Collaborative Sciences Center for ROAD SAFETY

FINAL REPORT

Advancing crash investigation with connected and automated vehicle data

July 2021

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Acknowledgement of Sponsorship

This project was supported by the Collaborative Sciences Center for Road Safety, www.roadsafety.unc.edu, a U.S. Department of Transportation National University Transportation Center promoting safety. We gratefully acknowledge the roles of Steven Richards, Ph.D. of the University of Tennessee, Knoxville, Alexandra Boggs, Ph.D. of Focus Forensics, Ramin Arvin, Ph.D. of the University of Tennessee, Knoxville, Katie Harmon, Ph.D. of the UNC Highway Safety Research Center, Justin F. Morgan, Ph.D. of JF Morgan, and Sgt. Anthony Barnes and Sgt. John Collins of the North Carolina State Highway Patrol.

The funding provided by CSCRS in this project has resulted in the following paper:

1. Clark, K., Clamann, M. and Khattak, A. (2020). Advancing Crash Investigation with Connected and Automated Vehicle Data. In Proc. of the 100th Annual Transportation Research Board Meeting, 20-02560, Washington, D.C.

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. CSCRS-R25.1	**2. Government Accession No.**	**3. Recipient's Catalog No.**
4. Title and Subtitle: Advancing crash investigation with connected and automated vehicle data		**5. Report Date** July 7, 2021 **6. Performing Organization Code** DUNS: 608195277
7. Author(s) Michael Clamann, Ph.D., C.H.F.P. 0000-0001-8862-7358 Asad J. Khattak, Ph.D. 0000-0002-0790-7794 Kinzee Clark, MS		**8. Performing Organization Report No.**
9. Performing Organization Name and Address The University of North Carolina, Chapel Hill, North Carolina The University of Tennessee Center for Transportation Research, Knoxville, Tennessee		**10. Work Unit No.** **11. Contract or Grant No.** Collaborative Sciences Center for Road Safety (Grant: 69A3551747113)
12. Sponsoring Agency Name and Address University Transportation Centers Program Office of the Assistant Secretary for Research and Technology U.S. Department of Transportation 1200 New Jersey Avenue, SE, Washington, D.C. 20590-0001		**13. Type of Report and Period Covered** Final Report: May 2019-Aug 2020 **14. Sponsoring Agency Code** Office of the Assistant Secretary for Research and Technology-RDT 30
15. Supplementary Notes Conducted through sponsorship by the U.S. Department of Transportation, Federal Highway Administration.		

16. Abstract

Understanding the contributing factors in more than 6 million vehicle crashes that occur annually in the U.S. is very challenging, and police officers investigating crashes need all the tools they can use to reconstruct the crash. Given that the Connected and Automated Vehicle (CAV) era is rapidly unfolding, this study seeks to leverage newly available CAV data to improve crash investigation procedures and obtain input from stakeholders, specifically law enforcement. In particular, law enforcement use of existing Event Data Recorders (EDRs), which store vehicle kinematics during a crash, is explored. Crash investigations are currently aided by EDRs, but this aid could be expanded to include the information gathered by Automated Driving System (ADS) technologies such as radar, cameras, LiDAR, infrared, and ultrasonic. This detailed data could improve the fidelity of future crash investigations, with potential new information such as driver/operator state, vehicle automation capabilities, location, objects and people in the immediate area, performance and diagnostic data, and environmental factors. Through text mining analysis of CAV and sensor-related literature and interviews with law enforcement, this study contributes by gathering evidence about crash investigations to pinpoint the contributing factors of a crash. Further we explore law enforcement involvement in the design of the current EDR retrieval process and their knowledge about using ADS data. Broadly, the project applies the safe systems approach by suggesting a framework that integrates CAV data in the new crash investigation procedures.

17. Key Words Accident investigation; connected and automated vehicles; advanced driver assistance systems; event data recorder; law enforcement; text analysis			**18. Distribution Statement**
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 39	**22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Introduction

Safety on U.S. roadways is a continuing concern, as more than 6 million crashes occur with nearly 40,000 fatalities every year. The cost of safety is estimated to be about $1 Trillion in the U.S. Therefore, understanding the contributing factors to traffic crashes is important, but also very challenging. Police officers investigating crashes rely on specialized tools and training to make a proper assessment of the role that driver, vehicle, and roadways/environmental factors play. These methods have evolved through decades of experience and research. Given that Connected and Automated Vehicles (CAVs) are rapidly diffusing through the transportation system, it can be concluded that many of these legacy methods will need to be updated to reflect the new technologies. This study seeks to leverage newly available CAV data to improve crash investigation procedures and obtain input from stakeholders, especially law enforcement.

In modern vehicles, event data recorders (EDRs) can automatically store important data to a file in the event of a crash. They appeared much before advanced driver assistance systems such as forward collision warning and braking systems. Data recording by vehicles is now standardized by the U.S. Code of Federal Regulations (CFR) Title 49 Part 563, which was amended in 2008 and made effective for vehicles manufactured on or after September 1, 2010. While this rule does not mandate installing EDRs in new light vehicles, it does require installed EDRs to maintain a minimum dataset that includes 15 specific fields. Adoption of EDRs is now widespread, and 99% of new vehicles have an EDR and methods for accessing the data. However, Part 563 was drafted in 2006 based on data elements that began appearing in cars in 1994, years before the public testing of automated vehicles, and data storage and retrieval capabilities have improved dramatically in the meantime. These advances provide new opportunities for improving the scope of automated crash data.

The radar, cameras, and LiDAR sensors utilized by Automated Driving Systems or ADSs (e.g., automatic emergency braking, adaptive cruise control, lane keeping assist), Basic Safety Messages used in V2X communications (e.g., vehicle position, speed, heading, acceleration) and driver monitoring could provide new detailed data to improve the fidelity of future crash investigations, such as driver/operator state, vehicle automation capabilities, location, objects and people in the immediate area, performance and diagnostic data, and environmental factors, just to name a few. Moreover, recent high-profile crashes involving automated vehicles (e.g., Tesla, Uber) show there is a need for law enforcement and crash investigators to rapidly review sensor data to reconstruct pre-crash events during an investigation (NTSB, 2017; NTSB, 2018a; NTSB, 2018b; NTSB, 2018c). Currently, this needs to be done in cooperation with the manufacturer, which introduces additional delays in an already complex investigation process. With these issues in mind, the goal of this project was to determine how the existing event data recorder elements could be enhanced by adding new data available to automated vehicles through sensors, assisting with more comprehensive crash investigations in the future. A key element of the project is the use of safe systems approach by involving key stakeholders, namely, law enforcement.

