Connected Vehicle Pilot Deployment Program Phase 3

System Performance Report - New York City

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16. Abstract

This report presents the performance measurement and evaluation results and methodology of the New York City (NYC) Connected Vehicle Pilot Deployment (CVPD). It describes the performance evaluation objectives and the use cases developed for NYC Connected Vehicle (CV) Pilot to address the safety and mobility issues in midtown Manhattan and Brooklyn. The experimental design included equipping 3,000 vehicles with Aftermarket Safety Devices (ASD) for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) applications. In addition to the data collection, this document explains the data sharing process with project stakeholders and the general public while protecting the privacy and security including any publicly identifiable information (PII).

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The project team wants to thank the USDOT for sponsoring this project and laying the foundation for future connected vehicle deployments. While Dedicated Short-Range Communications (DSRC) will no longer be the foundation for the future of connected vehicles, the project has collected a wealth of data about safety events that occur in the dense urban environment and processes for managing operations of connected vehicles. The extensive data set from the program will provide many opportunities for additional research over the next several years.

The project team also acknowledges the inspiration, strength, and tenacity of its initial project manager, Steven J. Galgano, P.E., Deputy Commissioner for Traffic Operations, in competing for this project and establishing its foundation. As many of his NYCDOT staff would agree, "His dedication, professionalism, and steadfast commitment to the people of the City of New York was second to none." as stated by Dr. Paul-Michael Kazas. This evaluation report honors his ability and spirit to persevere through all the details necessary to complete the project and produce the results.

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1 Introduction

1.1 NYC CVPD Background

In 2014, New York City (NYC) began its Vision Zero program to reduce the number of fatalities and injuries resulting from traffic crashes. The Mayor's Office developed the Vision Zero action plan which highlighted a set of initiatives for multiple city agencies to support the goal of improving street safety. One of the major ongoing initiatives has been the citywide speed limit reduction from 30 mph to 25 mph. According to the National Highway Transportation Safety Administration (NHTSA), speeding was a factor in more than one in four deaths. Also, human factors were the critical cause in about 94% of all crashes while vehicle-related factors only apply to about 2% of all crashes. In Manhattan, 73% of all crash fatalities involve pedestrians while this figure is only 14% nationwide. After pedestrian fatalities in NYC reached an all-time low in 2011 with 249, it surged to 297 in 2013. Senior citizens over age of 65 comprise of 12% of the population in NYC but about 33% of all pedestrian fatalities. Also, the primary reason for crash-related deaths of children under 14 was from being struck by a vehicle. The NYC Connected Vehicle Pilot Deployment (CVPD) has undertaken connected vehicle technology as another tool that could be used to help further the city's Vision Zero goals.

The NYC CVPD project area encompasses three distinct areas in the boroughs of Manhattan and Brooklyn. The following describes these deployment areas in terms of their roadway characteristics. The first area includes Franklin D. Roosevelt (FDR) Drive in the Upper East Side and East Harlem neighborhoods of Manhattan. The second area includes four one-way corridors of 1st Avenue, 2nd Avenue, and 5th Avenue from 14th Street to 67th Street and 6th Avenue from 14th Street to 59th Street in Midtown and Upper East Side neighborhoods of Manhattan. The segment lengths are 2.6 miles for 1st, 2nd, and 5th Avenues and 2.2 miles for 6th Avenue, respectively. The third area consists of the five two-way, bi-directional cross streets in Midtown Manhattan: 14th, 23rd, 34th, 42nd, and 57th Streets. The fourth area covers a 1.6-mile segment of Flatbush Avenue in Brooklyn from Tillary Street on the north and Grand Army Plaza near Prospect Park to the south. While FDR Drive is a freeway without signalized intersections, the four avenues in Manhattan include 281 signalized intersections and Flatbush Avenue in Brooklyn includes 28 signalized intersections. These locations are shown in Figure 1 below. The majority of the traffic signals along these corridors were equipped with road-side units (RSUs) to permit the various Vehicle-to-Infrastructure (V2I) applications.

In addition to the deployment corridors, Vehicle-to-Vehicle (V2V) applications were enabled to operate anywhere that two equipped vehicles came into close contact with each other, regardless of where those vehicles interacted. Due to the nature of the equipped vehicles, the vast majority of these events were seen within all five NYC boroughs, although some activity was also seen outside of the city limits. Additional concentration of the V2V alerts were see where the equipped vehicles more commonly traveled, such as key activity centers for those vehicles or near vehicle garages or terminus locations.

(Source: NYCDOT)

Figure 1. NYC CVPD Deployment Corridors

While many more details are available in the other NYC CVPD documents, to frame the context of the pilot deployment as it relates to the performance measurements, the deployed applications are presented in Table 1, along with which Connected Vehicle (CV) device the applications will run on. Devices include Aftermarket Safety Device (ASDs) for vehicles, smartphone based Pedestrian Interface Devices (PIDs) for pedestrians, and Roadside Units (RSUs) for signalized intersections and roadside locations.

Table 1. Deployed CV Application Deployment by Device

CV Application	Category	NYC City Agency Fleet Vehicles (3000 ASDs)	Pedestrian Information Devices / Cell Phones (10 PIDs)	Signalized Intersections and Other Infrastructure (470 RSUs)
Forward Crash Warning (FCW)	V2V	Yes	No	No
Emergency Electric Brake Light (EEBL)	V2V	Yes	No	No
Blind Spot Warning (BSW)	V2V	Yes	No	No
Lane Change Warning (LCW)	V2V	Yes	No	No
Intersection Movement Assist (IMA)	V2V	Yes	No	No
Vehicle Turning Right Warning (VTRW)	V2V*	Yes	No	No
Speed Compliance (SPDCOMP)	V2I	Yes	No	No
Curve Speed Compliance (CSPDCOMP)	V2I	Yes	No	No
Speed Compliance in Work Zone (SPDCOMPWZ)	V2I	Yes	No	No
Red Light Violation Warning (RLVW)	V2I	Yes	No	No
Pedestrian in Crosswalk Warning (PEDINXWALK)	V2I	Yes	No	No
Oversize Vehicle Compliance (OVC)	V2I	Conditional on Vehicle Size	No	No
Emergency Communications and Evacuation Information (EVAC)	V2I	Yes	No	No
Mobile Accessible Pedestrian Signal System (PED-SIG)	Pedestrian	No	Yes	No
Intelligent Traffic Signal System Data (I-SIGCVDATA)	Mobility	No	No	Yes

**Note: VTRW also requires messages from an RSU.*

1.2 Purpose of the Report

This report presents the Performance Measurement and Evaluation of the NYC CVPD that was conducted during the Phase 3 operational phase of the deployment. The report summarizes the data collection, performance measurements, evaluation methods, findings, and impacts of the CV deployment (i.e. equipment and CV applications) on travel within NYC.

This report is only one in a series of reports produced by the NYC CVPD team over the life of the deployment. Those other reports help to provide more context to the earlier stages of the deployment and should be considered as reference reading material to help inform the content of this report. Specific key reports related to the content in this report include the following:

- Concept of Operations (ConOps)
- Performance Measurement and Evaluation Support Plan (PMESP) (Phase 2 Update)
- Operational Capability Showcase Plan (OCSP)

These reports, along with all NYC CVPD reports are or will be available on the NYCDOT CVPD pages on USDOT's Joint Program Office CV Pilots website, available at https://www.its.dot.gov/pilots/pilots_nycdot.htm.

1.3 Organization of the Report

The report is organized according to the following sections:

Section 1 provides background on the NYC CVPD and this report.

Section 2 provides an overview of the user needs that the NYC CVPD was designed to meet and the performance measures that were planned and ultimately used to evaluate the CVPD in fulfilling or advancing those needs.

Section 3 provides background on the CV-equipped fleet vehicles and overview of the experimental designs for both the vehicle-based application evaluations and the field tests of the pedestrian interface devices. The section also presents some of the more important confounding factors and discusses their possible influence on the deployment.

Section 4 presents a high-level summary of the data collected during the deployment.

Section 5 provides details on the analysis methods that were used to conduct the various evaluations of the NYC CVPD.

Section 6 presents the performance measures as produced for each CV application and other elements of the evaluation.

Finally, section 7 provides conclusions to the evaluation and discusses some of the limitations encountered during the deployment that should be considered when reviewing the evaluation and the overall deployment.

2 CV Pilot Performance Evaluation Objectives

The goal of the performance evaluation of the NYC CVPD project is to demonstrate the impacts of the deployed CV applications that will help advance the City's existing Vision Zero program, which aims to reduce the number of fatalities and injuries on NYC's roadways.

To assess the safety impacts of the NYC CVPD program, NYCDOT has identified needs which encompass managing speed and reducing the number of crashes and their severity to improve safety. As a secondary goal, by reducing crashes and incidents that disrupt travel, improvements can be made in travel mobility and reliability in the heavily congested areas. While the NYC CVPD program is directly focused on safety, secondary mobility improvements are intertwined with safety improvements because fewer crashes will reduce crash related delays. Meanwhile, improvements to mobility can improve safety as well. For example, fewer stops may mean fewer occasions for rear end crashes.

Through the work in developing the NYC CVPD's Concept of Operations, seven use cases for user needs were identified for improvement in the system performance. The following sections present these seven use cases along with the CV applications deployed to address each use case.

2.1 Use Case 1: Manage Speeds

With speed being a factor in many crashes and fatalities, managing speeds to operate within safe limits is one way to improve on the safe operations of the city's roadways. Three different applications were deployed that aimed to manage the operating speed of the equipped vehicles under different circumstances.

2.1.1 Speed Compliance

The Speed Compliance (SPDCOMP) application was deployed to notify drivers when their speed exceeds the posted speed limits. A zero-tolerance approach was used, meaning that any travel speed above the posted limit would trigger a warning to the driver to reduce their speed to the posted limit. The speed limits were transmitted to the vehicle's ASD via Map Data Messages (MAPs) broadcast from the system RSUs along all study corridors, which all operated under the city's default 25 mph regulatory speed limit.

2.1.2 Curve Speed Compliance

The Curve Speed Compliance (CSPDCOMP) application was deployed to inform connected vehicles that they are approaching a sharp curve with a reduced advisory speed limit, thereby allowing the drivers to reduce vehicle speed to a safer speed prior to the curve. The reduced advisory curve speed limit was delivered to the vehicle's ASD via Traveler Information Messages (TIMs) broadcast from nearby RSUs for a preconfigured geofenced area approaching the curve. The application was deployed along selected on-ramps to the FDR parkway in Manhattan.

2.1.3 Speed Compliance in Work Zone

The Speed Compliance in Work Zone (SPDCOMPWZ) application was deployed to provide connected vehicles that are approaching a reduced speed work zone with information on the zone's reduced speed limit and warn the drivers if their speed is above the work zone's speed limit. The geofenced work zone area and it's reduced speed limit are delivered to the vehicle's ASD via TIM messages broadcast from nearby RSUs. In all cases deployed during Phase 3, the defined work zone speed limit was set to 15 mph, 10 mph below the default regulatory citywide 25 mph speed limit.

2.2 Use Case 2: Reduce Vehicle to Vehicle Crashes

The ultimate goal of Vision Zero program is to reduce the number of fatalities and injuries on roadways including vehicle-to-vehicle crashes. To reduce vehicle-to-vehicle crashes, the following CV applications were deployed under this use case:

- V2V safety application warnings
- Red light violation warning
- Vehicle turning right in front of bus warning

2.2.1 V2V Applications

V2V safety aims to improve overall vehicle-to-vehicle safety by deploying the following V2V applications in the NYC CVPD.

1. Forward Crash Warning (FCW): This application warns the driver of the host vehicle of an impending rear-end collision with a remote vehicle ahead in traffic in the same lane and direction of travel.
2. Emergency Electronic Brake Light Warning (EEBL): This application enables equipped vehicles to broadcast a self-generated emergency brake event to other surrounding connected vehicles. Upon receiving such event information, the host vehicle receiving that message determines the relevance of the event and provides a warning to the driver if appropriate.
3. Blind Spot Warning / Lane Change Warning (BSW and LCW): The two related applications aim to warn the driver of the host vehicle during a lane change attempt if the blind spot zone into which the host vehicle intends to switch is, or will soon be, occupied by another connected vehicle traveling in the same direction.
4. Intersection Movement Assist (IMA): The application warns the driver of a host vehicle when it is not safe to enter an intersection due to a high collision probability with other remote connected vehicles (usually at stop sign controlled and uncontrolled intersections).

In all cases, the applications are triggered in the host vehicle by processing BSM messages received from nearby vehicles. All deployed V2V applications were not geofenced, meaning that they would function wherever equipped CV vehicles interacted in conditions which the alerts would be triggered, regardless of proximity to any RSU.

2.2.2 Red Light Violation Warning

The Red Light Violation Warning (RLVW) application was deployed to warn drivers of potential red light violations. The application enables a connected vehicle approaching an RSU equipped signalized intersection to receive information regarding the signal timing and the geometry of the intersection. The application in the host vehicle uses its speed and acceleration profile, along with the current signal timing and geometry information to determine if it appears likely that the vehicle will enter the intersection in violation of a red traffic signal. If the violation seems likely to occur, a warning is provided to the driver. The application operates on the host vehicle's ASD by processing received MAP and Signal Phase and Timing (SPaT) messages broadcast from system RSUs connected to signalized intersections.

2.2.3 Vehicle Turning Right Warning

The Vehicle Turning Right Warning (VTRW) application was deployed to determines the movement of connected vehicles near to the host transit vehicle stopped at a transit stop and provides an indication to the transit vehicle operator that a nearby vehicle is pulling in front of the transit vehicle. This application will help the transit vehicle determine if the area in front of it will not be occupied as it begins to pull away from a transit stop. The application is technically a V2V application that operations by processing BSMs received from nearby equipped vehicles, but proximity to an RSU is also required as a broadcasted TIM message must also be received by the host to define the geofenced region of the transit stop. It is noted that the VTRW was only deployed in limited conditions and primarily under testing conditions during the pilot.

2.3 Use Case 3: Reduce Vehicle to Pedestrian Crashes

One new area of connected vehicle applications assessed within the NYC CPVD involved assisting and protecting pedestrians on defined crossings. This area of deployment is significant in the NYC environment due to the nature of heavy pedestrian and bike presence and the history of many crash-related fatalities occurring in pedestrian-involved crashes. Two different pedestrian-oriented applications were deployed: 1) a generalized warning to vehicles of pedestrian presence in the crosswalks and 2) support for vision disabled pedestrians at signalized crossings.

2.3.1 Pedestrian in Signalized Crosswalk Warning

The Pedestrian in Signalized Intersection Warning (PEDINXWALK) application was deployed using pedestrian detection equipment (dedicated field mounted infrared cameras) to inform the RSUs at an equipped intersection of the presence of pedestrians within a defined crosswalk at a signalized intersection. When pedestrians are detected, nearby connected vehicles are notified via RSU broadcasted SPaT messages (to define active pedestrian detection) and MAP messages (to define geometry and cross walk details). Using this information, the host vehicle's ASD warns the driver of the pedestrian presence as appropriate given the vehicle's trajectory.

2.3.2 Mobile Pedestrian Signal System (PED-SIG)

The version of PED-SIG deployed was a custom smartphone application that provided the pedestrian with information regarding the signalized intersection geometry conditions as well as the active traffic signals state of the pedestrian signals (walk / do not walk). The deployment included the use of ten portable personal Pedestrian Interface Devices (PIDs) by approximately 25 vision disabled pedestrian volunteers during limited supervised field tests. The application functioned by receiving both MAP and real-time SPaT messages on the PID smartphone unit via a cloud-based infrastructure and a location augmentation device to provide more detailed location data than can be derived from the native smartphone platform. No interaction with CV equipped vehicles was involved. Due to the safety concerns for the participants, all field tests of the PIDs in this pilot were directly overseen by Institutional Review Board (IRB) approved researchers to ensure the safety of the vision disabled participants.

2.4 Use Case 4: Reduce Vehicle to Infrastructure Crashes

To reduce vehicle to infrastructure crashes, the following application was deployed to address low clearance issues for oversized vehicles and enforce related truck route restrictions.

2.4.1 Oversize Vehicle Compliance

The Oversize Vehicle Compliance (OVC) application was deployed for use by connected trucks and other commercial vehicles to inform drivers of pending low clearance conditions based on the height of the equipped vehicle. The application functions on the host vehicle's ASD by receiving TIM messages broadcast from a nearby RSU that defines a geofenced region ahead of the low-height clearance condition and warns the driver when that region is entered of a potential impending bridge-strike collision. This application was deployed in limited conditions during the pilot.

2.5 Use Case 5: Inform Drivers of Serious Incidents

As the traffic manager and roadway infrastructure owner, NYCDOT needs to provide notification to drivers that an area is to be avoided and why. To inform drivers of serious incidents, Emergency Communications and Evacuation Information (EVAC) application was deployed.

2.5.1 Emergency Communications and Evacuation Information

The EVAC application was deployed to help transmit the information from NYC Office of Emergency Management (OEM) and from NYCDOT Office of Emergency Response (OER) to the connected vehicles near or within affected areas during defined incidents and events. The vehicle's ASD warns the driver of the event with a custom message when entering the geofenced area of concern as defined by the TIM message broadcast from a nearby RSU. It is noted that the application was only deployed under test conditions with test messages during the pilot, and no true emergency messages were broadcast during the evaluation period.

2.6 Use Case 6: Provide Mobility Information

To balance mobility and provide information in heavily congested areas, the NYC CVPD project deployed the application of Intelligent Traffic Signal System Connected Vehicle Data (I-SIGCVDATA).

2.6.1 CV Data for Intelligent Traffic Signal System

The CV Data for Intelligent Traffic Signal System (I-SIGCVDATA) application deployed in the pilot used the RSUs to monitor connected vehicle movements and to ultimately provide RSU to RSU travel time data for use in other NYCDOT systems, in particular the award-winning Midtown in Motion (MIM) adaptive traffic signal system. Travel time and speed data currently collected by toll tag reader system is used as an input to the existing MIM's Adaptive Control Decision Support System (ACDSS), and the intent of the project was to determine if the CV technology could provide input that is equivalent to the existing data collection mechanism used to allow more widespread deployment of the ACDSS adaptive control system with reduced infrastructure costs. The RSUs monitored when equipped vehicles entered defined areas (usually the intersection 'box') and reported those individual sightings back to the Traffic Management Center (TMC) in real-time. Additional software operating in the TMC then matched those sightings received from different RSUs to compute RSU to RSU link travel times.

2.7 Use Case 7: Manage System Operations

The NYCDOT needed to manage and track the complex CV system operations. While not directly related to individual deployed CV applications, the following system reports, databases, and management tools were developed to regularly monitor and assess the CV system operations throughout the Phase 3 deployment. Specifics on these tools and methods are provided in section 5.4.

2.8 Planned and Actual Performance Measures

As the performance evaluation of the NYC CVPD project aimed to demonstrate the benefits of the CV applications that could help advance the City's existing Vision Zero program, the primary measure of safety improvements can be measured by reductions in the number of and severity of crashes. It is acknowledged that within any transportation system as complex as the system in New York City, there are many more factors that can potentially affect the crash and incident rates beyond the influence of the deployment of the CV applications. As such, additional performance metrics were developed aside from observed crashes to help assess the potential for safer operations by using surrogate performance measures.

Specific performance metrics for each of the CV applications were developed during Phase 2 of the NYC CVPD and are summarized in Table 2. Details on the development and selection of those metrics can be found in the NYC CVPD Phase 2 Performance Measurement and

Evaluation Support Plan Report. While the below table presents the performance metrics that were planned to be evaluated during Phase 2, several issues encountered during the Phase 3 deployment prevented the meaningful measurement or estimation of some of those planned performance metrics. The column “Planned or Actual” in the table identifies which of the performance metrics were actual metrics evaluated during Phase 3 and summarized in this report, and which metrics were planned but not eventually evaluated. Details on the reasoning for the metrics which were not evaluated are summarized below.

Table 2. Planned and Actual Performance Metrics by User Need and Application

Use Case	Focus Area	NYCDOT Needs	CV Application	PM ID	Performance Measure	Evaluation Data Sources*	Planned / Actual	Reasons for not Evaluating
Manage Speeds	Safety, Mobility	Discourage Spot Speeding	Speed Compliance (SPDCOMP)	1a	Number of stops (average and distribution measures)	AL, MS	Actual	
				1b	Speeds (average and distribution measures)	FD, SD, MS	Planned	Low sample rates in the CV Travel Time system
				1c	Emissions	MS	Planned	Low measured mobility impacts negated the potential of emissions benefits
				1d	Reduction in speed limit violations	AL, MS	Actual	
				1e	Speed variation	FD, SD	Planned	Low measured mobility impacts negated the potential of emissions benefits
				1f	Vehicle throughput (average and distribution measures)	FD, MS	Planned	Low measured mobility impacts negated the potential of emissions benefits
				1g	Driver actions and/or impact on actions in response to issued warnings	AL	Actual	
Manage Speeds	Safety	Improve Truck Safety	Curve Speed Compliance (CSPDCOMP)	2a	Speed related crash counts, by severity	FD	Planned	Very limited crash data prevented meaningful analysis
				2b	Vehicle speeds at curve entry	AL	Actual	
				2c	Lateral acceleration in the curve	AL	Actual	
				2d	Driver actions and/or impact on actions in response to issued warnings	AL	Actual	
				2e	Number of curve speed violations at each instrumented location	AL	Actual	
Manage Speeds	Safety	Improve Work Zone Safety	Speed Compliance – Work Zone (SPDCOMPWZ)	3a	Speed in work zone (average and distribution measures)	FD, AL	Planned	Low sample rates in the CV Travel Time system

Use Case	Focus Area	NYCDOT Needs	CV Application	PM ID	Performance Measure	Evaluation Data Sources*	Planned / Actual	Reasons for not Evaluating
				3b	Speed variation (distribution) at work zone	FD, AL	Planned	Low sample rates in the CV Travel Time system
				3c	Number of vehicle speed limit violations in variable speed zone areas	FD, AL	Actual	
				3d	Driver actions and/or impact on actions in response to issued warnings	AL	Actual	
Reduce Vehicle to Vehicle Crashes	Safety	Reduce Vehicle to Vehicle Accidents	All V2V Applications (EEBL, FCW, IMA, BSW, and LCW)	4a	Fatality crash counts	FD	Actual*	*As crash type data permitted
				4b	Injury crash counts	FD	Actual*	*As crash type data permitted
				4c	Property damage only crash counts	FD	Actual*	*As crash type data permitted
				4d	Time to Collision (vehicle to vehicle)	AL, MS	Actual	
Reduce Vehicle to Vehicle Crashes	Safety	Reduce Accidents at High Incident Intersections	Red Light Violation Warning (RLVW)	5a	Red light violation counts	FD, AL	Actual	
				5b	Time To Collision (vehicle to cross vehicle path) at the intersection	AL, MS	Planned	ASD-based TTC analysis for RLVW because vehicle trajectories in the crossing direction of host vehicles are not recorded in the ASD data
				5c	Driver actions and/or impact on actions in response to issued warnings	AL	Actual	
Reduce Vehicle to Vehicle Crashes	Safety	Reduce Bus Incidents, Improve Safety	Vehicle Turning Right Warning (VTRW)	6a	Right-turning related conflicts	FD	Planned	Extremely limited number of collected VTRW event records prevented meaningful analysis and evaluation of all VTRW performance metrics.
				6b	Time to collision (vehicle to bus)	AL, MS	Planned	

Use Case	Focus Area	NYCDOT Needs	CV Application	PM ID	Performance Measure	Evaluation Data Sources*	Planned / Actual	Reasons for not Evaluating
				6c	Number of warnings generated	SD	Planned	
				6d	Driver actions and/or impact on actions in response to issued warnings	AL	Planned	
Reduce Vehicle to Pedestrian Crashes	Safety	Improve Pedestrian Safety on Heavily Traveled Bus Routes	Pedestrian in Signalized Crosswalk Warning (PEDINXWALK)	7a	Pedestrian related crash counts, by severity	FD	Planned	Too many confounding factors (including those related to signal timing variations by deployment site) prevented meaningful crash analysis
				7b	Number of warnings generated	SD	Actual	
				7c	Pedestrian-related conflicts/hard braking events	AL	Actual	
				7d	Time to collision (vehicle to pedestrian)	AL, MS	Actual	*Performance measure was only computed from simulations, as they were not recorded the action log data
				7e	Driver actions and/or impact on actions in response to issued warnings	AL	Actual	
Reduce Vehicle to Pedestrian Crashes	Safety	Improve Safety of Visually and Audibly Impaired Pedestrians	Mobile Accessible Pedestrian Signal System (PED-SIG)	8a	Qualitative Operator Feedback	SV	Actual	
				8b	Pedestrian Crossing Speed and Crossing Travel Time	AL	Actual	
				8c	Times Out of Crosswalk	AL	Actual	
				8d	Waiting time at intersection for crossing	AL	Actual	
Reduce Vehicle to Infrastructure Crashes	Safety	Address Bridge Low Clearance Issues/Enforce Truck Route Restriction	Oversized Vehicle Compliance (OVC)	9a	Number of Warnings generated	SD	Actual	

Use Case	Focus Area	NYCDOT Needs	CV Application	PM ID	Performance Measure	Evaluation Data Sources*	Planned / Actual	Reasons for not Evaluating
				9b	Number of truck route violations	FD	Planned	OVC TIM messages were not implemented on truck restricted routes as was originally planned, only at low bridge clearances
Inform Drivers of Serious Incidents	Mobility	Inform Drivers	Emergency Communications and Evacuation Information (EVAC)	10	Number of vehicles receiving information when generated	SD	Actual	
Provide Mobility Information	Mobility	Replace Legacy Measurements	Intelligent Traffic Signal System Connected Vehicle Data (I-SIGCVDATA)	11a	Segment speed (average and distribution measures) from CV compared to legacy detection systems	SD, MS	Actual	*Analysis only completed based on System data and not simulation
				11b	Travel time (average and distribution measures) from CV compared to legacy detection systems	SD, MS	Actual	*Analysis only completed based on System data and not simulation
Manage System Operations	System Oper-ations	Ensure Operations of the CV Deployment	NA	12	System performance statistics (system activity, down time, radio frequency monitoring range on ASD's and RSU's, number of event warnings by app)	SD	Actual	

Notes: * Evaluation Data Sources Legend: AL = Action Log or Event Warning Data Recordings, FD = Non-CV-Based Field Data Collection, MS = Microsimulation evaluations used where data was not measured or collected in field, SD = CV-based System Data Collection, SV = User Surveys. Details of how the different performance evaluations were completed using these data sources are discussed in Section 5 of this report.

3 Experimental Design

In order to evaluate the impacts of the CV technology on improving safe driving conditions, an experimental design required ways to differentiate between driver behaviors in similar conditions both with and without influence of the CV applications. This required the measurement and comparison of the performance of the system both with the CV technology and without. This section presents highlights on the final implemented experimental design used during Phase 3 deployment evaluation of the NYC CVPD.

Separate experimental designs were used to evaluate the impacts on drivers to evaluate the vehicle-based CV applications impacts and impacts on pedestrians to evaluate the PID CV application. A discussion of the confounding factors experienced during the Phase 3 that may have additional impacts on the evaluation outside of and external to the influences of the CV technologies is also presented. Further details regarding the development of the experimental design can be found in the Phase 2 Performance Measurement and Evaluation Support Plan report.

3.1 CV-Equipped Fleet Vehicles

The deployment installed ASD units into various vehicles used by numerous city agencies. Table 3 presents a summary of the installations of ASDs into different agencies, including the types of vehicles that were equipped. Of the approximate 3,000 vehicle installations, approximately 3% are buses (including transit and non-transit buses), 32% are pickups or work trucks, 9% are vans, and the remaining 55% are passenger cars and sports utility vehicles (SUVs).

The equipped vehicles are used by the various agencies for conducting their daily business for the city. Some vehicles are housed in common facilities located across the city and are used by numerous agency staff on an as-needed basis, while some vehicles are assigned to one individual staff member, some of whom may also be authorized to use the vehicle to commute to and from work in addition to conducting their work activities throughout the day. Some vehicles will be used as simple transportation from point to point in the city, while others are used in various field inspection, maintenance, and operations management for the city’s roads, signals, buildings, parks, and other infrastructure.

Thirteen different makes and numerous models of vehicles are included in the fleet of equipped vehicles. This proved to be a complicating factor in the installation of the ASD and DSRC antenna but even more so with the configuration of the connections to the vehicle’s on-board diagnostic (OBD)-II port. Table 4 presents the breakdown of the equipped vehicle fleet by model make and type.

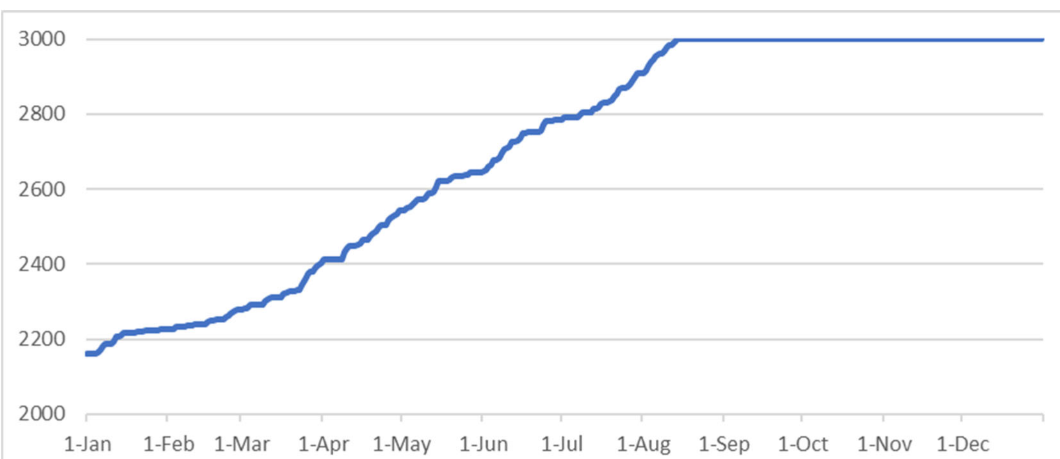
Table 3. ASD Deployment by Agency and Vehicle Type

Agency	Passenger Cars	Pickups and Trucks	Vans	Buses	Vehicle Installations
NYC Dept. of Transportation (DOT)	●	●	●		1238
NYC Dept. of Parks and Recreation (PARKS)	●	●	●		511
NYC Dept. of Correction (DOC)	●	●	●	●	293
NYC Dept. of Environmental Protection (DEP)	●	●	●		159
NYC Dept. of Homeless Services (DHS)	●		●		100
NYC Taxi and Limousine Commission (TLC-DCAS)	●	●	●		98
NYC Human Resources Administration (HRA)	●		●		86
NYC Dept. of Citywide Administrative Services Fleet (DCAS)	●				78
NYC Dept. of Education (DOE)	●	●	●		78
NYC Dept. of Buildings (DOB)	●				69
NYC Administration for Children's Services (ACS)	●	●	●		65
NYC Dept. of Housing, Preservation, and Development (HPD)	●				48
NYC Dept. of Health and Mental Hygiene (DHMH)	●	●	●		45
NYC Dept. of Design and Construction (DDC)	●				38
NYC Office of Chief Medical Examiner (OCME)	●	●	●		29
MTA Bus & NYCT				●	14
NYC Emergency Management (OEM)	●				12
NYC Dept. of Consumer Affairs (DCA)	●	●			12
Anheuser-Busch InBev (ABI)			●		10
NYC Dept. of Information Technology and Telecommunications (DoITT)	●				9
NYC Dept. of Probation (DOP)	●				6
NYC CVPD Team Vehicle		●			1
Taxi Limousine Commission (Yellow Cabs)	●				1
Total	**1,662**	**967**	**269**	**102**	**3,000**

Table 4. ASD Deployment by Vehicle Make and Type

Vehicle Make	Passenger Cars	Pickups and Trucks	Vans	Buses	Vehicle Installations
Chevrolet	165	162	168		495
Chrysler			2		2
Dodge			16		16
Ford	331	714	83		1,128
Freightliner		1			1
IC Corporation				85	85
International				3	3
New Flyer				3	3
Nissan	130				130
Nova				7	7
Orion				4	4
Ram		90			90
Toyota	1,036				1,036
Total	**1,662**	**967**	**269**	**102**	**3,000**

Due to complications of the COVID-19 pandemic restrictions in place in 2020, installations of CV equipment in fleet vehicles were delayed and the full 3,000 equipped vehicle fleet was not fully operational at the beginning of the Phase 3 deployment period (January 1, 2021). At the start of 2021, there were over 2,150 completed vehicle installations. CV vehicle installations continued through 2021 until the full 3,000 fleet size was achieved on August 17, 2021. Figure 2 shows the progression of the total number of equipped vehicles throughout 2021.



(Source: NYCDOT)

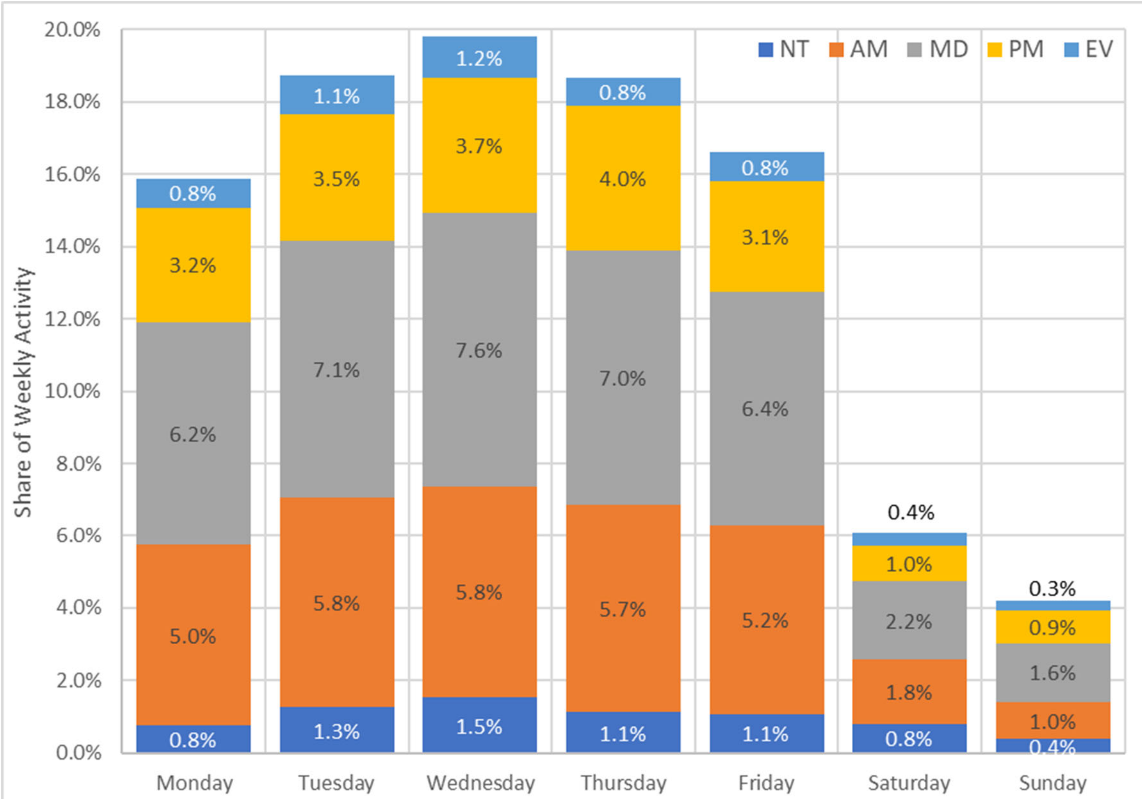
Figure 2. Total CV-Equipped Vehicles Throughout 2021

3.1.1 Vehicle Fleet Activity

To help assess how the equipped vehicles are utilized, the city's existing fleet management system named Geotab was leveraged. The Geotab system is installed on the majority of the city's vehicles, including many of the CV fleet vehicles. Of the 3,000 CV-equipped vehicles, approximately 75% are also equipped with the Geotab system.

While the city's Geotab system does not allow full Global Positioning System (GPS) tracking of the vehicle operations, some measures of the vehicles usage can be extracted from the system, including odometer readings and hours of operation reports. The system also allows tracking "exception" reports from the vehicles such as excessive idling periods, seat belt usage, service needed indicators from the vehicle, or unauthorized off-hours or off-hours use. To support the CVPD, the team added additional "V2I exceptions" which uses some basic geofencing around select RSU locations to report when a combined Geotab and CV equipped vehicle passes by those RSUs. Believing that the combined Geotab and CV equipped vehicles are similar in general behavior to the remaining 25% of the CV fleet that is not equipped with Geotab, a general sense of the entire CV equipped fleet vehicles' usage can be developed. It is noted that the Geotab data is highly protected due to the privacy concerns of its use, and only a very limited set of users within NYC DOT have access.

From examining the Geotab individual data, the equipped vehicles are predominantly operating in the standard business hours on weekdays. However, the 24x7 nature of some of the city agency's activities does extend the CV fleet operations into the overnight hours and to weekends. Figure 3 below presents the percentage of weekly activities (as measured by V2I exceptions) split by both the day of week and time of day. The data shown is aggregated over a three-week period from September 13 to October 3, 2021, a period with no holidays or other major disruptions of activity. Times of the day are reported in one of five categories: overnight (NT, midnight to 6:00 am), the morning peak (AM, 6:00 am to 10:00 am), midday (MD, 10:00 am to 3:00 pm), the afternoon peak (PM, 3:00 pm to 8:00 pm), or evening (EV, 8:00 pm to midnight). Approximately 90% of the exceptions occurred during weekdays, with 6 % on Saturdays and 4% on Sundays. The AM and Midday periods see the largest shares of activity, followed closely by the PM peak periods. Mid-weekdays (Tuesdays through Thursdays) see slightly higher levels of activity than the Mondays or Fridays.



(Source: NYCDOT)

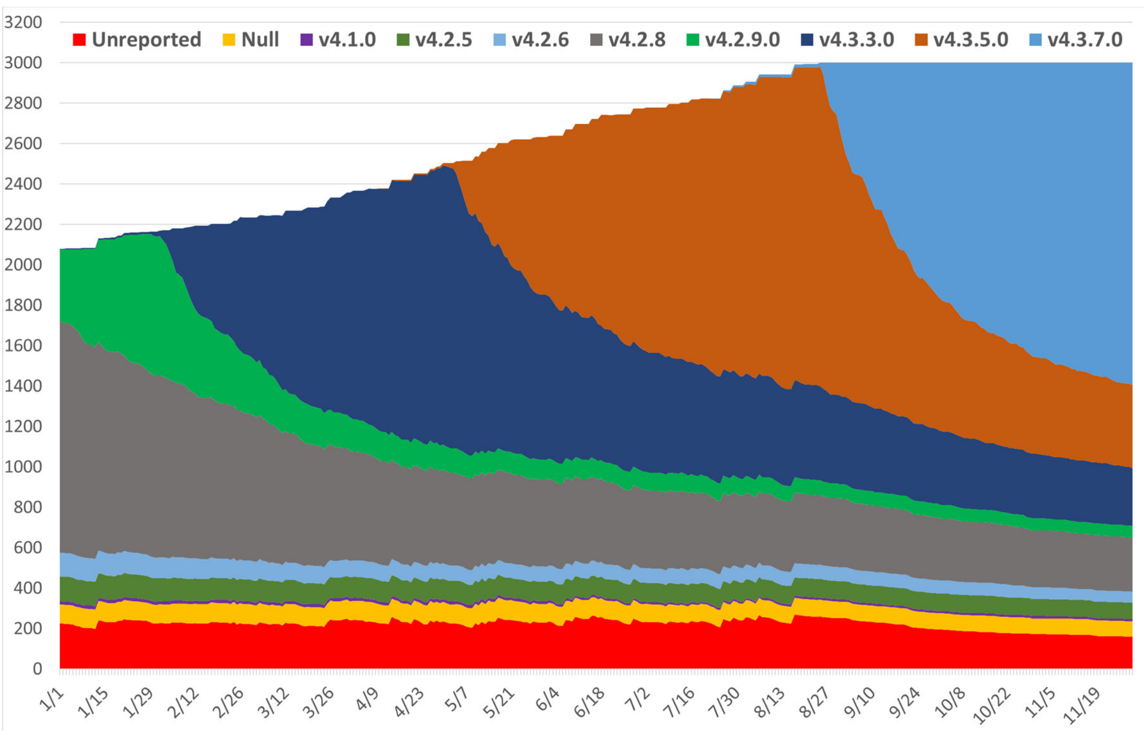
Figure 3. Geotab CV Exceptions Reports – Time of Day and Day of Week Summary

From the Geotab data, vehicles can also be seen moving across the city in all five boroughs using all road types, although activities do concentrate on areas of the city which are not predominantly residential.

3.1.2 Vehicle ASD Firmware and Contacts

Significant testing of ASD firmware and all CV applications was performed by NYC CVPD team members using test vehicles throughout Phase 2 and continuing into Phase 3 as further refinements and improvements to the ASD software were made. As improvements to the various applications and data collection systems were made by the ASD vendors and proven by the NYC CVPD team on test vehicles, new firmware releases of the ASD software were periodically released to the fleet. As the large fleet could not be physically updated, over-the-air (OTA) firmware updates were used to broadcast software updates to the ASDs. This required a DSRC-based transmission of the software update package from a series of RSUs broadcasting the update messages to the ASDs; upon receipt of this update, the ASD returned an OTA status file, which logged that the update message was received.

As different vehicles had different contact opportunities with the RSUs broadcasting the update messages, the transition from one set of firmware to another was more of a progression than a wholesale change. As the deployment moved from Phase 2 and into Phase 3, different levels of firmware were deployed. The first deployment-ready version of the firmware was version 4.2.9 for most applications and v4.3.3.0 for the RLVW and PEDINXWALK applications. Several earlier versions still existed on some ASDs that were installed early in Phase 2 and did not successfully update to the deployment-ready firmware via an OTA update. The unsuccessful OTA update could occur when an ASD did not have sufficient contact duration with a download RSU to completely receive the OTA update file, or could occur when hardware issues or damage prevented the ASD from successfully implementing the OTA update. Additional firmware versions (v4.3.3.0, v4.3.5.0, and v4.3.7.0) were rolled out just before or during the Phase 3 operations phase. While some updates addressed known issues in the way some application operated (e.g. v4.3.3.0 for RVLW and PEDINXWALK), changes also were made in the firmware to improve data collection protocols and other non-CV application related ASD operations and communication issues. Most notable in this type of update is the release of v4.3.7.0 which attempted to correct issues with data files sometimes being queued for upload to an RSU but never actually getting transmitted. Figure 4 shows the number of ASDs reporting as running different versions of the ASD firmware throughout the Phase 3 period in 2021.

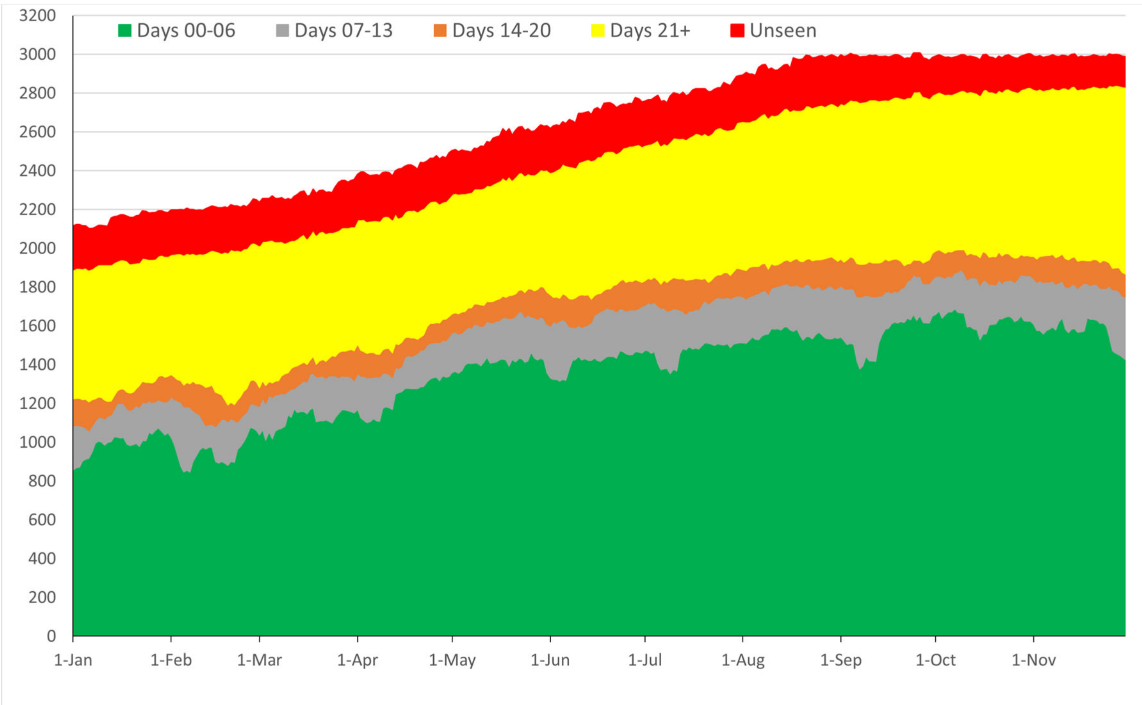


(Source: NYCDOT)

Figure 4. Number of ASDs Running Different Firmware Versions Throughout 2021

As can be seen, when new firmware versions were released, the number of ASDs running that new firmware grows quickly at first as vehicles come into contact with an OTA broadcasting RSU. The rate of change then incrementally grows slower over time as those vehicles still running older firmware versions eventually come into contact with the RSUs and are within range long enough to download the entire update package. Some ASDs were resistant to firmware updates and continued to run older versions of firmware well into 2021.

Additionally, some vehicles failed to upload any data files at all to the TMC. To better understand the issue, the CVPD team tracked the time since each vehicle had contacted the TMC to any uploaded data files. Figure 5 below presents the stratification of how many vehicles had been in contact with the TMC within one week (0 to 6 days), between one and two weeks (7 to 13 days), between two and three weeks (14 to 20 days), more than three weeks (21 or more days), or had never contacted the TMC.



(Source: NYCDOT)

Figure 5. Number of Vehicles Listed by Time Since Last Contact Throughout 2021

Generally in 2021, the TMC was in contact with half of the fleet each week, though this share increased slightly in the later months of 2021. Some deviations in regular contacts were related to vehicle usage, with noticeable dips in the weekly contacts correlated to weeks with holidays or weeks with large disruptions to normal activity from major weather events in NYC.

One reason for a lack of contact would be when vehicles failed to come into contact with the RSU equipment or otherwise did not successfully update any data. The CVPD team attempted to resolve these issues as was possible. For those vehicles equipped with Geotab, the typical use patterns of those particular vehicles were examined. As areas of activity for some vehicles regularly operated away from RSUs, additional RSUs were deployed to aid in OTA broadcasts for firmware updates and to provide additional data upload opportunities.

For vehicles that appeared in the Geotab system reports to be operating within the vicinity of data communication RSUs but still failing to provide any data contacts, the CVPD team conducted inspections as the vehicles they could be made available. Some inspections revealed hardware issues, such as being disconnections from the OBD-II ports or damaged or missing units or antennae. Other issues revealed software issues or damaged ASD partitions or otherwise failing software issues. These issues were resolved on a vehicle-by-vehicle basis; the process was both time and labor intensive. Many vehicles were also difficult to gain access to as they were being used regularly for work purposes and could not be made available for inspection by the NYC CVPD team.

3.2 Driver / ASD Experiment Design

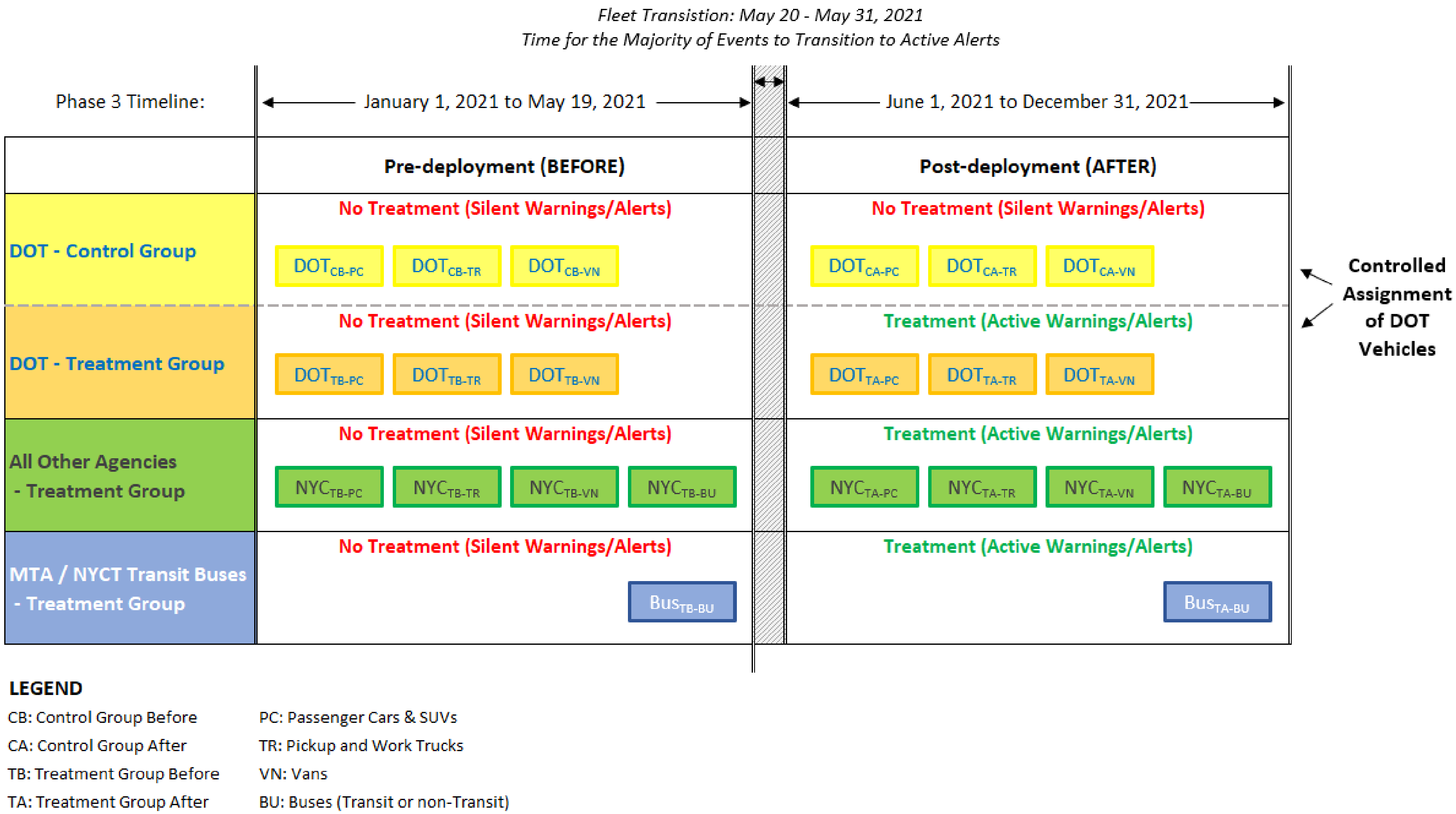
The driver experiment design consisted of both a before and after model and a control and treatment model. The Phase 3 deployment phase runs the entire duration of the 2021 calendar year. The before period was defined as running from January 1 through May 19. The after period was defined as running from June 1 to December 31. Between the before and active periods was a short transition period (May 20 to May 31) during which the fleet began to migrate from the silent model to the active warning mode. Figure 6 presents a visualization of the different components involved in the vehicle based experimental design.

3.2.1 Silent and Active Warning Modes

The experimental design to divide the before and after periods relied on the ASDs being able to operate in either a silent warning mode or an active warning mode.

- Silent Mode (or without CV): In silent mode, the CV applications are fully deployed and operational on the ASD but ***warnings are not audibly issued*** to the drivers. As a result, in silent mode the ASDs record the driver behaviors and reactions (via recorded BSMs) free of any influence of the CV deployment under conditions that the CV applications would have issued a warning if in active mode.
- Active Mode (or with CV): In active mode, the ASD is fully deployed and operational and ***warnings are audibly issued*** to the drivers by the CV applications. Now the ASDs record driver behaviors and reactions that are influenced by active warnings issued to the driver from the CV applications.

To transition from the before period to the after period, over-the-air update DSRC messages were broadcast to the ASDs via data communication RSUs to tell the ASDs to switch from silent mode to active mode. This activation message was first broadcast on May 20 and clearly defines the beginning of the transition period. The activation message was then continually broadcast throughout the remainder of Phase 3 to allow any vehicle still operating in silent mode after May 20 to switch to active mode once the message was successfully received. Since the exact moment the each ASD started delivering active warnings depended completely on the vehicle's proximity to a RSU broadcasting the activation message and the successful download and implementation of this update on the ASD, a transition period from before to after existed. It is noted that the update to active alerts on the ASD was designed to be a one-way transition; once an ASD switched into active alert mode, the ASD would not be permitted to transition back to silent alert mode.

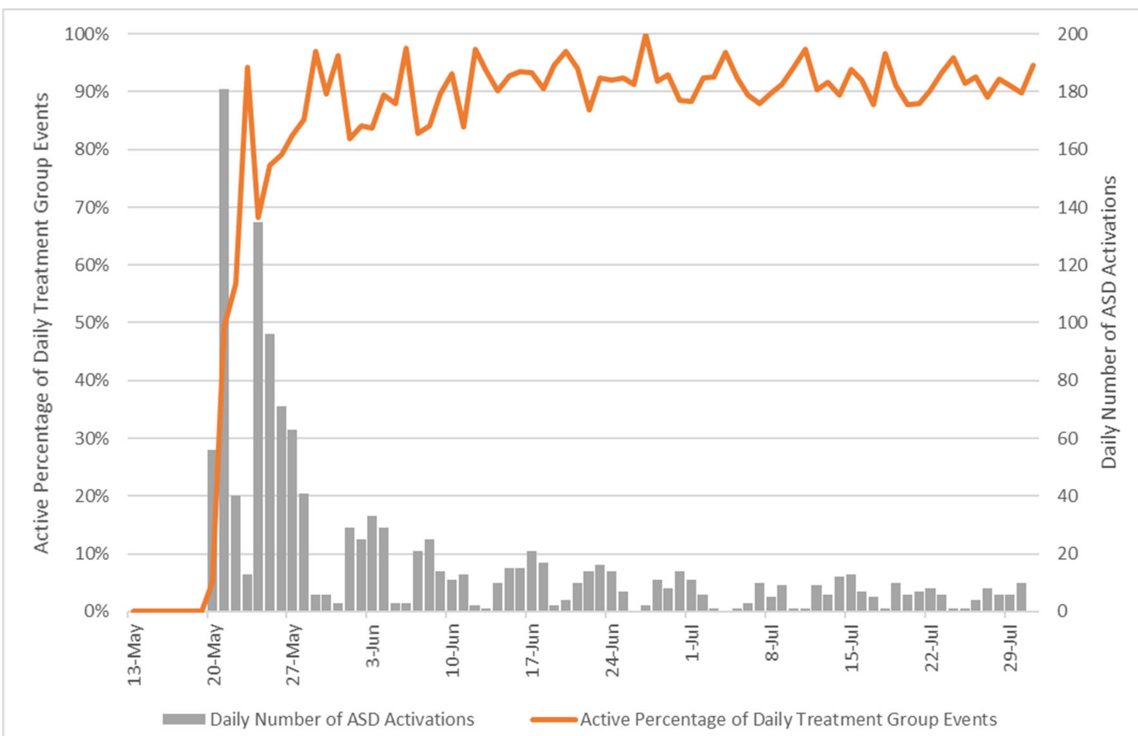


(Source: NYCDOT)

Figure 6. Vehicle Based Experimental Design

The transition period from before to after is identified as running from May 20 to May 31. This is the period in which the majority of events uploaded from ASDs to the NYCDOT TMC switch from reported as silent mode events to active mode events. However, the true transition from silent to active warning modes in fact slowly continued throughout the Phase 3 deployment. Figure 7 below reports both the percentage of daily treatment group events that are recorded as being in active mode and the number of ASDs reporting back to the TMC that they have received the activation message. The percentage of active alerts starts to rise shortly after the activation message was first issued on May 20. However, even well after this date, the daily number of ASDs reporting that they have received the activation update message continues to show low levels of ASD activations well into the after period during June and July. This discrepancy is due to the fact that the ASDs in more actively used vehicles will see more events occurring and will also have greater opportunities to communicate with the RSUs to not only transmit event data files back to the TMC but also successfully receive and implement the activation message as well. Since the evaluation is primarily based on the received event action log data, the stabilization of on average over 90% active alerts being reported after May 31 allows the after period to be well defined as starting on June 1.

It is noted that some vehicles did not conform to the experimental design, including vehicles in the treatment group that did not switch to active mode by June 1 and a small number of control vehicles that were accidently switched to active mode. Discussions of the special handling of events from these outlier vehicles are discussed in section 5.1.1.3.



(Source: NYCDOT)

Figure 7. Active Percentage of Received Events and ASD Active Mode Updates During the Before to After Transition Period

It is also noted that while the Phase 3 deployment and the after period extend to the end of December, the set of after event data used in the evaluation included in this report only extend through the end of September. This limitation to the after-period data was required to allow sufficient time for the evaluation analysis of the after-period data while still being able to meet contractual schedule requirements for completing the deployment evaluation.

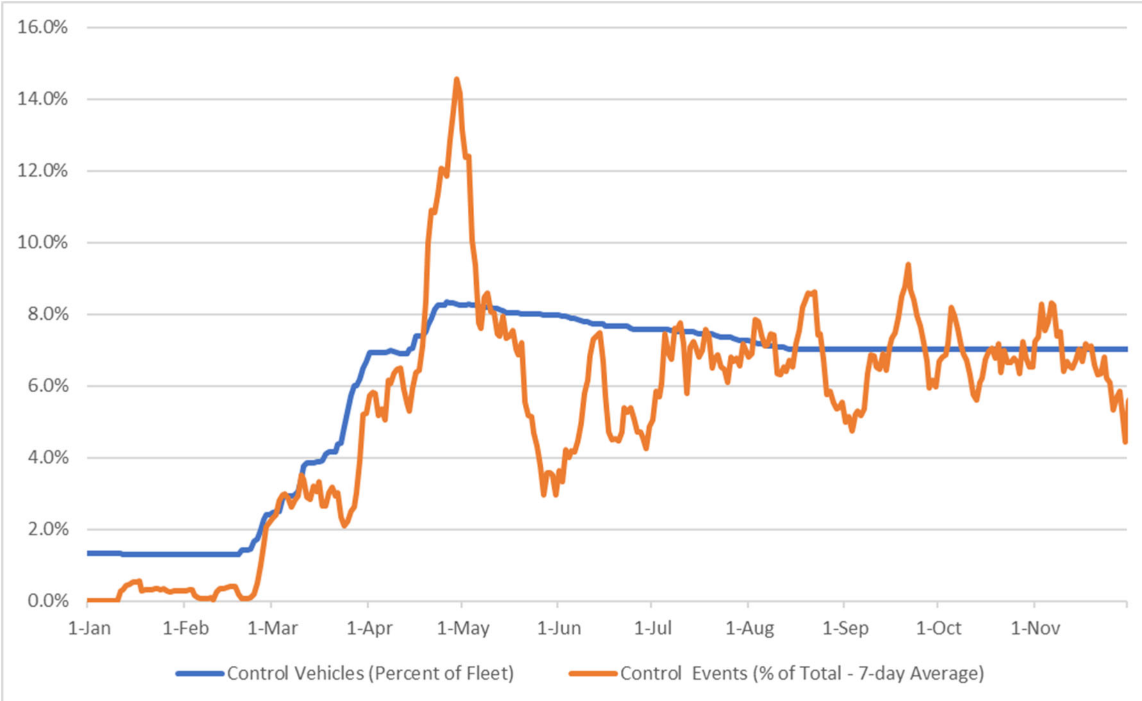
3.2.2 Control and Treatment Vehicles

In addition to the before and after components of the experimental design (shown in Figure 6), the use of treatment and control groups was also used to help isolate the impacts of confounding factors that may change over the full Phase 3 deployment period. All vehicles would operate in silent mode in the before period. In the after period, treatment group vehicles would switch to active mode while control group vehicles would remain in silent mode.

While the need for control group vehicles was identified as being necessary, the conflicting goal of having a treatment group as large as possible to maximize the potential of the deployment of CV technologies was also clearly recognized. The resulting compromise was to have a small control group of vehicles that would operate in silent alert mode during the before and after periods of the Phase 3 deployment. The goal for the deployment was to have a control group of at least 150 vehicles, or 5% of the total equipped fleet. Figure 8 below shows the percent of fleet vehicles in the control group and the percentage of total 7-day average number of events in 2021.

An additional complication of implementing a control group set of vehicles was that many of the fleet vehicle drivers transition on a day-to-day basis between different vehicles in a pool of fleet vehicles. Drivers could see inconsistent CV application behaviors of functioning warnings in a treatment vehicle and no warnings in a control vehicle on a day-to-day basis. To prevent this and to try and ensure a more consistent exposure of the drivers to only treatment vehicles or control vehicles, the vehicles assigned to the control group were carefully selected. This primary meant favoring the use of DOT vehicles as control group vehicles as the NYC CVPD team had more direct knowledge of the typical uses of specific DOT vehicles than vehicles owned and operated by other departments within the city. When selecting a vehicle to the control group, care was taken to select vehicles that were used as frequently and in a consistent manner as many of the treatment group vehicles.

