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UTC 1987 2026

Final Report

Smart, Green, Equitable, Safe, Complete Streets for All - Phase I: Development of a CAV Testbed-enhanced Smart Campus at Morgan State University

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Date
September 2024

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ACKNOWLEDGMENT

This research was supported by the Sustainable Mobility and Accessibility Regional Transportation Equity Research Center at Morgan State University and the University Transportation Center(s) Program of the U.S. Department of Transportation.

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1. Report No. SM02	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle: Smart, Green, Equitable, Safe, Complete Streets for All - Phase I: Development of a CAV Testbed-enhanced Smart Campus at Morgan State University		**5. Report Date: August 2024**
		6. Performing Organization Code
7. Author(s) *1. Mansoureh Jeihani, 0000-0001-8052-6931* *2. Di Yang, 0000-0002-7964-7872* *3. Anam Ardeshiri, 0000-0002-2497-3443* *4. Alireza Ansariyar, 0000-0002-5704-6347*		**8. Performing Organization Report No.**
9. Performing Organization Name and Address Morgan State University, 1700 E Cold Spring Ln, Baltimore, MD 21251		**10. Work Unit No.**
		11. Contract or Grant No. 69A3552348303
12. Sponsoring Agency Name and Address US Department of Transportation Office of the Secretary-Research UTC Program, RDT-30 1200 New Jersey Ave., SE Washington, DC 20590		**13. Type of Report and Period Covered** Final,
		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

This report aims to investigate and expand on five essential research areas related to connected and autonomous vehicle (CAV) testbeds and their contribution to enhancing road safety, especially for vulnerable road users. These areas include validating LiDAR data with CCTV systems, investigating CAV testbeds across the country, real-time communication between roadside units (RSUs) and onboard units (OBUs) for broadcasting static safety messages, leveraging LiDAR sensors for detecting jaywalking events at signalized intersections, and the role of CAV testbeds in identifying vehicle-to-pedestrian (V2P) conflicts. Each of these research domains plays a vital role in advancing traffic safety.LiDAR validation with CCTV ensures that real-time, high-accuracy data can be collected and verified, improving the precision of safety measures at intersections. CAV testbeds offer a controlled environment to test new technologies and communication protocols, contributing to the development of safer transportation networks. Real-time RSU-to-OBU communication is critical for delivering timely warnings to drivers and thus reducing the likelihood of crashes. The use of LiDAR in recognizing jaywalking events enhances pedestrian safety by identifying dangerous crossing behaviors in real time. Finally, detecting V2P conflicts at signalized intersections using advanced technologies is essential to minimizing crashes involving pedestrians and vehicles.Morgan State University's CAV testbed stands out for its integration of pioneering technologies, including advanced LiDAR sensors and real-time communication systems, which offer valuable insights for traffic management and safety innovations. This testbed exemplifies the importance of deploying cutting-edge technology in urban environments to address complex safety challenges.

17. Key Words: Connected and Autonomous Vehicles (CAV), LiDAR Sensor, Road safety, Real-time communication, Vehicle-to-Pedestrian (V2P) conflicts, Vulnerable Road Users	**18. Distribution Statement**		
19. Security Classif. (of this report): Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 40	**22. Price**

Morgan State University CAV Testbed

To create a smart campus and improve the safety of all road users around Morgan State University, a Connected and Autonomous Vehicle (CAV) testbed was implemented in April 2022. This testbed is equipped with two Roadside Units (RSUs), two Onboard Units (OBUs), two Light Detection and Ranging (LiDAR) sensors, and four Closed-circuit television (CCTV) cameras, all operating under Cellular-Vehicle-To-Everything (C-V2X) technology. The installation and connection of components such as LiDAR sensors, RSUs, OBUs, and CCTV cameras are essential for establishing a seamless and effective CAV testbed. LiDAR sensors provide precise environmental mapping, detecting obstacles and capturing detailed traffic data [1]. RSUs and OBUs facilitate V2X communication, allowing vehicles to receive and respond to traffic safety messages, thus enhancing situational awareness [2]. CCTV cameras contribute by monitoring traffic flow and capturing events for further analysis [3]. The connection between these components is established through robust communication protocols, often by wireless technologies like Dedicated Short-Range Communication (DSRC) or cellular networks [2]. This integrated network enables the exchange of critical information, allowing for dynamic traffic management, improved safety for Vulnerable Road Users (VRUs), and the potential for predictive analytics. Proper installation and connection ensure that these technologies work in harmony, providing a reliable platform for testing and advancing connectivity systems [4]. Figure 1 demonstrates Morgan State University's testbed.

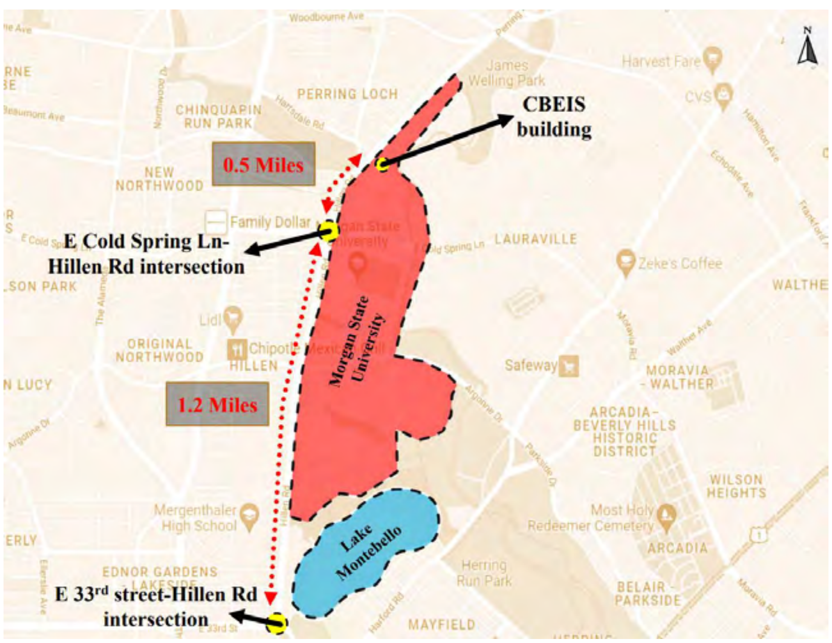

Figure 1 Morgan State University's CAV testbed

Figure 2 demonstrates the LiDAR sensor, RSU, and OBU on the CAV testbed.

Figure 2 LiDAR Sensor, RSU, and OBU Setup on the Morgan State University CAV Testbed

Figure 3 shows the CCTV cameras installed at both intersections on the CAV testbed.

Figure 3 CCTV Cameras Installed at Both Intersections on the CAV Testbed

The primary objectives of the testbed include improving the safety for all road users, and particularly VRUs, at two signalized intersections within the testbed. These intersections are at Cold Spring Lane – Hillen Road and East 33rd – Hillen Road. The latest generation of smart signal controllers was installed at those two intersections to broadcast Signal Phasing and Timing (SPaT) messages, intersection map data (MAP), and Traveler Information Messages (TIM) [5]. The testbed also provides a controlled environment for evaluating and refining CV systems and their impact on traffic management and safety. The integration of LiDAR sensors and CCTV cameras into the testbed allows for comprehensive data collection on vehicle and VRU movements [6]. The use of RSUs and OBUs facilitates communication between vehicles and infrastructure and provides real-time updates and coordination of traffic signals. This setup supports various research activities, including the assessment of traffic signal control strategies, the development of safety measures, and the evaluation of data collection methods.

This testbed will function as a controlled, intelligent environment where various elements of CAV technology can be rigorously tested, enhanced, and verified prior to their use on public roadways. By creating this advanced testbed, the study seeks to advance the development, assessment, and enhancement of CAV functions. This initiative promotes safer interactions between CAVs, conventional vehicles, and VRUs. To create a smart campus, the testbed will gather comprehensive data on vehicle behavior, sensor performance, and interactions, which can be utilized for analysis, benchmarking, and the ongoing refinement of CAV systems. The main deliverables of the CAV testbed include:

- Outfit test vehicles, both connected and conventional, with advanced sensors including LiDAR, CCTVs, RSUs, OBUs, and GPS.
- Establish robust data collection and storage infrastructure to capture sensor outputs, vehicle trajectories, and interactions with other vehicles, bicyclists and pedestrians.
- Execute extensive test runs with both CAVs and non-CAVs to gather detailed data on vehicle behavior, decision-making processes, and sensor inputs.
- Evaluate how CAVs react in situations involving human-driven vehicles, unexpected obstacles, and intricate traffic scenarios.
- Develop experiments to assess the interactions between pedestrians, human drivers, and CAVs.
- Facilitate communication between LiDARs, RSUs, and OBUs, and issue driver warnings based on these interactions to enhance safety and response times.

To effectively enhance road safety on the Morgan State University campus, a series of key tasks will be undertaken to integrate advanced technologies and analyze critical safety data. These tasks include:

Installing advanced LiDAR sensors and RSUs at strategically selected locations on the Morgan State campus.

- Establishing connections between LiDARs and RSUs, as well as between RSUs and OBUs, and ensuring seamless communication between OBUs.
- Issuing driver warnings based on real-time data from RSUs and OBUs, as well as communications between multiple OBUs.
- Analyzing pedestrian violations, including jaywalking, to determine the factors contributing to these unsafe behaviors.
- Identifying and analyzing traffic conflicts to pinpoint high-risk time periods.
- Providing evidence-based recommendations to improve safety for all road users.

This report aims to cover the above tasks and highlight recent research projects that have been conducted and published as technical reports or journal papers regarding "LiDAR validation with CCTV, CAVs testbeds in the country, real-time communication between RSUs and OBUs for broadcasting static warning messages, the advantages of LiDAR sensors in recognizing jaywalking events at signalized intersections, and the role of CAV testbeds in detecting V2P conflicts at signalized intersections."

LiDAR Validation With CCTV

To ensure the accuracy of the LiDAR sensors installed on the testbed under various weather conditions, LiDAR data was compared with CCTV camera footage [7]. Understanding how accurately LiDAR can detect objects in different weather conditions is essential because it directly impacts the reliability of real-time traffic safety measures, particularly in challenging environments like rain or fog [8]. LiDAR sensors and CCTV cameras are often compared in the field of traffic management, as each system has different capabilities and operates in different ways. This comparison is important since it helps identify the strengths and limitations of each technology, guiding decisions on their integration for optimal performance in detecting pedestrians, vehicles, and other objects at intersections. This knowledge is essential for improving safety measures and ensuring that the technology can reliably function in all weather conditions.

