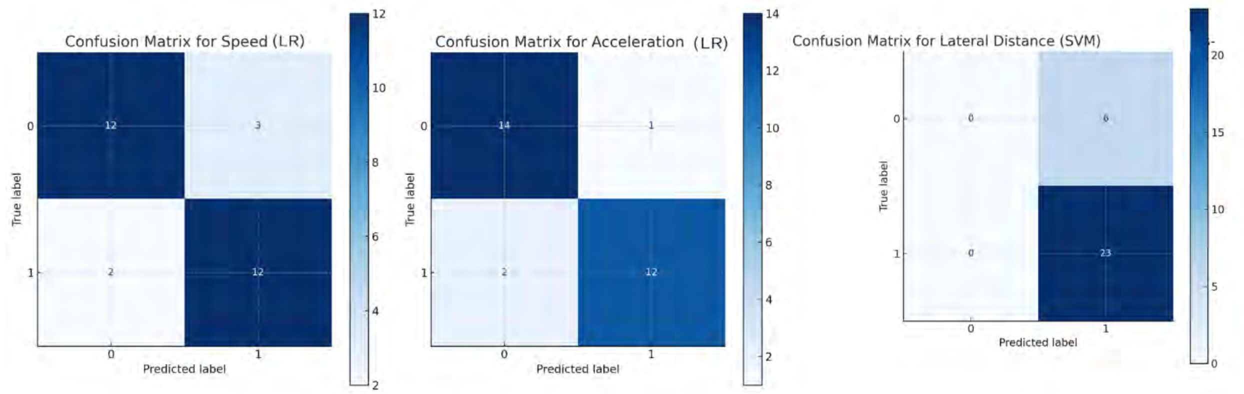

Figure 5 Confusion Matrices for Optimal Models Under Pedestrian Safety Messages (Scenario #2)

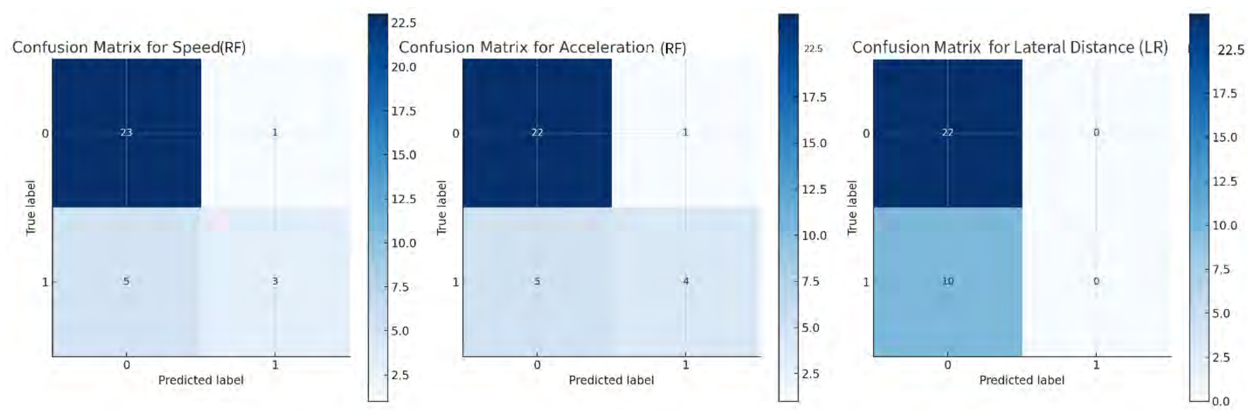

Figure 6 Confusion Matrices for Optimal Models Under Bicyclist Safety Messages (Scenario #2)

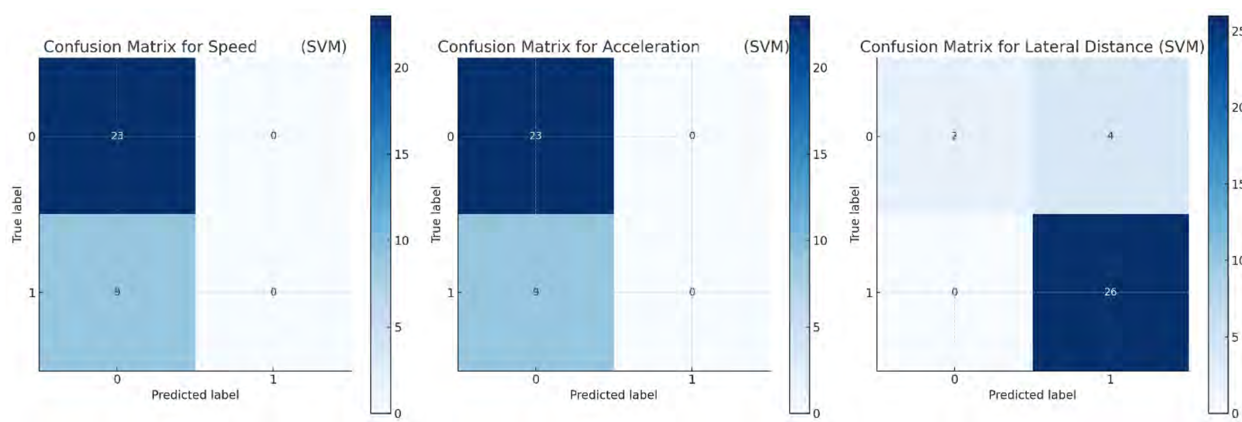

Figure 7 Confusion Matrices for Optimal Models Under Reduce Your Speed Message (Scenario #3)