As the designation of a vehicle as either a treatment or control group vehicle needed to be completed as part of the ASD installation and validation, the group assignment could not realistically be adjusted after the ASD installation was completed. As a result, the assignment of control group vehicles as part of new installations lagged the installations of treatment group vehicles during the early stages of the deployment before period.

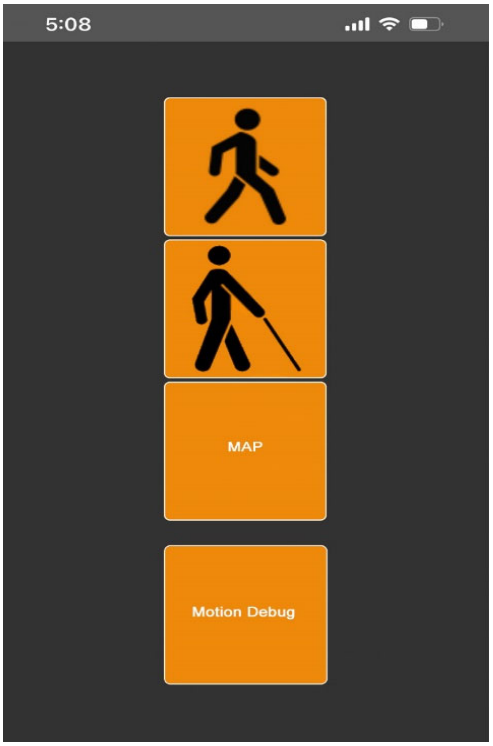


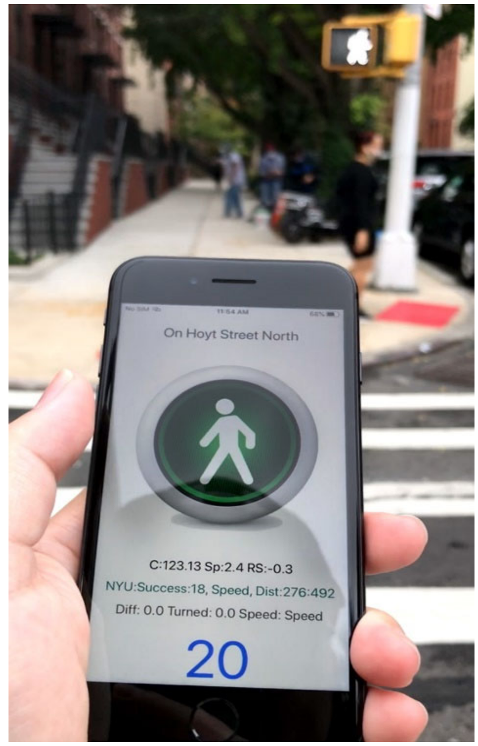
(Source: NYCDOT)

Figure 8. Control Percentage of Fleet and Events

3.3 Pedestrian PED-SIG Experimental Design

The PID is used in the “Mobile Accessible Pedestrian Signal System” (PED-SIG) application to assist pedestrians with vision disabilities in safely navigating crosswalks at signalized intersections. The user interface for the PED-SIG app is shown in the following Figure 9. The left side of the figure presents the launch screen of the app, while the right side illustrates the app during operation while crossing at a signalized intersection.





(Source: NYCDOT)

Figure 9. User Interfaces for the PED-SIG Mobile Phone Application

The experiment of the PID devices was conducted under specifically defined test conditions, albeit in the real-world operating environment of NYC city streets. Based on NYCDOT guidance from testing prototype PID devices, the study recruited volunteer participants with vision disabilities to participate in the field tests where PIDs were given to participants to be used, accompanied by at least one IRB-certified NYC CVPD team member to ensure their safety.

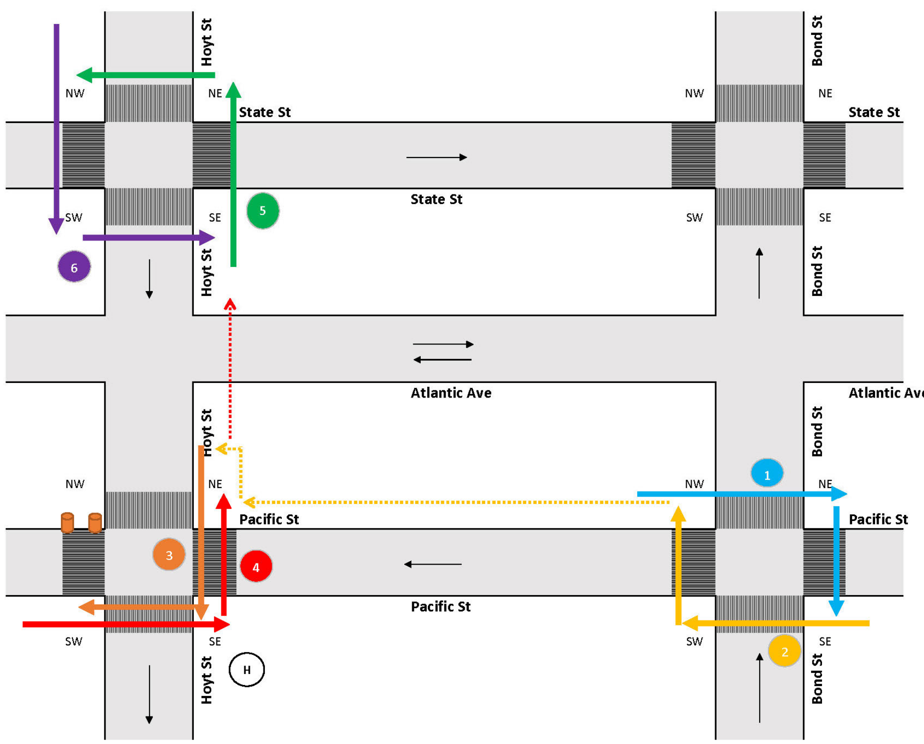
To ensure that the Ped App provided appropriate functionalities with intuitive and accessible design, the PID was introduced to 24 pedestrians with low or no vision to test the app in real-world scenarios. A wide range of potential users with diverse travel habits, mobility needs, and independence levels was sought, including:

- A range of vision ability, from low vision to totally blind
- A variety of mobility assistance mechanisms, from companions, guide dogs, and long canes to vision aids and GPS navigation or other assistive phone apps
- Pedestrians who were born with a vision disability as well as those who had lost their sight over time or later in life
- Pedestrians with co-existing disabilities, such as deafness.

The process involved two levels of recruitment. First, both local and national organizations working with blind communities were contacted. In the New York City area, this included the Helen Keller Services for the Blind, the Brooklyn Center for Independence of the Disabled, the Mayor's Office for People with Disabilities, Access VR, the Lighthouse Guild, the MTA

Accessibility Office, Helping Hands for the Disabled of NYC, the New York State Commission for the Blind, and Visions/Services for the Blind and Visually Impaired. Additional outreach was done with universities including the CUNY Coalition for Students with Disabilities, the NYU Accessibility Project, and the NYU Office of Disability and Inclusion. On a broader level, contacts included the National Federation of the Blind, Achilles International, Family Health International, the American Council of the Blind, the American Foundation for the Blind, the Center for Assistive Technology, and National Industries for the Blind. This first contact involved explaining to each organization the purpose of the study, the shape of the field test, and the goals of the CV Pilot. The second part of the recruitment process involved one-on-one conversations with each volunteer to provide an in-depth explanation of what the app does and what the field tests would entail, as well as answering any of their questions.

Six (6) predefined routes, each made up of two crosswalk crossings, were chosen to test the utility, accuracy, and connectivity of the PID, as well as to gauge the participants' experiences through multiple CV-equipped intersections. Six semi-protected intersections (with an overall low traffic volume and no or very low vehicle turning movements) were identified and tested; four of them were selected for the field tests with participants. The test intersections include Pacific Street and Bond Streets, Pacific Street and Hoyt Street, and State Street and Hoyt Street in Brooklyn, with one additional intersection (State Street and Bond Street) as a backup location. The backup intersection served as a supplement to the field tests when any of the three designated intersections were not available due to temporary road construction, emergencies, community events, or other unforeseen issues. The predefined routes and the study area are illustrated in Figure 10 below.



(Source: NYCDOT)

Figure 10. Predefined Routes for PID Field Tests

In the proposed plan, 10 PID devices were to be used. However, due to the difficulties in developing both iOS and Android applications at the same time, PED-SIG application development was determined to be exclusively on the iOS platform in the final scope. Therefore, the five (5) PID devices operating on the iOS system were used during the field tests. Each participant was asked to carry and engage with a PID device and a GPS augmentation device that connected with the PID via Bluetooth. The purpose of having the augmentation device is to enhance the GPS accuracy of the PID. In addition, each participant was asked to answer a pre-experiment and post-experiment survey to provide user feedback on the PID. Due to COVID-19 and in-person activity restrictions put in place by the IRB panel overseeing the PID deployment, the actual field tests were not conducted until the end of October 2021.

Operation data logs were collected from the PID units during participant use as well as observations from the field test and qualitative participant feedback surveys (detailed in 4.1.3). These measures were used to evaluate the performance of the PED-SIG application. All raw PID log data were securely transmitted from the PID cell phone units to the secure IRB approved servers in NYU and can only be accessed by IRB approved researchers. All personally identifiable information will be removed if data is shared outside of the IRB.

3.4 Confounding Factors

Several potential factors were established in Phase 2 of the study that could have impacts on the deployment and confound analysis of the CV applications. As outlined in the Phase 2 PMESP, those factors that were considered the most probable to have impacts included the following:

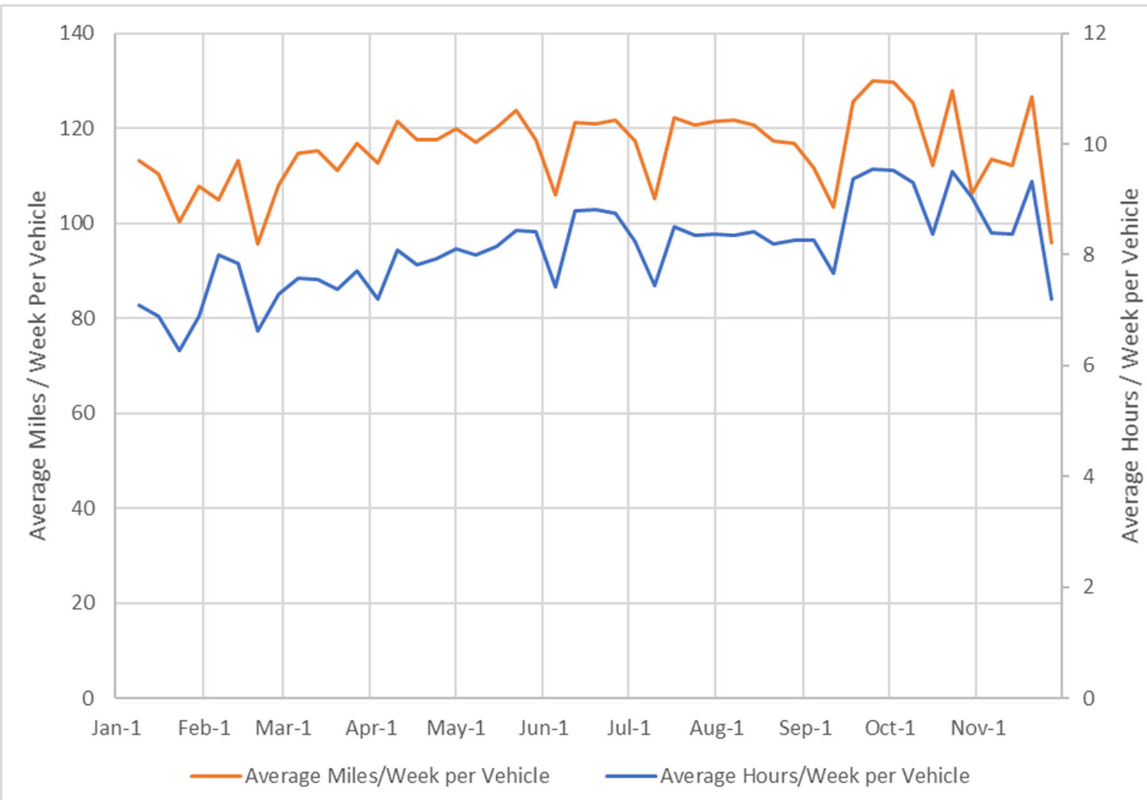
- Traffic Demand Variations
- Weather
- Accidents and Incidents
- Traffic Signal Timing Updates
- Work Zones (Short Term and Long Term)
- Planned Special Events
- E-Hail and For-Hire Vehicles
- Changes in Transit
- Vision Zero Projects
- COVID-19 Impacts
- CV Fleet Size and Activity

Details on how some of the key elements were tracked throughout the deployment are available in Appendix C. However, there are a few elements that had noticeable impacts on the deployment that are addressed here as needed context to the evaluation.

3.4.1 COVID-19 Impacts

The most significant and persistent confounding factor was the ongoing impacts of the COVID-19 pandemic throughout the evaluation period of 2021. While the most significant impacts were seen in 2020 prior to the evaluation periods, the longer lasting impacts of changing traveler behaviors, mode choices, time of day of travel, and work from home conditions continue to be noticeable across the NYC (and indeed beyond). While many regional bridge and tunnel crossings are seeing daily traffic volumes that are now similar to pre-pandemic levels, the time of day and trip purpose may be different. Additionally, transit ridership for buses and in particular subways are still well below pre-pandemic levels.

While these impacts on the operations of the NYC CVPD vehicles usage may be less impactful, the general trend observed in the average reported miles and hours of operation for the combined CV and Geotab equipped vehicles shows a consistent increase over the 2021 calendar year. Based on Geotab reports, Figure 11 presents the average (mean) weekly miles traveled and hours of operations per vehicle.



(Source: NYCDOT)

Figure 11. Average Weekly Miles Traveled and Hours of Operation

3.4.2 Weather and Other Disruptions to Normal Activity

Drivers can alter their driving style and aggressiveness based on the weather conditions. Knowing the prevailing the weather conditions at the time of an event is an import consideration in evaluating driver responses. For this reason, all collected event data includes observed weather data at the time of the event warning to provide context to the warning message and the driver behavior responses to the warning. All weather data was provided by the National Weather Service (NWS) system of weather stations reporting hourly METeorological Aerodrome Reports (METARs) data. Additionally, when snowy or icy conditions were encountered, data from the PlowNYC snow-plow tracking system was included to provide insights into the possible road surface conditions.

In addition to weather data in context of the event warnings, some significant weather events in 2021 also created large disruptions to the normal operations of the city. During these events, fleet activity can be seen to drop significantly in response to the changing travel patterns of many drivers in the CV fleet. The following severe weather events and timeline are noted:

- Winter Storm Orlena produced heavy snowfall and extended winter weather and clean-up conditions (January 31 to February 3)
- Winter weather with heavy snow, sleet, and ice conditions (February 7, February 18 to 19)
- Remnants of Tropical Storm Henri caused very heavy rainfall and some flash flooding (August 21 to 23)
- Remnants of Hurricane Ida caused historic rainfall rates and flash flooding (September 1 to 2)

In addition to the weather events, the annual United Nations General Assembly (September 21 to September 27) regularly creates disruptions to traffic flows on the east side of Manhattan for several blocks around the United Nations Headquarters building complex.

Finally, the impacts of holiday or other special days were seen to directly relate to reduce fleet activities. The following days were seen to reduce the overall fleet activity in NYC:

- New Year’s Day (January 1)
- Martin Luther King Jr. Day (January 18)
- NYC Schools Spring Recess (March 29 to April 2)
- Memorial Day (May 31)
- Independence Day (July 4)
- Labor Day (September 6)
- Rosh Hashanah (September 7)
- Yom Kippur (September 16)
- Columbus Day (October 11)
- Election Day - NYC offices closed (November 2)
- Veterans Day (November 11)
- Thanksgiving (November 25)

3.4.3 CV Fleet Drivers

It is noted that the drivers operating city fleet vehicles (including the CV fleet vehicles) may not necessarily be considered ideal surrogates for a typical or general private vehicle driver in NYC. Not only have many been driving for work in NYC for several years and may drive more regularly with more miles and hours traveled than a general driver, the fact that they are driving for work may produce different driver behaviors than what is typical.

Additional, as the Geotab system exists on the majority of fleet vehicles, drivers may realize that the Geotab system is monitoring for speeding and other aggressive driving conditions and may adjust their driving styles while in a city-owned vehicle accordingly.

It is noted that while the fact that drivers of the NYC CVPD fleet vehicles may not be a surrogate for the typical driving population for the above reasons, it is not considered a confounding factor in the evaluation of this pilot deployment as it is a common element to all CV-equipped vehicles and their drivers. It is listed here as an important consideration in the use of data or findings of the NYC CVPD to the larger private vehicle driving population.

4 Data Collection and Sharing

Numerous data elements were collected as part of the NYC CVPD. Highlights of some of these data items are provided below, however, additional details are provided in Appendix C.

4.1 Data Sources

Data sources can be broadly categorized by the source of the data; namely CV-based data sets recorded from ASDs, RSUs, and PID collected data, driver and pedestrian participant surveys, and additional non-CV-based data sets. Each are discussed it the following sections.

4.1.1 ASD Recorded Data

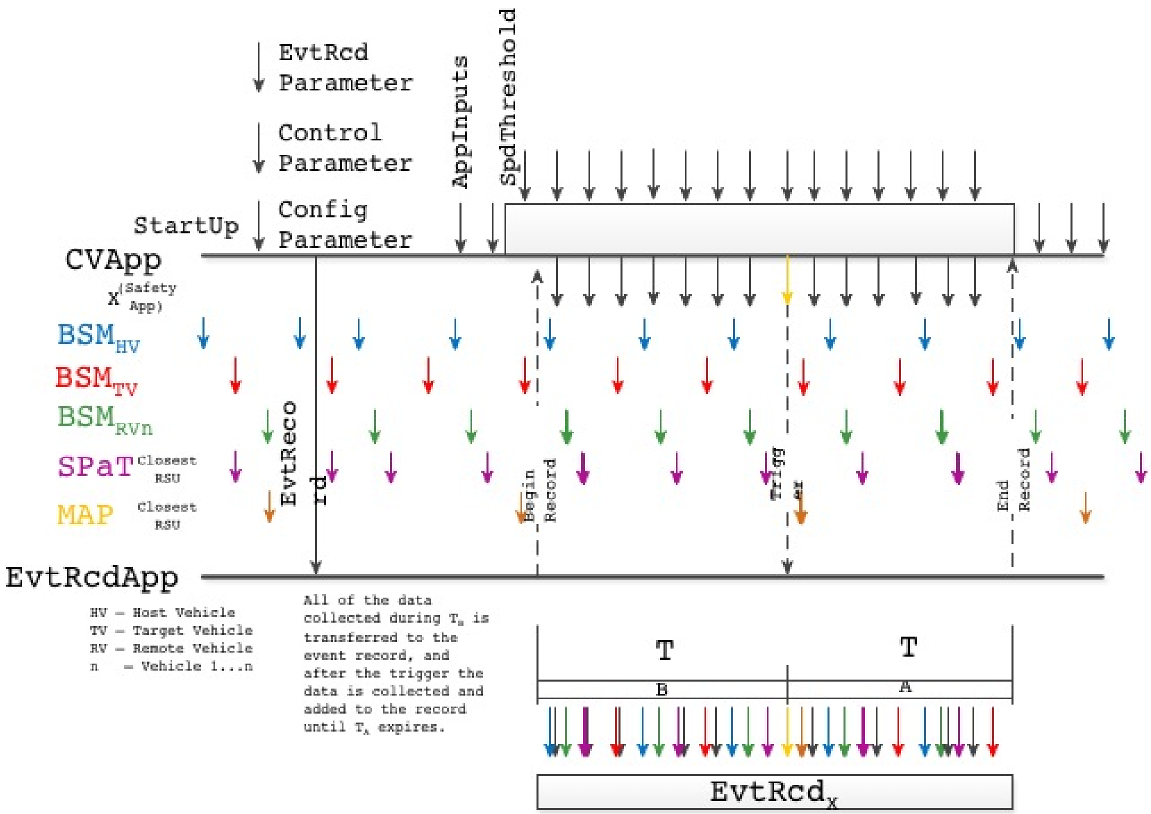
The data collected and recorded by the ASD for ingest are described in the following sub-sections.

4.1.1.1 Action Log or Event Data

The ASDs log the relevant information surrounding a triggered event as shown in Figure 12. The log entry consists of the host vehicle (HV) BSMs (BSM_{HV}), remote vehicle (RV) n's BSMs (BSM_{RVn}), and the subsequent (denoted by n+1) remote vehicle's BSMs (BSM_{RVn+1}) from the ASDs. It also records the SPaT, MAP, and TIM messages heard from the nearby RSU. Collectively, this aggregation of CV-based messages and data from the host vehicle are referred to as either Action Logs or simply as Event Data.

For the NYC CVPD, the trigger for event data recording was any CV application warning generated by the ASD (either in silent or active alert mode). The time periods for collecting data before and after the trigger event are configurable for each event trigger based on the event record (EvtRcd), control, and configuration parameters. These periods consist of a few seconds before and a few seconds after the trigger's activation. The relevant information (data) is limited to what the ASD provides, and it may include vehicle data when the ASD is connected to the vehicle's data bus (i.e., CAN, J1939). For instance, each event log entry includes the location (i.e., latitude, longitude, elevation, 3-axis acceleration), indicated warnings, and the action (i.e., lights, wipers, turn signals, steering angles, brakes) of the vehicle. More importantly, this event log is stored on the vehicle for later retrieval when the vehicle returns to its fleet terminal where the data will be offloaded.

Note that the definition of an event was configured by CV application warning type in order to collect either short-term driver behavioral data (hard braking, steering, accelerations, etc.) for detailed safety based performance measures or longer-term driver behavior data (speed, heading, path choice) over a few minutes. However, such data is cleansed of any traceable personal data (including the exact location and time) to prevent from being correlated to other records such as police reports.



(Source: NYCDOT, 2017)

Figure 12. ASD Event Data Collection "Raindrops"

4.1.1.2 Mobility Logs (Breadcrumbs): BC Data Files

The ASD breadcrumb (BC) data are less detailed than the event log data surrounding a CV safety application warning. Its data collection intervals are configurable based on distance, time, or both parameters depending on which one occurs first. It does not include detailed BSMs from remote vehicles surrounding the host vehicle, as the remote ASDs generate their own breadcrumb information.

4.1.1.3 Radio Frequency: RF Data Files

The ASD collects RF data for measuring the ASD's RF status and performance for operation and maintenance. The RF data files consist of V2V (ASD to ASD) and V2I (ASD to RSU) sightings. They are used to detect the presence or absence of ASDs by tracing the RF radiation issues to a specific vehicle in the NYC CVPD system.

For V2V, the ASD logs its own as well as the remote vehicle's available power level information and the BSMs. However, it only stores the first and last data during the encounter. Similarly, for

V2I the ASD logs its own RF and BSM and the nearby RSU's RF and SPaT message. If it continues to receive the data from the same RSU, the latest set of messages replaces the last message log entry each time. When no further entries are recorded, the first and last messages during the encounter are logged.

The ASD RF data is uploaded when the ASD encounters a support RSU that is programmed to look for nearby ASDs. When this occurs, the RSU collects the ASD RF data through a properly signed WAVE Service Advertisement (WSA) on the identified service channel. Once the RSU acknowledges receipt and processes the RF log entries, the ASD purges the log entries transmitted to the RSU.

4.1.1.4 Systems Operations: SSL data

In addition to the event data and RF data, the ASD also collects its system status log (SSL). This provides the information regarding the health of the ASD. The SSL consists of messages that describe the ASD's operational status including any errors and/or failures.

4.1.1.5 Over-the-Air Messages: OTA Data Files

A critical element of the NYC CVPD was the implementation of OTA for managing and updating the ASD. The ASD can communicate with the RSU to verify its firmware version against the advertised available version. If the ASD's firmware version is outdated, it can initiate the request from the RSU that has the updated OTA software and firmware for download. Also, configuration management applications and parameters can be downloaded OTA to the ASDs.

4.1.2 RSU Recorded Data

Outside of operation status reports, two main sets of data were recorded from the RSUs. Both involved related to sighting information of ASDs.

4.1.2.1 RF Sightings of ASDs

To help assess the level of contact with ASDs and to help establish the communications footprint of the RSUs, sighting data of individual ASDs were recorded by the RSUs. As RSUs heard BSMs broadcast from CV-equipped vehicles, the time and location of the first and last BSMs heard from that vehicle (as identified by the vehicle temporary ID) within established time windows were recorded. These sightings were used to help establish the radio frequency (RF) footprint and effective communication range of each RSU. This was extremely helpful in establishing RSU locations to use for prioritized different data communications (e.g. OTA message broadcasts and data uploads requests) for different RSUs across the city to help manage the operations of the deployment.

4.1.2.2 RSU-Based CVPD Travel Time Reporting System

As part of the CV Pilot Program, selected RSUs deployed at along 1st Avenue and 2nd Avenue in Manhattan and along Flatbush Avenue in Brooklyn were set to record specific sighting data as equipped vehicles pass through the signalized intersection. The sighting data simply recorded the temporary ID of the equipped vehicle (as broadcast in the BSM) and a time stamp of the sighting. These sightings were then transmitted back to the NYCDOT TMC and are matched to other sightings from other RSUs, and RSU to RSU travel times could be developed from these individual sightings. This data is then aggregated into discrete time intervals for defined segments recording the mean and median travel times, as well as a confidence score based on the number of samples and the distribution of travel times within those samples. Those timestamped aggregations comprise the stored data for the CVPD Travel Time Reporting System.

Reporting segments were defined by pairing selected neighboring RSUs set to record the travel time sighting data. Travel times based on CV-equipped vehicle sightings were recorded throughout the Phase 3 deployment. Figure 13 below presents the locations of RSUs and Segments. RSUs were set to collect sightings at all intersections along the corridor. Segments were defined on a block-by-block basis, for a total of 131 defined segments.

(Source: NYCDOT)

Figure 13. CV Travel Time Segment Map Overview

4.1.3 Driver Participant Surveys

While significant amounts of data were collected from the ASDs regarding the operations and details of the CV application warnings, more qualitative assessments of the applications performance was also desired. This was completed through a series of periodic driver surveys to solicit feedback on the CVPD deployment. The surveys are presented in Appendix B.

Three related driver surveys were conducted: the pre-deployment survey, the early-deployment survey, and the late-deployment survey. All surveys included the same sets questions for parts one, two, and four. Part three questions were only asked in the early- and late-deployment surveys.

- Part 1: Vehicle Usage: Questions about the drivers' typical vehicle usage and driving patterns when driving for work in NYC.
- Part 2: User Attitude / Perception: Questions regarding perceptions and attitudes towards CV technology and about the perceived safety of driving for work in NYC in general.
- Part 3: User Experience: Questions about drivers' experiences with the active CV applications warnings provided to the drivers (not collected in the pre-deployment survey).
- Part 4: Demographics: Questions to help identify basic demographics of the respondents.

All surveys were all collected via a Microsoft Forms online survey tool. Some questions were conditionally asked based on answers provided to previous questions. All surveys were completed anonymously, and no details of the respondents' identities were recorded, and the only item recorded outside of the asked questions were the times that the survey was initiated and completed. Since the NYC CVPD team did not have any direct communication with the drivers, the URL to access each of the surveys was provided to the various fleet vehicle managers with equipped vehicles in their fleets for distribution to their respective drivers.

The pre-deployment survey was open and available to be completed by drivers between May 17 and May 28. The early-deployment survey was open between August 13 and September 29. The late-deployment survey was open between October 26 and November 17.

4.1.4 Pedestrian Participant Surveys

To collect qualitative user feedback from the participants on the effectiveness of the PED-SIG application deployed during the CV Pilot, pre-experiment and post-experiment surveys were administrated during the field tests. Individual interviews were conducted with the participants, with the questions read aloud and spoken responses recorded by the surveyors. The pedestrian surveys are presented in Appendix B.

The pre-experiment survey is designed to establish baseline conditions for study participants. The questionnaire in the pre-experiment survey includes a few key demographic questions, self-ratings of mobility and travel proficiency, and questions about assistive technology usage in navigating city streets.

The post-experiment survey aims to collect useful feedback on participants' perceptions and experiences with the PED-SIG application during the field test and suggestions for improving the application. It includes an additional set of questions on attitudes, perceived impact on participants' safety and mobility, institutional issues (e.g., privacy), and other relevant topics. It is noted that, while the user feedback is important, it is not sufficient to conduct robust statistical analyses due to the small sample size of the survey.

4.1.5 Non-CV Data

Additional data was collected from more traditional non-CV based sources to help in the evaluation of the NYC CVPD. Much of this data was related to the tracking of identified confounding factors and to help provide additional context to the operational condition in which the CV application warnings were occurring. Details on these data sets can be found in the Performance Measurement and Evaluation Support Plan report and selective details are provided in Appendix C.

Data sets can be split into two categories; those that have elements fused into the Event Action Log data, and those that are not fused but are provided as historic records of activities during the evaluation phase of the NYC CVPD.

- CV-Event Fused Data Sets:
  - Weather
  - Transcom Link Conditions data
  - DSNY Snow Plow Activity Data
- Non-Fused Data Sets:
  - NYPD Crash records
  - Volume data
  - TLC speed data
  - Transcom Event data

4.2 Data Sharing

Data from the NYC CVPD was made available outside of the NYC CVPD team to provide for an independent evaluation of the NYC CVPD as undertaken by USDOT, to help provide collected CV data for use by the larger research community, and to inform the general public about the deployment. Due to the privacy concerns of the data collected during the deployment, access to different data sets varied between project stakeholders and the general public.

4.2.1 Project Stakeholders

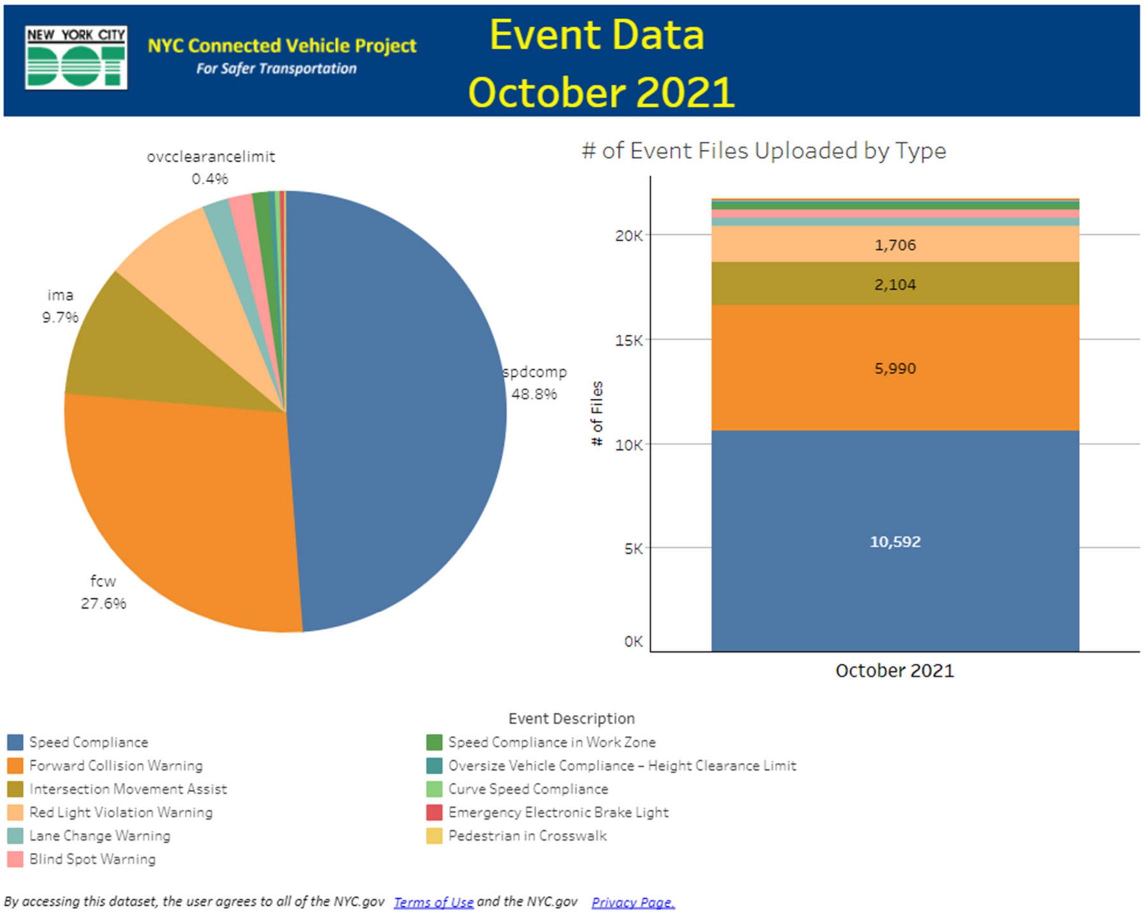
Several sources of the CV collected data were provided directly to the USDOT and their independent evaluators (IE). This included the obfuscated event data, as well as RF, OTA, and SSL data file logs from ASDs, data collected by the CV Travel Time system, and various other confounding data sets collected throughout the deployment.

To provide additional insights to stakeholders outside of the NYC CVPD team, a set of Tableau based dashboards were developed to track the daily performance of the deployment. While these dashboards were not made available to the public, they were used by the NYC CVPD team and by USDOT and Independent Evaluators to track the deployment during the evaluation periods. It is noted that not all stakeholders received access to all data reports. Key metrics on the dashboards included:

- Vehicle Sightings
    - Number of equipped vehicles over time
    - Daily unique vehicles reporting to the TMC (via data uploads)
    - Aging reports of the unique vehicle contacts to the TMC (weeks since last contact)
    - Number of vehicles seen by weekday for historical context of any particular day
    - Daily ingested data files by different file time, the number of CV installed vehicles
    - Notes and comments regarding key milestones or disruption events occurring during the deployment
- Data File Ingests
    - Total number of CV warning events ingested at the TMC by CV application warning
    - Number of files from ASDs ingested at the TMC; reported both by day and cumulative over a period
    - Number of files from ASDs ingested at the TMC by file type; EVT, RF, BC, OTA, and SSL files
    - Number of Events from ASDs by CV application warning (before filtering, cleaning, and obfuscation event counts)
- RSU-based Sighting Data
    - Reports of sightings from the CV Travel Time System; total and by RSU

4.2.2 Publicly Accessible Data

In addition to the identified individual stakeholder agencies, additional information regarding the NYC CVPD was released via the NYC CV pilot project website (https://www.cvp.nyc) to the general public. Information was release that provided background on the project, the CV applications deployed, updates on the deployment progress, and a monthly report of the number of events or warnings by each CV application. Figure 14 presents the monthly summary report on the NYC CV pilot project website for the month of October 2021.



(Source: NYCDOT)

Figure 14. Monthly Event Data Overview on the Project's Public-Facing Website

A major release of data to the public was the release of obfuscated event action log data records and documenting metadata to the ITS DataHub[1] on a weekly basis. All obfuscated event logs for 2021 for both control and treatment vehicles are uploaded for use by independent researchers.

From January to November 2021, over 150,000 event records have been shared to the ITS DataHub which contains an estimated 19.5 million BSMs, and nearly 1 million related SPaT, MAP, and TIM messages. Data currently being collected for December 2021 will also be uploaded to provide a full calendar year of CV warning messages on the ITS DataHub.

[1] https://data.transportation.gov/stories/s/Connected-Vehicle-Pilot-Sandbox/hr8h-ufhq#new-york-city-dot-(nycdot)-pilot

5 System Evaluation Methodology

The following section outlines the fundamental methods used to compute performance metrics for different CV applications and perform evaluations. As previously discussed in Section 2.8 and listed in Table 2, a set of performance measures were identified for each CV application using data from CV-based action log or event data, microsimulation analysis, deployment system data, or other field data collected outside of the NYC CVPD. Different methods were required to ingest data, clean, analyze, and compute the performance metrics for the various data sources and evaluation methods. Discussed below are steps and details of the evaluation methods for CV-based data (e.g. data recorded by ASDs, RSUs, or PIDs), crash data analyses, simulation based assessments, and survey methods.

5.1 CV-Based Data Evaluations

Much of the data processing and analysis involved in the evaluation of the individual CV applications are the same for all applications given the similarities of the data being analyzed. The following presents a summary of the system evaluation methods organized by data sources used.

5.1.1 ASD-Based

5.1.1.1 Event Data Ingestion, Filtering, and Obfuscation

The action log or event data collected and recorded in the ASDs were uploaded to the RSUs and then forwarded to the NYCDOT TMC for additional decryption, decoding, and additional processing prior to use in any evaluation or data sharing beyond the TMC environs. Highlights of this processing are provided as follows, with more details available in the NYC CVPD's Performance Measurement and Evaluation Support Plan Report.

The event data records were reviewed for known data logging errors or for data from older versions of the ASD firmware or configuration settings earlier than the first identified deployment-ready firmware. Data logging errors identified and filtered out included files with missing BSM or other required MAP, SPaT, or TIM messages required to interpret the event recording, incorrect location coordinates not matching to any NYC public roadway or roadway heading (if within city limits), bad timestamp records, or when an invalid window of BSM records are returned considering the type of warning. Additionally, event files from vehicles used by the NYC CVPD team for application testing were also removed, as the situations recorded may be contrived circumstances specifically to test the CV applications under varying conditions. Details on the number of events filtered out of consideration for evaluation or release to the ITS DataHub can be found in Appendix C.

To protect the privacy of the participants, the event files remaining after the above filtering underwent an obfuscation process. All unique identifiers that could identify the driver or vehicle were removed. All details that could identify the event record's exact time and location were also removed to prevent matching of a specific event record data file to other non-CV data that contains personably identifiable information (PII). Since the precise time and location is observed, to provide some additional information regarding the operating conditions the event was recorded under, details regarding the weather conditions and the reported average operating speed of the roadway segment the event occurred on (if available) were fused into the event file prior to any obfuscation of exact time and location details.

All unique identifiers in the event record, including the ASD serial number of the host vehicle and any unique identifier of MAP or SPaT intersections or TIM messages, were removed. The temporary vehicle IDs broadcast as part of the standard BSM were left unchanged, as this ID changes periodically to prevent matching of IDs across time. All unique intersection IDs used in MAP and SPaT messages were replaced with event-specific letter codes to allow matching of related MAP and SPaT messages within the event record.

All time elements recorded in any CV message in the event record were removed and replace with an artificial time scale defined by the time of the CV application warning of zero seconds. Negative time values occurred before the warning, while positive time values occurred after the warning. Details of the time of messages were retained at the millisecond level of precision. The same time scale was used to define all time elements, including SPaT message details.

All location details of latitude, longitude, and elevation were removed and reprojected onto an artificial (X, Y, Z) metric coordinate system defined as point (0, 0, 0) being the location of the host vehicle's trigger BSM, where the CV application determined conditions where a warning should be issued to the driver. The relative precision of all BSMs coordinate data was converted to at least a millimeter level of precision. All offset information contained in a MAP message was also converted to the same metric cartesian coordinate system.

To allow for some context of the time of the event warning, a system of time and location bins were developed and used to classify each event record. Time bins were developed to remove the exact date of the event and retain only the month and day of week that the event occurred on. Time-of-day information was also removed and replaced with the classification of the event into one of five possible time-of-day bins defined in local NYC time zones as follows:

- NT: Overnight period (12:00 am – 6:00 am)
- AM: Morning Peak (6:00 am – 10:00 am)
- MD: Midday Period (10:00 am – 3:00 pm)
- PM: Afternoon Peak (3:00 pm – 8:00 pm)
- EV: Evening Period (8:00 pm – 12:00 am)

Location context was also provided by the classification of the event into a location bin defined by the NYC borough and the roadway classification that the event occurred on. The NYC borough was identified by a two-letter code (Manhattan = MN, Queens = QN, Brooklyn = BK, The Bronx = BX, and Staten Island = SI). The roadway classification varied if the roadway was RSU-equipped (in the immediate vicinity of an RSU broadcasting V2I safety MAP, SPaT or TIM data) or non-equipped (away from an RSU). The following classifications were used:

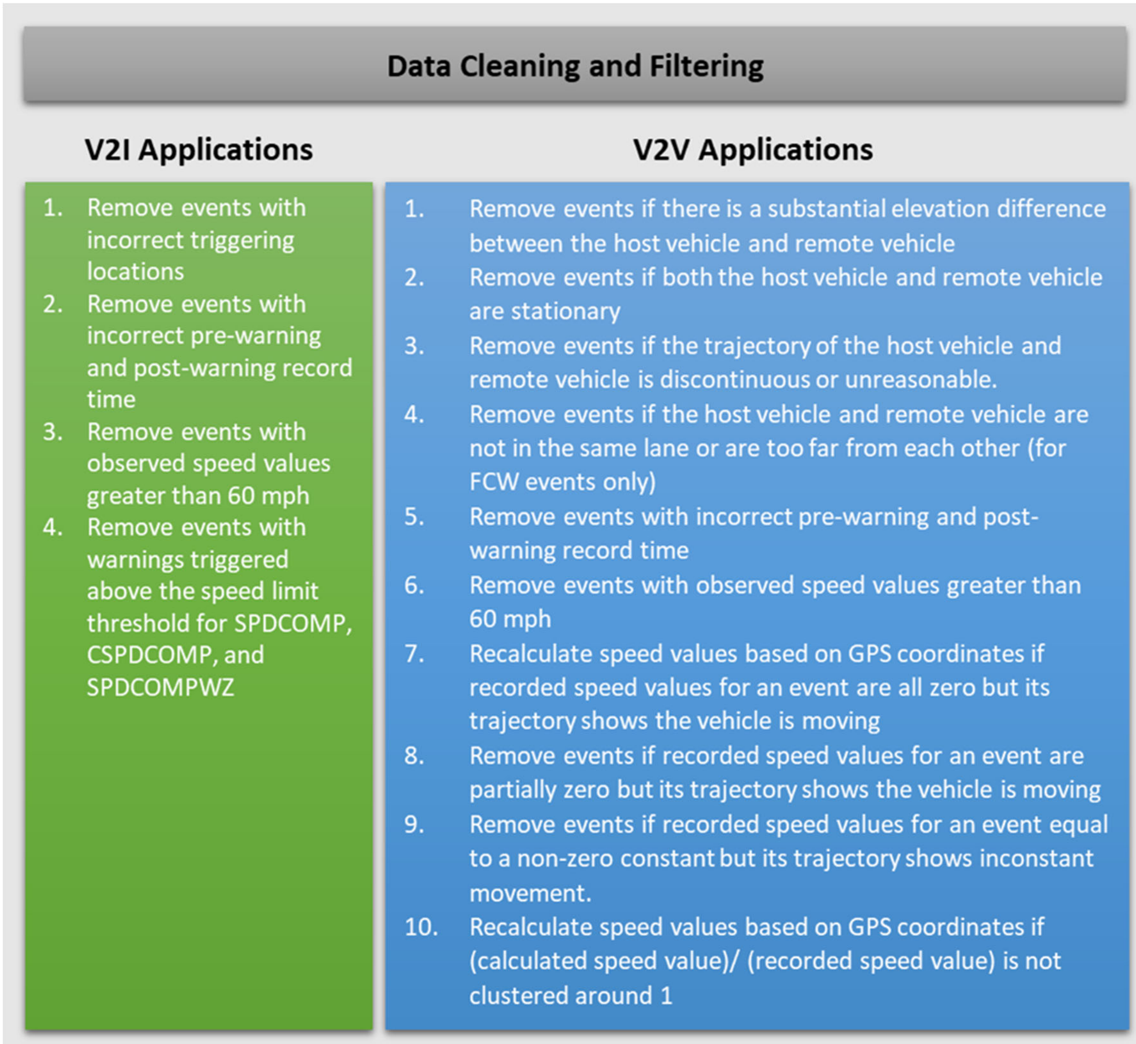
- RSU Equipped: Avenue or Street, plus a one-way or two-way identifier for Manhattan roadways
- Non-Equipped: Freeway, Arterial, or Other (lower class roadways).

Finally, to prevent reversing the obfuscation process, event data records were only released for evaluation and to the ITS DataHub when a sufficient number of events was placed in the combination of application warning type, time bin, and location bins for each month. As events were collected throughout any month of the evaluation phase of the NYC CVPD, events with less than five samples in each combination of warning type time and location bins were held back and only events with five or more samples in each combination of bins was released.

At the end of each month after all event data for the previous month was ingested, an additional time and location bin obfuscation process was undertaken for all event data not released with standard time and location bins. The location bin data for all remaining low-sample events were first adjusted to remove the identification of the NYC borough and road classification code, and the location was simply recorded as “N/A”. Following this adjustment, the unreleased event counts in the time location bins only were recalculated, and those events now meeting the five-sample threshold were released. Those events still unreleased with low sample rates were then adjusted to remove time bin details as well, with the modified time bin recording only the month in which the event occurred. At this point, all remaining event files were released for evaluation and to the ITS DataHub.

5.1.1.2 Detailed Event Cleaning and Filtering

One focal issue that needs to be addressed before system evaluation is data cleaning and filtering, both of which essentially try to detect outliers and remove invalid warnings. While the initial ingestion and error filtering of the raw data prior to the generation of the obfuscation data filters out some event action logs with more evident issues (e.g. logs from old firmware, data recording errors, etc.) further investigations of the detailed trajectory contents of the obfuscated action log data revealed additional needs to conduct additional data cleaning and filtering methods prior the performance measurement calculations and evaluations. Two different methods of cleaning and filtering were developed, one for V2I and one for V2V applications. The process and steps for detailed cleaning and filtering are summarized in Figure 15 below and described in the following sections.



(Source: NYCDOT)

Figure 15. Data Cleaning and Filtering Methods for V2I and V2V Applications

5.1.1.2.1 Vehicle to Infrastructure (V2I) Related Applications

There are six V2I applications in the NYC CVPD: Speed Compliance (SPDCOMP), Curve Speed Compliance (CSPDCOMP), Speed Compliance in Work Zone (SPDCOMPWZ), Red Light Violation Warning (RLVW), Pedestrian in Signalized Crosswalk Warning (PEDINXWALK), and Oversized Vehicle Compliance (OVC). Based on the observed ASD data and the corresponding CV application algorithms, four steps are used in the data cleaning and filtering process for V2I applications.

1. Step 1 removes events with incorrect triggering locations. Warnings from the V2I applications are triggered when equipped vehicles approach the spatial locations which are instrumented with the corresponding V2I applications. Therefore, it is necessary to only keep events that are triggered near the relevant locations. For example, events that do not display a curvature in their trajectories are removed for CSPDCOMP applications.

Similarly, all SPDCOMPWZ events occurring in boroughs that do not contain any instrumented locations are removed.

2. Step 2 removes events with incorrect pre-warning and post-warning record times. Each CV application has its own specific pre-warning and post-warning record time. Events with record times longer than the preset record time are considered erroneous and are removed before subsequent analysis. A one second buffer is added to the preset record time to account for potential measurement errors. For detailed pre-warning and post-warning record times for each V2I application, please refer to Table 7 of the Phase 2 PMESP report.

3. Step 3 is meant to remove events with observed speed values greater than 60 mph. This step addresses erroneous and outlying speed values because some large speed values were observed (e.g., greater than 300 mph). The threshold of 60 mph was based on the observed speed values after applying the first two steps discussed above.

4. Step 4 removes events with warnings triggered with recorded excessive speed limit values for SPDCOMP, CSPDCOMP, and SPDCOMPWZ. In the three applications related to speed limit, there are three configuration parameters (namely *excessiveSpd*, *excessiveCurveSpd*, and *excessiveZoneSpd*) that represent the excessive speed or threshold above the posted (for SPDCOMP) or advisory (for CSPDCOMP and SPDCOMPWZ) speed limit for determining whether or not a vehicle's speed violates that speed limit. According to the NYC CVPD implementation of SPDCOMP, CSPDCOMP, and SPDCOMPWZ, warnings were to be triggered when the speed of a CV reached the established speed limit, meaning the excessive speed parameters were to be set to zero. Thus, events with warnings triggered with incorrectly set non-zero excessive speed limit thresholds were be removed.

After the above data cleaning and filtering steps, the percentages of data removed for V2I applications ranged from 12% to 28%, excluding the CSPDCOMP application that included a relatively large proportion of events removed with incorrect triggering locations from an early TIM message creating false (but silent) alerts in the before period. Details on the number of obfuscated V2I events that were filtered out of consideration in the evaluation from each of the above steps can be found in Appendix C.

5.1.1.2.2 Vehicle to Vehicle (V2V) Related Applications

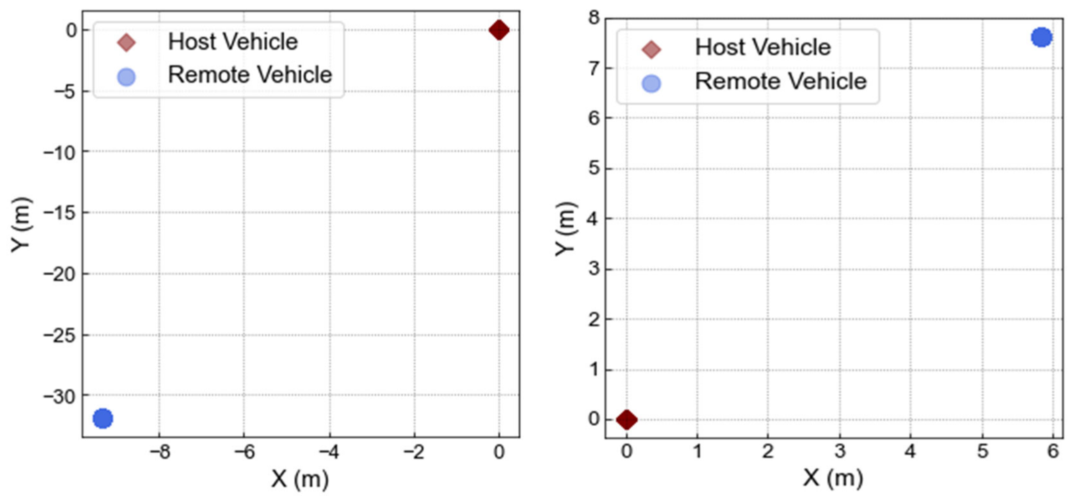
The event trajectories extracted from the BSM data of the six V2V applications are visualized and investigated. Several data cleaning and filtering steps are then applied to remove outliers and events with invalid warnings based on the issues that are identified from the trajectory and event data.

The data cleaning/filtering procedure for V2V applications contains 10 steps in total. Step 1 to 4 concentrate on data issues observed from the event trajectories that are specifically related to the vehicle pairs in each event, which results in somewhat different data cleaning and filtering steps comparing to V2I related application discussed above.

1. Step 1 removes events if there is a substantial elevation difference between the host vehicle and remote vehicle. In some cases, warnings are found to be triggered for host vehicles when the remote vehicle may be moving on a different road above or below it.

To eliminate events with this type of invalid warning, the distance between the host vehicle and remote vehicle based on the Z-axis value in the same event is calculated. Events with an elevation difference larger than a predefined threshold are removed. Based on a trial-and-error approach, 32.8 feet (10 meters) is used as the threshold.

2. Step 2 removes events if both the host vehicle and remote vehicle are stationary as shown in Figure 16 below for the entire event record. Although a sequence of data points was received from both the host and remote vehicle, these data points were overlapping, indicating the stationary status of the two vehicles. Warnings given under this scenario are considered invalid. Events with these warnings should not contribute to the analysis of the application and drivers' behavior of a vehicle in motion, necessitating a data filtering process before further analysis. These events can also be identified when calculating the surrogate safety measures such as time to collision (TTC).

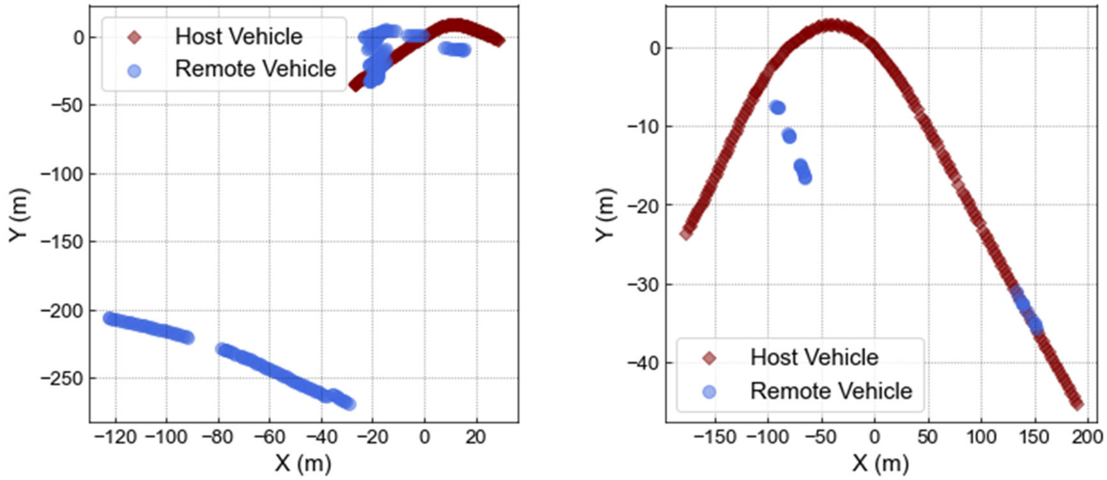


(Source: NYCDOT)

Notes: Left: example from a FCW event; Right: example form a BSW event.

Figure 16. Event Trajectory Example When Host Vehicle and Remote Vehicle are Both Stationary

3. Step 3 removes events if the trajectory of the host vehicle and remote vehicle is discontinuous or unreasonable. Figure 17 illustrates examples of such events. This issue may be due to malfunctioning of the location positioning (e.g. GPS) of the ASD when collecting data from host and/or remote vehicles. These types of events will affect the calculation of surrogate safety measures and need to be filtered. The filtering process is performed by checking the distance of every pair of consecutive records of the trajectory of both the host and remote vehicle in each event. If the distance of any pair of consecutive records is greater than a predefined threshold, then it means the trajectory is discontinuous and the event is discarded. Based on a review of the varying degree of these errors in the event data, a value of 164 feet (50 meters) was used as the threshold.

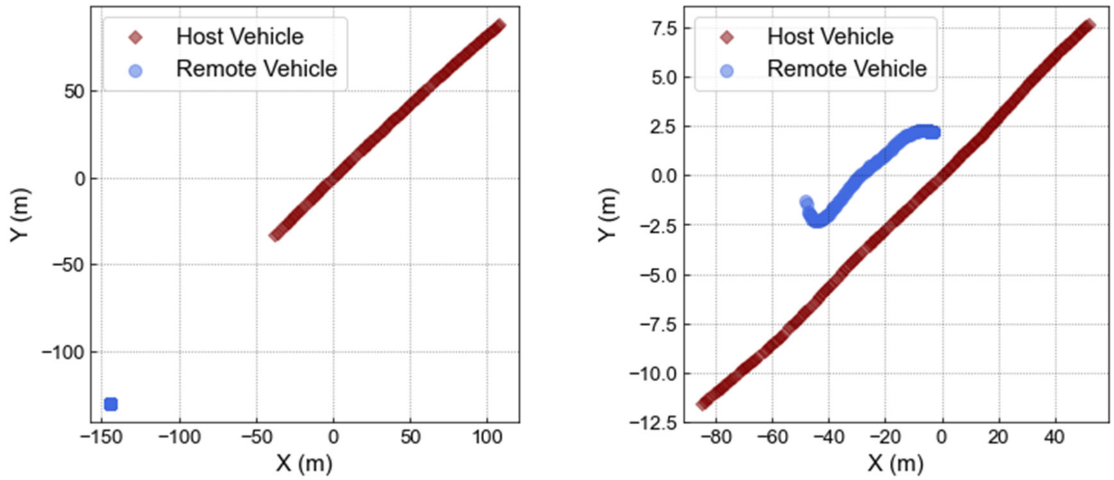


(Source: NYCDOT)

Notes: Left: Example from an IMA Event; Right: Example From a LCW Event

Figure 17. Example When the Event Trajectory of The Host Vehicle and Remote Vehicle is Discontinuous or Unreasonable

4. Step 4 filters FCW events if the host vehicle and remote vehicle are not in the same lane or are too far from each other. This is an issue identified specifically from the FCW application. The FCW is designed in a way that the host vehicle and the remote vehicle should be in the same lane when driving on a straight roadway segment, and the distance between the two vehicles should be lower than a preset threshold. However, for some event records, the host vehicle and remote vehicle are either running in different lanes, or the distance is too large (greater than the threshold) even though they are in the same lane (Figure 18). To filter these event records, the smallest distance between a host vehicle and a remote vehicle on the X-Y plane in the same event is measured and compared with the predetermined threshold. If the distance is greater than the threshold, the event is removed. If the two vehicles are not in the same lane, the event will be identified as “no conflict risk” when calculating the safety performance measure (i.e., TTC) since the two trajectories will not cross, and the event is removed before further analysis.



(Source: NYCDOT)

Figure 18. Event Trajectory Examples Shows the Host Vehicle and Remote Vehicle Are Not in the Same Lane or Are Too Far From Each Other for a FCW Event

5. Step 5 removes events with incorrect pre-warning and post-warning record times. Similar to V2I applications, each V2V application has its own specific pre-warning and post-warning record time (FCW/EEBL with 7 second pre-warning time and 10 second post-warning time, IMA/BSW/LCW with 10s pre-warning time and 10s post-warning time). Hence, events with record times longer than the preset value are considered erroneous and are removed before subsequent analysis. A one-second buffer is considered with the preset record time to account for potential measurement errors.

6. Step 6 is the first of four steps that cleans and filters the data based on issues observed for speed values, and removes events with observed speed values greater than 60 mph. This step removes erroneous and outlying speed values since some very large speed values were observed (e.g., > 300 mph). The threshold of 60 mph was based on the observed speed values after applying the steps discussed above and the typical nature of travel within NYC limits.

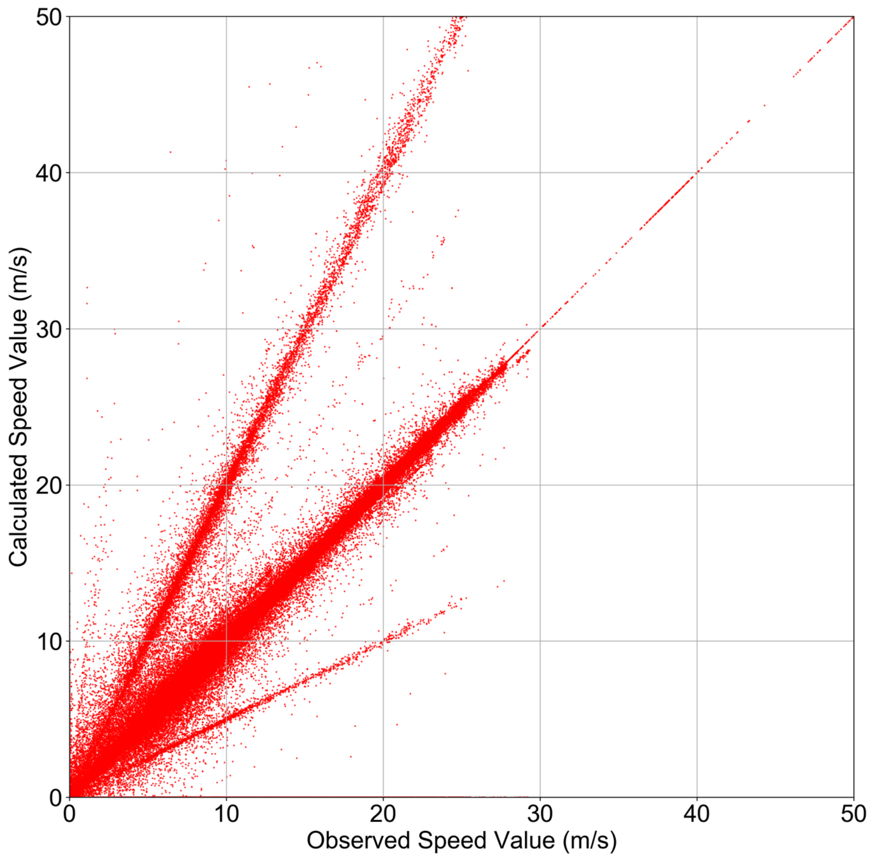
7. Step 7 recalculates speed values based on the corresponding BSM coordinates if recorded speed values for an event are all zero, but its trajectory shows that the vehicle is moving. This step corrects speed observations if observed speed values are all zero during the entirety of the event record time, but the corresponding vehicle is moving. After identifying all the erroneous speed observations, calculations of speeds based on corresponding BSM coordinates were calculated.

8. Step 8 removes events if recorded speed values for some (but not all) BSMs within one action log are zero, but its trajectory shows the vehicle is moving. The proportion of events corresponding to this type is very small and as such any events with these errors were removed from consideration.

