

# Safety testing for connected and automated vehicles through physical and digital iterative deployment

The University of Tennessee, Knoxville



# R27-Phase II Project Team

## ▪ **UT Knoxville**

- Prof. Subhadeep Chakraborty
- Prof. Asad J. Khattak

Students involved:

- Nastaran Moradloo
- Latif Patwary
- Iman Mahdinia
- Joe Beck



## Overview: Research Objectives

Goal-Investigate a new framework for independent testing and establishing safe thresholds for operating Level 2 and 3 connected and automated vehicles. The key objectives are:

1. Explore the reasons for automated vehicle disengagements. This is done using real-world data.
2. Explore edge cases in real-life crashes of vehicles equipped with automated driving systems (ADS).
3. Provide analysis of different crash types involving different levels of vehicle automation.
4. Explore the effectiveness of pedestrian crash prevention systems.
5. Develop a comprehensive testing protocol for connected and automated vehicles (CAVs) in a hybrid physical-digital world, enabling the future creation of certification standard recommendations.

# Overview-Research Questions

1. Who initiates disengagements in high-level AVs (ADS or humans), and what are the correlates of the disengagement initiator?
2. What are the edge cases in high-level AV crashes that deviate substantially from typical ones, and what factors contribute to initiating these cases?
3. What are the differences in crash types between vehicles equipped with ADS and those with advanced driver assistance systems (ADAS), specifically in intersection environments?
4. How effective are pedestrian crash prevention systems in improving pedestrian safety?
5. How can a hybrid testing protocol, integrating vehicle-in-the-loop (VIL) and software-in-the-loop (SIL) simulations, systematically assess the safety of CAVs before they are deployed on public roads?

# R27-Phase II Project: Studies Conducted

## Study I:

Automated Vehicle Disengagements: An Examination of Initiators and Reasons

## Study II:

Safety in Higher Level Automated Vehicles: Investigating Edge Cases in Crashes of Vehicles Equipped with Automated Driving Systems

## Study III:

Comparison of Crash Types in Automated Vehicles with Different Levels of Automation

## Study IV:

How effective are pedestrian crash prevention systems in improving pedestrian safety? Harnessing large-scale experimental data

## Study V:

A study of implementing accelerated testing protocols for connected and automated vehicles in a hybrid physical-digital world

# Study I (Project R27-Phase II)

## Automated Vehicle Disengagements: An Examination of Initiators and Reasons

Moradloo, N., Mahdinia, I., & Khattak, A. J. (2024). Who Initiates Automated Vehicle Disengagement—Humans or Automated Driving Systems? TRBAM-23-04324. Presented at the 103rd Transportation Research Board Annual Meeting in 2024, Washington, D.C.

# Introduction

- Failure of Automated Driving Systems (ADS) to operate safely causes disengagements.
- **Two types of Disengagement**
  - ✓ Active disengagement: Initiated by humans due to precarious situations
  - ✓ Passive disengagement: Initiated by AV due to system failure



## Key Question

- Who initiates disengagements in high-level AVs (ADS or humans)?
- What are the correlates of the disengagement initiators?



Active Disengagement



Passive  
Disengagement



# Study Framework

## Objective

Investigate AV disengagements as a safety-critical event  
Examine the relationship between disengagement initiator (ADS or Human) and disengagement attributes



## Data

California Automated Vehicle Disengagement Report  
December 2020 to November 2022



## Data Preprocessing

Data aggregation

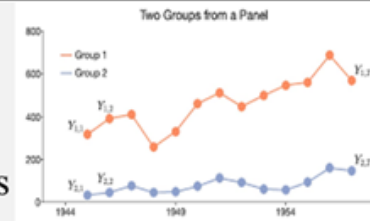
Cleaning data and  
error-checking

Collecting vehicle  
features

## Method

Random-Effect Binary Logit Model with Panel Data

- Address the inherent panel structure of the data
- Address unobserved heterogeneity across AV companies



## Outcome

- AV-initiated disengagements are more likely for electric vehicles
- SUVs/vans are more prone to AV-initiated disengagement than sedans
- Older vehicles are more prone to passive disengagement partly due to wear and tear

# Disengagement Reasons

## Reasons Over Time

❖ Decreasing trend

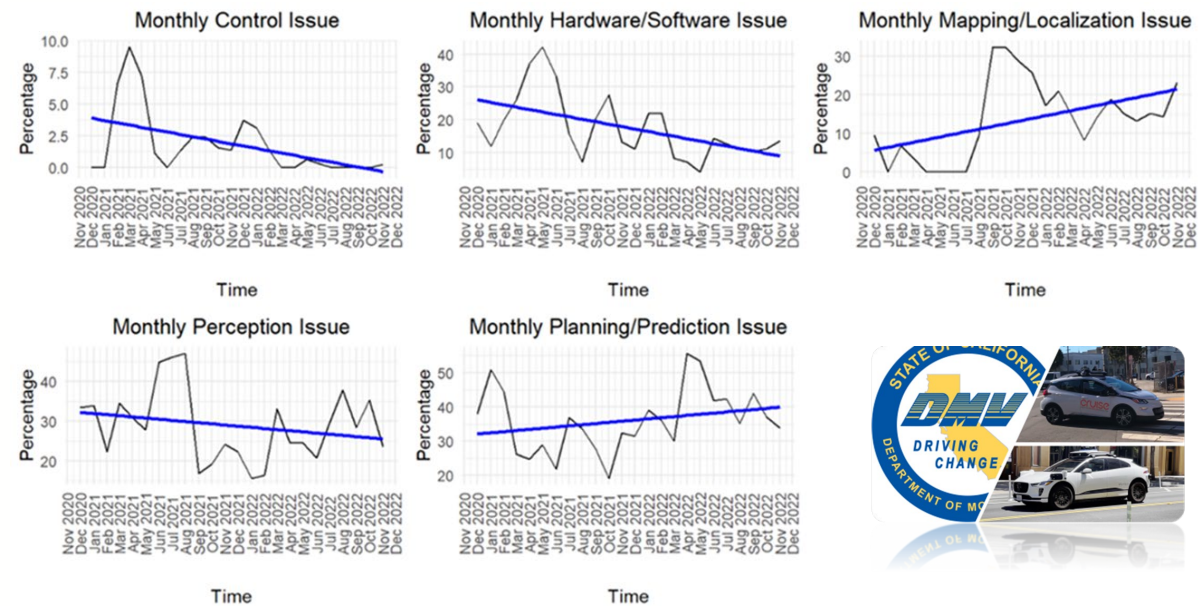
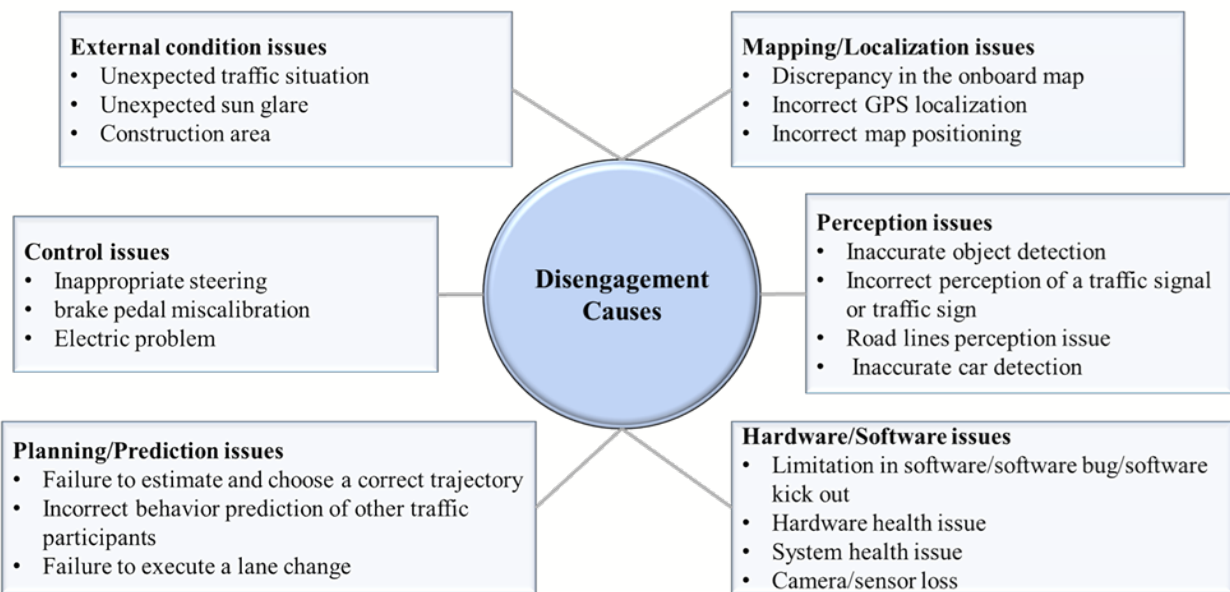


- Control
- Perception
- Hardware/software

❖ Increasing trend



- Planning/Prediction
- Mapping/Localization

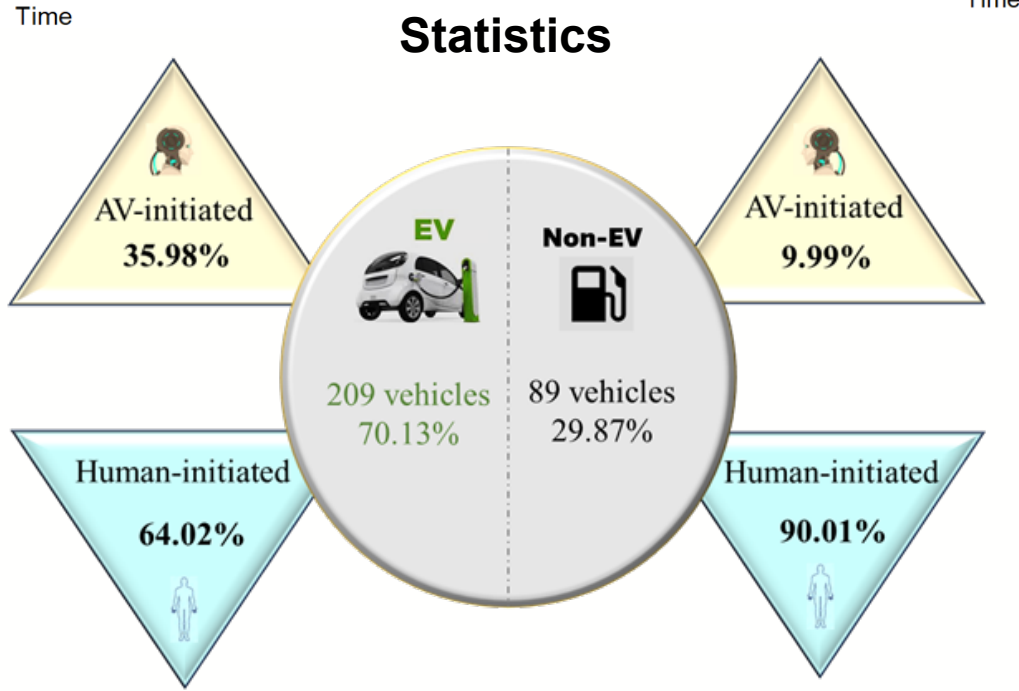
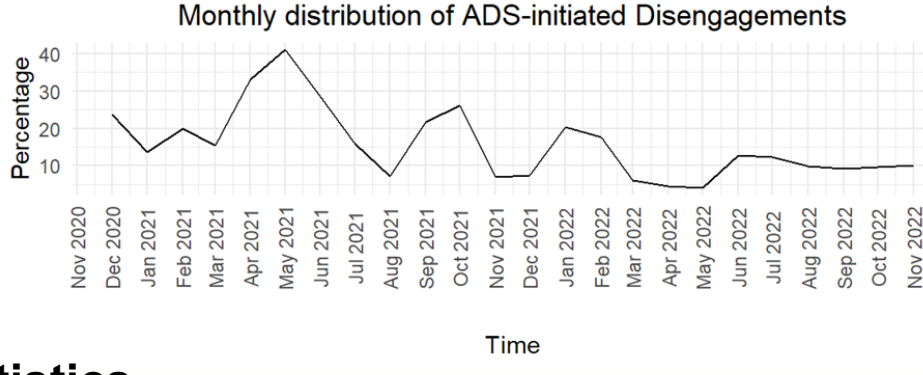
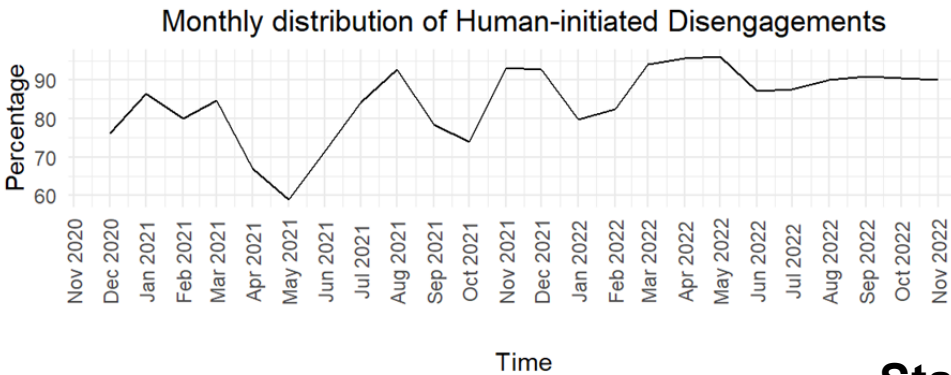