The adoption of advanced sensor technologies such as LiDAR, radar, and high-definition CCTVs, enables CAVs to detect and respond to obstacles, traffic signals, and road conditions with high precision. Additionally, the integration of CAV technologies can lead to more efficient use of road space, reduced emissions through optimized traffic flow, and enhanced accessibility for individuals with mobility impairments. In essence, CAV testbeds serve as a vital proving ground for the innovations that will shape the future of safe, efficient, and inclusive transportation systems.

This section of the report investigates the effectiveness of LiDAR and CCTV technologies in collecting vehicle and pedestrian counts at a signalized intersection under various weather conditions [7]. Data was collected over a two-hour interval during peak morning and evening traffic using both technologies. Vehicle counts were analyzed through trajectory tracking, identification of entry and exit points, and anomaly filtering. Pedestrian counts were meticulously assessed by examining LiDAR point cloud data and CCTV footage, focusing on movement patterns in key areas. The analysis revealed that vehicle and pedestrian counts varied depending on weather conditions, with the most significant differences observed during rainy weather and the least during snowy conditions.

The installation process was meticulously planned to position the sensors optimally, ensuring comprehensive coverage of the intersection. Calibration was a critical step, involving adjustments to parameters like laser pulse frequency and scanning angles to enhance measurement accuracy. By emitting laser pulses and analyzing the reflected signals, the LiDAR sensors created detailed 3D point clouds, which served as the basis for object detection and classification [9]. Machine learning algorithms, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), were integral to this process, as they were trained on extensive datasets to accurately distinguish between different types of objects, including vehicles and pedestrians. The use of SVM and CNN algorithms provided significant advantages in adapting to various environmental conditions. SVMs, with their ability to handle noisy data and perform nonlinear classification, were particularly effective in ensuring accurate object classification within the LiDAR data [10]. Meanwhile, CNNs, inspired by the human visual system, utilized layers of filters to automatically learn important features from raw data, thereby improving the detection and classification of objects based on their distinct characteristics [11]. This combination of advanced algorithms allowed the LiDAR sensors to continuously refine their accuracy, even in the dynamic and unpredictable conditions of a real-world intersection.

Complementing the LiDAR data, CCTV cameras were installed to capture video footage for additional traffic monitoring. These cameras were carefully selected for their high imaging capabilities and strategically positioned to cover key areas of the intersection while minimizing blind spots and distortions. Image processing algorithms, such as clustering and segmentation, were employed to analyze the recorded footage, extracting crucial traffic parameters like vehicle and pedestrian counts and trajectories. Both the LiDAR and CCTV systems underwent thorough calibration to ensure their accuracy and reliability across different weather conditions, such as sunny, rainy, and snowy days.

To compare the accuracy of vehicle and pedestrian count data obtained from LiDAR and CCTV technologies, a Bland-Altman analysis [12] was conducted. This method assesses the agreement between the two datasets by plotting the difference between vehicle/pedestrian counts obtained from LiDAR (Li) and CCTV (Ci) against their mean count (Mi) for each movement and time period. Furthermore, the Bland-Altman plot is created by calculating the difference (Di = Ci – Li) between vehicle and pedestrian counts obtained from LiDAR and CCTV. Then, the Bland-Altman plot is drawn by plotting the differences (Di) on the y-axis against the mean counts (Mi) on the x-axis. This chart provides a visual comparison of the two datasets, revealing any biases or patterns. Moreover, the mean difference (D*) is computed to offer assessments of bias and variability between the LiDAR and CCTV datasets. Figures 4, 5, and 6 depict the mean difference (D*) of vehicle counts for all time intervals and movements in snowy, sunny, and rainy weather conditions (right figure), as well as discrepancies in pedestrian counts between LiDAR and CCTV cameras during snowy, sunny, and rainy weather (left figure), respectively.

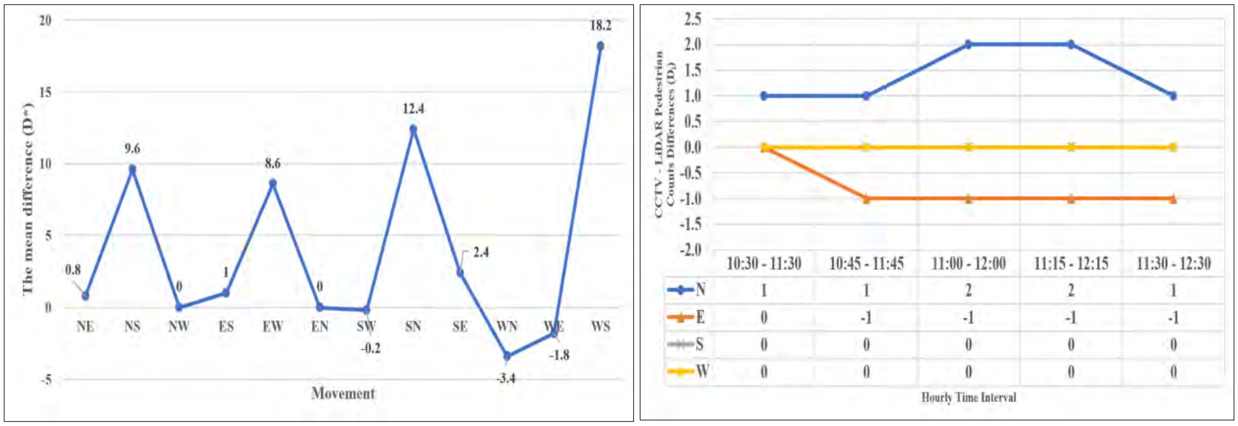

Figure 4 The Mean Differences (D) of Vehicle Counts (left figure) and Pedestrian Counts (right figure) in Snowy Weather Conditions*

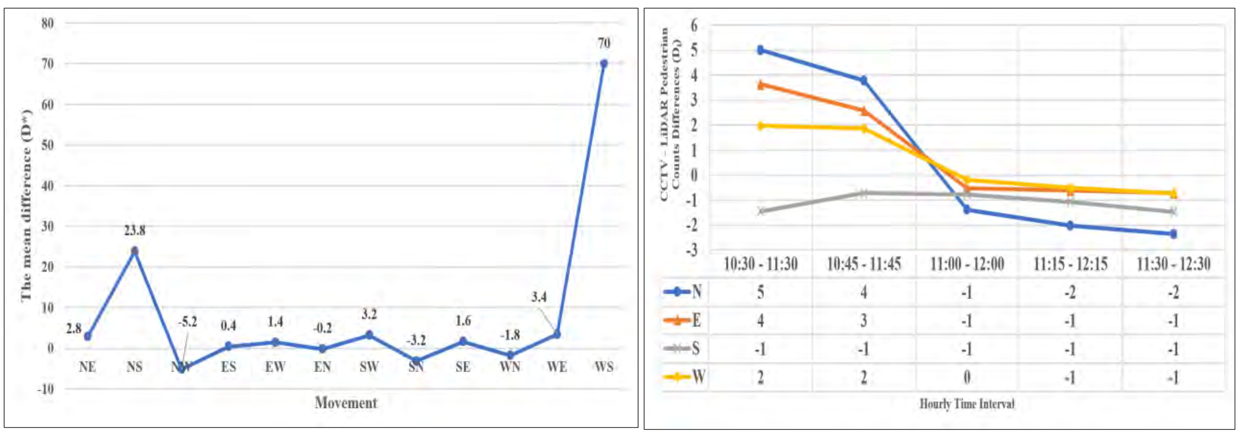

Figure 5 The Mean Differences (D) of Vehicle Counts (left figure) and Pedestrian Counts (right figure) in Sunny Weather Conditions*

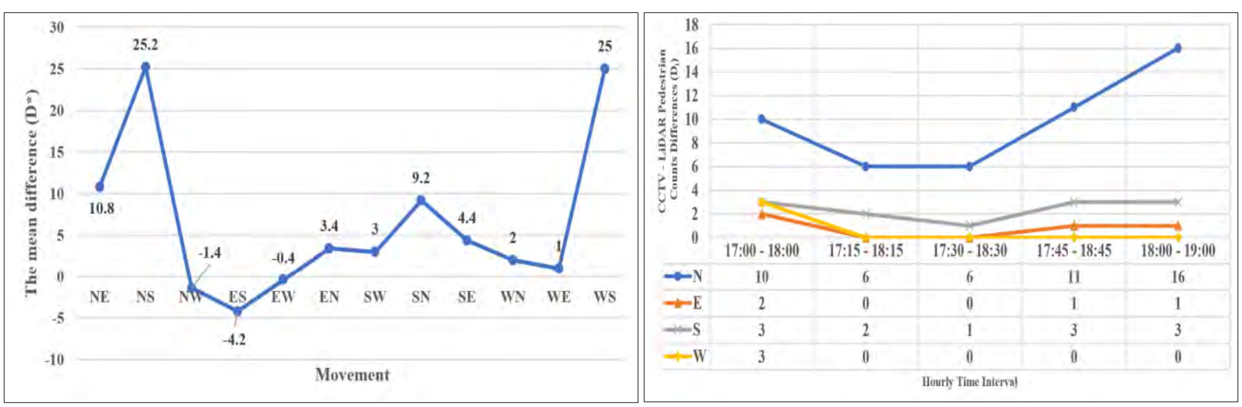

Figure 6 The Mean Differences (D) of Vehicle Counts (left figure) and Pedestrian Counts (right figure) in Rainy Weather Conditions*

The results highlighted that during snowfall, LiDAR sensors demonstrated greater reliability, showing minimal discrepancies in vehicle counts, while CCTV cameras were less reliable due to visibility issues caused by the snow. As the intensity of snowfall increased, the discrepancies between the vehicle counts recorded by the two technologies widened, highlighting the limitations of CCTV in adverse weather. In sunny conditions, both LiDAR and CCTV cameras performed relatively well, with only minor differences in vehicle counts. However, some larger discrepancies were observed due to factors such as objects obstructing the camera's view or lighting variations affecting image quality. LiDAR sensors consistently provided more accurate data, as their laser-based detection system is less affected by external factors like lighting or shadows, making them more dependable for traffic monitoring in clear weather. Under rainy conditions, significant differences emerged between the two technologies. CCTV cameras struggled with reduced visibility and obstructions caused by water droplets on lenses, leading to inaccuracies in vehicle counts. LiDAR sensors, on the other hand, maintained their performance, providing reliable data despite the rain. The study concluded that LiDAR sensors offer superior accuracy and consistency across different environmental conditions compared to CCTV cameras, making them more suitable for reliable traffic monitoring and safety improvements, particularly in adverse weather scenarios.