9. Step 9 removes events if recorded speed values for an event are equal to a non-zero constant throughout the action log, but its trajectory shows inconstant movement. The

proportion of events corresponding to this type is very small and as such any events with these errors were removed from consideration.

10. Step 10 recalculates speed values based on BSM coordinates if the calculated speed value divided by the observed speed value is not near 1. To further check the observed speed values, calculations for all speed values were developed using BSM coordinates and plotted against the observed speed observations. An example scatterplot that corresponds to speed data from FCW events from July 2021 is shown in Figure 19. Generally, one expects to see the points scattered around the 45-degree line (i.e., the $y = x$ line, indicating y/x ≈ 1), and the vast majority of the points are. However, as can be seen from Figure 19, there are some points that scattered around the $y = 2x$ and $y = 0.5x$ lines, respectively. To correct these types of erroneous speed values, all erroneous speed observations where the ratio of the calculated speed over the observed speed is greater than 1.75 or below 0.75 are identified and replaced in the action log data with speed values calculated from BSM coordinates.



(Source: NYCDOT)

Figure 19. Scatter Plot of Calculated Speed Values vs Observed Speed Values Using FCW Events Collected in July 2021

After all the above data cleaning steps, the percentages of data removed for FCW, EEBL, IMA, BSW, LCW and VTRW are 26%, 43%, 32%, 27%, 28% and 0%, respectively.

Details on the number of obfuscated V2V events that were filtered out of consideration in the evaluation from the above steps can be found in Appendix C.

5.1.1.3 Statistical Methodology Used for Evaluating the Safety Impacts from ASD-Based Data

The experimental design approach applied to ASD data is before-after control-treatment group design. The actual start dates for the before period and after period are January 1, 2021 and May 21, 2021, respectively. However, considering that the detailed date information is obfuscated in the ASD data, the before period and after period within May 2021 cannot be distinguished using the obfuscated ASD data. Thus, ASD data collected in May 2021 is removed to have a clean experimental design for conducting the before-after analysis. After removing the ASD data collected in May, the before period is now defined as the period between January 1 and April 30 and the after period is defined as the period between June 1, 2021 and September 30, 2021. The selection of an end date for after period for use in the evaluation that is prior to the end of Phase 3 (December 31, 2021) was required to ensure the analysis and evaluation could be completed within the contract schedule requirements.

To identify treatment and control groups, the *grpID* variable in the ASD data is used. CVs in the control group are indicated with *grpID* of 20 while CVs in the treatment group are indicated with *grpID* greater than 20. Combining the grpID variable with the start and end dates of the before and after periods, each event can be uniquely identified as either in the before period or the after period and as either in the control group or the treatment group. Another key variable in the ASD data is the *alertActive* variable, which indicates whether the ASD is in active mode and an audio warning was issued to the drivers (*alertActive* = True) or if the ASD was operating in silent mode and no warning was audibly delivered (*alertActive* = False). Based on the experimental design, all CVs in the before period should have *alertActive* = False while CVs in the treatment group in the after period should have an *alertActive* of True and CVs in the control group in the after period should have *alertActive* of False. Accordingly, each event was uniquely classified into the following categories: before or after periods, treatment or control groups, and audio warnings issued or not.

Based on the experimental design approach, audio warnings should be silenced for all equipped vehicles in the control group during both the before and after periods and equipped vehicles in the treatment group in the before period. However, there are some events containing conflicting information that does not conform to the experimental design. These conflicting information events consist of cases in which:

- Treatment group vehicles issuing audio warnings during the before period, or
- Control group vehicles issuing audio warnings during the before period, or
- Treatment group vehicle’s audio warnings were still silent during the after period.

To avoid introducing more confounding factors into the analysis, all events corresponding to these three types of outliers from the experimental design were removed from consideration in the analysis. The number of events removed for each of the above identified conditions are presented in Table 5.

Table 5. Events Not Conforming to the Experimental Design

CV Application	Number of Events After Data Cleaning	Number of Treatment Group Events Active in Before Period	Number of Control Group Events Active in After Period	Number of Treatment Group Events Silent in After Period	Percent of Events Not Conforming to Experimental Design
SPDCOMP	41,766	19	0	1,104	2.7%
CSPDCOMP	27	0	0	0	0.0%
SPDCOMPWZ	2,808	38	9	96	5.1%
RLVW	2,227	0	0	254	11.4%
FCW	12,929	0	2	672	5.2%
BSW	741	0	0	45	6.1%
LCW	862	0	0	45	5.2%
IMA	2,634	1	0	226	8.6%
EEBL	108	0	0	1	0.9%

To evaluate the safety impact of the treatment effect based on the clean before-after control-treatment group design, the gain score method, a commonly used method to analyze this type of design is adopted (Kim and Steiner 2021). The gain score method starts by calculating the mean group change on the value of the safety performance measure from the before period to the after period for both the treatment and control groups, respectively. The mean group change of the control group from the before period to the after period represents the change in the value of the safety performance measure that could be expected to occur without the exposure to the treatment. Analogously, the mean group change of the treatment group from the before period to the after period indicates the change in the value of the safety performance measure that could be expected to occur with the exposure to the treatment. Finally, the gain score method calculates the difference between the mean change in the treatment group and the mean change in the control group, which is the amount of change in the value of the safety performance measure that can be attributed solely to the influence of the treatment after accounting for potentially unobserved confounding factors. The mathematical representation of safety effect of the gain score method is shown below.

$$\text{Safety Effect} = \left(\frac{1}{n_{T,A}}\sum_{i=1}^{n_{T,A}} \mathrm{PM}_i - \frac{1}{n_{T,B}}\sum_{j=1}^{n_{T,B}} \mathrm{PM}_j\right) - \left(\frac{1}{n_{C,A}}\sum_{k=1}^{n_{C,A}} \mathrm{PM}_k - \frac{1}{n_{C,B}}\sum_{l=1}^{n_{C,B}} \mathrm{PM}_l\right)$$

where, $n_{T,A}$ and $n_{T,B}$ represent the total number of events in the treatment group in the after period and before period respectively. $n_{C,A}$ and $n_{C,B}$ represent the total number of events in the control group in the after period and before period respectively. PM is the safety performance measure used in the evaluation.

Due to the obfuscation of the precise date information contained in the event action log data (e.g., only the month and day of week are provided in the time bin in the obfuscated data), safety performance measures are aggregated at the monthly level to apply the gain score design method. Confidence intervals for the estimated treatment effect are constructed by assuming that the sampling distribution of the treatment effect follows student *t*-distribution (Kim and Steiner 2021) and a 0.05 significance level is used to indicate statistical significance. The underlying null hypothesis in the safety analysis of the CV applications can thus be formulated as the estimated safety effect equals zero. If there are no events from the control group during the study period, the step of accounting for unobserved confounding factors by using data from the control group in the gain score method discussed above is omitted. In other words, the second term in the gain score method equation above will be equal to zero in this case. The gain score method is used for ASD-based safety performance measures except crash analysis and for each CV application individually.

5.1.1.4 Driver Behavior Response to Issued Warnings

The majority of the safety performance measures developed from previous studies that can quantify the driver behavior response to in-vehicle warnings can be categorized into the following two categories[2]: deceleration-based measures and time-based measures (see Whitmire II et al. (2011), Yan, Liu, and Xu (2015), J. Yang et al. (2019), and Zhao et al. (2021) for examples). Based on the design logic of CV applications developed in the NYC CVPD, the following three safety performance measures adapted from the literature (Table 6) are proposed to evaluate driver behavior response to CV applications. One corresponds to the deceleration-based measures and two correspond to the time-based measures.

Table 6. Performance Metrics used to Evaluate Driver Behavior Response to Issued Warnings

Identifier	Measures	Definition
DBRPM 1	Deceleration Difference	Difference between maximum deceleration after a warning is given and the deceleration when the warning is given.
DBRPM 2	Time Duration to Slow Down to Speed Limit After Warning	The time duration between the time when a warning is issued to the first time the observed speed is below the corresponding speed limit.
DBRPM 3	Time Duration to First Deceleration After Warning	The time duration between the time when a warning is issued to the first time the driver decelerates.

[2] Note that several studies also used speed-based measures to evaluate driver behavior response. However, considering that deceleration-based measures can also reflect the change in speed and detailed traffic condition and environment at the precise time of warnings are unavailable in NYC CVPD project, this direction was not pursed.

5.1.1.4.1 Driver Behavior Response Performance Measure: Deceleration Difference

The deceleration difference was defined as the difference between maximum deceleration after a warning is given and the deceleration when the warning is given. The goal of deceleration difference is to assess the driver's tendency to slow down, i.e., the driver's response degree (J. Yang et al. 2019). To calculate deceleration difference from the ASD event data based on this definition, the following algorithm is used for each ASD event:

- **Step 1:** Obtain the maximum deceleration value during T_s > 0. In the obfuscated event records, the artificial time scale of T_s provides the time (in seconds) of all BSMs and other CV messages relative to the time of the CV application warning (defined as T_s = 0).
- **Step 2:** Obtain the mean deceleration value between T_s = -0.5 and T_s = 0.5 in accounting for potential random fluctuations and measurement errors in deceleration observations around the time when warning criteria are met.
- **Step 3:** Calculate the difference between the maximum deceleration value obtained in Step 1 and the deceleration value obtained in Step 2.

Based on the algorithm, the deceleration difference represents the difference between the maximum deceleration after the warning and the deceleration at the time of warning. This performance measure is applied across all the CV applications that require the evaluation of driver behavior responses.

5.1.1.4.2 Driver Behavior Response Performance Measure: Time Duration to Slow Down to Speed Limit After Warning

The time duration for slowing down to the speed limit after warning was defined as the time duration between the time when a warning is issued and the first time the observed speed is below the corresponding speed limit. This performance measure is designed specifically for speed-related CV applications, including SPDCOMP, CSPDCOMP, and SPDCOMPWZ. The goal of this performance measure is to assess how fast drivers respond to speed-related warnings to reduce travel speed to the speed limit (Zhao et al. 2021).

To obtain the time duration to slow down to the speed limit after warning from the ASD event data, one only needs to obtain the time when the speed is below the corresponding speed limit for the first time after the warning is issued (in range of T_s > 0) based on the definition above. Since all of the speed-related CV applications aim to reduce vehicle's speed to speed limit after warnings are issued, this performance measure is used across all the speed-related CV applications that require the evaluation of driver behavior responses, namely SPDCOMP, CSPDCOMP, and SPDCOMPWZ.

5.1.1.4.3 Driver Behavior Response Performance Measure: Time Duration to First Deceleration After Warning

The time duration to first deceleration after warning was defined as the time duration between the time when a warning is issued to the first time the driver decelerates. This performance measure is designed specifically for CV applications that do not have specific speed limit thresholds, such as RLVW, VTRW, and PEDINXWALK. The goal of this performance measure is to assess how fast drivers respond to CV applications that aim for deceleration (Zhao et al. 2021).

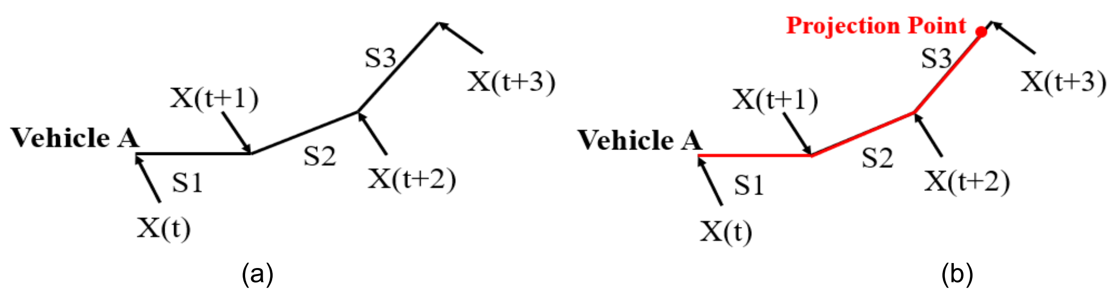
Similar to the second performance measure "time duration to slow down to speed limit after warning" above, to obtain the time duration to first deceleration after a warning is issued from the ASD event data, one only needs to obtain the time when the vehicle decelerates for the first time in the range of T_s > 0 based on the definition above. The logic of this performance measure can be applied to RLVW, VTRW, and PEDINXWALK applications. However, considering that the sample sizes of VTRW and PEDINXWALK events are very small with no data from the before period and control group, this performance measure is only applied for RLVW.

5.1.1.5 Time to Collision Calculation Methods

Time to collision is defined as the time for two vehicles to collide if they continue at their present speeds and on the same path. Based on the Surrogate Safety Assessment Model and Validation: Final Report (Gettman et al. 2008), the calculation of time to collision (TTC) is based on the current location, speed, and future trajectory of two vehicles at a given instant and whether or not there is a conflict event based on preset TTC threshold. The identification of conflicts and the calculation of TTC are discussed briefly in this section. For a more comprehensive discussion of the calculation of TTC, please refer to Gettman et al. (2008).

Based on the preset TTC threshold $\text{TTC}^*(t)$, the conflict identification algorithm projects the expected location of each vehicle in the current vehicle pair as a function of its current speed, if it were to continue traveling along its future trajectory for up to the duration of $\text{TTC}^*(t)$. For example, Figure 20 (a) shows the trajectory of vehicle A between timestamp t and (t +3). Suppose the speed of vehicle A at timestamp t is $v_A(t)$, the projected travel length of vehicle A is defined as $D_{\text{proj}} = v_A(t) \times \text{TTC}^*(t)$. Suppose D_{proj} is larger than $S1 + S2$ and less than $S1 + S2 + S3$, where $S1, S2, S3$ are the lengths of the three segments in Figure 20. Then the projection point can be uniquely located between $X(t + 2)$ and $X(t + 3)$ as illustrated in Figure 20 (b) with the length of the red path equals to D_{proj}.

In this project, the TTC threshold value is set to 5 seconds to identify as many potential conflicts as possible.



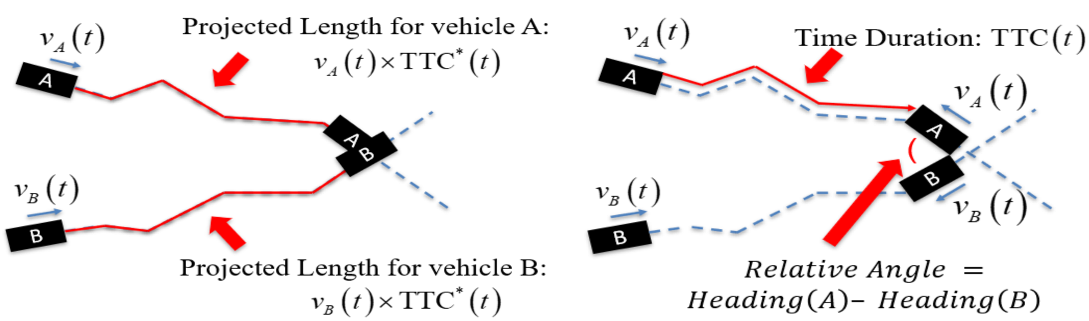
(Source: NYCDOT)

Notes: (a) trajectory of vehicle A for three timestamps starting at timestamp t (adopted from Gettman et al. (2008)); (b) illustration of the projection point of vehicle A.

Figure 20. Illustration of Sample Trajectory and Projection of Future Location

Applying the method described above to the second vehicle in a vehicle pair, one can obtain the projection points for both vehicles. If, after considering the individual vehicle sizes, the two vehicles overlapped at the projection points, as illustrated in Figure 21 (a), then a temporary conflict is recorded. If the two vehicles do not overlap at the projection points, then no conflict is recorded based on the preset TTC threshold.

Suppose a temporary conflict is identified for the current vehicle pair; the next step is to obtain the TTC value corresponding to the current timestamp, i.e., TTC(t). This is done by going backward iteratively by a tenth of a second from the projection points according to the corresponding speeds and the trajectories until the pair of vehicles no longer overlaps in their projected locations, as illustrated in Figure 21 (b). The time duration between timestamp t and the timestamp when the vehicles in the pair no longer overlaps is thus TTC(t). The relative angle, defined as the difference of the headings of the two vehicles at the timestamp when the vehicles forming the pair no longer overlap, is also recorded.



(a) (b)

(Source: NYCDOT)

Notes: (a) a conflict is identified between vehicle A and vehicle B; (b) obtaining the TTC value and the relative angle for this vehicle pair at timestamp. Adopted from NCHRP 03-137 (2021)

Figure 21. Illustration of Conflict Identification

Rear-end conflicts correspond to the absolute value of the relative angle less than 30 degrees, lane-change conflicts correspond to the absolute value of the relative angle larger than 30 degrees and below 85 degrees, and crossing conflict correspond to the absolute value of the relative angle larger than 85 degrees (Gettman et al. 2008). The algorithm then moves on to process all the vehicle pairs and all the timestamps accordingly.

To implement the TTC algorithm discussed above, vehicle trajectories need to have observations that are equally spaced in time and consistent across different vehicles. Due to the delay in BSM data transmission and potential measurement errors, the time of warning may not be exactly at zero second in the observed ASD events and the time intervals between consecutive trajectory points may not be exactly 0.1 second as specified in Phase 2 of NYC CVPD. Thus, ASD event data needs to be post-processed by interpolating vehicle trajectories based on a universal time scale that starts from zero and increases by 0.1 second every step in both the positive and negative directions.

The TTC calculation results suggest that approximately 15% of events with minimum TTC equals zero, which indicates that the corresponding vehicles collide at the time of conflicts. These potentially erroneous result may be due to inaccurate GPS locations and inaccurate vehicle size information. Events with minimum TTC equaling zero are thus removed before conducting the final analysis.

5.1.2 RSU-Based

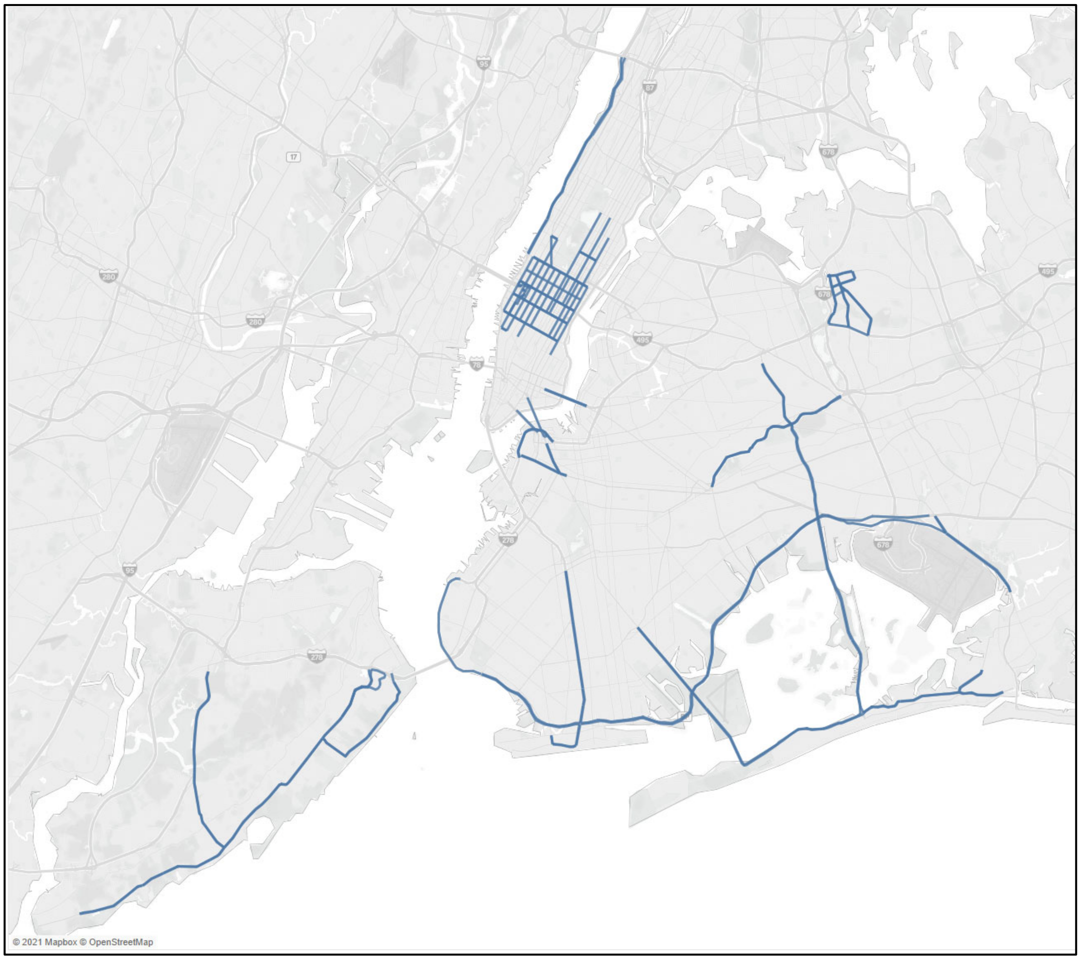
The main performance metric that is collected using data collected from the RSUs relates to the I-SIGDATACV application. The goal of this application is to use CV-based equipment to record probe-vehicle sightings that can be used to calculate travel times of the same equipped vehicles between RSUs. For the NYC CVPD, the question the evaluation is seeking to answer is if the RSU-based data can be used to compute reliable travel time measures for the RSU-equipped roadways and to compare these travel times against those currently collected by non-CV-based technologies, namely the NYCDOT electronic toll collection (ETC) Travel Time System.

5.1.2.1 Travel Time Analysis Methodology

The existing NYCDOT ETC Travel Time System is composed of ETC readers which detect E-ZPass toll tags at key locations. These sightings are then processed to calculate travel time for a set of predefined links which encompass multiple city blocks. Currently, there are 346 ETC defined links throughout NYC. The ETC readers were initially installed to provide travel time data for MIM Active Traffic Management System (ATMS) in Midtown Manhattan in 2011. Over the years, the system has expanded into the outer boroughs. Figure 22 below provides an overview map of ETC Links across NYC.

The ETC Travel Time System data is recorded and processed continuously at the TMC and used in multiple applications including MIM, travel speed flow maps, and data sharing with TRANSCOM for regional data sharing with other agencies. Data recorded in the ETC Travel Time system are individual sightings of an ETC tag traveling along a defined link and record the timestamp, the IDs of the start and stop ETC reader, and the travel time in seconds.

As discussed in section 4.1.2.2, the CV travel time data computed from RSU-based CV sightings uses a similar concept of probe-vehicle based travel time measurements.



(Source: NYCDOT)

Figure 22. ETC Travel Time Link Map Overview

To compare travel time data between the two systems, the analysis considered one ETC Link and the overlapping CV Segments. Figure 23 shows an example on 2nd Avenue from 49th St to 42nd Street.

(Source: NYCDOT)

Figure 23. Sample Comparison of an ETC Link and CV Segments

As the CV segments are shorter than the ETC Link, individual CV segments (6 blocks between 49th Street and 42nd Street) were aggregated to match the single ETC segment. The ETC Travel Time System filters out any data points which are greater than 3600 seconds (on average a 7-8 block segment), and a similar filtering was applied to the CV travel time data where in data points greater than 300 seconds were excluded (usually only one block segment). See

Table 7 below for a sample calculation. Due to the differences in spatial coverage between the two systems and differences in travel time processing methodology, the CV sightings data was used to calculate individual travel time observations for each CV segment. The ETC Travel Time System filters out any data points which are greater than 3600 seconds, therefore, this same filtering was applied to the CV travel time data. These CV segment travel times were then aggregated to match the full ETC Link. See

Table 7 below for a sample calculation.

Table 7. Sample CV Travel Time Aggregation

ETC Link ID	CV Segment ID	Date	Hour Starting	Median Travel Time (seconds)	Aggregated Median Travel Time (seconds)
46-42	120-119	10/13/2021	6:00am	15	n/a
	119-117	10/13/2021	6:00am	35	n/a
	117-116	10/13/2021	6:00am	24	n/a
	116-115	10/13/2021	6:00am	23	n/a
	115-114	10/13/2021	6:00am	45	n/a
	114-113	10/13/2021	6:00am	18	n/a
	Aggregated CV Segments	10/13/2021	6:00am	n/a	15 + 35 + 24 + 23 + 45 + 18 = 160

If there was a period where no sightings were observed for a particular CV segment, then the aggregated travel time is adjusted by applying a scale factor computed as the total aggregated segment distance divide by the sum of the CV segment distances with reported travel time values as shown in Table 8.

Table 8. Sample CV Travel Time Aggregation (Adjusted for Missing Data)

ETC Link ID	CV Segment ID	CV Segment Distance (feet)	Median Travel Time (seconds)	CV Segment Distance with Reported Travel Time (feet)	Unadjusted Aggregated Median Travel Time (seconds)	Adjusted Aggregated Median Travel Time (seconds)
46-42	120-119	254	15	254	n/a	n/a
	119-117	***554***	***No data***	***n/a***	n/a	n/a
	117-116	252	24	252	n/a	n/a
	116-115	290	23	290	n/a	n/a
	115-114	***245***	***No data***	***n/a***	n/a	n/a
	114-113	338	18	338	n/a	n/a
	Aggregated CV Segments	1,933	n/a	1,134	15 + 24 + 23 + 18 = 80	80 * (1,933 / 1,134) = 136.4

In addition, sample size was calculated for each dataset by hour and by time period for comparison. The ETC travel time data sample size is simply the total number of observations for the defined period. Due to the block-by-block coverage of CV segments compared to the single ETC Link, the CV travel time sample size is calculated as an average across the corresponding CV segments as shown below in Table 9.

Table 9. CV Travel Time Sample Size Calculation Example

ETC Link	CV Segment	Date	Hour Starting	Number of Samples	Aggregated CV Sample Size
46-42	120-119	10/13/2021	6:00am	2	n/a
	119-117	10/13/2021	6:00am	3	n/a
	117-116	10/13/2021	6:00am	1	n/a
	116-115	10/13/2021	6:00am	5	n/a
	115-114	10/13/2021	6:00am	1	n/a
	114-113	10/13/2021	6:00am	2	n/a
	Aggregated CV Segments	10/13/2021	6:00am	n/a	(2+3+1+5+1+2) / 6 = **2.3**

Once the CV data was processed, the metrics of sample size, travel time, and speed were compared.

5.1.3 PID-Based

5.1.3.1 Operational Data Logs

To support the evaluation of the PED-SIG application, data logs are collected from the PID units (cell phones running the PID application) when being used by vision impaired pedestrians to cross equipped signalized intersection crosswalks. These log files record time using series-based metrics of the location and movement of the pedestrian, SPaT and MAP messages from the relevant intersection, and system information about the device and its operation (including the messages delivered by and any user interactions with the PID application). The log data are exported in JavaScript Object Notation (JSON) formats.

From this raw log data, performance metrics regarding the use of the PID application are generated and produced. Both aggregated and disaggregated user-based performance measures are computed and all the PII information is removed. The following performance measures are produced based on the raw data source messages:

- Pedestrian crossing speed and crossing travel time
- Times out of crosswalk
- Waiting time at intersection for crossing

Most performance measures focus on the PID log files with LogType: *"MOVEMENT"*. Observations of the participants in the field test are also collected and used as supplemental information for certain performance measures, such as times out of crosswalk (number of times participants veered out of the crosswalk), that need visual field observation and manual data extraction.

It is important to note that no PID data was collected before deployment or during silent operations, as no participants were asked to navigate with the PID unit operating in a silent mode. PIDs will only collect log data while the application is actively being used.

5.2 Crash-Based Analysis

All analyses completed for the evaluation used the Survival Analysis Approach for crash analysis.

5.2.1 Survival Analysis Approach

A survival analysis approach originally proposed by Xie et al. (2019) is adopted to conduct before-after crash analysis for CV applications, especially V2V applications. Compared to traditional before-after methods in traffic safety, such as Empirical Bayes and Full Bayesian methods that often require a proper reference group, the survival analysis approach proposed by Xie et al. (2019) relaxes requirements for the reference group. Considering that V2V warnings can be triggered at any location in NYC as long as the corresponding criteria are met and the exact locations of V2V warnings events are obfuscated in the action log data, it is basically impossible to find a proper reference group for crash analysis. Thus, the survival analysis approach is a suitable observational before-after method for evaluating the safety benefits of V2V applications.

Briefly, the survival analysis approach is often used to analyze data of the time until the event is of interest. The response variable is often referred to as a failure time, survival time, or event time. In traffic safety, the response variable is the time until a crash occurs, which can be viewed as a transportation system failure. By modeling the time between each pair of consecutive crashes as the Exponential distribution, the distribution of cumulative crash counts is the Poisson distribution. Considering that crash frequency often follows Negative Binomial distribution (i.e., Poisson-Gamma mixture), the Exponential distribution is mixed with Gamma distribution to account for the potential overdispersion in crash frequency (Lord and Mannering 2010). By regressing the time between each pair of consecutive crashes on a binary treatment indicator that equals 0 during the before period and 1 during the after period as well as other relevant variables, the estimated coefficient of the binary treatment indicator represents the change in the number of crashes due to the treatment. The model specification is shown in the following equations.

$$f\left(t_{ij}|\lambda_{ij}\right) = \lambda_{ij}\, exp\left(-\lambda_{ij} t_{ij}\right)$$

$$\log(\lambda_{ij}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{pij} + \beta_T \text{Treatment}_{ij} + \varepsilon_j$$

where, λ_{ij} denotes the crash hazard parameter during the ith time interval at the jth site. t_{ij} denotes the ith time interval at the jth site. β_0, β_p, and β_T are model coefficients to be estimated. A random effect term ε_j is incorporated to account for the unobserved heterogeneity across different sites, where $\exp(\varepsilon_i) \sim gamma(1/k,\ 1/k)$. k is the dispersion parameter. Based on the model specification, the crash modification factor (CMF), a multiplicative factor used to compute the expected number of crashes after implementing a given countermeasure, can thus be calculated as $\mathrm{CMF} = \exp(\beta_T)$. After estimating the CMF, the expected number of crashes after implementing a given countermeasure is thus $CMF \times number\ of\ crashes\ in\ the\ before\ period$. Please refer to Xie et al. (2019) for more details about the survival analysis approach. The survival analysis method is used for crash-based safety performance evaluations.

As discussed in section 5.1.1.3, in order to obtain a clean experimental design, the start date of the after period for evaluating safety effect using ASD event data is set as June 1st, 2021. Thus, to be consistent with the ASD-based safety performance evaluation, the before and after periods of crash analysis are defined as January 1st, 2021 to May 31st, 2021 and June 1st, 2021 to September 30th, 2021.

To assess the safety effect of CV applications, crashes and crash records need to be acquired to calculate exposure of crashes, a key variable in crash analysis in traffic safety. There are two major databases that possess crash records in NYC: the NYPD database that is open to the public on NYC Open Data Portal and the NYS DMV database generated by regularly reconciling DMV records with NYPD database. The update of NYPD crash records is much faster than NYS DMV crash records with only a few days lag, but the contributing factors of NYPD crash records are not very detailed compared to NYS DMV crash records. Hence, to conduct crash-based analysis given schedule demands of the NYC CVPD, the NYPD crash database with relatively short update time lag is preferred despite the lack of detailed crash contributing factors.

There are two V2I applications and five V2V applications that require crash-based analysis, namely CSPDCOMP, PEDINXWALK, FCW, EEBL, BSW, LCW, and IMA. Because police crash records cannot be tied to the equipped vehicles due to privacy/liability concerns, crash records corresponding to each CV application are selected based on the instrumented locations and targeted crash types. Specifically, crashes corresponding to CSPDCOMP and PEDINXWALK are selected based on the instrumented locations.

In terms of FCW and EEBL applications, since they both target rear-end crashes, FCW and EEBL applications need to be grouped together for before-after crash analysis (i.e., only the combined safety effect for both FCW and EEBL can be estimated). Rear-end crashes are selected by choosing crashes with contributing factors equal to “following too closely” in the NYPD crash database. Similarly, BSW and LCW applications both target side-swipe crashes, so applications are also grouped together for before-after crash analysis. Side-swipe crashes are selected by choosing crashes with “unsafe lane changing” in the NYPD crash database. The IMA application mainly targets left-turn crossing and head-on crashes. However, there is no clear contributing factors that correspond to these two types of crashes. Thus, crash analysis for IMA application is not conducted as discussed in section 6.8.

Crashes need to be further divided into three severity levels: fatal (at least one death), injury (at least one person injured but no death), and property damage only (PDO) (no injury or death) for subsequent before-after analysis. The following two variables in the NYPD crash database, namely *Number of Persons Injured* and *Number of Persons Killed*, are used to divide crashes into the three severity levels. Specifically, PDO crashes correspond to *Number of Persons Injured* = 0 and *Number of Persons Killed* = 0. Injury crashes correspond to *Number of Persons Injured* > 0 and *Number of Persons Killed* = 0. Fatal crashes correspond to *Number of Persons Killed* > 0.

In addition to crash records, a key variable that is commonly used in crash analysis in the field of traffic safety is traffic volume, which is often treated as the main exposure indicator for crashes. The need to account for traffic volume in crash analysis stems from the fact that the implementation horizon of the NYC CVPD overlaps with the COVID-19 recovery process in NYC. There are two primary requirements for choosing traffic volume for crash analysis for NYC CVPD, which are: 1) traffic volume data needs to reflect the general COVID-19 recovery process in NYC, and 2) the aggregation level of traffic volume data needs to be detailed enough so that traffic volume between each two consecutive crashes can be obtained, which is required by the survival analysis approach. As a result, MTA bridges and tunnels traffic volume data (New York's Open Data Portal 2020) that are open to the public and aggregated at the hourly level and cover major bridges and tunnels on the east side of NYC were selected as the exposure for crashes in crash-based before-after analysis. For details on how to prepare traffic volume data for the survival analysis approach, please refer to Xie et al. (2019).

5.3 Simulation Assessment

In order to help evaluate performance metrics that cannot be adequately collected in the field or are infeasible to collect given the nature of the NYC CVPD, additional analysis was completed using traffic simulation assessments.

5.3.1 SSM Simulation Analysis Methods

Besides analyzing ASD-based data and crash records, a surrogate safety measure (SSM) based simulation analysis method is also used to quantify safety benefits associated with changing driver behaviors. The goal of using this SSM-based simulation approach is to isolate the benefits from individual CV apps and eliminate the impacts of confounding factors, both items that cannot be reasonably achieved in the direct field observations planned. TTC, a commonly used SSM, is obtained from vehicle trajectories as indicators of safety performance.

Using existing research on surrogate safety measures and simulation modeling, an open-source micro-simulator called Simulation of Urban Mobility (SUMO), is used for this study. Simulation-based SSM has been proved to be an effective tool for conducting safety assessment of traffic systems (Ozbay et al. 2008) and several studies suggest the use of SUMO to investigate the safety impact of connected and automated vehicles (Zuo et al. 2020; Richter et al. 2019; Lücken et al. 2019). In addition, FHWA uses SUMO as one of the core simulation components in their Cooperative Automation Research Mobility Application (CARMA) platform for automated vehicles research (FHWA 2021).

A SUMO-based microsimulation model covering Flatbush Avenue in the CV pilot test area is used to reduce the stochastic noise in large scale models and to better isolate just the impacts of the before and after effects on driver behaviors and actions from the CV deployment. This microsimulation model differs from the traditional approaches that calibrate only operational measures such as traffic counts and speed, instead combining both operational and safety measures to match real-world traffic conditions (e.g., traffic conflict distribution) and multi-objective stochastic optimization into the model calibration process. Real-world driver behaviors are extracted from ASD data and the observed behavior changes are incorporated into the SSM simulation approach.

5.3.1.1 Model Background and Calibration

As a supplemental safety evaluation approach to the observational data, the use of the microscopic traffic simulation model allows for confounding factors to be controlled in the simulation environment. To implement and test the CV applications in simulation, the prerequisite is to calibrate and validate a base model which represents the real-world pre-CV deployment traffic conditions. The base model used in this program is based on an urban road segment in Brooklyn, NY. The 1.6-mile road segment is on Flatbush Avenue between Tillary Street and Grand Army Plaza, which is one of the pilot test sites. Flatbush Avenue is a bi-directional, North-South urban corridor with eight lanes (four in each direction) with a median from Tillary Street to Fulton Street, and six lanes (three in each direction) from Fulton Street to Grand Army Plaza. There is one parking lane on each side. Intersections within two or three blocks from Flatbush Avenue/Tillary Street and Flatbush Avenue/Grand Army Plaza are also included as buffer intersections in the model. The studied time period is the morning peak period (between 6:00 AM and 10:00 AM).

The simulation software used in this study is an open-source micro-simulator called SUMO. Compared with other commonly used commercial simulation software packages (Hong Yang (2012b)), the advantages of SUMO are three-fold. Firstly, it is an open-source software which provides flexibility in building a CV environment and programming CV application algorithms and in allowing developers to make constant improvements. Several studies have utilized SUMO in a connected and automated vehicle environment (Gao et al. 2017; Zuo et al. 2020). SUMO was also adopted as one of the key simulation components for FHWA's CARMA℠ platform (FHWA 2021), in advancing Transportation Systems Management and Operations (TSMO) strategies with cooperative driving automation (CDA). Secondly, it can represent real-world traffic scenarios more realistically with its combination of embedded functions and flexible modules. Lastly, it can be run in a parallel mode which significantly reduces simulation running time. This is crucial for simulating large traffic networks and calibrating simulation models that utilize complicated algorithms, as is the case with this project. For these reasons, SUMO was selected as the preferred simulation software for this project. The simulation network of the Flatbush Avenue built using SUMO is shown in Figure 24 below.

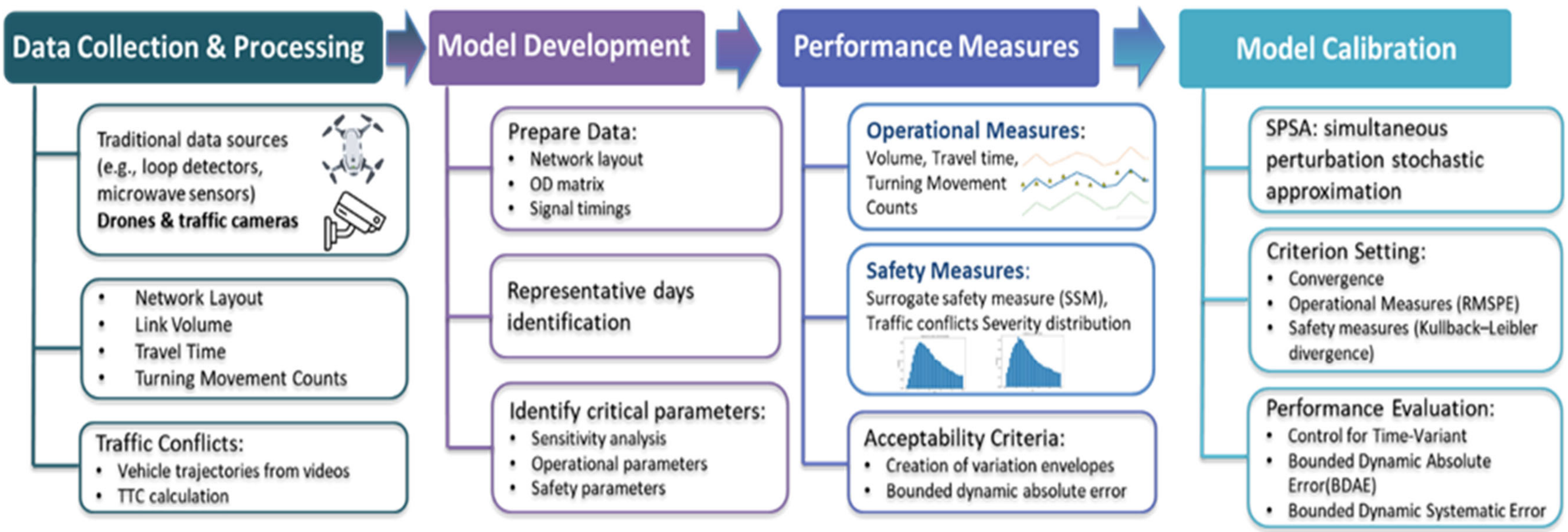
(Source: NYU C2SMART Center)

Figure 24. Flatbush Avenue Simulation Network Developed in SUMO

Roadway geometry, lane usage, link capacity, speed limit, lane and turn connectivity, and other parameters were thoroughly included in the base model. Besides network topology, other basic road network information (such as signal timings and bus stops) was obtained and integrated into the development of the simulation network.

The unique modeling challenge of the base scenario is that the data for safety measures, such as traffic conflicts, must be calibrated along with the operational measures. This model differs from the traditional approaches that calibrate only operational measures such as traffic counts and speed, instead combining traffic conflict techniques and multi-objective stochastic optimization into the model calibration process (H. Yang 2012a; Mudigonda and Ozbay 2015). Real-world conflicts are extracted using vehicle trajectories from a total of 14 hours of drone and traffic camera videos. Field data including traffic counts, travel times, and traffic conflict distributions were collected in 2019 to be compared with the simulation outputs for model calibration and validation purposes of the before CV conditions model.

Instead of simply comparing the number of traffic conflicts between simulated and observed data, the conflict distribution of different severity levels categorized by TTC values is employed as the main safety performance measure. The concept of Kullback–Leibler divergence is adopted to quantify the discrepancy between simulated and observed conflict distributions. Simultaneous perturbation stochastic approximation (SPSA) (James C. Spall 1999; J. C. Spall 1988) can efficiently approximate the gradient of the multi-objective stochastic loss function at a large scale. SPSA is used to find the optimal simulation model parameters that minimize the total simulation error of both operational and safety performance measures (Sha, Ozbay, and Ding 2020). Figure 25 demonstrates the calibration framework used for the base model.



(Source: NYU C2SMART (New York University C2SMART Center (2020))

Figure 25. Calibration Framework for the Base Model

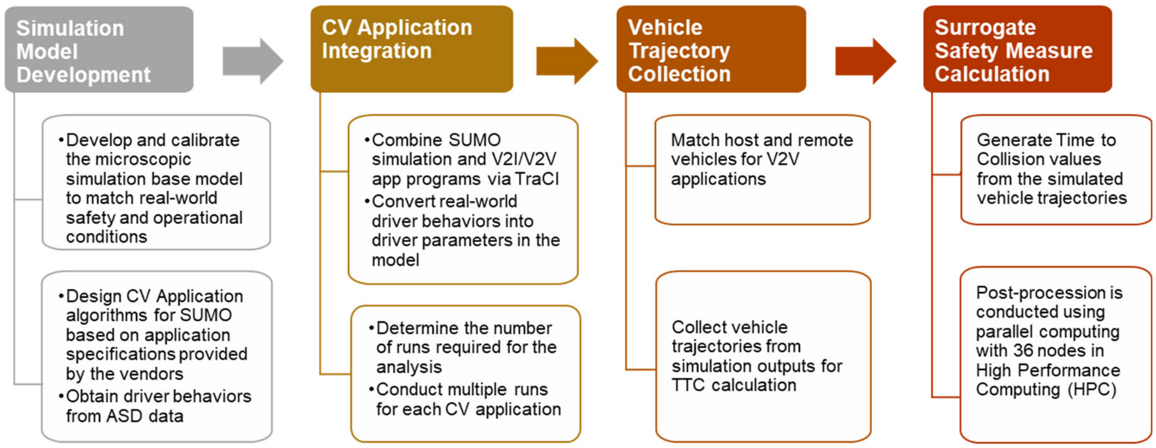
Multiple key parameters, such as acceleration and minimum gap, are considered random variables and are calibrated as probability distributions based on the “trajectory data” extracted from the drone videos to capture the real-world conditions. Considering the stochastic nature of microscopic simulation and the variance of the input data, multiple simulation runs with different random seeds are conducted to achieve a pre-determined level of variance reduction of the output of stochastic simulation model with the objective of calibrating simulation parameters that are accurate at an acceptable level with a significance level of 95%. Representative days are identified to create variation envelopes for travel times and traffic volumes. Four acceptability criteria suggested by the FHWA 2019 Guidelines are used for performance evaluation: control for time-variant outliers and inliers, bounded dynamic absolute, and system error (Wunderlich, Vasudevan, and Wang 2019).

The results show that the calibrated parameters can significantly improve the performance of the simulation model to represent real-world traffic conflicts as well as operational conditions. The simulated outputs are in good agreement with the observed traffic counts, travel times, and conflict distributions. A relatively low average Kullback–Leibler divergence value of 0.0223 is found, confirming the similarity between simulated and observed conflict distributions. This also demonstrates the usefulness of vehicle trajectory data and the applicability of the proposed model calibration framework for calibrating both operational and safety measurements simultaneously. By setting up the calibration problem as a multi-objective stochastic optimization problem, the calibrated model can be used to more accurately evaluate the safety benefits of CV applications. More details about the base model calibration can be found in the report by the research team (New York University C2SMART Center (2020)).

5.3.1.2 Simulation-based SSM Analysis Framework

Figure 26 shows the framework of the proposed simulation based SSM analysis. Four key steps are introduced: 1) simulation model development, 2) CV application integration, 3) vehicle trajectory collection and 4) SSM calculation. After the base scenario of the microscopic simulation model has been fully developed, calibrated, and validated, the algorithm of the seven CV applications that are being field tested as a part of NYC CVPD are developed using python language. All the algorithms are designed based on the CV applications specifications provided by the vendors. In addition, real-world driver behavior information is obtained from the ASD data. Second, these driver behaviors are analyzed using cluster analysis and converted into driver parameters in the SUMO model. Each application algorithm with its driver behavior model is imported into SUMO separately as an internal module and the simulation runs are conducted via a real-time traffic control interface. The mechanism of this interface will be described in detail in Section 5.3.1.3.

Next, to accurately account for the stochasticity due to random seeds, the simulation model of each application is run multiple times and a sequential approach is used to determine the proper number of runs to meet the required sample size (see more details in Section 5.3.1.5). In this step, vehicle pairs (host and remote vehicle for each event) are also identified for V2V applications. Information including timestamps, coordinates, speed, and heading angles, are obtained from the simulation outputs for TTC calculation. The detailed TTC calculation algorithm is described in Section 5.1.1.5. The High Performance Computing (HPC) system and the parallel computing technique are used to increase the computing speed since the TTC calculation demands considerable computing power to compute the large number of objects in the simulation outputs. Thirty-six computing nodes are used, and each node utilizes 25 cores and 30GB memories simultaneously.



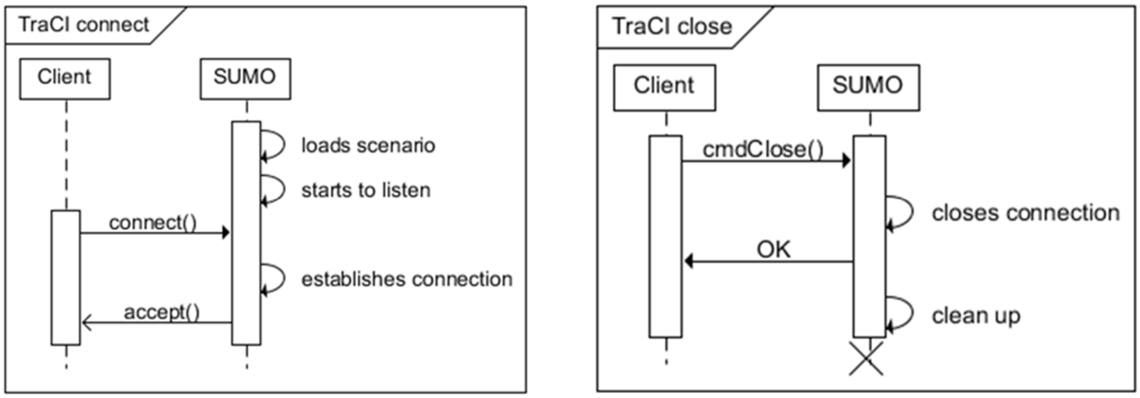
(Source: NYU C2SMART Center)

Figure 26. Framework of the Proposed Simulation Based SSM Analysis Using SUMO

5.3.1.3 Connected Vehicle APP Integrations into the calibrated SUMO simulation model

After the base case simulation model has been fully calibrated and validated, seven CV applications that are being field tested as a part of NYC CVPD are integrated into the SUMO model for safety evaluation. These seven applications are: forward collision warning (FCW), electronic emergency brake light (EEBL), blind spot warning (BSW), lane change warning (LCW), red light violation warning (RLVW), vehicle turning right in front of bus warning (VTRW), and pedestrian in signalized crosswalk warning (PEDINXWALK). It is noted that the design logic and integration of the application into SUMO are based on the CV application specifications provided by the CV application vendors as of July 22, 2020.

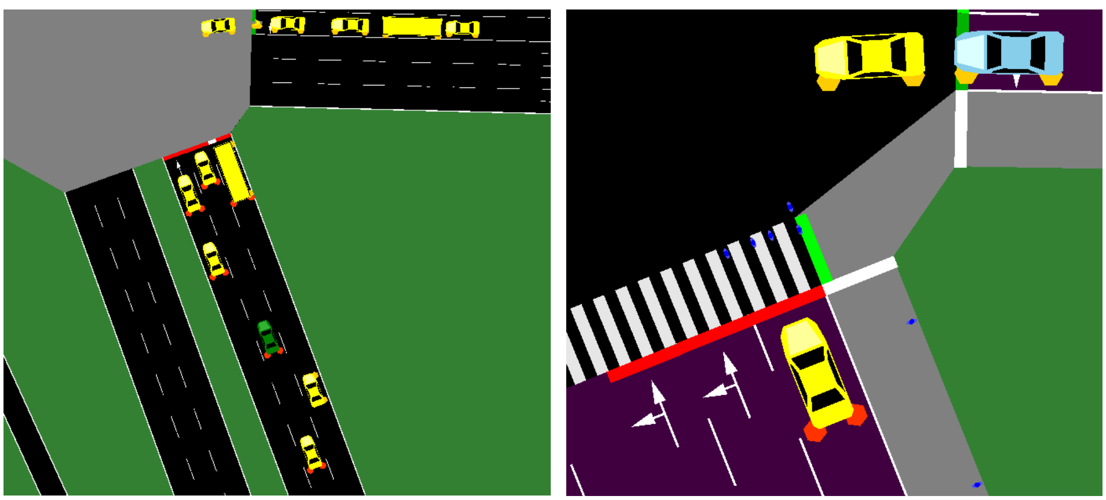
The key feature used to embed customized CV applications into the SUMO model is called Traffic Control Interface (TraCI), which is one of the most important features of SUMO. It is developed by an external institution and expands SUMO's functionality by connecting an external application to SUMO using sockets, providing a platform to interact with a running simulation online (Wegener et al. 2008). TraCI allows users to retrieve attributes of vehicles, traffic lights, induction loops, road infrastructure, and other simulation objects to control or change the state of simulated objects (e.g., the phase of signals and the route choice of vehicles). TraCI can be written using different coding languages such as Python, Java, C++, MATLAB, and .NET. It combines SUMO with communication network simulators for simulating vehicular communication. The mechanism of interaction between TraCI and SUMO is shown in Figure 27 (Wegener et al. 2008).



(Source: (Wegener et al. 2008))

Figure 27. Calibration Framework for the Base Model Mechanism of TraCI Interacting with SUMO

Demonstrations of the simulation producing FCW and PEDINXWALK events are illustrated in Figure 28. The left image shows a FCW event, where the green vehicle has received a FCW warning. The right image shows a PEDINXWALK event, as the blue vehicle receives a PEDINXWALK warning based on pedestrians it the conflicting crosswalk.



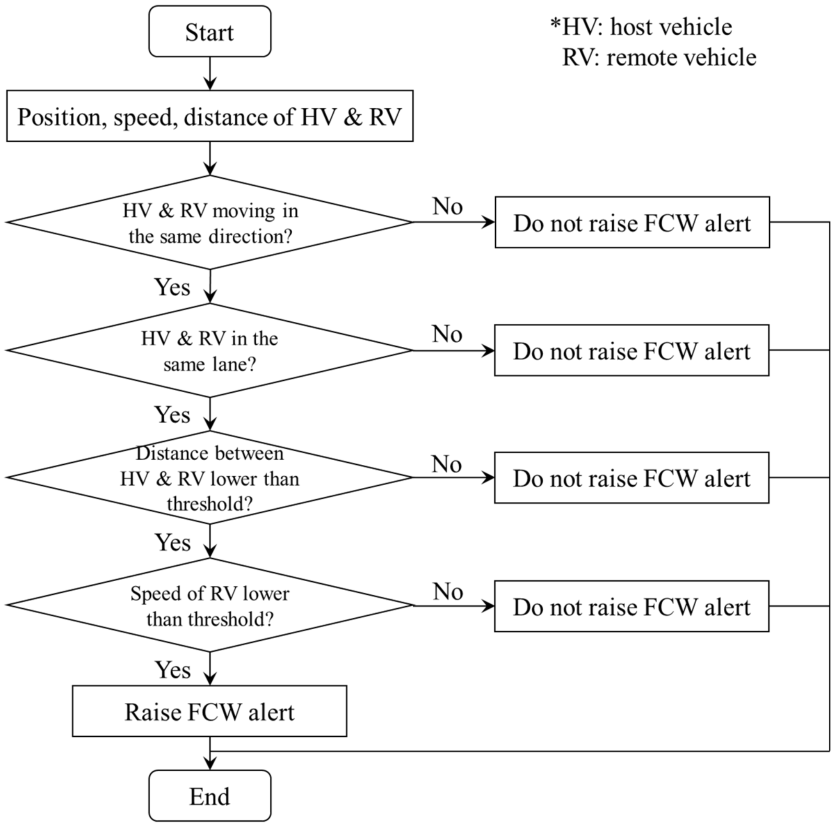
(Source: NYU C2SMART Center)

Figure 28. Demonstrations of the SUMO Simulation (FCW and PEDINXWALK)

In the following subsections, the design logic and integration methodology of seven NYC CV pilot applications in the simulation environment are introduced.

5.3.1.3.1 Forward Crash Warning (FCW)

The objective of FCW application is to inform the driver about a slowed or stopped vehicle ahead in traffic. When moving on a straight road segment, the host vehicle and remote vehicle should be in the same lane, which is an important condition for implementation. To implement this application under the simulation environment, two remote vehicles that are right ahead of the host vehicles need to be checked. To ensure the FCW application is triggered under the right use cases, different scenarios are checked with the consideration of the relative positions of the host vehicle and remote vehicles, such as if they are in the same lane, near lane, or far lane while traveling in the same direction or opposite direction. Figure 29 below shows this scenario checking process and the design logic of FCW application. As mentioned previously, the logic to integrate the CV application into SUMO are designed by the research team based on the NYC CVPD application specifications provided by the vendors as of July 22, 2020.



(Source: NYU C2SMART Center)

Figure 29. Design Logic of the FCW Application in SUMO

In SUMO, the FCW application can be implemented through TraCI. This interface allows users to retrieve vehicles' leading vehicle ID, speed, acceleration information. For the implementation of FCW application, the following functions are used:

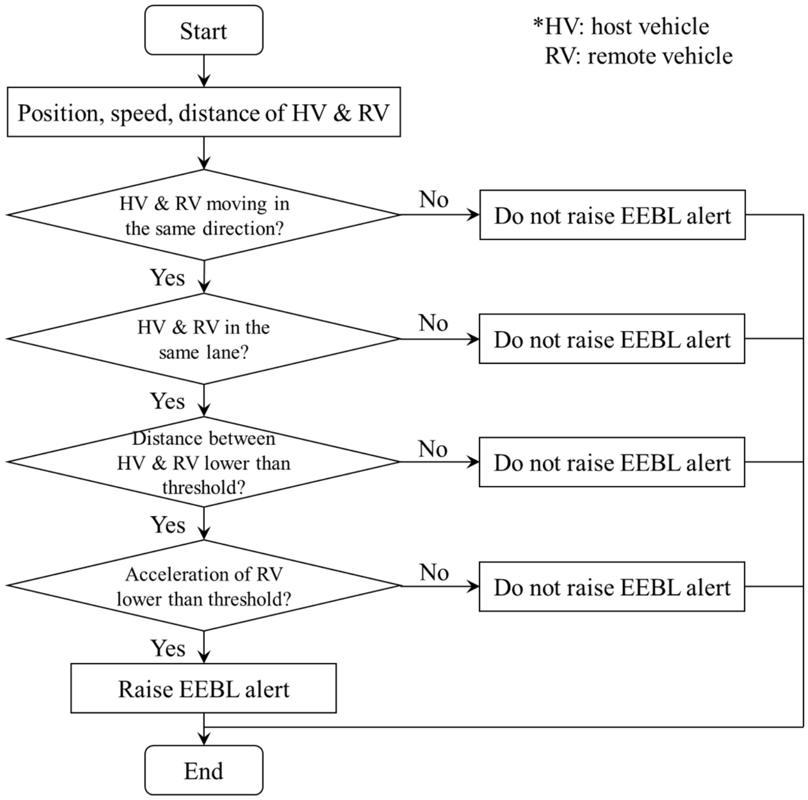
- *getLeader* (Retrieve the leading vehicle's ID and distance of the named vehicle)
- *getLanePosition* (Retrieve the position of the named vehicle along the lane)
- *getSpeed* (Retrieve the speed of the named vehicle)
- *getAcceleration* (Retrieve the acceleration of the named vehicle)
- *setSpeed* (Update the speed of the named vehicle)
- *setAccel* (Update the maximum acceleration of the named vehicle)

The pseudo code for the implementation of FCW application in SUMO is shown below.

```
Initialize HV ID
Retrieve the leading vehicle ID of HV as RV_1
Retrieve the lane position of HV and RV_1
Retrieve the acceleration of RV_1
If the distance between HV and RV_1 is below threshold & speed of RV_1 is below threshold
        Raise FCW alert
Else
        Retrieve the leading vehicle ID of RV_1 as RV_2
        Retrieve the lane position of HV and RV_2
        Retrieve the acceleration of RV_2
        If the distance between HV and RV_2 is below threshold & speed of RV_2 is below threshold
                Raise FCW alert
        Else
                Do not raise FCW alert
```

5.3.1.3.2 Electronic Emergency Brake Light (EEBL)

The objective of the EEBL application is to inform the driver about a hard braking event by a vehicle ahead in the traffic stream. Like the FCW application, the EEBL application also requires that the host and remote vehicle to be in the same lane when moving on a straight road segment. To implement this application under the simulation environment, two remote vehicles that are right ahead of the host vehicle need to be checked. To make sure the EEBL application is triggered under the right use cases, different scenarios are checked with consideration of the relative positions of the host vehicle and the remote vehicle, such as in the same lane, near lane, or far lane while traveling in the same direction or opposite direction. Figure 30 below shows this scenario checking process and the design logic of EEBL application.