Background

The approaching deployment of CAVs is anticipated to bring about numerous safety improvements. These improvements will be a result, in part, of the vast amount of real-time data collected by CAVs to support navigation and sustained sensing of the surrounding environment. These vehicles represent an opportunity to fully utilize the data generated to be extracted, used, and stored to advance transportation safety, especially in the Big Data era (Shay, Khattak & Boggs, 2019). Unfortunately, due to the dynamic nature of the human-vehicle-roadway environment, crashes will continue to occur, particularly as conventional vehicles struggle to systematize with CAVs. Evidence shows that with the deployment of the California Autonomous Vehicle Tester Program in 2014, the frequency and causes of certain types of CAV-involved crashes are different, with human-driven vehicles more likely to rear-end CAVs, and CAVs being overrepresented in rear-end crashes (Teoh & Kidd, 2017). Moreover, many types of collisions are expected to continue, even with ADS deployments, including those that occur due to technology limitations (Biever, Angell & Seaman, 2020). This points to the need to investigate in detail the causes of CAV-involved crashes, harnessing the more detailed data available from CAVs (Boggs, Khattak & Wali, 2019). In these cases, when real-time data fails to prevent a crash, it could still be used to provide insight into the causes, which, in turn, could inform future safety improvements. The research question is how we can use the newly available ADS data to better reconstruct a crash and understand the causal factors? Additionally, which of these newly available data points should be included to complement mandated EDR reports?

Crash Investigation

Law enforcement officers have numerous responsibilities at the scene of a collision. First and foremost, they need to protect the public and others responding to the scene. In addition, they need to preserve evidence, identify and interview the drivers and passengers involved along with witnesses, inspect the vehicles, and determine if additional assistance is needed (North Carolina Justice Academy, 2019). If the collision is determined to be a *reportable crash*, then additional investigation is required. According to North Carolina General Statutes (20-4.01(33b)) a reportable crash is a collision involving a motor vehicle and one of the following conditions:

- Death or injury of a human being
- Total property damage of one thousand dollars ($1,000) or more
- Property damage of any amount to a vehicle seized

If the crash is reportable, the officer is then responsible for documenting a wide range of crash data including the following categories:

- Local conditions (e.g., locality, development, road surface, weather)
- Series and sequence of harmful events (crash level & vehicle level)
- Contributing Circumstances (roadway, driver, vehicle)
- Driver and occupant information
- Non-motorist information
- Vehicle information and condition
- Vehicle speed
- Date and time
- Location
- Insurance information
- Commercial vehicle information (if applicable)
- EMS information
- Fixed objects

The North Carolina crash report form (i.e., DMV-349) includes 80 discrete fields that could be completed by the officer within 24 hours of the crash. The total number of fields that are filled out depend on the type of crash. For example, there are special fields for commercial vehicles that do not need to be completed unless a commercial vehicle is involved. There are also special fields that apply to work zones, etc. Due to the volume of data that must be collected, officers are not always able to collect and record all the relevant data at the scene. In addition to ensuring the safety of everyone at the scene, the officer also has to re-open the roadway to traffic and allow the witnesses and individuals involved to leave the scene. Therefore, the officer often collects important information from people present, composes an explanatory narrative, and creates a comprehensive diagram of the scene that can be used to enter when the officer is safely offsite. It is also important to note that the information collected from witnesses, drivers, and passengers is not always reliable. Human perception, attention, and memory are limited and fallible (Green & Senders, 2009). If some of the objective data could be recorded automatically, the officer could focus on public safety, ensuring the people involved receive the services they need, and the logistics of reopening the roadway are complete.

EDR background

Most modern motor vehicles include an Event Data Recorder (EDR), which is a device (or collection of devices) that automatically records operational and occupant information for a few seconds before, during, and after a crash. While EDRs are loosely comparable to black boxes installed in airplanes, ships, and trains, there are several important differences. Black boxes continuously record data throughout operation, and they often record sound and voice communications. EDRs only collect a few seconds of data before and after a triggering event indicative of a crash, and they do not record sound or visual data.

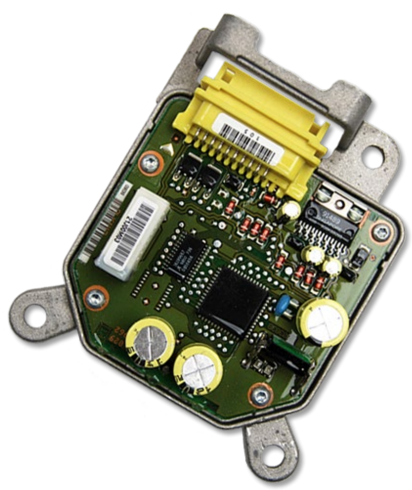

Figure 1. An Event Data Recorder (Image: Crash Data Group, www.https://www.crashdatagroup.com/)

Safety researchers have been interested in collecting objective data about vehicle crashes since flight data recorders became popular in the aviation industry; however, compared to other transportation modes, EDRs are a more recent addition to motor vehicles. Manufacturers and researchers made some progress in developing predecessors to modern EDRs between the 1970s and the 1990s (NHTSA, 2005); however, some key events that occurred in the late 1990s were instrumental in the widespread adoption that we have today. In 1997 the National Transportation Safety Board (NTSB) and the National Aeronautics and Space Administration (NASA)'s Jet Propulsion Laboratory recommended that NHTSA should investigate the use of EDRs for collecting crash information. Soon afterward, the NHTSA Office of Research and Development created a working group including government, industry, and academic stakeholders to study how

EDRs data could be collected and utilized. The result was a report that included 29 key findings related to EDRs (NHTSA, 2001). NHTSA expanded on these results by sponsoring a second EDR working group in 2000. A few years later, NHTSA issued regulations that standardized EDR data on vehicles manufactured on September 1, 2010, or later. Specifically, this included defining a minimum data set for manufacturers voluntarily installing EDRs. Many manufacturers developed and installed EDRs in their vehicles during and following the establishment of the NHTSA EDR working groups. Figure 1 provides a timeline of EDR deployments by the manufacturers since 1994.