CAVs Testbeds in the country

The establishment of CAV testbeds is essential for advancing traffic safety and efficiency in real-world environments [6,13]. These testbeds serve as controlled settings where CAV technologies can be rigorously tested and refined before widespread deployment. By integrating vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [14], CAV testbeds allow researchers to evaluate how these technologies interact with existing transportation systems. This controlled experimentation is vital for understanding how CAVs can reduce traffic congestion, improve traffic flow, and enhance overall roadway safety. The insights gained from CAV testbeds can guide the development of standards and protocols, ensuring that CAV technologies are reliable and effective when implemented on a larger scale.

CAV testbeds are also pivotal in addressing traffic safety goals, particularly for vulnerable road users (VRUs) such as pedestrians, bicyclists, children, the elderly, and individuals with disabilities. By employing Vehicle-to-Everything (V2X) communication, which includes V2V, V2I, vehicle-to-pedestrian (V2P), and vehicle-to-network (V2N) interactions, these testbeds create a comprehensive network that enhances situational awareness for both vehicles and road users. For instance, CAVs can receive real-time information about pedestrians crossing the road, enabling automated systems to take proactive measures to avoid collisions [15]. This level of integration not only protects VRUs but also contributes to a safer and more inclusive transportation environment. Furthermore, CAV testbeds contribute significantly to improving crash safety and reducing crash rates. Additionally, testbeds help in fine-tuning CAV responses to potential hazards. This proactive approach to safety allows for the identification and mitigation of risks before they lead to crashes. Additionally, the data collected from these testbeds can inform the design of safer infrastructure, optimized traffic signal timings, and adaptive traffic management strategies, all of which are integral to creating safer roadways for both CAVs and human-driven vehicles.

This section examines the diverse applications, technologies, geographic contexts, administrative structures, and challenges associated with CAV testbeds, providing a comprehensive foundation for planning future CAV and connected vehicle (CV) initiatives in the U.S. By analyzing these topics, this section highlights how CAV technologies can fundamentally transform transportation systems, enhance safety, and improve the overall mobility experience for all road users, including vehicles and VRUs. Figure 7 illustrates the planned and operational CAV testbed projects in the U.S. [16]. As shown in Figure 7, 70 operational sites and 101 planned sites have been implemented by the U.S. Department of Transportation (USDOT).

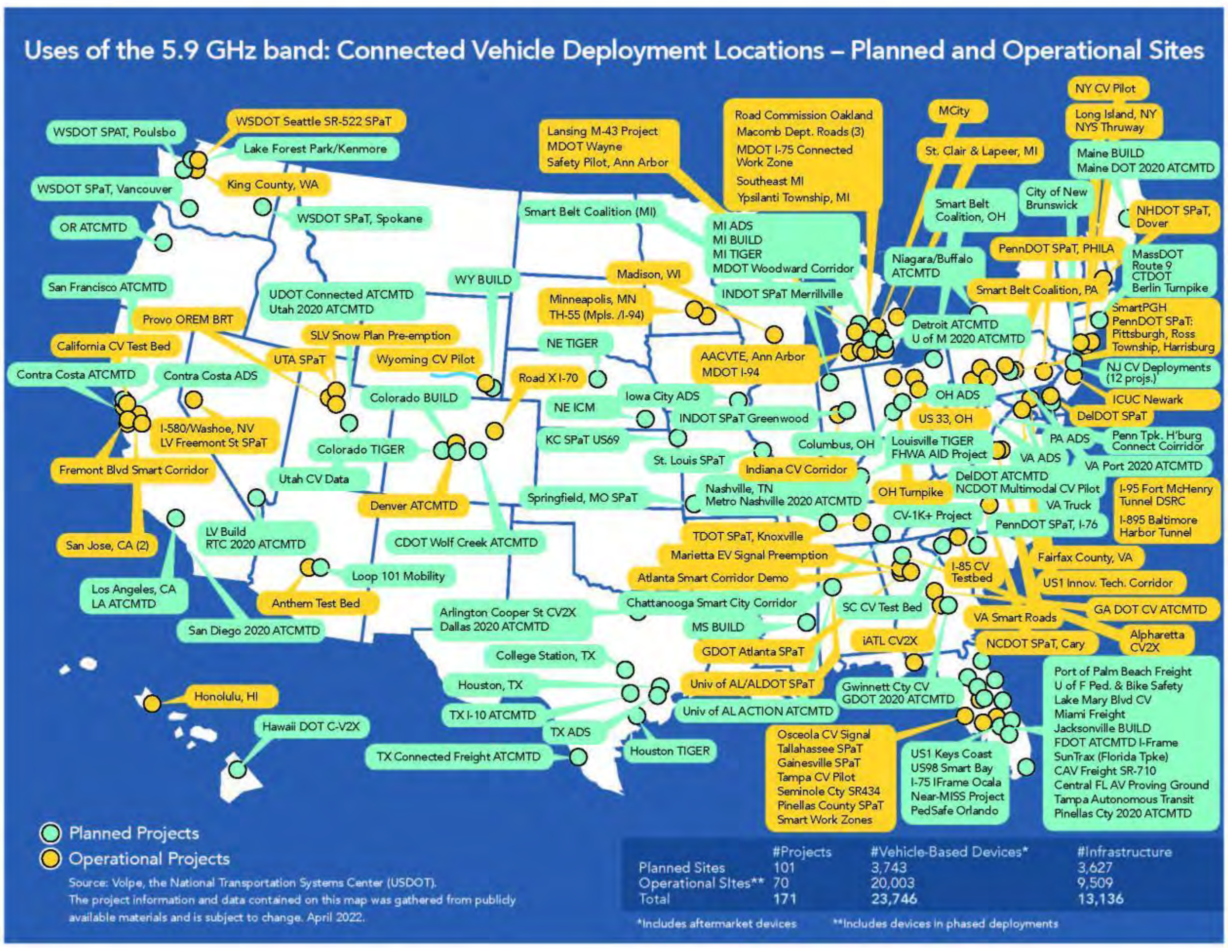

Figure 7 Operational Connected Vehicle Deployments in the U.S. [16]

As shown in Figure 7, CAV testbeds have been deployed in diverse geographical contexts, owing to the unique opportunities and challenges presented by urban, suburban, and rural environments. Urban areas, for instance, may focus on reducing congestion and improving pedestrian safety, while rural areas might prioritize connectivity and emergency response efficiency. This geographic differentiation allows for a tailored approach to deploying CAV technologies. To provide a summary of CAV testbeds in the nation, Tables 1 and 2 [17] present the project titles, locations, equipment used in each testbed, communication technologies implemented, and a brief description for connected testbeds and autonomous testbeds, respectively.

Table 1 CV Testbeds in the Country

State	Project Title	Location	Equipment	Communication	Brief Description
AZ	Arizona Connected Vehicle Test Bed (Anthem)	along 5.5-mile area of West Daisy Mountain Drive, Anthem	RSUs on 11 intersections	DSRC	Providing pilot test opportunities for applications such as transit signal priority and emergency vehicle preemption.
CA	California CV Test Bed, Palo Alto	along Highway 82 also known as El Camino Real (approximately 2.1 miles) on 16 intersections, Palo Alto	replacing the DSRC RSUs with C-V2X RSUs on 16 intersections	C-V2X	to demonstrate Multi-Modal Intelligent Traffic Signal System (MMITSS), including CV-based traffic signal control and signal priority for transit, freight, and pedestrians, and Environmentally Friendly Driving
FL	Gainesville SPAT Deployment	along 4 corridors, Gainesville	27 RSU on 27 signals, 71 OBUs on a variety of vehicles including emergency vehicles, transit buses, UF fleet, City of Gainesville vehicles, and research vehicles.	DSRC	to improve travel time reliability, safety, throughput, and traveler information. also deployed and tested pedestrian and bicyclist safety smartphone-based applications.
FL	Tallahassee US90 SPaT Challenge Deployment	along US-90 Mahan Drive, Tallahassee	RSU on 22 signals, OBU	DSRC	to evaluate the operational and safety benefits of the SPaT applications along US 90. The short-term goal is to verify if SPaT will work effectively in hilly and forested terrain along US 90, while the overall long-term goal is to evaluate Dedicated Short-Range Communications (DSRC) efficiency and safety for road users along a signalized arterial corridor.
FL	Seminole County SR 434	Seminole County	RSUs on 6 intersections, OBU	DSRC	to implement CV technology and Signal Performance Metrics (SPM)
FL	Osceola County CV Signal Project	Osceola County	RSU on two signalized intersections	DSRC	to test Dedicated Short-Range Communications equipment and intersection processing equipment to gain experience and compile lessons learned in the deployment of CV infrastructure and applications.