(Source: NYU C2SMART Center)

Figure 30. Design Logic of the EEBL Application in SUMO

In SUMO, TraCI functions that allow users to retrieve vehicles' position, speed, acceleration, and leading vehicle information can be applied to implement the EEBL application. In this study, the following functions are used:

- *getLeader* (Retrieve the leading vehicle's ID and distance of the named vehicle)
- *getLanePosition* (Retrieve the position of the named vehicle along the lane)
- *getSpeed* (Retrieve the speed of the named vehicle)
- *getAcceleration* (Retrieve the acceleration of the named vehicle)
- *setSpeed* (Update the speed of the named vehicle)
- *setAccel* (Update the maximum acceleration of the named vehicle)

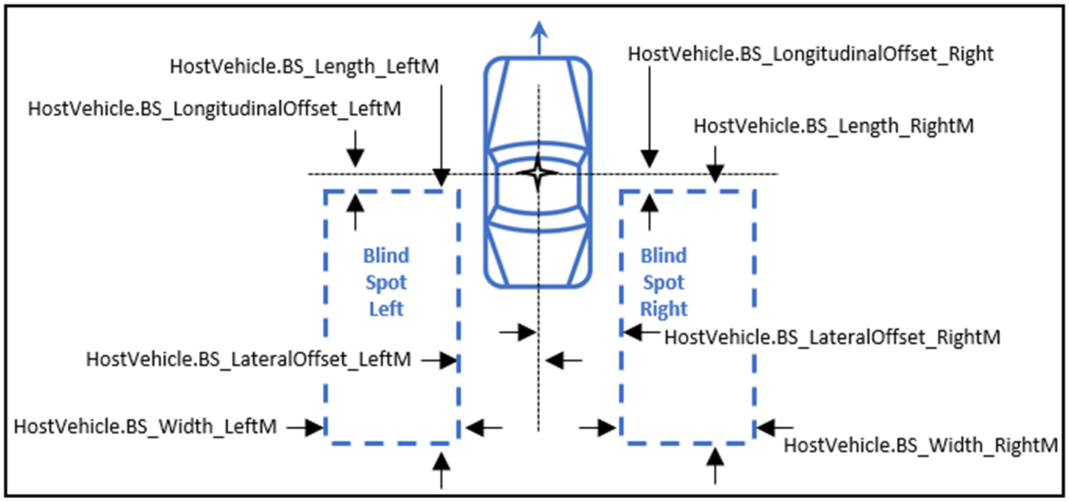
The pseudo code for the implementation of the EEBL application in SUMO is shown below.

```
Initialize HV ID
Retrieve the leading vehicle ID of HV as RV_1
Retrieve the lane position of HV and RV_1
Retrieve the acceleration of RV_1
If the distance between HV and RV_1 is below threshold & RV_1 has hard braking
        Raise EEBL alert
Else
```

```
Retrieve the leading vehicle ID of RV_1 as RV_2
Retrieve the lane position of HV and RV_2
Retrieve the acceleration of RV_2
If the distance between HV and RV_2 is below threshold & RV_2 has hard braking
        Raise EEBL alert
Else
        Do not raise EEBL alert
```

5.3.1.3.3 Blind Spot Warning (BSW)

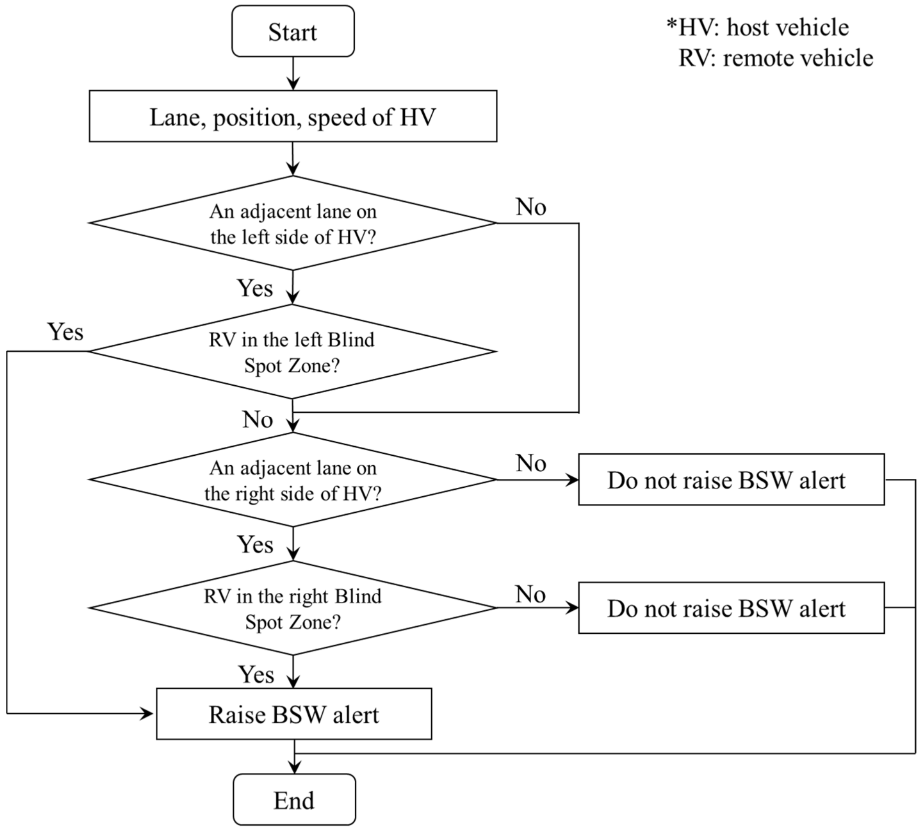
The objective of the BSW application is to provide drivers with advisory alerts when there is a remote vehicle inside the configured Blind Spot Zone of the host vehicle. The Blind Spot Zone configuration is shown in Figure 31 below.



(Source: Adapted from CohdaWireless 2017)

Figure 31. Illustration of Blind Spot Zone Configuration

To implement the BSW application, the adjacent lanes on both sides of the host vehicle need to be checked. If there is a remote vehicle inside the configured Blind Spot Zone on either side, the alert should be activated. Figure 32 below shows the Blind Spot Zone checking process and the design logic of BSW application.



(Source: NYU C2SMART Center)

Figure 32. Design Logic of the BSW Application in SUMO

In SUMO, TraCI functions that allow users to retrieve vehicles' lane, position, and speed information can be applied to implement the BSW application. In this study, the following functions are used:

- *getLaneID* (Retrieve the ID of the lane of the named vehicle)
- *getLanePosition* (Retrieve the position of the named vehicle along the lane)
- *getSpeed* (Retrieve the speed of the named vehicle)
- *setSpeed* (Update the speed of the named vehicle)
- *setAccel* (Update the maximum acceleration of the named vehicle)

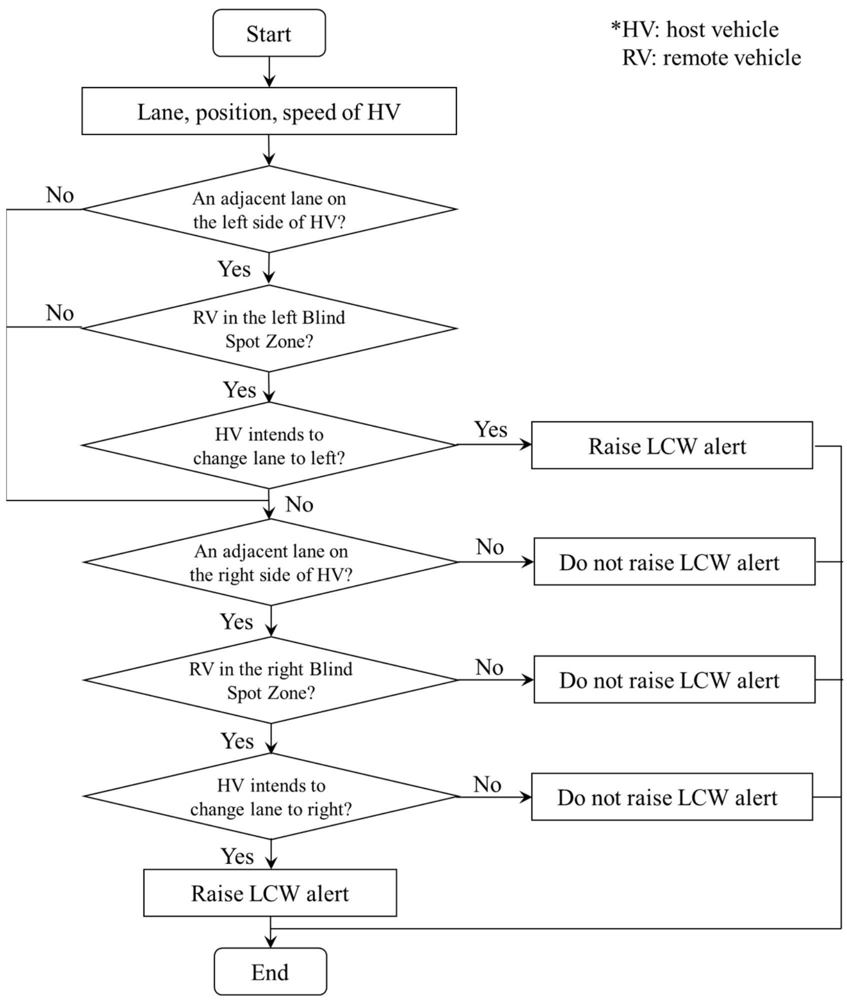
The pseudo code for the implementation of BSW application in SUMO is shown below.

```
Initialize HV ID
Retrieve the lane of HV
Retrieve the lane position and speed of HV
If there is an adjacent lane on the left of HV
    If there is an RV inside the left Blind Spot Zone & speed of HV is greater than threshold
        Raise BSW alert and Break
If there is an adjacent lane on the right of HV
    If there is an RV inside the right Blind Spot Zone & speed of HV is greater than threshold
```

```
        Raise BSW alert
    Else
        Do not raise BSW alert
Else
    Do not raise BSW alert
```

5.3.1.3.4 Lane Change Warning (LCW)

The objective of the LCW application is to warn the driver when it is not safe to change lanes due to a high collision probability with other remote vehicles. In other words, when the host vehicle intends to change lane and there is a remote vehicle inside the configured Blind Spot Zone at the same time, the application will be activated and warn the driver to react to the situation (e.g., preparation for braking, stopping unsafe lane change, etc.). The design logic of LCW application is similar with the BSW application. However, an important requirement for the LCW application to be activated is that the host vehicle should have an intention to change lanes to the side where a remote vehicle is inside the configured Blind Spot Zone. The design logic of LCW application is shown in Figure 33 below.



(Source: NYU C2SMART Center)

Figure 33. Design Logic of the LCW Application in SUMO

In SUMO, TraCI functions that allow users to retrieve vehicles' lane, position, speed, and signal information can be applied to implement the LCW application. In this study, the following functions are used:

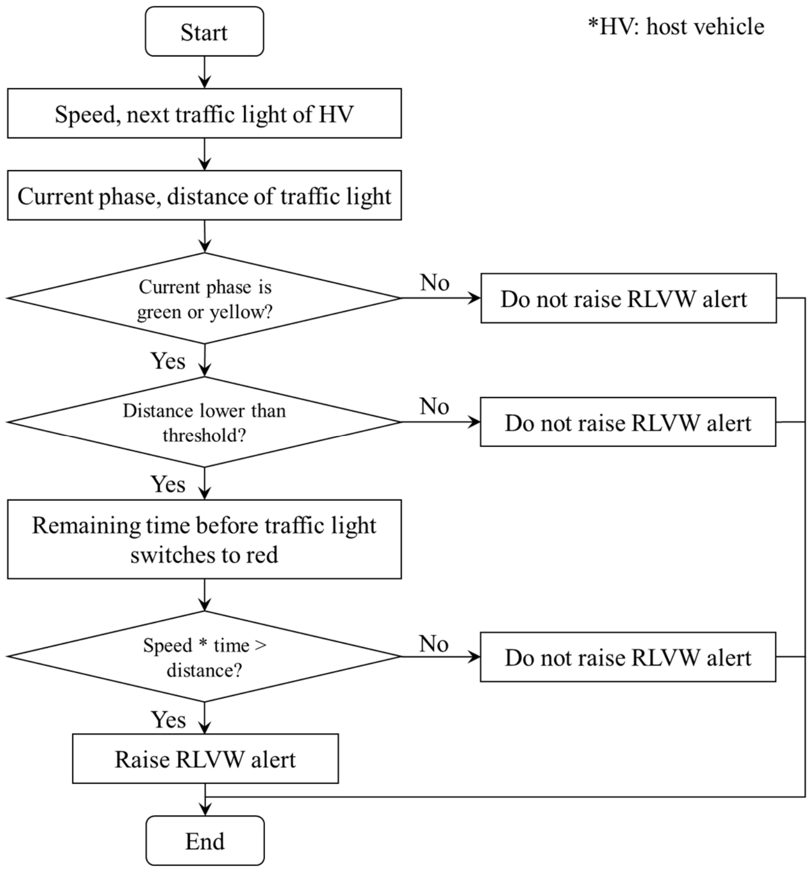
- *getLaneID* (Retrieve the ID of the lane of the named vehicle)
- *getLanePosition* (Retrieve the position of the named vehicle along the lane)
- *getSpeed* (Retrieve the speed of the named vehicle)
- *getSignals* (Retrieve the signal state of the named vehicle, including blinking right, blinking left, brake light, etc.)
- *setSpeed* (Update the speed of the named vehicle)
- *setAccel* (Update the maximum acceleration of the named vehicle)

The pseudo code for the implementation of LCW application in SUMO is shown below.

```
Initialize HV ID
Retrieve the lane of HV
Retrieve the lane position and speed of HV
If there is an adjacent lane on the left of HV & HV's signal indicates left
        If there is an RV inside the left Blind Spot Zone
                Retrieve the speed of RV
                If the speed of RV is greater than HV
                        Raise LCW alert and Break
If there is an adjacent lane on the right of HV & HV's signal indicates right
        If there is an RV inside the right Blind Spot Zone
                Retrieve the speed of RV
                If the speed of RV is greater than HV
                        Raise LCW alert and Break
                Else
                        Do not raise LCW alert
        Else
                Do not raise LCW alert
Else
        Do not raise LCW alert
```

5.3.1.3.5 Red Light Violation Warning (RLVW)

The objective of the RLVW application is to warn the driver about the potential risk of violating the red light of the upcoming signalized intersection. In the simulation environment, the distance of the host vehicle to the next traffic light and current signal phase needs to be checked so that the potential risk of the host vehicle violating a red light can be assessed. If the current phase of a traffic light is green or yellow, an approaching host vehicle is at risk of violating a red light signal if the host vehicle's speed multiplied by the remaining time before traffic light turns into red is greater than the host vehicle's distance to the traffic light. Figure 34 below shows the use case of the RLVW application.



(Source: NYU C2SMART Center)

Figure 34. Design Logic of the RLVW Application in SUMO

In SUMO, there are TraCI functions that can retrieve traffic light-related information, including its current phase and remaining time of switching to next phase. For the implementation of RLVW application, the following functions are used:

- *getNextTLS* (Retrieve the ID, distance, phase information of the upcoming traffic lights)
- *getNextSwitch* (Retrieve the time at which the traffic light will switch to the next phase)
- *getSpeed* (Retrieve the speed of the named vehicle)
- *setSpeed* (Update the speed of the named vehicle)
- *setAccel* (Update the maximum acceleration of the named vehicle)

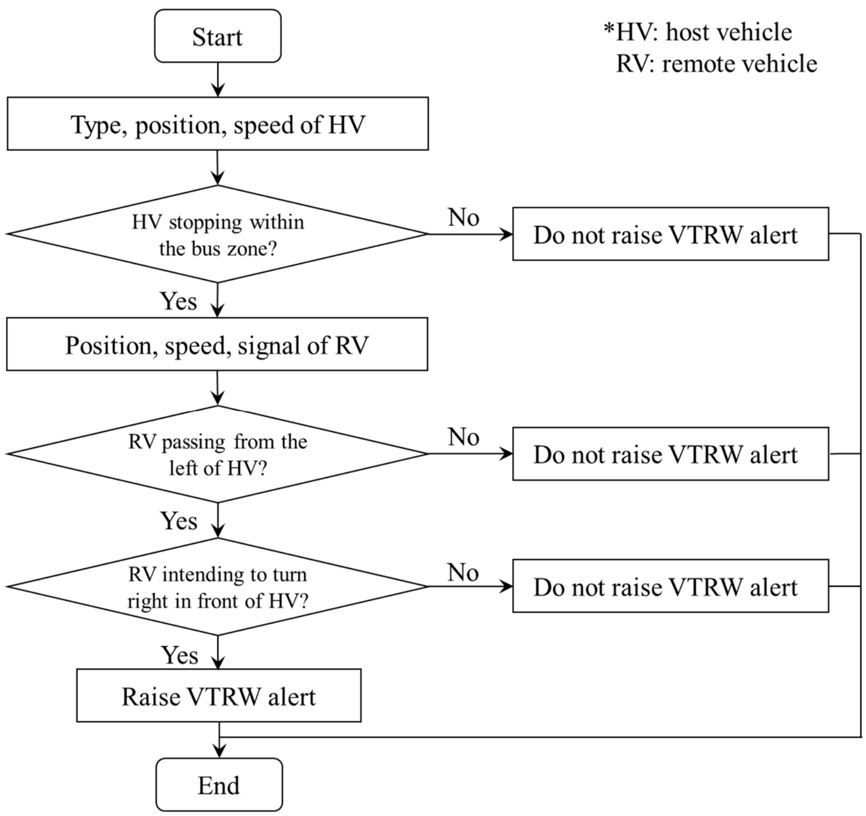
The pseudo code for the implementation of RLVW application in SUMO is shown below.

```
Initialize HV ID
Retrieve the ID of HV's next traffic light
Retrieve the current phase of the traffic light and HV's distance to it
If the current phase is green or yellow & the distance is below threshold
        Retrieve the speed of HV
        Retrieve the remaining time before traffic light switches to red
```

```
        If speed multiplied by time is greater than distance
                Raise red light violation warning
        Else
                Do not raise red light violation warning
Else
        Do not raise red light violation warning
```

5.3.1.3.6 *Vehicle Turning Right in Front of Bus Warning (VTRW)*

The objective of the VTRW application is to warn the driver when a RV intends to turn right in front of the HV and return to or cross the lane of the HV. The VTRW safety application requires the host vehicle to be a bus and be within the bus stop geographical zone. It enables the host vehicle to be alerted about the collision threat based on the Basic Safety Message (BSM) received from passing vehicles from the left. To ensure the VTRW safety application is triggered under the right use cases, an important requirement is that the host vehicle is within the bus stop geographical zone. When this requirement is satisfied, the passing vehicles from the left of the host vehicle are then checked to decide if the VTRW should be triggered. The use cases and design logic of the VTRW application is shown in Figure 35 below.



(Source: NYU C2SMART Center)

Figure 35. Design Logic of the VTRW Application in SUMO

In SUMO, TraCI functions that allow users to retrieve vehicles' type, position, speed, and signal information can be applied to implement the VTRW application. In this study, the following functions are used:

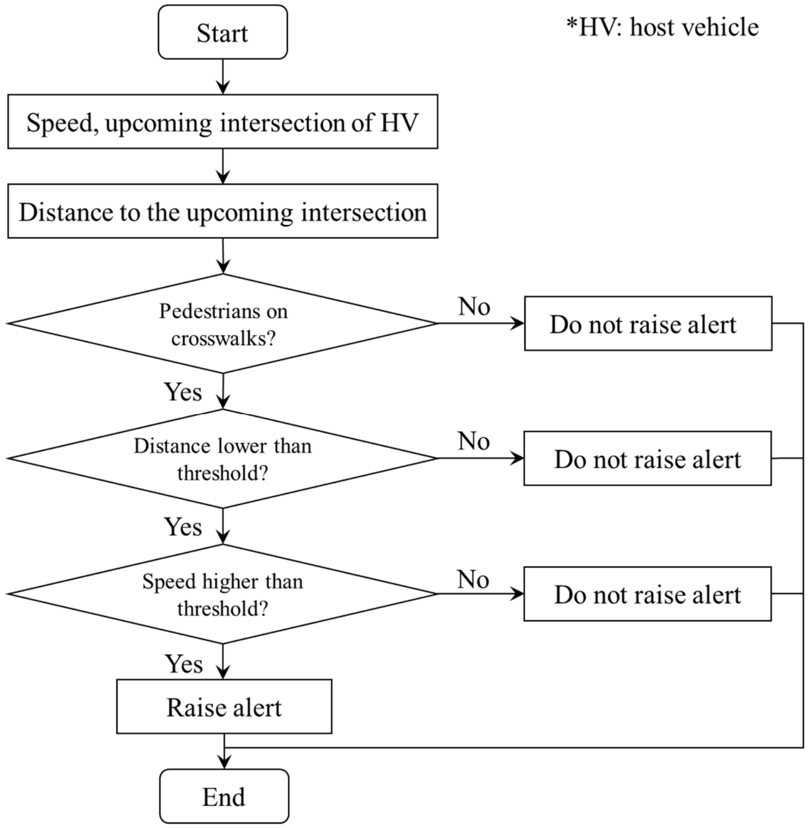
- *getTypeID* (Retrieve the ID of the type of the named vehicle)
- *getLanePosition* (Retrieve the position of the named vehicle along the lane)
- *getSpeed* (Retrieve the speed of the named vehicle)
- *getSignals* (Retrieve the signal state of the named vehicle, including blinking right, blinking left, brake light, etc.)
- *setSpeed* (Update the speed of the named vehicle)
- *setAccel* (Update the maximum acceleration of the named vehicle)

The pseudo code for the implementation of VTRW application in SUMO is shown below.

```
Initialize HV ID
Retrieve the type and speed of HV
Retrieve the lane position of HV
If HV is stopping in the bus stop zone
        Retrieve the speed, lane position, and signal state of RV
        If RV is passing from the left and intending to turn right in front of HV
                Raise VTRW alert
        Else
                Do not raise VTRW alert
Else
        Do not raise VTRW alert
```

5.3.1.3.7 Pedestrian in Signalized Crosswalk Warning (PEDINXWALK)

The objective of the PEDINXWALK application is to inform the driver about pedestrian presence on the crosswalk of the approaching intersection. In the simulation environment, the distance of the host vehicle to the approaching intersection and the presence of pedestrians at crosswalks of the intersection need to be checked so that the potential risk of vehicle-pedestrian conflicts can be assessed. If there are pedestrians on the crosswalks of the upcoming intersection, the host vehicle should be alerted if its speed is greater than a threshold within a relatively short distance. The use case checking process and design logic of the PEDINXWALK application is shown in Figure 36 below.



(Source: NYU C2SMART Center)

Figure 36. Design Logic of the PEDINXWALK Application in SUMO

In SUMO, apart from TraCI functions that can retrieve vehicles' position, speed, acceleration information, there are also functions that can check the presence of pedestrians on crosswalks. These functions are applied to implement the PEDINXWALK application. In this study, the following functions are used:

- *getSpeed* (Retrieve the speed of the named vehicle)
- *getLastStepPersonIDs* (Retrieve the list of IDs of pedestrians that are on the named crosswalk)
- *getNextTLS* (Retrieve the ID, distance, phase information of the upcoming traffic lights)
- *setSpeed* (Update the speed of the named vehicle)
- *setAccel* (Update the maximum acceleration of the named vehicle)

The pseudo code for the implementation of PEDINXWALK application in SUMO is shown below.

```
Initialize HV ID
Retrieve the ID of HV's upcoming intersection
Retrieve HV's distance to the upcoming intersection
If there are pedestrians on crosswalks & the distance is below threshold
        Retrieve the speed of HV
```

```
        If speed of HV is higher than threshold
                Raise pedestrian in intersection warning
        Else
                Do not raise pedestrian in intersection warning
Else
        Do not raise pedestrian in intersection warning
```

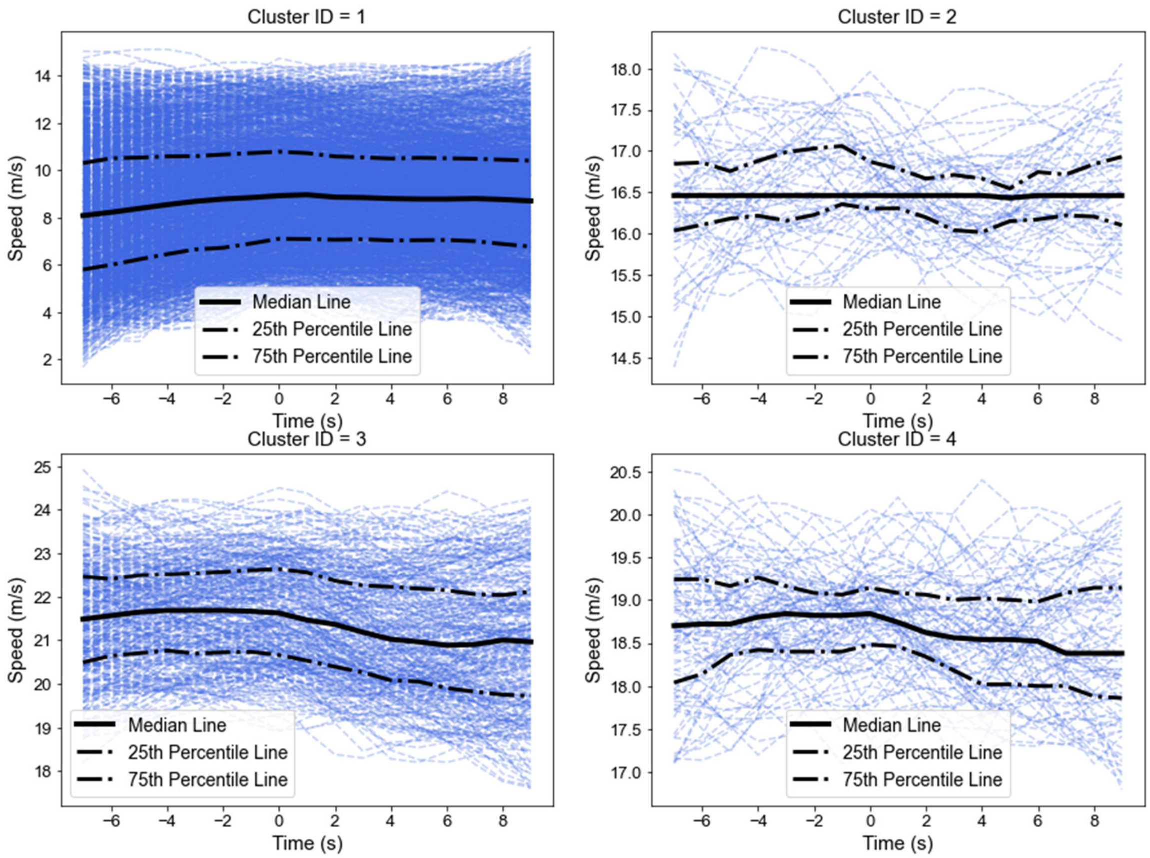
5.3.1.4 Incorporation of Driver Behavior Changes into the Simulation Model

The changes in driver behavior arising from the adoption of the CV technology must be incorporated into the simulation model. The CV pilot event record data collects the individual vehicle traces from the ASDs for both with and without active warnings, capturing changes in driver behavior resulting from the active warning from the ASD. This driver action data is analyzed to modify the default driver behavior used in the microscopic simulation.

The speed profile of the host vehicle can help gain insight of the driver's behavior pattern at different timestamps during an event, especially after an alert is activated. In order to cluster the vehicles based on their speed profiles, one of the most common clustering algorithms, the density-based spatial clustering of applications with noise (DBSCAN) method proposed by Ester et al. (1996) is applied. DBSCAN is a data clustering algorithm used for clustering a set of points in a space by grouping the points that are closely packed together (points with many neighbors). The DBSCAN algorithm can be used to discover clusters of arbitrary shape with noise observations (Wen et al. 2021) and the key idea of DBSCAN is that a point belongs to a cluster if it is close to many points from the cluster. An open-source Python library, named *sklearn.cluster.DBSCAN*, is used to implement the DBSCAN algorithm to perform clustering analysis.

To obtain the optimal clustering results, the DBSCAN algorithm is performed with varying values of two key parameters, namely, the maximum distance between two samples for them to be considered as neighbors and the minimum number of data points to define a cluster. This better represents different driver behavior patterns for each CV application. In the remainder of this section, the clustering results of each application are provided to support the driver reaction behavior modeling in the SUMO model. The speed profiles being used for clustering analysis are extracted from the host vehicles ASDs from the treatment group.

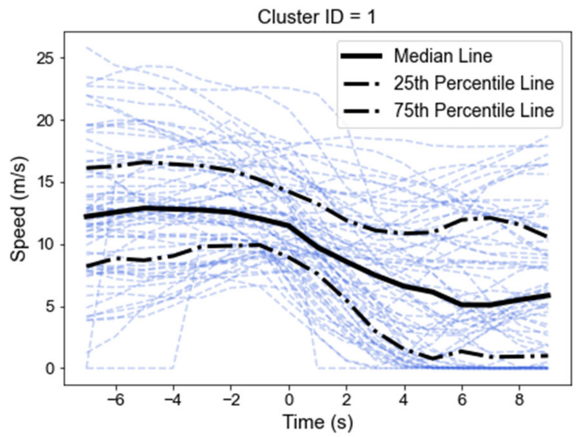
For the FCW application, the host vehicle drivers are grouped into four clusters based on the speed-time relationship as shown in Figure 37. The statistical summary of the four behavioral patterns is also provided, including the median speed line, the 25th and 75th percentile speed lines. For clusters 1 and 2, the drivers barely decelerate after they receive the alert. The speeds in clusters 3 and 4 show a slightly decreasing trend after time 0s when the alert is activated, which indicates that these drivers decelerated in response to the alerts by the applications.



(Source: NYU C2SMART Center)

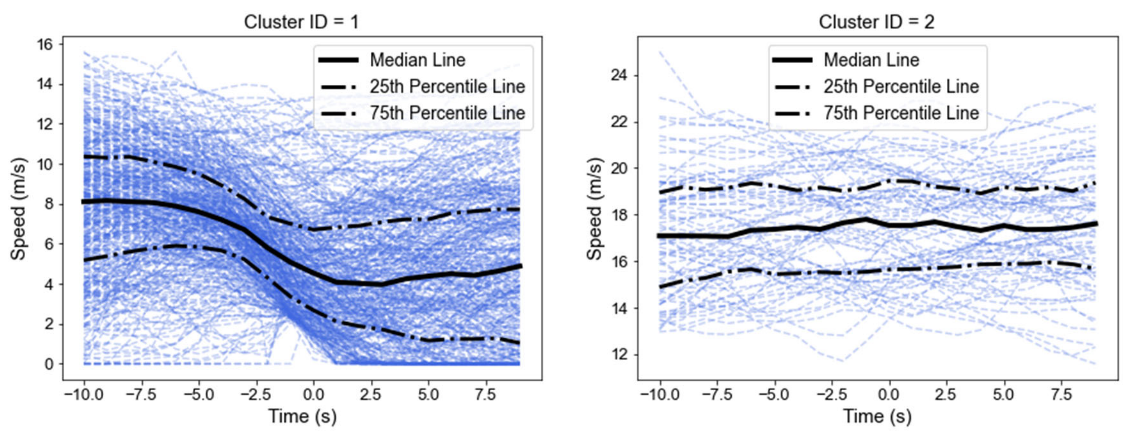
Figure 37. Clustering of FCW Application Based on Speed-time Relationship

Using the same clustering analysis approach, the clustering results for the EEBL, BSW, and LCW applications are shown in Figure 38 to Figure 42. For the EEBL application, only one cluster is identified from the ASDs, in which the drivers are found to make obvious deceleration decision after receiving an EEBL alert. The BSW and LCW applications both have two clusters. In one cluster, the drivers reacted (i.e., decelerated) to the alerts, while the drivers in the other cluster did not show noticeable reaction before and after the alert was issued. The RLVW and PEDINXWALK applications both have only one cluster which shows the deceleration behavior of drivers after the alert were issued. It is worth noting that there is not sufficient action log data for clustering analysis for the VTRW application. Therefore, driver behavior in SUMO for this application adopts the results from another application, the LCW, because their use cases share some similarities in terms of the lane changing conditions.



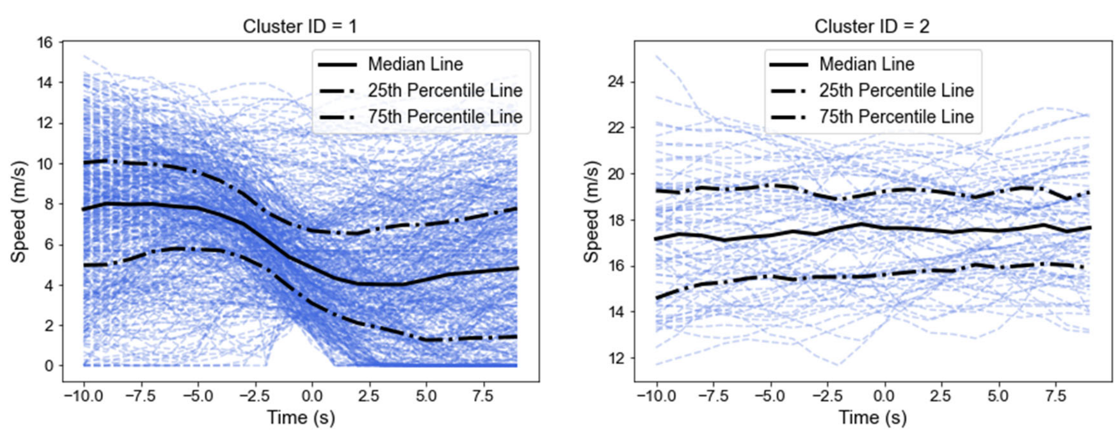
(Source: NYU C2SMART Center)

Figure 38. Clustering of EEBL Application Based on Speed-Time Relationship



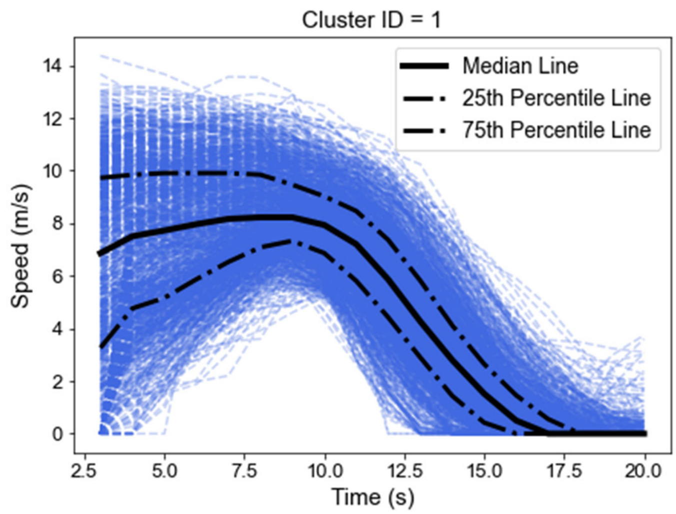
(Source: NYU C2SMART Center)

Figure 39. Clustering of BSW Application Based on Speed-Time Relationship



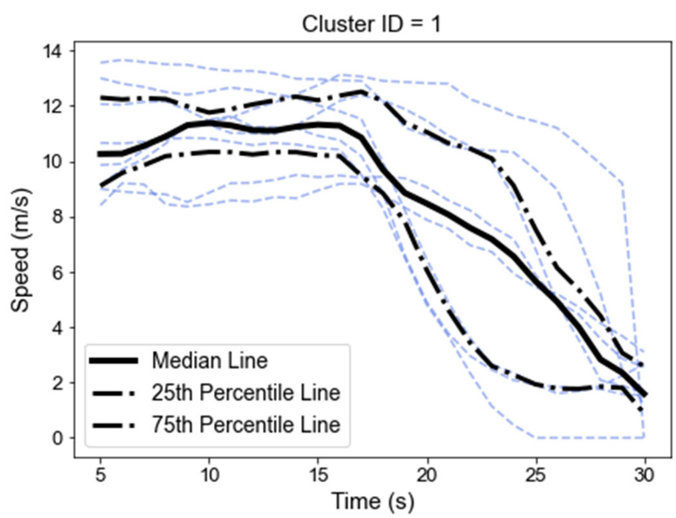
(Source: NYU C2SMART Center)

Figure 40. Clustering of LCW Application Based on Speed-Time Relationship



(Source: NYU C2SMART Center)

Figure 41. Clustering of RLVW Application Based on Speed-Time Relationship



(Source: NYU C2SMART Center)

Figure 42. Clustering of PEDINXWALK Application Based on Speed-Time Relationship

As can be seen from the above figures, results for each application can be summarized as two clusters: a reaction group and a nonreaction group. For EEBL, RLVW, and PEDINXWALK applications, they can be considered to have a nonreaction group with the proportion of zero percent. Table 10 summarizes the number of observations in each cluster and the proportion of each type of behavior pattern for the CV applications. The driver reaction of each application is modeled in the simulation according to the proportion shown in table and the mean speed line shown in Figure 37 to Figure 42.

Table 10. Summary of Clustering Results Based on Drivers' Speed Profiles

CV Application	Number of Observations	Percent Reacted	Percent No Reaction
FCW	2,263	18%	82%
EEBL	68	100%	0%
BSW	473	84%	16%
LCW	472	84%	16%
RLVW	1,114	100%	0%
PEDINXWALK	8	100%	0%

5.3.1.5 The Method of the Sample Size Determination

To evaluate the safety performance of each application in the simulation environment, the simulation model of each application needs to be run multiple times for accurately considering the stochasticity due to random seeds. To determine the proper number of random seeds to be used, a sequential approach documented in Law, Kelton, and Kelton (2007) and applied in Hong Yang (2012b) is adopted. This statistical procedure aims to obtain the mean $\mu = E(X)$ of the performance measure X with a pre-specified precision. If one estimates $\bar{X}$ such that $|\bar{X} - \mu|/|\mu| = \gamma$, then γ is called the relative error of $\bar{X}$. The specific objective of this approach is to obtain an estimated μ with a relative error of γ and a confidence level of $100(1 - \alpha)$ percent. Denote the half-length of the confidence interval by $\delta(n, \alpha)$, then the procedure of this approach is as follows:

1) Make an initial number of n_0 replications of the simulation model and set $n = n_0$;
2) Calculate the initial (crude) estimates $\bar{X}(n)$ and $S^2(n)$ from $X_1, X_2, \ldots, X_n$;
3) Specify the size of allowable relative error γ;
4) Calculate the adjusted relative error $\gamma' = \gamma/(1 - \gamma)$;
5) Decide the level of significance α;
6) Calculate the half-length of the confidence interval $\delta(n, \alpha) = t_{n-1,1-\alpha/2}\sqrt{S^2(n)/n}$;
7) If $\delta(n, \alpha)/|\bar{X}(n)| \leq \gamma'$, use $\bar{X}(n)$ as the point estimate of μ and stop. Else make one more replication and set $n = n + 1$ (i.e., make an additional replication of the simulation), then go back to step 2.

This approach assumes identical, independent (IID) outcomes, but they need not be normally distributed. Thus, the estimates of $\bar{X}(n)$ and $S^2(n)$ for the mean and variance, as well as for the estimation of the confidence interval, will become better with additional replications. This procedure is applied to the simulation model of each application to determine the sufficient sample size required for the analysis. Based on the above sample size determination algorithm, the simulation model of each application being implemented was run multiple times with different random seeds. The performance measure used to evaluate safety between the before and after periods of the implementation of CV applications in the simulation model is the 15th percentile of the TTC values.

5.3.1.6 Simulation Scenarios

The implementation of CV applications in SUMO is based on TraCI, requiring frequent checks on the interaction between the host vehicle and remote vehicle at each simulation time step. With the increase of the pairs of equipped vehicles in the network and the scale of the simulation network, the simulation time can increase exponentially. To isolate the benefits from individual CV apps, eliminate the impacts of confounding factors and allow an acceptable running time of the simulation model, the CV applications are evaluated separately, with each application being implemented in the Flatbush Avenue model area with specific driver behavior models described in 5.3.1.4. Vehicle trajectories and information are recorded from a single intersection for the SSM-based evaluation. While higher than the field market penetration of CV-equipped vehicles, a 5% market penetration rate of CV vehicles is used to obtain sufficient sample sizes of data for the safety evaluation.

In this study, it is important to consider different demand scenarios and/or weather conditions, such as snow, heavy rain, and ice, since these are likely to influence driver behavior and in turn will influence the crash risk. The significance of driver behavior changes of the seven CV applications that requires SSM-based simulation evaluation was evaluated under different weather and operational conditions during the initial testing and before period. The goal is to determine whether additional simulation scenarios are needed for these conditions.

Apart from normal weather conditions (labeled as “clear” in the action logs), there are several inclement weather conditions being recorded in the ASD data such as rainy, snowy, foggy, winter-mix conditions, and a mixture of the above conditions. These weather conditions are categorized into three levels which are clear, rainy, and severe conditions (snowy, foggy, winter-mix conditions) for analysis. Four behavior parameters (vehicle’s maximum speed (*maxSpeed*), acceleration, deceleration, and drivers’ reaction time (*tau*)) are investigated using the before period ASD data from January 1 to May 20 in 2021 (

Table **11**). It is found that the values of maximum speed, acceleration, and deceleration are slightly lower under rainy and severe weather conditions than those under normal weather conditions, but the difference is not found to be statistically significant. The reaction time parameter (*tau*) of drivers shows no significant differences among different weather conditions. This may be because the parameter's value is too small (mostly lower than 1 second) to exhibit significant changes. Based on the statistical results of the driver behaviors extracted from these specific seven CV applications, different weather scenarios are not simulated.

Table 11. Statistics of Behavior Parameters Under Different Weather Conditions

Parameter	Weather Condition	Mode	50th Percentile	75th Percentile	95th Percentile
MaxSpeed (m/s)	Clear	12.15	13.16	16.32	24.4
MaxSpeed (m/s)	Rainy	11.25	12.96	15.68	22.52
MaxSpeed (m/s)	Severe	11.4	12.96	15.58	23.5
Acceleration (m/s^2)	Clear	0.425	0.613	1.04	2.052
Acceleration (m/s^2)	Rainy	0.425	0.596	0.96	1.971
Acceleration (m/s^2)	Severe	0.325	0.582	0.962	1.799
Deceleration (m/s^2)	Clear	0.375	0.532	0.995	2.045
Deceleration (m/s^2)	Rainy	0.375	0.506	0.922	1.897
Deceleration (m/s^2)	Severe	0.375	0.482	0.891	1.778
Reaction time (*tau*) (s)	Clear	0.425	1.308	2.625	5.051
Reaction time (*tau*) (s)	Rainy	0.425	1.311	2.632	5.079
Reaction time (*tau*) (s)	Severe	0.425	1.302	2.536	4.903

Other impact factors to consider are the operational conditions of the studied traffic network. Varying traffic demands or disruptions, such as an incident, may affect drivers' travel speed and travel time. Travel time data was used to identify different operational conditions of the Flatbush Avenue network during morning peak period. Available INRIX travel time data from 326 weekdays for the road segment from Atlantic Avenue to Tillary Street were analyzed using DBSCAN clustering techniques. Only one cluster (used in the base scenario) is identified, thus no other operational scenarios for the morning peak period of the Flatbush Ave network was simulated for the safety evaluation of CV applications.

5.3.2 Mobility Simulations

The plan for the use of simulation in the evaluation of the NYC CVPD was to help assess if the deployment would have mobility impacts on travel in NYC. While also to be determined with empirical data, simulation could be used to help fill in gaps in what could feasibly be captured in the field. The existing Manhattan Traffic Model (MTM) was designated as the simulation platform to simulate network performance for non-safety metrics for the NYC CVPD evaluations. The model was developed in the Aimsun platform and includes both regional mesoscopic components and a detailed microscopic model of Midtown Manhattan.

The Midtown microscopic model includes the complete street network in Manhattan between 14th and 66th Streets from the Hudson River to the East River and is shown in Figure 43. The simulation model was updated in Phase 2 of the NYC CVPD to represent 2018 pre-deployment conditions for typical weekday morning (6 to 9 AM) and afternoon (3 to 7 PM) peak periods. The model simulates passenger vehicles, trucks, and transit buses operating on fixed schedules, as well as time of day parking regulations, reversible lanes at crossings, reserved bus lanes, and pickup and drop off activities of taxi and for-hire vehicle in active travel lanes.

(Source: NYCDOT, 2017)

Figure 43. MTM Microscopic Model Geographic Extents

As detailed in the Phase 2 PMESP, a hierarchical structure of plans was developed for the potential use of simulation for non-safety simulations developed: (1) a comparison of separate models calibrated to both before and after deployment periods, (2) the adaption of driver behaviors in the before model to approximate an after period conditions of modified driver behaviors, and (3) the use of simulation to help assess the impacts of the CV deployment through improved mobility and reliability from prevented crashes or reduced severity crashes.

The plan to develop unique before and after models was originally considered to be potentially unfeasible due to the dynamic nature of the NYC driving environment and the large number of compounding factors that cannot adequately be quantified via field data collection. This concern was amplified with the introduction of large changes in the traveling behavior in NYC resulting from the COVID-19 pandemic. From shifting commuting patterns to modified transit usage to increased work from home behaviors to modified curb space usage for new and non-transportation related needs, attempting to quantify these impacts to develop a new after deployment model was deemed fruitless, and the second level plan of analysis was examined.

The second plan involved determining the driver behavior changes observed in the event file action log data as they relate to mobility and speed compliance and to adjust those changes to develop separate with CV and without CV driver models. While the analysis of driver behaviors from the event action log data (see Section 6) did result in some minor changes in the willingness of drivers to better adhere to the posted speed limits, the changes were only for a minority of the events observed. Therefore this change would apply to only a minority of the simulated CV vehicles, which in itself is a small minority of all simulated vehicles. The share of the vehicles reacting to the speed compliance application relative to the overall vehicle count operating in Midtown Manhattan on a typical weekday, the expected changes in non-safety performance measures would be exceedingly difficult to impossible to statistically identify within the simulation results of a large stochastic simulation like the MTM and as such the second analysis plan was not pursued.

The third plan involved simulating scenarios of different crashes to assess the overall potential benefits to mobility and general user costs associated with a prevented crash. While this would not identify the specific benefits of the true CV deployment in preventing specific crash types, it would estimate costs associated with generalized crashes in Midtown Manhattan and could help identify the range of the benefits to the system of prevented crashes. This final plan was pursued under the Phase 3 evaluation of the CV deployment.

Based on a review of the available crash data from the NYPD, four different hypothetical crash conditions were located along the CV equipped corridors to analyze during the PM peak period. As no data was available on the typical response and clearance times for different level severity crashes, hypothetical crashes were developed that blocked traffic for 30 minutes for either one or two lanes. The details of each presumed crashes are listed in

Table 12 below.

Table 12. Analyzed Crashes within Mobility Simulations

Simulated Crash	Location (Network Link)	Crash Time	Lane Blockage Duration	Lanes Blocked
Crash 1	1st Avenue North of 63rd Street (1AV_63ST_64ST)	16:30	30 minutes	1 lane (lane #4)
Crash 2	5th Avenue South of 55th Street (5AV_55ST_54ST)	16:30	30 minutes	2 lanes (lanes #1 and #2)
Crash 3	2nd Avenue South of 23rd Street (2AV_23ST_22ST)	17:15	30 minutes	1 lane (lane #4)
Crash 4	6th Avenue North of 47th Street (6AV_47ST_48ST)	17:15	30 minutes	2 lanes (lanes #3 and #4)

The crashes were simulated as lane blockages using Aimsun's built-in traffic management condition tools, where the time, network section, and specific lanes to be closed define the crash. At the time of the crash in the simulation, the blocked lane(s) is(are) closed to all simulated traffic, and simulated drivers react to the new conditions, including the potential for simulated drivers that are aware of current traffic conditions (and not simply following habitual travel paths) to change paths dynamically should an improved path exist. Signal timings were not adjusted in response to the crash conditions and no traveler alerts were issued asking simulated drivers to avoid the area of the crash.

Models were simulated both with and without crashes occurring. The simulation results of crash models were then compared to the results of the model without the simulated crash to derive the impacts. To isolate the inherent stochastic noise of the simulation model, each model was run for five different seeds and the average of the five seed results were compared and analyzed.

Simulated performance metrics of crash section throughput, total vehicle delay, and average travel time were extracted and compared between the with crash and without crash simulations to quantify the mobility impacts. The comparison was conducted for the section where the incident occurred as well as for areas upstream of the crash location that may be directly impacted by the incident. This selection was done to help limit the stochastic influences of the simulation model.

5.4 System Operations Monitoring

In anticipation of operating a CV system, a series of management facilities were envisioned. These facilities focused on the new CV devices as well as communications between the devices themselves and the TMC. Daily data regarding activities was recorded in the system database and daily summary report data was produced and imported into spreadsheets for temporal analysis. These data were accumulated into three reports used to monitor the system.

The core of these facilities centered on tracking device firmware versions in both the ASDs and RSUs. This data enabled understanding of the distribution of firmware updates and the makeup of firmware among the fleet vehicles throughout the project life-cycle.

Another key facility was the reporting of other CV devices heard by recording the first and last message heard in the RF logs. This enabled the monitoring of device radios and assessment of RF “footprints” around RSUs. These sightings were visible on the system map and aided in identifying RSUs which were not communicating as well as being taken out of service due to construction. The RSU tracking reports provided monitoring tools driving maintenance visits and reports in the System Operation and Maintenance Summary (SOMS).

While not a report, the RSU RF logs of ASD’s heard were displayed on the control system’s map. The map supported multiple displays for each RSU showing a “heat map” of the first/last sightings over the previous week as well as a user customizable display that enabled the user to categorize the sightings into shorter periods for display.

Additional reports addressed the quantity of data being collected and provided a problem detection mechanism. Due to the data retention, counts were accumulated upon data ingestion into the TMC as well as after accounting for the data retention period. Following the data retention period data was stored and counted using coordinated universal time (UTC) timestamp of the data’s occurrence.

Events impacting system operations were recorded in the above reports as well as the weekly Performance Measurement Evaluation and Schedule Summary (PMESS). These notations and logs became useful tools when analyzing data collection and unexpected data observations.

5.5 Surveys

In addition to the quantitative evaluation methods presented above, additional qualitative feedback on the effectiveness and impacts of the CV application deployments were solicited from those directly experiencing the CV technology firsthand – the drivers of the ASD equipped vehicles and the vision disabled participants for the PID field tests. Accordingly, two different sets of surveys were developed for each of these participant groups to collect this qualitative feedback.

5.5.1 Driver Surveys

As detailed in Section 4.1.3, driver feedback surveys were developed to solicit feedback on four different areas: the drivers’ typical vehicle usage and driving patterns when driving for work in NYC, their perceptions and attitudes about both CV technology and about the safety of driving for work in NYC, their experiences with the CV applications while driving (only collected in post-deployment surveys), and some limited demographic data about the respondents. Reviews of the survey results were compared to see if results altered over time or after exposure to the CV technology by comparing the pre-deployment survey results to the early- and late-deployment survey results.

5.5.2 PID Participant Surveys

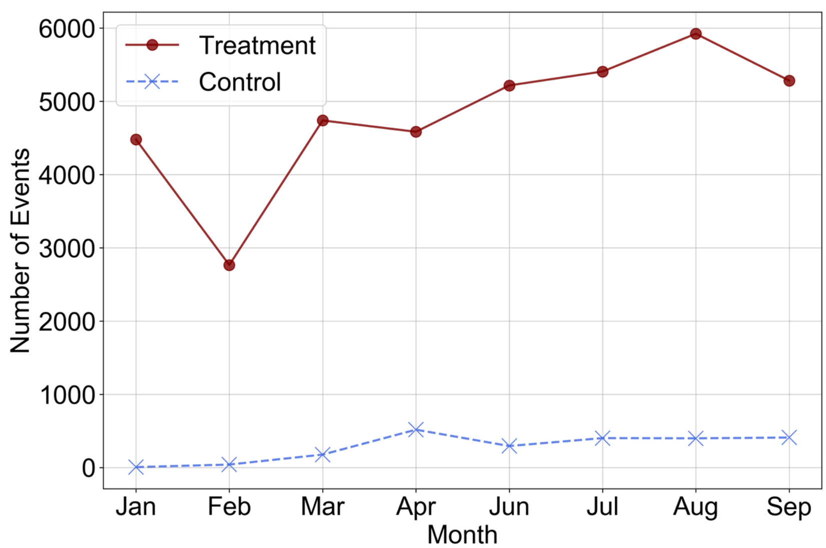
Descriptive analysis is used to evaluate qualitative user feedback collected from pre-experiment and post-experiment surveys (as detailed in Section 4.1.4) as the sample size of target group is small. This analysis focuses on the evaluation of PID ease-of-use, user experience (familiarity, confidence, reliability), application functionality (sufficient audio/haptic assistance, alert accuracy, etc.), and user perception of safety.

6 System Evaluation Results

Using the methods outlined in the previous chapter, the following findings can be reported on the NYC CVPD data. Results are presented first by CV application to assess the safety impacts, followed by the more general mobility analysis, overall CV system operations, and finally for the collected driver surveys.

6.1 Speed Compliance

After employing the data cleaning and filtering steps discussed in Sections 5.1.1.2 and 5.1.1.3, the total number of SPDCOMP events from January 2021 to September 2021 (excluding May 2021) is 40,635. The breakdown of the number of SPDCOMP events by months and treatment and control groups is illustrated in Figure 44. The ratio of control events and treatment events are generally in proportion to the overall percentages of control vehicles across Phase 3 (see Section 3.2.2 for details).



(Source: NYCDOT)

Figure 44. Number of SPDCOMP Events for Control and Treatment Groups During the Study Period After Data Cleaning

6.1.1 Reduction in Speed Limit Violations

A speed limit violation was defined as when the driver's speed is not reduced to/below the speed limit after a speed compliance warning is issued. Based on this definition, the following algorithm to extract speed limit violations from the speed compliance BSM event data was used:

For each speed compliance event:

- Step 1: Obtain minimum speed value after the warning is issued (when T_s > 0).
- Step 2: If the obtained minimum speed value is greater than the speed limit, then the driver failed to reduce speed to the speed limit in response to the alert is identified.

The speed limit is set as 25 mph to be consistent with the speed limit of the CV equipped roadways (all fall under the city-wide 25 mph speed limit for surface streets).

6.1.1.1 Overall Performance

The performance measure was obtained by calculating the change in the normalized number of events that drivers do not slow down to the speed limit in the treatment group from the before period to the after period minus the change in the normalized number of events in the control group from the before period to the after period. The control group is used to account for potential confounding factors throughout the study period. The gain scores for the control group and treatment group used in 6.1.1.1 are 0.0263 and 0.0741 respectively, which yields a safety effect of 0.0741 - 0.0263 = 0.0477, i.e., 47.7 speed limit violations per 1,000 events. The gain score results show that based on all speed compliance events, there is a reduction of approximately 47.7 speed limit violations per 1,000 events with a 95% confidence interval with lower and upper bounds of 17.2 and 78.3 ([17.2, 78.3]). This means compared to silent warning scenarios, there will be additional 48 events per 1,000 SPDCOMP events that driver slowed to the speed limit when treatment was enabled. By setting the null hypothesis as the estimated safety effect being equal to zero, since the 95% confidence interval does not include zero, it was concluded that the estimated reduction in speed limit violations is statistically significant at a 0.05 significance level. This indicates that during the NYC CVPD implementation, drivers tended to comply with the preset speed limit after the speed compliance warnings were issued.

6.1.1.2 Performance for different weather conditions

Weather conditions are a major confounding factor that can potentially affect the performance of this application. Thus, it is necessary to investigate the impact of weather conditions on the reduction in speed limit violations. To achieve this objective, a specific weather condition must be observed in both the before and after periods because otherwise counterfactuals and potential unobserved confounding factors cannot be properly accounted for.

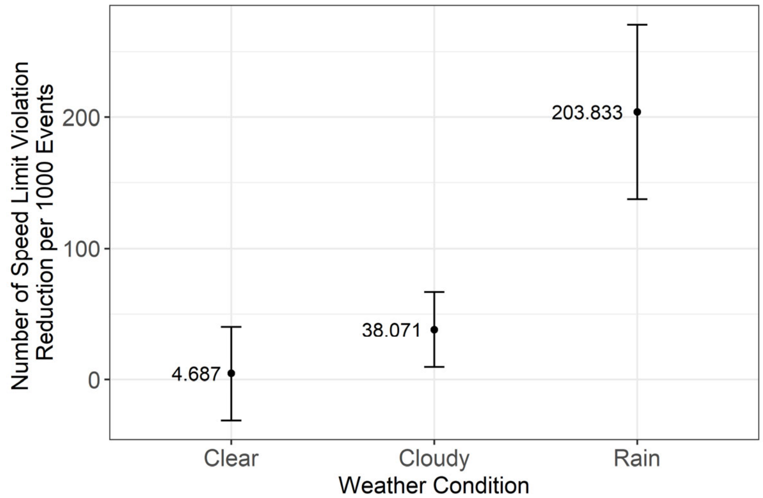
Based on the *weatherCondition* column in the ASD event data, there are six weather conditions that appear in all eight months (i.e., from January to September except May): clear, mostly clear, partly clear, mostly cloudy, overcast, and rain. Based on their definitions listed in Table 13 below, these six weather conditions are regrouped into the following three categories to increase sample size for each group for before-after analysis. Despite the seasonality of weather, the proportion of events categories into the modified weather categories for the before and after period were quite similar. Event data reported conditions as cloudy in 39.8% of the before period events and in 41.3% of the after-period events. Similarly, rain was reported in 4.9% of the before period events and in 4.2% of the after-period events.

Table 13. Weather Condition Categories

Modified Weather Category	Recorded Weather Condition	Definition
Clear	Clear	1/8 or less opaque cloud coverage[3]
Clear	Mostly clear	1/8 to 3/8 opaque cloud coverage[3]
Cloudy	Partly cloudy	3/8 to 5/8 opaque cloud coverage[3]
Cloudy	Mostly cloudy	5/8 to 7/8 opaque cloud coverage[3]
Cloudy	Overcast	7/8 to 8/8 opaque cloud coverage[3]
Rain	Rain	Precipitation that falls to earth in drops more than 0.5 mm in diameter[4]

The reductions in speed limit violations per 1,000 events and the corresponding 95% confidence intervals for Clear, Cloudy, and Rain weather categories are illustrated in Figure 45. The null hypothesis represents that the estimated safety effect equals zero. As can be seen from the figure, the reduction in speed limit violations for the Clear weather category is statistically insignificant at a 0.05 significance level while reductions in speed limit violations for the Cloudy and Rain weather categories are positive and statistically significant. The potential explanation for this is that drivers may tend to drive more carefully when it is raining and thus exhibit higher levels of compliance with the speed limit after being issued the speed compliance warnings.

[3] https://www.weather.gov/bgm/forecast_terms
[4] https://w1.weather.gov/glossary/index.php?letter=r



(Source: NYCDOT)

Figure 45. Reduction in Speed Limit Violation for Different Weather Categories

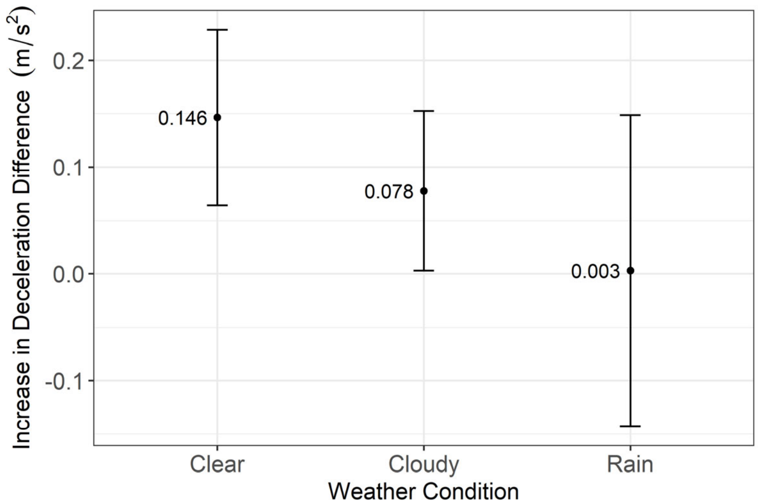
6.1.2 Driver Actions and/or Impact on Actions in Response to Issued Warnings

According to the discussion in Section 5.1.1.4, DBPRM 1 (deceleration difference) and DBPRM 2 (time duration to slow down to speed limit after warning) are used to assess the performance of driver behavior response to SPDCOMP warnings.

6.1.2.1 Increase in Deceleration Difference

Based on section 5.1.1.4, deceleration difference is defined as the difference between the maximum deceleration after the warning and the deceleration at the time of warning. The increase in deceleration difference is approximately 0.148 m/s^2 with a 95% confidence interval [0.074, 0.223]. By setting the null hypothesis as the estimated safety effect equals zero, since the 95% confidence interval does not include zero, the deceleration difference is statistically significant at the 0.05 significance level. This indicates that there was approximately 0.148 m/s^2 extra deceleration on average after speed compliance warnings were issued, which means that drivers tended to decelerate more after speed compliance warnings were issued during the NYC CVPD implementation.

The increase in deceleration difference for Clear, Cloudy, and Rain weather conditions are illustrated in Figure 46. The increases in deceleration difference are 0.146 m/s^2 and 0.078 m/s^2 under Clear and Cloudy weather conditions, respectively, and are statistically significant at the 0.05 significance level while the increase in deceleration difference is 0.003 m/s^2 under Rain weather conditions and is statistically insignificant. This indicates that drivers of the equipped vehicles intended to slightly decelerate more during Clear and Cloudy weather condition while the deceleration difference for Rain weather condition is inconclusive as the value is very small and statistically insignificant.



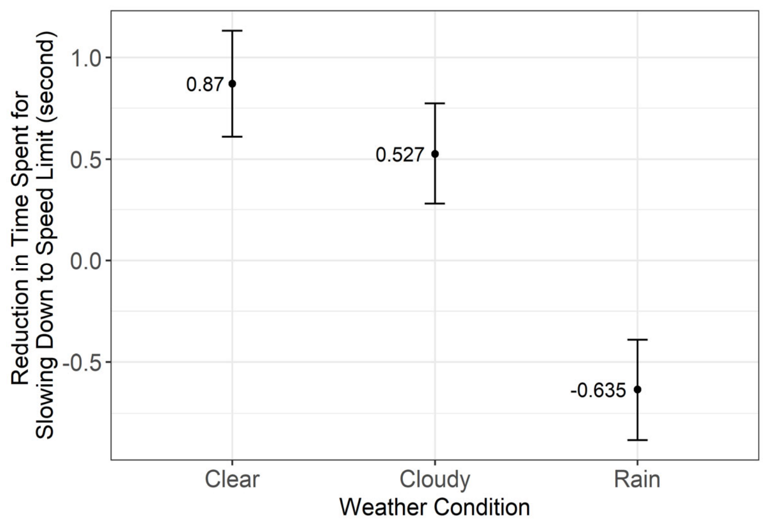
(Source: NYCDOT)

Figure 46. Increase in Deceleration Difference (m/s^2) for Different Weather Categories

6.1.2.2 Reduction in Time Duration to Slow Down to Speed Limit

The reduction in time duration to slow down to speed limit after warning (DBPRM 2) was obtained by calculating the difference between the change of the time duration to slow down to speed limit based on before and after periods as well as the change in that based on the control and treatment groups. Based on all the SPDCOMP events, the reduction of DBPRM 2 is approximately 0.619 seconds with a 95% confidence interval [0.380, 0.857]. By setting the null hypothesis as the estimated safety effect equals zero, since the 95% confidence interval does not include zero, the estimated reduction in time spent for slowing down to speed limit is statistically significant at the 0.05 significance level. This indicates that drivers tended to reduce their travel speed to the speed limit earlier when speed compliance warnings were issued compared to no warnings, although the reduction is relatively small (0.619 seconds).