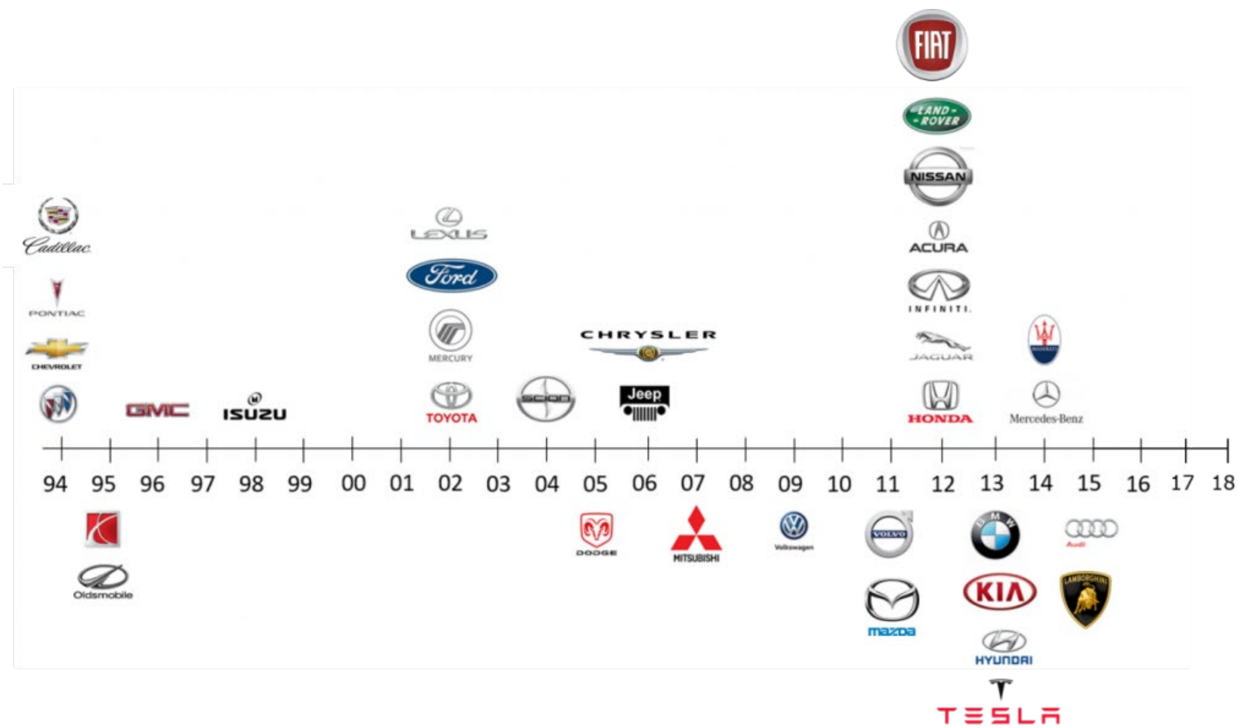

Figure 2. Timeline of EDR coverage by manufacturer (Image: National Biomechanics Institute)

The EDR is generally located in a well-protected location so it will survive a crash event (e.g., under the driver's seat). This location will vary according to the manufacturer. Additional supporting sensors are located throughout the vehicle, depending on the functions performed. Data will be sent from the sensors to the EDR when an event or impact[1] exceeding a specific threshold is detected. Currently, crash data is recorded using EDRs installed in most light vehicles. The EDR is defined by CFR Title 49 Part 563 as:

> "a device or function in a vehicle that captures the vehicle's dynamic, time-series data during the time period just prior to a crash event (e.g., vehicle speed vs. time) or during a

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[1] Note: The airbag control module (considered the EDR for most vehicles) senses accelerative (lateral and/or longitudinal) events over time. Based on the manufacturer threshold, the event is classified as a deployment (seatbelt pretensioner, airbags, fire) or a non-deployment (no safety systems deployed). Given that near-crash events can cause significant accelerations (e.g., a near-rollover), event or impact can be used as descriptors. Additionally, some collision events are not reliably recorded by EDRs, e.g., collisions between automobiles and pedestrians or bicycles.

crash event (e.g., delta-V vs. time), such that the data can be retrieved after the crash event... The event data does not include audio and video data."

Table 1 lists the required EDR elements:

Table 1. Data Elements Required for All Vehicles Equipped with an EDR (adapted from CFR Title 49 Part 563.7)

Element	**Recording Interval**	**Sampling Rate (Hz)**
Delta-V, longitudinal	0 to 250 ms	100
Maximum delta-V, longitudinal	0 to 300 ms	N/A
Time, maximum delta-V	0-300 ms	N/A
Speed, vehicle indicated	5 seconds	2
Engine throttle, % full	5 seconds	2
Service brake, on/off	5 seconds	2
Ignition cycle, at time of crash	1 second	2
Ignition cycle, at time of download	At download	N/A
Safety belt status, driver	1 second	N/A
Frontal air bag warning lamp, on/off	1 second	N/A
Frontal air bag deployment, time to deploy – Driver	Event	N/A
Frontal air bag deployment, time to deploy – Passenger	Event	
Multi-event, number of events	Event	N/A
Time from "event 1" to "event 2"	As needed	N/A
Complete file recorded (yes/no)	At end of file	N/A

EDR data are generally obtained by investigators or technicians using the Bosch Crash Data Retrieval (CDR) tool. This process is referred to as *imaging* the data. The CDR tool reads the data stored in the EDR and uses it to provide crash information to the investigator in a report format. The CDR tool includes software and hardware. The hardware includes cables and adapters that make connections to the EDR through different access points, depending on the state of the vehicle following the crash. The CDR tool (Bosch, 2020) can be used to access and download EDR data from 88% of vehicles (Ruth, 2017). Not all manufacturers use the Bosch CDR. Hyundai and Kia use a tool manufactured by Global Information Technologies, and Jaguar, Land Rover and Mitsubishi sell their own retrieval tools. This means that crash investigators need to have multiple hardware and software tools to be able to download or image the data for all vehicle types.

Ownership of EDR data varies according to state law. The owner can give permission to image EDR data, or the data can be subpoenaed through court orders. Other states collect data under laws governing crash investigations.

EDR data is rarely imaged at the scene of a crash. While there is no certification required for EDR use, qualification depends on knowledge, training and, experience with the equipment. Not all officers are trained as technicians, and qualified technicians with the required equipment are not always available. Consequently, the records are often imaged offsite after some delay. Typically, this occurs after the vehicles are removed from the scene and a search warrant is obtained. Law enforcement officers who perform the imaging include *technicians* and *analysts*. To access, technicians image EDR data, and analysts use the data in crash reconstruction. Some officers are qualified to perform both roles.[2] In North Carolina, EDR data are only imaged following severe crashes, including those resulting in a fatality and those involving a law enforcement vehicle. However, when the frequency of fatal crashes exceeds the local law enforcement resources to image the EDR data for all of them, priority may be assigned to collisions involving a possible felony. Generally, EDR data is not used on its own; rather the EDRs are used to confirm the officer's investigation using the physical evidence.