FL	Pinellas County SPAT	along a portion of US 19 corridor, Pinellas County	23 RSUs on intersections	DSRC	Broadcasting SPaT info.
FL	Tampa Hillsborough Expressway Authority (THEA) Connected Vehicle Deployment	Tampa	1,000 enhanced rearview mirror installed to display safety messages, 47 RSUs on intersections, 10 bus OBU, 8 street car OBU	DSRC, Sattelite communication	to transform the experience of automobile drivers, transit riders, and pedestrians in downtown Tampa by preventing crashes, enhancing traffc flow, improving transit trip times, and reducing greenhouse gas emissions.
GA	iATL CV2X	Alpharetta	55 RSUs	C-V2X	to test a wide range of safety applications provided by C-V2X on public roads and in real traffic
GA	Marietta GA Emergency Vehicle Signal Preemption	Marietta	RSUs on 120 Intersections, driver safety app	DSRC	First responders' preemption
GA	North Fulton Community Improvement District	Fulton County	RSU on 44 intersections	4G LTE, DSRC, C-V2X	Green light priority for emergency vehicles and transit buses. Drivers can connect to the app with TravelSafely app
GA	I-85/"The Ray" CV Testbed	An 18-mile stretch of Interstate 85 in Georgia	6 RSUs	DSRC, C-V2X	to immediately detect a crash and generate an alert to warn drivers about a crash on the road ahead.
GA	City of Atlanta Smart Corridor Project	Atlanta	1000+ RSU at intersections	DSRC, C-V2X	Emergency Vehicle Preemption Pilot, Transit Signal Priority Pilot, Incident Responder interchange preemption, Freight signal priority
IN	Indiana Connected Vehicle Corridor Deployment Project	I-94	10 RSU at intersections	DSRC	Part of SPaT Challenge,
MI	U.S. Army Tank Automotive Research, Development & Engineering Center (TARDEC) "Planet M Initiative"	along a 21-mile portion of I-69, St. Clair & Lapeer Counties,	6 RSUs	DSRC	Curve speed warning, lane closure warning, speed recommendation and disabled vehicle warning
MI	Macomb County Dept. Roads DSRC Deployment (MDOT/SMART Pilot)	Macomb County, MI	750 RSU at signalized intersections, Wi-Fi Vehicle Detectors	DSRC	Broadcasting SPaT information
MI	I-75 Connected Work Zone (Oakland County)	3 Miles of I-75 in Oakland County, Michigan	CCTV, Vehicle detectors at every mile, DMS sign, RSU at every mile, Environmental Sensor Station	DSRC	Automatically detect incidents and respond faster, notify motorists about travel times, traffic queues, speeds and weather-related events, Notify motorist of adverse conditions through use of safety applications such as Curve Speed Warning and Bride Deck Warning Systems (read more about these systems below), Improve safety through the work zone through use of advanced connected vehicle applications
MI	Road Commission for Oakland County DSRC	Farmington Hills	17 RSU	DSRC	Broadcasting SPaT information
MI	Southeast Michigan Testbed	Along I-96/I-696	22 RSU	DSRC	Dynamic Speed Harmonization, Incident Scene Work Zone Alerts, Eco Approach and Departure at Signalized Intersections, Motorist Advisories and Warnings

MI	Safety Pilot Model Deployment	U.S. 23 and Plymouth Road, Ann Arbor, Washtenaw Avenue, MI	2700 OBU, 29 RSU, 12 TSC	DSRC	to demonstrate the readiness of DSRC-based connected vehicle safety applications for nationwide deployment.
MI	MCity Testbed	University of Michigan, Ann Arbor, MI	RSU, Edge Computing	5G, V2X	Transit Signal Priority, Emergency Vehicle Preemption, Dynamic Signal Optimization with Green Wave Advisory, and Vulnerable Road User Notification
MI	Ann Arbor Connected Vehicle Test Environment (AACVTE)	27-square miles of the City of Ann Arbor	25 RSU, 2500 OBU	DSRC	to assess the effectiveness of connected vehicle safety technology at reducing crashes.
MI	American Center for Mobility (Willow Run)	Ypsilanti Township, MI	RSU	DSRC	A facility for testing autonomous cars
MI	Michigan DOT Wayne County Project	Wayne County, MI	12 RSU, 250 OBU	DSRC	to document lessons learned, benefits, and evaluate potential business models for future deployment opportunities.
NV	Las Vegas SPaT Corridor	Freemont St. Las Vegas, NV	RSU in 5 intersections	DSRC	Broadcasting SPaT and map information.
NV	Nevada DOT DSRC for Rural ITS (Washoe County)	I-580/Washoe County, NV	RSU, CCTV, Radar, Thermal/infrared, Lidar, Microwave	DSRC	to optimize flow and respond to road conditions, including construction, special events, pedestrian and cyclist.
NY	New York City Connected Vehicle Project Deployment	Manhattan, Brooklyn, NYC	450 RSU, 3000 OBU	DSRC	Emergency Electronic Brake Lights, Forward Crash Warning, Intersection Movement Assist, Blind Spot Warning, Lane Change Warning, Vehicle Turning Right in Front of Bus Warning, Red Light Violation Warning, Speed Compliance, Curve speed compliance, Speed Compliance in Work Zone, Oversize Vehicle Compliance, Emergency Communications and Evacuation Information, Pedestrian in Signalized Crosswalk Warning, Mobile Accessible Pedestrian Signal System
OH	Ohio Turnpike & Infrastructure Commission DSRC Projects	60-mile section of Ohio turnpike	15 RSU	DSRC	Proof of concept project
OH	NW US33 Smart Mobility Corridor	Marysville, Dublin, OH	800-1000 OBUs, 27 RSUs	DSRC	Improves Travel Time Reliability, Traffic Volumes Increase to Optimize Travel Lanes, Reduce Crashes
PA	PennDOT Signal Phase and Timing (SPaT) Deployments & Test Beds	Cranberry Township, PA	11 RSUs at intersections	DSRC	Improve Safety, Enhance Mobility, Prepare Workforce, Foster and Sustain Partnerships, Increase Public Awareness, Strengthen Economic Collaboration
PA	SmartPGH	Pittsburgh, PA	135 intersections, 293 CCTV, 37 Radio advisory transmitter, 200 microwave traffic detector, 24 RSU, 93 Radar	DSRC	Transit signal priority implementation
PA	PennDOT Ross Township Test Bed	Baum Centre Ave Pittsburgh, PA	45 RSUs, 726OBUs	DSRC	The FHWA grant will be used to deploy adaptive traffic signal controls & DSRC along the McKnight Road corridor.
WI	Connected Park Street Corridor	along Park Street, Madison	RSUs at 15 signalized intersections	DSRC	Transmit basic safety messages, give information about speed, location and heading
NH	SPaT Challenge	Dover	Traffic Controller, DSRC RSU, DSRC OBU, V2I Hub, Traffic Server, LTE Radio	DSRC, 4G LTE	Comparing performance of DSRC with 4G LTE
NJ	Integrated Connected Urban Corridor in New Jersey (ICUC NJ) Initiative	Newark	8 RSU, air pollution sensor	DSRC	Provide traffic data analytics that can be useful in evaluating alternative traffic operation strategies.

DL	DelDOT SPaT Challenge Deployment	Smyrna	11 RSUs at intersections	DSRC	Broadcasting SPaT information.
MD	Howard County, MD	Howard County, MD	2 RSUs at intersections	DSRC	Broadcasting SPaT information.
MD	Montgomery County and Prince George County Connected Vehicles Pilots	Montgomery County, MD Prince George County, MD	More than 40 RSUs	DSRC/CV2X	Broadcasting Spat messages, intersection map data (MAP), pedestrian warning, and traveler and/or information messages
MD	Morgan State University Testbed	Baltimore, MD	2 RSUs at intersection, 2 OBUs, 2 Lidar and 4 CCTV cameras	CV2X	Broadcasting Spat messages, intersection map data, and traveler and/or information messages.
VI	Virginia Smart Roads	including sections of Interstate 66, Interstate 495, U.S. 29, and U.S. 50	49 roadside units (RSUs)	DSRC	The Virginia Smart Roads are controlled-access test tracks built to Federal Highway Administration standards. The roads are equipped with advanced research infrastructure and are supported by a full-time staff that serve to coordinate all road activities and oversee operations.
NC	NC DOT DSRC	Cary	16 RSUs at intersections	DSRC	Signal Preemption, Transit Signal Priority, Broadcasting SPaT info.
GA	Georgia DOT SPaT Project	Atlanta	54 RSUs at intersections and 12 RSUs at freeways	DSRC	Broadcasting SPaT info and receiving basic safety messages.
FL	Smart Work Zones	6 state road corridors: US 1, Dixie Highway, Powerline Road, US 441, Hillsboro Boulevard, and Sample Road	2 RSUs, CCTV Cameras, 2 Vehicle Detectors	DSRC	Traffic Queue Warning, Travel Time Advisory, Alternate Route Advisory
AL	University of Alabama, Center for Advanced Vehicle Technologies & Alabama DOT	Tuscaloosa	85 RSUs on intersections.	DSRC	Broadcasting SPaT info.
TN	TnDOT SPaT Challenge Project	Cumberland Ave, Knoxville	17 RSUs on intersections	DSRC	Broadcasting SPaT info.
MN	Roadway Safety Institute (RSI) Connected Vehicle Testbed	Minneapolis	1 RSU, 1 OBU, 7 radars	DSRC	to implement and evaluate the next generation of vehicle-based freeway safety applications, to establish the backbone of the sensor communication network and data collection system along the testbed length.
WY	Wyoming Connected Vehicle Project Deployment	I-80 Wyoming	75 RSUs, 450 OBUs	DSRC	Reducing delays, improving safety, reducing severe weather-related accidents
UT	Salt Lake Valley Snowplow Preemption	Salt Lake Valley	5 corridors, 55 intersections	DSRC	Preemption for Snowplow vehicles
UT	Utah Transit Authority (UTA) DSRC Traffic Signal Pilot Project	Redwood Road, Salt Lake City area	24 RSUs on intersections	DSRC	to keep UTA buses on schedule.
ID	Ada County Highway District	Ada County	20 RSUs, 20 OBUs	DSRC	Validating communication architecture and control technology readiness
WA	Washington State Transit Insurance Pool (WSTIP) Safety-Collision Warning Pilot Project	Washington State	4 cameras on 38 buses	Internet	to test and analyze a collision avoidance system that could help bus drivers reduce the number and severity of collisions
HI	Nimitz Corridor Project	Honolulu	RSUs on 16 traffic signals	C-V2X	Red Light Violation Warning, Pedestrian and Cyclist Collision Warnings, Emergency Vehicle Preemption, Transit Signal Priority, Traffic Queue Warning, the TravelSafely™ smartphone app, and Signal-Phase and Timing (SPAT).