The reduction in time duration to slow down to speed limit after warning for Clear, Cloudy, and Rain weather conditions are illustrated in Figure 47. Specifically, the reduction in time duration is 0.870 and 0.527 seconds under Clear and Cloudy weather conditions, respectively, and is statistically significant at the 0.05 significance level while the reduction in time spent for slowing down to speed limit is -0.635 seconds under Rain weather conditions and is statistically significant. The rationale behind the opposite effect between Clear and Cloudy weather conditions and Rain weather conditions may be because drivers tend to drive more smoothly and carefully when raining, which thus increases the reaction time to speed compliance warnings under bad weather conditions. Although these reductions are statistically significant, since the difference are relatively small (all <1 second), further evaluation is needed when more data becomes available.



(Source: NYCDOT)

Figure 47. Reduction in Time Spent for Slowing Down to Speed Limit for Different Weather Categories

6.1.3 Limitations and Lessons Learned

Several challenges and limitations were found from the data analysis and evaluation of the speed compliance application. In summary:

- Obfuscation of the ASD data provided an efficient way to ensure the data privacy and security of the participants in the NYC CVPD and prevent matching of data to a particular time and date. However, it also brings several challenges in evaluating the performance of the CV applications.

  1. Due to the obfuscation of exact date information in the event data, the team had to aggregate safety performance measures, especially count type of measures, to a monthly level to obtain a clean experimental design that can be analyzed using the corresponding before-after method. This is one of the main limitations of the before and after analysis. Moreover, due to the obfuscation of the location information in the event data, conditions regarding the actual location where a speed compliance warning occurred cannot be obtained, bringing challenges in validating the estimated safety benefits. If more detailed before-after analysis is required in future deployments, an enhanced data obfuscation method that can preserve spatial and temporal information and still ensure that driver privacy requirements are met could be developed.
  2. Due to the obfuscation of time information and the fact that the activation of the CV applications for the treatment group were gradually turned on, the team had to remove one month of data to ensure a clean experimental design. In future deployments, if an obfuscation method is applied to BSM data, it is suggested that the start and end times of the before and after periods be coordinated with the temporal aggregation levels in the obfuscation method to minimize data loss in subsequent analysis.

- Since the CV application warnings were gradually turned on in the treatment group during the after period, events with suppressed CV application warnings in the treatment group during the after period had to be removed to obtain a clean experimental design for the subsequent analysis. In future deployments, the CV application warnings should be turned on as soon as the after period starts to avoid data loss in subsequent analysis.
- In the above analysis, the speed limit is set as 25mph to be consistent with the speed limit used in the speed compliance application. In future analysis, considering that drivers may not follow the speed limit in real world conditions, different speed limit values somewhat higher than the actual speed limit may be tested. Sensitivity analysis on speed limit thresholds in before-after evaluations may also be conducted.

6.2 Curve Speed Compliance

After employing the data cleaning and filtering steps discussed in Sections 5.1.1.2 and 5.1.1.3, the total number of CSPDCOMP events from January 2021 to September 2021 (excluding May 2021) is 27 and there is only one CSPDCOMP event in the control group in April 2021. Thus, the design for the CSPDCOMP application corresponds to the before-after design (i.e., the one event from the control group is discarded) and the gain score method discussed in Section 5.1.1.3 is utilized for before-after evaluations.

6.2.1 Vehicle Speeds at Curve Entry

To obtain the vehicle speeds at curve entry, the curve entry point of each event is manually identified based on the shape of the vehicle trajectory. Then, the corresponding speed at the curve entry is obtained. Considering the small sample size, performance evaluations could only be conducted based on all the curve speed compliance events instead of separating different weather conditions.

Based on all the curve speed compliance events, there is a reduction in the speed at curve entry of approximately 8.750 mph with a 95% confidence interval [1.742, 15.757]. By setting the null hypothesis as the estimated safety effect equals zero, since the 95% confidence interval does not include zero, it was concluded that the estimated reduction in speed at curve entry is statistically significant at the 0.05 significance level. This implies that during the NYC CVPD implementation, drivers tended to reduce the speed at curve entry after the curve speed compliance warnings are issued.

6.2.2 Lateral Acceleration in the Curve

To obtain the lateral acceleration in the curve, the curve exit point of each event is also manually identified based on the shape of the vehicle trajectory in addition to the curve entry point of each event. Then, the mean lateral acceleration in the curve is calculated. Based on all the curve speed compliance events, there is a reduction in the lateral acceleration in the curve of approximately 0.691 m/s^2 with a 95% confidence interval of [0.117, 1.265]. By setting the null hypothesis as the estimated safety effect equals zero, since the 95% confidence interval does not include zero, it was concluded that the estimated reduction in the lateral acceleration in the curve is statistically significant at the 0.05 significance level. This implies that during the NYC CVPD implementation, drivers tended to reduce the lateral acceleration in the curve entry after the curve speed compliance warnings were issued.

6.2.3 Driver Actions and/or Impact on Actions in Response to Issued Warnings

According to the discussion in Section 5.1.1.4, DBPRM 1 (deceleration difference) and DBPRM 2 (time duration to slow down to speed limit after warning) are used to assess the performance of driver behavior response to CSPDCOMP application. For DBRPM 1, the decrease in deceleration difference based on all the speed compliance events is approximately 0.908 m/s^2 with a 95% confidence interval [1.545, 0.271]. The null hypothesis assumes the estimated safety effect equals zero. Since the 95% confidence interval does not include zero, the decrease in deceleration difference is statistically significant at the 0.05 significance level. This indicates that in general, drivers did not decelerate after being given the curve speed compliance warning. For DBRPM 2, because none of the CSPDCOMP events show reduction in speed after warnings (see section 6.2.4 for detailed discussion), this performance measure was not applied.

6.2.4 Number of Curve Speed Violations at Each Instrumented Location

A curve speed limit violation was defined as occurring when the driver's speed does not reduce to/below the advisory speed after a curve speed compliance warning is issued. To extract curve speed limit violations from the curve speed compliance BSM event data based on this definition, the following algorithm was used:

For each curve speed compliance event,

- Step 1: Obtain minimum speed value during T_s > 0.
- Step 2: If the obtained minimum speed value is greater than the advisory speed, then a speed violation is identified.

The advisory speed for the instrumented location of CSPDCOMP is 15 mph, which is used in the algorithm above to extract curve speed limit violations. As a result, the total number of curve speed limit violations is the same as the total number of curve speed compliance events. In other words, for the 27 valid CSPDCOMP events, drivers did not reduce their speed to the curve speed limit after the curve speed compliance warnings were issued. This finding may be attributed to the small sample size of curve speed compliance events that may result in an underrepresentation of actual driver behavior toward curve speed compliance warnings. Additional factors for the lack of a return to the advisory speed could include the fact that the speed limit was set to a rather low 15 mph advisory speed limit and that warning was issued in advance of the curve and not entering the curve.

6.2.5 Limitations and Lessons Learned

In addition to the limitations and lessons learned from the speed compliance applications, the following lessons and limitations were identified for curve speed compliance applications:

Due to the GPS/elevation inaccuracy, drivers traveling on the FDR highway may receive false CSPDCOMP alerts to slow down. In future CV deployments, it is suggested to enhance the GPS/elevation accuracy and fine-tune the curve speed compliance application to account for more curve-related factors. For example, checking the vehicle speed closer to the entry point (i.e., whether the vehicle is entering the curve and not just approaching it or near the curve).

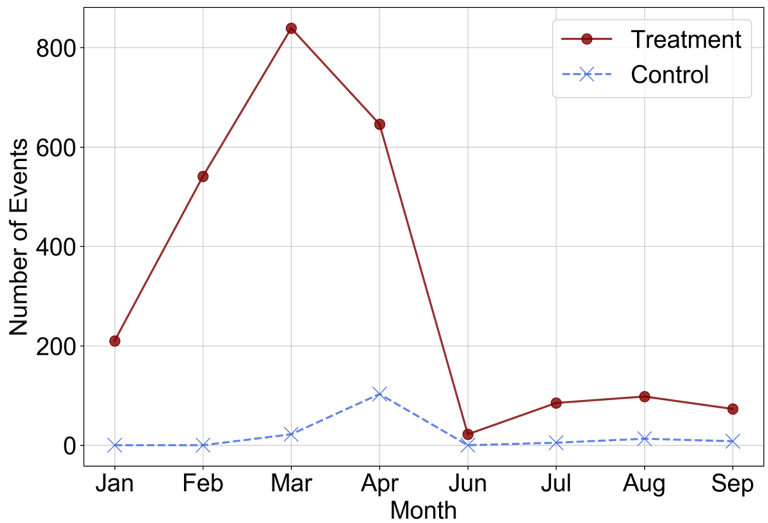
Due to the small sample size of the curve speed compliance events, data from the control group and the treatment group is very limited and may underrepresent the actual driver responses with respect to curve speed compliance events. As a result, unobserved confounding factors may not be properly controlled in the before-after analysis and the estimated treatment effect may thus be biased. In future CV deployments, it is suggested to increase the number of instrumented locations with curve speed compliance application or increase CV market penetration rate to increase the sample size of curve speed compliance warnings.

The sample size of crash records at the instrumented location is very small with only four crashes during the study period, which prevents the team from conducting a comprehensive crash-based evaluation of the CSPDCOMP application. A longer evaluation period is needed to further investigate safety impacts of CSPDCOMP using crash data.

6.3 Speed Compliance in Work Zone

After employing the data cleaning and filter steps discussed in Sections 5.1.1.2 and 5.1.1.3, the total number of SPDCOMPWZ events from January 2021 to September 2021 (excluding May 2021) is 2,665. The breakdown of the number of SPDCOMPWZ events by months and treatment and control groups is illustrated in Figure 48.

As can be seen from the figure, there are no SPDCOMPWZ events from the control group during the first two months of the study period, i.e., January 2021 and February 2021. Considering that there are still two months with SPDCOMPWZ events from the control group in the before period, the design for SPDCOMPWZ application corresponds to the before-after treatment-control group design. It is also noted that there is a large decrease in the number of events for the after period from April 2021 to June 2021, which corresponds to the presence of some SPDCOMPWZ test messages that were in effect during the before period but terminated prior to the initiation of the active alerts in the after period.



(Source: NYCDOT)

Figure 48. Number of SPDCOMPWZ Events for Control and Treatment Groups During the Study Period After Data Cleaning

6.3.1 Driver Actions and/or Impact on Actions in Response to Issued Warnings

According to the discussion in Section 5.1.1.4, DBPRM 1 (deceleration difference) and DBPRM 2 (time duration to slow down to speed limit after warning) are used to assess the performance of driver behavior response to SPDCOMPWZ warnings.

6.3.1.1 Increase in Deceleration Difference

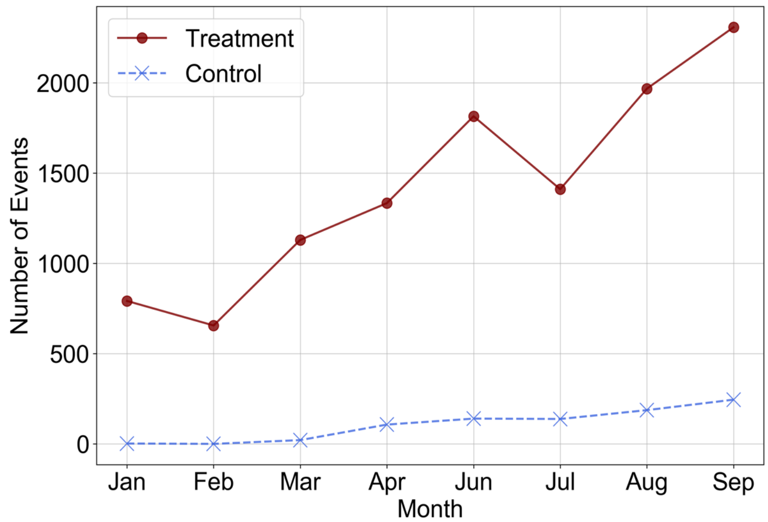
The increase in deceleration difference based on the ASD data of the SPDCOMPWZ application is approximately 0.427 m/s^2 with a 95% confidence interval of [0.265, 0.588]. By setting the null hypothesis as the estimated safety effect equals zero, since the 95% confidence interval does not include zero, the increase of the deceleration difference is statistically significant at the 0.05 significance level. This indicates that there is an extra 0.427 m/s^2 deceleration from the drivers on average after being issued the warnings, which implies that drivers tended to decelerate more after SPDCOMPWZ warnings were issued during the study period.

6.3.1.2 Reduction in Time Duration to Slow Down to Speed Limit

The reduction in time duration to slow down to speed limit after warning based on all the SPDCOMPWZ events is approximately 2.260 second with a 95% confidence interval [1.195, 3.325]. The null hypothesis assumes the estimated safety effect equals zero. Since the 95% confidence interval does not include zero, the estimated reduction in time spent for slowing down to speed limit is statistically significant at the 0.05 significance level. This indicates that drivers tended to reduce their travel speed to speed limit earlier after speed compliance warnings were issued and this reduction is significant (2.260 seconds).

6.4 Forward Crash Warning

After employing the data cleaning and filter steps discussed in Sections 5.1.1.2 and 5.1.1.3, the total number of FCW events from January 2021 to September 2021 (excluding May 2021) is 12,255. The breakdown of the number of FCW events by months and treatment and control groups is illustrated in Figure 49.



(Source: NYCDOT)

Figure 49. Number of FCW Events for Control and Treatment Groups During the Study Period After Data Cleaning

6.4.1 Crash Analysis

This section presents before-after crash analysis results for rear-end type of crashes involving all vehicles in NYC during the study horizon. Due to the privacy/liability concerns raised in Phase 2 of the NYC CVPD, crash records in the NYPD crash database cannot be linked to instrumented vehicles. In other words, it is not possible to separate crashes caused by non-instrumented vehicles and instrumented vehicles. The impact of instrumented vehicles in terms of crashes is expected to be marginal compared to various other safety-related confounding factors that occurred simultaneously with the NYC CVPD, such as the COVID-19 pandemic, Vision Zero projects, planned special events, and so on. Thus, the results presented below should be interpreted as a combined treatment effect for all the potential safety-related "treatments" that occurred simultaneously around NYC during the NYC CVPD implementation period and may not be solely due to the FCW and EEBL applications.

As discussed in Section 5.2, rear-end crashes identified from the NYPD crash database are used to assess the combined safety effect of FCW and EEBL applications. A total of 4,581 number of rear-end crashes occurred between January 2021 to September 2021 in NYC after removing invalid longitude and latitude observations and missing values. Rear-end crashes are further divided into three severity levels: fatal, injury, and PDO. The most severe level namely, fatal, was removed as there is no fatality among the observed rear-end crashes during the study period. As a result, all the rear-end crashes are further divided into two severity levels, namely injury and PDO, for subsequent before-after crash analysis.

The results of the survival analysis model for rear-end crashes are summarized in Table 14. The logarithm of the traffic volume at MTA bridges and tunnels is found to be positively associated with injury and PDO rear-end crashes, respectively, which is consistent with a previous study (see Xie, Ozbay, and Yang (2019)). According to the 95% Bayesian credible interval (BCI) (similar to the confidence interval in the Frequentist framework), the estimated coefficients of the logarithm of traffic volume for both injury and PDO rear-end crashes are statistically significant at the 0.05 significance level. Specifically, for the log-transformed traffic volume, a 1% increase in traffic volume is associated with 1.387% and 1.237% increases in injury and PDO rear-end crashes, respectively.

The estimated CMF of injury rear-end crashes is 0.947 ($e^{-0.054}$) and is marginally statistically insignificant according to 95% BCI while the CMF of PDO rear-end crashes is 0.906 ($e^{-0.099}$) and is statistically significant according to 95% BCI. The slight insignificance of treatment effect for the injury rear-end crashes may be due to the relatively smaller sample size of injury crashes than that of the PDO rear-end crashes. This finding suggests that comparing to the before period, both injury and PDO rear-end crashes decreased by 5.3% $(1 - 0.947 = 0.053)$ and 9.4% $(1 - 0.906 = 0.094)$, respectively, in the after period after accounting for the effect of exposure (i.e., traffic volume). It is important to note that although an increasing trend in raw crash records was observed for the before and after periods, the estimated CMF is found to be less than 1 (indicating a decrease in crash) after accounting for crash exposure (e.g., traffic volumes). The increasing trend in raw crash records is potentially due to the recovery of the traffic volumes after COVID-19 and other related factors.

Table 14. Estimated Parameters of the Survival Analysis Model for Rear-end Crashes

	Injury Mean	Injury 2.5% BCI	Injury 97.5% BCI	PDO Mean	PDO 2.5% BCI	PDO 97.5% BCI
Intercept	-17.487	-18.070	-16.650	-15.081	-15.620	-14.560
Log (Traffic Volume)	1.387	1.328	1.428	1.237	1.201	1.275
Treatment Effect	-0.054	-0.144	0.037	-0.099	-0.173	-0.027
Dispersion	0.002	0.001	0.003	0.003	0.002	0.005

6.4.2 Time to Collision (Vehicle to Vehicle)

TTC values were assessed both empirically from the FCW action log data as well as through simulation modeling assessments.

6.4.2.1 Action Log Data

TTC values between the host and remote vehicles for FCW events are calculated based on the method discussed in Section 5.1.1.5. Since FCW applications mainly aim to reduce rear-end crashes, only TTC values that correspond to rear-end conflicts are selected for subsequent analysis. To reflect extreme TTC values while avoiding outliers, the 15^{th} percentile of TTC values is used as the final TTC measure (St-Aubin, Saunier, and Miranda-Moreno 2015).

There is a total of 632 FCW events with TTC values below the 5 second threshold. Since these FCW events are observed from both before and after periods as well as treatment and control groups, the design for the TTC evaluation of FCW application corresponds to the before-after treatment-control group design. Considering that there are no events with TTC values less than 5 seconds from January 2021 to March 2021 from the control group, performances for different weather conditions are not pursued.

After implementing FCW warnings, there is a 0.198 second increase in 15^{th} percentile TTC values with a 95% confidence interval [-0.032, 0.428]. By setting the null hypothesis as the estimated safety effect equals zero, since the confidence interval includes zero, the increase in 15^{th} percentile TTC values is marginally statistically insignificant at the 0.05 significance level. This implies an inconclusive safety effect after implementing the FCW application.

6.4.2.2 Simulation Modeling

Following the statistical methodology described in Section 5.3.1.5, the simulation model with the FCW application being implemented was run for six times with different random seeds. An average increase of 1.60 seconds was observed in the 15^{th} percentile of TTC values, with a 95% confidence interval of [-0.23, 3.43]. The microscopic traffic simulation model allows for confounding factors to be controlled in the simulation environment. By setting the null hypothesis as the estimated safety effect equals zero, since the confidence interval includes zero, the increase in 15^{th} percentile TTC values is statistically insignificant at the 0.05 significance level. This implies an inconclusive safety effect after implementing the FCW application at a 95% confidence level.

6.4.3 Limitations and Lessons Learned

Although various types of erroneous speed observations were removed during data cleaning and filtering, there are still several events observed with TTC = 0, potentially due to measurement errors in the recorded vehicle trajectories.

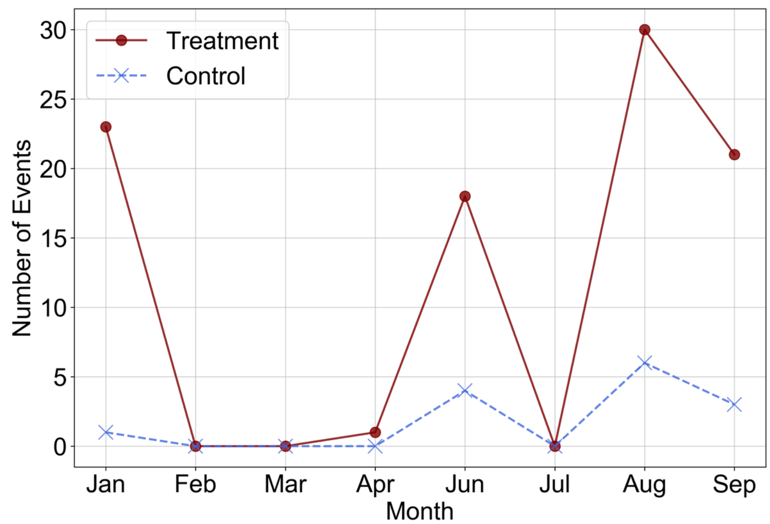
Since the true local environment and traffic conditions when FCW events occurred are not known, there are some challenges and uncertainties to the validation of the estimated safety effect.

Various safety-related confounding factors occurred during the CV testing period, such as COVID-19 pandemic, Vision Zero projects, and so on. To protect privacy, the details of crashes that occurred with the equipped vehicles are unknown. Therefore, the crash reductions estimated above represent the effect of the combination of all safety-related interventions including the NYC CVPD project. While records of equipped vehicle crashes would be more effective than an analysis of all crashes in NYC, the privacy designs of the NYC CVPD prevented this reporting and analysis.

The current microscopic simulation scenarios were designed to evaluate each CV application individually. In the future deployment, it is suggested to further test the safety impacts of combined/bundle of multiple applications.

6.5 Emergency Electronic Brake Lights

After employing the data cleaning and filter steps discussed in Sections 5.1.1.2 and 5.1.1.3, the total number of EEBL events from January 2021 to September 2021 (excluding May 2021) is 107. The breakdown of the number of EEBL events by months and treatment and control groups is illustrated in Figure 50. As can be seen from the figure, there is only one event in the control group in the before period.



(Source: NYCDOT)

Figure 50. Number of EEBL Events for Control and Treatment Groups During the Study Period After Data Cleaning

6.5.1 Crash Analysis

As discussed in Section 5.2, crash analysis of EEBL application is combined with FCW application. Please refer to Section 6.4.1 for the corresponding discussion.

6.5.2 Time to Collision (Vehicle to Vehicle)

TTC values were assessed both empirically from the EEBL action log data as well as through simulation modeling assessments.

6.5.2.1 Action Log Data

TTC values between the host vehicle and remote vehicle for EEBL events are calculated based on the method discussed in Section 5.1.1.5. Similar to the FCW application, the EEBL application aims to reduce rear-end crashes. Thus, only TTC values that correspond to rear-end conflicts are selected for subsequent analysis and 15th percentile of TTC values is used as the final TTC measure (St-Aubin, Saunier, and Miranda-Moreno 2015).

There are a total of 10 EEBL events with TTC values below the 5.0 second threshold. Since these EEBL events are only observed from the treatment group, not the control group, and from both before and after periods, the TTC of EEBL applications is evaluated using the before-after design. Due to the small sample size of events, the effect of different weather conditions was not pursued.

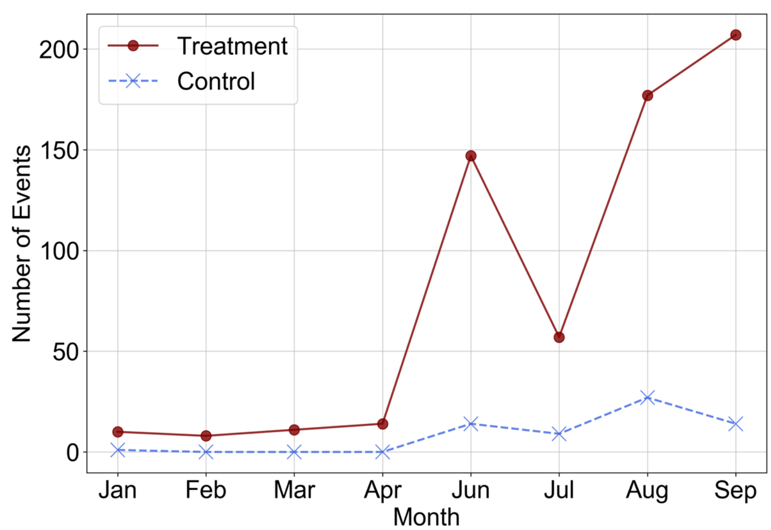
After implementing EEBL warnings, there is a 0.896 second decrease in the 15th percentile TTC values with a 95% confidence interval of [-0.138, 1.929]. By setting the null hypothesis as the estimated safety effect equals zero, since the 95% confidence interval includes zero, the decrease in 15th percentile TTC values is statistically insignificant at the 0.05 significance level. The inconclusive results may be due to the very small sample size of EEBL events.

6.5.2.2 Simulation Modeling

Following the statistical methodology described in Section 5.3.1.5, the simulation model with the EEBL application being implemented was run for six times with different random seeds. An average increase of 1.58 seconds was observed in the 15th percentile of TTC values, with a 95% confidence interval of [-0.50, 3.67]. By setting the null hypothesis as the estimated safety effect equals zero, since the confidence interval includes zero, the increase in 15th percentile TTC values is statistically insignificant at the 0.05 significance level. This implies an inconclusive safety effect after implementing the EEBL application at a 95% confidence level.

6.6 Blind Spot Warning

After employing the data cleaning and filtering steps discussed in Sections 5.1.1.2 and 5.1.1.3, the total number of BSW events from January 2021 to September 2021 (excluding May 2021) is 738. The breakdown of the number of BSW events by months and treatment and control groups is illustrated in Figure 51.



(Source: NYCDOT)

Figure 51. Number of BSW Events for Control and Treatment Groups During the Study Period After Data Cleaning

6.6.1 Crash Analysis

This section presents before-after crash analysis results for side-swipe crashes involving all vehicles in NYC during the study horizon. Similar to the rear-end crash analysis presented in Section 6.4.1, due to the privacy/liability concerns, crash records cannot be linked to instrumented vehicles, thus it is not possible to separate crashes caused by non-instrumented vehicles and instrumented vehicles. The impact of instrumented vehicles in terms of crashes is expected to be marginal compared to various other safety-related confounding factors that occurred simultaneously with the NYC CVPD, such as the COVID-19 pandemic, Vision Zero projects, planned special events, and so on. Thus, the results presented below should be interpreted as a combined treatment effect for all the potential safety-related “treatments” that occurred simultaneously around NYC during the NYC CVPD implementation period and may not be solely due to the BSW and LCW applications.

As discussed in Section 5.2, side-swipe crashes identified from the NYPD crash database are used to assess the combined safety effect of BSW and LCW applications. There is a total of 1,471 side-swipe crashes which occurred between January 2021 to September 2021 in NYC after removing invalid longitude and latitude observations and missing values. Similar to rear-end crashes, side-swipe crashes are further divided into three severity levels: fatal, injury, and PDO. However, there are only two fatal crashes among all the observed side-swipe crashes during the study period. Considering that two crashes are not enough to be categorized as an individual severity level and modeled using the survival analysis approach, these two fatal crashes are grouped together with injury crashes.

The results of the survival analysis model for side-swipe crashes are summarized in Table 15. The logarithm of the traffic volume at MTA bridges and tunnels is found to be positively associated with injury and PDO rear-end crashes, respectively, which is consistent with a previous study (see Xie, Ozbay, and Yang (2019)). According to the 95% BCI, the estimated coefficients of logarithm of traffic volume for both injury and PDO side-swipe crashes are statistically significance at the 0.05 significance level. Specifically, for the log-transformed traffic volume, a 1% increase in traffic volume is associated with 1.932% and 1.592% increases in injury and PDO side-swipe crashes, respectively.

The estimated CMF of injury side-swipe crashes is 0.985 ($e^{-0.015}$) and is statistically insignificant according to 95% BCI while the CMF of PDO side-swipe crashes is 0.850 ($e^{-0.163}$) and is statistically significant according to 95% BCI. The insignificant of treatment effect for the injury side-swipe crashes may be due to the relatively smaller sample size of injury crashes than that of the PDO side-swipe crashes. This finding suggests that compared to the before period, both injury and PDO side-swipe crashes decreased by 1.5% $(1 - 0.985 = 0.015)$ and 15% $(1 - 0.850 = 0.150)$, respectively, in the after period after accounting for the effect of exposure (i.e., traffic volume). It is noted that the estimated CMFs are less than 1 (indicating a decrease in crash) after accounting for crash exposure (i.e., traffic volumes), although an increasing trend in raw crash records was observed for the before and after periods. The increasing trend in raw crash records is potentially due to the recovery of the traffic volumes after COVID-19 and other related factors.

Table 15. Estimated Parameters of the Survival Analysis Model for Side-swipe Crashes

	Injury Mean	Injury 2.5% BCI	Injury 97.5% BCI	PDO Mean	PDO 2.5% BCI	PDO 97.5% BCI
Intercept	-26.030	-27.980	-23.920	-20.270	-22.200	-19.010
Log (Traffic Volume)	1.932	1.778	2.071	1.592	1.471	1.698
Treatment Effect	-0.015	-0.201	0.168	-0.163	-0.293	-0.037
Dispersion	0.013	0.005	0.027	0.006	0.003	0.014

6.6.2 Time to Collision (Vehicle to Vehicle)

TTC values were assessed both empirically from the BSW action log data as well as through simulation modeling assessments.

6.6.2.1 Action Log Data

TTC values between the host vehicle and remote vehicle for BSW events are calculated based on the method discussed in Section 5.1.1.5. Unlike FCW and EEBL applications, BSW applications aim to reduce side-swipe crashes. Thus, only TTC values that correspond to side-swipe conflicts are selected for subsequent analysis and the 15th percentile of TTC values are used as the final TTC measure (St-Aubin, Saunier, and Miranda-Moreno 2015).

There are a total of 15 BSW events with TTC values below the 5 second threshold. Events from the control group are observed only in two months (June and July) in the after period, thus the TTC of the BSW application is only evaluated using before-after design.

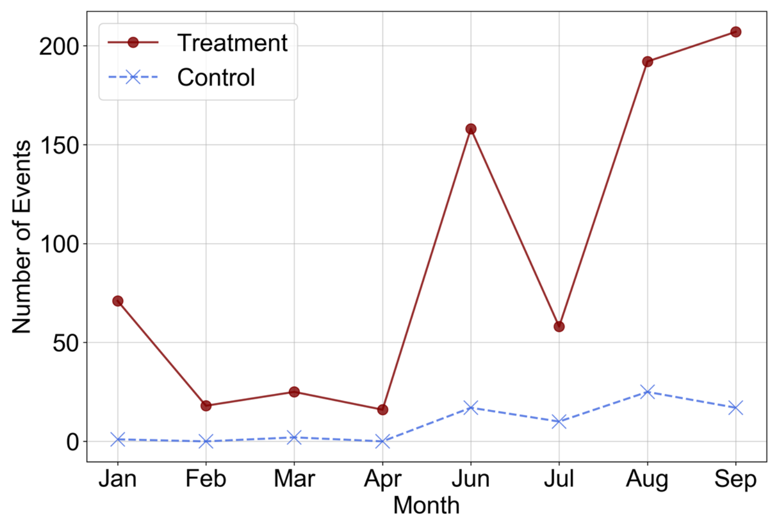
After implementing BSW warnings, there is a -0.097 second increase in the 15th percentile TTC values with a 95% confidence interval [-1.121, 0.928]. Although there is a reduction in TTC, by setting the null hypothesis as the estimated safety effect equals zero, it is not statistically significant at the 0.05 significance level, which indicates that the results are inconclusive. The inconclusive results may be due to the very small sample size of BSW events.

6.6.2.2 Simulation Modeling

Following the statistical methodology described in Section 5.3.1.5, the simulation model with the BSW application being implemented was run for eight times with different random seeds. An average increase of 2.43 seconds was observed in the 15th percentile of TTC values, with a 95% confidence interval of [1.80, 3.06]. The simulation results indicate a positive effect of BSW application in terms of reducing conflict risks.

6.7 Lane Change Warning

After employing the data cleaning and filtering steps discussed in Sections 5.1.1.2 and 5.1.1.3, the total number of LCW events from January 2021 to September 2021 (excluding May 2021) is 873. The breakdown of the number of LCW events by months and treatment and control groups is illustrated in Figure 52.



(Source: NYCDOT)

Figure 52. Number of LCW Events for Control and Treatment Groups During the Study Period After Data Cleaning

6.7.1 Crash Analysis

As discussed in Section 5.2, the crash analysis of LCW application is combined with crash analysis of BSW application. Please refer to Section 6.6.1 for the corresponding discussion.

6.7.2 Time to Collision (Vehicle to Vehicle)

TTC values were assessed both empirically from the LCW action log data as well as through simulation modeling assessments.

6.7.2.1 Action Log Data

Similar to BSW, LCW applications aim to reduce side-swipe crashes. Thus, only TTC values that correspond to side-swipe conflicts are selected for subsequent analysis.

There are a total of 15 LCW events with TTC values below the 5 second threshold. Events from the control group are only observed in June in the after period, thus the TTC of the LCW application is only evaluated using the before-after design.

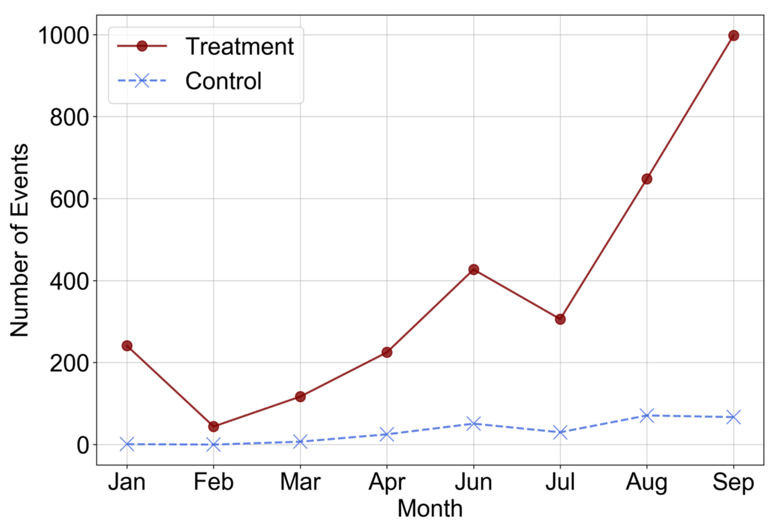
After implementing LCW warnings, there is a 0.265 second increase in the 15th percentile TTC values with a 95% confidence interval [-0.057, 0.586]. By setting the null hypothesis as the estimated safety effect equals zero, since the confidence interval includes zero, the increase in 15th percentile TTC values is marginally statistically insignificant at the 0.05 significance level. This implies an inconclusive safety effect after implementing the LCW application.

6.7.2.2 Simulation Modeling

Following the statistical methodology described in Section 5.3.1.5, the simulation model with the LCW application being implemented was run for eight times with different random seeds. An average increase of 2.03 seconds was observed in the 15th percentile of TTC values, with a 95% confidence interval of [0.88, 3.19]. As the null hypothesis that assumes the estimated safety effect equals zero was rejected, the simulation results indicate a positive effect of LCW application in terms of reducing conflict risks.

6.8 Intersection Movement Assist

After employing the data cleaning and filter steps discussed in Sections 5.1.1.2 and 5.1.1.3, the total number of IMA events from January 2021 to September 2021 (excluding May 2021) is 2,666. The breakdown of the number of IMA events by months and treatment and control groups is illustrated in Figure 53. As can be seen from the figure, there are relatively large number of events for each month and for each group. Thus, evaluation of the IMA application uses the before-after treatment-control group design and the gain score method.



(Source: NYCDOT)

Figure 53. Number of IMA Events for Control and Treatment Groups During the Study Period After Data Cleaning

6.8.1 Crash Analysis

As discussed in Section 5.2, the extraction of left-turn crossing, and head-on crashes that are targeted by the IMA application is relatively difficult since there are no clear contributing factors that correspond to these two types of crashes. Consequently, crash analysis for the IMA application was not pursued.

6.8.2 Time to Collision (Vehicle to Vehicle)

Due to complications and difficulties in implementing the details of the IMA application within the microsimulation environment, TTC values were assessed by examining the IMA action log data.

6.8.2.1 Action Log Data

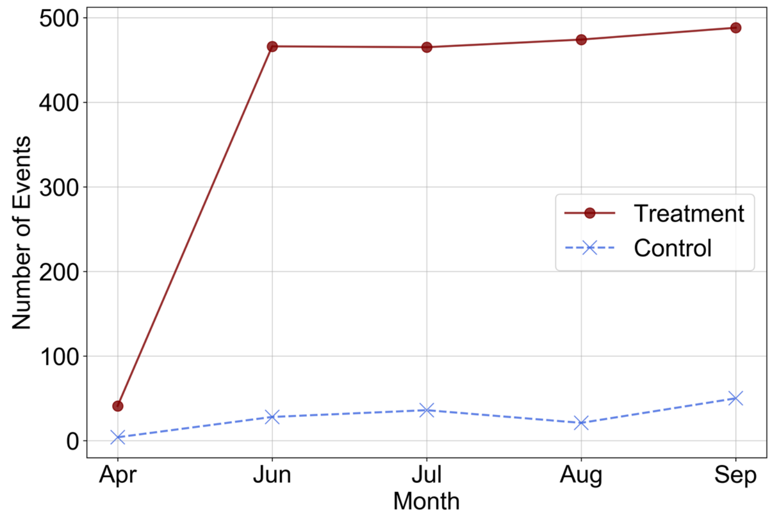
Unlike the above CV applications, IMA applications aim to reduce crossing or left-turning crashes. Thus, TTC values that correspond to crossing conflicts are selected for subsequent analysis and the 15th percentile of TTC values is used as the final TTC measure (St-Aubin, Saunier, and Miranda-Moreno 2015).

There are a total of 29 IMA events with TTC values below the 5 second threshold. IMA events were observed from both before and after periods as well as treatment and control groups. Considering that there are only two months with TTC values less than 5 seconds, namely March 2021 and July 2021, performances for different weather conditions are not pursued.

After receiving IMA warnings, a 2.951 second increase in 15th percentile TTC values with a 95% confidence interval [1.780, 4.122] is observed. By setting the null hypothesis as the estimated safety effect equals zero, since the 95% confidence interval does not include zero, the positive increase in 15th percentile TTC values is statistically significant at the 0.05 significance level. This indicates a reduction of the conflict risk between host and remote vehicles after being given the IMA warning.

6.9 Red Light Violation Warning

The total number of RLVW ASD events from January 2021 to September 2021 (excluding May 2021) is 2,073 events. After employing the data cleaning and filter steps discussed in Sections 5.1.1.2, the breakdown of the number of RLVW events by months and treatment and control groups is illustrated in Figure 54. Issues experienced early in Phase 3 involving the signal controller security certificates interrupted the broadcast of SPaT messages until signal controller firmware modifications could be diagnosed, solutions developed, tested, and deployed. SPaT message broadcast resumed in late April 2021. As such, there were no valid RLVW events from January 2021 to March 2021 and low numbers of events in April 2021. As a result, the before period for RLVW application is set as April 2021 and the after period is from June 2021 to September 2021. While the number of events in April 2021 is low, the relative number of control and treatment group events is relatively consistent from April 2021 to September 2021.



(Source: NYCDOT)

Figure 54. Number of RLVW Events for Control Treatment Groups During the Study Period After Data Cleaning

6.9.1 Likely Red Light Violations

Because of the data obfuscation, it is difficult to identify if the driver was actually running the red light, therefore likely red light violation counts are obtained from the ASD event data. A likely red light violation was defined as when the driver's speed does not reduce to zero (i.e., the vehicle does not come to a full stop) after a RLVW is issued. To extract likely red light violations from the RLVW event data based on this definition, the following algorithm was used.

For each RLVW event:

- Step 1: Obtain minimum speed value after the warning was issued (T_s > 0).
- Step 2: If the obtained minimum speed value is greater than 0.1 mph, then a likely red light violation is identified.

To account for potential measurement errors in the low-speed observations, instead of using zero to identify vehicles' full stops, 0.1 mph is used when extracting red light violations from the ASD event data. Considering that there is only one month (i.e., April 2021) of observations in the before period and the sample size of RLVW events in April 2021 is relatively small as shown in Figure 54, the safety effect corresponding to likely red light violation counts is only estimated using all the observed events rather than separating different weather conditions.

Compared to silent warning scenarios, there are approximately 152 fewer likely red light violation events per 1,000 RLVW events when treatment was enabled. By setting the null hypothesis as the estimated safety effect equals zero, the result is found to be statistically significant at the 0.05 significance level, with a 95% confidence interval of [87.80, 216.34]. This indicates that drivers were more likely to come to full stops instead of running the red lights after the RLVWs were issued.

6.9.2 Time to Collision (Vehicle to Crossing Vehicle Path)

As discussed in Section 5.1.1.5, vehicle trajectories from the host vehicle and other vehicles in its crossing path are both needed to calculate the TTC. Considering that the trajectories of the crossing vehicles were not recorded in the ASD RLVW data (e.g., they were not equipped vehicles), evaluation of 5b is conducted using solely the simulation modeling method.

6.9.2.1 Simulation Modeling

The simulation model with the RLVW application being implemented was run for six times with different random seeds. An average increase of 1.22 seconds was observed in the 15th percentile of TTC values, with a 95% confidence interval of [0.72, 1.71]. Since the null hypothesis was rejected, the simulation results indicate a potential positive effect of RLVW application in terms of reducing conflict risks.

6.9.3 Driver Actions and/or Impact on Actions in Response to Issued Warnings

According to the discussion in Section 5.1.1.4, DBPRM 1 (deceleration difference) and DBPRM 3 (time duration to first deceleration after warning) are used to assess the performance of driver behavior response to RLVW warnings.

6.9.3.1 Increase in Deceleration Difference

The increase in deceleration difference based on all the action log data of the RLVW application is approximately 0.137 m/s^2 with a 95% confidence interval of [0.020, 0.254]. By setting the null hypothesis as the estimated safety effect equals zero, since the 95% confidence interval does not include zero, the increase of the deceleration difference is statistically significant at the 0.05 significance level. This indicates that drivers tended to decelerate approximately 0.137 m/s^2 more after RLVWs were issued.

6.9.3.2 Reduction in Time Duration to First Deceleration After Warning

The reduction in time between the warning issue to first deceleration (DBRPM 3) based on all the observed RLVW events is approximately 0.083 seconds with a 95% confidence interval of [-0.017, 0.183]. Since the 95% confidence interval includes zero, the null hypothesis (the estimated safety effect equals zero) was not rejected. Thus, the estimated reduction in time spent for slowing down to speed limit is statistically insignificant at the 0.05 significance level. Considering the estimated reduction in time between the warning issue to first deceleration is also very close to zero, the impact of the RLVWs on reducing the drivers' reaction time to decelerate is insignificant and inconclusive.

6.9.4 RLVW Limitations and Lessons Learned

Several challenges and limitations were identified during the evaluation of RLVW application:

- The RLVW application was not available during the first three months of the before period due to the issues described, which leaves only one month of data during the before period for subsequent analysis. This may lead to unobserved confounding factors during the before-after analysis, which may bias the estimated safety effect of RLVWs.

- Trajectories of vehicles in crossing directions of the host CVs were not collected in the action log data. As a result, crossing conflicts between host vehicles and other vehicles in the crossing directions of the intersections cannot be obtained using the action log data, which hinders a comprehensive safety evaluation of the RLVW application. In future deployments, trajectories of non-equipped vehicles in crossing directions of the host vehicle could be collected and recorded along with the trajectories of the host vehicle to enable a more comprehensive evaluation of whether RLVWs can reduce crossing conflicts. While this data collection could not be accommodated in the scope of the NYC CVPD, it would allow for a more robust analysis of the impacts of the RLVW application's impacts.
- An extensive matching process is needed to extract the detailed SPaT and MAP information (e.g., signal group ID) and corresponding vehicle position, heading, and distance to the stop bar at each timestamp. This was not included in the current analysis due to the level of complexity and additional data extrapolation and map inference. In literature, the analysis of driver behavior responses of RLVW application was mostly analyzed by associating the time when drivers take actions with corresponding signal timing. For example, in Yan, Liu, and Xu (2015), drivers' braking behavior was measured as the time elapsed from the onset of the yellow signal until the driver started stepping on the brake pedal. For future evaluation, a matching pipeline between signal status and vehicle location to the stop bar for each timestamp is suggested to be developed to provide a more accurate analysis of the safety effect of RLVW application.

6.10 Vehicle Turning Right Warning

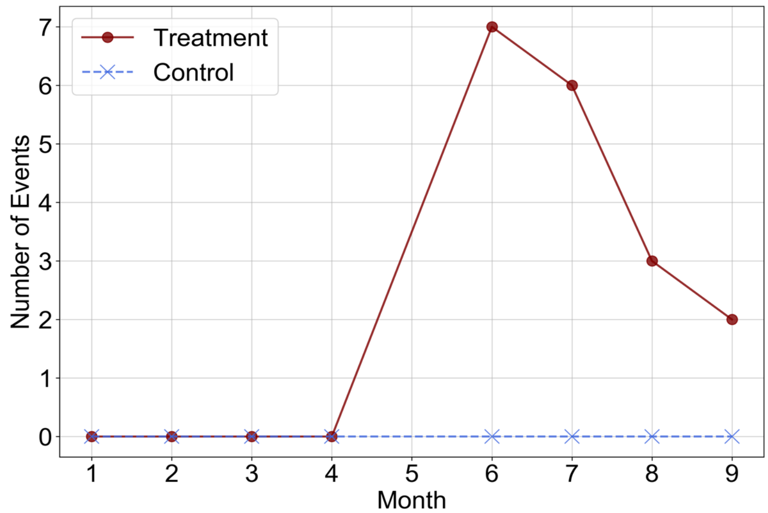
During the entire study period, there was only one VTRW event that occurred in the treatment group in February 2021. Considering that there were no other events during the after period and in the control group, it is not feasible to conduct meaningful before-after evaluations for VTRW application based on ASD data.

In addition, although six simulation runs were conducted with the VTRW application, no VTRW warnings were activated for any of the vehicles. This is due to the very specific requirements of the application. According to the algorithm, the VTRW application requires the host vehicle to be a connected bus waiting within the bus stop zone. However, both the proportion of buses and the market penetration rate of CVs are very low in the simulation model. Since the number of the simulated VTRW events was very small (<=1 on average across multiple simulations) and only one VTRW action log or event record existed, no further evaluation was conducted.

6.11 Pedestrian in Signalized Crosswalk Warning

The total number of PEDINXWALK events from January 2021 to September 2021 (excluding May 2021) is 20 after data cleaning/filtering, among which only 18 events have complete month information. Thus, the 18 events with complete time information are used in subsequent analysis. The breakdown of the number of PEDINXWALK events by months and treatment and control groups is illustrated in Figure 55. There were no PEDINXWALK events from January 2021 to

April 2021 due to signal controller issues (as discussed in the RLVW section), and there is no PEDINXWALK events from control group. As a result, descriptive analysis is performed instead of the before-after treatment-control group evaluation.



(Source: NYCDOT)

Figure 55. Number of PEDINXWALK Events for Control and Treatment Groups During the Study Period After Data Cleaning

6.11.1 Number of Warnings Generated

There were a total of twenty pedestrian in crosswalk warnings generated from January 2021 to September 2021. As mentioned, due to no before period events, no analysis on the impact of the implantation of PEDINXWALK warnings can be conducted.

6.11.2 Pedestrian-related Hard Braking Events

Hard braking is defined to occur when a vehicle's longitudinal deceleration is greater than a certain pre-determined threshold (Wu and Jovanis 2011). An analysis of undesirable driving events such as hard braking, sharp turning, and sudden lane changes showed that looking at the frequency of such events could prove to be a valuable surrogate for determining driver behavior and accident risk (Musicant, Bar-Gera, and Schechtman 2010). A six-month study of drivers in Georgia traveling on freeways, arterials, and local roads found that those involved in a crash tend to more frequently hard brake than those not involved in a crash (Jun, Ogle, and Guensler 2007).

A pedestrian-related hard braking event was defined as hard braking after a warning was given, and when that hard braking deceleration is lower than an established threshold. According to the literature, the range of the commonly used hard braking thresholds is reported to be between -2 m/s^2 and -4.5 m/s^2. In this study, -2 m/s^2 was chosen as the hard braking threshold to include as many hard braking events as possible. Considering the small sample size and inadequate information in the control group and before period's data, the performance of this application was only based on the proportion of the pedestrian-related hard braking events in all the pedestrian in crosswalk warning events.

There are only two PEDINXWALK warning events out of the total 20 events that contain pedestrian-related hard braking actions. Although both drivers braked after the PEDINXWALK warning was issued, findings are inconclusive due to the small sample size.

6.11.3 Time to collision (vehicle to pedestrian)

The simulation model with the PEDINXWALK application being implemented was run for eight times with different random seeds. The social force model (Helbing and Molnar 1995) that describes the dynamics of pedestrian was used to define the shape of pedestrians when calculating TTC. An average increase of 1.80 seconds was observed in the 15th percentile of TTC values, with a 95% confidence interval of [1.27, 2.33]. By setting the null hypothesis as the estimated safety effect equals zero, the simulation results indicate a positive effect of PEDINXWALK application in terms of reducing conflict risks.

6.11.4 Driver actions and/or impact on actions in response to issued warnings

The driver actions in response to PEDINXWALK warnings was discussed in Section 5.3.1.4 and Figure 42. Based on the events identified for the treatment group, all the drivers in the treatment groups decelerated after receiving the PEDINXWALK warnings.

6.11.5 Limitations and Lessons Learned

During the evaluation of PEDINXWALK application, several challenges and limitations were presented. In summary:

- The current V2I communication of PEDINXWALK is not able to record any trajectory data of the pedestrians in crosswalk, but merely a presence of a pedestrian somewhere within the crosswalk. As a result, conflicts between vehicles and pedestrians cannot be obtained, limiting the ability to conduct a safety analysis of this application.
- The action log data and literature (Bokare and Maurya 2017) show that drivers will approach signalized intersections with a low speed in an urban area. Furthermore, if the sight of drivers is clear, drivers will generally have enough time to decelerate. Thus, the PEDINXWALK application can be more useful when the driver’s sight is blocked, or in places with complicated intersection geometries, or in poor visibility environmental conditions.

6.12 Mobile Accessible Pedestrian Signal System (PED-SIG)

The following presents a summary of the findings of the field trials of PID use by pedestrians with vision disabilities.

6.12.1 PED-SIG Qualitative Operator Feedback

Field tests were conducted between October 29, 2021 to November 18, 2021. The pre-experiment and post-experiment survey collected responses from all 24 participants.

6.12.1.1 Pre-experiment Survey

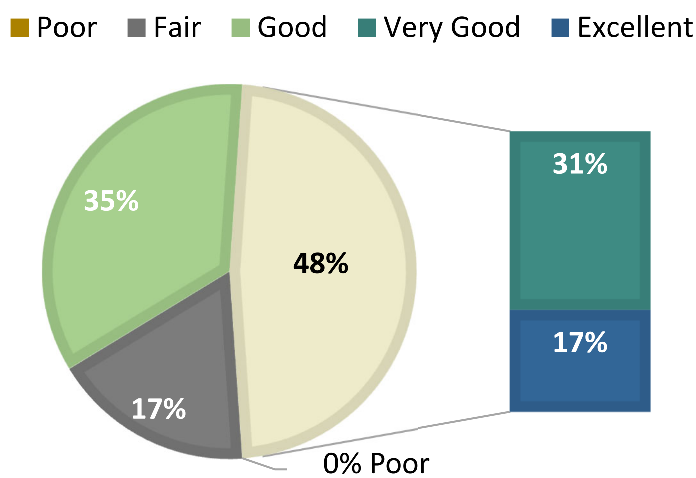
The purpose of the pre-experiment survey is to understand the baseline conditions for study participants. The respondents of the survey ranged a diverse age group, vision ability, mobility assistance mechanisms, and frequency in daily signalized intersection crossing. The breakdown of each demographic and background factor is presented in Table 16 below. All participants used smart phones. Of these, 22 (92%) use the iOS system and 2 use Android-based phones in their daily life. 80% of the participants have used GPS to navigate the city streets.

Table 16. Demographic and Background Information of the Surveyed PID Participants

Factors	Groups	Participants (N=24)
Age group (%)	18-24	0%
	25-44	58%
	45-64	25%
	Older than 65	17%
Vision ability (%)	Partially-sighted or low vision	29%
	Blind	29%
	Totally blind	42%
Signalized intersection crossing frequency (%)	6 or more intersections a day	50%
	4 or 5 intersections a day	29%
	2 or 3 intersections a day	21%
	Less than 2 intersections a day	0%
Mobility assistance mechanisms (%)	Long or white cane	58%
	Guide dog	21%
	Electronic travel aid (e.g., laser cane)	0%
	Personal navigation device / GPS on the phone	0%
	Asking other pedestrians I pass	8%
Proficiency in signalized street crossings (%)	Well above average	13%
	Above average	37%
	Average	33%
	Below Average	17%
	Well below average	0%

6.12.1.2 Participants Perceptions About PED-SIG Technologies

The post-experiment interview aims to collect useful feedback on participants' perceptions and experiences with the PED-SIG application after the field test is done. The first five questions ask about user experience. Figure 56 shows that, overall, about 83% of the participants gave positive feedback ('Good', 'Very Good' or 'Excellent') when rating the overall impression for the PED-SIG application.

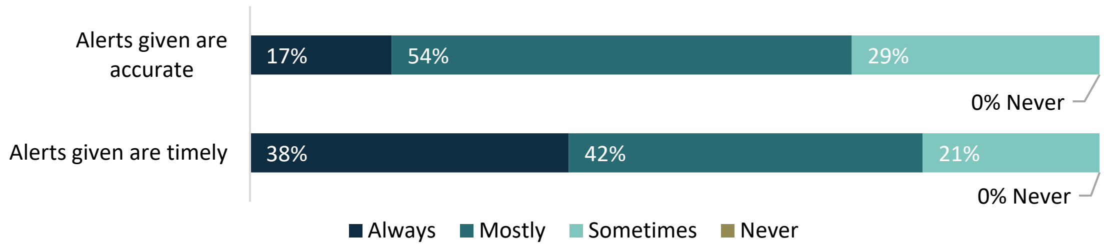


(Source: NYU C2SMART Center)

Figure 56. Overall PED-SIG Application Rating

The main problems experienced when using the PED-SIG application (at least once by the same participant during the field test) were that the location information provided was not accurate (75%), there were slow responses (25%), and the orientation was not accurate (21%). 96% of the participants felt they were given sufficient time to cross the intersection and 63% of them felt they stayed oriented on the crosswalk when using the PED-SIG application. The majority of participants (92%) thought the application is easy to use. While 71% of the participants strongly or somewhat agreed that they felt more confident in their ability to cross a signalized intersection with the application than with other assistive technologies they have used before, about 25% of them kept a neutral opinion and one participant (4%) expressed some form of disagreement.

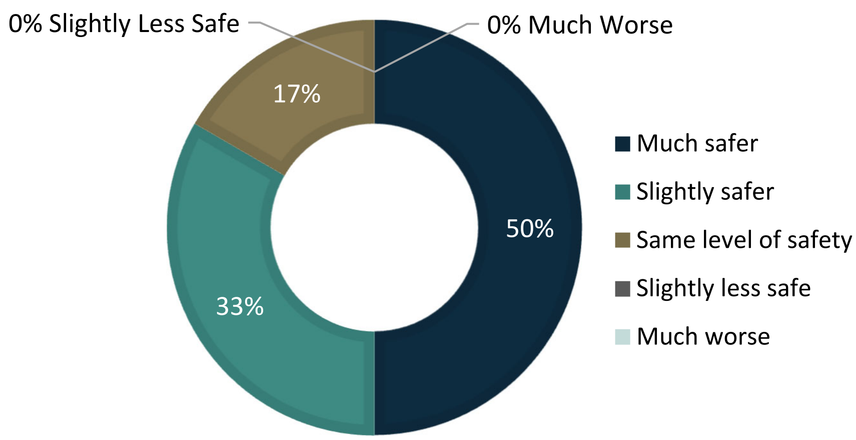
The second part of the post-experiment survey asked questions about the performance of the PED-SIG application. All participants (100%) agreed that the application provided sufficient information through audio to assist their intersection crossing. However, the perception of the vibration function was mixed, with about 13% of the participants thinking that vibration information was not sufficient, and about half of the participants (46%) stating that they did not know or did not notice the vibrations. Approximately 80% of the participants received timely alerts/information from the application always or most of the time. This rate drops to 71% when asking if the alerts given were accurate as shown in Figure 57 below. All the participants agreed that the information provided by the PED-SIG application is helpful, with 67% strongly agreeing and 33% somewhat agreeing.



(Source: NYU C2SMART Center)

Figure 57. PED-SIG Application Alerts Were Accurate/Timely

As the primary goal of the NYC CVPD is to improve safety, it is important to assess and measure the user's perception of the application's impact on safety. Based on the survey results as shown in Figure 58 below, 50% of the participants felt much safer when using the PED-SIG application in comparison to not using it, 33% felt slightly safer, and the remaining 17% of the participants retained the same level of perceived safety. All the participants anticipated that pedestrians would benefit from PED-SIG technologies, especially pedestrians with visual disabilities.



(Source: NYU C2SMART Center)

Figure 58. PED-SIG Application Safety Perception

Open-ended survey responses are useful for gaining insight into the issues that are not fully covered by multi-choice and Likert scale questions. The open-ended question asking about suggestions to improve the current PED-SIG application and the main takeaway from the responses are listed as follows:

- Participants want to test this application on more intersections, especially the ones with complex geometry (5-leg intersections, pedestrian island, etc.) and locations with leading pedestrian interval (LPI) signals.
- Use the application without an additional device and integrate it with other existing accessible or navigation applications, so they do not need to launch multiple applications. Integration with a wearable device, such as armband or smartwatch, was also mentioned by a few participants.

- Add more information about the streets; for example, if it is a one-way or two-way street, unsignalized intersection, how many lanes, crosswalk width, orientation of intersections (4-way vs. 5-way).
- Enable options for experienced users to choose what information they get (e.g., frequency of the alerts, enable or limit haptic feedback).
- Participants want to be alerted when they are veering off the crosswalk.
- Concern about having the phone “in hand”, especially when the participants were already using a cane or guide dog. The application should also be compatible with screen readers.

6.12.2 PED-SIG Operational Data Logs

Approximately 170 runs, each made up of two crosswalk crossings, were completed by the 24 participants during the field tests. Pedestrian crossing speed and crossing travel time, waiting time at intersection for crossing, and times out of crosswalk were evaluated using data extracted from PID operation data logs, supplemented by field observations. A demonstration of the PED-SIG application operational data logs is shown in Figure 59.

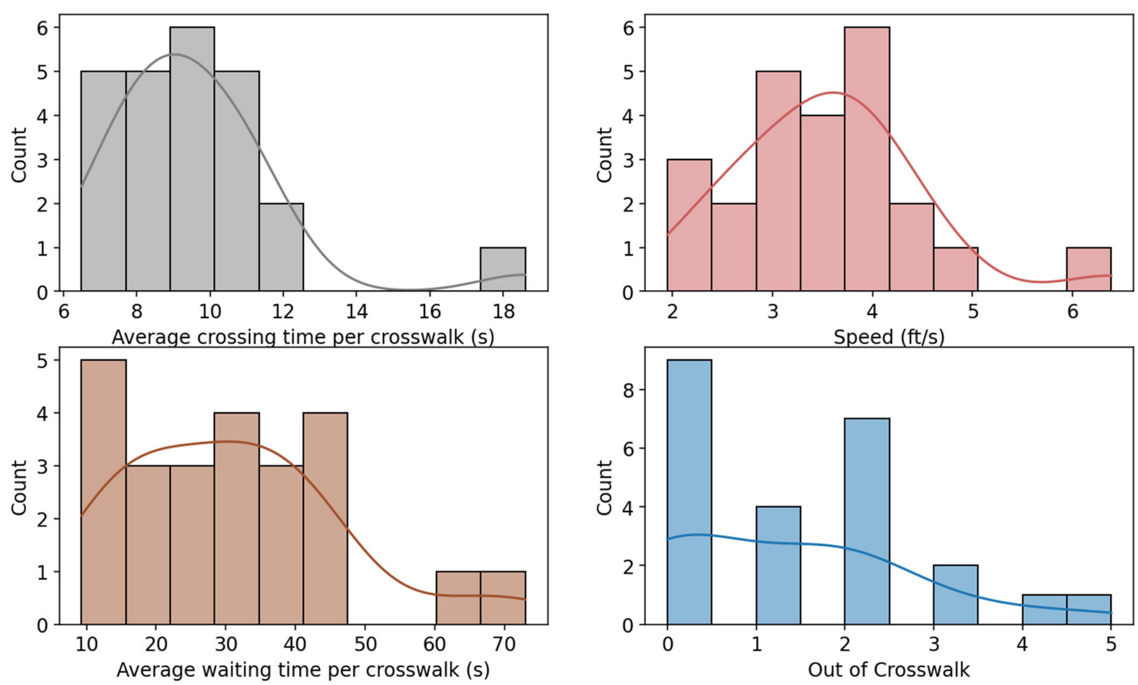
(Source: NYU C2SMART Center)

Figure 59. Visualization of the PED-SIG Application Data Logs

Based on the extracted information, both aggregated performance measures (for all participants) and disaggregated information (distributions of individual data) were generated. Table 17 shows the aggregated performance measures for all participants and Figure 60 illustrates the distribution of disaggregated performance measures. The waiting time per crosswalk varies among different participants, with some of them started crossing the street right after receiving the “Walk signal is on” audio message from the application. A few of them waited for a red light and one participant always waited multiple signal cycles to ensure she can safely cross the street after receiving the notification from the PED-SIG application. In addition, 63% of the participants veered off the crosswalk at least once during the field tests. It is worth noting that field observations show that many participants tended to walk faster when crossing the signalized streets; 54% of them crossed the streets faster than the 3.5 ft/s assumption used for signal timing design. Potential contributing factors may include the use of guide dogs (100% of participants who used a guide dog crossed the street faster than 3.5 ft/s) and proficiency in independent travel (77% self-rated “above or well above average” in the fast-walking group, compared with 45% in the slow-walking group).