EDR Limitations for Automated Vehicles

While EDRs are helpful in augmenting evidence collected during the physical investigation, the data can have some flaws. For example, EDR speed is derived by measuring speed at the drive wheels. In cases when the wheels leave the road surface in the seconds before a crash (e.g., vehicle is airborne) the speed can be over-reported. For these reasons, EDR data is treated as a supplement that corroborates crash reconstruction. Another limitation of EDR is that tires that vary from stock sizes or have significant wear can influence the accuracy of EDR-reported speed. Wheels that lock during a recorded event can also misrepresent speed. While there is a minimum standard for the fields collected by the EDR, the data and the format of the reports vary according to vehicle make, model, and year Singleton, Daily & Manes, 2008).

The list of EDR elements (Table 1) was agreed on after years of discussion within NHTSA working groups and made public just as early versions of lane keep assist technology first became available in Infiniti and Lexus luxury sedans. Another modern technology that could influence the list of EDR elements is Toyota Techstream and Vehicle Control History (VCH), which takes photographs during pre-collision braking and collects a wealth of control data. Consequently, EDR elements do not account for modern advanced driver assistance systems (ADAS), let alone advanced automation that would allow drivers to dynamically swap lateral and longitudinal control responsibilities with a computer for prolonged periods.

As partially automated vehicles are penetrating the market, the National Transportation Safety Board (NTSB) has investigated three fatal crashes involving automated vehicles in Florida, California, and Arizona. The crash depicted in Figure 3 below demonstrates the extreme nature of the observed AV crashes, and the need for expanding on EDR elements within vehicles with ADAS capabilities.

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[2] As of 2021, a full application that allows imaging can cost about $30,000 and requires about $3,000 per year in maintenance. Given the high direct and indirect costs of training officers on the EDR system and its use, many times the officer doing the imaging also does the reconstruction. Due to their high costs, many agencies only image vehicles involved in fatal crashes.

Figure 3. Tesla Model S Crash in Williston, Florida (9)

Depicted in the preliminary and final reports of the crashes, investigators were able to obtain pre-crash data that became available due to the emerging technology. For example, from the NTSB's final report on the fatal Tesla Model S crash in Williston, Florida, investigators were able to access, with the aid of Tesla, 53 distinct variables of stored data on a secure digital (SD) card covering 42 hours before the fatal crash (NTSB, 2017). The Tesla Model S did not have an EDR; rather, the crash data was acquired from the engine control unit (ECU) by Tesla engineers, because at the time of the crash there was no commercially available tool for accessing and reviewing the data (NTSB, 2017). Additionally, image data were collected but did not provide informing material on the crash. However, as depicted in Figure 4, investigators were able to determine the locations and duration of "Autopilot" use, the instances of visual and auditory warnings, and when the vehicle operator interacted with the steering wheel before the crash.

Figure 4. Tesla Model S Autopilot State & Warning of Tesla Duration prior to Fatal Crash (3)

As vehicle sensor and control technology has been added to newer vehicles, there has been some interest in augmenting EDRs. In testimony during a Senate hearing on the Automated & Self Driving Vehicle Revolution, former National Safety Council President and CEO Deborah Hersman pointed out that, "there is no easy way for manufacturers, law enforcement, investigators or vehicle owners to understand whether deployed systems were active during a crash, whether they malfunctioned, or whether they helped mitigate damage or injury or returned the car to a safe state in event of a malfunction," describing this information as a "minimum requirement" for EDRs (Hersman, 2016). In their report on the Williston, Florida Tesla crash (Figure 3), NTSB investigators concluded that the EDR data was "inadequate to comprehend even the simplest questions of who/what controlled an automated vehicle at the time of a crash" (NTSB, 2017, p. 36). Similar opinions have been offered by the Property Casualty Insurers Association of America, the American Association of Motor Vehicle Administrators, and NHTSA (AAMVA, 2018).

The fifth version of the Model Minimum Uniform Crash Criteria (MMUCC), which provides guidance to states by identifying a minimum set of motor vehicle crash data elements to include in state crash reports, introduced Motor Vehicle Automated Driving Systems as a new element to be included in crash reports (NHTSA 2017). The new recommended automated driving systems element allows law enforcement to indicate on a crash form which automation level was engaged at the time of a crash. This new element is supported by the NTSB, which provided a related recommendation following its investigation of the fatal Tesla crash in Florida:

> "Define the data parameters needed to understand the automated vehicle control systems involved in a crash. The parameters must reflect the vehicle's control status and the frequency and duration of control actions to adequately characterize driver and vehicle performance before and during a crash" (recommendation H-17-37).

SAE Level 2 remains a critical issue here, as the vehicle is assuming a driver is present and will correct their mistakes. A key issue before Level 4 diffusion through the transportation system is the status of the driver. Driver monitoring systems and the data from those systems are going to be critical in these determinations. However, these data raise important privacy concerns.

Determining which automated systems are available on a vehicle can be difficult. Neither the model number nor the VIN reliably identifies the available systems for all vehicles. A trained officer might be able to physically locate radar and camera sensors by inspecting the windshield, bumper, and dashboard controls; however, these physical inspections can also be challenging as the sensors can be hidden for aesthetic reasons and vary in design among vehicle models. Even when the sensors are identified correctly, the data are not always made available to law enforcement when requested from manufacturers.

MMUCC guidelines recommend that states adopt these new elements; however, the information cannot always be obtained through observation, and many drivers may not know which information is available on their vehicles. While it will be important for states to determine how different levels of automation influence safety, changes to the crash reporting process and that of downloading EDR data should not result in any additional time or training burden on law enforcement, and, if possible, strive to reduce those burdens.

New forms of automation added to vehicles offer new opportunities for recording pre-crash data beyond these minimal fields. Computer vision sensors, including radar, cameras and LiDAR provide a detailed view of objects surrounding the vehicle at any given time (including vulnerable road users); GPS data mark a vehicle's position; the human-machine interface (HMI) knows whether the human driver or driving automation activated a control; and automated controls informed by planning algorithms know precisely when brake, accelerator, or steering inputs were applied. Connected vehicles will be able to communicate basic safety messages that could also be recorded, and driver monitoring systems will have some measure of driver attentiveness. Figure 5 illustrates the existing EDR data for conventional vehicles and potential CAV data sources for crash reconstruction.