Table 2 Autonomous Vehicle (AV) Testbeds in the Country

State	Title	Location	Connected/Not Connected	Equipment	Communication	**Brief Description**
MI	Mcity	Ann Arbor	Connected	RSUs, OBU, Self-Driving Cars	V2X	In 32 acres area, it simulates urban and suburban environments to test autonomous technologies in various scenarios.
CA	GoMentum Station	Concord	Connected	RSU at 3 intersections (2 more are planned), OBU	DSRC, V2X	In a 5000 acres area, multiple tests including Transit signal priority, Conditional transit signal priority, Vulnerable Road user (VRU) detection, red light violation warning, and Signalized left turn assist can be performed
MI	American Center for Mobility	Ypsilanti	Connected	RSUs, OBU, Self-Driving Cars	DSRC, V2X	On over 500 acres, it provides an Advanced Mobility Proving Ground with test environments featuring specialized infrastructure in various environment including urban, rural, and offroad for connected and autonomous vehicles
PA	Pittsburgh Autonomous Vehicle Test Site	Pittsburgh	Connected	RSUs, OBU, Self-Driving Cars	V2X	Focus on the transportation safety, research and operational needs of the region by three entities: Aurora, Carnegie Mellon University AV Center, Motional
TX	Texas A&M University RELLIS Campus	Bryan	Not Connected	Self-Driving Shuttles, cars, trucks	-	Aims to unify research and development of autonomous vehicles and systems including autonomous ground vehicles (shuttles, cars, trucks) Safety for autonomous vehicles (virtual, scaled, Slow moving, cars, trucks)
TX	Texas Innovation Alliance	Arlington, Houston, Frisco	Not Connected	Slow peed Self-Driving Shuttles	-	Fixed route off main road tests, idling in place until boarded.
OH	Ohio State University Center for Automotive Research	Columbus	Connected	RSU, OBU, Self-Driving Cars	V2X	This testing focuses on Smart Autonomous Shuttles, Autonomous Vehicle Path Planning and Tracking, Hardware-in-the-Loop Evaluation, Collision Avoidance for Road and Pedestrian Safety, and Connected Vehicle Technologies for Safety and Mobility.
MA	Massachusetts AV Testing Program	Arlington, Boston, Braintree, Brookline, Cambridge, Chelsea, etc.	Not Connected	Self-Driving Cars	-	For Authorized testing of automated vehicles on public street
GA	Curiosity Lab AV test track	Peachtree Corners	Not Connected	Self-Driving Cars	-	A 1.5-mile AV test track, complete with steep grades, curves and trees. Even though there were connected vehicle infrastructure in the area. It wasn't used for the AV testing.

Real-time Communication Between RSUs and OBUs for Broadcasting Static Warning Messages

Enhancing the safety of VRUs, including pedestrians and cyclists, is a crucial aspect of urban traffic management [18]. Protecting VRUs requires the implementation of advanced technologies and strategic planning to protect these two at-risk groups in urban environments. Signalized intersections can be especially risky for VRUs because of the frequent interactions between vehicles and VRUs at these locations [19]. Moreover, pedestrians and bicyclists face unique risks at intersections due to their limited visibility and lack of protection compared to drivers [20]. Protecting VRUs requires the implementation of advanced technologies and strategic planning to protect these two at-risk groups in urban environments. One effective strategy involves using RSUs in CAV environments [21,22]. RSUs 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, drivers can be better informed and make safer decisions, especially in areas with high pedestrian and cyclist activity [23].

This section evaluates the effectiveness of two different safety messages: a pedestrian safety message at the Cold Spring Ln - Hillen Rd intersection (the first intersection in the CAV testbed) and bicyclist safety message at the E 33rd - Hillen Rd intersection (the second intersection in the CAV testbed). In the study, thirty-two (32) participants were invited to drive on the CAV testbed with their personal vehicles. Their vehicles were equipped with OBUs, which could detect the geographic location of the vehicles, communicate with the LiDAR and RSU systems [24], and broadcast both pre-configured safety messages to the drivers. The effectiveness of the messages in improving safety at congested intersections was assessed by analyzing data on speed changes, acceleration, braking habits, and road positioning collected from the participants before and after the messages were broadcast.

The locations were chosen based on their high pedestrian and bicycle traffic, with the former located near major university buildings and the latter adjacent to recreational areas. Moreover, the set of messages was strategically broadcasted 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 by allowing more time for drivers to react. Advising drivers to stay in the right lane prevents dangerous lane changes and reduces conflicts with VRUs.

The two safety messages adhered to the J2735 standard, which outlines the necessary protocols for vehicular communication and ensures the interoperability and reliability of the transmitted messages [25]. The safety messages were generated and verified by the USDOT's TIM message website [26]. The content of the messages was then uploaded to the OBUs' dashboards, which was displayed on a tablet 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 8 illustrates the tablet's interface and the real-time communication between the OBU, RSU, signal controller, and LiDAR on the CAV testbed.

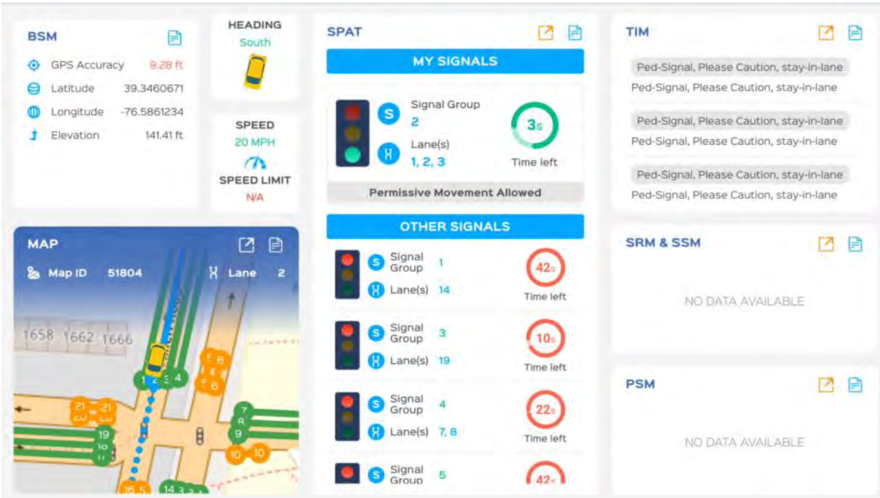

Figure 8 Real-Time Communication and Tablet View on the CAV Testbed

The tablet also 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 impacts 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 [27] and the USDOT decoder [26] 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.

Prior to the live test, 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.

The design of scenarios 2 and 3 was carefully planned to assess specific safety situations in line with industry standards, particularly the J2735 standard [25]. 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. 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 affect driving behavior under different conditions. Thus, it provides valuable insights into driver reactions to unforeseen alerts. Based on this variability, participants face unexpected messages on the testbed, thus validating the practical utility of the safety messages.~~ Adhering to these standards was essential for maintaining the study's integrity and ensuring reliable results, as variations in message content or timing could influence participants' perceptions and responses. The placement of RSUs and the timing of message broadcasts were carefully managed to ensure effective communication while minimizing delays. A key aspect of the study was the random broadcasting of safety messages, which aimed to replicate real-world driving conditions where hazards and alerts do not follow predictable patterns. While one might argue that random broadcasting makes the messages appear less precise to participants, such variability is essential for maintaining the study's ecological validity. In real-life scenarios, drivers are not primed to expect alerts at specific times or intervals—unexpected events are the norm. If the safety messages were delivered at fixed or predictable intervals, participants might adapt their behavior or develop anticipatory responses, which could undermine the authenticity of their reactions. In contrast, random intervals prevent participants from anticipating the alerts, ensuring that their responses remain spontaneous and reflective of how drivers typically react to unforeseen hazards on the road. This randomness also allows the study to capture a wider range of participant behaviors across varying situations, providing a more comprehensive understanding of how safety messages influence driving behavior under diverse conditions. For example, drivers might react differently when alerts are received in dense traffic compared to lighter traffic or during moments of high cognitive load. The unpredictability introduced by random broadcasting enables the evaluation of these nuanced responses, ultimately validating the practical utility of safety messages. Thus, this approach ensures that the insights gained from the study are both reliable and applicable to real-world scenarios, where precise timing of alerts is rarely guaranteed.

In scenario 2, safety messages were broadcast at two intersections to enhance driver awareness. At Cold Spring Ln - Hillen Rd intersection, the message "Pedestrian signal, please caution, stay in lane" alerted drivers to pedestrian crossings near the university. At E 33rd - Hillen Rd intersection, the message "Bicyclists on roadway, please cross intersection with care" warned drivers about cyclists' presence on the road. Scenario 3 introduced messages for specific road conditions including "reduce your speed" near the Morgan Bridge to prevent pedestrian crashes and "keep to the right lane" at E 33rd - Hillen Rd to accommodate bike lanes and enforce speed limits. These messages aimed to promote safer interactions with pedestrians and cyclists and reduce collision risks.

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 analysis of driver behavior before and after receiving safety messages was conducted over a 20-second period [28, 29] 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. Table 3 and 4 illustrate the changes in speed and acceleration observed before and after receiving the safety messages, respectively.

Table 3 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 4 Percentage Changes in Acceleration in Scenarios 2 and 3 by Participant Gender

Scenario	Message Content	Interval: The Message Receiving Point to 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

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

- Pedestrian Safety Message: During the 20 second interval prior to receiving the message, 46.9% of males decreased speed. After the message, the proportion of males who decreased their speed 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: Prior to receiving the bicyclist safety message, 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, 59.4% of males decreased their speed demonstrating greater 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 [30]. 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' tendencies 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 5 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 5 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 5 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% of participants 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 9 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.

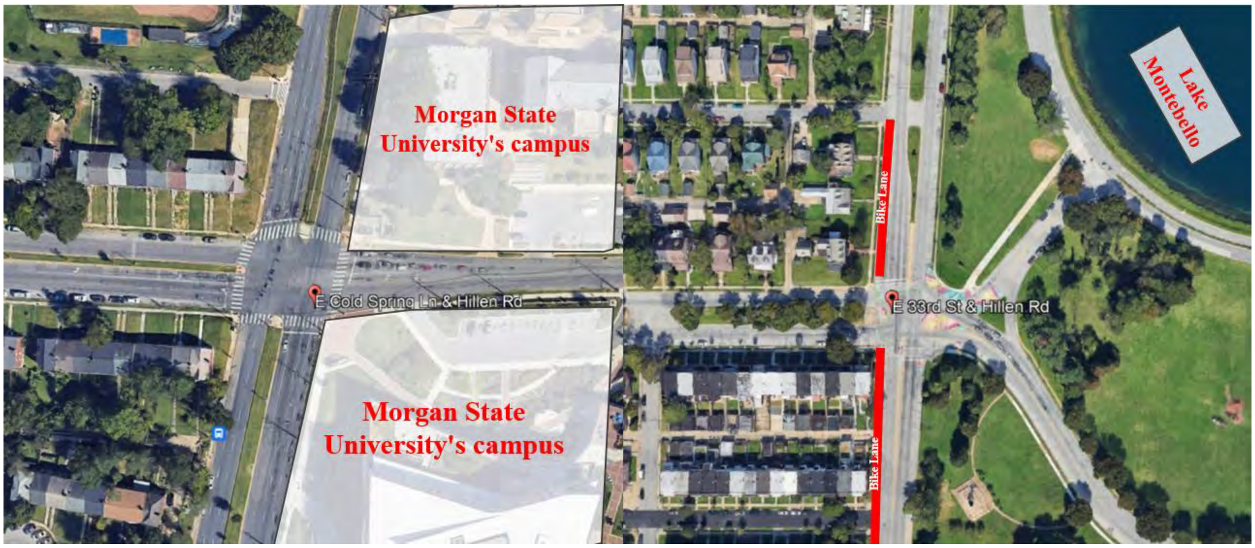

Figure 9 Positions of Left and Right Curbs at E Cold Spring Ln - Hillen Rd (Left Figure) and E 33rd St - Hillen Rd (Right Figure) Intersections

To accurately interpret the dataset and analyze driver behavior in response to safety messages broadcasted within the CAV testbed, it is essential to select machine learning models that are both effective and precise. This section evaluates 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 and make an informed decision. 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.