# Findings

Increasing trend



Decreasing trend



# Modeling Results

Random-effects binary logistic model with panel data (N=5,259)

Variable		Coefficient <sup>a</sup>	Z-value	Marginal effect
Constant		-2.96	-4.92	-
Vehicle Fuel type <sup>s</sup>	EV	5.26	2.99	0.352
	Reason <sup>c</sup>			
Reason <sup>c</sup>	Hardware/Software	5.32	3.75	0.612
	Mapping/Localization	-3.29	-2.16	-0.119
	Perception	-2.86	-2.02	-0.115
	Planning/Prediction	-2.76	-1.96	-0.113
	External condition	0.52	1.13	0.047
	Vehicle size-location <sup>d</sup>			
Vehicle size-location <sup>d</sup>	Hatchback/Sedan-Highway	1.89	1.71	0.025
	Hatchback/Sedan-Local street	5.12	3.04	0.100
	SUV/Van-Freeway	6.35	5.42	0.128
	SUV/Van- Highway	7.17	5.90	0.149
	SUV/Van- Local street	6.58	6.19	0.134
	Vehicle age <sup>e</sup>			
Vehicle age <sup>e</sup>	2 to 4 years	3.56	2.00	0.076
	>= 5 years	4.08	2.32	0.089

Summary Statistic		
Intraclass correlation ( $\rho$ )		0.41
likelihood-ratio test of $\rho=0$	39.34 (Prob > $\chi^2= 0.000$ )	
LL at the model	-364.54	
LL at the null	-1662.2	
McFadden's $R^2$	0.78	
Chi-squared ( $\chi^2$ ) test	671.33 (Prob > $\chi^2 = 0.000$ )	

<sup>a</sup>Base of the model: Human; <sup>b</sup>Base of fuel type: Non-EV; <sup>c</sup>Base of reason: Control; <sup>d</sup>Base of vehicle size-location: Hatchback/sedan-freeway; <sup>e</sup>Base of Vehicle age: <2 years

# Conclusions & Future Work

- Most of the ADS disengagements (88.02%) are initiated by humans.
- Disengagements occurred mainly due to planning/prediction and perception issues.
- AV-initiated disengagements are more likely for EVs.
- SUVs/vans are more prone to AV-initiated disengagement than sedans.
- Older vehicles are more prone to passive disengagement partly due to wear and tear.
- ADS-initiated disengagements are less likely to happen with perception, mapping/localization, and planning/prediction issues than control issues.
- ADS-initiated disengagements are more likely to occur with hardware/software issues.

## Future Work

- Analysis from other states/nations about AV tests on public roads will provide valuable and insightful comparisons.
- Providing more detailed information about software and hardware used in AVs can result in a better understanding of AV disengagement.

# Study II (Project R27-Phase II)

## Safety in Higher Level Automated Vehicles: Investigating Edge Cases in Crashes of Vehicles Equipped with Automated Driving Systems

Moradloo, N., Mahdinia, I., & Khattak, A. J. (2024). Safety in Higher Level Automated Vehicles: Investigating Edge Cases in Crashes of Vehicles Equipped with Automated Driving Systems. *Accident Analysis & Prevention*, 203, 107607.



# Introduction

- One of the most important reasons for emerging AVs:
  - ✓ Improve roadway safety by reducing **human errors**.
- Challenges in developing novel technologies:
  - ✓ Managing complex or unusual circumstances called **“Edge cases.”**
  - ✓ AV technologies are subject to this fact.



**ZERO IS OUR GOAL**  
A SAFE SYSTEM IS HOW WE GET THERE



Increasing  
fatalities/  
injuries of  
road users

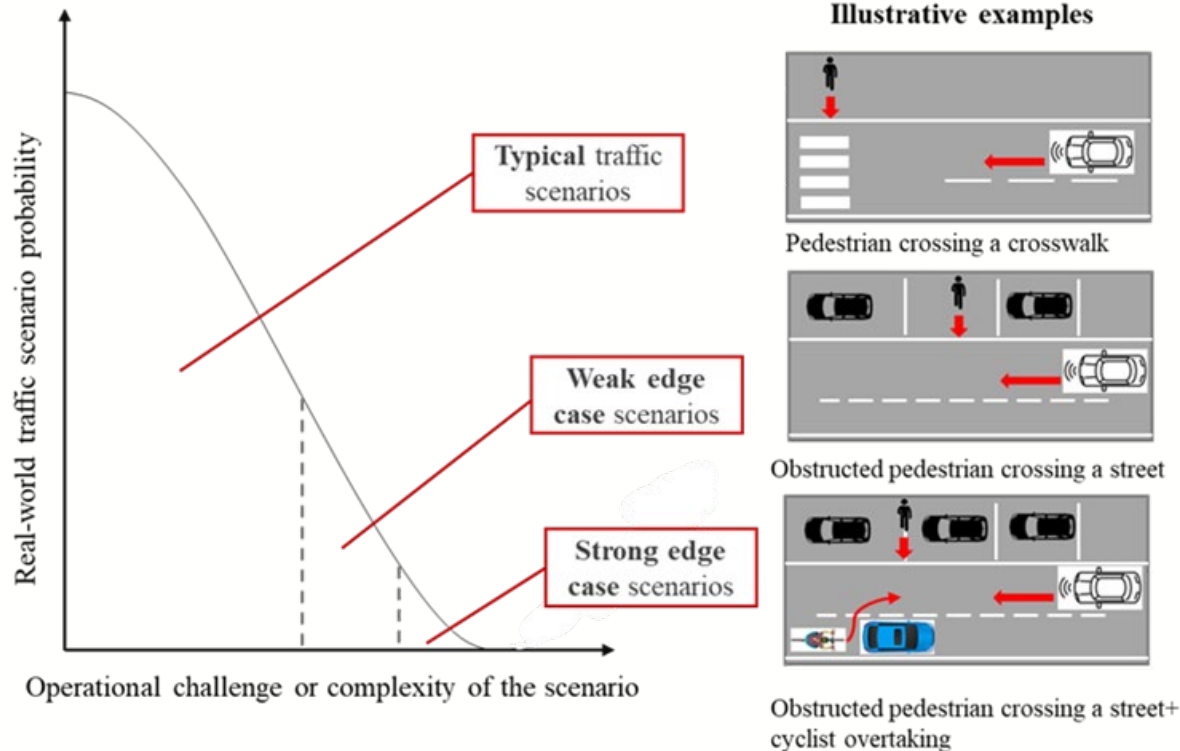
Safe vehicle  
technologies can  
reduce crash risk

Safe mobility  
is critical in  
transportation  
systems

**93% of crashes  
happen due to  
human errors**

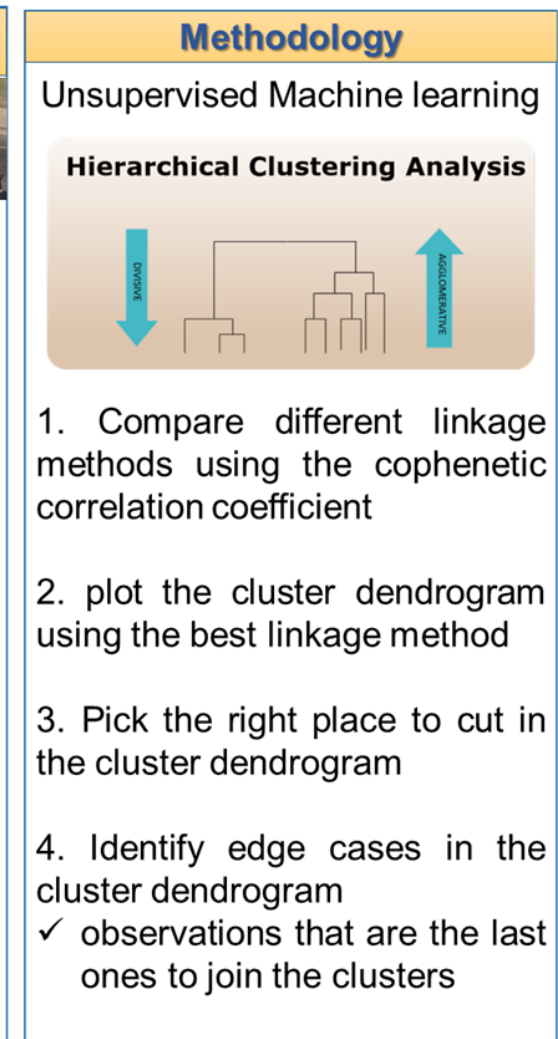
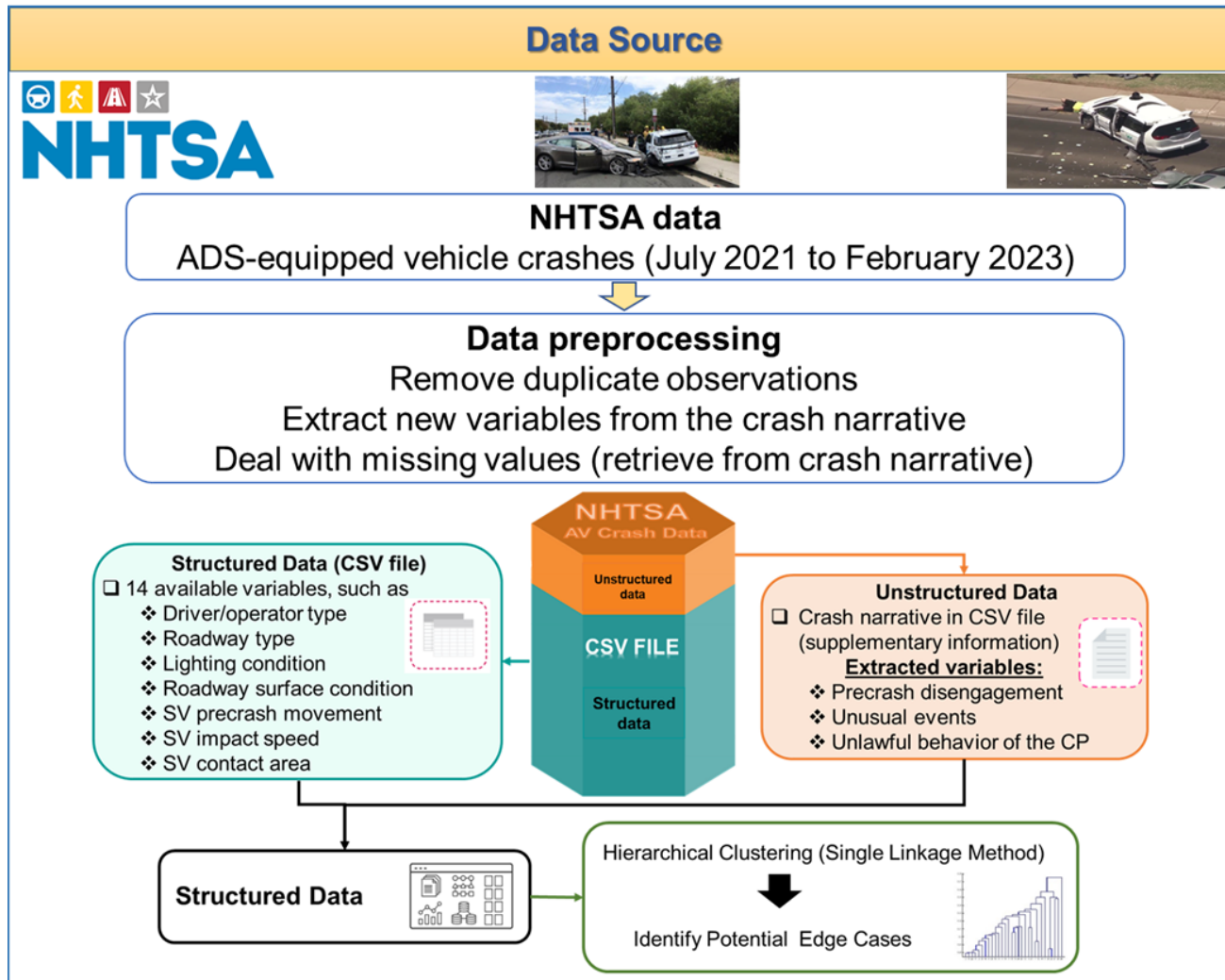
# Key Question