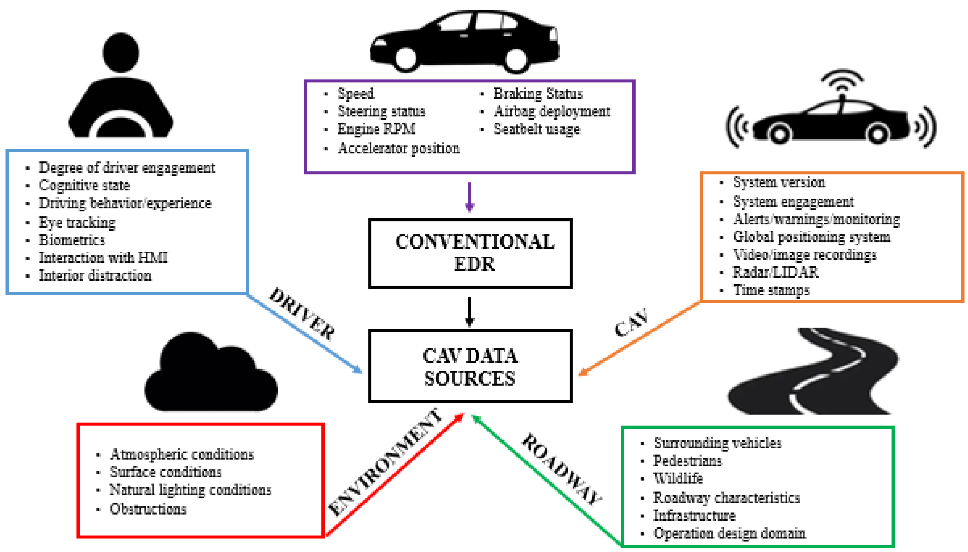

Figure 5. Current data and potential data sources for CAV-involved crash reconstruction

The idea of expanding on the data captured by EDRs is not new. There was disagreement over the number of fields to maintain during the comment period before CFR Title 49 Part 563 went into effect. Some organizations observed that the number and type of data elements were insufficient, while others felt them excessive, with many groups speculating on the future effects of the rule (NHTSA, 2004). The current list of EDR elements, therefore, is the result of considerable deliberation. However, the rule has now been in effect since 2012, and numerous law enforcement personnel now have extensive first-hand experience utilizing EDR data. In this respect, law enforcement personnel are important customers for EDR systems and are uniquely qualified to assess the value of the current EDR system and comment on future needs.

CAV data have the potential to provide important information for crash investigation, related crash reports, and for determining causation. The data will be needed by CAV manufacturers to help reduce future crashes. However, there will be a challenge to ensure the data can be provided in a non-proprietary format that is consistent among manufacturers, and that CAV manufacturers and government agencies can agree on a system to make their data promptly accessible to law enforcement (GHSA, 2019).

While law enforcement is clearly an important stakeholder for CAV deployment, their participation in discussions surrounding CAVs has been limited to date. Jim Hedlund of Governors Highway Safety Association (GHSA) observed that while law enforcement is at the forefront of AV traffic safety issues, law enforcement has not been involved in the discussions around AVs (Hedlund, 2017). There is evidence for lack of law enforcement involvement in the design of the current EDR retrieval process as well. In fact, CFR Title 49 Part 563 refers to the topic of training for law enforcement as “out of scope” for the EDR discussion, even though accessing and reporting EDR data currently requires additional training and equipment. The complexity of the process increases investigation time, leading many crash investigators to ignore the EDR entirely to focus on other aspects of an investigation. In North Carolina, for example, obtaining EDR data is just one of 35 tasks performed by state troopers during an investigation, according to the “Collision Investigation Checklist” (NCSHP form HP-49). The report downloaded from the EDR, which varies in length and can be up to 30 pages, is often appended to a longer Collision Investigation Form. These paper copies of case dockets are stored for a minimum of five years, but there is no central

EDR data archive maintained for NC State Highway Patrol. According to the Collision Investigation Training Coordinator at NC State Highway Patrol, there is no estimate of the number of NC State Highway Patrol cases with EDR reports, because this information has never been tabulated.

A recent RAND report (Goodison et al., 2020) identifying high priority problems and associated needs for law enforcement related to AVs summarizes many of the key issues motivating this study. Law enforcement officers are already performing traffic stops and investigations that involve different types of automated vehicles. These incidents can only be expected to increase over time. In their summary, the RAND authors identified 17 "top-tier" needs related to law enforcement and AVs. A key issue, related to the present work states:

> "At present, law enforcement does not have a thorough understanding of the kinds of information that is being collected by AVs and how long it is maintained so that they can request the most appropriate information (for the purposes of crash reconstruction)" (Goodison, et al., 2020; p.8).

In response, RAND recommended that a survey of law enforcement and crash reconstruction experts be conducted to identify the "type and quality of information that would be most useful" (p.8). This conclusion is consistent with the motivation and goals of the present study.

For this research effort, we investigated how the potentially rich dataset available through CAVs can be leveraged to improve crash investigations in the future and overall transportation safety (Figure 4), with a focus on the needs of the law enforcement personnel who access the data. As CAVs are still in a testing phase, there is an opportunity to standardize the data before deployment, after which it will become more difficult to make changes.

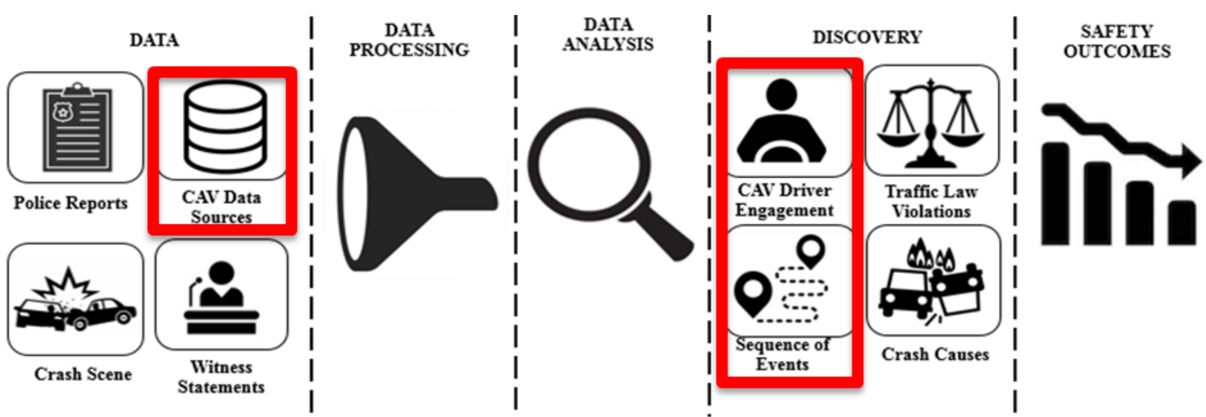

Figure 6. Data framework of accident reconstruction for CAV-involved crashes

Law enforcement is a key stakeholder with respect to AV safety issues, but they have had little involvement in AV discussions. Thus, a goal of this study is to begin to include law enforcement by collecting their opinions on the effectiveness of EDR data for crash investigations. Including law enforcement in discussions around crash investigation allows us to leverage current crash investigation procedures including EDR technology as we progress to accommodate CAV technology.