LR is valuable for its simplicity and effectiveness in binary classification tasks, while RF provides robust predictions even when the data contains noise or missing values. RF was 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. Hereupon, the report concentrated on LR, RF, and SVM models.

As the machine learning model results suggest, 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 often being 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 interactions with warning systems, familiarity and comfort with the technology may improve, thereby improving reaction times and decision-making during critical moments. In addition, it can help drivers gain a better understanding of the capabilities and limitations of the system, thereby promoting a more informed and safer driving style. Table 6 illustrates the highly correlated independent variables identified by machine learning models, the training models used, and the accuracy rates of the developed models. Table 6 illustrates the machine learning models used in this study.

Table 6 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

The results shown in Table 6 demonstrate 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 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 RF model demonstrated the highest accuracy in predicting vehicle speed, achieving a score of 0.785. This finding highlights the significance of variables such as gender, age, and ethnicity in shaping driver behavior when cyclists are present. However, the RF model's accuracy in predicting acceleration was lower at 0.692, suggesting that additional factors may influence driver responses in these situations. In addition, the LR model demonstrated a suitable level of accuracy when it came to assessing lateral distance, with an accuracy of 0.683. Consequently, the LR model may be useful in understanding how drivers position themselves in relation to cyclists on the road.

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.

The Advantages of LiDAR Sensors in Recognizing Jaywalking Events at Signalized Intersections

Regarding the jaywalking events detection by the LiDAR sensor, two research studies have been conducted and published. This section provides a summary of both studies.

The first study [31] gathered real-time data on jaywalking incidents using LiDAR sensors at the Hillen Rd - E 33rd Street intersection in Baltimore. Over a three-month period, the study detected 585 events of jaywalking and analyzed factors contributing to these events. The research employed generalized linear regression and K-means clustering to identify key variables linked to jaywalking frequency, including pedestrian speed, average pedestrian-vehicle time gaps, vehicle-pedestrian conflict rates, and weather conditions. Findings indicate that increased jaywalking correlates with a higher frequency and severity of vehicle-pedestrian conflicts, with faster jaywalking speeds exacerbating the risks. Additionally, adverse weather conditions, particularly cloudy and rainy days, significantly influence the propensity for jaywalking, highlighting the need for targeted safety improvements.

This analysis examined jaywalking patterns across different approaches to an intersection by collecting various metrics such as average vehicle speeds, daily vehicle and pedestrian counts, and the frequency and severity of vehicle-pedestrian conflicts. LiDAR technology was employed to track jaywalkers' trajectories with high precision, capturing geographical coordinates and movement from the moment they entered the intersection until they existed. The study identified potential jaywalking zones outside crosswalks based on precise positional data. The time duration and average speed of jaywalking events were computed using LiDAR data. Over a three-month period, additional factors including weather conditions, vehicle speeds, traffic signal timings, road gradients, and infrastructure features (e.g., medians, building entrances, and vegetation) were assessed. Statistical analysis was conducted using SPSS software to evaluate the impact of these variables on jaywalking frequency and severity. The LiDAR sensor, installed with a 60-meter (197 ft.) detection radius, identified a total of 585 jaywalking pedestrians over a three-month period. The data showed a significant concentration of jaywalkers in the northern approach, with 572 detected events, while the western approach had 12, and the eastern approach had just 1. Figure 10 illustrates the heat map depicting the distribution of jaywalkers across the different approaches to the intersection.

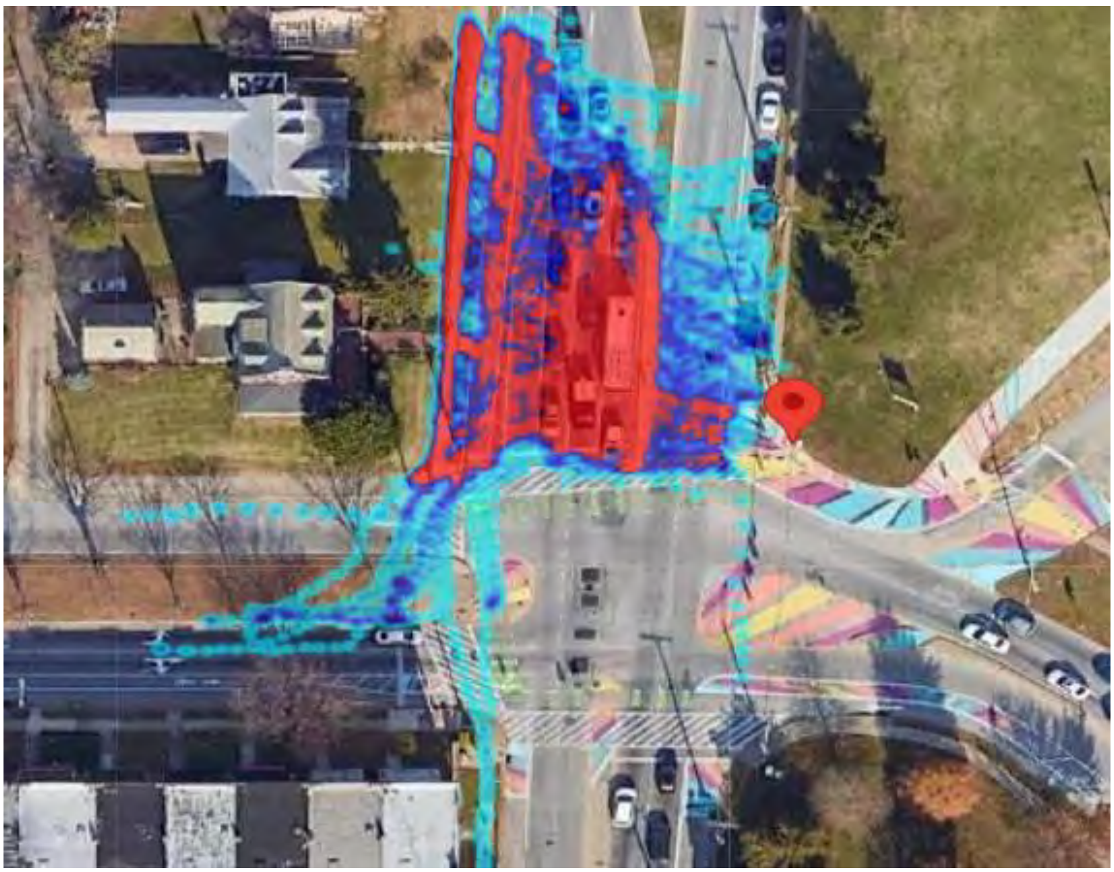

Figure 10 The Frequency of Jaywalkers at Different Approaches to the Intersection

Figure 11 illustrates the average speed of jaywalkers across different times of day and varying traffic conditions, providing insights into pedestrian behavior patterns and the potential impact of traffic flow on jaywalking tendencies.

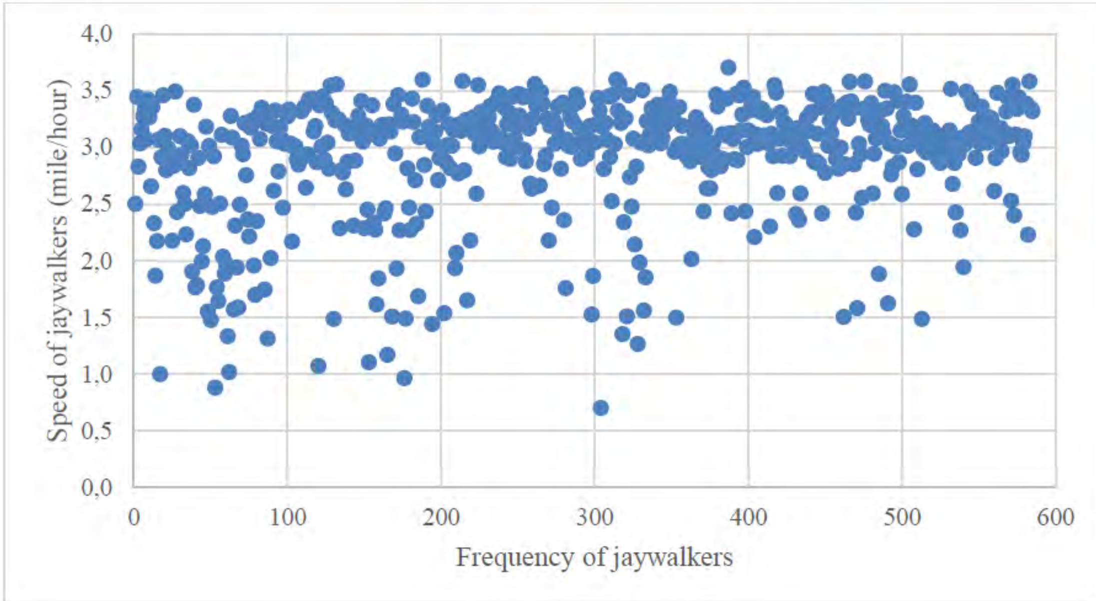

Figure 11 Average Speed of Jaywalkers

To analyze jaywalking behavior on the northern approach of the intersection, where 98% of events were detected, several independent variables were examined over a three-month period. These variables included the average speed of jaywalkers, duration of jaywalking, pedestrian traffic signal performance, average Post Encroachment Time (PET), frequency of vehicle-pedestrian conflicts, and weather conditions. The performance of pedestrian signals was monitored using CCTVs. The study investigated the relationship between jaywalking behavior and various factors, including the influence of residential and environmental features on pedestrian behavior. The analysis found that jaywalking frequency was positively correlated with average speed, average PET, and weather conditions, but negatively correlated with the duration of jaywalking and frequency of vehicle-pedestrian conflicts. The K-means clustering, which categorized the data into five clusters with significant accuracy, revealed a strong relationship between jaywalking frequency and the aforementioned factors.

