

# **Advancing Crash Investigation with Connected and Automated Vehicle Data – Phase 2**

**Collaboration:**

**University of Tennessee, Knoxville &  
University of North Carolina, Chapel Hill**

# R42 Project Team



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# Project Overview

**Objective:** To investigate how automated vehicle (AV) data can be used to advance crash investigation

**Res. questions, given 6+ million annual crashes:**

1. What insights can be gained from AV crashes?
2. What are the gaps in AV safety performance?
3. Which crash contributors are revealed by AV sensors?
4. What pertinent information is missing in crash investigations?
5. What is the preparedness of law enforcement to utilize AV data for crash investigations?
6. What insights can be gained from AV crash narratives?

# R42 Project: Studies Conducted

## Study I:

Automated vehicle data pipeline for accident reconstruction: New insights from LiDAR, camera, and radar data

## Study II:

Advancing investigation of automated vehicle crashes using text analytics of crash narratives and Bayesian analysis of crash data

## Study III:

Survey for Law Enforcement: Advancing Crash Investigation with Automated Vehicle Data

# Study I (Project R42)

## Automated Vehicle Data Pipeline for Accident Reconstruction: New Insights from Lidar, Camera, and Radar Data

**Relevant Paper:** Beck, J., Arvin, R., Lee, S., Khattak, A., & Chakraborty, S. (2023). Automated vehicle data pipeline for accident reconstruction: New insights from LiDAR, camera, and radar data. *Accident Analysis & Prevention*, 180, 106923

# Introduction

- Crash investigators currently use event data recorders (EDRs) to obtain data
  - However, EDRs collect limited data from the subject vehicle
  - Not connected to ADAS or ADS (automation systems)
- With the emergence of AVs and more vehicles equipped with ADAS/ADS → Need to investigate AV crashes and how sensor data can supplement crash analyses
- Gap: Need a framework for integrating AV sensor data (LiDAR, camera, and radar) in crash investigations

# Data

- **Data Source:** California Autonomous Vehicle Tester Program
- 94 AV crashes were carefully selected after analyzing AV-crash statistics to find cases that are representative of a large proportion of AV crashes
- Around 70% were rear-end collisions and a significant portion (7.5%) of cases involved pedestrians or bicyclists