Table 17. Aggregated Performance Measures of the Participants

Statistic	Crossing speed (m/s)	Crossing speed (ft/s)	Average crossing time per crosswalk (s)	Average waiting time per crosswalk (s)	Average Number of Times Out of Crosswalk
Mean	1.1	3.6	9.6	31.0	1.4
Standard Deviation	0.3	0.9	2.4	15.9	1.4
[15^{th} ,85^{th}] Percentile	[0.8, 1.3]	[2.6, 4.2]	[7.7, 11.0]	[14.9, 43.0]	[0.0, 2.3]



(Source: NYU C2SMART Center)

Figure 60. Distribution of Pedestrian Crossing Speed and Crossing Travel Time, Waiting Time at Intersection for Crossing, and Number of Times Participants Stepped Out of Crosswalk

6.12.3 PID Lessons Learned

Several valuable lessons were learned during the application development, recruitment process, and field tests.

During the development of the application:

- Some proposed functions/requirements were found to be infeasible during the development stage, such as logging the exact number of steps taken. Although this information could be very beneficial, not even the leading step-counting technologies (Fitbit, Apple, etc.) are able to achieve this when GPS is not accurate.
- Aligning the application development on both Android and iOS proved to be very difficult since the two different operating systems give two different sets of utilities and environments. This required two different implementation methods, which doubled the effort in any development, testing, debugging, updates, and enhancements. For a trial-version of a similar application, selecting a single platform is highly recommended.

During the recruitment process:

- First, it is vital that organizations and agencies requesting time and travel from volunteers with any type of disability arrange transportation to and from the test site for volunteers. Travel throughout the city is significantly more difficult for individuals with low or no vision, and for those unable to use public transportation, it can be expensive (when taking a taxi) or difficult to effectively time. Access-a-Ride no longer offers specific appointment slots due to COVID-19, requiring large blocks of potential waiting time and potentially multiple people sharing a trip.
- Secondly, many of the tools that researchers are used to using for scheduling and communication may not be accessible to volunteers with disabilities, and it is important to have a variety of options for individuals. For example, Google scheduling calendars are not accessible to screen readers. Some volunteers prefer talking on the phone to using email; others may prefer email to talking on the phone. Researchers ought to proactively determine volunteers' preferred methods of communication and adapt to them.
- Finally, it is important that any research concerning specific communities involves the input of those communities from conception. Every aspect of the research, from project design to final product, should be co-designed with the intended userbase. There will be many aspects of life about which individuals without disabilities have no or limited understanding, and these experiences will shape how the end user interacts with the research and its outputs. For this reason, projects like this one should continually solicit and iterate based off feedback from and involvement of the community it seeks to aid.

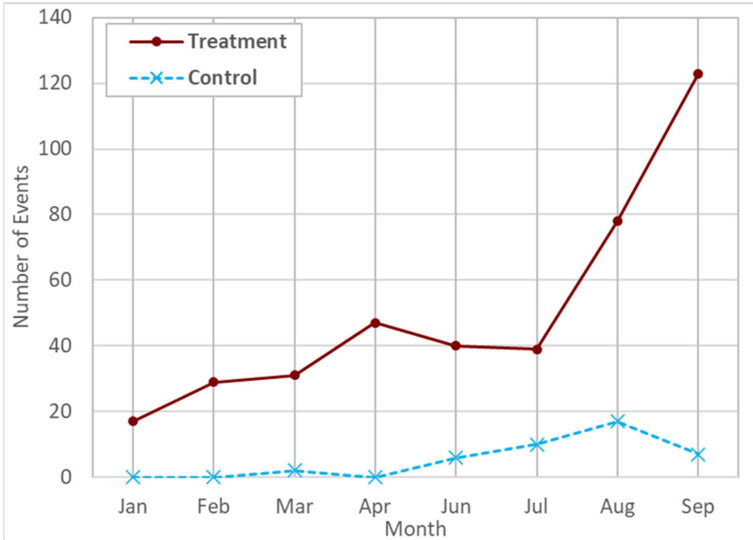
During the field tests and data analysis:

- GPS accuracy remains a major challenge. Even with a dual band Global Navigation Satellite System (GNSS), the urban environment is still difficult to get consistently accurate GNSS. A potential solution could involve Real-time Kinematic Positioning (RTK) or another location correction software. However, RTK or other location correction software is not available natively on iOS or Android and there can be an additional cost for this type of service (usually a monthly subscription or something similar). An external GNSS device will still be needed in the short-term.

- Any location correction service must be thoroughly tested before deployment – there may be locations/time periods with better or worse performance.
- All the proposed application functionality and use scenarios should be well documented, tested, and validated, especially if the functionality is demanded by the user group. For example, although the “veering off the crosswalk” audio message is included in the application functions, it was not heard in any of the pre-tests and actual field tests. Based on the post-experiment survey, this is a functionality that the participants are interested in.
- Be aware of potential compass issues over the mobile phones. It was found that even using the same phone model, compass information can vary on different phones. In addition, environmental factors can have an impact on the compass. During the field test, the test phone compass was consistently rotated at an angle at one street corner that was near a hospital, which potentially may be due to magnet applications in medical equipment.
- Additional factors that were out of control of the smartphone application (positioning, data streams from the TMC, cellular connectivity) negatively affected the User Experience (UX). Many of these factors need to be communicated with multiple stakeholders. For future deployment, real-time monitoring of data stream connection (e.g., SPaT) and cellular/Bluetooth connection of the phone is needed. It is recommended to also add notifications alerting users when the connection is lost.
- GPS inaccuracy and how the current application collects the data also brought challenges in computing the performance measures. For example, an “reaching the end of the crosswalk” alert may be triggered after a participant has reached the sidewalk curb for a certain distance (usually 2-10 feet) due to GPS issues. If the participant already knew he/she has reached the curb and stopped walking, this alert will not be triggered and logged into the data. The team had to use algorithms, map visualization, and field observation notes together (e.g., crossing start times and end times) to filter and compensate for the actual position of the data points. This issue needs to be considered for future large-scale testing and deployment as field observation data may not be available/feasible.

6.13 Oversize Vehicle Compliance

The Oversize Vehicle Compliance (OVC) application was deployed at one location throughout the evaluation period, though some additional sites were active for testing purposes early in the before period. After filtering the collected OVC event records to those at the true deployment site 446 events remained. Figure 61 below presents the breakdown of the treatment and control events for the before period (January through April) and the after period (June through September).



(Source: NYCDOT)

Figure 61. Number of OVC Events for Control and Treatment Groups After Data Cleaning

The OVC deployment site had the defined clearance height set artificially low at 78 inches (1.98 meters) to be broadcast in the TIM message in order to test the performance of the application as very few tall vehicles were included in the CVPD fleet.

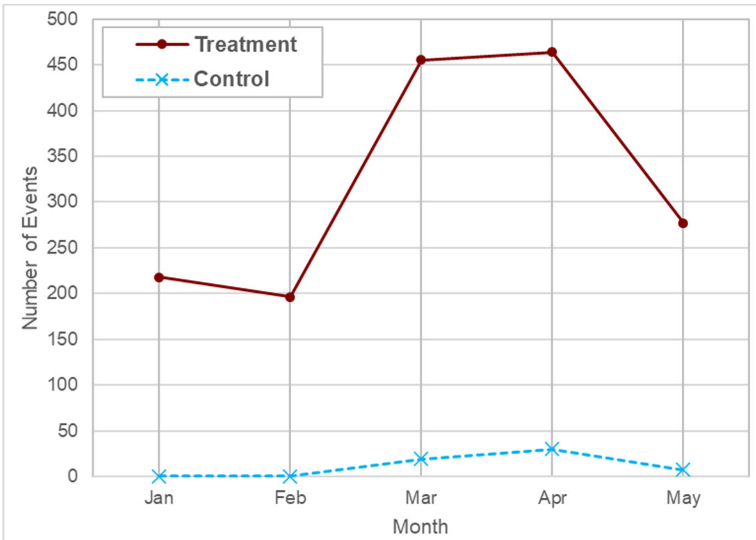
For all 446 events recorded at the deployment site, all vehicles receiving the alert were above 2.00 meters in height and were therefore valid alerts considering the artificially low clearance threshold that was set within the TIM message. The application also provided advance warning to all 446 events prior to the bridge location, including several warnings as vehicles turned into the city block with the OVC application.

As none of the host vehicles in the OVC events were taller than the true low bridge clearance height, there was never a true potential for a low-bridge strike event. As such, there are no meaningful conclusions or evaluations on the efficacies of the warnings in changing vehicle motions or evaluating driver responses to the OVC warnings.

6.14 Emergency Communications and Evacuation Information

The Emergency Communications and Evacuation Information (EVAC) application was never implemented for a true emergency condition throughout the deployment. Instead, a handful of locations were actively broadcasting EVAC test messages during the very early stages of the before period, and one site continued broadcasting the test EVAC message throughout the before period. All EVAC test messages were halted prior to the beginning of the after period. This was to prevent any EVAC test messages being shared with the fleet and potentially causing confusion, concern, or simply distraction.

After filtering EVAC events to those related to the site that broadcast throughout the before period, a total of 1,666 messages remained after error checking and obfuscation. While other applications do not consider events from May due to the transition period, the fact that all EVAC events were recorded prior to the start of the transition period in May allows consideration of those events in the before analysis. The breakdown of the events by month are shown in Figure 62 below.



(Source: NYCDOT)

Figure 62. Number of EVAC Events for Control and Treatment Groups After Data Cleaning

No direct analysis of driver response can be measured as the messages were only issued during the before period. However, the range of the EVAC message in an urban canyon environment can be examined and is presented in Table 18. Most of the warnings were triggered when the vehicle was within 100 meters of the center of the TIM zone and over 95% from within 200 meters. However, there were several warnings triggered from more than 200 meters away with the farthest event approximately 1,150 meters from the TIM broadcast site.

Table 18. EVAC Events Received by Radius from TIM Broadcast Site

Radius (m)	EVAC Messages	Percent of Total
0-50	634	38.1%
50-100	500	30.0%
100-200	460	27.6%
200-300	14	0.8%
300-400	21	1.3%
400-500	10	0.6%
500-750	21	1.3%
750-1,000	4	0.2%
1,000-1,250	2	0.1%
Total	**1,666**	**100.0%**

6.15 Travel Time Evaluation (I-SIGCVDATA)

The following presents the findings of a comparison of the data collected as part of the CV Travel Time system deployed as a I-SIGCVDATA application under the NYC CVPD and the legacy data collected from the ETC Travel Time system.

6.15.1 Sample Sizes

There are 19 possible comparisons of ETC segments to aggregated CV segments, as shown in Table 19. The average daily number of observations was calculated and compared between ETC travel time system and CV travel time system for October 2021. The CV system has significantly fewer number of samples for all segments. This is as expected due to the relative difference in the market penetration of the toll tags (approximately 80%) compared to the ASDs (less than 1%).

Table 19. High-level Sample Size Comparison across all ETC Segments

ETC Segment	ETC Segment Description	ETC Sample Size	CV Sample Size
45-102	1st Avenue from 23rd Street to 34th Street	740	26
102-48	1st Avenue from 34th Street to 42nd Street	115	10
48-40	1st Avenue from 42nd Street to 49th Street	511	6
40-41	1st Avenue from 49th Street to 57th Street	1,729	11
45-105	23rd Street from 1st Avenue to 2nd Avenue	816	4
105-45	23rd Street from 2nd Avenue to 1st Avenue	649	9
103-105	2nd Avenue from 34th Street to 23rd Street	2,684	13
42-103	2nd Avenue from 42nd Street to 34th Street	1,660	14
46-42	2nd Avenue from 49th Street to 42nd Street	2,098	14
55-46	2nd Avenue from 57th Street to 49th Street	3,323	12
102-103	34th Street from 1st Avenue to 2nd Avenue	93	3
103-102	34th Street from 2nd Avenue to 1st Avenue	1,673	16
40-46	49th Street from 1st Avenue to 2nd Avenue	1,252	3
41-55	57th Street from 1st Avenue to 2nd Avenue	103	1
55-41	57th Street from 2nd Avenue to 1st Avenue	434	1
71-70	Flatbush Avenue from Atlantic Avenue to Willoughby Street	4,745	6
73-70	Flatbush Avenue from Tillary Street to Willoughby Street	8,283	2
70-71	Flatbush Avenue from Willoughby Street to Atlantic Avenue	5,105	2
70-73	Flatbush Avenue from Willoughby Street to Tillary Street	7,642	4

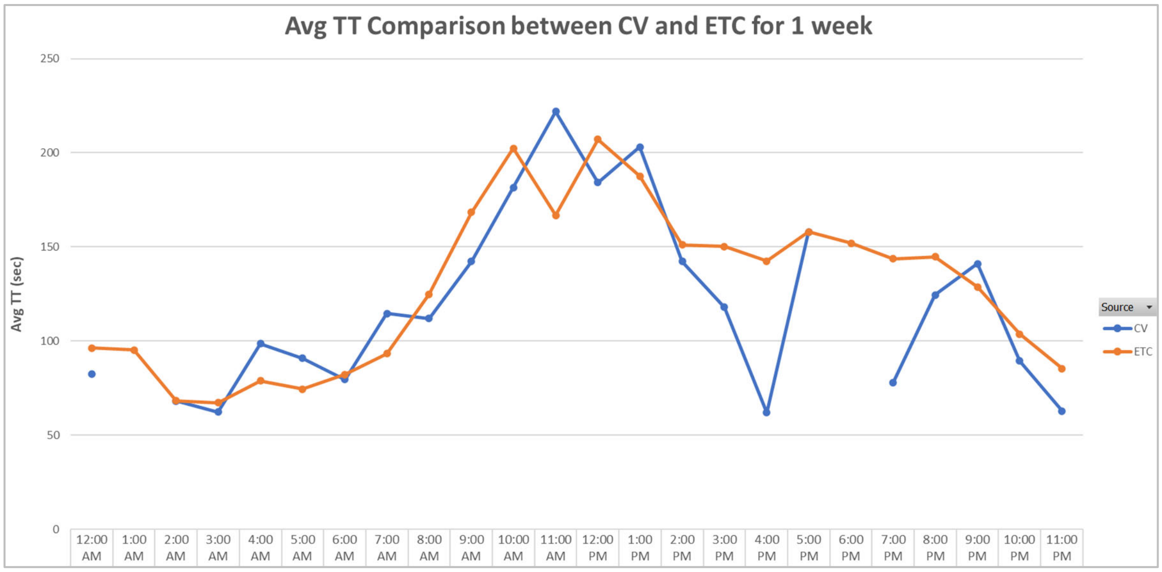
As shown in the table, the average CV sample sizes (calculated based on methods presented in Section 5.1.2.1) vary across all segments. For a detailed comparative analysis, the segment covering 2nd Avenue between 49th St and 42nd St was used. Table 20 shows a comparison of the sample size for 2nd Avenue between 49th St and 42nd St over 3 different time horizons: 1-day (October 13, 2021), 1-week (October 11-15, 2021) and 1-month (October 2021). The limited CV travel times sample sizes for 1-day prevented a meaningful comparison, however, the 1-week and 1-month time periods were considered for further analysis.

Table 20. Average CV and ETC Sample Size Comparison

Hour Start	1-Day CV	1-Day ETC	1-Week CV	1-Week ETC	1-Month CV	1-Month ETC
12:00 AM	2.0	71	3.0	411	12.5	1,514
1:00 AM	n/a	28	n/a	275	2.8	1,056
2:00 AM	3.0	25	4.8	189	18.2	864
3:00 AM	1.3	28	3.2	156	7.7	746
4:00 AM	n/a	45	2.8	229	3.8	987
5:00 AM	1.3	63	2.7	363	16.3	1,669
6:00 AM	2.7	123	6.7	625	27.7	2,705
7:00 AM	1.0	125	3.0	709	11.5	3,133
8:00 AM	n/a	134	6.0	720	13.8	3,057
9:00 AM	1.0	131	4.5	699	15.0	2,725
10:00 AM	1.5	106	6.3	570	17.0	2,346
11:00 AM	2.0	102	2.5	569	13.0	2,370
12:00 PM	2.0	110	8.5	585	23.3	2,316
1:00 PM	1.0	122	3.7	584	19.5	2,315
2:00 PM	1.0	114	4.2	578	19.8	2,494
3:00 PM	n/a	144	2.5	688	11.2	2,834
4:00 PM	n/a	127	1.0	699	9.0	2,838
5:00 PM	1.0	146	5.3	732	11.7	3,097
6:00 PM	n/a	148	n/a	758	2.7	3,133
7:00 PM	n/a	145	1.5	651	4.2	3,105
8:00 PM	n/a	142	2.8	637	6.5	3,028
9:00 PM	n/a	132	2.7	531	6.2	2,563
10:00 PM	n/a	149	2.0	577	4.7	2,278
11:00 PM	n/a	115	2.2	525	6.3	2,166

6.15.2 Travel Time

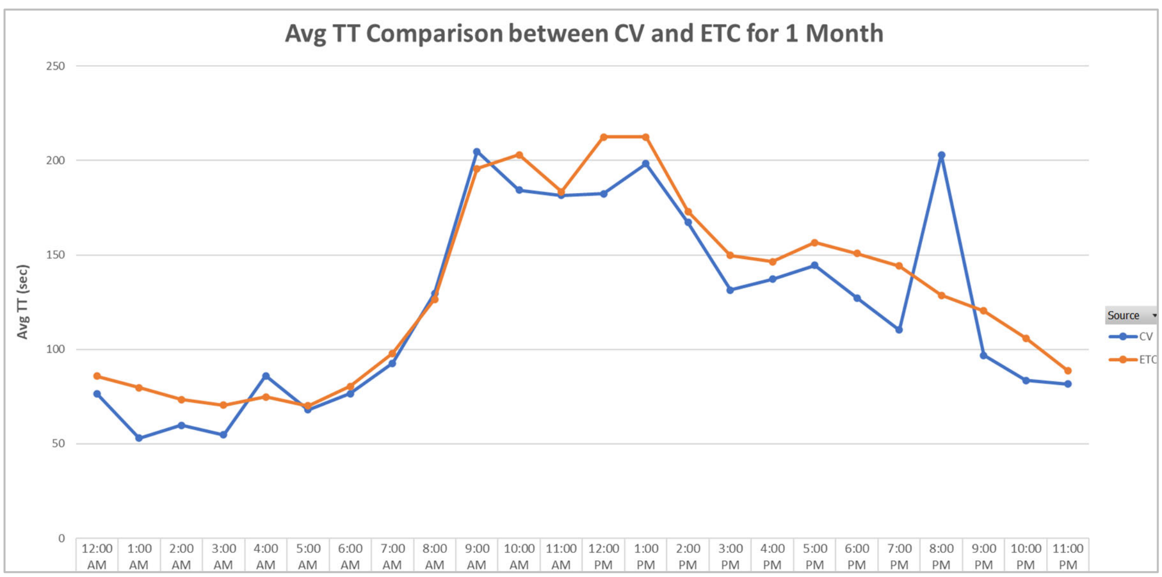
As shown in Figure 63, for 1-week analysis, the CV travel time has a similar profile to the ETC travel time over the 24-hour period. However, there are hours where there are large differences in average travel time, which could be attributed to the smaller sample size compared to the other hours (see Table 20). Additionally for the 4:00pm to 5:00pm and 7:00pm to 8:00pm hours the CV segment data was incomplete, and the travel time was scaled which could contribute to the large differences.



(Source: NYCDOT)

Figure 63. Average Travel Time Comparison for 1-Week (10/11/2021 to 10/15/2021)

As shown in Figure 64, for 1-month analysis, the CV travel time has a similar profile to the ETC travel time over the 24-hour period. However, there are hours where there are large differences in average travel time, which can be attributed to the smaller sample size compared to the other hours.

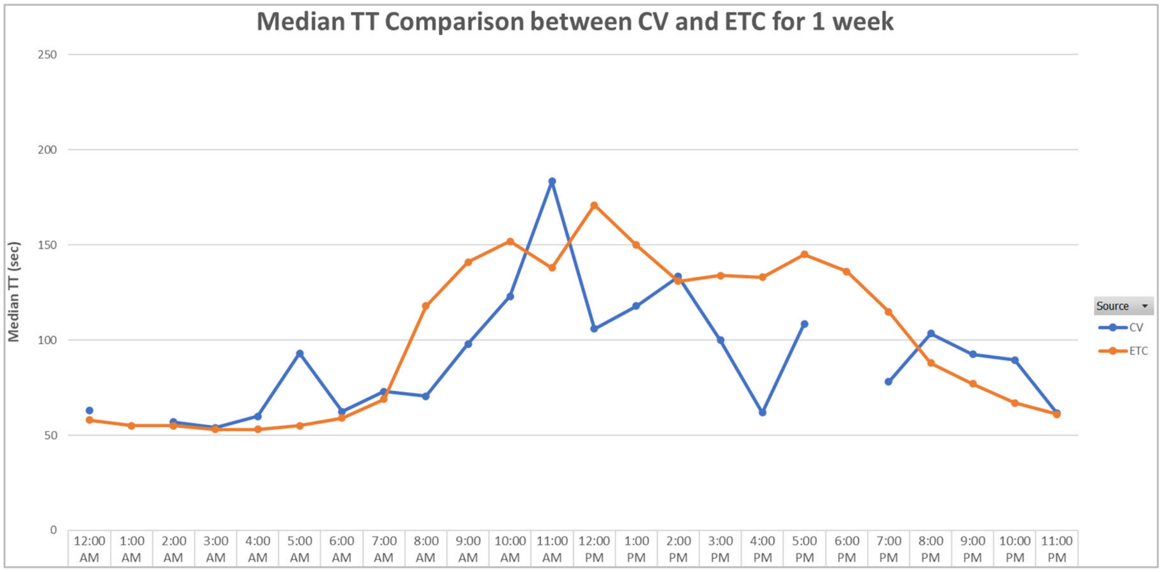


(Source: NYCDOT)

Figure 64. Average Travel Time Comparison for 1-Month (October 2021)

As an alternative to the average, the median travel was calculated and compared. As shown in Figure 65, for 1-week analysis, the CV travel time has a similar profile to the ETC travel time over the 24-hour time period. The median travel times are lower than the average as expected, and there are certain hours with larger differences similar to the comparison of the averages.

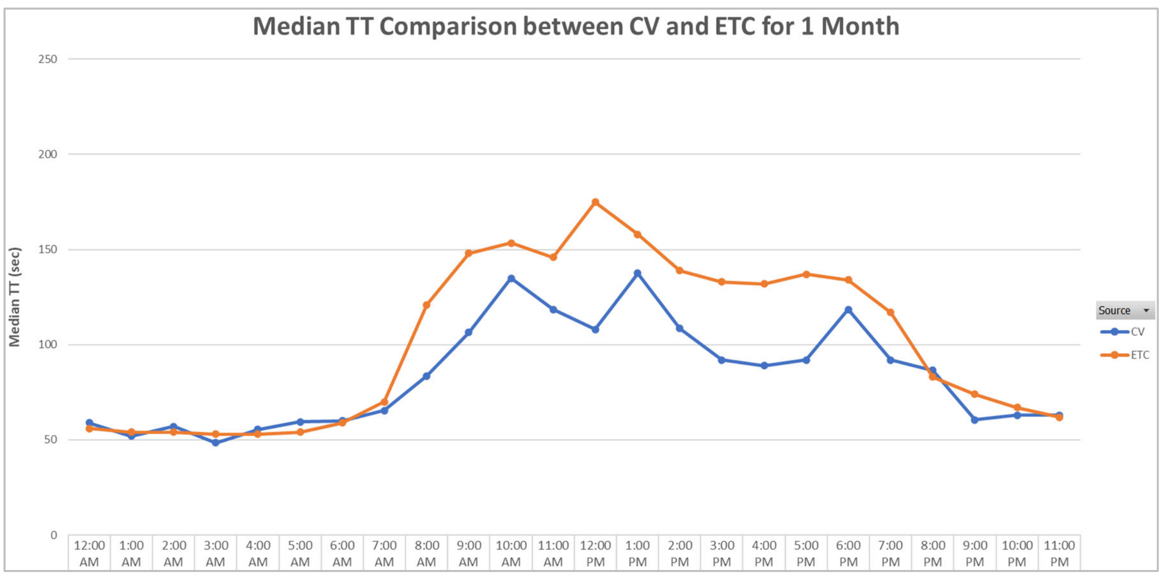
However, CV travel time is generally less than ETC travel time. For 4:00pm to 5:00pm and 7:00pm to 8:00pm, the CV segment data was incomplete. And the travel time was scaled, which could be attributed to the large differences.



(Source: NYCDOT)

Figure 65. Median Travel Time Comparison for 1-Week (10/11/2021 to 10/15/2021)

As shown in Figure 66, for 1-month analysis, the CV travel time has a similar profile to the ETC travel time over the 24-hour time period. However, CV travel time is generally lower than ETC travel time.

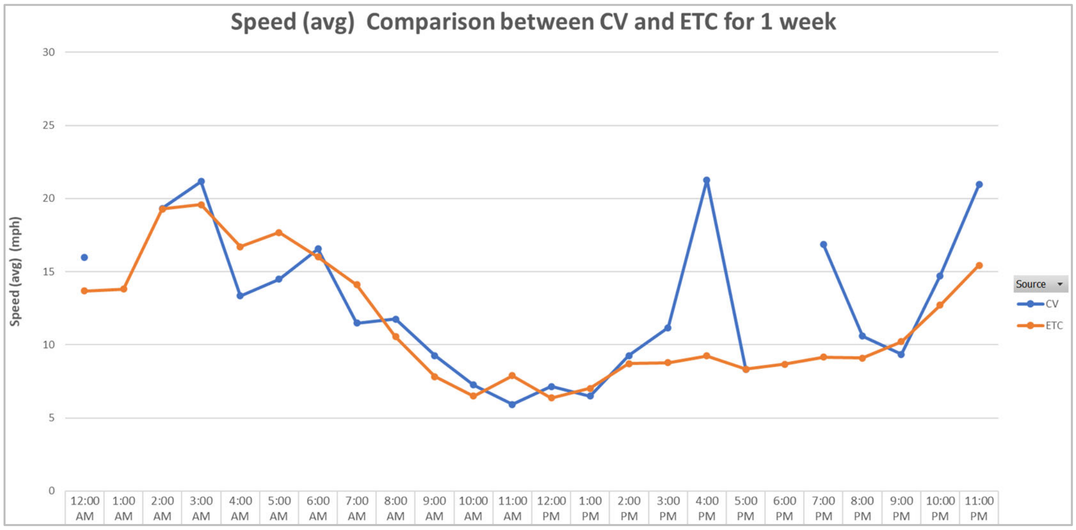


(Source: NYCDOT)

Figure 66. Median Travel Time Comparison for 1-Month (October 2021)

6.15.3 Speed

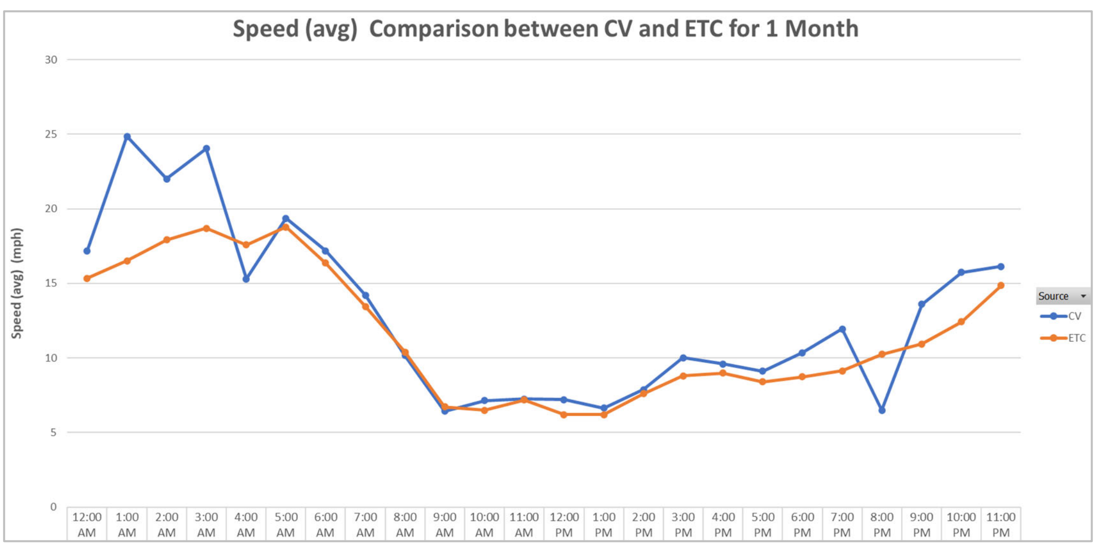
As shown in Figure 67, for 1-week analysis, the CV average speed has a similar profile to the ETC average speeds (as calculated from travel times and link lengths) over the 24-hour time period. However, there are some hours with large differences in average speed. This can be attributed to the lower sample size compared to the other hours.



(Source: NYCDOT)

Figure 67. Speed based on Average Travel Time for 1-Week (10/11/2021 to 10/15/2021)

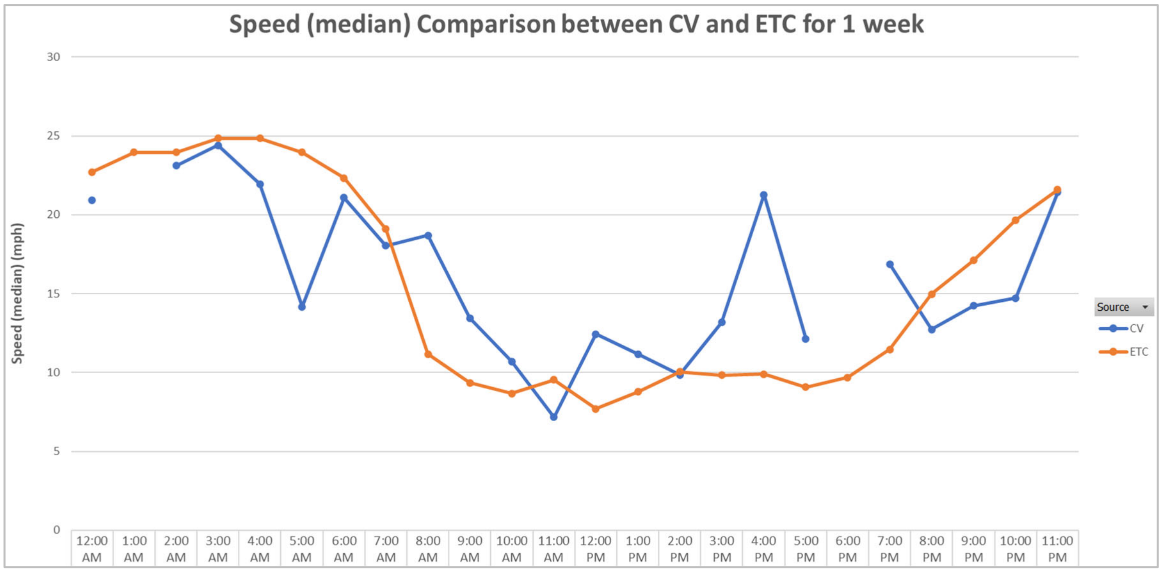
As shown in Figure 68, for 1-month analysis, the CV average speed has a similar profile to the ETC average speed over the 24-hour period. However, there are some hours where there are large differences in average speed, this can be attributed to due to lower sample size compared to the other hours.



(Source: NYCDOT)

Figure 68. Speed based on Average Travel Time 1-Month (October 2021)

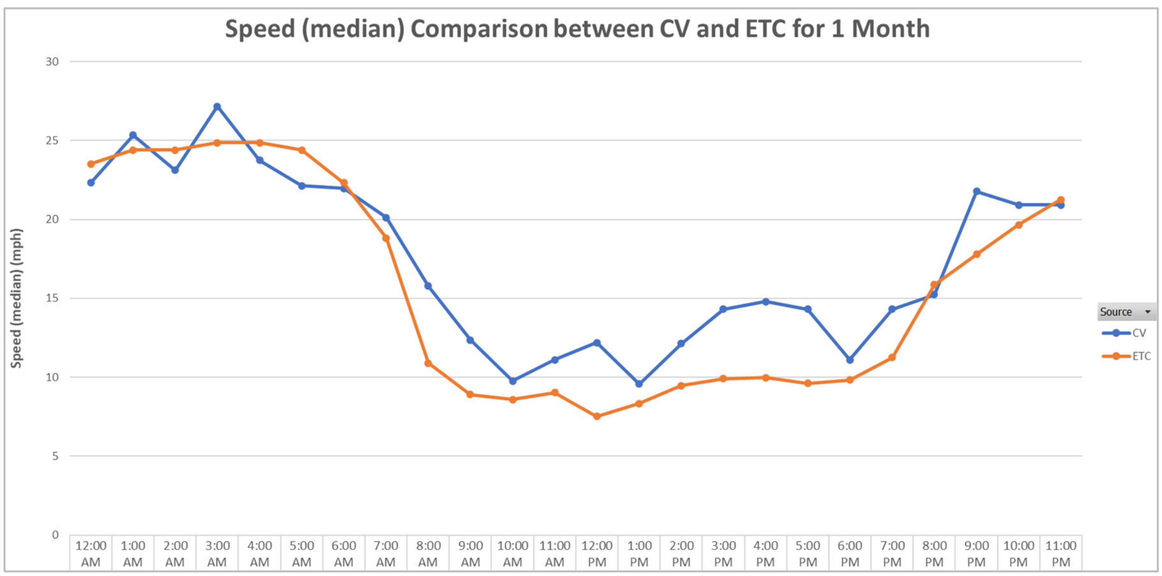
As shown in Figure 69, for 1-week analysis, the CV median speed has a similar profile to the ETC average speed over the 24-hour period, which some large differences at certain hours.



(Source: NYCDOT)

Figure 69. Speed based on Median Travel Time 1-Week (10/11/2021 to 10/15/2021)

As shown in Figure 70, for 1-month analysis, the CV median speed has a similar profile to the ETC average speed over the 24-hour period. However, CV median speeds are generally higher than ETC average speeds.



(Source: NYCDOT)

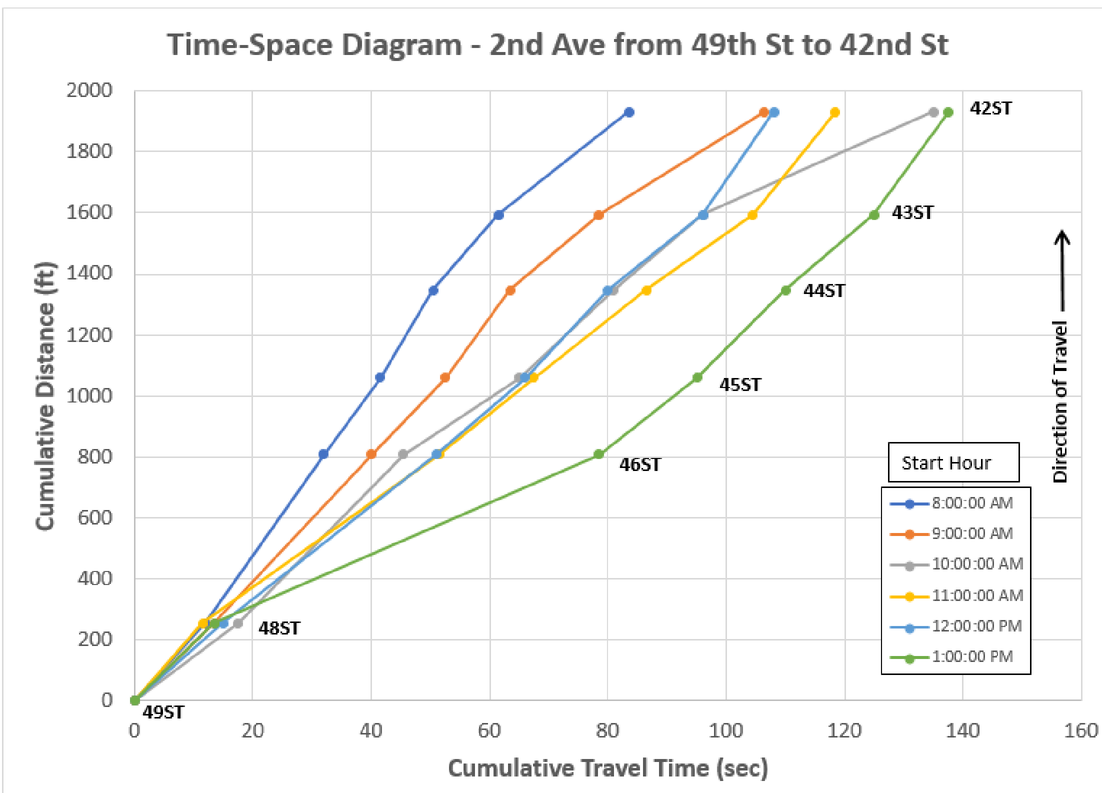
Figure 70. Speed based on Median Travel Time 1-Month (October 2021)

6.15.4 Bottleneck Analysis

A key difference between the ETC Travel Time System and the CV Travel Time System is the spatial resolution of travel time links. As stated previously, the ETC Links cover several blocks, and the CV segments cover individual blocks. This resolution allows for the analysis of congestion on a block-by-block basis and a better estimate of bottleneck locations and severity to be produced.

The median CV travel time data from the month of October 2021 has been used to develop a Time-Space Diagram as presented below in Figure 71 to represent details of the bottleneck conditions along 2nd Avenue from 49th Street to 42nd Street. Presenting travel time in this manner symbolizes the spatial and temporal evolution of traffic patterns. While this section of roadway is only reported as a single travel time in the ETC Travel Time system, the block-by-block travel times produced by the CV Travel Time System allow for a more refined assessment of travel between 49th and 42nd Streets under different hours of the day. Using this analysis, bottleneck conditions can be better identified. For example, as seen in the figure:

- Travel between 49th St to 46th St is slower at 1pm to 2pm (80 seconds) compared with 8am to 9am (30 seconds), despite both hours have a similar travel time (approximately 135 seconds) as measured by the ETC link (from 49th Street to 42nd Street).
- Travel between 43rd St to 42nd St is slowest between 10:00am and 11:00am.

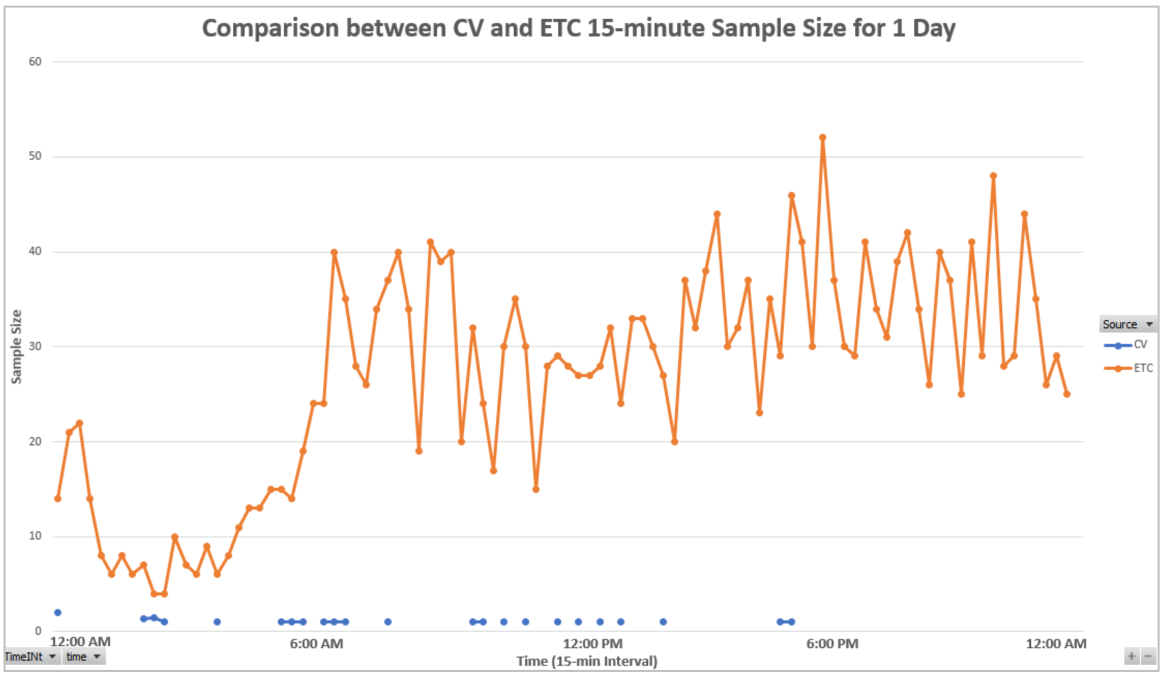


(Source: NYCDOT)

Figure 71. Time-Space Diagram for 2nd Ave from 49th Street to 42nd Street based on CV Travel Time Data from October 2021

6.15.5 Feasibility of using CV Travel Time Data for Real-Time Adaptive Control Systems

The current MIM system in NYC uses travel time measurement provided by the ETC Travel Time System at 15-minute intervals. The system requires data in 15-minute intervals in real-time to recommend the most effective proactive action for the variable traffic conditions. For each 15-minute interval, the system generally requires a minimum sample size between 10-15 to best capture the average traffic condition. Figure 72 below compares the 15-minute sample size for 1 day between the CV and ETC travel time systems. As shown, the CV sample size is less than five. Due to the limited sample size and lack of availability of data in real-time, the travel time from the current CV deployment cannot be used as part of the real-time control systems.



(Source: NYCDOT)

Figure 72. Comparison between CV and ETC 15-Minute Sample Size for 1 Day (10/13/2021)

6.15.6 Key Findings

When comparing CV Travel Time data to the ETC Travel Time data it can be concluded that:

- The current CV travel time system produces small sample sizes on any given day across the 24-hour period.
- Looking at the 1-week and 1-month analysis periods average travel time and speeds, both data sets have similar profiles across the day. However, there are some large differences observed for certain hours which can be attributed to the smaller sample sizes.
- Looking at the 1-week and 1-month analysis periods median travel time and speed, both data sets have similar profile across the day. The CV median travel time is generally

lower compared to the ETC median travel time. This is observed in the speed comparisons as well.

- The availability of CV travel time data block-by-block can better help identify bottleneck conditions than the ETC travel time data by understanding the spatial and temporal evolution of traffic patterns. This is valuable for traffic management and traffic operations.
- Due to the limited sample sizes at 15-minute intervals, the use of CV-based travel time data for real-time applications is not feasible under the current level of CV-equipped vehicles. A higher level of CV-equipped vehicles to produce more regular and reliable travel time measures at the 15-minute interval level would be needed to leverage CV-based data for such systems.

6.16 Systems Operations Evaluation

In monitoring system operations, the project team found that two additional input sources were needed for system operations. These two inputs became important assets to managing the system and understanding the operational characteristics of the fleet and its exposure.

The first input involved an existing NYC system used to monitor vehicle usage produced by Geotab. Geotab is a fleet management system and its data enabled the project team to accumulate information on the fleet's overall operational hours and mileage. This data was aggregated into a utilization report for the fleet. It also became useful in analyzing RSU placement to maximize opportunities to provide support services (firmware and configuration downloads, access to security certificates, and data collection uploads) for the fleet.

The second input came from the Security Credential Management System (SCMS). The need for this input evolved as the ASDs were installed in the fleet and data collection reports demonstrated that the vehicle contacts lagged the project team's expectations. Working with the SCMS provider a series of reports were developed to quantify the status of certificates in each of the fleet's vehicles. When these reports come on-line, they became a weekly addition to the project's status reports. These data provided a long-term overview of the fleet's certificate status as we worked to identify data collection issues. These reports were our only insight into the security "black box" infrastructure that underlies the entire system operation. Over the period of May through September 2021 the project team found that 2/3rds of the fleet had current security credentials at any given time.

Management of security credentials would have changed over the course of the project had we had previous experience. The initial decision to store two weeks of security credentials on the vehicle was driven by the situation at the beginning of the project. The situation can be summarized by three key points. These are that a) the acceptable period for storing credentials on an RSU was two weeks, b) misbehavior detection algorithms did not exist, and c) a mechanism for distributing certificate revocation lists (CRL) did not exist. Due to the different operating characteristics of the fleet between the initial taxis and the government vehicles, it was found that longer periods of on-board security credentials would have been preferable. Using a longer period may have resulted in a higher percentage of the vehicles having valid security credentials at any given time over the actual 2/3rds value observed.

The real-time communications between the RSU and ASDs was difficult to assess. We could observe that messages were flowing to/from the RSU when users interactively engaged with an individual RSU's firmware. This interface permitted the user to observe that messages were being sent by the RSU and received by the RSU on specific DSRC channels although the individual messages within that traffic were not categorized. The only "window" into the ASDs communication traffic existed through the uploading of RF logs, BC logs, and SSL files. Therefore, the project team could only assess which vehicles were contributing was through the post-processing of this log data.

The SSL files provided useful information however their potential was not fully realized. With respect to useful information, they provided firmware version information and some performance information. One performance indication was the DSRC channel busy ratio (CBR) when it exceeded a threshold value. In the sparse DSRC environment this information served more as an interference indicator rather than a true indication that there were many DSRC devices contesting for channel usage. The limitation here was that the specific channel involved was only identified for the safety and the control channels. Messages with respect to the other service channels did not identify the specific channel observing the high CBR. While the requirements were fulfilled, more detailed logging requirements going into the procurement may have been a benefit although with additional cost implications that are difficult to evaluate in foresight.

The RF logging provided substantial information about DSRC radio signals in the urban environment. The project team could assess signal ranges effectively for RSUs however assessing signal ranges for ASDs required manual processes. The project team did not invest in these processes as this information no longer has value considering the FCC Docket 19-138 First Report and Order obsoleting DSRC and driving the industry to cellular vehicle-to-everything (C-V2X).

6.17 Mobility Simulations

Using the methods identified in section 5.3.2, large scale simulations were conducted to determine the possible benefits that could be seen from the NYC CVPD from preventing crashes from occurring. While the simulated crashes were modeled as generic lane blockage events for the mobility impact assessments, the deployment of CV technologies could help reduce the occurrence of rear-end crashes (FCW and EEBL warnings), side-swipe crashes (BSW and LCW warnings), left-turn crossing and head-on crashes (IMA warnings), side collision crashes (RLVW warnings), pedestrian involved crashes (PEDINWALK warnings), or any crash where speeding was a contributing factor (SPDCOMP, CSPDCOMP, and SPDCOMPWZ warnings). This section presents the results and findings of those generic crash simulations for the mobility impact analysis.

6.17.1 Disruptions at Crash Location

Disruptions on traffic operations in the immediate location of the crash were first examined by comparing simulated performance metrics for the no crash and crash scenarios. Comparisons of throughput (vehicles traversing the section during the 30 minute crash event) and average speed (mph) on the block where the crash occurred are presented in Table 21 and Table 22, respectively.

Table 21. Throughputs at Crash Location During Crash

Simulated Crash	Location (Network Link)	No Crash Scenario Section Throughput (vehicles)	Crash Scenario Section Throughput (vehicles)	Change (vehicles)	Percent Change
Crash 1	1st Avenue North of 63rd Street	1217.8	1029.8	-188.0	-15%
Crash 2	5th Avenue South of 55th Street	443.3	421.5	-21.8	-5%
Crash 3	2nd Avenue South of 23rd Street	874.8	834.8	-40.0	-5%
Crash 4	6th Avenue North of 47th Street	718.3	685.8	-32.5	-5%

Table 22. Average Speeds at Crash Location During Crash

Simulated Crash	Location (Network Link)	No Crash Scenario Section Speed (mph)	Crash Scenario Section Speed (mph)	Change (mph)	Percent Change
Crash 1	1st Avenue North of 63rd Street	19.4	12.1	-7.3	-38%
Crash 2	5th Avenue South of 55th Street	24.2	14.3	-9.9	-41%
Crash 3	2nd Avenue South of 23rd Street	17.2	16.9	-0.3	-2%
Crash 4	6th Avenue North of 47th Street	25.3	22.6	-2.7	-11%

While dependent on the local traffic conditions and congestion, the throughputs at the crash locations are reduced from between 5% and 15% and speeds reduce by 2% to 41%. These metrics include the impacts of any self-diverted drivers changing from their original path to a new path once informed of the impacts of the crash (e.g. via typical means of cell phone traffic apps or 511 notifications, or simply by observing increased congestion on the roadways). In a large, regular urban grid network like Manhattan where many alternative routes are possible, it is not uncommon that drivers will change the paths to avoid crashes or congestions. Except for Crash 3, where the change may be within the stochastic noise inherent to the model, the other three crashes show statistically sound impacts on the local operations.

6.17.2 System Disruptions from Crashes

To further examine the crash impacts, the traffic condition on the ten upstream street blocks and their immediate connecting side streets were used to generate aggregate metrics and to estimate the system delay impacts from the crashes. The area upstream of the crash was selected based on a review of the stochastic noise of the simulations to isolate the impacts of the crash from the overall noise of the model across all of Midtown Manhattan. Aggregate metrics of total vehicle miles traveled (VMT), vehicle hours traveled (VHT), vehicle hours of delay (VHD), and the average harmonic speed (computed as VMT divided by VHT) were computed and are presented in Table 23, Table 24, Table 25, and Table 26, respectively.

Table 23. System Impacts of Crash – VMT

Simulated Crash	Location (Network Link)	No Crash Scenario VMT (veh-miles)	Crash Scenario VMT (veh-miles)	Change (veh-miles)	Percent Change
Crash 1	1st Avenue North of 63rd Street	988.5	788.3	-200.2	-20%
Crash 2	5th Avenue South of 55th Street	550.0	541.4	-8.6	-2%
Crash 3	2nd Avenue South of 23rd Street	633.4	634.2	0.8	0%
Crash 4	6th Avenue North of 47th Street	808.6	774.2	-34.4	-4%

Table 24. System Impacts of Crash – VHT

Simulated Crash	Location (Network Link)	No Crash Scenario VHT (veh-hours)	Crash Scenario VHT (veh-hours)	Change (veh-hours)	Percent Change
Crash 1	1st Avenue North of 63rd Street	139.9	184.5	44.5	32%
Crash 2	5th Avenue South of 55th Street	78.2	81.2	3.0	4%
Crash 3	2nd Avenue South of 23rd Street	64.5	63.6	-0.9	-1%
Crash 4	6th Avenue North of 47th Street	88.6	102.7	14.2	16%

Table 25. System Impacts of Crash – VHD

Simulated Crash	Location (Network Link)	No Crash Scenario VHD (veh-hours)	Crash Scenario VHD (veh-hours)	Change (veh-hours)	Percent Change
Crash 1	1st Avenue North of 63rd Street	102.9	154.8	51.9	50%
Crash 2	5th Avenue South of 55th Street	57.1	60.4	3.3	6%
Crash 3	2nd Avenue South of 23rd Street	40.9	39.9	-0.9	-2%
Crash 4	6th Avenue North of 47th Street	58.1	73.6	15.5	27%

Table 26. System Impacts of Crash – Harmonic Speed

Simulated Crash	Location (Network Link)	No Crash Scenario Speed (mph)	Crash Scenario Speed (mph)	Change (mph)	Percent Change
Crash 1	1st Avenue North of 63rd Street	102.9	154.8	51.9	50%
Crash 2	5th Avenue South of 55th Street	57.1	60.4	3.3	6%
Crash 3	2nd Avenue South of 23rd Street	40.9	39.9	-0.9	-2%
Crash 4	6th Avenue North of 47th Street	58.1	73.6	15.5	27%

While the results vary depending on the crash locations, VMT can be seen to reduce by as much as 20%, VHT increase by as much as 32%, and VHD increase by as much as 50%. Most of the simulated crashes see logical impacts; however, results in the aggregate metrics results for Crash 3 may be more related to the stochastic noise of the model for a crash at a less congested location, as was seen in the examination of the performance metrics at the immediate site of the simulate crash.

6.17.3 Findings of Crash Impacts on Mobility

In reviewing the simulations of hypothetical crash scenarios in Midtown Manhattan and comparing the results to the same models without crashes, the results show that removing these crashes would improve mobility by an average of 17.5 vehicle hours and has many as 52 vehicle hours per crash. While the results are not dramatically high in terms of total vehicle hours of delay per crash, they are significant relative to the percent change of the typical (no crash) conditions) and will accumulate over time as more and more crashes can be prevented from CV technology.

6.18 Driver Survey Results

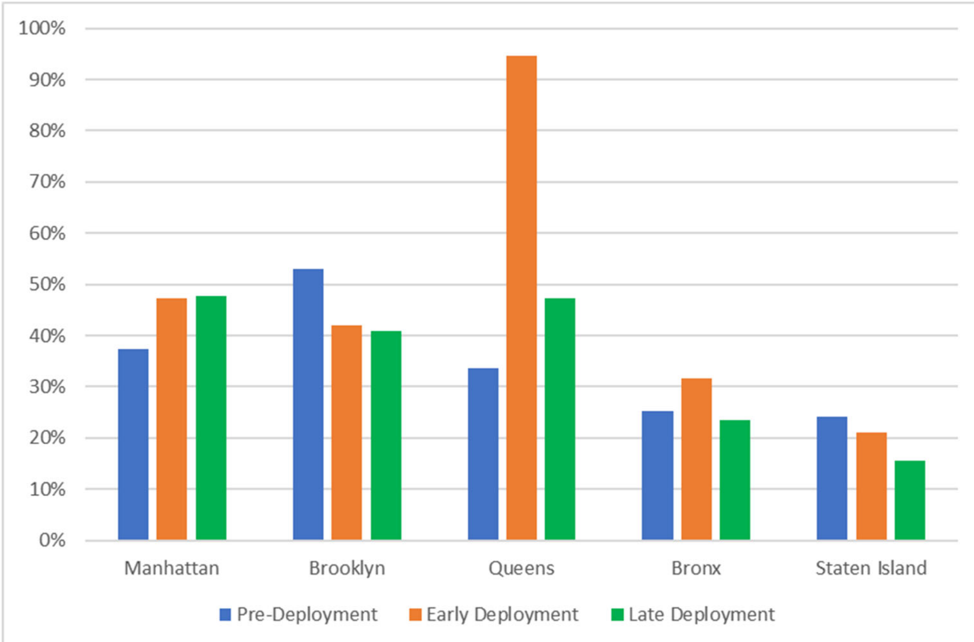
The number of responses to the three driver surveys was varied. Efforts were taken to encourage drivers of the CV equipped fleet vehicles to complete each of the three surveys through messages from the various fleet and department management, however no direct contact between the NYC CVPD team and the participating drivers existed and no mechanism was available to further incentivize responses. The pre-deployment survey received 83 responses, the early deployment survey received only 19 responses, and the late deployment survey received 161 responses. Given the relatively low response rates compared to the driver population, responses are presented as recorded and no estimates of statistical significance on representing the entire population or changes between the three surveys were attempted. This is especially important to note when considering the case of the early-deployment survey, which generated a very low number of responses.

6.18.1 Survey Response Demographics

The responses to the demographic questions were generally consistent between all three surveys. Almost half of the respondents were between 25 to 44 years old and the other half were between 45 to 65 years old, with very few responses from drivers over 65 years of age. Approximately 85 to 90% of the respondents were fluent in English, with the remainder responding good with English. Approximately 60 percent have been driving for work in NYC for more than 10 years, with the remaining generally evenly distributed from none to 10 years.

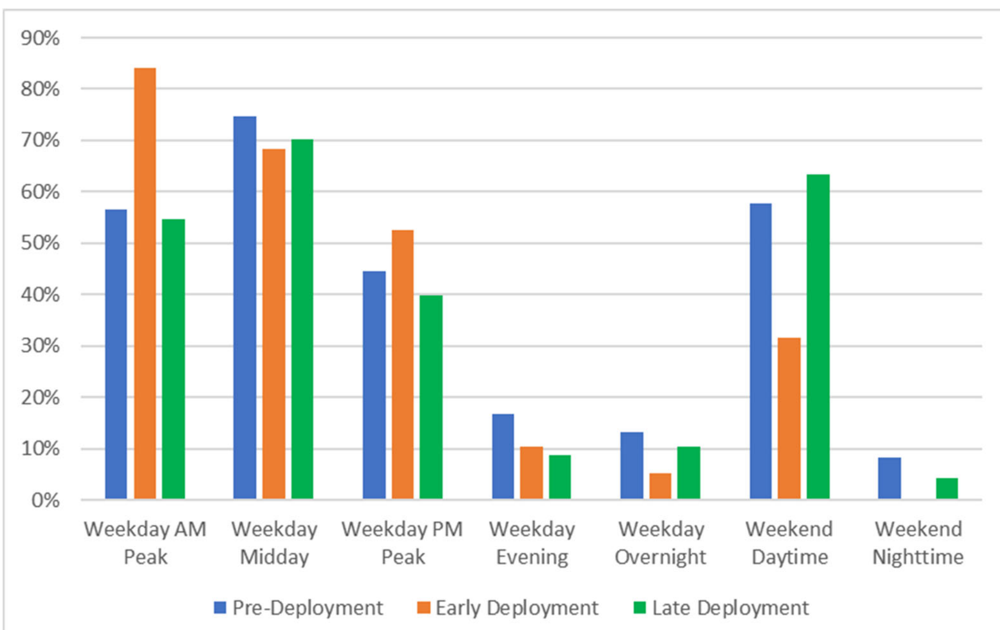
6.18.2 Survey Responses on Typical Vehicle Usage

Respondents reported throughout all boroughs, with just under half reporting typically driving in each of Manhattan, Queens, and Brooklyn, with approximately one-quarter drive in the Bronx or Staten Island (see Figure 73). The majority drive during the weekday AM peak, midday, and PM peak periods, about half during weekend daytime hours, and less than 10 percent during either the weekday or weekend evening and overnight hours (see Figure 74). The vast majority drive the same vehicle consistently; most drive passenger cars and a small minority drive pickup trucks or vans; and most drive at least five days per week.



(Source: NYCDOT)

Figure 73. Driver Survey Reponses for Primary Areas of Vehicle Usage



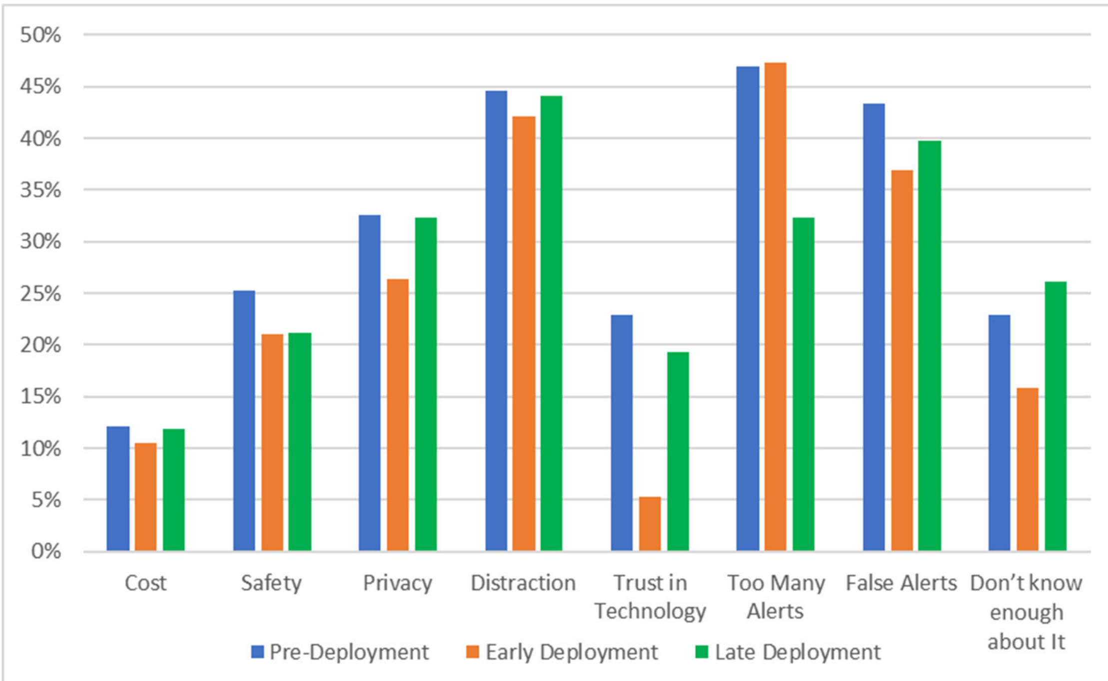
(Source: NYCDOT)

Figure 74. Typical Time Periods of Driving for Work

Most respondents are reported typically driving a minimum of 10 to 40 miles per day and a maximum of 20 to 70 miles, with an average between 20 and 50 miles. Some responses indicated driving over 100 miles per day. Approximately half reported driving eight to twelve hours per day and the other have distributed between one and seven hours per day.

6.18.3 Survey Responses on User Perception / Attitude

In response to questions regarding the user's perceptions of CV technology, a variety of concerns were raised about CV technology as shown in Figure 75 below. The top three responses were distractions, false alerts or warnings, and too many alerts or warnings.