Methods

This research included three main components. First, we assessed the capabilities of CAV sensors with a review of relevant literature to understand which are best suited for informing crash reconstruction. Next, we performed text mining with the results of the literature review to assess which topics were of key interest to researchers to determine whether the topics of interest for researchers would align with law enforcement interests. Finally, we interviewed and surveyed law enforcement officers to collect their opinions on how EDR data should be augmented with CAV data during investigations.

Literature Review and Synthesis

A systematic literature review and synthesis was completed to determine the function, data collection ability, and limitations of various CAV technologies including onboard units (OBU), GPS, ultrasound/ultrasonic, infrared, LiDAR, radar, and cameras. Most of the papers used in this literature review were found through Google Scholar by searching the name of each sensor technology that was analyzed (as mentioned above). These sensor terms also included additions such as “AV”, “CAV”, “automated vehicles”, and “limitations”. Additional sources were found using the references listed in the initially selected papers. The NTSB evaluations on crashes involving automated vehicles were included in this study to aid in the determination of the faults in the sensors used.

An assessment was performed to determine the technical capabilities of various CAV sensors. The technical capabilities of various CAV sensors (GPS, OBU, Infrared, Ultrasound, LiDAR, radar, and cameras) were then measured and compared based on the results of a systematic text analysis and literature synthesis.

Literature Review and Synthesis Results

CAV sensors are presented and evaluated including GPS, OBU, and five external sensors (camera, radar, LiDAR, infrared, and ultrasound). The following discussion includes the limitations and ADAS applications associated with each AV sensor studied. GPS sensors can be installed in vehicles to detect position and speed information including linear acceleration, angular velocity, and real time position information (Du & Barth, 2008; Hernandez & Kuo, 2003; Milanes, et al., 2008). However, GPS typically has a slow update rate and may not support acceleration calculations in real time; they cannot work properly in the presence of obstacles that block atmospheric signals including trees, tall buildings, and tunnels (Milanes, et al., 2008). In addition, GPS is susceptible to several errors including atmospheric errors, refraction, multipath errors, and satellite clock errors (Redmill, Kitajima & Ozguner, 2001).

OBUs are used as a communication tool for CAVs that work in combination with roadside units (RSUs) and designated short-range communications (DSRC). These units collect data from individual sensors within the CAV and generate information-rich Basic Safety Messages (BSMs) that are used in V2V and V2I communications (Alam, Saini & Saddik, 2014; Luo & Liu, 2018; Hoque et al., 2018; Hoque et al., 2020). BSMs are so rich in information that they can be used to understand behavior of other drivers (Ahmed, Hoque & Khattak, 2016; Arvin, Kamrani & Khattak, 2019; Kamrani et al., 2020; Khattak & Wali, 2017). OBUs are utilized for collision warnings (Liu & Khattak, 2016; Zhao et al., 2019), pathfinding (Hoseinzadeh et al., 2020), merge assistance (Ahmed et al., 2017), and speed suggestions (Cheng-Hsuan et al., 2014). One mutual weakness of both OBUs and GPS systems is that they are vulnerable to cybersecurity attacks (Luo & Liu, 2018; Sharma et al., 2017; Petit & Shladover, 2014). Notably, cybersecurity concerns have resulted in automobile manufacturers moving to place additional security features on the vehicles. This has changed how the EDRs are accessed in some cases. Therefore, cybersecurity is not only a concern for future CAVs, but a current concern as well.

Millimeter Wave Radars (MMWR) have been used for detection of obstacles, roadways (Kodagoda et al., 2002), and pedestrians (Combs et al., 2019; Bartsch et al., 2012; Manston, 2011; Turnbull et al., 2017). Radar is robust in most types of extreme weather (Steijbaeck et al., 2017). A known limitation of radar technology is the low capability of the sensor to the detect lateral movement due to Doppler effect technology (NTSB, 2017; Kellner, et al., 2013). Another known limitation of radar technology is the poor resolution, which makes the detection of stationary objects unreliable (Combs et al., 2019; Bartsch et al., 2012; Manston, 2011; Turnbull et al., 2017), and the detection of children and pedestrians difficult (Combs et al., 2019).

Ultrasound sensors are environmental sensors that are used in object and pedestrian detection (Arai & Nakano, 1983). The limitations of ultrasound sensors include their lack of robustness in detecting various types and colors of clothing due to varying degrees of reflection (Kremser, 1997). Other issues associated with ultrasound technology include distinguishing the echoes of obstacles and interfering signals caused by other vehicles or objects along the roadway (Kremser, 1997).

The central application of infrared sensors in automated vehicles is pedestrian and vehicle detection (Bertozzi et al., 2005; Broggi et al., 2004; Der et al., 2004). Infrared sensors are robust when detecting pedestrians with different kinds and color of clothing (Der et al., 2004). Infrared sensors are limited in function because noise generated by surrounding buildings, moving and parked cars, road signs, traffic signals, and different illumination conditions (Der et al., 2004). In addition, these sensors operate optimally at night and in low temperature conditions as warm weather conditions can interfere with the detection capabilities of the sensor (Bertozzi et al., 2005).

LiDAR is a range finding environmental sensor that can be used for adaptive cruise control, collision avoidance (Catapang & Ramos, 2016; Liu et al., 2014), and object recognition (Kodagoda et al., 2002; Lehtomaki et al., 2010; Gudigar et al., 2016; McElhinney et al., 2010).[3] In addition, LiDAR has been found to have an improved spatial resolution and range accuracy compared to MMWR (Kidono et al., 2011). LiDAR systems function best with good lighting (Petit et al., 2015), but they can operate well at night (Combs et al., 2019). A limitation of LiDAR technology is its inability to work in foggy weather (Kidono et al., 2011) and in most extreme weather conditions due to wet, reflective surfaces (Combs et al., 2019).