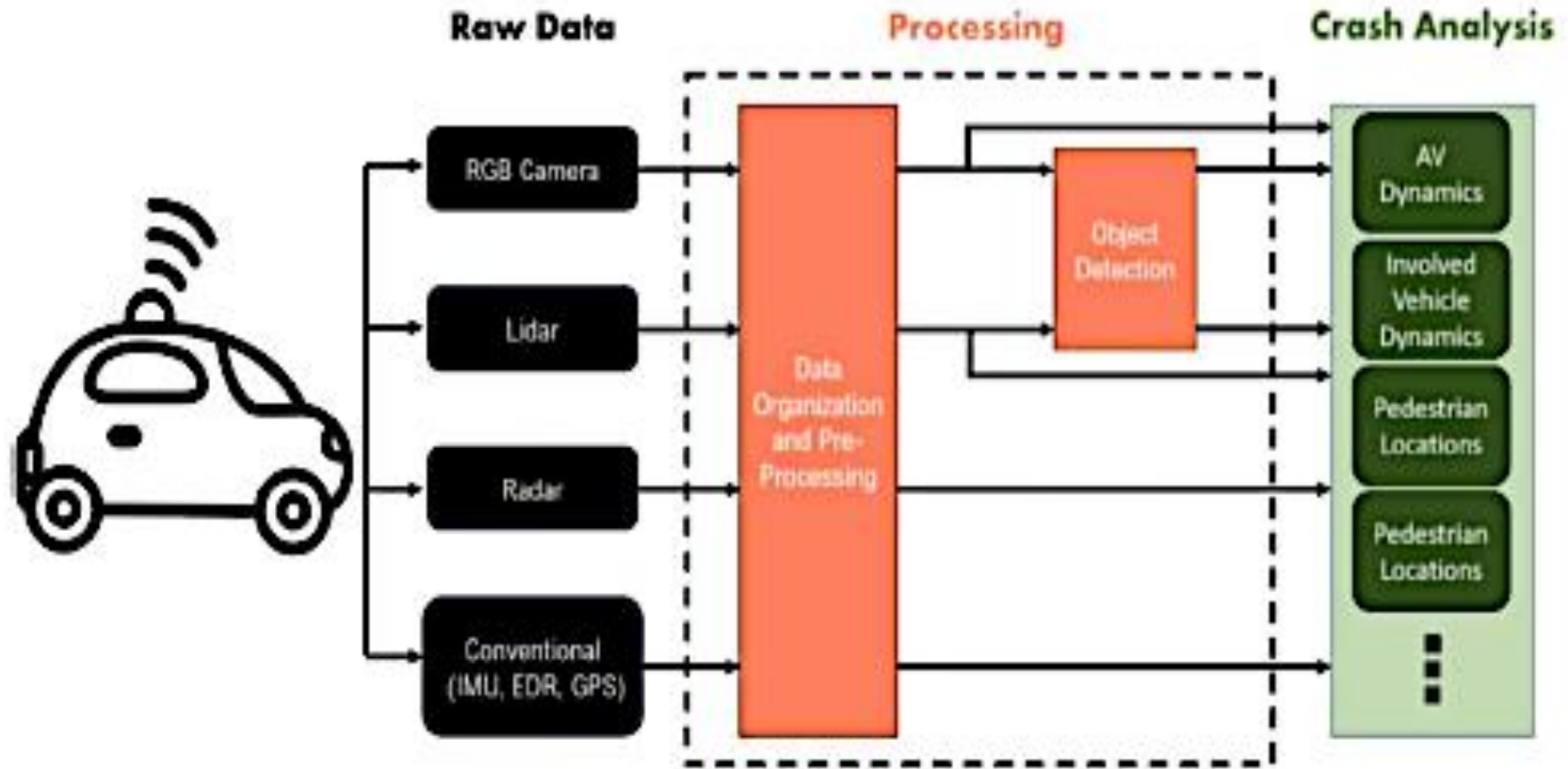
# Methodology

- The safe system framework used
- Two crash scenarios developed for the analysis:
  - An interaction between a pedestrian and an AV
  - A rear-end conflict between AVs and conventional vehicles
- Data processed to simulate crash scenarios in CARLA software (can simulate down to sensors)
- Data types:
  - AV data-LiDAR 3D point cloud data, video from all cameras, position and velocity data from in-vehicle Inertial Measurement Units (IMUs)
  - Conventional vehicle data: From sensors-IMU, EDR, GPS
  - Data organized to create AV dynamics, Involved Vehicle Dynamics, and Pedestrian Location



# Methodology

## Proposed Data Pipeline



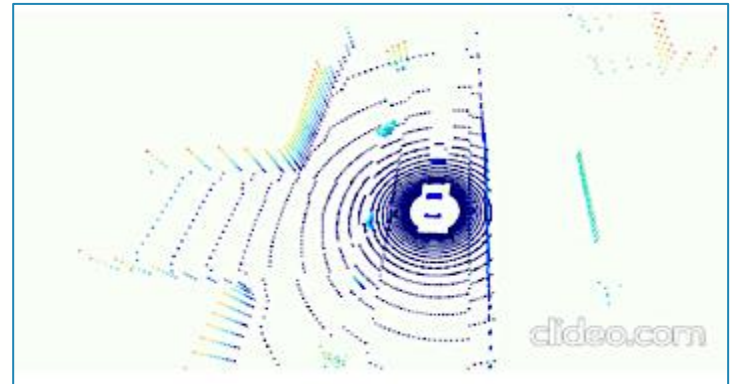
# Methodology & Results

## Simulation of a real-life AV Crash in CARLA software

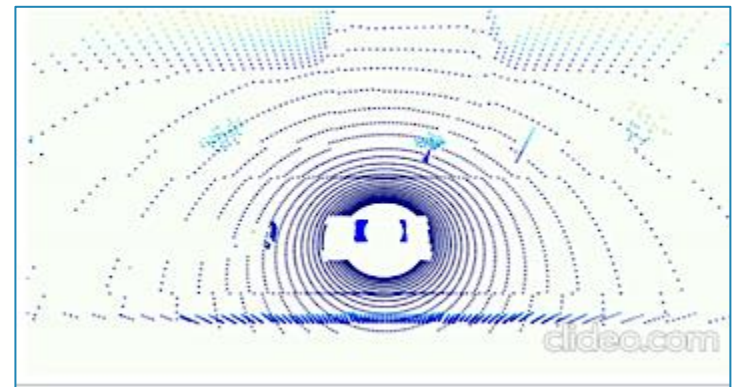
**Crash Description:** AV is yielding to a pedestrian who is jaywalking – A human-driven vehicle struck the AV from behind



Rear Camera



Front Camera



Lidar Data

# Findings

## Overview of Data Input into the Pipeline for CARLA Simulations

| Sensor    | Data Type                                  | Data Size       | Range            | Update Rate           |
|-----------|--|-----------------|------------------|-----------------------|
| Camera    | Image                                      | 480x720 Pixels  | ≈ 10 (detection) | 60 Hz                 |
| Radar     | 3D Point Cloud<br>(Position +<br>Velocity) | ≈ 300 points    | 20 m             | 50 Hz                 |
| LiDAR     | 3D Point Cloud<br>(Position +<br>Velocity) | ≈ 30,000 points | 50 m             | 50 Hz                 |
| GPS + IMU | Vehicle Position +<br>Velocity             | 1 point         | N/A              | Greater than<br>60 Hz |

# Conclusions and Future Research

- The vehicle trajectory information is provided by AV sensors but is typically not available from EDR
- AV sensors provide new details to crash investigators
  - State of the driver & vehicle movements
  - Trajectories of surrounding objects and people
- Future research could harness basic safety message (BSM) and driver alert/warning message data to enhance the crash investigation process

# Study II (Project R42)

## Advancing Investigation of Automated Vehicle Crashes using Text Analytics of Crash Narratives and Bayesian Analysis

**Relevant Paper:** Lee, S., Arvin, R., & Khattak, A. J. (2023). Advancing investigation of automated vehicle crashes using text analytics of crash narratives and Bayesian analysis. *Accident Analysis & Prevention*, 181, 106932.