- What are the edge-case AV crashes that deviate substantially from typical ones?
- What factors contribute to initiating these cases?





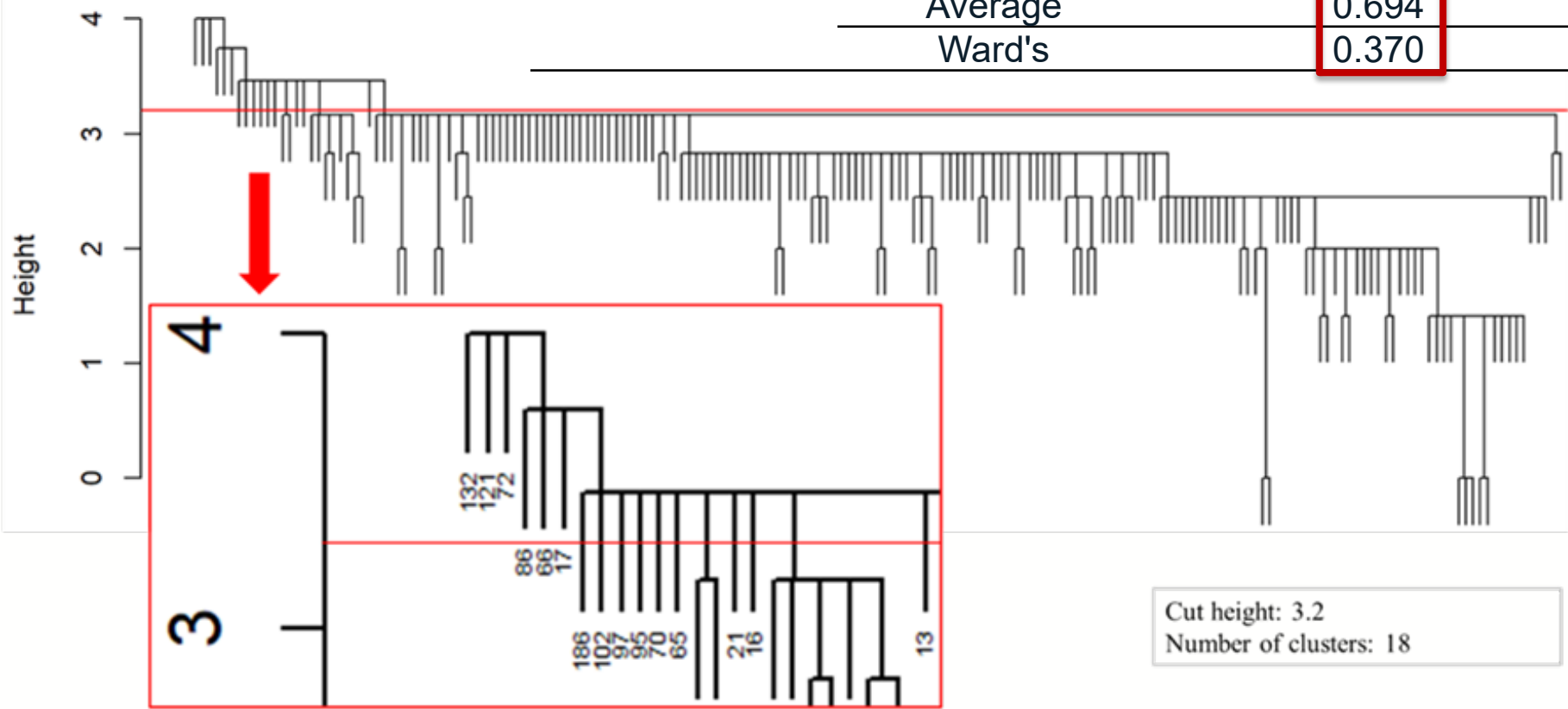
# Data Source and Methodology



Number of observations after data preprocessing: 189

# Key Findings

Distance measure	Clustering method	Cophenetic correlation coefficient
Euclidean	Single	0.609
	Complete	0.421
	Average	0.694
	Ward's	0.370

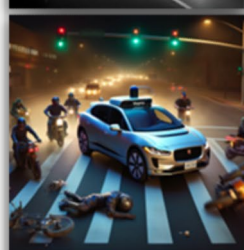


\*The zoomed-in area illustrates the observations that join the clusters very late in the merging process (potential edge cases)

15 observations (8% of the population) are identified as edge cases

# Sample of detected Edge Cases

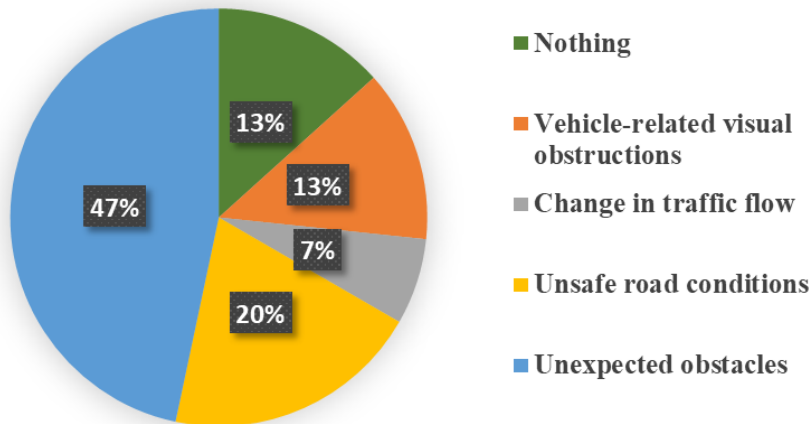
#	Roadway type	Crash with	Driver Type	Unusual event	disengagement	Lighting
186	Street	Unusual object ( <b>pallet</b> , height below the bottommost front LiDAR)	<b>Consumer</b>	<b>unexpected obstacle</b> and wet surface	No	Daylight
16	Highway/Freeway	Unusual object ( <b>loose wheel/tire</b> )	In-vehicle	<b>unexpected obstacle</b> (from behind the box truck)	Yes	Dark-not lighted
97	Intersection	Motorcycle (minibike)	<b>None</b>	<b>unexpected obstacle</b> (minibike rider in the group lost control and fell off)	No	Dark-not lighted
17	Highway/Freeway	Passenger car	In-vehicle	Unsafe road condition ( <b>sudden traffic incident</b> ) and <b>unusual movement of CP</b> (the hit car spun 90 degrees and partially entered the AV lane)	Yes	Daylight
121	Street	Pedestrian	In-vehicle	Unexpected pedestrian entry from median, ran towards AV, and intentionally jumped onto hood to vandalize ( <b>safety and security issue</b> )	Yes	Dark-lighted



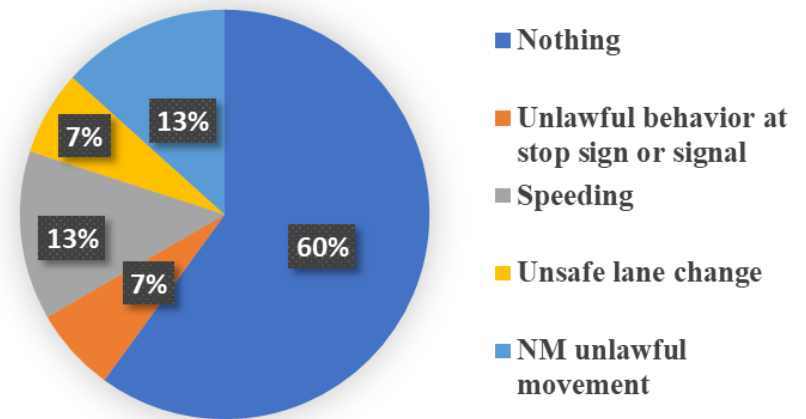
# Main Scenarios for Edge Cases

- ❑ Presence of unusual events (**87%** of edge cases):
  - 1) Unexpected obstacles in the roadway
  - 2) Unclear road markings
  - 3) Vehicle-related visual obstructions
  - 4) Sudden change in traffic flow
- ❑ Unlawful and unexpected behavior of the CPs (**40%** of edge cases):
  - 1) Speeding
  - 2) Unsafe lane change
  - 3) Unlawful behavior at stop sign or signal: red light violation and failing to yield
  - 4) Non-motorists unlawful and unexpected behavior
- ❑ Precrash Disengagement (**60%**)
- ❑ Injury crash (**27%**)
- ❑ Absence of Safety driver within AVs (**27%**)