Cameras have been used in moving vehicles for lane detection, landscape detection, object detection, object tracking, and video-based navigation (Petit et al., 2015). Some challenges faced by cameras include vision-based object detection include a non-constant landscape, differing lighting conditions, and the possibility of remote cyber-attacks (Petit et al., 2015; Betke et al., 2000). Additional limitations of cameras include limited visibility (at night or in extreme weather

[3] Note that radar or machine vision is more typical for adaptive cruise control and automation functions. In 2021, LiDAR remains relatively expensive and hence it has not been used widely.

conditions), the need for constant calibration, and the easily obstructed line of sight (by buildings, large trucks, or dirt and grime build-up on the lenses (Wan et al., 2014)).

As each sensor has its own limitations, sensor fusion is a very common practice that allows a system to leverage several sources of data for greater reliability. Within the range of environmental sensors included in this study, Schiffmann et all (2017) suggested the combining camera and radar technologies with the key advantage of this combination being an object tracking system. Similarly, Broggi et al. (2004) merged infrared technology and cameras to generate an enhanced pedestrian detection system. Steinbeck et al. (2017) suggests the combination of radar and LiDAR data, which would create a comprehensive representation of the environment outside of the vehicle. Additionally, WaveSense has combined radar, LiDAR, and GPS data to map the terrain below the road, and then match this information with GPS tags to allow for vehicle location estimation (Wavesense, 2019).

Literature Review and Synthesis Summary

The results of the text analysis informed the measures (i.e., maximum detection distance and object detection) used to compare the studied sensors (OBU, GPS, ultrasound, infrared, LiDAR, and radar) in the literature synthesis. The literature synthesis aided in the determination of the most comprehensive and user-friendly combination of the studied environmental sensors. This comprehensive environmental sensor was informed by the outcome of the surveys.

An effort was made to have numerous sources for each sensor type, but there could exist selection bias in the limited selection of sensors. This study was completed by evaluating each sensor separately, but these sensors are not likely to be standalone in application, instead the expectation is that several sensors are merged in CAVs. This study examines a limited number of specific sensors that are used within CAVs. They are increasingly being used as low-level automation technologies, i.e., advanced driver assistance systems that are SAE Levels 1 and 2.

Text Mining

Text mining was performed on the references identified for the review using a combination of QDA Miner 5 and WordStat 8 to evaluate the literature to find the key words and their frequency. The references used in this text analysis were chosen through the completion of a systematic review of the CAV technologies: GPS, OBU, LiDAR, radar, infrared, ultrasound, and cameras. Within the text analysis software, an inclusion dictionary was developed to perform content analysis of the references used in this study. After the initial analysis, data processing was completed to exclude words from the analysis with little discriminative value. These excluded words were added to an exclusion list. The selected outputs of the software include a the most frequently used topics and keywords. The most frequent keywords from the text analysis were then used to inform the literature synthesis.

The created corpus of literature from this review contained 55 bodies of relevant work. In the end, text analysis was completed on 47 references (see Appendix B for full list). Some texts chosen for the analysis (Appendix B, references 58-65) were unable to be extracted into the text analysis software and were therefore not included in the text analysis. The results of text analysis then informed the measures utilized in our study to determine the usefulness of each sensor. Such measures include the function and various limitations of the chosen technologies.

Keyword Frequency

A key output of the text analysis is the measure of keyword frequency i.e., the number of occurrences of the keyword in the corpus of collected literature. The keyword “control” has the highest measured frequency of the keywords in the inclusion dictionary, appearing 923 times in 75.44% of case documents. Other frequently appearing words are “radar”, “object”, “range”, and “detection”, with frequencies of 782, 723, 715, and 522, respectively.

Topic Frequency

Table 3 lists the results of the completed topic extraction of the text mining software QDA Miner. The software was used to identify seven topics that most frequently appeared in the created corpus. Each of the studied sensors is represented in some capacity in this table. LiDAR technologies is one of the main detected topics (topic 5). Radar is represented directly in topic 7 and is indirectly represented by “doppler” in topic 2. Topic 7 includes camera technology along with the associated keywords of bounding boxes which are used for pedestrian detection with cameras.

For the topics “LiDAR”, “object detection”, and “steering control and movements”, the order of the most frequently occurring topics coincides with the percentage of cases in which the topic appears. “LiDAR” is the most frequently occurring topic (1485 occurrences) and is present in 94.12% of the cases in the corpus. The topic of “object detection” has the next highest frequency, (with 1166 occurrences) and the next highest percentage of cases (88.24%). The topic “steering control and movements” has a frequency of 786 and is present in 84.31% of cases in the corpus.

Table 2. Topics Table from CAV technology literature

No.	Topic	Keyword Examples	Coherence (Eigenvalue)	Frequency (Keyword Occurrences)	% Cases
1	**Security challenges**	ATTACKS; THREATS; SECURITY; MALWARE; MALICIOUS; MALWARE ATTACK; SECURITY THREATS; …	0.505	655	84.31%
2	**Sensor coverage**	ANTENNA; DOPPLER; AMPLITUDE; FREQUENCY; RANGE; PULSES; PHASE; RECEIVE ANTENNA; RANGE FREQUENCY; OVERLAPPING RANGE; STAGE DOPPLER; SUGGESTED SPEED RANGE; RANGE SPECTRUM; PROCESSING TIME; …	0.465	571	80.39%
3	**Monitoring Driver**	SLEEP; DISTRACTED; VIGILANCE; REACTION; FATIGUED; WARNINGS; CONFLICT; REACTION TIME; SLEEP DEPRIVED; REACTION TIMES; DIMINISHED VIGILANCE; SLEEP DEPRIVATION; …	0.439	437	19.61%
4	**Steering control and movements**	LATERAL; STEERING; CURVATURE; GPS; WHEEL; STEERING WHEEL; LATERAL DISPLACEMENT; LATERAL ACCELERATION; …	0.429	786	84.31%
5	**LiDAR**	LiDAR; LASER; SCANNING; ENVIRONMENT; BEAMS; RESOLUTION; RANGE; SENSING; DETECTION; DETECTION AND RANGING;	0.406	1485	94.12%
6	**Adverse Weather**	ADVERSE; ADVERSE WEATHER; SURFACE CONDITION; DAYLIGHT TIME; WEATHER CONDITION; …	0.391	497	68.63%
7	**Object Detection**	PEDESTRIANS; VISION; PEDESTRIAN; FRAMES; DETECTION; CAMERA; TRACKING; OBJECTS; SCENE; HUMAN; FRAME; RECOGNITION; PIXELS; MOTION; RADAR; HEAD; VIDEO; BOUNDING BOXES; PEDESTRIAN DETECTION; …	0.360	1166	88.24%