# Background and Research Question

## Background

- Testing of automated vehicles (AVs) underway in CA
- Uncertainty of safety impacts in mixed traffic with human-driven vehicles

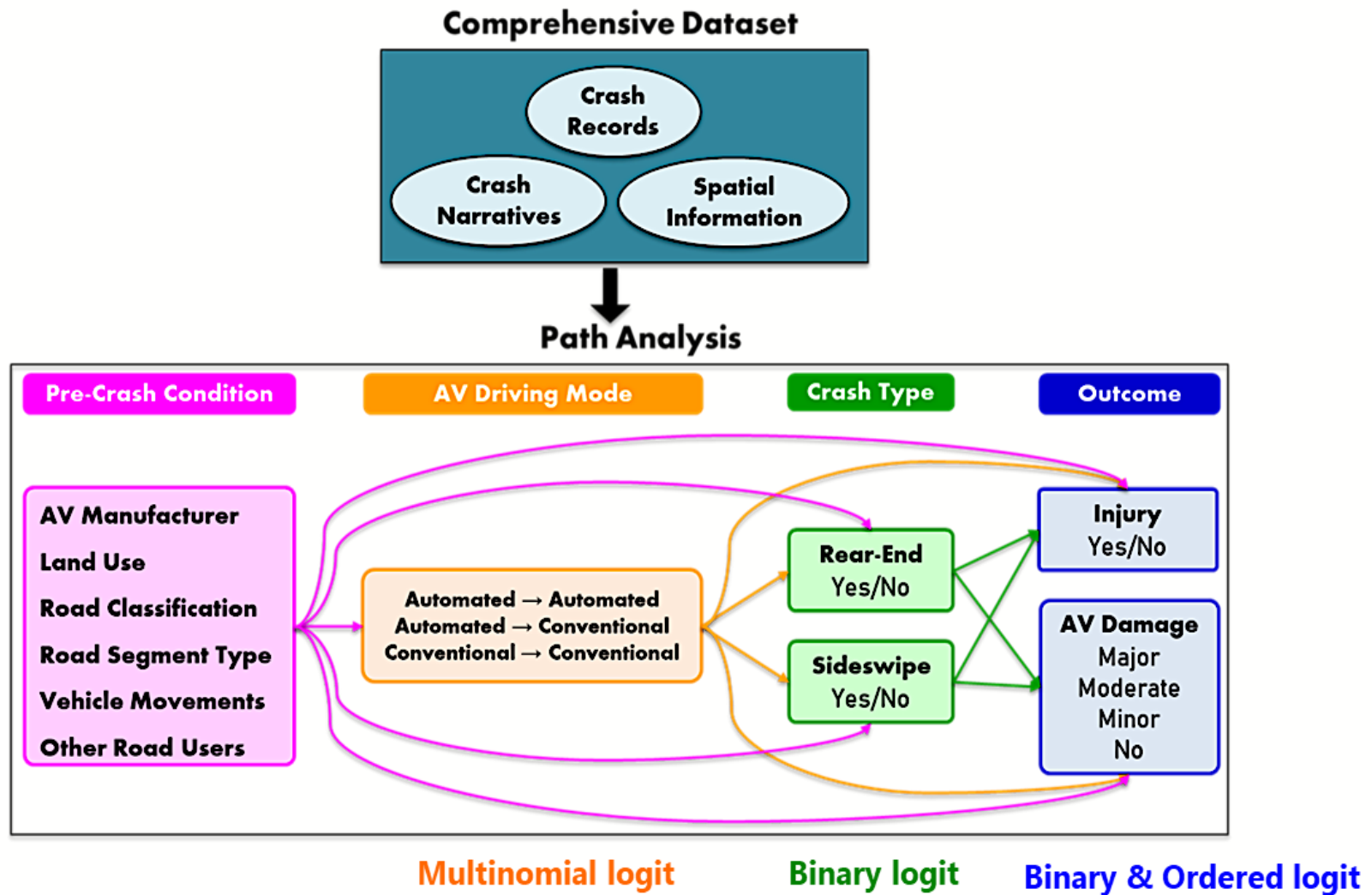
## Research Question

What do AVs tell us when they fail on the road?