Unusual Events



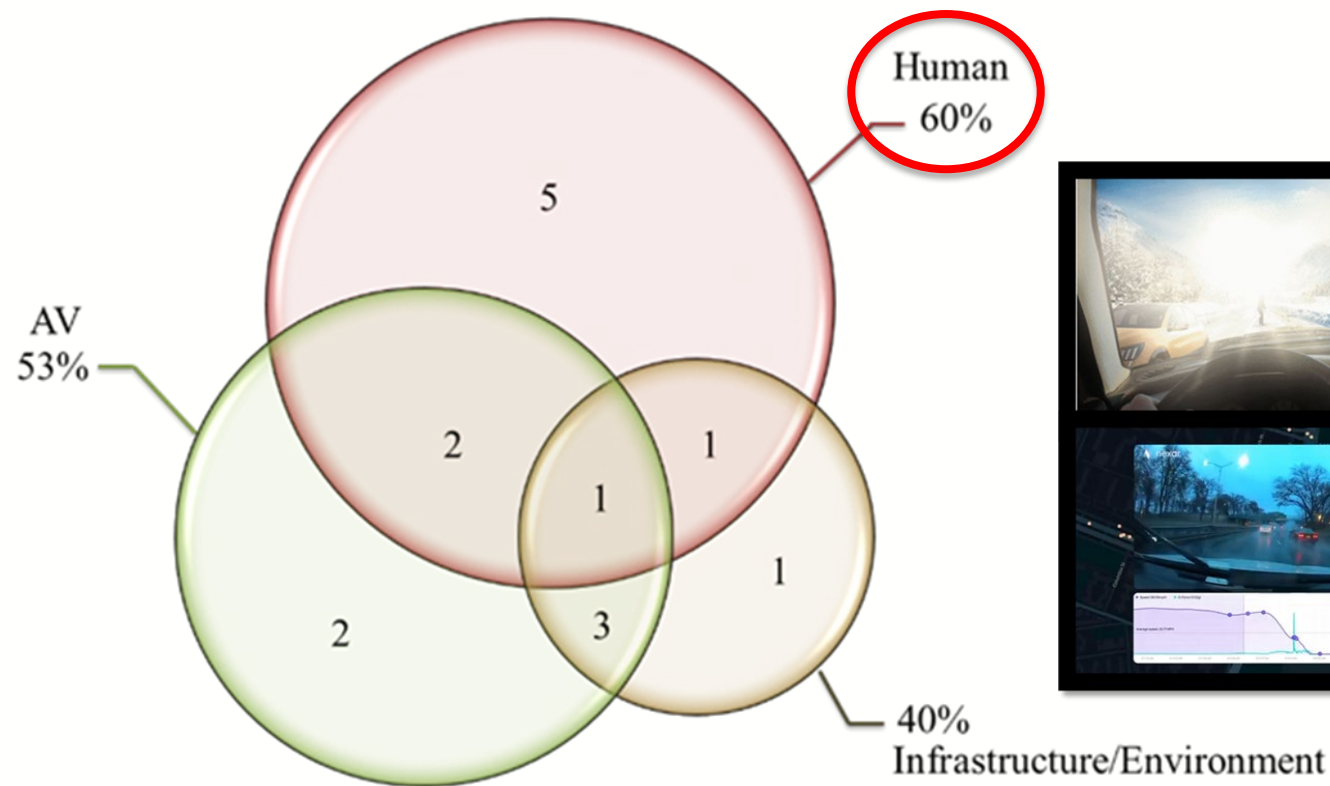
Unlawful behavior of the CP



# AV Edge Cases – Potential Reasons

Edge cases could be initiated by:

- **AV** (vehicle/system failure, e.g., perception issues)
- **Human** (Unlawful and unexpected behavior of non-AV drivers or other road users)
- **Infrastructure or environment** (unsafe road conditions such as unclear road markings, severe weather, and sudden changes in traffic flow)



# Conclusions & Future Work

- Human actions contribute to 60% of edge cases.
- The main scenarios for edge cases include:
  - ✓ Unexpected behaviors of crash partners
  - ✓ Absence of safety drivers within AVs
  - ✓ Precrash disengagement
  - ✓ Unusual events. e.g., unexpected obstacles, unclear road markings, and sudden and unexpected changes in traffic flow
- Injury rates in edge cases are higher than in usual crashes (27% compared to 8%)

## Future Work

- Future studies can focus on ADAS crashes to identify edge cases.
- connectivity may be critical in the future and may introduce new risks.
- More data should be collected for ADS crashes in different weather conditions, roadway characteristics, and levels of AV penetration.

# Study III (Project R27-Phase II)

## Comparison of Crash Types in Automated Vehicles with Different Levels of Automation

SafariTaherkhani, M., Patwary, A. L., & Khattak, A. J. Comparison of Crash Types in Automated Vehicles with Different Levels of Automation. TRBAM-23-05272, Presented at the Transportation Research Board Annual Meeting, Washington, D.C. 2023.



# Introduction

- Currently, many vehicles on the road are equipped with low-level automation features (Levels 1 and 2) - **Advanced Driver Assistance Systems (ADAS)**
- Higher-level automation (3 and 4) equipped with **Automated Driving Systems (ADS)** are also being tested on public roads
- New crash data on the performance of these technologies offer opportunities to improve safety
- Emerging contributing factors for intersection AV crashes explored (40% of conventional vehicle crashes occur at intersections)

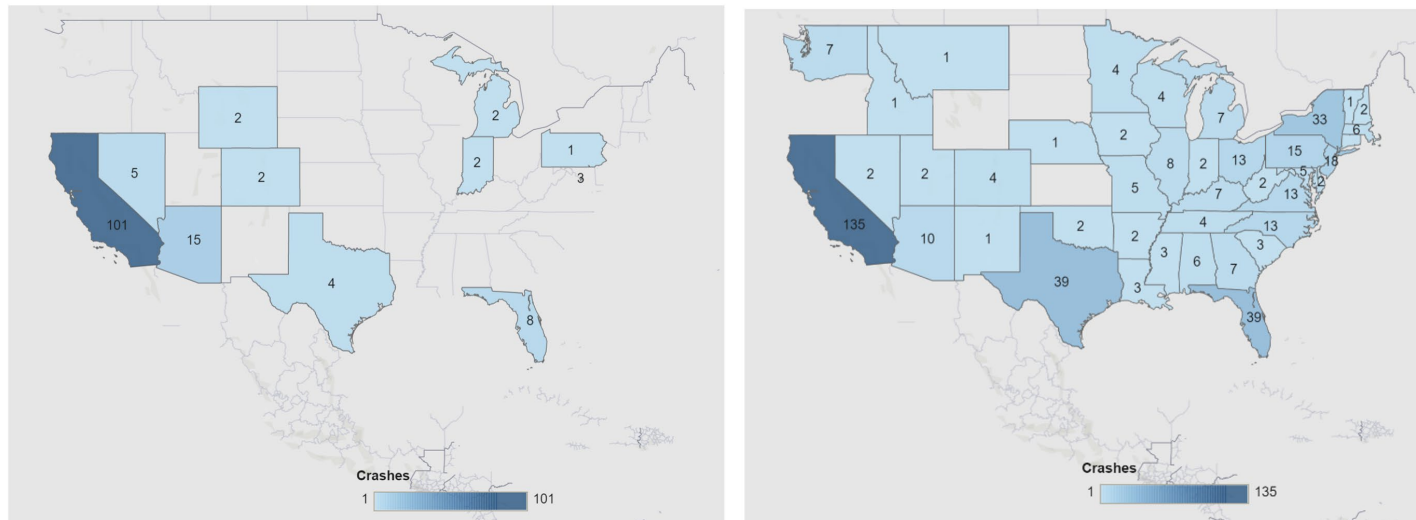
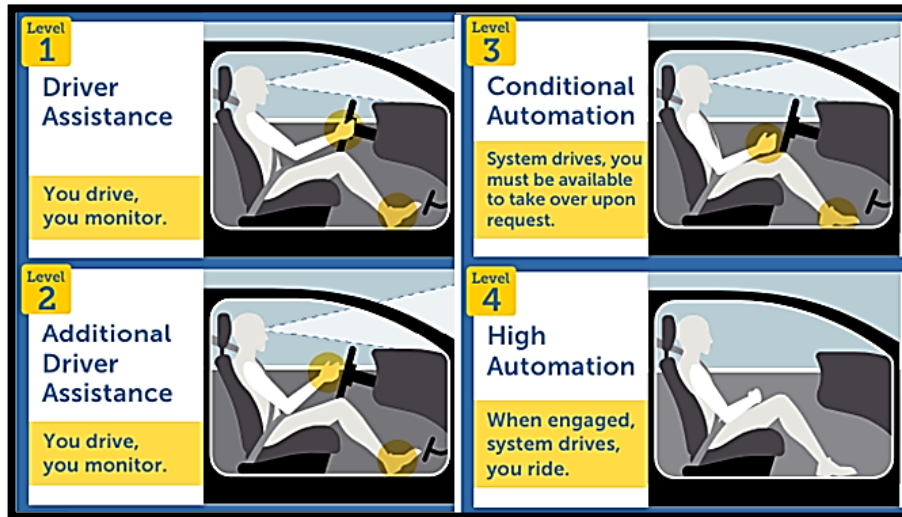


Fig: ADS crashes by state on the left and ADAS crashes by state on the right

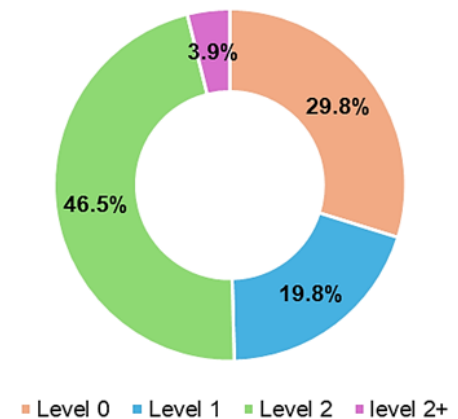


# Key Questions

- How do crash types differ between vehicles equipped with ADS and those with ADAS, specifically in intersection environments?
- Are ADS-equipped vehicles more likely to be rear-ended compared to ADAS-equipped vehicles?
- What are the usual precrash movements of ADS and ADAS-equipped vehicles?



United States Automated Vehicle Sales (2022)

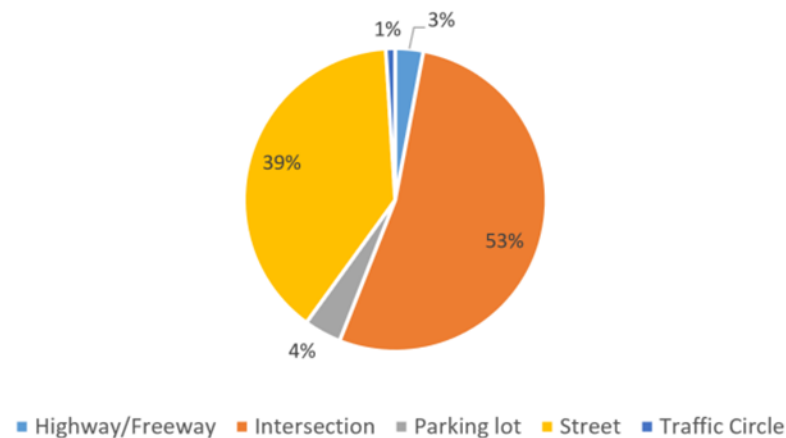


# Data/Method

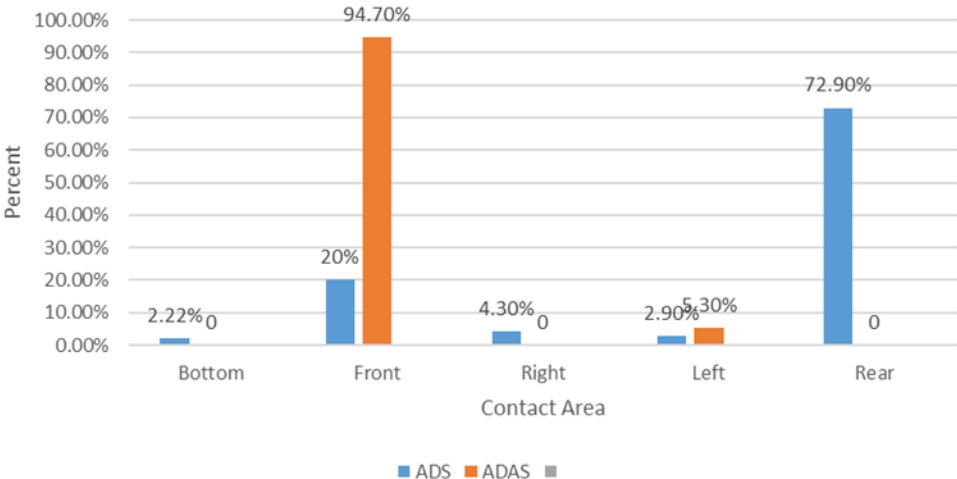
- Data: **National Highway Traffic Safety Administration (NHTSA)**
  - ✓ If ADS technology has been active at any time within 30 seconds before the accident, it is considered in this dataset
  - ✓ Data covers different locations in the US, not just in California
  - ✓ Cleaned; N= **70** crashes at intersections for **ADS** and N= **19** at intersections for **ADAS** vehicles
  