In the second study [32] examined 1,000 jaywalking events over a six-month period, identifying key independent variables that are highly correlated with jaywalking frequency. These variables include traffic signal controller patterns, signal phases, vehicle-pedestrian conflicts, weather conditions, vehicle and pedestrian volumes, walking patterns towards medians, and the ratio of jaywalkers. Advanced statistical regression models, particularly an optimal Poisson regression model, were employed to uncover insights into the complexities of jaywalking behavior. The analysis revealed significant findings, such as a notable decrease in jaywalking frequency during morning and mid-day signal controller patterns compared to evening patterns, with reductions of 44.7% and 34.4%, respectively. The study also finds that the severity of vehicle-pedestrian conflicts increases with the number of jaywalkers, highlighting the need for measures that manage pedestrian flow to reduce conflict risks. Additionally, the presence of vegetation in medians is identified as a critical factor that significantly raises the frequency of jaywalking.

These results offer a detailed understanding of the interactions between environmental, temporal, and behavioral factors affecting jaywalking. They provide valuable insights for decision-makers and transportation specialists to develop targeted safety interventions, ultimately enhancing pedestrian safety and improving infrastructure at key urban intersections.

By using SPSS software, two regression models including Poisson and Negative Binomial were developed, and the response variable was the number of jaywalking events per day. The LiDAR sensor was installed on the northeast side of the Hillen Rd – E 33rd Street intersection in Baltimore City, MD. This intersection was selected due to its high frequency of vehicle-pedestrian conflicts and the significant pedestrian interest in crossing outside designated crosswalks to reach Montebello Lake located to the south. Figure 12 illustrates the location of Hillen Rd and E 33rd street Intersection in Baltimore City.

Figure 12 Hillen Rd and E 33rd Street Intersection

The vehicle speed analysis revealed changes in average speed across various directions: from 20.5 to 30.5 mph in the north-south direction, from 21.1 to 26.1 mph in the south-north direction, from 21.7 to 24.2 mph in the east-west direction, and from 18.6 to 25.5 mph in the west-east direction. Vehicle-pedestrian crashes are more likely to occur in north-south and south-north directions due to the higher average daily speed.

The V2P conflict analysis revealed that more frequent and severe vehicle-pedestrian conflicts occurred in the WN (EBL), EN (WBR), WE (EBT), and SN (NBT) movements. A significant percentage of conflicts between vehicles and pedestrians occur when either the origin or destination of the movement is in the north of the intersection. Considering the frequency and severity of conflicts, the movements WN or EBL (1381 conflicts with a severity of 538.3), EN or WBR (967 conflicts with a severity of 353.5), and SN or NBT (809 conflicts with a severity of 299.1) have a higher probability of vehicle-pedestrian crashes. The severity of conflicts at signalized intersections refers to the potential risk or intensity of collisions based on factors like vehicle speeds, trajectories, and proximity. The hourly frequency of vehicle-pedestrian conflicts was also analyzed. The intervals 14:00-15:00 PM (10.2% of total conflicts), 08:00-09:00 AM (9.4% of total conflicts), and 15:00-16:00 PM (8.9% of total conflicts) were recognized as critical daily intervals.

The LiDAR sensor recorded 1000 jaywalking events over six months, with a significant number occurring in the northern approach (southbound) to the intersection. The intervals 15:00–16:00 PM (12.8% of total jaywalking events), 16:00–17:00 PM (11.8% of total events), and 09:00–10:00 AM (9.7% of total events) were identified as critical daily intervals. The trajectory of jaywalking events revealed that many occurred in the southbound direction between residential areas and the lake. Despite the pedestrian signal functioning well at all intersection approaches, pedestrians often choose to cross outside of the crosswalk in the northern approach (southbound).

As an insightful contribution, the negative binomial model revealed a significant correlation between the frequency of vehicle-pedestrian conflicts and the occurrence of jaywalking events. Specifically, the presence of vegetation in the median was associated with a 42.3% increase in jaywalking events. The Poisson model similarly confirmed the impact of median vegetation on jaywalking frequency. Additionally, an increase in jaywalking events was found to raise the likelihood of vehicle-pedestrian conflicts by 4.3%. The analysis also showed that jaywalking rates are notably lower during morning and mid-day compared to the evening, with reductions of 47.5% and 36.8%, respectively, in relation to the evening signal controller patterns.

To compare the results of both models, the Likelihood Ratio (LR) test was employed to assess the relative efficiency of Poisson versus negative binomial regression models. This test evaluates the overall model fit by comparing it to a baseline model with no predictors (the "null" model). In comparing the LR statistics of the Poisson and negative binomial models, a higher LR statistic indicates a superior fit of the model to the data. Additionally, models with lower Akaike Information Criterion (AIC) values are typically favored, as they suggest a more parsimonious fit. Based on the higher Chi-Square value and lower AIC observed, the Poisson model demonstrates a better fit for the data compared to the negative binomial model.

The Role of CAV Testbeds in Detecting V2P Conflicts at Signalized Intersections

This study examined the real-time traffic data collected at the Cold Spring Ln – Hillen Rd intersection in Baltimore City, focusing on a period from May 1st to August 31st, 2022 [33]. The data encompassed daily vehicle volumes, including passenger cars, buses, trucks, as well as VRUs such as pedestrians and bicyclists. The analysis covered key metrics like Post Encroachment Time Threshold (PET), which measures the time interval between the departure of an encroaching vehicle or pedestrian from a conflict point and the arrival of the vehicle or pedestrian with the right-of-way. The study identified 848 vehicle-pedestrian conflicts over the four-month period, with a new methodology proposed for classifying PET values and a novel risk index introduced. This index integrates conflict frequency and severity, along with vehicle and pedestrian volumes and trajectories, to provide a comprehensive safety assessment. The findings highlight the need for enhanced safety measures at the intersection, particularly at the western and southern approaches.

Based on the trajectory analysis of leading and following objects in vehicle-pedestrian conflicts, four categories have been established to classify the severity of these conflicts. "Serious" conflicts, characterized by a higher potential for fatalities and injuries, are distinguished from other types of conflicts by their severity. A higher PET is associated with a lower likelihood of pedestrian injuries or fatalities, making general conflicts less severe compared to serious conflicts [34]. The same methodology applies to slight and potential conflicts, with potential conflicts indicating a greater longitudinal distance between the leading and following objects. In such cases, the pedestrian can often pass the conflict point before the motorized vehicle arrives. By analyzing the time to collision for all recorded near-crash conflicts, a numerical value for each conflict was determined. The proposed PET categories are as follows:

- PET < 0.7 seconds: Serious conflict (highest severity)
- 0.7 seconds ⩽ PET < 1.31 seconds: General conflict
- 1.31 seconds ⩽ PET < 2.25 seconds: Slight conflict
- 2.25 seconds ⩽ PET ⩽ 5 seconds: Potential conflict (least severity)

The longitudinal and lateral positions of conflicts were analyzed using an image processing plugin in MATLAB to generate a conflict heat map. This analysis of vehicle-pedestrian conflicts was approached from three perspectives:

- Conflicts based on leading-following vehicle interactions.
- Conflicts categorized by right- and left-turn movements.
- Conflicts occurring during different phases of the traffic signal.

For each approach, a risk index value was determined, offering a comprehensive assessment of conflict severity at the intersection. Figure 13 demonstrates the total frequency of conflicts analysis in each of the eight sections of the intersection.

Figure 13 The Frequency of Total Conflicts in Each Section of the Intersection (left figure) and Zoning of the Intersection (right figure)

Figures 14 and 15 illustrate, respectively, the hourly frequency and severity (1/PET) of total collected conflicts over a four month interval.

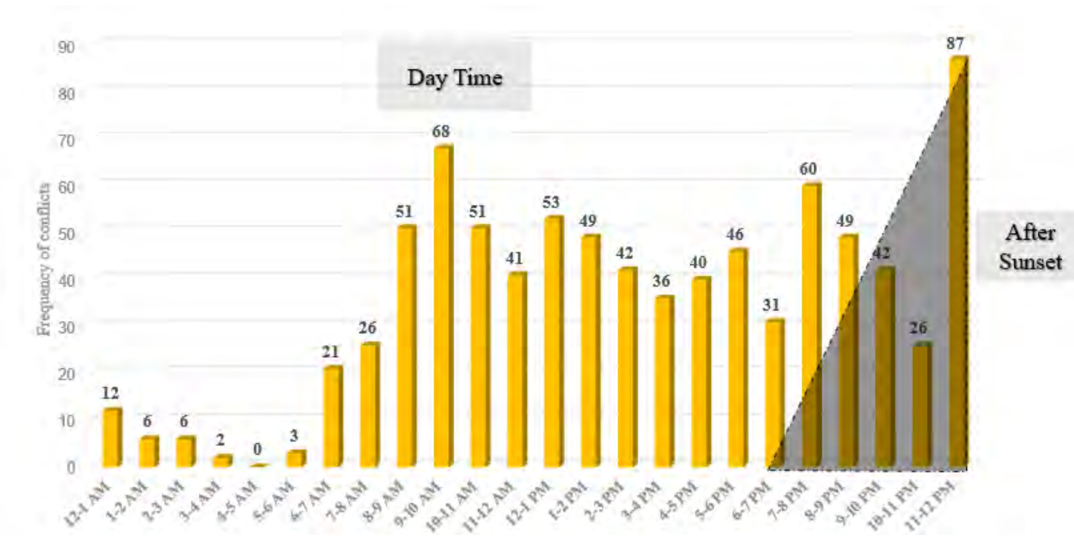

Figure 14 The Hourly Frequency of Total Collected Conflicts

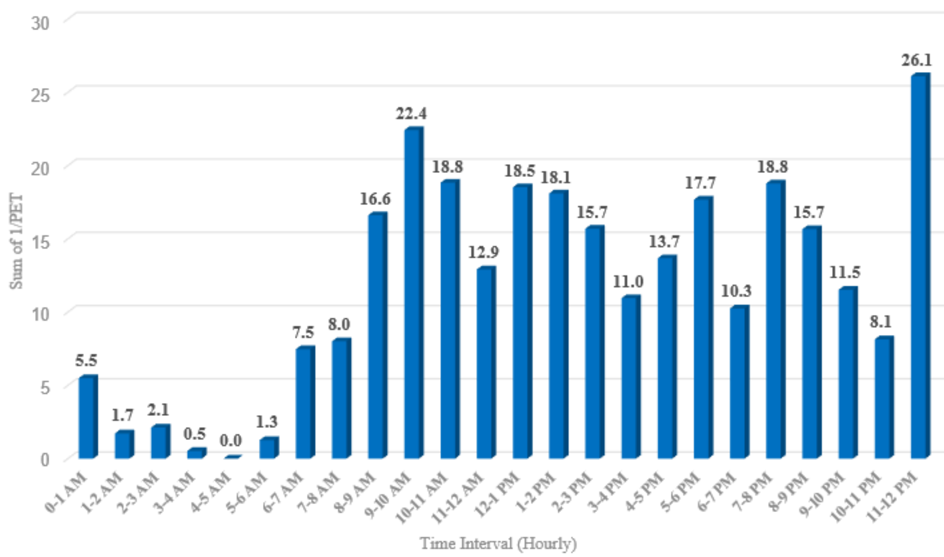

Figure 15 The Hourly Severity of Total Collected Conflicts

By analyzing conflicts based on leading-following vehicle interactions, the results presented in Figure 16 were assessed. The suggested Measure of Effectiveness (MOE) can also be seen in Figure 16.