- Gaps in the AV Safety Performance



# Data and Methodology



# Key Results and Findings

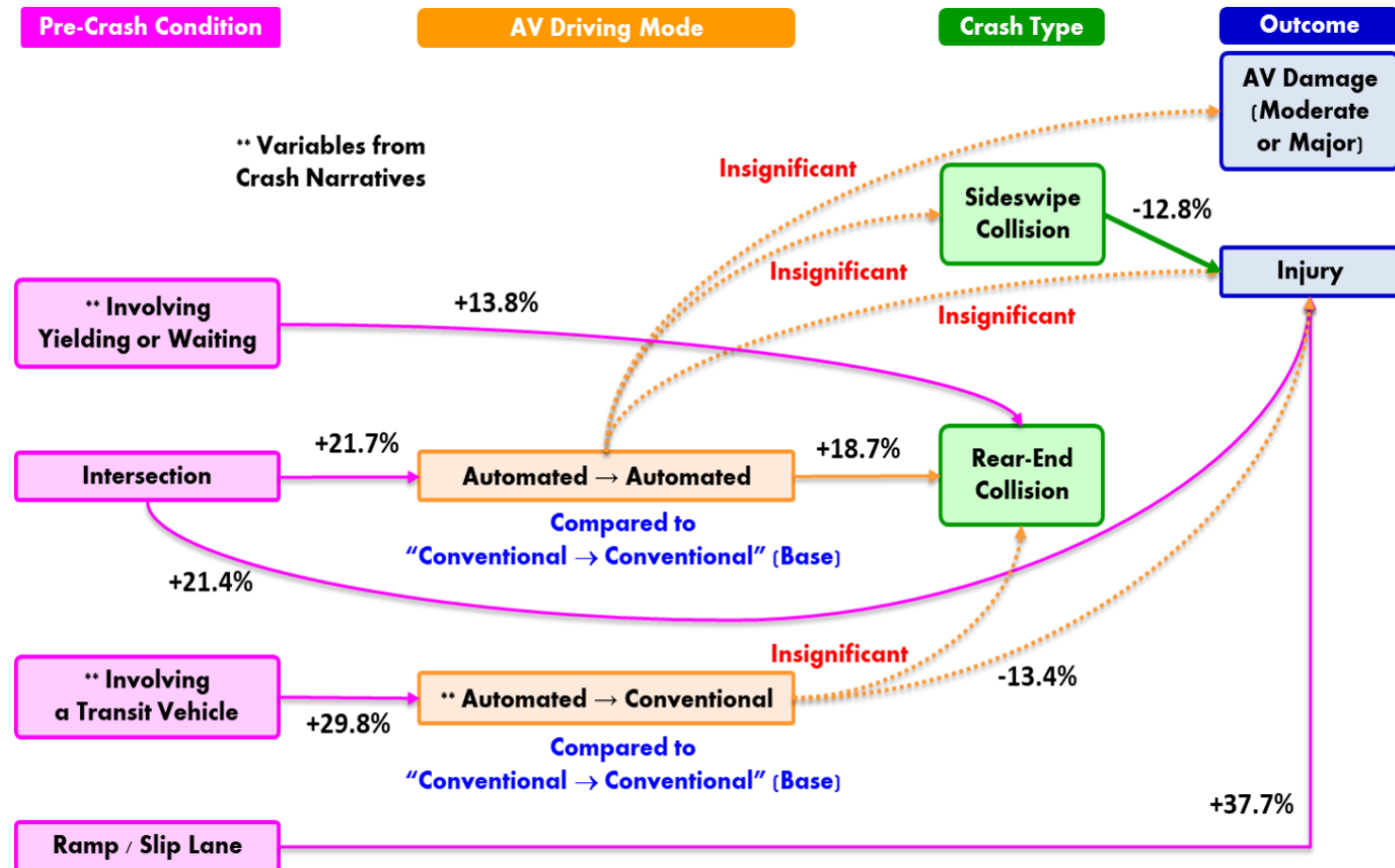
## Key Statistics (N=260 crashes)

| Variable  | Frequency | Percentage (%) |
|---|-----------|----------------|
| <b>Vehicle manufacturer</b>                           |           |                |
| Cruise LLC  | 105       | 40.4           |
| Waymo LLC   | 98        | 37.7           |
| Other   | 57        | 21.9           |
| <b>AV driving mode</b>                                |           |                |
| Automated → Automated                                 | 104       | 40.0           |
| Automated → Conventional (Manual Disengagement)       | 62        | 23.9           |
| Conventional → Conventional                           | 94        | 36.2           |
| <b>Land use</b>                                       |           |                |
| Residential   | 102       | 39.2           |
| Commercial  | 103       | 39.6           |
| Recreational  | 11        | 4.2            |
| Other   | 44        | 16.9           |
| <b>Road classification</b>                            |           |                |
| Freeway / Expressway / Highway                        | 11        | 4.2            |
| Street  | 222       | 85.4           |
| Other   | 27        | 10.4           |
| <b>Road segment type</b>                              |           |                |
| Intersection  | 215       | 82.7           |
| Ramp / Slip Lane                                      | 6         | 2.3            |
| Other   | 39        | 15.0           |
| <b>Vehicle movements (AV, Second Vehicle)</b>         |           |                |
| (Stopped, Straight)                                   | 61        | 23.5           |
| (Slowing/Stopping, Straight)                          | 11        | 4.2            |
| (Straight, Straight)                                  | 24        | 9.2            |
| (Straight, Changing Lanes)                            | 16        | 6.2            |
| (Left, Straight)                                      | 10        | 3.9            |
| Other   | 138       | 53.1           |
| <b>Involving an AV's yielding or waiting</b>          |           |                |
|   | 60        | 23.1           |
| <b>Other road users</b>                               |           |                |
| Involving a transit vehicle                           | 6         | 2.3            |
| Involving a pedestrian or bicyclist                   | 16        | 6.2            |
| <b>Crash type</b>                                     |           |                |
| Rear-End  | 135       | 51.9           |
| * 129 AVs (95.6%) were rear-ended by another vehicle. |           |                |
| Sideswipe   | 52        | 20.0           |
| * 36 AVs (69.2%) were sideswiped by another vehicle.  |           |                |
| Other   | 73        | 28.1           |
| <b>Involving injury to at least one person</b>        |           |                |
|   | 50        | 19.2           |
| <b>AV damage level</b>                                |           |                |
| None  | 21        | 8.1            |
| Minor   | 198       | 76.2           |
| Moderate  | 38        | 14.6           |
| Major   | 3         | 1.2            |