- Method: Exploratory analysis techniques

# Results

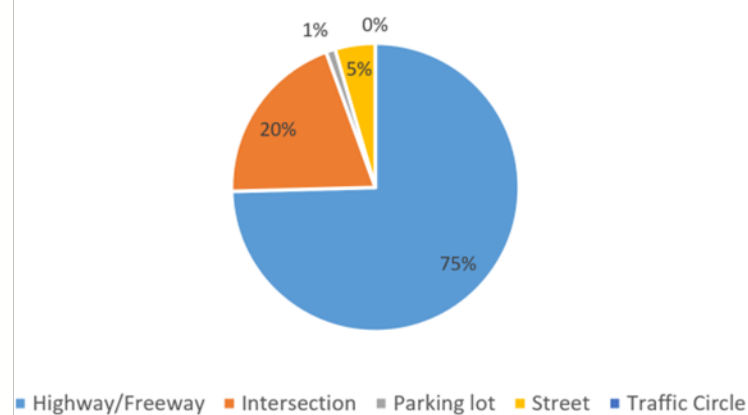
ADS crashes in different road types



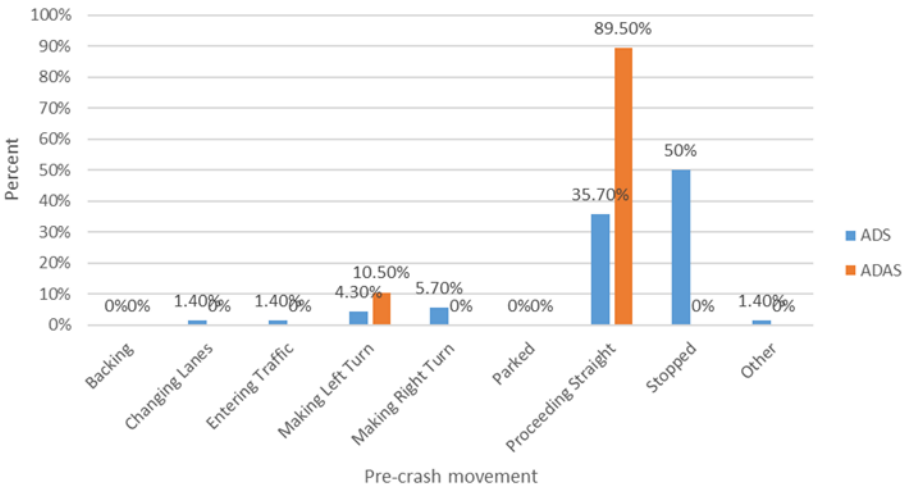
ADS and ADAS body contact area



ADAS crashes in different road types



ADS and ADAS pre-crash movements



# Conclusions

- The study compares crash types of ADS and ADAS technologies at intersections
- The contact area for **94.7%** of ADAS-equipped crashes is the **front**
- The contact area for **72.4%** of ADS-equipped crashes is the **rear**
  - ✓ ADS vehicles are being hit by other vehicles on the road most of the time
- ADAS were stopped or proceeding straight **89%** of the time
  - ✓ Showing difficulty in performance in a mixed environment at intersections
- In **50%** of the crashes, ADS vehicles were found to be stopped
  - ✓ May be due to VRUs (e.g., pedestrians crossing the street) or hazards

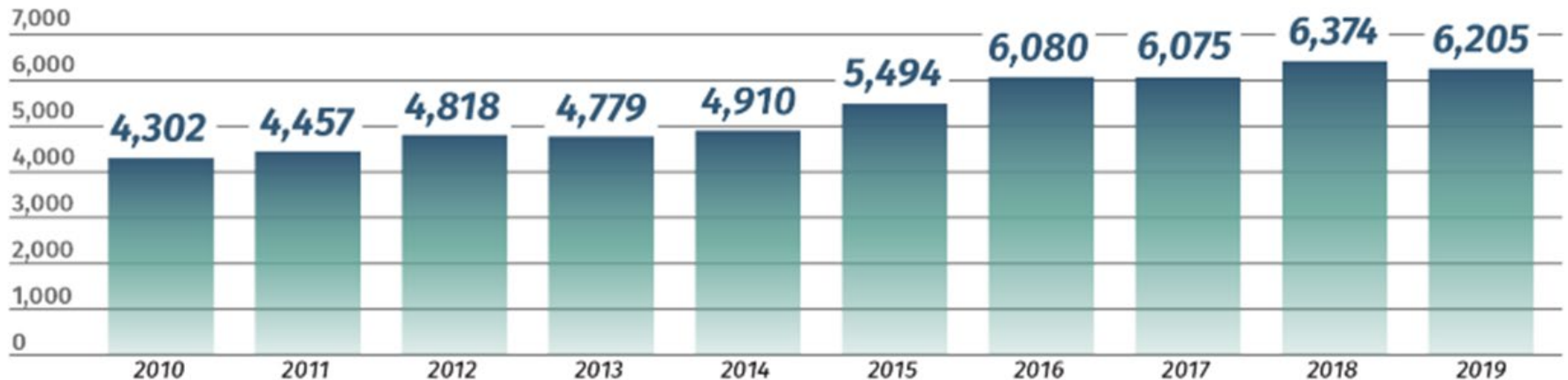
# Study IV (Project R27-Phase II)

How effective are pedestrian crash prevention systems in improving pedestrian safety?  
Harnessing large-scale experimental data

Mahdinia, I., Khattak, A. J. & Haque, A. How effective are pedestrian crash prevention systems in improving pedestrian safety? Harnessing large-scale experimental data, Accident Analysis & Prevention, 171, 106669, 2022.

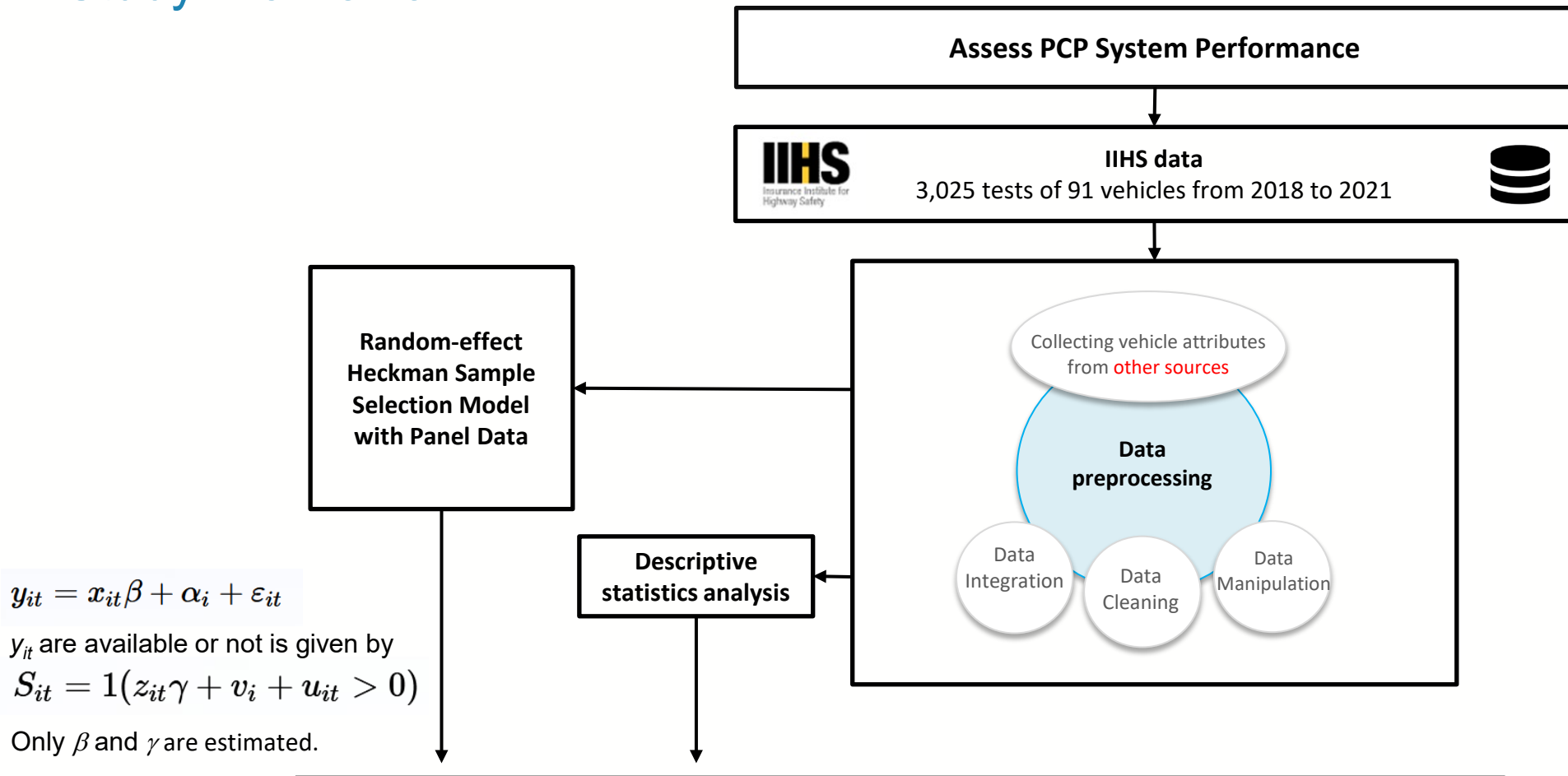
# Introduction

- Fatal pedestrian crashes increase every year
  - ✓ 14% increase from 2020 to 2022
- Promising solution → Pedestrian Crash Prevention (PCP) Systems
  - ✓ An emerging safety technology in vehicles with ADAS (low level of automation-L2)
  - ✓ Automatic braking when facing pedestrians & driver has taken insufficient action to avoid an imminent crash



Source: FARS 2010 to 2018 Final File, NHTSA's Preview of Motor Vehicle Traffic Fatalities in 2019

# Study Framework



## Outcomes

- Is the PCP system performing well during the day?
- What are the correlates of PCP performance?
- Identify hazardous pedestrian crossing scenarios