Zone	Sum (1/PET)	Daily (1/PET)	Vehicle Volume	Ped Volume	MOE*e-06
A	54.27	0.44	540	41	19.9
B	17.26	0.14	608	41	5.62
C	58.03	0.47	1012	40	11.6
D	54.26	0.44	854	40	12.9
E	40.92	0.33	671	17	28.9
F	13.13	0.11	690	17	9.38
G	23.91	0.19	286	29	22.9
H	20.63	0.17	357	29	16.4
SUM	282.41	2.29	5018	254	127.6

$$MOE = \frac{Daily\ (\frac{1}{PET})}{Vehicle\ Volume\ * Ped\ Volume}$$

E, G, A, H, D, C, F, B

Figure 16 The Results of Leading and Following Interactions Analysis

The second method, "conflicts categorized by right- and left-turn movements," revealed the results shown in Figure 17.

Zone	Right-turn		Left-turn	
	Sum (1/PET)	Average speed	Sum (1/PET)	Average speed
A	24.44	18.7	29.83	25.2
B	8.70	15.3	8.56	21.1
C	25.66	17.4	32.37	29.2
D	28.79	16.1	25.47	19.1
E	21.84	19.2	19.08	28.4
F	0.79	19.3	12.34	23.2
G	3.67	18.6	20.24	30.4
H	5.20	16.4	15.43	17.1
SUM	126.69	140.98	155.72	193.76

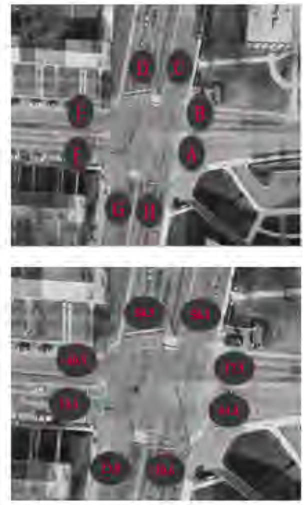

Figure 17 The Results of Right- and Left-Turn Movements Analysis

Considering the phase patterns shown in Figure 18, the third method "conflicts occurring during different phases of the traffic signal" revealed the results shown in Tables 7 (Frequency) and 8 (Severity).

Figure 18 Different Phases of The Traffic Signal

Table 7 Frequency of Conflicts in Different Phases of the Traffic Signal

Phase	Zone								SUM
	A	B	C	D	E	F	G	H	
ϕ1	0	0	0	0	57	0	0	41	98
ϕ2	0	0	0	90	68	0	0	0	158
ϕ3	16	19	0	0	0	0	72	0	107
ϕ4	0	0	0	0	0	2	11	0	13
ϕ5	79	9	0	42	0	0	0	0	130
ϕ6	82	0	0	0	0	0	0	16	98
ϕ7	0	0	100	0	0	41	0	0	141
ϕ8	0	24	79	0	0	0	0	0	103
SUM	177	52	179	132	125	43	83	57	848

Table 8 Severity of Conflicts in Different Phases of the Traffic Signal

Phase	Zone								SUM
	A	B	C	D	E	F	G	H	
ϕ1	0	0	0	0	19.72	0	0	17.08	36.8
ϕ2	0	0	0	28.79	21.84	0	0	0	50.63
ϕ3	4.79	4.6	0	0	0	0	18.57	0	27.96
ϕ4	0	0	0	0	0	0.79	3.67	0	4.46
ϕ5	26.08	2.96	0	19.98	0	0	0	0	49.02
ϕ6	24.44	0	0	0	0	0	0	5.2	29.64
ϕ7	0	0	34.05	0	0	15.49	0	0	49.54
ϕ8	0	8.7	25.66	0	0	0	0	0	34.36
SUM	55.31	16.26	59.71	48.77	41.56	16.28	22.24	22.28	282.41

The recorded video files of vehicle-pedestrian conflicts were analyzed using an image-processing plugin in MATLAB to evaluate the frequency and severity of these conflicts. The analysis identified the maximum frequency of conflicts across various zones and phases of the intersection. Specifically, 46% of conflicts in zone A occurred during phase ϕ6 (SBR & SBT), 46% in zone B during phase ϕ8 (EBR & EBT), 56% in zone C during phase ϕ7 (WBL), 68% in zone D during phase ϕ2 (NBR & NBT), 54% in zone E during phase ϕ2 (NBR & NBT), 95% in zone F during phase ϕ7 (WBL), 87% in zone G during phase ϕ3 (EBL), and 72% in zone H during phase ϕ1 (SBL). A notable gradient at the northern approach (NW, NS, NE directions) was observed, contributing significantly to both the frequency and severity of vehicle-pedestrian conflicts in this area. Figure 19 and 20 illustrates the heatmap of conflicts' frequency from May to August 2022.

Figure 19 Vehicle-Pedestrian Conflicts Heat Map in May (left figure) and June (right figure)

Figure 20 Vehicle-Pedestrian Conflicts Heat Map in July (left figure) and August (right figure)

In the "vehicle-pedestrian conflicts based on leading-following vehicles" method, the results revealed significant conflict severity in zone C (northern approach with a severity of 58.1 as 1/PET), zone D (northern approach with 54.3 as 1/PET), and zone A (eastern approach with 54.3 as 1/PET). Additionally, a high frequency of conflicts was observed in zone C (175 conflicts), zone A (173 conflicts), zone D (151 conflicts), and zone E (122 conflicts). In the "vehicle-pedestrian conflicts based on right- and left-turn movements" method, zones A, C, D, and E were identified as having the highest severity of conflicts during turn movements. Lastly, in the "vehicle-pedestrian conflicts in different phases of the traffic signal" method, most conflicts were recorded during phase ф2 (158 conflicts), phase ф7 (141 conflicts), and phase ф5 (130 conflicts). Severe conflicts were predominantly observed in the same phases: ф2, ф7, and ф5.

Consequently, zone E consistently emerges as a critical zone for vehicle-pedestrian conflicts across the three proposed methods. Similarly, the results indicate that zone E has the highest MOE value based on conflict frequency and severity. However, the safety index has yet to be validated. To achieve this, it is necessary to move the LiDAR sensor infrastructure to other intersections as part of the validation process. The authors are keen to evaluate the proposed MOE at other signalized intersections in Baltimore City. Cold Spring Lane was selected as the initial case study because it was already equipped with two CCTVs, allowing for efficient verification of LiDAR data collection accuracy against manual CCTV counts. Additionally, the necessary infrastructure and connection of the LiDAR sensor to the controller cabinet were already established at the time of installation, making further validation efforts at other intersections more time-consuming.

A new safety index was proposed to assess pedestrian safety, where 1/PET represents the severity of vehicle-pedestrian conflicts [35]. In the proposed MOE, 1/PET serves as the numerator, highlighting its critical role in determining the safety index. Traffic flow, including vehicle and pedestrian volumes, forms the denominator of the MOE. Factors such as road geometry, including approach gradients and sight triangles, also influence conflict frequency and severity. Based on the safety index results, improvements are necessary in the western approach (zone E) and southern approach (zone G) to enhance pedestrian safety. The poor performance of pedestrian traffic signals, particularly in the southern approaches (zones G and H), has led to increased conflict frequency.

Conclusion

This report provides a comprehensive analysis of key areas in the realm of CAV technology, focusing on LiDAR validation with CCTV systems, CAV testbeds, real-time communication between RSUs and OBUs, the detection of jaywalking events, and V2P conflicts detection at signalized intersections. These five areas are fundamental to enhancing road safety, particularly for VRUs such as pedestrians and cyclists. LiDAR validation with CCTV ensures the accuracy of real-time data, which is crucial for effective traffic management and safety interventions. CAV testbeds across the country serve as vital platforms for evaluating new technologies and communication protocols, helping to create safer and more efficient transportation systems. The ability of RSUs and OBUs to broadcast static safety messages in real-time plays a key role in reducing traffic incidents by delivering timely warnings to drivers. Additionally, the use of LiDAR technology to detect jaywalking events at intersections helps prevent pedestrian conflicts/crashes by identifying risky behavior early. Detecting V2P conflicts through CAV testbeds further enhances pedestrian safety by minimizing the risk of collisions between vehicles and pedestrians.

Morgan State University's CAV testbed exemplifies the potential of advanced research and technology integration in transportation safety. With its innovative deployment of LiDAR sensors, RSUs, OBUs, and new signal controllers with the ability of broadcasting SPaT messages and real-time communication systems, it provides a unique platform to test and optimize solutions for a variety of traffic scenarios. The testbed not only supports the validation of cutting-edge technologies but also offers actionable insights into real-world applications, enabling researchers to address urban mobility challenges more effectively. By serving as a model for future CAV deployments, Morgan State’s testbed highlights the transformative impact of advanced traffic safety technologies that enhance pedestrian safety. Its role in advancing research and practical solutions makes it a valuable asset in the ongoing efforts to improve road safety and reduce V2V, V2P, and V2B crashes, especially for VRUs in complex urban environments.

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