# Key Results and Findings

## Interrelationships Found

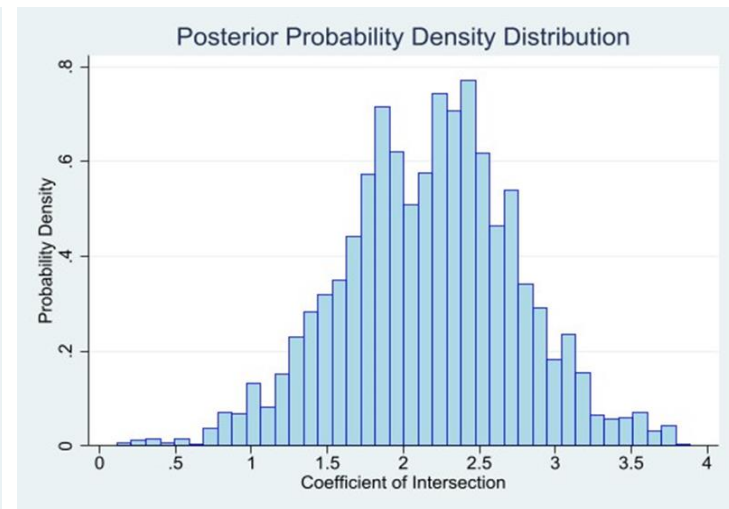
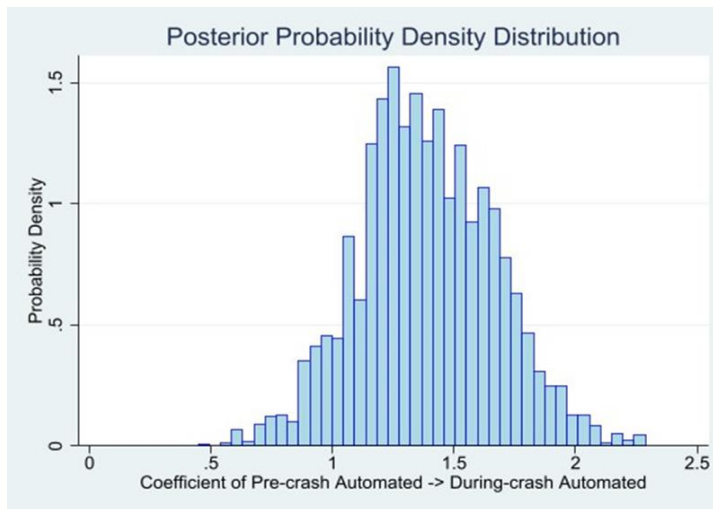


# Key Results and Findings

- AVs' interaction with a **transit vehicle** → a higher chance of **manual disengagement** (29.8%), given a crash
- AVs' **yielding** to or **waiting** for other road users → a higher chance of **rear-end collision** (13.8%), given a crash
- AVs' operating on a **ramp or slip lane** → a higher chance of **injury crash** (37.7%), given a crash

## Bayesian analysis-Quantify uncertainty & infer factors associated with crashes

- Informative priors and evidence from sample → Posterior probabilities
  - Automated driving mode → Rear-end collision
  - Intersection → Injury crash



# Conclusions

- **Implications for high-level (SAE Levels 4-5) automation**
  - AVs require more thorough testing to adapt to critical roadway features (e.g., intersections, ramps, and slip lanes)
  - How can transportation automation be supported by improving roadway features?
- **Developing vehicle-to-vehicle and vehicle-to-infrastructure technologies can include:**
  - Improvements needed in interactions with transit vehicles
  - Enhancements in yielding to or waiting for other road users
  - Operating more smoothly at intersections, ramps, or slip lanes
  - Dealing better with distance to other vehicles and objects
- **AV crash narrative data can be harnessed further to improve knowledge of AV safety in mixed traffic**

# Study III (Project R42)

## Survey for Law Enforcement: Advancing Crash Investigation with Connected and Automated Vehicle Data

**Relevant Paper:** King M., M. Adeel, S. Usman, & A. Khattak, Advancing Crash Investigation with Connected and Automated Vehicle Data: Insights from a Survey of Law Enforcement, Presented at Transportation Research Board 103rd Annual Meeting, Transportation Research Board, TRBAM-24-02430, 2024.

# Introduction

- Detailed crash investigations often require a variety of tools for reconstruction
- Opportunity and imperative: Automated vehicle data, including LiDAR, radar, and cameras could enhance investigation accuracy
- Automated systems offer crucial information lacking in currently used EDRs, such as vehicle trajectories, driver behavior, and surrounding conditions

# Introduction

## Automated Vehicle (AV) Sensors



Source: <https://innovationnetwork.ieee.org/lidr-is-the-latest-game-changing-advancement-for-autonomous-vehicles/>

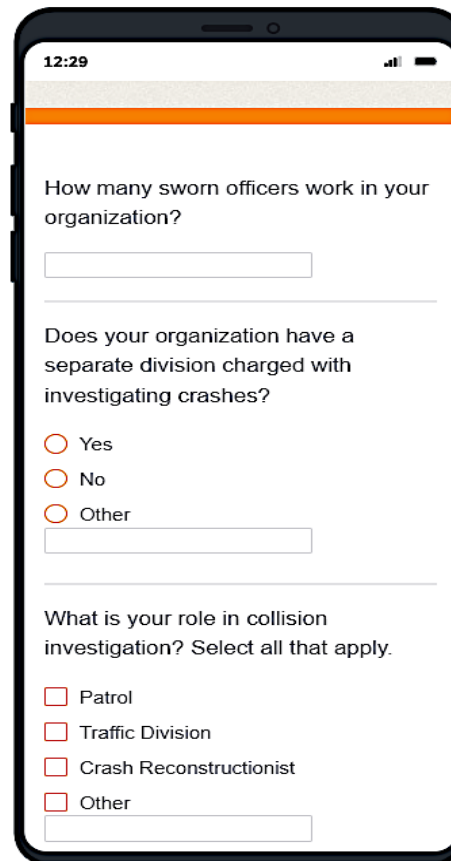
# Research Objectives

- To leverage connected and automated vehicle (CAV) data to improve crash investigations
- To explore law enforcement's involvement in training for CAV data application, assessing their knowledge of automated vehicle technology data, and inform curriculum development for CAV technology training

# Methodology

A survey with law enforcement officials was conducted to investigate use of AV data in crash investigations

## Sample of Survey Questions



12:29

How many sworn officers work in your organization?