# Test Scenarios



**Perpendicular adult:**  
(CPNA\_25)

**Scenario 3:**

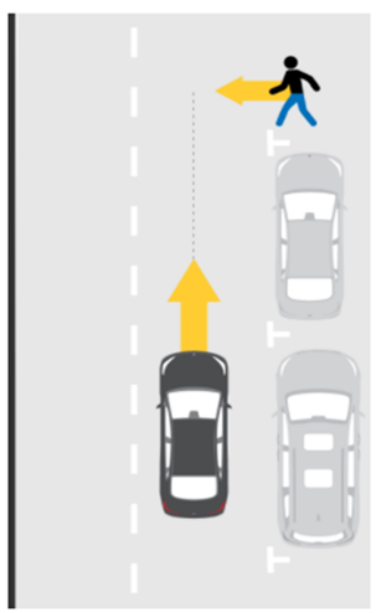
Adult walks across road

Tests run at 20 km/h (12 mph)

**Scenario 4:**

Adult walks across road

Tests run at 40 km/h (25 mph)



**Perpendicular child:**

**Scenario 1: (CPNC\_50)**

Child runs into road;

Parked vehicles obstruct view;

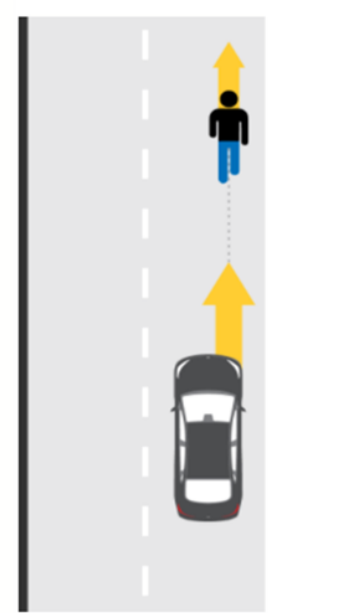
Tests run at 20 km/h (12 mph)

**Scenario 2:**

Child runs into road;

Parked vehicles obstruct view;

Tests run at 40 km/h (25 mph)



**Parallel adult: (CPLA\_25)**

**Scenario 5:**

Adult in right lane near edge of road, facing away from traffic;

Tests run at 40 km/h (25 mph)

**Scenario 6:**

Adult in right lane near edge of road, facing away from traffic;

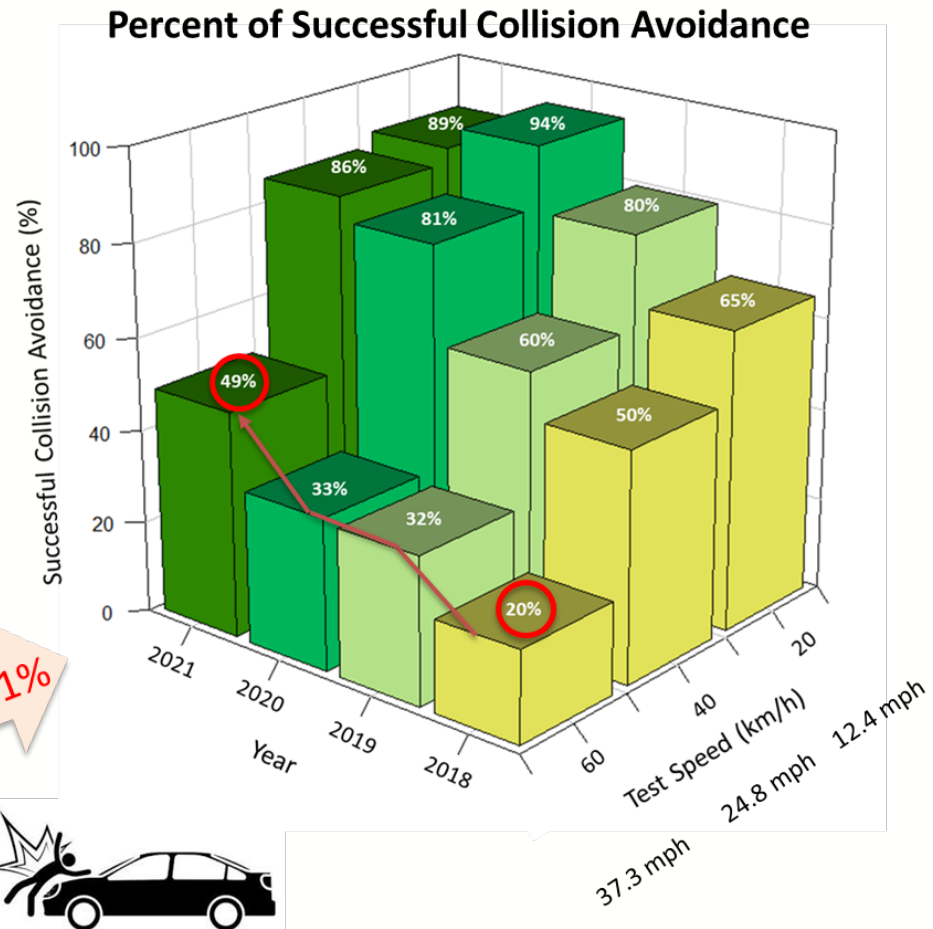
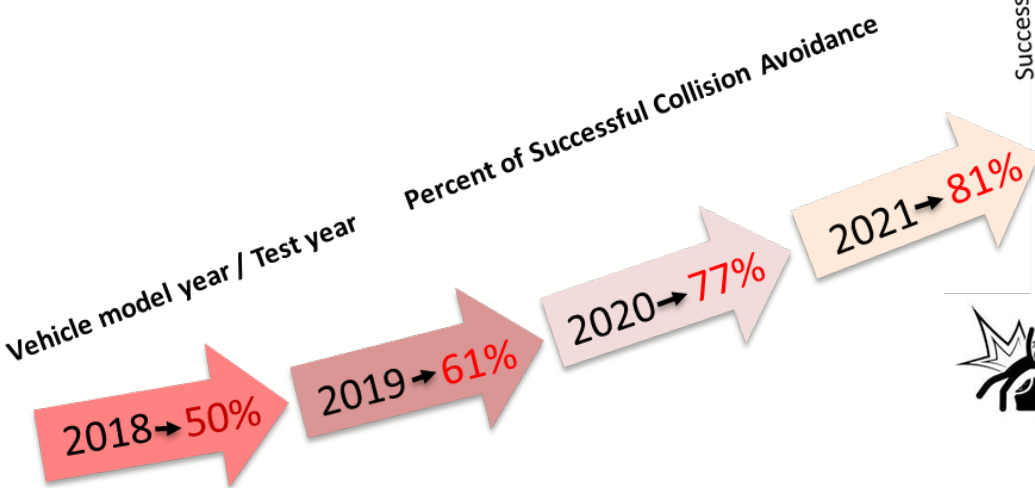
Tests run at 60 km/h (37 mph)





# Crash Avoidance Results-Daytime: 2018-2021

- Collisions with pedestrians occurred in **30%** (=933/3095) of cases, but in **70%**, PCP systems avoided pedestrian crashes
- Test speed is a major factor
- Successful collision avoidance rate increased over time

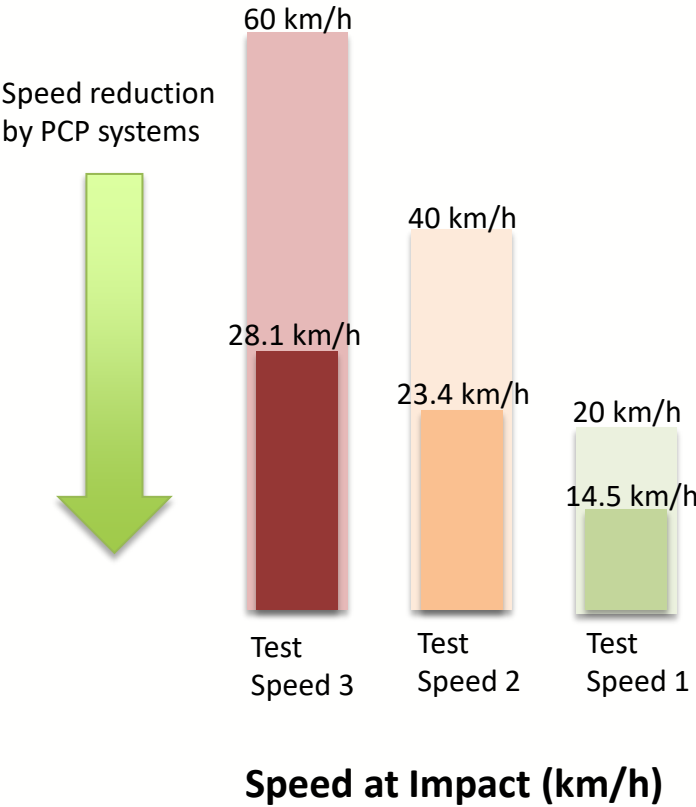
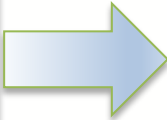


# Speed Reduction Results-Daytime

Given a crash, PCP systems, on average, **mitigated impact speeds** by more than **50%**

Descriptive Statistics of Variables.

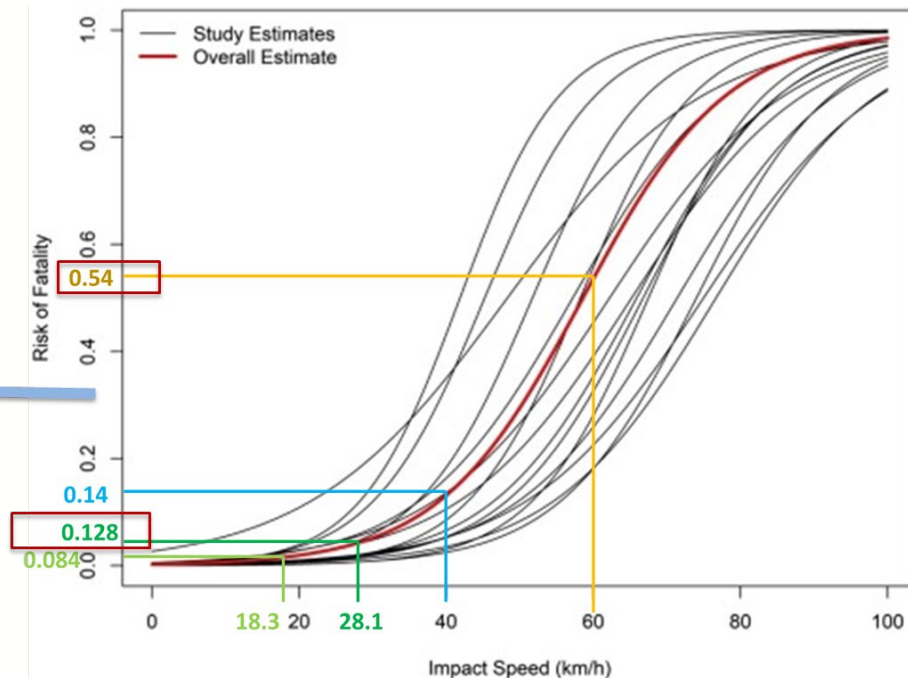
Variable (N = 91 Vehicles and 3095 Tests)		Min	Max	Mean	SD
Speed at Impact with Pedestrians (km/h)	All Years and Test Speeds	0	60.78	7.15	13.34
Conditional Speed at Impact with Pedestrians (Given that Collisions Occurred, N = 933 Tests)	All Test Speeds	0.03	60.78	23.70	14.07
	20 km/h	0.50	20.71	14.53	5.53
	40 km/h	0.03	40.89	23.41	11.49
	60 km/h	2.70	60.78	28.06	17.40
Conditional Speed	All Test	0	56.77	20.38	16.39
Reduction by PCP System (Given that Collisions Occurred, N = 933 Tests)	Speeds				
	20 km/h	0	19.54	5.33	5.37
	40 km/h	0	39.88	16.34	11.47
	60 km/h	0	56.77	31.94	17.37



# Speed vs. fatality risk-Daytime

- 70% crash avoidance-for the 30% remaining...
- Impact speed of 60 kph → 54% risk of fatality
- PCP reduces speed to 28 kph → 12.8% risk of fatality

No PCP system		PCP system (only tests with crashes)	
Impact speed	Risk of fatality	Average impact speed	Average risk of fatality
20 km/h	2%	14.5 km/h	2.2%
40 km/h	14%	23.4 km/h	5.4%
60 km/h	54%	28.1 km/h	12.8%



# Modeling Results

- Increase in the **maximum deceleration rate** of PCP system (8 to 10 m/s<sup>2</sup>)
- **Lower weight of vehicles**



Decrease in speeds at impact with peds

Random-effects Heckman Sample Selection Regression with Panel Data.