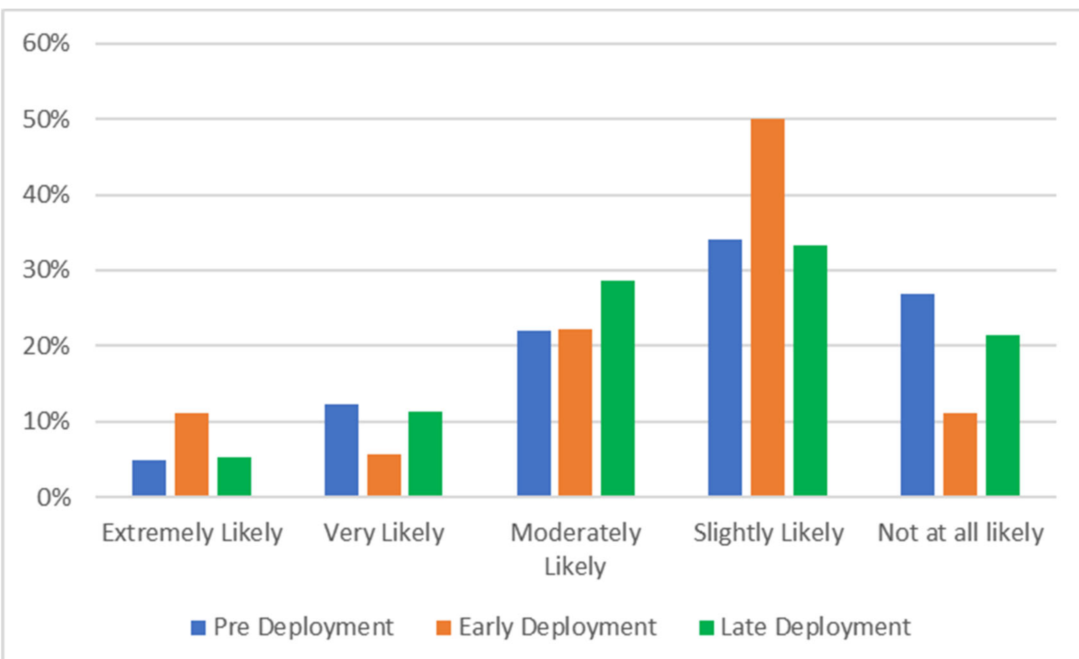
(Source: NYCDOT)

Figure 75. Concerns About CV Technology Systems

When asked about the perceived safety of driving for work in NYC, most reported likelihood of a crash or near-crash with either another vehicle (Figure 76) or a pedestrian or bicyclist (Figure 77), while most reported a crash or near-crash with infrastructure or off-road crash being not at all likely (Figure 78). In general, the majority of respondents reported feeling moderately safe driving for work in NYC, while less than 15% of responses indicated feeling slightly safe or not at all safe (Figure 79).

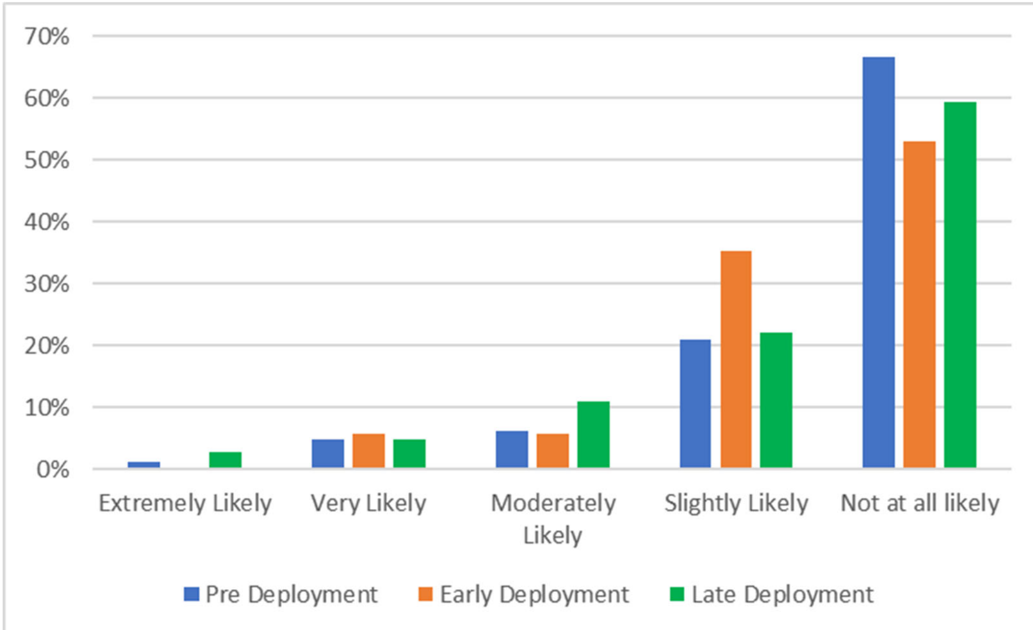
(Source: NYCDOT)

Figure 76. Perceived Likelihood of a Crash or Near-Crash With Another Vehicle



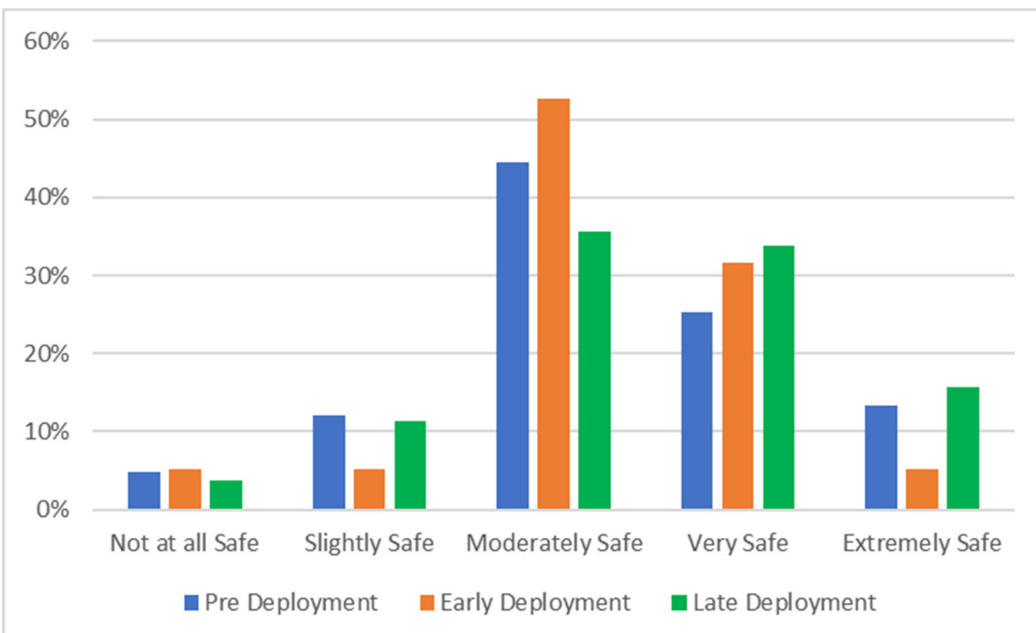
(Source: NYCDOT)

Figure 77. Perceived Likelihood of a Crash or Near-Crash With a Pedestrian or Bicyclist



(Source: NYCDOT)

Figure 78. Perceived Likelihood of a Crash or Near-Crash With Infrastructure or Off-Road Crash



(Source: NYCDOT)

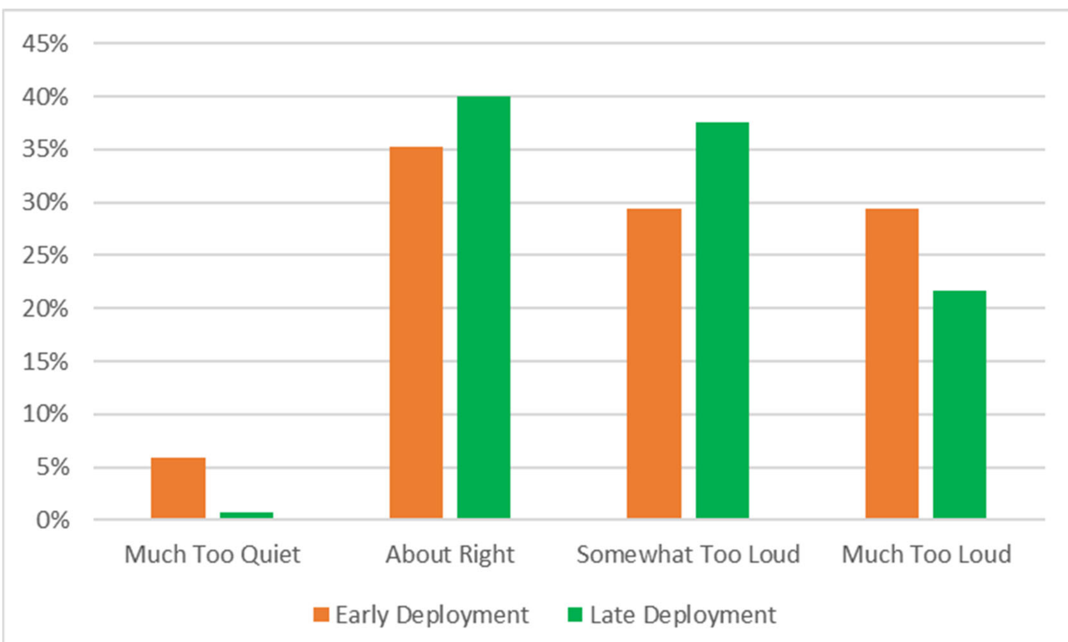
Figure 79. Perceived Level of Safety Driving in NYC for Work

6.18.4 Survey Responses on CV User Experiences

During the early-deployment and late-deployment survey results, feedback on the respondents' experiences with the CV applications while driving was solicited. The responses indicated a wide range on the frequency of hearing alerts while driving (Figure 80). Of those that heard the alerts, many reported that the alerts were either somewhat or much too loud (Figure 81) and reported varying levels of distraction from the alerts (Figure 82). Out of those who heard the alerts, the majority of respondents reported that the alerts were at least slightly helpful (Figure 83).

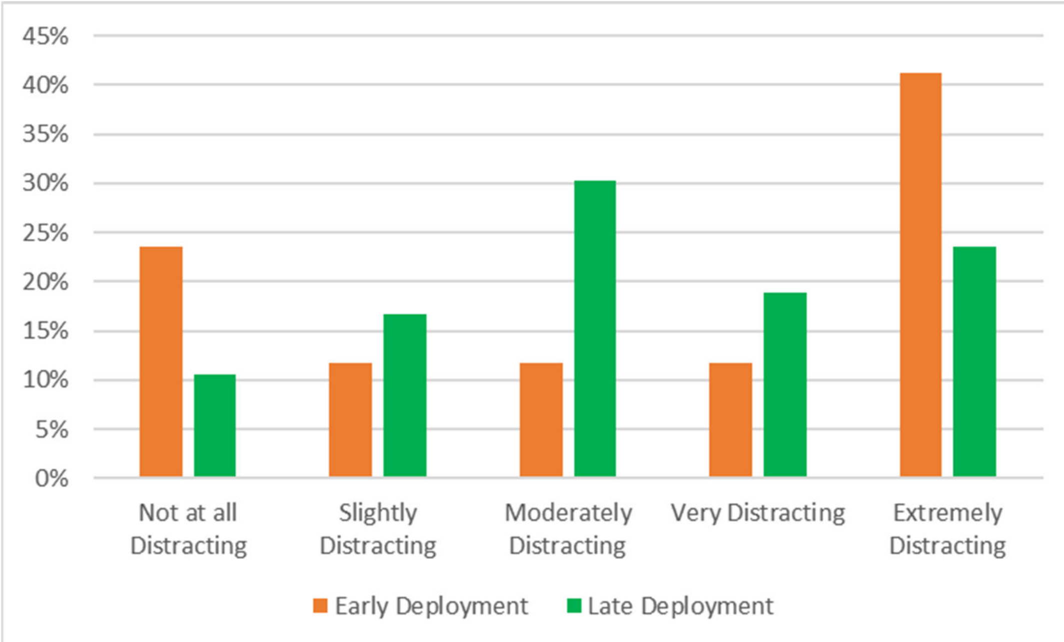
(Source: NYCDOT)

Figure 80. Frequency of Alerts Heard



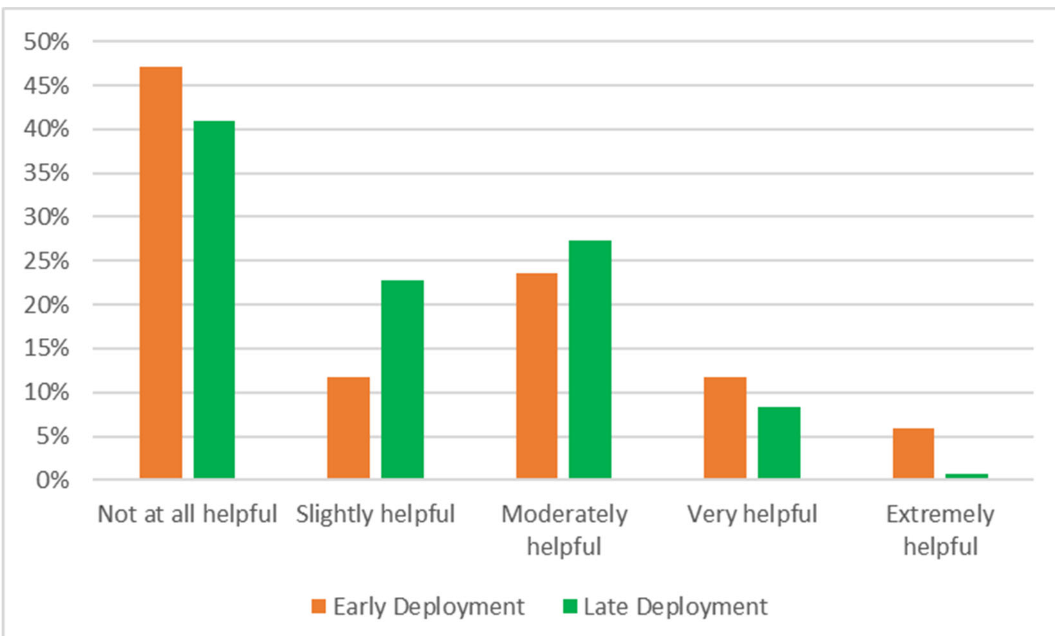
(Source: NYCDOT)

Figure 81. Audio Level of Warnings



(Source: NYCDOT)

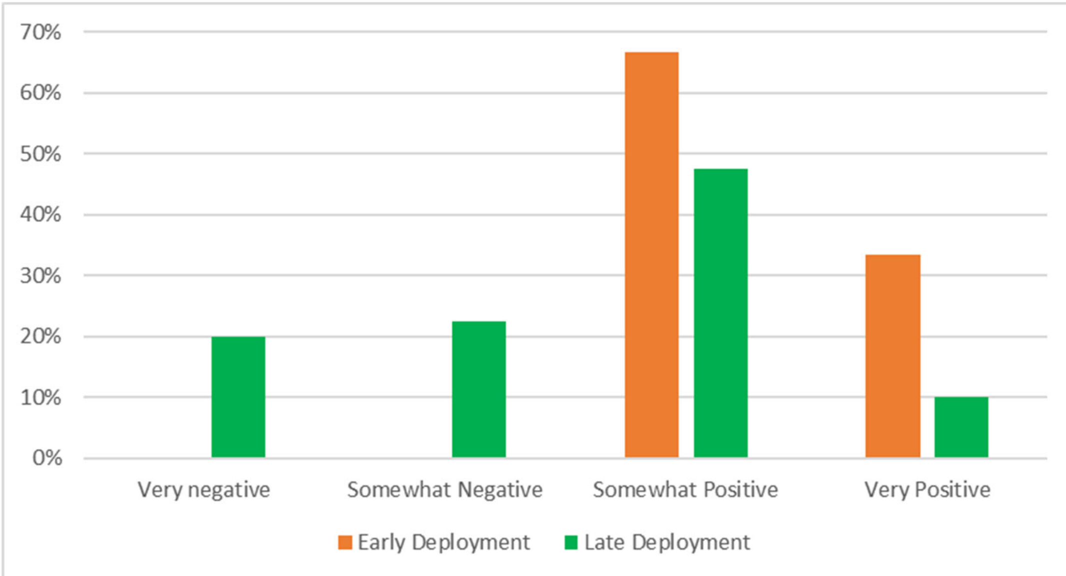
Figure 82. Opinions on if Alerts are Distracting



(Source: NYCDOT)

Figure 83. Opinions on if Alerts are Helpful

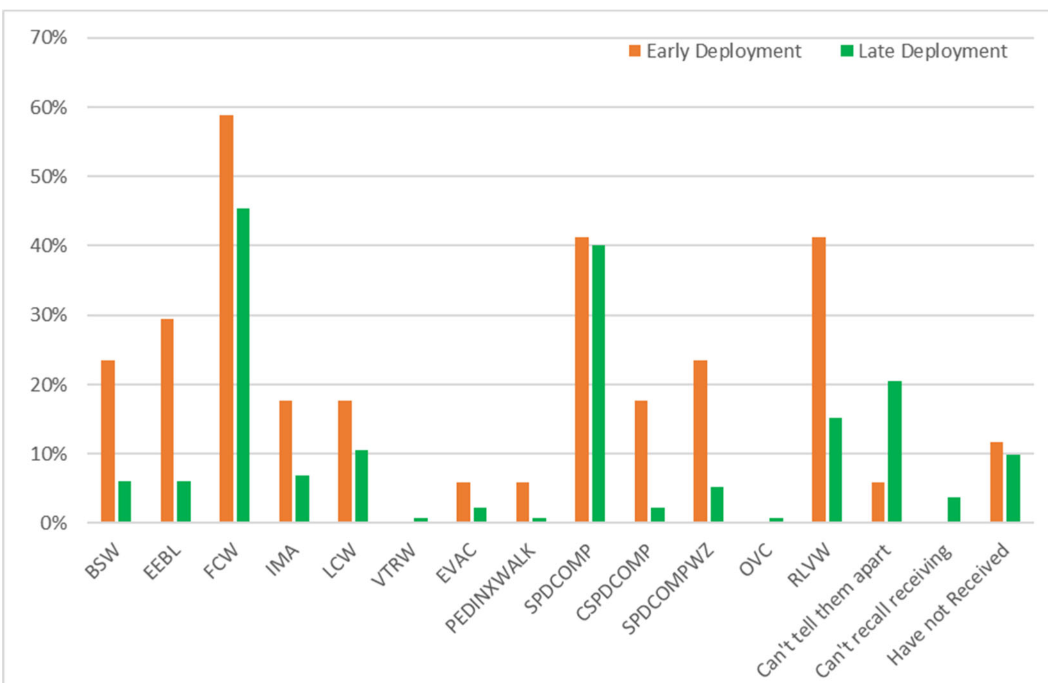
When asked if the alerts had any effect on the way they drive for work in NYC, approximately one-third replied yes. Of that third responding yes, the majority reported a somewhat or very positive impact (Figure 84).



(Source: NYCDOT)

Figure 84. How Alerts Impacted Driving

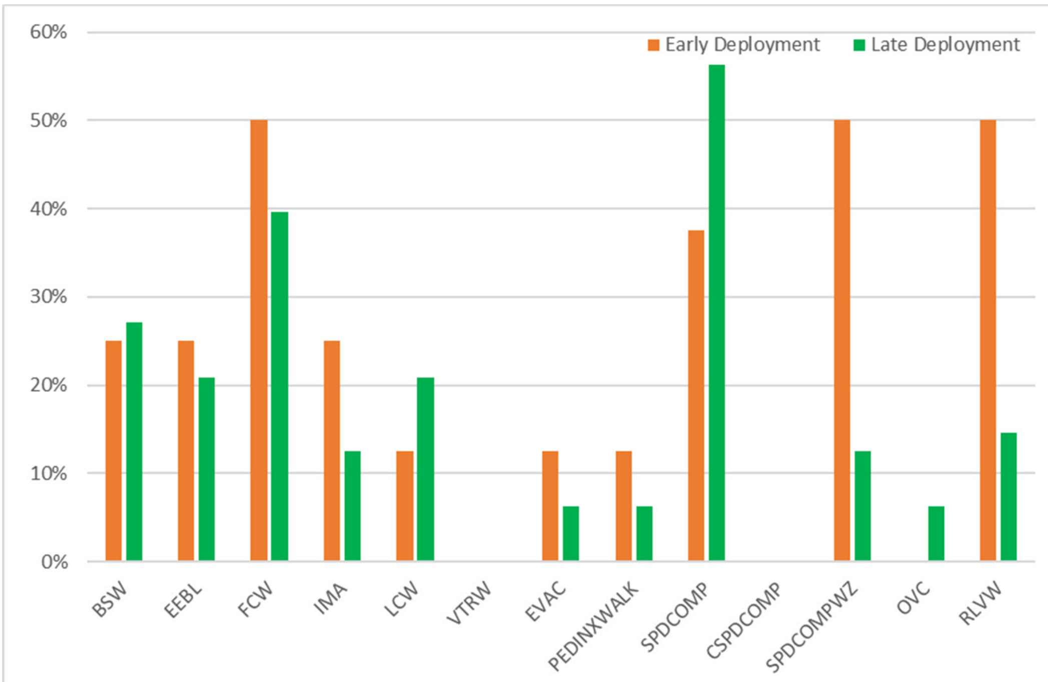
When asked about which applications the drivers recalled hearing (Figure 85), the most commonly reported alerts were FCW, SPDCOMP, and RLVW. A minority of respondents reported that they could not tell them apart, that they could not recall receiving them, or that they heard no warnings.



(Source: NYCDOT)

Figure 85. Alerts Recalled Hearing

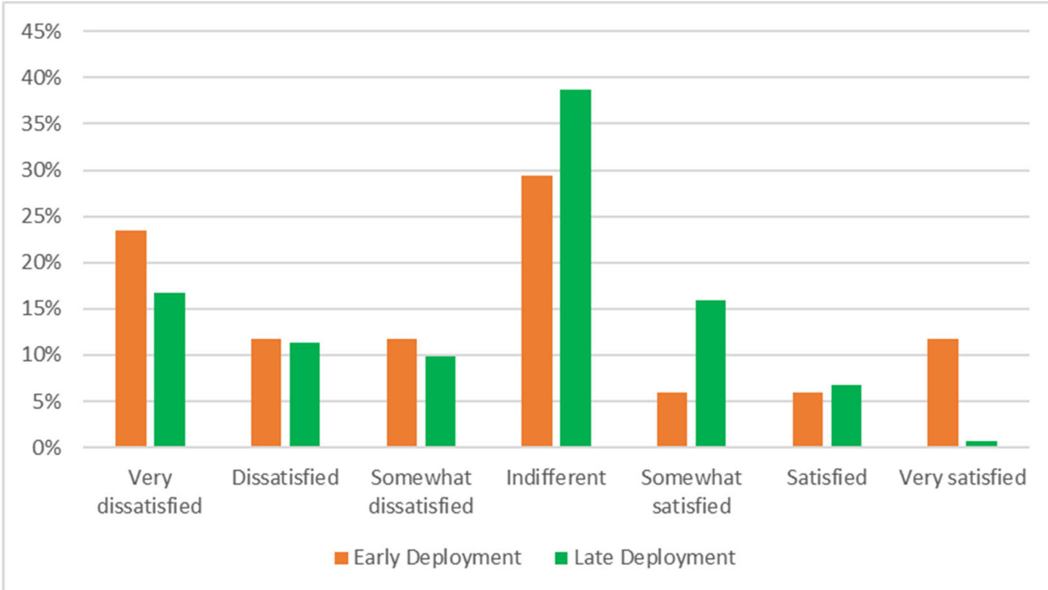
When asked if the drivers found the alerts helpful, an average of 38% of the respondents indicated they thought the alerts had helped them drive more safely. Of those respondents indicating the CV applications were helpful (Figure 86), more than half of responses indicated that the SPDCOMP application was helpful, while nearly half indicated that FCW was helpful. Additionally, the less frequently heard V2V applications of BSW, EEBL, LCW also were reported by at least 20% of the respondents as being helpful.



(Source: NYCDOT)

Figure 86. Alerts Helpful in Driving More Safely

Finally, when drivers that responded that they had heard alerts were asked about their overall satisfaction with the CV applications and alerts that they were exposed to (Figure 87), 39% of respondents said they were dissatisfied at least somewhat, 38% were indifferent, and 23% were satisfied at least somewhat with CV technology.



(Source: NYCDOT)

Figure 87. Overall Satisfaction with CV Technology

6.18.5 Correlation Analysis

Additional analysis was completed to test for correlation in response between several pairs of questions that the team thought might be related.

Table 27 below summarizes the results of the that correlation analysis. Correlation between two categorical variables was analyzed with a chi-squared test and correlation between numerical and categorical variables was measured with analysis of variance (ANOVA). For both cases, a p value of 0.05 was set as threshold to accept or reject correlation between variables, meaning that the probability of the variables being correlated by random chance is less than 5%. It should be noted that this analysis only tested for correlation and not for causality.

Table 27. Result of Tested Question Response Correlation

First Question	Second Question	Correlated ($p<0.05$)
Familiarity with CV technology	Anticipation of usefulness	Yes
Familiarity with CV technology	Overall satisfaction	Yes
Likelihood of crash with ped/bike	Are audible alarms helpful?	No
How safe do you feel driving in NYC?	How many years you have been driving?	No
How safe do you feel driving in NYC?	Are audible alarms helpful?	No
Rate the sound volume of the alerts	Are the audible alerts distracting or not?	Yes
Typical minimum miles driven per day	How safe do you feel driving in NYC?	No
Typical minimum miles driven per day	Likelihood of crash with ped/bike	No
Typical minimum miles driven per day	Likelihood of crash with other vehicles	No
Typical maximum hours driven per day	Are audible alerts helpful?	No
Typical maximum hours driven per day	Do you think warnings have helped you drive more safely?	No
Typical maximum hours driven per day	Anticipation of usefulness	No
Heard alarm frequency	Are the audible alerts distracting or not?	Yes
Heard alarm frequency	Overall satisfaction	Yes
Which alerts heard the most	Overall satisfaction	No

6.18.6 Key Findings from Driver Surveys

The following key takeaways can be derived from the review of the driver survey responses:

- Approximately half of respondents drive an average of 20 to 50 miles per day for work, about half drive 8 or more hours per day, and the majority drive at least 5 days per week.
- Among all respondents, 56% were somewhat or very familiar with CV technology. This proportion was higher among respondents in the late deployment stage.
- 84% of the respondents feel moderately, very, or extremely safe driving in the city for work.

- The largest concerns about CV technology were regarding distractions, false alerts, and too many alerts with CV technology. The proportion of responses with these concerns was only slightly lower in the post-deployment surveys as compared to the pre-deployment surveys.
- The most useful alerts to improve safety were SPDCOMP and FCW. These were also the two alerts that the drivers reported hearing the most.
- 72% of respondents found the alerts moderately, very, or extremely distracting.
- 23% of respondents reported some level of satisfaction with the experienced CV technology, while 39% reported some level of dissatisfaction.
- Familiarity with CV technology was correlated with both anticipation of usefulness and overall satisfaction with the pilot.
- No correlation was found between length of driving and likelihood of crash with pedestrian, vehicles, or infrastructure objects.
- Both the frequency and the perceived loudness of the alerts were highly correlated with the reported level of distraction from the alerts.
- No correlation was found between driver's assessment of their safety during driving for work and usefulness of the audible alerts.

7 Conclusions

7.1 Evaluation Findings

As a deployment project, the NYC CVPD successfully established a large scale connected vehicle infrastructure and applications. The NYC infrastructure demonstrated a different approach to collecting data regarding CV applications and reporting it for further analysis. Previous research programs had collected every over-the-air DSRC message transmitted or heard. As an intended long-term deployment, only relevant message traffic was captured to support the research requirements and operational objectives. From the above performance evaluations of the applications, it is easy to see that the project was successful in meeting its initial goals.

The project's intent was not to develop the CV applications as first-generation concepts and evaluate whether the application itself works; its intent was to evaluate whether the CV applications can impact driver behavior in the dense urban environment. And to that end the project results demonstrate that overall, the CV applications influenced the vehicle operator's behavior.

This success included overcoming several significant external events impacting the project. These factors include:

- The economic impacts of for-hire-vehicles (FHV) on the original taxi fleet.
- A global COVID-19 pandemic that changed travel patterns over the timespan of the project and had a tremendous impact on fleet installations and testing.
- Changes to regulations governing the connected vehicle radio communications technology.
- Initial full-scale deployment of the security infrastructure ensuring trusted communications.

The impacts of these are discussed in the following section.

The performance measurement and evaluation matrix (Table 2) lists 42 measures. Of these, 28 measures were assessed, and 14 planned measures were unable to be assessed due to limitations in data collection, inconsistencies between anticipated data sources, or external factors that effected the project.

For several of the CV applications, the low quantity of post-cleansing events limited the evaluation. These applications include the curve speed compliance, the pedestrian in crosswalk, work zone speed compliance, over-height vehicle clearance, and vehicle turning right in front of bus. The low quantity of analysis events results from a variety of causes including low transit bus participation (14 transit buses), few pedestrian detection locations (10 intersections), limited fleet trucks, and potentially the pre-deployment behaviors of experienced drivers operating vehicles in NYC for work or work-related travel.

Two applications dominating the data collection were FCW and SPDCOMP producing over 75% of all alerts/warnings. The analysis shows that drivers responded to the alerts and tended to reduce speeds after the audible alerts, though FCW analysis of statistical significance was inconclusive.

There were lessons identified as event data processing was refined and as analysis was conducted. Event action logs analysis would have benefited from additional data element recording. For example, in V2V events, the direct recording of the ASD's internal calculated time to collision (TTC) values would have helped analysis, as would the recording of the target intersection and approach details that triggered the V2I RLVW events. As many of the individual event lessons reported in Section 6 state, a different process to preserve location/temporal data for the analysis would have enabled more detailed research about locations and site-specific factors that may have impacted driver decisions. While this would be desirable, any different process would still have to address the privacy issues that drove the adopted data processing methodology. This example of research needs versus deployment perspective was an on-going dilemma throughout the project and required reviewing many decisions as the project progressed.

7.2 Study Limitations

There were several issues that were encountered throughout the deployment that impacted the original deployment plans as documented in the Phase 1 ConOps report. While these issues do not negate any of the above findings on the evaluation of the application, they created significant deviations from the original deployment plans and on the eventual data collection for the evaluations. The NYC CVPD pilot team attempted to mitigate these issues to best of our abilities, however some impacts remained and are discussed below.

7.2.1 Fleet Change

The project did not collect the quantity of data originally anticipated due to the change in the targeted fleet. The original ConOps envisioned that the major fleet participants were to be the taxis. This fleet, operating heavily in Manhattan and the airports, would have very high hours of operation (some up to 24x7 hours each week) and vehicle miles of travel (200+ average miles per vehicle per day). Due to economic issues of the taxi industry (caused predominantly by pre-COVID growth of the app-based for-hire vehicle market in NYC) and the constraints on taxi participation enticements, the fleet transitioned from taxis to NYC government vehicles. The government vehicle fleet operation differs from the taxis and resulted in approximately 1 million hours of operation and 12 million vehicle miles of operation during the Phase 3 operations of the calendar year 2021. While this is still a significant level of activity for the deployed CV fleet vehicles, it is well below the original projected fleet activity that would have existed with a potential taxi-based CV fleet.

The project team was hampered in its attempt to accommodate the revised fleet by the Federal Communications Commission's actions. The team's open RSU licenses were "frozen" (i.e. suspended) by the FCC's December 19, 2019 public notice DA 19-1298. This freeze effected over 60 pending applications and a backlog of applications that were in the pipeline. This freeze was not lifted until July 2021 hence preventing any effective adjustment to the change in fleet operations as the Phase 3 evaluation period was 50% complete at that time.

The data collection on the vehicles was subject to a life-cycle data retention period to preserve privacy should devices be removed from vehicles. To accommodate the original fleet operations in Manhattan this value had been set to 48-hours in ASD firmware versions 1.0 through 4.2.8. With the transition in fleet and different operating characteristics, it became necessary to increase the data retention period to 10 days beginning with firmware version 4.2.8.8 to address fewer daily interactions with locations providing data collection services. This 10-day data retention period remained in effect throughout the Phase 3 operations. Note that vehicles running older firmware continued to operate with the 2-day data retention period. Approximately 500 vehicles in the fleet had the older firmware as of the closure of Phase 3. These vehicles may represent data loses as they may not have been able to upload their data prior to expiration of the retention period. The project team do not have any insights to quantify the potential amount of data which may have been lost due to these circumstances.

7.2.2 COVID-19 Impacts

The pandemic reduced travel and limited trips by staff operating the fleet vehicles; see the discussion of fleet operating characteristics and utilization in Section 3.1 and Appendix C. While the most significant impacts on travel occurred in 2020 prior to the beginning of the Phase 3 operations, work from home orders and staggered office working days prevailed for government staff through 2021 until mid-September and hampered overall travel throughout Phase 3.

While data collection in the last quarter of the year increased, partially due to reduced COVID impacts and partially due to updates to the final version 4.3.7 of ASD firmware, any attempts to scale previous data collection would only magnify data collection errors and issues. Therefore none of the data collection values are explicitly adjusted for COVID-19 impacts.

7.2.3 CV Trust

The CV fleet's security credentials were valid for a specific week and up to two weeks of certificates could be loaded onto a vehicle at any given time. Replacement (i.e. new) security credentials could be loaded through various infrastructure sites as the vehicles passed by the site. These certificate durations and renewal facilities were designed to protect the system as misbehavior detection and certificate revocation facilities did not exist as the project began.

At most times only 2/3rds of the fleet vehicles (i.e. ~2000 vehicles) had valid certificates available. With the valid certificates the vehicles could broadcast Basic Safety Messages (BSM) and could demonstrate the trust necessary to interact with other similarly credentialed vehicles and the infrastructure. Vehicles without valid certificates could not transmit CV messages thereby limiting their interactions with other equipped vehicles and infrastructure.

The 2/3rds value is the result of monitoring the credentials via the SCMS facilities. The monitoring was performed on a weekly basis for the period of April 28 thru September 15, 2021 totaling 24 weeks. The system reported whether devices were in one of four states (Up-to-date, Behind, No active certificates, or Deactivated) with the first two states considered acceptable. Vehicles with no active valid certificates could not transmit BSMs thereby limiting their interaction with other vehicles and in receiving CV application warnings.

There are several potential causes for vehicles not having current certificates. The vehicles could be part of a “pool” available on an as needed basis thereby only being driven when necessary. Vehicles could also travel within the city but still infrequently have the opportunity to interact with an RSU providing support services that would provide updated certificates. Other hardware issues may have also impacted the ability of the CV equipment to operate such as broken harness wiring, shorted fuses, broken antenna connection cabling, and so on.

The project team cannot assess the potential quantity of data that could have been generated by these vehicles if active certificates could be retained. As vehicle operations varied widely over the fleet, it is not possible to scale the actual data collection for these vehicles. A weighted average would need to be developed to address the operational differences (i.e. hours of operation and vehicle miles of travel of the vehicles without active certificates) to prepare any reasonable estimate.

To address the situation, the project team took several steps. Foremost it attempted to utilize the external Geotab data to assess the opportunities for vehicles to travel near support services RSUs. These analyses resulted in identifying vehicles that required further investigation and the team instituted a vehicle inspection program in attempts to correct the issue. However, these investigations and inspections were extremely time consuming and could not be feasible be scaled for all vehicles reporting as being without active certificates.

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Appendix A. List of Acronyms

Table 28 below provides a list of the acronyms used in this Phase 3 System Performance Report document.

Table 28. Acronyms List

Acronym	Meaning
ABI	Anheuser-Busch InBev
ACDSS	Adaptive Control Decision Support System
ACS	Administration for Children's Services
ANOVA	Analysis of Variance
AO	Agreement Officer
AOR	Agreement Officer Representative
ASD	Aftermarket Safety Devices
ASTC	Advanced Solid-state Traffic Controller
ATC	Advanced Traffic Controller
ATMS	Active Traffic Management System
BC	Bread Crumb
BCI	Bayesian Credible Interval
BSM	Basic Safety Message
BSW	Blind Spot Warning
C-V2X	Cellular vehicle to everything
CARMA	Cooperative Automation Research Mobility Application
CBR	Channel Busy Ratio
CDA	Cooperative Driving Automation
CMF	Crash Modification Factor
ConOps	Concept of Operations
CRL	Certificate Revocation List
CSPDCOMP	Curve Speed Compliance
CUNY	City University of New York

Acronym	Meaning
CV	Connected Vehicle
CVPD	Connected Vehicle Pilot Deployment
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DCA	Department of Consumer Affairs
DCAS	Department of Citywide Administrative Services Fleet
DDC	Department of Design and Construction
DEP	Department of Environmental Protection
DHMH	Department of Health and Mental Hygiene
DHS	Department of Homeless Services
DOB	Department of Buildings
DOC	Department of Correction
DOE	Department of Education
DOP	Department of Probation
DoITT	Department of Information Technology and Telecommunications
DOT	Department of Transportation
DSRC	Dedicated Short Range Communications
EEBL	Emergency Electric Brake Light
ETC	Electronic Toll Collection
EVAC	Emergency Communications and Evacuation Information
EVT	Event Data Action Logs
FCW	Forward Crash Warning
FDR	Franklin D. Roosevelt
FHV	For Hire Vehicle
FHWA	Federal Highway Administration
GPS	Global Positioning System
HPC	High Performance Computing
HPD	Department of Housing, Preservation, and Development
HRA	Human Resources Administration
IE	Independent Evaluator
IMA	Intersection Movement Assist
IRB	Institutional Review Board

Acronym	Meaning
I-SIGCVDATA	Intelligent Traffic Signal System Data
ITS	Intelligent Transportation System
JSON	JavaScript Object Notation
LCW	Lane Change Warning
MAP	Map Data Message
METAR	METeorological Aerodrome Reports
MIM	Midtown in Motion
MTA	Metropolitan Transportation Authority
MTM	Manhattan Traffic Model
NWS	National Weather Service
NYC	New York City
NYCT	New York City Transit
NYCDOT	New York City Department of Transportation
NYU	New York University
OBD	On-Board Diagnostic
OCMC	Office of Chief Medical Examiner
OCSP	Operational Capability Showcase Plan
OEM	Office of Emergency Management
OER	Office of Emergency Response
OTA	Over-the-Air
OVC	Oversize Vehicle Compliance
PARKS	Department of Parks and Recreation
PASS	Pedestrians for Accessible and Safe Streets
PDO	Property Damage Only
PED	Pedestrian
PED-SIG	Mobile Accessible Pedestrian Signal System
PEDINXWALK	Pedestrian in Crosswalk Warning
PID	Pedestrian Information Device
PMESP	Performance Measurement and Evaluation Support Plan
RLVW	Red Light Violation Warning
RF	Radio Frequency

Acronym	Meaning
RSU	Roadside Unit
PMESP	Performance Measurement and Evaluation Support Plan
PMESS	Performance Measurement and Evaluation Support Schedule
SCMS	Security Credential Management System
SOMS	System Operation and Maintenance Summary
SPaT	Signal Phase and Timing
SPDCOMP	Speed Compliance
SPDCOMPWZ	Speed Compliance in Work Zone
SSL	System Status Log
SSM	Surrogate Safety Measure
SUMO	Simulation of Urban Mobility
SUV	Sports Utility Vehicle
TIM	Traveler Information Message
TLC	Taxi and Limousine Commission
TMC	Traffic Management Center
TraCI	Traffic Control Interface
TTC	Time to Collision
UTC	Coordinated Universal Time
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VHD	Vehicle Hours of Delay
VHT	Vehicle Hours Traveled
VMT	Vehicle Miles Traveled
VTRW	Vehicle Turning Right Warning
WSA	WAVE Service Advertisement
USDOT	United States Department of Transportation

Appendix B. Participant Surveys

ASD Driver Surveys:

Different sets of questions are asked depending on the time the survey is conducted:

Pre-deployment survey:	Parts 1, 2, and 4 only
Early-deployment survey:	Parts 1 to 4
Late-deployment survey:	Parts 1 to 4

Part 1: Vehicle Usage

Note: These questions are asked in all surveys.

1. Where do you primarily operate the vehicle during a typical work week? *(Select all that apply):*
   a) Manhattan - Lower Manhattan (South of 14th St)
   b) Manhattan - Midtown Manhattan
   c) Manhattan - Upper East Side
   d) Manhattan - Upper West Side
   e) Manhattan - Upper Manhattan (North of 96th St)
   f) Brooklyn - Downtown Brooklyn
   g) Brooklyn - Outer Brooklyn
   h) Staten Island
   i) Queens - Long Island City
   j) Queens - LaGuardia Airport
   k) Queens - John F. Kennedy Airport
   l) Queens - Other
   m) Bronx - Southern Bronx
   n) Bronx - Northern Bronx

2. At what times of day do you typically operate during WEEKDAYS? *(Select all that apply):*
   a) AM Rush (6AM-9AM)
   b) Mid-day (9AM-3PM)
   c) PM Rush (3PM-7PM)
   d) Evening (7PM-12AM)
   e) Other (12AM-6AM)

3. At what times of day do you typically operate during WEEKENDS? *(Select all that apply):*
   a) Daytime (7AM-7PM)
   b) Nighttime (7PM-7AM)
   c) N/A (Not Applicable)

4. Which agency owns the vehicle you drive for work?
    a) NYC Department of Transportation (DOT)
    b) NYC Department of Corrections (DOC)
    c) NYC Department of Environmental Protection (DEP)
    d) NYC Department of Homeless Services (DHS)
    e) NYC Department of Parks and Recreation (Parks)
    f) NYC Taxi and Limousine Commission (TLC)
    g) NYC Human Resources Administration (HRA)
    h) NYC Department of Citywide Administrative Services (DCAS)
    i) NYC Department of Design and Construction (DDC)
    j) NYC Department of Buildings (DOB)
    k) NYC Administration for Children's Services (ACS)
    l) Metropolitan Transit Authority – Bridges and Tunnels (MTA B&T)
    m) Metropolitan Transit Authority – Bus (MTA Bus)
    n) New York City Transit (NYCT)
    o) Other: ____

Q5 conditionally asked if Q4 response is NOT "NYCT" or "MTA"

5. What is the make/model* of the fleet vehicle you typically drive?
    (Select all that apply):
    a) Chevrolet Bolt
    b) Chevrolet Express
    c) Chevrolet Silverado
    d) Ford E350
    e) Ford Explorer
    f) Ford F150
    g) Ford F250
    h) Ford F350
    i) Ford F550
    j) Ford Fusion
    k) Nissan Leaf
    l) Ram 2500
    m) Toyota Camry
    n) Toyota Prius
    o) Toyota Rav4
    p) Other: ____________________

Q6 conditionally asked if Q4 response IS "NYCT" or "MTA"

6. What is the make/model* of the fleet vehicle you typically drive?
    (Select all that apply):
    a) New Flyer
    b) Nova Bus
    c) Orion
    d) Other___

7. Do you typically drive the same vehicle, or do you drive different vehicles within common fleet?
    a) Typically same assigned vehicle
    b) Different vehicles within common fleet

8. What is the typical MINIMUM number of miles you drive your fleet vehicle per workday?
    ______ miles

9. What is the typical MAXIMUM number of miles you drive your fleet vehicle per workday?
   ______ miles

10. What is the typical MINIMUM number of hours you drive your fleet vehicle per workday?
    ______ hours

11. What is the typical MAXIMUM number of hours you drive your fleet vehicle per workday?
    ______ hours

12. What is the typical MINIMUM number of days you drive your fleet vehicle per work week?
    ______ days

13. What is the typical MAXIMUM number of days you drive your fleet vehicle per work week?
    ______ days

Part 2: User Perception/Attitude

Note: These questions are asked in all surveys.

1. Please indicate your level of familiarity with Connected Vehicles and Connected Vehicle applications:
   a) Very familiar (I've heard about many of the applications and understand how they work)
   b) Somewhat familiar (I've heard about some of the applications and understand how they work)
   c) Not too familiar (I've heard about some of the applications but don't know how they work)
   d) Not at all familiar (I had not heard of Connected Vehicles before this study and have no information about the applications)

2. Do you anticipate that drivers will benefit from the use of Connected Vehicle technologies?
   a) Yes
   b) No
   c) Don't know enough about the technology

3. Do you have any of the following concerns about the Connected Vehicle technology system? *(Select all that apply):*
   a) Cost (i.e., it will be too expensive for you to purchase for your own personal vehicle)
   b) Safety
   c) Privacy
   d) Distraction (i.e., the system will be distracting)
   e) Trust in the technology
   f) Too many alerts or warning
   g) False alerts or warning (i.e., when there is no real danger
   h) Other (please specify: ____)
   i) Don't know enough about the technology

4. Based on your perceptions when you are driving in the City for work, what is your likelihood of a crash or near-crash with a pedestrian or bicyclist?
    a) Extremely Likely
    b) Very Likely
    c) Moderately Likely
    d) Slightly Likely
    e) Not at all likely
    f) Not applicable

5. Based on your perceptions when you are driving in the City for work, what is your likelihood of a crash or near-crash with another vehicle?
    a) Extremely Likely
    b) Very Likely
    c) Moderately Likely
    d) Slightly Likely
    e) Not at all likely
    f) Not applicable

6. Based on your perceptions when you are driving in the City for work, what is your likelihood of a crash or near-crash by yourself (e.g., hit roadway barrier or off-road crash)?
    a) Extremely Likely
    b) Very Likely
    c) Moderately Likely
    d) Slightly Likely
    e) Not at all likely
    f) Not applicable

7. In general, how safe do you feel when driving in the City for work (i.e., that you won't be involved in a crash)?
    a) Extremely safe
    b) Very safe
    c) Moderately safe
    d) Slightly safe
    e) Not at all safe
    f) Not applicable (Do not drive in the City for work)

Part 3: User Experience

Note: These questions are asked only in the early-deployment and late-deployment surveys.

1. How often do you hear the alerts?
    a) Many times per day
    b) Few times per day
    c) Few times per week
    d) Less than weekly
    e) Never

If Q1 response is "Never", skip remaining Part 3 question

2. How would you rate the sound volume of the alerts?
    a) Much Too Loud
    b) Somewhat too Loud
    c) About right

d) Somewhat too Quiet
e) Much Too Quiet

3. Are the audible alerts distracting or not?
   a) Extremely distracting
   b) Very distracting
   c) Moderately distracting
   d) Slightly distracting
   e) Not at all distracting

4. Do you find the audible alerts helpful or not?
   a) Extremely helpful
   b) Very helpful
   c) Moderately helpful
   d) Slightly helpful
   e) Not at all helpful

5. Have the audible alerts affected how you drive in the City or not?
   a) The alerts have affected my driving
   b) The alerts have not affected my driving

Q6 conditionally asked if Q5 response is "The alerts have affected my driving":

6. How would you define the effect on your driving?
   a) Very Positive
   b) Somewhat Positive
   c) Somewhat Negative
   d) Very negative

Q7 conditionally asked if Q5 response is "The alerts have affected my driving":

7. Please indicate the reason for your previous response:
   ____

8. Which of these warnings do you recall hearing?
   (Select all that apply):
   a) Blind Spot Alert
   b) Emergency Brake Light
   c) Emergency Communications and Evacuation Information
   d) Forward Crash Warning
   e) Intersection Movement Assist
   f) Lane Change Warning
   g) Pedestrian Warning
   h) Reduce Speed
   i) Reduce Speed Curve
   j) Reduce Speed Work Zone
   k) Stop Height Restriction
   l) Stop Red Light
   m) Vehicle Turning Right in Front of Bus Warning
   n) I have received warnings, but I cannot tell them apart
   o) I can't recall if I received warnings
   p) I have not received any warnings

9. Which three warnings do you recall hearing most often?
   (Select up to three):
   a) Blind Spot Alert

b) Emergency Brake Light
c) Emergency Communications and Evacuation Information
d) Forward Crash Warning
e) Intersection Movement Assist
f) Lane Change Warning
g) Pedestrian Warning
h) Reduce Speed
i) Reduce Speed Curve
j) Reduce Speed Work Zone
k) Stop Height Restriction
l) Stop Red Light
m) Vehicle Turning Right in Front of Bus Warning
n) I have received warnings, but I cannot tell them apart
o) I can't recall if I received warnings
p) I have not received any warnings

10. Do you think any of the warnings have helped you drive more safely?
    a) Yes
    b) No

Q11 conditionally asked if Q10 response is "Yes":

11. Check all that have helped you drive more safely:
    (Select all that apply):
    a) Blind Spot Alert
    b) Emergency Brake Light
    c) Emergency Communications and Evacuation Information
    d) Forward Crash Warning
    e) Intersection Movement Assist
    f) Lane Change Warning
    g) Pedestrian Warning
    h) Reduce Speed
    i) Reduce Speed Curve
    j) Reduce Speed Work Zone
    k) Stop Height Restriction
    l) Stop Red Light
    m) Vehicle Turning Right in Front of Bus Warning

12. Overall, how satisfied or dissatisfied are you with the warning system?
    a) Very dissatisfied
    b) Dissatisfied
    c) Somewhat dissatisfied
    d) Indifferent
    e) Somewhat satisfied
    f) Satisfied
    g) Very satisfied

Part 4: Demographics

Note: These questions are asked in all surveys.

1. How many years have you been driving for work in New York City?
    a) 0-2 years
    b) 3-5 years

   c) 6-10 years
   d) More than 10 years

2. What is your age?
   a) 18-24
   b) 25-44
   c) 45-64
   d) Older than 65

3. What is your proficiency with English?
   a) Fluent
   b) Good
   c) Limited
   d) None

PID Pedestrian Survey:

I. Pre-Experiment Interview Protocol

The purpose of this pre-experiment interview is to understand the baseline conditions for study participants.

Demographic Information

1. Name: ___________________________________

2. What is your age:
   - 18-24
   - 25-44
   - 45-64
   - Older than 65

3. Which borough do you reside in?
   - Manhattan
   - Bronx
   - Brooklyn
   - Queens
   - Staten Island

4. Which of the following best describes your vision disability?
   - Partially-sighted or low vision
   - Blind
   - Totally blind

5. At what age did you develop a vision disability or become blind?
   - _______ years old
   - __ visually impaired since birth

6. On average, how often do you cross a signalized intersection per day?
   - 6 or more intersections a day
   - 4 or 5 intersections a day
   - 2 or 3 intersections a day
   - Less than 2 intersections a day

Self-ratings: Technology

7. Have you participated in any orientation and mobility training?
   - Yes
   - No

8. Do you currently use a mobile phone?
   - Yes: iOS or Android
   - No

9. Do you currently use a mobile navigation assistant / Global Positioning System (GPS)?
   - Yes

- No

10. Have you experienced an Accessible Pedestrian Signal before? These signals give you audio or tactile information about the state of the light at the intersection or the location of the crosswalks in addition to a light signal.
    - Yes
    - No

Navigation & Mobility

11. What is your preferred method of assistance while navigating to a destination (select only one)?
    - Long or white cane
    - Guide dog
    - Electronic travel aid (e.g., laser cane)
    - Personal navigation device / GPS on the phone
    - Asking other pedestrians I pass
    - Other (please specify____________)

12. How often do you use each of the following methods of assistance while navigating to a destination?
    A. Many times per day B. Few times per day C. Few times per week D. Less weekly E. Never

    - Long or white cane: _______
    - Guide dog: _______
    - Electronic travel aid (e.g., laser cane): _______
    - Personal navigation device / GPS on phone: _______
    - Asking other pedestrians I pass: _______
    - Other (please specify: ___________): _______

13. In general, how safe do you feel when you cross a signalized intersection?
    - Extremely Safe
    - Very safe
    - Moderately safe
    - Slightly safe
    - Not at all safe

14. How would you rate your proficiency in each of these travel skills? Are you well below average, below average, average, above average, or well above average? *[INTERVIEWER: REPEAT RESPONSE CATEGORIES AS NEEDED]*

	Well below average	**Below average**	**Average**	**Above average**	**Well above average**
General sense of direction					
Independent travel					
Signalized street crossings					

II. Post-Experiment Interview Protocol

The post-experiment interview aims to collect useful feedback on participants' perceptions and experiences with the Ped App after the field test is done. It includes an additional set of questions on attitudes, safety, and other relevant topics.

User Experience:

1. How do you rate the Ped App overall?
   - Poor
   - Fair
   - Good
   - Very good
   - Excellent

2. Did you experience any of the following problems in using the Ped App? Select all that apply.
   - Slow response
   - Location information provided not accurate
   - Type of advisory provided (i.e., signal timing) not useful
   - Other. Please specify. ____

3. When using the Ped App, do you feel you have sufficient time to cross the intersection or not?
   - Yes
   - No
   - Don't know

4. When using the Ped App, do you feel you stay oriented within the crosswalk?
   - Yes
   - No
   - Do not know

5. For each of the following statements, please tell me whether you strongly disagree, somewhat disagree, neither agree nor disagree, somewhat agree, or strongly agree. *[INTERVIEWER SHOULD REPEAT RESPONSE CATEGORIES AS NEEDED]*

   a. The operation of the Ped App is easy to use.

Strongly Disagree	Somewhat Disagree	Neither agree nor disagree	Somewhat Agree	Strongly Agree
○	○	○	○	○

   b. I am more confident in my ability to cross a signalized intersection with the CVP pedestrian application compared to other assistive technologies I have used before.

Strongly Disagree	Somewhat Disagree	Neither agree nor disagree	Somewhat Agree	Strongly Agree
○	○	○	○	○

6. Does the Ped App provide sufficient information through AUDIO to assist your intersection crossing?
   - Yes

- No
- Do not know

7. Does the Ped App provide sufficient information through VIBRATION to assist your intersection crossing?
   - Yes
   - No
   - Don't know

8. For each of the following statements, please select the answer that apply. *[INTERVIEWER SHOULD READ AND REPEAT RESPONSE CATEGORIES AS NEEDED]*

   a. Alerts given by the Ped App are timely.

Always	Mostly	Sometimes	Never
○	○	○	○

   b. Alerts given by the Ped App are accurate.

Always	Mostly	Sometimes	Never
○	○	○	○

   c. Type of alerts (i.e., signal information) given by the Ped App are helpful.

Strongly Disagree	Somewhat Disagree	Neither agree nor disagree	Somewhat Agree	Strongly Agree
○	○	○	○	○

9. In general, how safe do you feel when using the Ped App in comparison with not using it?
   - Much Safer
   - Slightly Safer
   - Same level of safety
   - Slightly less safe
   - Much worse

10. How would you rate your ability to easily navigate the pedestrian crosswalk when using the Ped App?
    - Excellent
    - Very Good
    - Good
    - Fair
    - Poor
    - Very Poor

11. Do you anticipate that pedestrians will benefit from the use of Ped App technologies?
    - Yes
    - No

12. Do you have any of the following concerns about the Ped App technologies? Check all that apply.
    - Safety
    - Privacy
    - Trust in the technology

- Too many alerts or warnings
- False alerts or warnings (i.e., when there is no real danger)
- Distraction (i.e., the system will be distracting)
- Don’t know enough about the technology
- Other (please specify: ______________________________)
- No concerns

13. Do you have any suggestions for improving the Ped App?

____

14. Would you recommend the Ped App to other prospective users? Please specify why or why not.
    - Yes
    - No

____

Appendix C. System Performance Data Details

The following outlines additional details regarding the different data sets collected as part of the NYC CVPD system performance evaluation process.

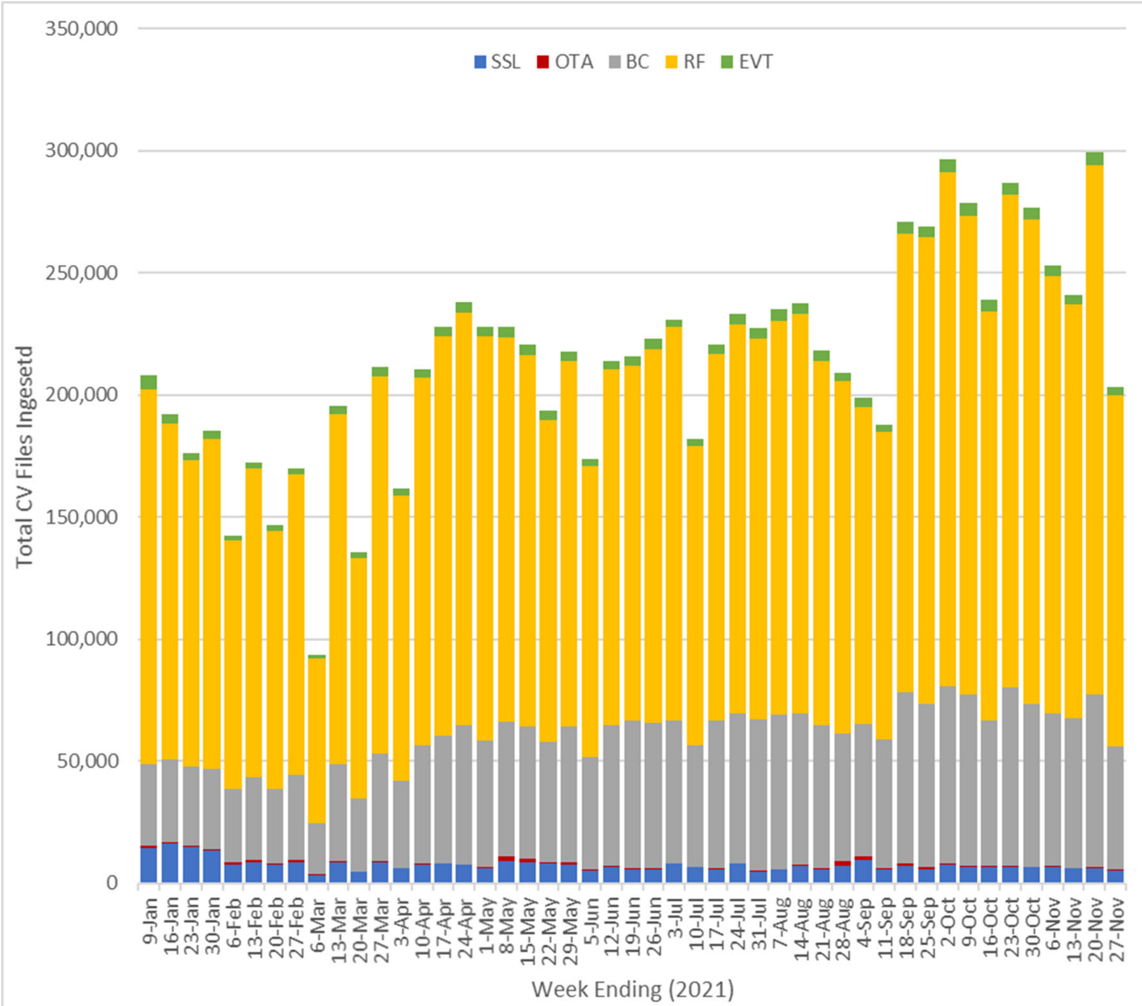
ASD-Based Data:

ASD-based data is collected onboard the CV-equipped fleet vehicles. Five file types are recorded on the ASDs:

- System Status Logs (SSL): SSL files record various system operations messages and status logs as generated by the ASD software as the vehicle operates, including error messages generated by the ASD.
- Over-the-Air Messages (OTA): OTA messages record the receipt of new ASD firmware or configuration update files as received by the ASD from RSUs broadcasting the messages.
- Mobility Logs or Breadcrumbs (BC): BC files record periodic BSMs that the host vehicle successfully broadcasts as the vehicle is in operation.
- Radio Frequency (RF): RF files record the first and last sighting of BSMs from other vehicles or MAP, TIM, or SPaT messages from RSUs.
- Event Data Action Logs (EVT): Event logs are recorded for a defined period of time both before and after a CV application issues a warning alert to the driver (or would have issued the warning but the device is operating in silent mode).