Does your organization have a separate division charged with investigating crashes?

☐ Yes

☐ No

☐ Other

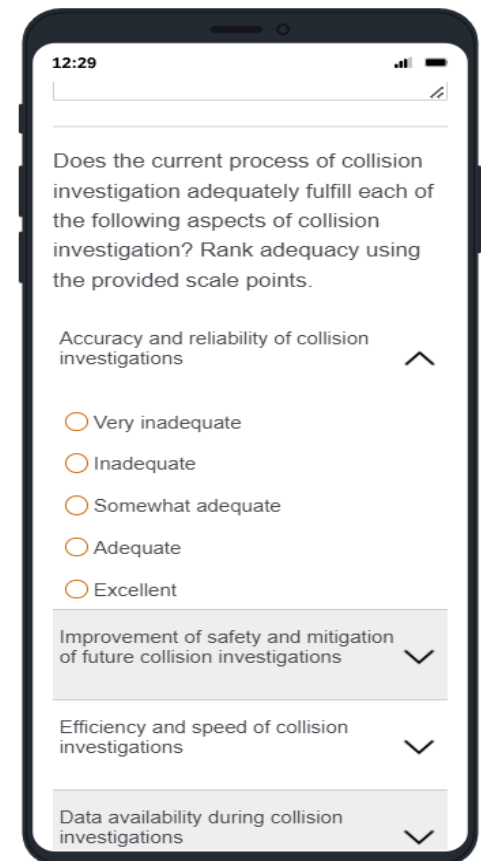
What is your role in collision investigation? Select all that apply.

☐ Patrol

☐ Traffic Division

☐ Crash Reconstructionist

☐ Other



12:29

Does the current process of collision investigation adequately fulfill each of the following aspects of collision investigation? Rank adequacy using the provided scale points.

Accuracy and reliability of collision investigations ^

☐ Very inadequate

☐ Inadequate

☐ Somewhat adequate

☐ Adequate

☐ Excellent

Improvement of safety and mitigation of future collision investigations v

Efficiency and speed of collision investigations v

Data availability during collision investigations v



# Methodology

## Step 1 – Survey

- Qualtrics survey: 26 Questions (11 multiple-choice questions, 9 short answer questions, and 6 Likert scale matrix questions)
- Data cleaning
- N = 61 Tennessee law enforcement officials who specifically work in vehicle crash investigations

## Step 2 – Exploratory Factor Analysis

- 15 variables were extracted from survey responses, and the final dataset had 61 entries for each variable
- Factor analysis chosen, after conducting Bartlett's test of Sphericity and Keiser-Meyer-Olkin factor adequacy test

# Key Results and Findings

## Familiarity Rankings – Automated Vehicle Sensors

|   | Not at all familiar | Slightly familiar | Somewhat familiar | Moderately familiar | Extremely familiar | Total |
|---|---------------------|-------------------|-------------------|---------------------|--------------------|-------|
| <b>Global Positioning System (GPS)<br/>(N = 51)</b> | 3.9%                | 23.5%             | 15.7%             | 51.0%               | 5.9%               | 100%  |
| <b>Onboard Units (OBU)<br/>(N = 51)</b>             | 41.2%               | 33.3%             | 13.7%             | 51.0%               | 0.0%               | 100%  |
| <b>Millimeter Wave Radar<br/>(N = 51)</b>           | 64.7%               | 25.5%             | 9.8%              | 51.0%               | 0.0%               | 100%  |
| <b>Ultrasound Sensors<br/>(N = 51)</b>              | 60.8%               | 25.5%             | 7.8%              | 51.0%               | 0.0%               | 100%  |
| <b>Infrared Sensors<br/>(N = 50)</b>                | 54.0%               | 28.0%             | 10.0%             | 51.0%               | 0.0%               | 100%  |
| <b>LiDAR (N = 51)</b>                               | 33.3%               | 27.5%             | 15.7%             | 51.0%               | 2.0%               | 100%  |
| <b>Cameras (N = 51)</b>                             | 3.9%                | 15.7%             | 15.7%             | 51.0%               | 5.9%               | 100%  |