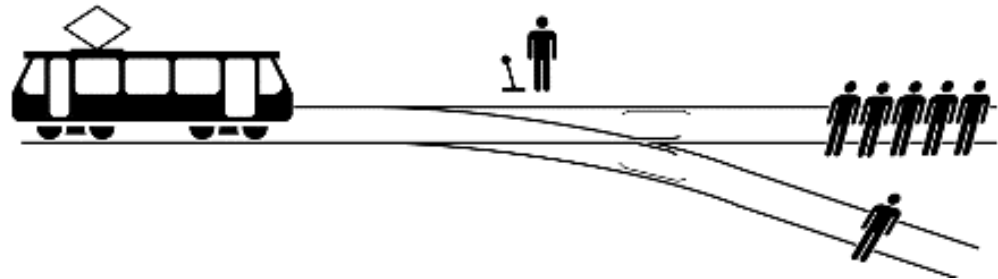
Speed at Impact (km/h) (N = 3095)				
Variables		$\beta$	Z-statistic	P-value
Constant		21.416	8.730	0.000
Maximum Deceleration (m/s <sup>2</sup> )		-2.999	-20.570	0.000
Scenario	1-Perpendicular Child 20 km/h (base)			
	2-Perpendicular Child 40 km/h	19.270	10.950	0.000
	3-Perpendicular Adult 20 km/h	-3.760	-1.680	0.093
	4-Perpendicular Adult 40 km/h	9.543	5.050	0.000
	5-Parallel Adult 40 km/h	6.304	2.800	0.005
	6-Parallel Adult 60 km/h	23.345	13.140	0.000
Vehicle Model Year	2018	3.621	1.440	0.151
	2019	4.428	2.710	0.007
	2020	-1.109	-0.650	0.516
	2021 (base)			
Vehicle Manufacturer's Reported Weight (base model)	≤3,000 lbs. (base)			
	3,001 – 3,500 lbs.	1.310	0.890	0.376
	3,501 – 4,000 lbs.	2.050	1.350	0.176
	4,001 – 4,500 lbs.	4.489	2.440	0.015
	> 4,500 lbs.	4.370	2.220	0.026

# Conclusions & Future Work

- PCP Technology substantially reduces vehicle-ped risks
- PCP performance has improved in recent years
- **Day: Did not detect/stop in 30% of the tests—in 70% of the tests avoided pedestrian crashes (2018-2021)**
- For crashes, PCP systems mitigated impact speeds by about 50% (**daytime**)
- **Higher market penetration → reduction in ped crashes, injuries/fatalities**

## Future research

- Vision zero-safe systems & edge cases
- Disadvantaged communities
- Trolley problem (ethical dilemma—AI)

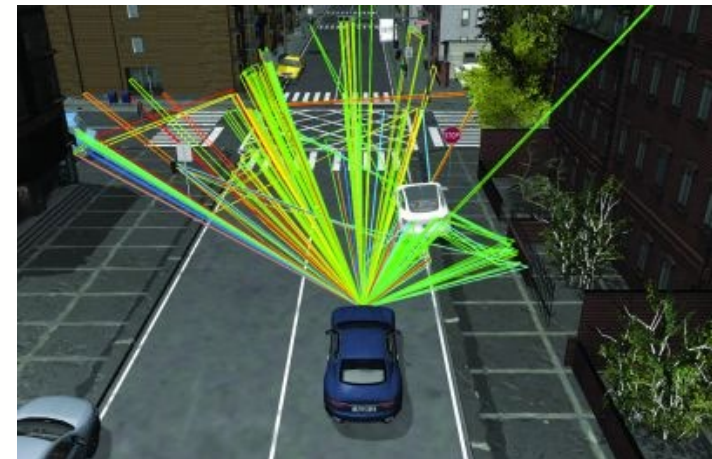


# Study V (Project R27-Phase II)

A study of implementing accelerated testing protocols for connected and automated vehicles in a hybrid physical-digital world

# Introduction

- Despite the advancement in automated driving systems, safety concerns persist within the automotive industry and public consciousness.
- Traditional on-road testing alone is insufficient for high safety confidence.
- Simulation-based testing aids development but often lacks full vehicle integration.
- **Hybrid physical-digital testing** environments can bridge this gap.
  - ✓ Develop vehicle-in-the-loop (VIL) simulation test-bed
  - ✓ Comparison with Software-in-the-Loop (SIL)

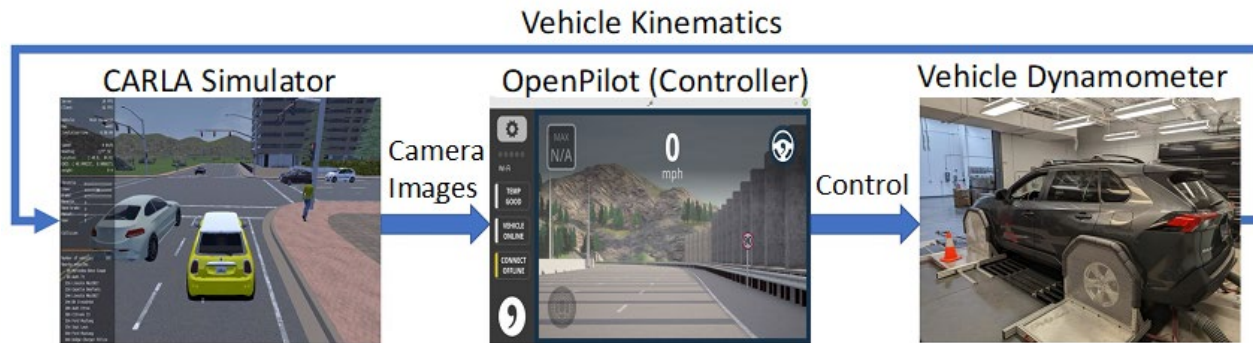




# Methodology

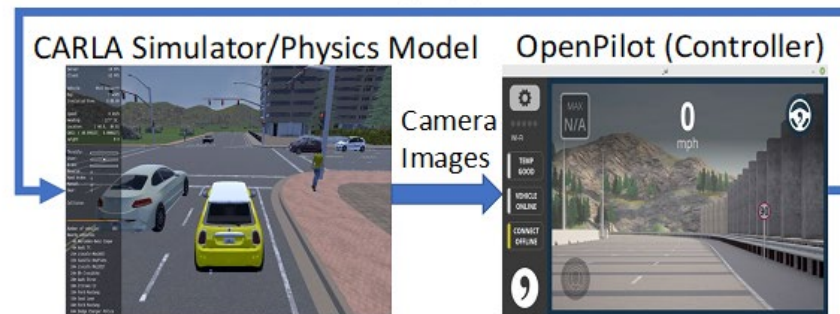
- In VIL, the feedback to the simulator is vehicle kinematics measured from the CAN bus of the vehicle directly.
- In SIL, the controller feeds control commands directly to the simulator, and the physics model within CARLA determines the dynamic response.
- The vehicle used for the experiments → Level 3 SUV built and instrumented with a dedicated computer with ROS and CAN communication

## VIL



## SIL

Control



An overview of the SIL and VIL control loops



# Controller & Hardware

## Controller: OpenPilot v8.13 by Comma.AI

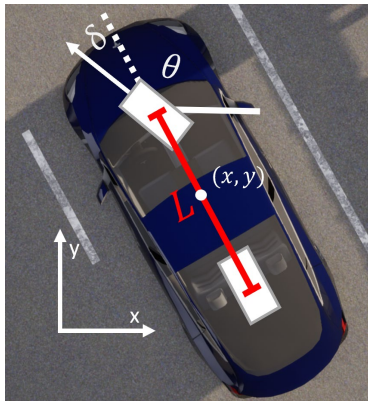
- Level: SAE Level 2 Autonomous Controller
- Function: Uses camera and radar data to perceive road conditions.
- Implementation: Open-source software with a proprietary vision model called Supercombo.

## Hardware Integration

- 2019 Toyota RAV4
- Single-roller dynamometer for applying road load
- Communication through CAN buses (OBD II and ADAS)

## Simulation Setup

- OpenPilot and CARLA simulator run simultaneously on a laptop
- Camera images from CARLA fed directly into OpenPilot
- Radar and sensor-based localization disabled for vision-only perception



$$x_{t+1} = (v \cos \theta) \Delta t + x_t$$

$$y_{t+1} = (v \sin \theta) \Delta t + y_t$$

$$\theta_{t+1} = \left( \frac{v \tan \delta_w \cos \beta}{L} \right) \Delta t + \theta_t$$

Position:  $(x, y)$   
Orientation:  $\theta$

The kinematic model used to update the vehicle's position in CARLA

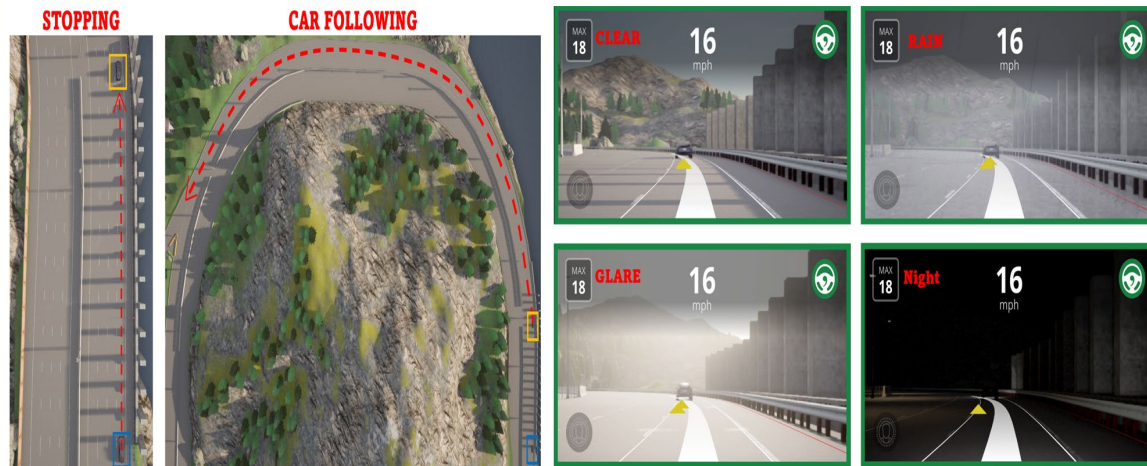
# Experimental Setup

## Driving Types

- Stopping **S**: Test of obstacle detection and ability to stop smoothly with sufficient distance
- Car Following **F**: Test of lead vehicle detection and consistent throttle/brake control