Weekly CV Files Ingested to the TMC

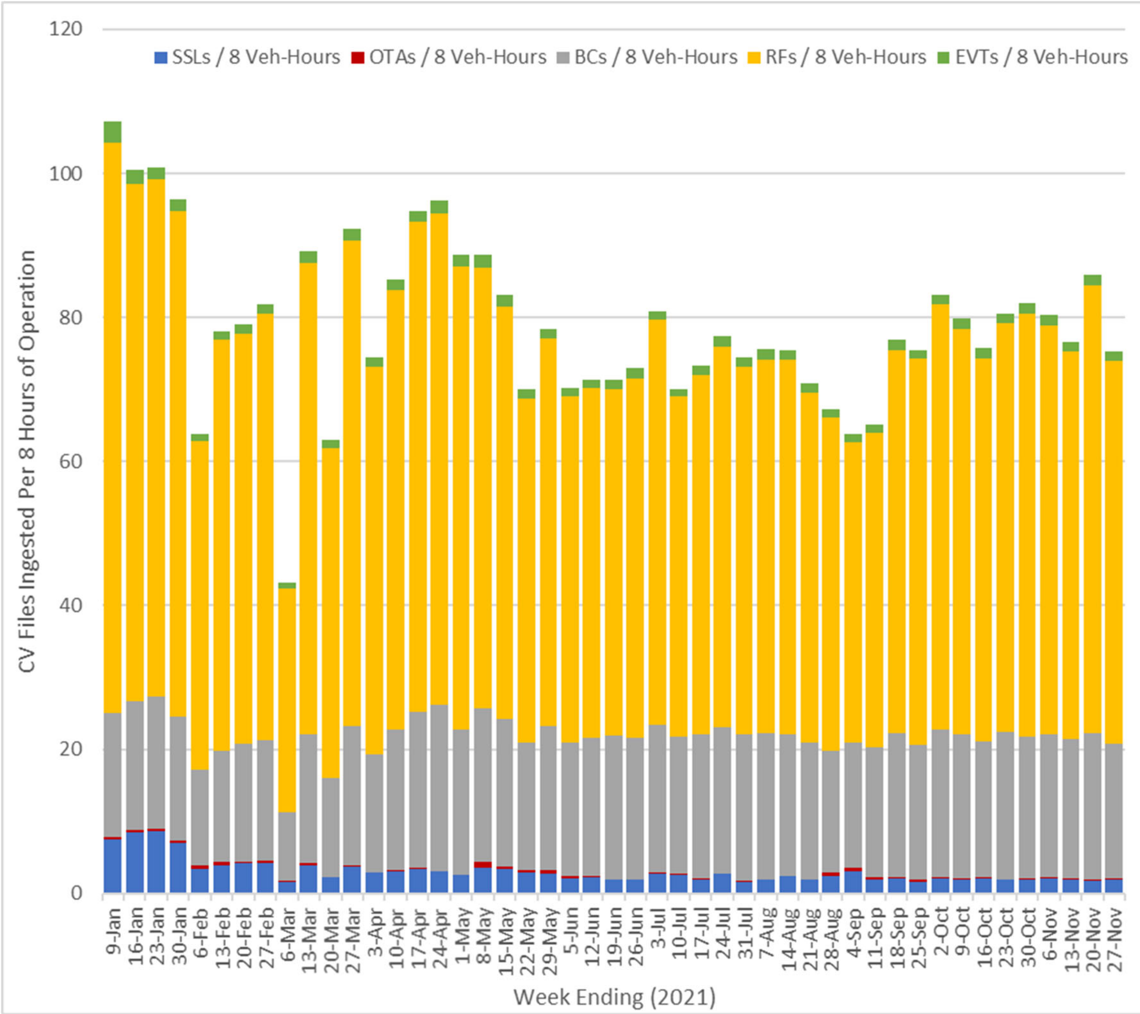
Figure 88 presents the weekly number of CV files that are uploaded via a secure DSRC file transfer from the ASD to an upload RSU and subsequent transmission to the TMC servers since the beginning of the before data collection period of Phase 3 (January 1, 2021).



(Source: NYCDOT)

Figure 88. Weekly ASD-Generated Files Uploaded to TMC

The number of equipped vehicles grew through the first half of 2021 until the full 3,000 vehicle fleet was achieved. Additionally, based on the Geotab fleet management system, the average use of the fleet vehicles was also growing slightly through 2021 as conditions continued to evolve with the recovery from modified COVID-19 pandemic conditions. Figure 89 presents the average weekly ingested file counts per 8-hours of vehicle operation. These file counts are normalized against both the total number of installed ASDs into CV fleet vehicles as well as the average weekly vehicle usage reports provided by the Geotab system.



(Source: NYCDOT)

Figure 89. Weekly ASD-Generated Files Uploaded per 8-Hours of Operation

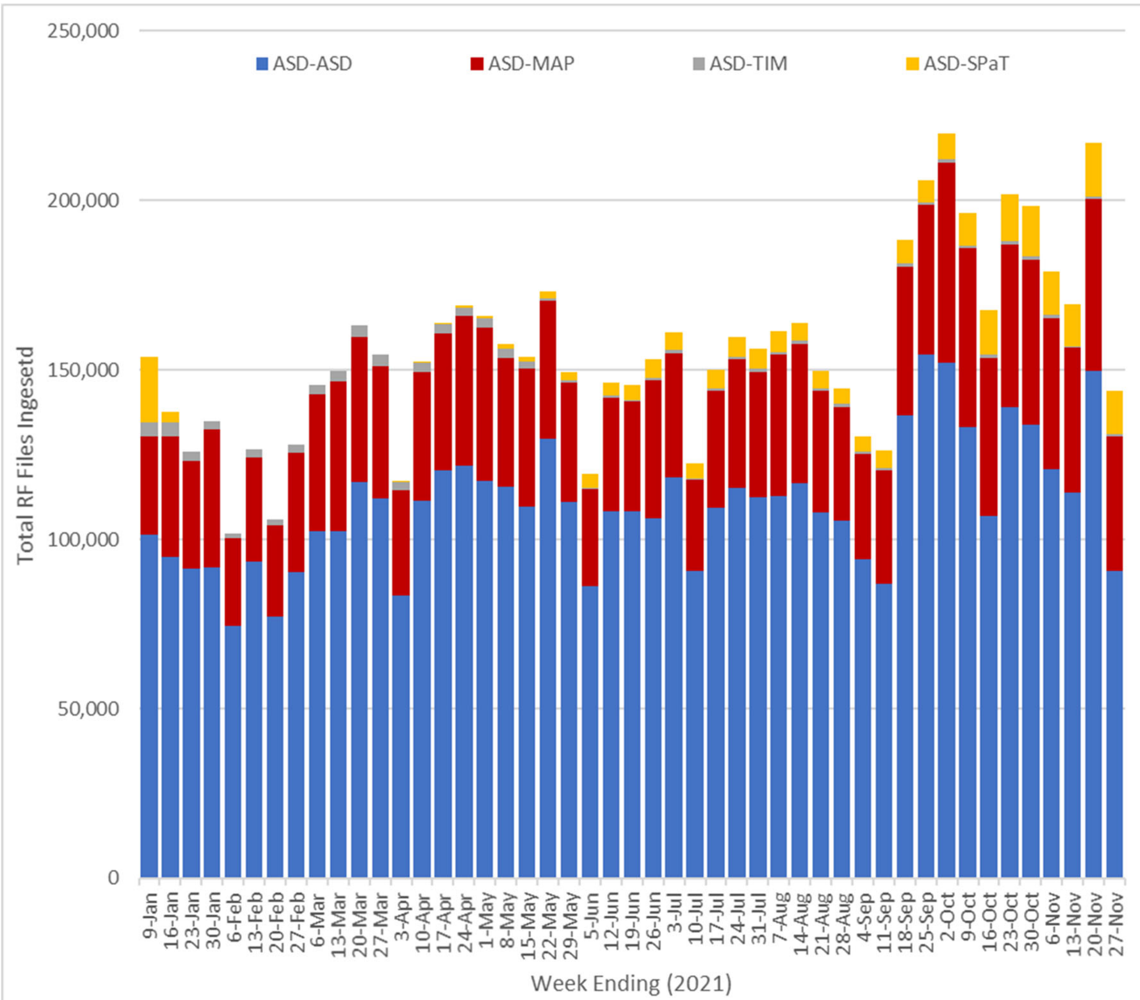
Weekly Radio Frequency (RF) Files

The RF files recorded by ASDs allows an estimation of the degree to which the CV-equipped vehicles encounter other CV-equipment deployed in the field. RF files are classified to which CV message are heard or sighted by the host ASD vehicle:

- ASD-ASD: V2V sightings of other CV-equipped vehicles broadcasting BSMs
- ASD-MAP: V2I sightings of RSU broadcast MAP messages
- ASD-TIM: V2I sightings of RSU broadcast TIM messages
- ASD-SPaT: V2I sightings of RSU broadcast SPaT messages

While hearing another CV message does not equate to an opportunity for a V2V or V2I safety application warning conditions, the degree to which other CV messages are heard by host vehicles allows some estimate of the relative potential for V2V or V2I interactions over time.

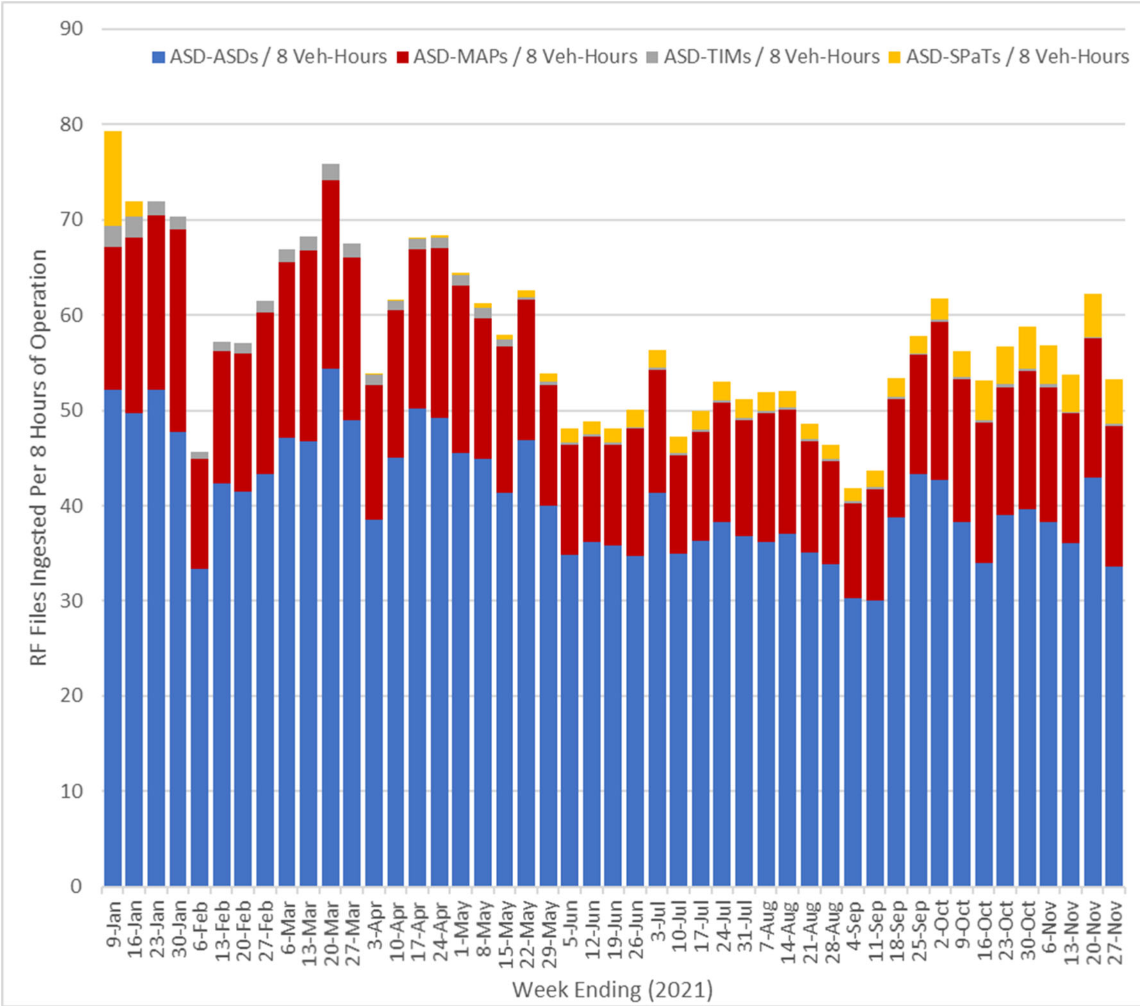
Figure 90 presents the weekly ingest of ASD-based RF files that were uploaded for the CV fleet vehicles to the TMC. It should be noted that ASD-ASD interactions can include logs from each vehicle involved in the V2V interaction (assuming that both vehicles heard the other's BSMs and those RF log files were successfully uploaded to the TMC).



(Source: NYCDOT)

Figure 90. Weekly ASD-Generated RF Files Uploaded to TMC

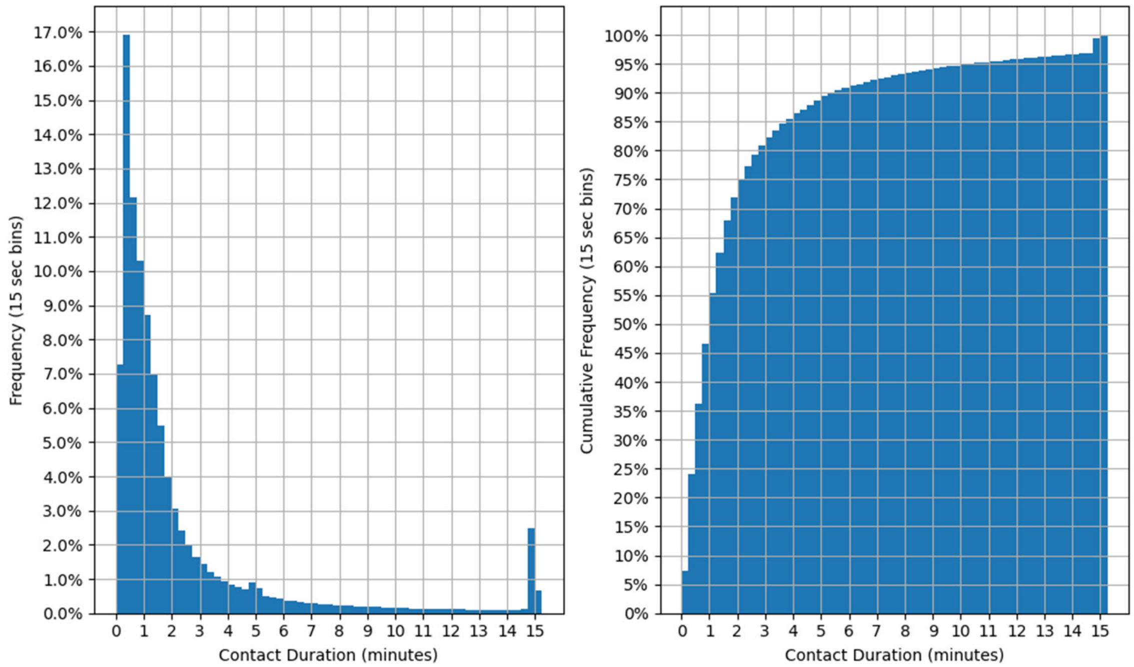
Similar to the overall CV file counts present earlier, Figure 91 presents a normalization of the average number of RF files that could be expected for every 8-hours of vehicle operation.



(Source: NYCDOT)

Figure 91. Weekly ASD-Generated RF Files Uploaded per 8-Hours of Vehicle Operation

Another meaningful metric contained in the ASD-ASD RF files is the duration of the contacts between the two CV-equipped vehicles in the field. Figure 92 shows the distribution of the contact duration in minutes of the ASD-ASD files from January through November 2021. Approximately 17% of the ASD-ASD interactions lasted between 15 and 30 seconds, while approximately half of the ASD-ASD encounters lasted less than one minute. Approximately 10% of the interactions more than six minutes, and 5% lasted more than 10 minutes. The long durations of interactions can be expected to occur with two CV-equipped vehicles traveling along the same roadway. While this could simply be two equipped vehicles traveling in proximity to each other on a heavily traveled roadway, these interactions may also occur with groups of related CV vehicles traveling together as they move from one common location to another in the course of their related work activities.



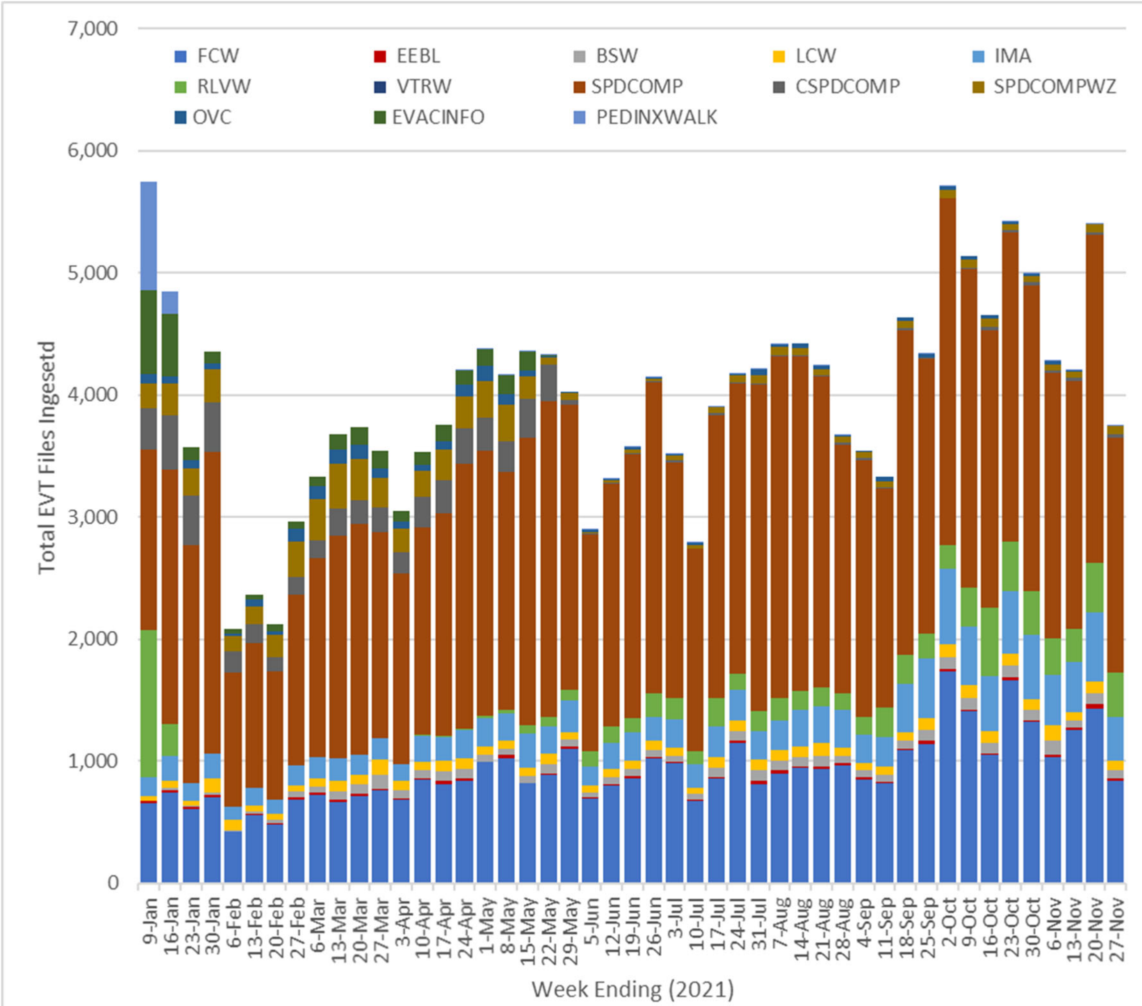
(Source: NYCDOT)

Figure 92. Distribution of ASD to ASD RF Contact Durations

Weekly Event (EVT) Files Ingested

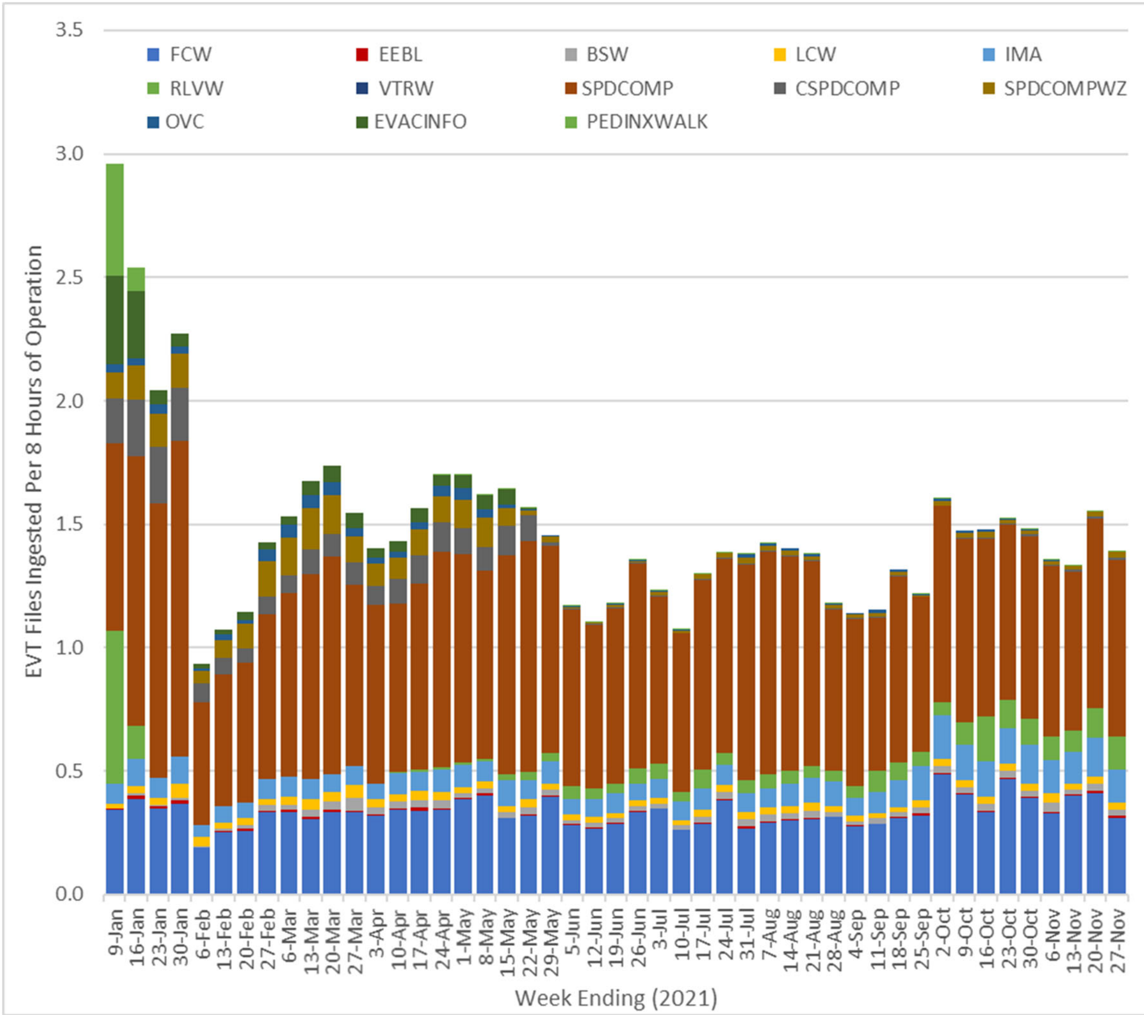
Event files, or Action Logs, are recorded by the ASDs for every CV application warning that is generated in response to the immediate operating conditions by one of the 13 CV applications running on the ASD. The logs are either recorded in silent mode (for before period treatment vehicles and before and after period control vehicles) or in active mode (after period treatment vehicles).

Figure 93 presents the total weekly number of Event files that were successfully uploaded to the TMC, stratified by the CV application that generated the warning for which the Event file recorded data. Figure 94 presents the normalized average number of event files generated per 8-hours of vehicle operation. It is noted that these figures both present all ingested Event files, including those with known data logging errors, old versions of software firmware, or from the NYC CVPD team's test vehicles.



(Source: NYCDOT)

Figure 93. Weekly Event Files by Type Uploaded to TMC



(Source: NYCDOT)

Figure 94. Weekly Event Files by Type Uploaded per 8-Hours of Vehicle Operation

Monthly Event File Obfuscation

During the event file review, cleaning, and obfuscation process conducted on ingested Event files prior to use in evaluation or public release on the ITS DataHub, several reviews of the files are conducted. These reviews include identify records which have at least one of several possible known errors, are from pre-deployment version of the ASD firmware, or are from the NYC CVPD team's test vehicles. The following event files are removed from consideration for analysis and public release if the following errors are found:

- Data Log Error: Multiple different types of data logging errors have been seen in the Event data records. These issues can include incorrect timestamp records, missing BSM, MAP or SPaT messages when required based on the CV application warning, invalid or indeterminable BSM message sequence IDs preventing knowing which BSM triggered the warning, or an incorrect time recording window surrounding the issued warning. Data logging errors account for 8.5 % of the total ingested files throughout the evaluation period.

- Location Error: When the location of the event's warning location trigger BSM is within NYC city limits and is also located more than 30 meters from the centerline of a public roadway or when the heading of the trigger BSM is in contradiction to the heading of the any nearby roadway, the event file is removed due to concerns over the location accuracy of the event. Location errors account for 2.6 % of the total ingested files throughout the evaluation period.
- Old Firmware: Older versions of the ASD firmware can be found in some vehicles from early deployment installations prior to the deployment-ready firmware versions, despite attempts to update the devices via over-the-air updates. Old ASD firmware versions account for 6.0 % of total ingested event files throughout the evaluation period.
- Test Vehicles: The small number of vehicles installed and operated by the NYC CVPD team for application testing purposes are removed from consideration as well. While these data records do not have data log, location, or firmware errors, the data files may contain abnormal behaviors and vehicle motions that were deliberate to test various conditions of the CV applications. Test vehicles account for 3.1 % of the total ingested event files throughout the evaluation period.

Table 29 presents the number of event files ingested that fall into the above categories, including the number of files that remain to be obfuscated and released. Following the removal of event files for the above reasons, 79.8 % of the total event files in the evaluation period from January to November 2021 remain and were obfuscated for unique vehicle identifiers and exact time and location data for use in the evaluation and for public use on the ITS DataHub. It is noted that this share increased through the duration of the evaluation period, with later months averages over 85% of the data being obfuscated and released.

Table 29. Monthly Event Files Ingested, Filtered, and Released after Obfuscation

Month	Total Ingested	Data Log Error	Location Error	Old Firmware	Test Vehicles	Total Filtered	Events Released	Percent Released
Jan 2021	19,323	5235	366	3,775	862	10,238	9,085	47.0%
Feb 2021	9,843	736	210	1,014	473	2,433	7,410	75.3%
Mar 2021	16,294	493	389	1,209	1,341	3,432	12,862	78.9%
Apr 2021	16,213	471	539	821	793	2,624	13,589	83.8%
May 2021	17,549	1,318	393	752	572	3,035	14,514	82.7%
Jun 2021	15,870	1,121	401	578	379	2,479	13,391	84.4%
Jul 2021	16,479	1,205	444	655	331	2,635	13,844	84.0%
Aug 2021	18,000	1,404	452	607	327	2,790	15,210	84.5%
Sep 2021	18,924	1,404	546	635	223	2,808	16,116	85.2%
Oct 2021	21,698	1,397	697	736	315	3,145	18,553	85.5%
Nov 2021	19,181	1,220	571	577	241	2,609	16,572	86.4%
Jan-Nov Total Count	**189,374**	**16,004**	**5,008**	**11,359**	**5,857**	**38,228**	**151,146**	**79.8%**
% of Total Ingested	**100%**	**8.5%**	**2.6%**	**6.0%**	**3.1%**	**20.2%**	**79.8%**	**--**

Detailed Monthly Event File Cleaning and Filtering

Following the data obfuscation processing but prior to the safety analysis, an addition step of detailed data review and cleaning was undertaken. This examined the details of the Event's BSM trajectory data and applied other logic checks to ensure the application data made sense relative to the application. The process and steps for detailed cleaning and filtering are summarized section 5.1.1.2.

The data filtering and cleaning focused on removing or repairing the following conditions: illogical event warning time scales; unreasonably high, zero, or constant speeds; large elevation deltas between host and target vehicles; stationary vehicles; illogical trajectories such as large gaps in BSMs; illogical relations between host and target vehicles; and detail vehicle trajectory speed corrections (illogical speeds or speeds inconsistent with trajectory coordinates). Two different cleaning and filtering methods were developed, one for V2I and one for V2V applications.

Table 30 and Table 31 present the number of monthly V2I and V2V event files available after obfuscation, filtered, and remained after data filtering and cleaning. Following the removal of event files for the above reasons, about 67.2% - 70.0 % of the total event files from January to September 2021 remained and were used for the safety analysis. It is important to note that when excluding the CSPDCOMP application that includes a relatively large proportion of events with incorrect triggering locations, the percentages of data removed for V2I applications range from 12% to 28%.

Table 30. Monthly V2I Event Files Collected, Filtered, and Remained After Data Filtering and Cleaning (SPDCOMP, CSPDCOMP, SPDCOMPWZ, and RLVW)

Month	Control Events After Obfuscation	Treatment Events After Obfuscation	Control Events Remaining After Step 1	Treatment Events Remaining After Step 1	Control Events Remaining After Step 2	Treatment Events Remaining After Step 2	Control Events Remaining After Step 3	Treatment Events Remaining After Step 3	Control Events Remaining After Step 4	Treatment Events Remaining After Step 4	Total Filtered	Total Events Remaining	Percent Remaining
Jan	17	6,547	16	5,713	16	5,666	16	5,522	5	4,709	1,850	4,714	71.8%
Feb	58	4,698	54	4,281	54	4,268	54	4,237	40	3,331	1,385	3,371	70.9%
Mar	291	8,038	261	7,324	260	7,301	260	7,254	203	5,590	2,536	5,793	69.6%
Apr	932	7,974	829	7,339	828	7,312	828	7,233	628	5,294	2,984	5,922	66.5%
Jun	448	8,445	397	7,212	393	7,171	393	6,994	329	5,905	2,659	6,234	70.1%
Jul	602	8,503	534	7,492	532	7,452	532	7,314	442	6,191	2,472	6,633	72.9%
Aug	623	9,679	524	8,309	524	8,262	524	8,107	432	6,805	3,065	7,237	70.2%
Sep	661	9,364	581	8,146	575	8,043	573	7,670	467	6,457	3,101	6,924	69.1%
Jan-Sep Total	**3,632**	**63,248**	**3,196**	**55,816**	**3,182**	**55,475**	**3,180**	**54,331**	**2,546**	**44,282**	**20,052**	**46,828**	**70.0%**
%Total Filtered	**--**	**--**	**12.0%**	**11.8%**	**0.4%**	**0.5%**	**0.1%**	**1.8%**	**17.5%**	**15.9%**	**30.0%**	**--**	**--**

Table 31. Monthly V2V Event Files Obfuscated, Filtered, and Remained after Detailed Data Filtering and Cleaning (FCW, BSW, LCW, IMA, and EEBL Events)

Month	Control Events After Obfuscation	Treatment Events After Obfuscation	Control Events Remaining After Steps 1-4	Treatment Events Remaining After Steps 1-4	Control Events Remaining After Steps 5 & 6	Treatment Events Remaining After Steps 5 & 6	Control Events Remaining After Step 8 *	Treatment Events Remaining After Step 8 *	Control Events Remaining After Step 9 *	Treatment Events Remaining After Step 9 *	Total Filtered	Events Remaining	Percent Remaining
Jan	6	1,739	6	1,435	6	1,148	6	1,148	6	1,119	620	1,125	64.5%
Feb	2	988	2	854	2	737	2	734	2	723	265	725	73.2%
Mar	50	1,990	41	1,655	29	1,301	29	1,300	29	1,273	738	1,302	63.8%
Apr	190	2,342	171	1,965	133	1,651	131	1,650	130	1,573	829	1,703	67.3%
Jun	270	4,174	240	3,244	224	2,858	224	2,855	224	2,782	1,438	3,006	67.6%
Jul	237	2,952	214	2,388	186	1,902	186	1,899	186	1,875	1,128	2,061	64.6%
Aug	417	4,392	371	3,441	310	3,081	310	3,078	309	3,049	1,451	3,358	69.8%
Sep	448	5,511	361	4,121	332	3,787	330	3,765	328	3,666	1,965	3,994	67.0%
Jan-Sep Total	**1,620**	**24,088**	**1,406**	**19,103**	**1,222**	**16,465**	**1,218**	**16,429**	**1,214**	**16,060**	**8,434**	**17,274**	**67.2%**
%Total Filtered	**--**	**--**	**13.2%**	**20.7%**	**11.4%**	**11.0%**	**0.2%**	**0.1%**	**0.2%**	**1.5%**	**32.8%**	**--**	**--**

Notes: * Erroneous speeds were recalculated in steps 7 and 10, therefore no events were removed in these two steps.

Non-CV Based Data

The following provides additional details regarding two non-CV-based data sets; COVID-19 impact data from the MTA, and NYPD Crash records.

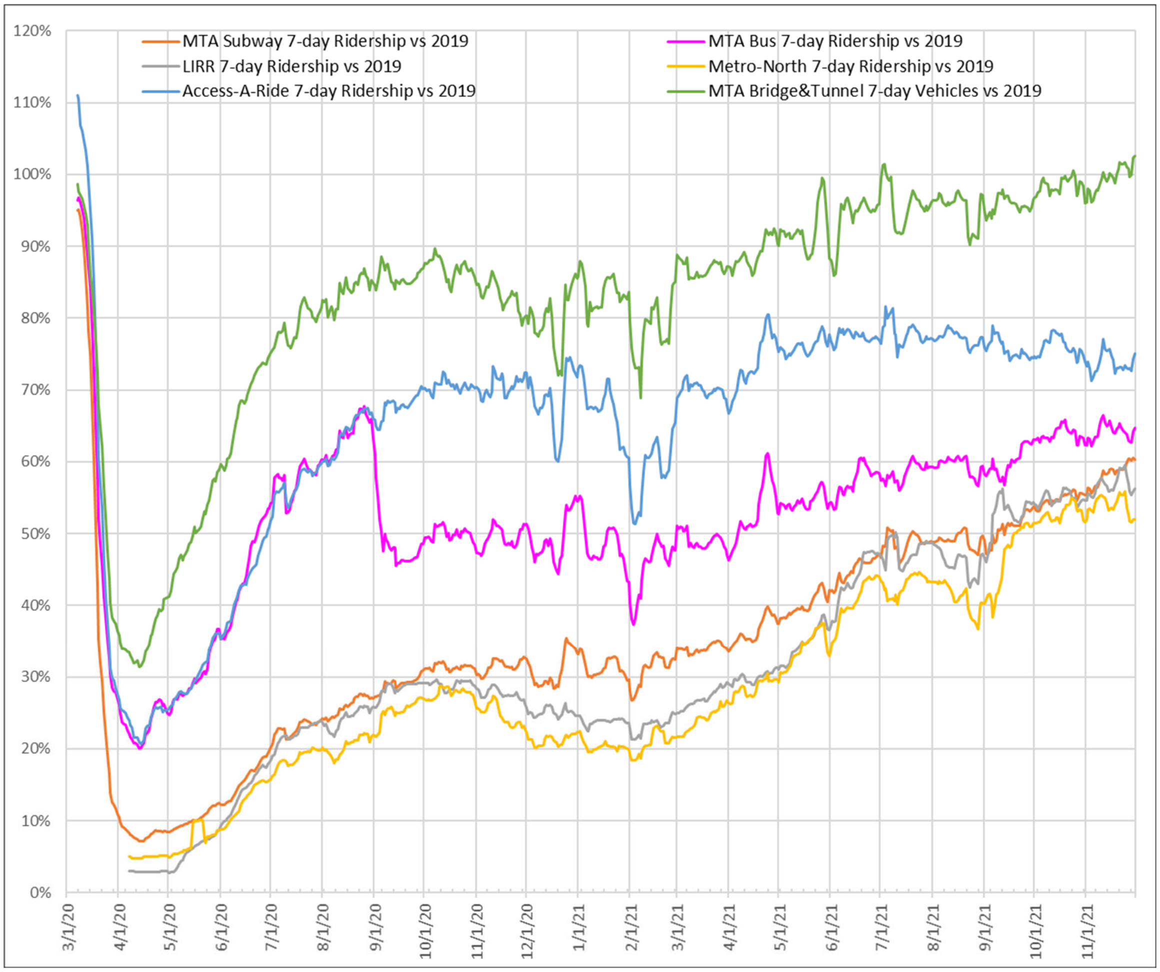
COVID-19 Recovery Data

As the first wave of inflections of COVID-19 reached the United States, the NYC region saw dramatic increases in the daily number of positive cases of COVID-19, along with associated hospitalizations and deaths from the pandemic. As a response, a state of emergency was issued in New York State on March 7, 2020, with additional stay-at-home orders for non-essential services and gatherings issued on March 20, 2020. As conditions in the summer of 2020 improved, restrictions were lifted in stages to allow for selected business sectors to reopen in phases through June and July. Some additional restrictions on large gatherings or limited capacity to ensure social distancing were continued past July 2020 through later stages of the pandemic.

While effects during the stay-at-home orders severely altered normal traveling behaviors in NYC, the effects have continued through 2020 and 2021, as the additional waves of infections have hit the NYC region. Overall, travel patterns have remained disrupted to varying degrees as compared to 2019 conditions. Two sets of data are provided to track the effects on the pandemic on travel in NYC.

The first data set is data publicly released by the Metropolitan Transportation Authority (MTA), which operates bus, subway, heavy rail, paratransit systems, and several toll bridges and tunnels within NYC.

The MTA has been publishing daily summaries of the use of its services to track the impacts of the pandemic at https://new.mta.info/coronavirus/ridership. Figure 95 below summarizes the percent changes seen since March 2020 as compared to comparable days for pre-COVID-19 conditions (2019). Data shown is a moving 7-day average for all data series.



(Source: NYCDOT)

Figure 95. Recovery From COVID-19: Daily MTA Service Volumes Versus Comparable 2019 Conditions (7-Day Moving Averages)

MTA services have returned from pre-COVID conditions to varying degrees. Through the CV deployment period (January 2021 to December 2021), the following ranges of services were seen as compared to pre-COVID (2019) conditions.

- MTA bridge and tunnel toll volumes were between 80% and 100% of pre-COVID conditions.
- Long-Island Rail Road and Metro-North Railroad (heavy rail) services ranged from 20% to 55% of pre-COVID conditions.
- Bus ridership ranged between 45% and 65% of pre-COVID conditions.
- Subway ridership ranged between 30% and 60% of pre-COVID conditions.
- Access-A-Ride (paratransit) services ranged from 55% to 80% of pre-COVID conditions.

It is noted that in response to COVID-19 conditions, selected MTA services were altered from normal scheduled services as follows:

- Local bus service was offered fare-free from March 23, 2020 to August 30, 2020. Normal fares for local bus service were reintroduced on August 31, 2020.
- Access-A-Ride services were offered fare-free from April 2020 to January 26, 2021.
- All subway service was suspended overnight to allow for train and station disinfections from 1 am to 5 am from May 6, 2020 to February 21, 2021, and from 2 am to 4 am from February 22, 2021 to May 16, 2021. Subways returned to 24-hour service starting May 17, 2021.
- Bus and Subway schedules were revised early in the pandemic in response to reduced ridership; normal services returned in June 2020.
- MTA Bridge and Tunnel volumes presented are only for tolled directions of travel. Tolls collected at the Verrazano-Narrows Bridge were switched from a one-way toll collection system to a two-way toll collection system on December 1, 2020. The change was not related to COVID responses but a planned change.

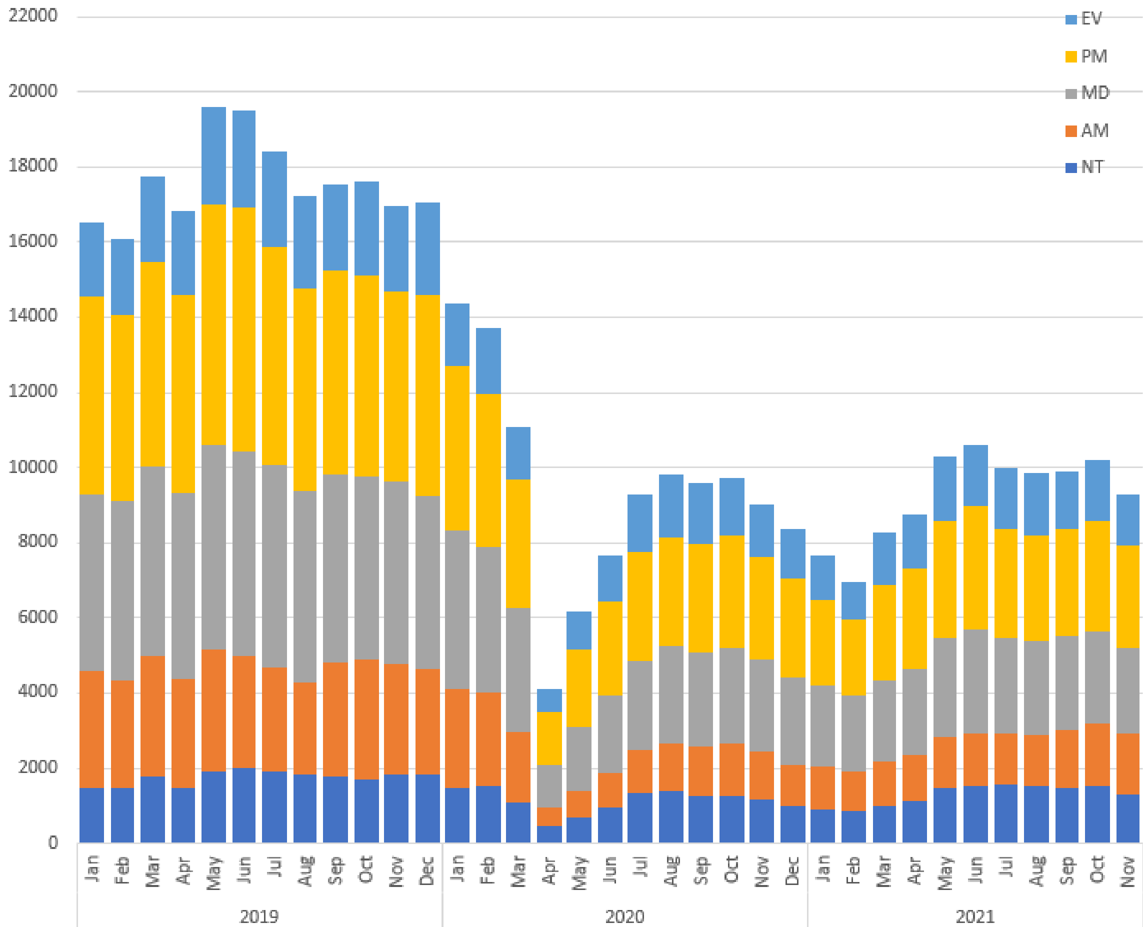
Crash Records

All crash data is available via the NYC Open Data portal at the following URL: https://data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Crashes/h9gi-nx95/data

Figure 96 presents a summary of the monthly number of reported crashes between January 2019 and November 2021. Each month's crashes are shown classified by the time of day that the crash occurred:

- Overnight (NT) from 12 am to 6 am
- Morning Peak (AM) from 6 am to 10 am
- Midday (MD) from 10 am to 3 pm
- Afternoon Peak (PM) from 3pm to 8 pm
- Evening (EV) from 8 pm to 12 am

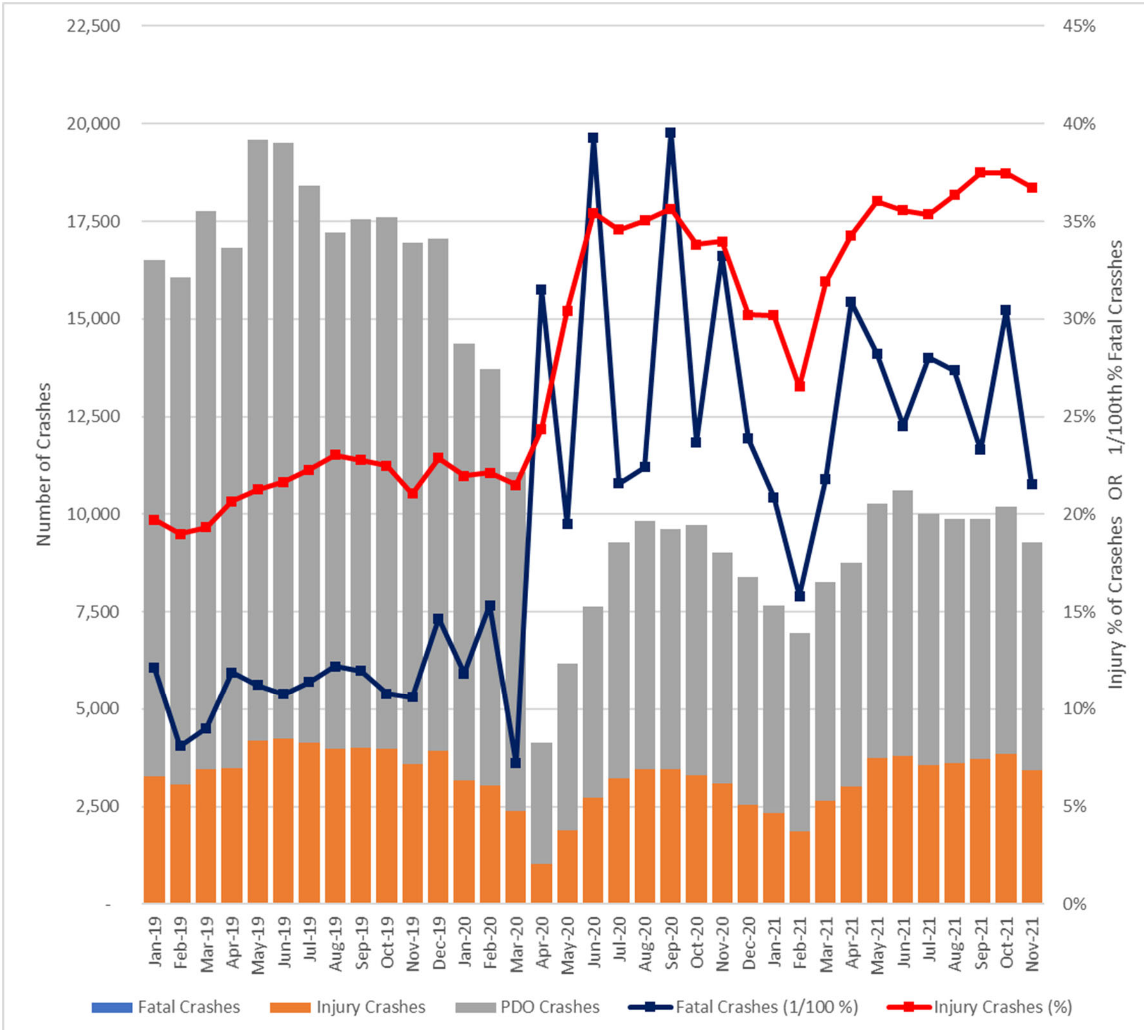
The impacts of the COVID-19 pandemic are clearly evident as travel patterns changed significantly during stay-at-home orders and throughout 2020 and 2021.



(Source: NYCDOT)

Figure 96. Monthly NYC Crashes by Time of Day

Figure 97 presents the same number of monthly crashes, but instead classified by the injury severity of the crash: crashes involving fatalities, crashes involving injuries, and crashes involving no injuries. Also shown in the figure in the line graphs are the monthly percentage of fatal and injury crashes. While the overall number of crashes can be seen to drop in March 2020 related to COVID-19 conditions, the relative share of fatal and injury crashes increases. Table 32 presents the same data in a tabular format.



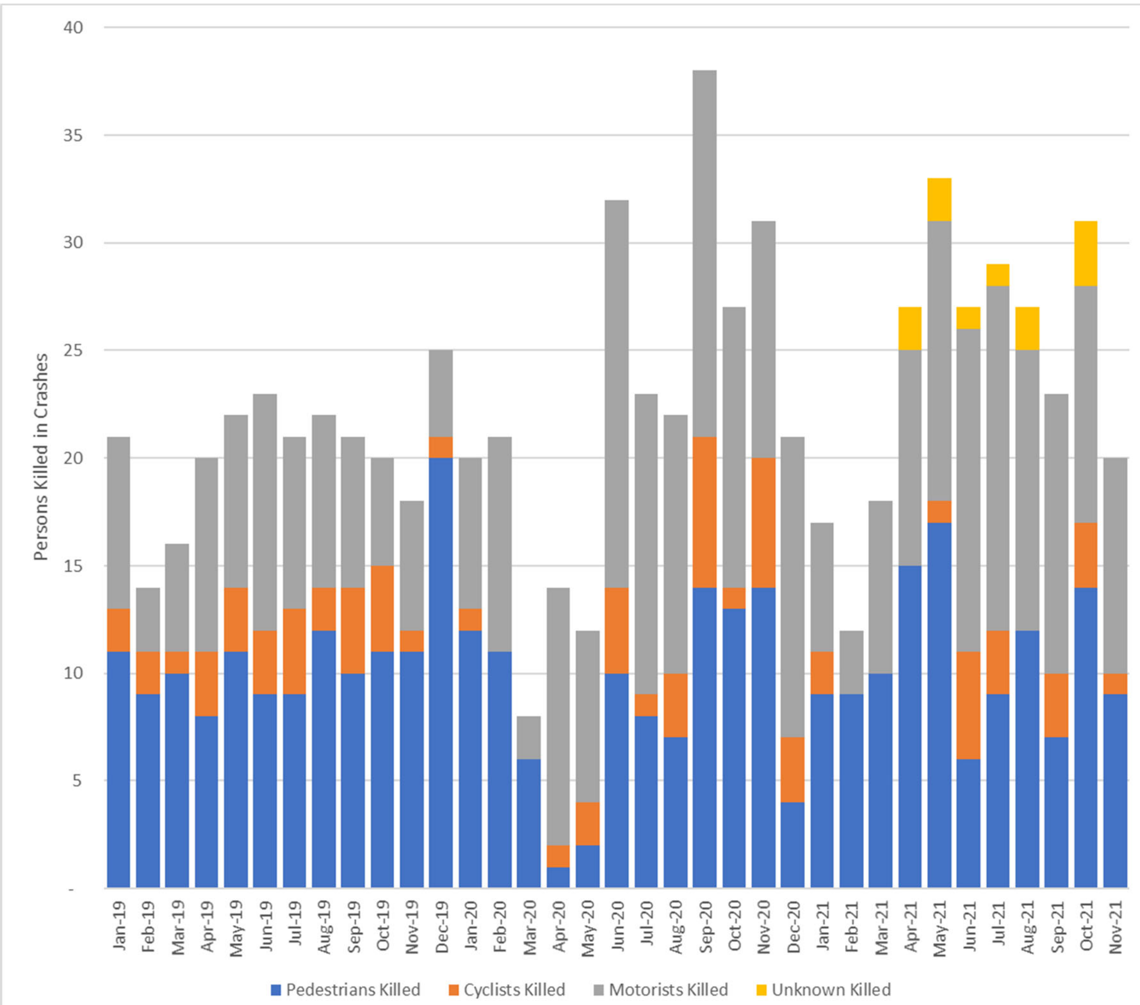
(Source: NYCDOT)

Figure 97. Monthly NYC Crashes by Severity

Table 32. Monthly Crashes in NYC by Severity of Injuries

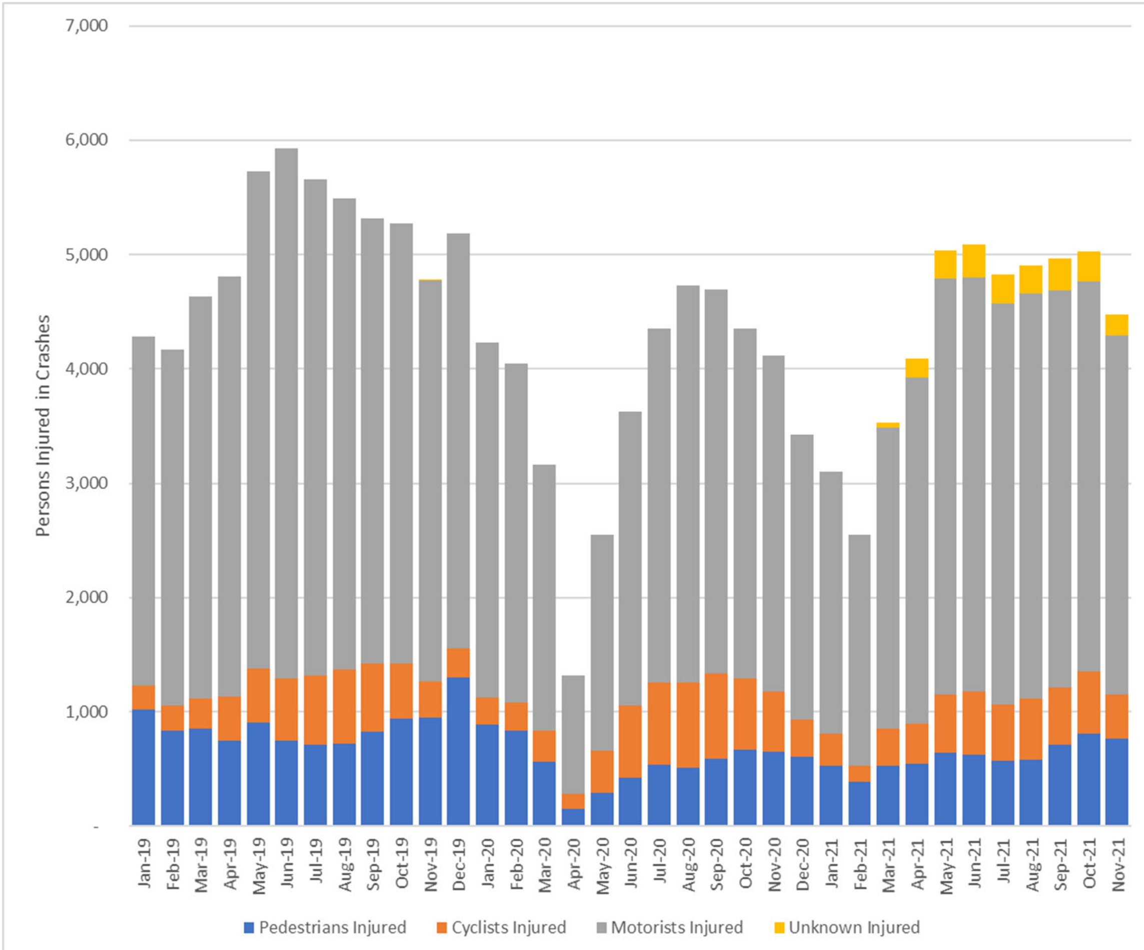
Month Reported	Fatal Crashes	Injury Crashes	Non-Injury Crashes	Total Number of Crashes	% Fatal Crashes	Injury Crashes (%)
Jan 2019	20	3,253	13,226	16,499	0.12%	19.7%
Feb 2019	13	3,050	13,002	16,065	0.08%	19.0%
Mar 2019	16	3,431	14,312	17,759	0.09%	19.3%
Apr 2019	20	3,475	13,334	16,829	0.12%	20.6%
May 2019	22	4,165	15,401	19,588	0.11%	21.3%
Jun 2019	21	4,227	15,268	19,516	0.11%	21.7%
Jul 2019	21	4,102	14,297	18,420	0.11%	22.3%
Aug 2019	21	3,967	13,227	17,215	0.12%	23.0%
Sep 2019	21	3,993	13,527	17,541	0.12%	22.8%
Oct 2019	19	3,958	13,634	17,611	0.11%	22.5%
Nov 2019	18	3,570	13,365	16,953	0.11%	21.1%
Dec 2019	25	3,901	13,133	17,059	0.15%	22.9%
Jan 2020	17	3,153	11,193	14,363	0.12%	22.0%
Feb 2020	21	3,031	10,652	13,704	0.15%	22.1%
Mar 2020	8	2,379	8,687	11,074	0.07%	21.5%
Apr 2020	13	1,005	3,109	4,127	0.31%	24.4%
May 2020	12	1,875	4,276	6,163	0.19%	30.4%
Jun 2020	30	2,708	4,903	7,641	0.39%	35.4%
Jul 2020	20	3,207	6,050	9,277	0.22%	34.6%
Aug 2020	22	3,440	6,358	9,820	0.22%	35.0%
Sep 2020	38	3,424	6,147	9,609	0.40%	35.6%
Oct 2020	23	3,282	6,405	9,710	0.24%	33.8%
Nov 2020	30	3,067	5,931	9,028	0.33%	34.0%
Dec 2020	20	2,531	5,827	8,378	0.24%	30.2%
Jan 2021	16	2,316	5,338	7,670	0.21%	30.2%
Feb 2021	11	1,847	5,104	6,962	0.16%	26.5%
Mar 2021	18	2,636	5,605	8,259	0.22%	31.9%
Apr 2021	27	2,999	5,723	8,749	0.31%	34.3%
May 2021	29	3,704	6,545	10,278	0.28%	36.0%
Jun 2021	26	3,772	6,808	10,606	0.25%	35.6%
Jul 2021	28	3,534	6,436	9,998	0.28%	35.3%
Aug 2021	27	3,587	6,256	9,870	0.27%	36.3%
Sep 2021	23	3,704	6,150	9,877	0.23%	37.5%
Oct 2021	31	3,815	6,340	10,186	0.30%	37.5%
Nov 2021	20	3,409	5,849	9,278	0.22%	36.7%

Figure 98 and Figure 99 report the total number of persons killed and persons injured, respectively, in reported NYC crashes per month, while Table 33 presents the same data in a tabular format. In both, persons killed or injury are listed as either pedestrian, cyclist, motorist (driver or occupant), or unknown (i.e. not classified in the crash records). While the previous figures show significant decreases in the total number of crashes, these figures indicate that the number of persons killed in crashes is the reverse trend, with more persons killed in crashes during the pandemic related recovery conditions of late 2020 and 2021 as compared to 2019. The reported injuries are generally consistent in scale across the 2019 to 2021 timeline, with only slightly fewer persons injured in COVID-19 impacted conditions in 2020 and 2021 than in 2019, with the exception of months significantly impacted by COVID-19 restrictions (March to May 2020) or high levels of COVID-19 infection rates and/or severe winter weather conditions in NYC (January to March 2021).



(Source: NYCDOT)

Figure 98. Persons Killed Monthly in NYC Crashes



(Source: NYCDOT)

Figure 99. Persons Injured Monthly in NYC Crashes

Table 33. Persons Killed and Injured in NYC Crashes per Month

Month	Pedes-trians Killed	Cycl-ists Killed	Motor-ists Killed	Un-known Killed	Total Persons Killed	Pedes-trians Injured	Cycl-ists Injured	Motor-ists Injured	Un-known Injured	Total Persons Injured
Jan 2019	11	2	8	-	21	1,014	216	3,052	-	4,282
Feb 2019	9	2	3	-	14	835	216	3,122	-	4,173
Mar 2019	10	1	5	-	16	853	259	3,525	-	4,637
Apr 2019	8	3	9	-	20	747	383	3,681	-	4,811
May 2019	11	3	8	-	22	902	477	4,350	-	5,729
Jun 2019	9	3	11	-	23	749	541	4,635	-	5,925
Jul 2019	9	4	8	-	21	707	611	4,339	-	5,657
Aug 2019	12	2	8	-	22	724	642	4,128	-	5,494
Sep 2019	10	4	7	-	21	826	594	3,892	-	5,312
Oct 2019	11	4	5	-	20	942	481	3,847	-	5,270
Nov 2019	11	1	6	-	18	949	311	3,509	1	4,770
Dec 2019	20	1	4	-	25	1,298	249	3,637	-	5,184
Jan 2020	12	1	7	-	20	883	243	3,102	-	4,228
Feb 2020	11	-	10	-	21	833	242	2,969	-	4,044
Mar 2020	6	-	2	-	8	561	272	2,330	-	3,163
Apr 2020	1	1	12	-	14	147	137	1,028	-	1,312
May 2020	2	2	8	-	12	289	368	1,894	-	2,551
Jun 2020	10	4	18	-	32	420	634	2,575	-	3,629
Jul 2020	8	1	14	-	23	537	721	3,095	-	4,353
Aug 2020	7	3	12	-	22	508	743	3,480	-	4,731
Sep 2020	14	7	17	-	38	590	739	3,365	-	4,694
Oct 2020	13	1	13	-	27	669	624	3,063	-	4,356
Nov 2020	14	6	11	-	31	646	531	2,941	-	4,118
Dec 2020	4	3	14	-	21	606	321	2,498	-	3,425
Jan 2021	9	2	6	-	17	526	282	2,294	-	3,101
Feb 2021	9	-	3	-	12	389	142	2,018	-	2,549
Mar 2021	10	-	8	-	18	530	324	2,633	40	3,527
Apr 2021	15	-	10	2	27	541	355	3,030	168	4,094
May 2021	17	1	13	2	33	642	510	3,638	243	5,033
Jun 2021	6	5	15	1	27	627	547	3,626	285	5,085
Jul 2021	9	3	16	1	29	569	496	3,507	254	4,826
Aug 2021	12	-	13	2	27	583	532	3,545	247	4,907
Sep 2021	7	3	13	-	23	712	497	3,480	276	4,965
Oct 2021	14	3	11	3	31	805	543	3,416	262	5,026
Nov 2021	9	1	10	-	20	760	391	3,137	184	4,472

Weather Data

All weather data was provided by the National Weather Service (NWS) system of weather stations reporting hourly METeorological Aerodrome Reports (METARs) data. Details of the METAR dataset, including live data and metadata are available at https://www.aviationweather.gov/metar.

Archives of decoded METAR data for the country are available from the Iowa Environmental Mesonet at the Iowa State University, at https://mesonet.agron.iastate.edu/request/download.phtml.

PlowNYC Data

Additionally, when snowy conditions were encountered, data from the PlowNYC snow-plow tracking system was included to provide insights into the possible road surface conditions. When snowplows are active, the PlowNYC system operates a user-friendly website to present the current PlowNYC data at https://plownyc.cityofnewyork.us/plownyc/.

Archived data from the PlowNYC system is published at https://data.cityofnewyork.us/City-Government/DSNY-PlowNYC-Data/rmhc-afj9.

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