# Key Results and Findings

## Familiarity Rankings – Automated Advanced Driver Assistance Systems (ADAS)

|   | Not at all familiar | Slightly familiar | Somewhat familiar | Moderately familiar | Extremely familiar | Total |
|---|---------------------|-------------------|-------------------|---------------------|--------------------|-------|
| <b>Adaptive Cruise Control (ACC) (N = 51)</b>     | 13.7%               | 17.6%             | 25.5%             | 33.3%               | 9.8%               | 100%  |
| <b>Lane Departure Warning (LDW) (N = 51)</b>      | 13.7%               | 15.7%             | 27.5%             | 33.3%               | 9.8%               | 100%  |
| <b>Blind Spot Monitoring (BSM) (N = 51)</b>       | 17.6%               | 13.7%             | 19.6%             | 37.3%               | 11.8%              | 100%  |
| <b>Rear Cross Traffic Alert (RCTA) (N = 51)</b>   | 45.1%               | 11.8%             | 19.6%             | 19.6%               | 3.9%               | 100%  |
| <b>Forward Collision Warning (FCW) (N = 51)</b>   | 11.8%               | 23.5%             | 23.5%             | 33.3%               | 7.8%               | 100%  |
| <b>Automatic Emergency Braking (AEB) (N = 51)</b> | 19.6%               | 21.6%             | 19.6%             | 29.4%               | 9.8%               | 100%  |
| <b>Park Assist (N = 51)</b>                       | 15.7%               | 39.2%             | 11.8%             | 25.5%               | 7.8%               | 100%  |
| <b>Night Vision (N = 50)</b>                      | 40.0%               | 30.0%             | 14.0%             | 14.0%               | 2.0%               | 100%  |
| <b>Heads-Up Display (N = 50)</b>                  | 22.0%               | 30.0%             | 16.0%             | 24.0%               | 8.0%               | 100%  |
| <b>Driver Monitoring Systems (DMS) (N = 51)</b>   | 23.5%               | 33.3%             | 23.5%             | 17.6%               | 2.0%               | 100%  |

# Key Results and Findings

## Familiarity Rankings – Law Enforcement Training Topics

|  | Not at all familiar | Slightly familiar | Somewhat familiar | Moderately familiar | Extremely familiar | Total |
|--|---------------------|-------------------|-------------------|---------------------|--------------------|-------|
| <b>Understanding automated vehicle technology (N = 51)</b> | 66.7%               | 23.5%             | 7.8%              | 2.0%                | 0.0%               | 100%  |
| <b>Legal and ethical considerations (N = 51)</b>           | 36.0%               | 32.0%             | 16.0%             | 14.0%               | 2.0%               | 100%  |
| <b>Traffic enforcement and regulation (N = 51)</b>         | 45.1%               | 27.5%             | 21.6%             | 5.9%                | 0.0%               | 100%  |
| <b>Incident response and crash investigation (N = 51)</b>  | 41.2%               | 35.3%             | 11.8%             | 11.8%               | 0.0%               | 100%  |
| <b>Cybersecurity (N = 51)</b>                              | 66.7%               | 23.5%             | 9.8%              | 0.0%                | 0.0%               | 100%  |
| <b>Human factors (N = 51)</b>                              | 39.2%               | 43.1%             | 11.8%             | 5.9%                | 0.0%               | 100%  |
| <b>Communication and community engagement (N = 51)</b>     | 51.0%               | 29.4%             | 15.7%             | 3.9%                | 0.0%               | 100%  |