## Weather and Lighting Conditions

- Clear **C**: Clear weather conditions in mid-afternoon.
- Rain **R**: The hardest possible rain setting within Carla, mid-afternoon.
- Sun Glare **S**: The sun is positioned in front of the lead vehicle.
- Night, headlights **N+H**: Clear weather at night with headlights on
- Night, no headlights **N**: Clear weather at night without headlights
- Rain, night, headlights **R+N+H**: Hard rain at night with headlights on
- Rain, night, headlights reversed **R+N+HR**: Reversed lead vehicle simulating oncoming traffic in the rain at night



# Safety & Performance Metrics

- **Average Centerline Distance** (Stopping & Following)

- ✓ Centerline distance is the smallest distance between the line representing the middle of the current lane, and the midpoint of the ego vehicle.

$$CD_{mean} = \frac{1}{N} \sum_t \left| \frac{c_{1t} - c_{2t} \times e_{pt} - c_{1t}}{\|c_{1t} - c_{2t}\|^2} \right|$$

- **Minimum time-to-collision** (TTC) (Stopping)

- ✓ Measures how long it would take to impact the lead vehicle if the ego vehicle continues at its current speed indefinitely

$$TTC_{min} = \min_t \frac{e_{st}}{\|e_{pt} - l_{pt}\|^2}$$

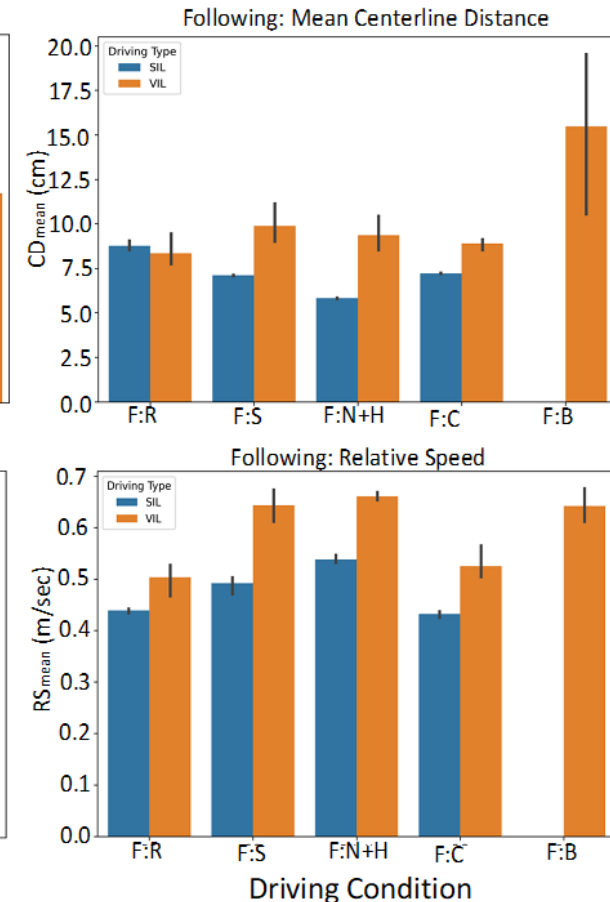
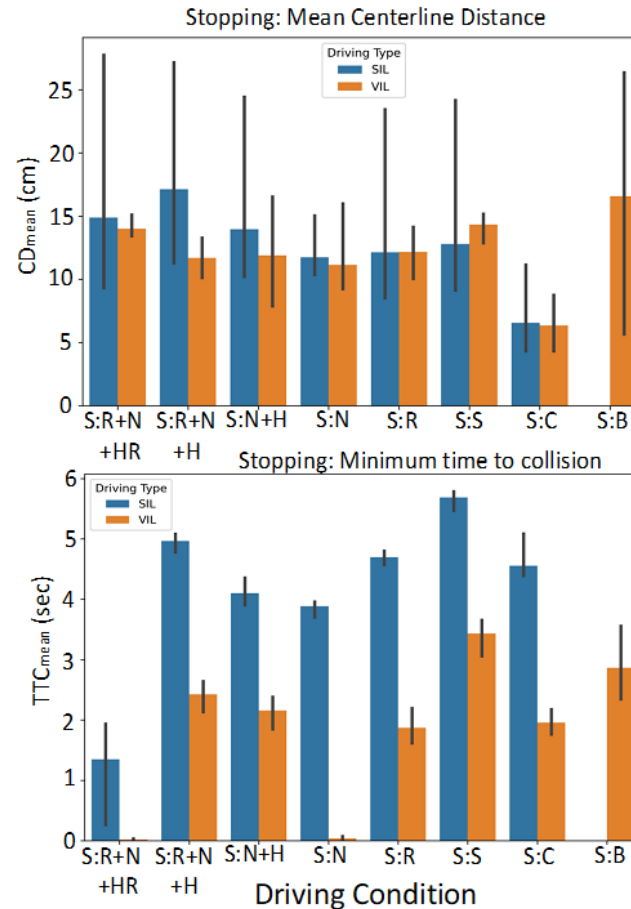
- **Average Relative Speed** (Following)

$$RS_{mean} = \frac{1}{N} \sum_t |e_{st} - l_{st}|$$

2D Cartesian position and speed of the ego vehicle are defined as the vector  $e_p$  and the scalar  $e_s$ , respectively. The location and speed of the lead vehicle are defined as  $l_p$  and  $l_s$ , respectively.

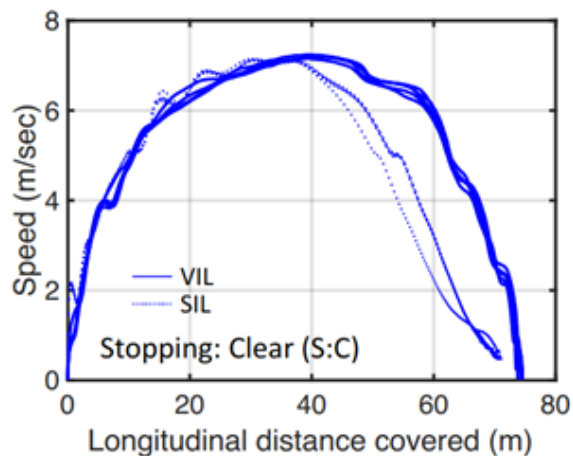
# Results

- VIL consistently outperforms SIL in maintaining a lower centerline distance, demonstrating better lane-keeping ability under various conditions.
- VIL shows a less conservative approach in 'Minimum Time to Collision,' suggesting a more realistic engagement with potential obstacles.
- SIL simulation generally had a much more aggressive response to control stimulus than the VIL simulation.

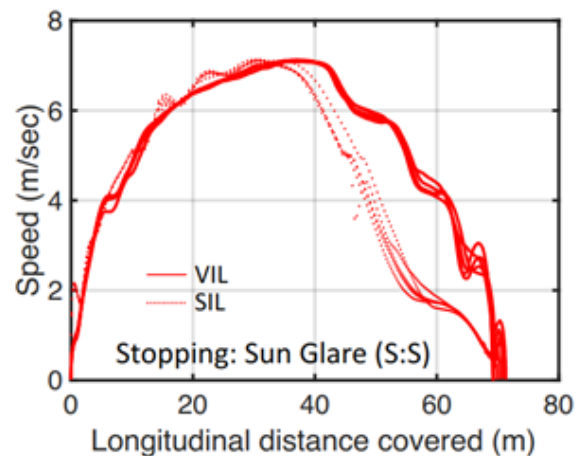


# Results

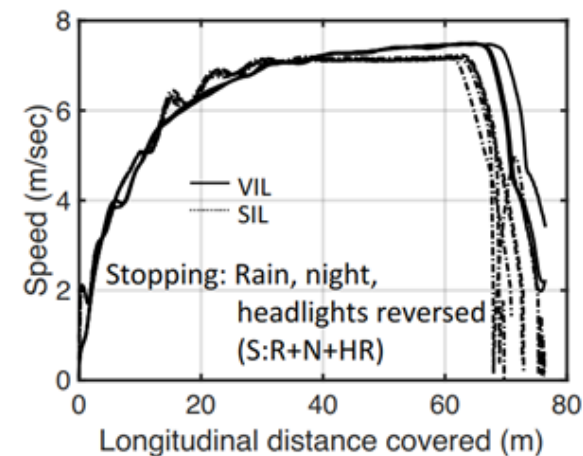
- More aggressive response within SIL simulation.
- VIL provides a more realistic and cautious deceleration profile, especially in adverse conditions.
- Clear Weather (S:C): VIL simulations show a more consistent deceleration profile compared to SIL.
- Sun Glare (S:S): SIL simulations exhibit more aggressive braking, while VIL maintains a cautious approach.
- Rain, Night, Headlights Reversed (S:R+N+HR): SIL simulations show strange behavior, including loss of detection and re-acceleration.



(a)



(b)



(c)

# Conclusions

- VIL provides a more realistic assessment of vehicle behaviors.
- SIL, while useful for initial assessments, may not fully capture the nuances of real-world dynamics.
- Safety and Performance Metrics
  - ✓ Centerline distance, time-to-collision, and relative speed
  - ✓ VIL simulations generally show more reliable and consistent performance, especially under varied environmental conditions.
- Weather and Lighting Variability
  - ✓ The ability to test under different atmospheric conditions enhances the understanding of how perception systems and controllers handle real-world complexities.
- Exploration of Edge Cases
  - ✓ VIL's incorporation of actual vehicle responses allows for the identification and analysis of critical safety scenarios that may not be apparent in SIL setups.

# Answers to research questions

Who initiates disengagements in high-level AVs (ADS or humans), and what are the correlates of the disengagement initiator?

- Most disengagements in the data (88.02%) are initiated by humans.
- Disengagements predominantly occur due to planning/prediction and perception issues.
- AV-initiated disengagements are more likely for EVs, SUVs/vans, and older vehicles and more common with hardware/software issues.



# Answers to research questions

What are the edge cases in high-level AV crashes that deviate substantially from typical ones, and what factors contribute to initiating these cases?

- The main scenarios for edge cases include:
  - ✓ Unexpected behaviors of crash partners
  - ✓ Absence of safety drivers within AVs
  - ✓ Precrash disengagement
  - ✓ Unusual events. e.g., unexpected obstacles, unclear road markings, and sudden and unexpected changes in traffic flow
- Edge cases could be initiated by AVs, Humans, and Infrastructure/Environment.
- Human actions contribute to 60% of edge cases.

# Answers to research questions

What are the differences in crash types between vehicles equipped with ADS and those with ADAS, specifically in intersection environments?

- The contact area for **94.7%** of ADAS-equipped crashes is the **front**.
- The contact area for **72.4%** of ADS-equipped crashes is the **rear**.
- ADAS were stopped or proceeding straight **89%** of the time.
- In **50%** of the crashes, ADS vehicles were found to be stopped.

How effective are pedestrian crash prevention systems in improving pedestrian safety?

- PCP systems reduce vehicle-ped crash risks (**70%** of the tests avoided ped crashes)
- Daytime: Hit pedestrian in **30%** of the tests-needs improvement.
- For crashes, PCP systems mitigated impact speeds by about **50%**.

# Answers to research questions

How can a hybrid testing protocol, integrating VIL and SIL simulations, systematically assess the safety of CAVs before they are deployed on public roads?

- VIL provides a more **realistic** assessment of vehicle behaviors.
- SIL, while useful for initial assessments, may not fully capture the nuances of real-world dynamics.
- VIL's incorporation of actual vehicle responses allows for the identification and analysis of critical safety scenarios (**edge cases**) that may not be apparent in SIL setups.