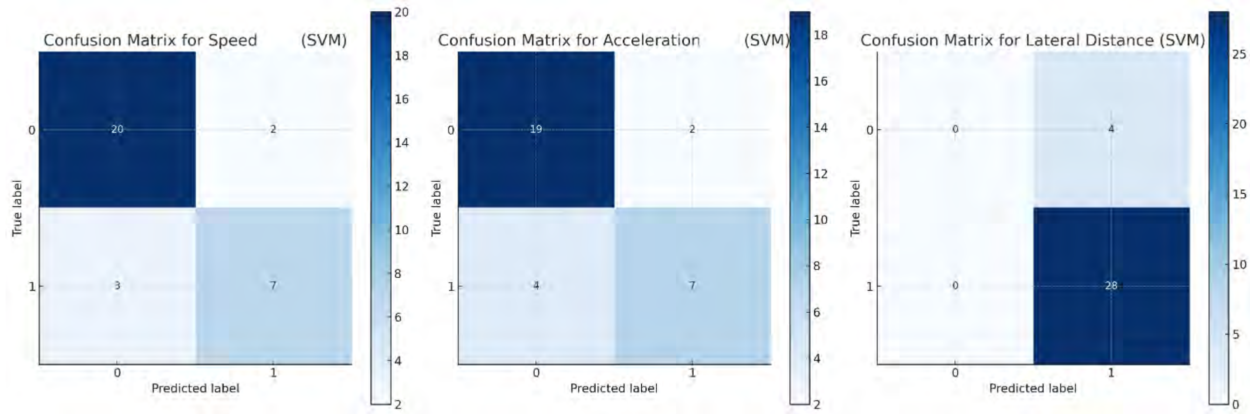

Figure 8 Confusion Matrices for Optimal Models Under Keep to The Right Lane Message (Scenario #3)

Expanding on the initial analysis, the confusion matrices in Figures 5 to 8 reveal nuanced insights into the model's predictive strengths and weaknesses when assessing driver responses to various safety messages. For instance, the confusion matrix for pedestrian safety messages shows a higher rate of true positives, indicating the model's reliability in accurately identifying compliant driver behaviors. Moreover, the confusion matrices for the "reduce your speed" and "keep to the right lane" messages further highlight the differential effectiveness of these messages. The "reduce your speed" message, for example, shows a relatively balanced distribution between true positives and true negatives, suggesting that the model is adept at distinguishing between compliant and non-compliant behaviors. However, the presence of false positives in this scenario indicates that the model might sometimes misinterpret cautious driving as non-compliance, potentially due to over-sensitivity to speed variations in certain traffic conditions. In contrast, the "keep to the right lane" message exhibits a lower false positive rate, suggesting that the model is better calibrated to recognize this specific behavior. These results not only demonstrate the varying levels of accuracy across different safety messages but also highlight areas where further model training and data enrichment could lead to improved safety outcomes. Hereupon, the models reduce both the likelihood of unnecessary driver alerts and the risk of unaddressed hazardous behaviors.

Conclusions

Traffic safety at signalized intersections is of utmost importance, particularly for VRUs. VRUs are particularly at risk due to their limited visibility and reduced protection compared to vehicle occupants. As part of the Intelligent Transportation Systems (ITS) initiative and to establish a comprehensive and robust CAV testbed, a state-of-the-art facility was meticulously developed at Morgan State University. This advanced testbed integrates a wide range of cutting-edge technologies, including LiDAR for precise environmental scanning, CCTV cameras for detailed surveillance, RSUs for efficient communication with vehicles, OBUs for in-vehicle data collection and processing, and smart signal controllers for adaptive traffic management by transmitting and receiving signal phasing and timing data. These technologies are seamlessly interconnected to facilitate real-time communication and data exchange. The real-time communication provides a dynamic and highly adaptable testing environment that supports the development, evaluation, and optimization of CAV systems and their interactions with intelligent transportation infrastructure.

RSUs can broadcast real-time alerts and warnings regarding traffic conditions, pedestrian crossings, and other hazards directly to vehicles equipped with OBUs. This communication allows drivers to receive critical information about potential risks and adjust their behavior. Consequently, the likelihood of crashes is reduced. Key independent variables such as familiarity with CAV technology, demographic factors (e.g., gender, age, ethnicity), and driving experience played a significant role in shaping driver responses. To provide a better understanding of drivers' behaviors in response to traffic safety messages, 32 participants were invited to drive on the CAV testbed. Comprehensive datasets, including speed, acceleration, and lateral movement, were collected for each participant under two different sets of safety messages.

By leveraging various machine learning models, including Logistic Regression, Random Forest, and Support Vector Machine, and analyzing their performance across different scenarios, the research provides valuable insights into accurately predicting driver reactions and optimizing safety interventions. The analysis revealed that the Support Vector Machine model excelled in predicting lateral distance, achieving the highest accuracy rates. Logistic Regression and Random Forest models also demonstrated strengths, particularly in predicting speed and acceleration. The main contributions of this report include the identification of key demographic and behavioral factors influencing driver responses to safety messages, the demonstration of the efficacy of advanced machine learning techniques in this domain, and the validation of communication technologies in enhancing traffic safety.

The main limitations of this study include the scope and generalizability of the data used. The dataset was collected from a specific CAV testbed, which may not fully represent the diverse range of driving conditions and behaviors found in real-world settings. Additionally, the study focused primarily on a limited set of demographic variables and did not account for other potentially influential factors such as weather conditions, traffic density, or psychological state of the drivers. Future research can explore several areas to build on and enhance the findings of this study. One promising direction is the inclusion of a more diverse set of environmental and contextual variables, such as weather conditions, time of day, and varying traffic densities. Additionally, examining psychological and cognitive factors, such as driver stress levels or distraction sources provide deeper insights into the nuances of driver responses.

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