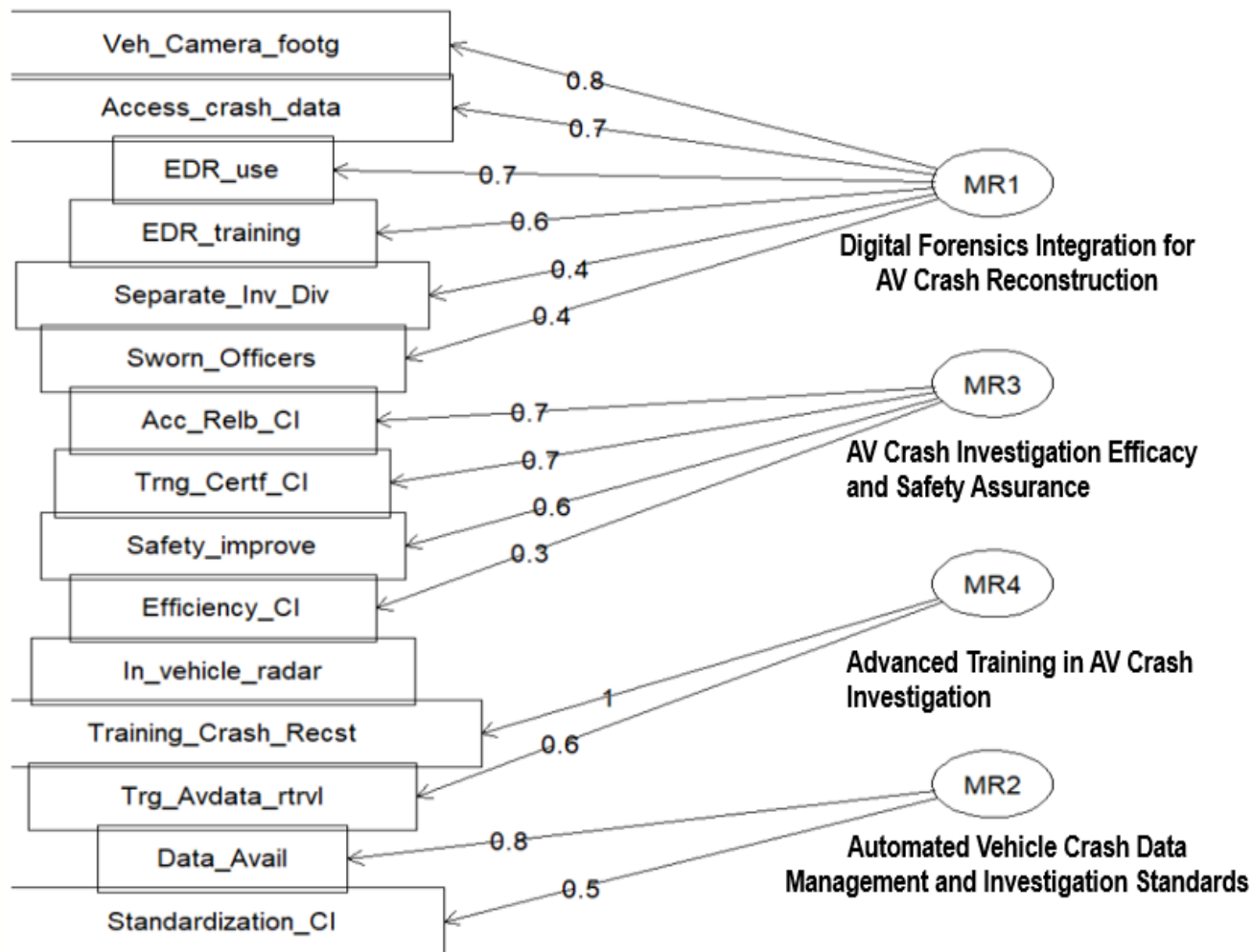
# Key Results and Findings

## Pertinent Automated Vehicle Training Topics for Crash Investigators in Law Enforcement

|    |   |  |
|----|---|--|
| 1. | <b>Understanding AV Technology</b>                    | This topic covers multiple facets of learning, including what sensors are used in different make and models of AVs, what data can be collected from these sensors, and how this new technology can impact human and roadway factors. According to the survey, the most unfamiliar AV technologies are Ultrasound Sensors, Millimeter Wave Radar, Infrared Sensors, and Onboard Units. Cameras and GPS are relatively familiar. Training officers to access the cameras and GPS sensors in AVs is needed. |
| 2. | <b>Accessing AV Data</b>                              | Accessing AV sensor data may require 1) coordination with vehicle manufacturers and 2) data retrieval equipment. Crash investigators should be trained in data retrieval process.  |
| 3. | <b>Applying AV Sensor Data to Crash Investigation</b> | After data retrieval, crash investigators should be trained to analyze and apply crash data as evidence. This requires familiarity with handling multiple data types from various sensors and using different software programs for analysis.  |
| 4. | <b>Cybersecurity Concerns</b>                         | AVs can face cybersecurity threats, introducing new road hazards. Crash investigators should know these threats and learn how to mitigate and respond to cybersecurity concerns.   |
| 5. | <b>Traffic Enforcement and Regulation</b>             | AVs operate differently than conventional vehicles, which may lead to shifting traffic enforcement and regulation practices shortly. Law enforcement can be trained in local traffic regulations regarding AVs.  |
| 6. | <b>Communication and Community Engagement</b>         | Once trained in AV technology, law enforcement can be trained to raise public awareness of new CAV technologies, regulations, and potential risks.   |
| 7. | <b>Legal and Ethical Implications</b>                 | AVs introduce new driver-vehicle relationships to the roadway, and with these shifting relationships, the ethical and legal landscape also evolves. It is not always clear how AV crashes can be handled and who is at fault. Therefore, crash investigators should be trained in the ethical and legal principles that guide crash culpability.   |

# Key Results and Findings

## Exploratory Factor Analysis Plot



# Conclusions

- The survey revealed a need and demand for vehicle and occupant dynamics information and standardization in data retrieval processes
- Factor analysis emphasizes the need for integrating digital data provided by AV sensors, specialized and sophisticated training of crash investigative officers
- Consider adopting standardized protocols for AV crash investigation to improve its efficiency



# Outcomes-Answers to research questions

## What insights can be gained from automated vehicle (AV) crashes?

- AV sensors provide precise information on vehicle trajectories, helping to understand the sequence of events leading to a crash
- AV data includes information on driver behavior and environmental conditions, offering a more comprehensive view of crash circumstances
- Integration of LiDAR, camera, and radar data allows for more accurate accident reconstruction and identification of contributing factors

## What are the gaps in AV safety performance?

- AVs require improved performance in mixed traffic conditions, especially in complex situations, e.g., at intersections and ramps
- Insufficient data on AV behavior during manual disengagements and emergency situations

# Outcomes-Answers to research questions

## Which crash contributors are revealed by AV sensors?

- Higher likelihood of manual disengagement during interactions with transit vehicles
- Increased risk of rear-end collisions when AVs yield or wait for other road users
- Increased risk of injury crashes on ramps, slip lanes, and intersections

## What pertinent information is missing in crash investigations?

- Lack of comprehensive data on AV system status and sensor functionality during crashes
- Lack of standardized protocols for integrating AV data with traditional crash investigation methods
- Limited information on driver behavior and decision-making processes during crashes

# Outcomes-Answers to research questions

## What is the preparedness of law enforcement to utilize AV data?

- Law enforcement officials need training in accessing and interpreting AV sensor data
- Many officers are not familiar with advanced AV technologies and data retrieval processes
- Standardization in AV data retrieval and training processes is needed
  - A list of pertinent training curricula for law enforcement is provided in the study

## What insights are gained from on-road AV crash narratives?

- Text analytics: Qualitative insights into AV performance and interaction with other road users → Knowledge of AV safety in mixed traffic
- Identification of common failure points in AV systems during real-world operation → Comprehensive portrayal of crash events