Text Analysis Summary

The most frequently appearing keyword “control” has the highest measured frequency of the keywords in the inclusion dictionary. Other frequently appearing words are “radar”, “object”, “range”, and “detection”. With 715 occurrences, radar is the only sensor directly included in the five most frequent keywords. However, the remaining top keywords refer to CAV applications of the studied sensors. For example, the keyword “detection” can refer to pedestrian detection, or it can reference its combination with the other frequent keyword “object”, as in object detection tracking. “Range” refers to the maximum distance that a sensor can detect. These frequent keywords were then used to influence measures of sensors which were evaluated in the literature synthesis. Thus, range, object detection, and pedestrian detection are included in the compared capabilities of the studied CAV sensors.

Although the most frequent topics are “LiDAR”, “object detection”, and “steering control and movements”, the important topics in Table 3 are object detection, sensor coverage, and steering control. Object detection and pedestrian detection are detected topics that are repetitions of the findings in the keyword frequency analysis. This repetition of the topics object and pedestrian detection confirm the relevance of these topics and in turn support the use of these measures being used to compare the selected CAV sensors.

Table 2 is a compilation of the limitations of the studied sensor technologies including range, pedestrian/object detection, vulnerability to cyber-attack, ability to work at night, and robustness against weather. Comparing the external sensors in Table 2, one can determine the sensor with the least reductive limitations. Generally, sensor technology, sensor fusion, and algorithm performance are all determining factors in real-world performance. In terms of their performance, a weakness of ultrasound sensors is their struggle to detect pedestrians in different colors and types of clothing (Arai & Nakano, 1983). A limitation of the infrared technology is the inability to successfully operate in warmer temperatures, such as during the summertime. Cameras are limited by line-of-sight detection distance and their loss of function at night and in extreme weather conditions. This leaves LiDAR and radar as the front runners of the studied environmental sensors. Radar is capable of functioning in adverse weather, but LiDAR is limited by fog. On the other hand, LiDAR has detection capabilities that are nearly twice that of radar vision. Based on function in adverse weather and vision/detection capabilities, LiDAR can be considered the sensor with the most comprehensive rendering of the environment outside of the vehicle. This conclusion can be combined with the familiarity of cameras and their outputs translates to the combination of cameras and LiDAR technologies providing comprehensive and user-friendly environmental data from an autonomous vehicle.[4]

Table 3. Sensor Limitations found in the literature

Sensor	Pedestrian & Object Detection	Pedestrian & Object Speed / Tracking	Robust against clothing color/type?	Robust against weather?	Work at night?	Vulnerable to Cyber-Attack?	Max. Detection Distance (m)
GPS	-	-	-	Yes	Yes	Yes	-
OBU	-	-	-	Yes	Yes	Yes	-
US	Yes (Poor)	No	No	Yes	Yes	No	Line of Sight
IR	Yes	No	Yes	No (high temps)	Yes	No	20
LiDAR	Yes (Very Good)	Yes	Yes	Yes (except fog)	Yes (Very Good)	Yes	300
Radar	Yes	Yes (If v>0)	Yes	Yes	Yes (Very Good)	No	160
Camera	Yes	Yes	Yes	No	Yes (Limited)	Yes	Line of Sight

A limitation of this portion of the review was that the text analysis was completed using a software that was not able to extract the content from a few of the relevant sources. While there were only a few studies which were not able to be used in the text analysis with QDA Miner, the information

[4] Notably, the data are not always user-friendly. For instance, some of the raw data can be messy and difficult to interpret. The user of these data must correctly interpret the information. Using basic EDR data requires ensuring that it is both valid and related to the collision in question. Along these lines, using data from CAVs will require much more careful validation and interpretation by law enforcement users and accident reconstruction experts.

from these sources may have had the potential to reveal additional topic relationships and keyword frequency.

Law Enforcement Survey

The assessment of law enforcement opinions on augmenting EDR data included three parts. Each part was designed to inform the subsequent part completed by the research team. Part 1 included small group semi-structured interviews with expert crash investigators who provided an overview of the crash investigation process with an emphasis on EDR data analysis. Part 2 was a workshop conducted with law enforcement in-person to collect law enforcement opinions. Part 3 expanded on Part 1 and Part 2 by distributing a survey to law enforcement participants nationwide.

The semi-structured interview (also referred to as ethnographic interview) is a common qualitative research technique that includes a combination of open- and closed-ended as well as follow-up questions. The technique allows a researcher to collect open-ended data and explore participant thoughts, feelings, and beliefs about a topic. This interview format is ideal for collecting information to inform the design of large-scale surveys, configuring a focus group, and constructing a research strategy.

The semi-structured interviews included two state troopers with the North Carolina State Highway Patrol and two professional accident reconstructionists. The officers are experienced crash analysts and reconstructionists. One professional reconstructionist is a forensic Human Factors scientist accredited in traffic accident reconstruction, and the other is a reconstructionist and adjunct professor with the University of Tennessee-Knoxville who teaches graduate courses in Traffic Accident Reconstruction. The purpose of the semi-structured interview was to develop the language for the subsequent workshop and survey design and to begin collecting law enforcement perspectives on how AV sensor data could benefit crash reconstruction. The in-person session lasted two hours and follow-up questions were addressed via email.

The content of the semi-structured interviews was used to inform the framework for a law enforcement workshop conducted at the 2019 North Carolina Traffic Safety Conference & Expo, a statewide event devoted to traffic safety education, programming, and enforcement. The purpose of the workshop was to collect additional opinions on which AV data to use during crash investigations along with opinions on current EDR data collection procedures. 45 law enforcement officers participated, along with other transportation professionals. The workshop was also used to pilot the online survey developed following the previous interviews.

A brief Qualtrics survey was distributed to state law enforcement offices in California, Arizona, Florida, Michigan, North Carolina, Washington, Texas, Pennsylvania, New York, and Virginia. These states were selected due to activity in AV development, testing, and/or regulation. The survey included the following three questions (see Appendix A for the complete survey):

1. *Thinking of the future of collision investigation, what are the top three pieces of information (that are not available today) you would most like to get from a vehicle automatically after a collision?*
2. *What do you like most about the current process of using Event Data Recorders (EDRs) for collision investigation?*
3. *What could be improved about the current process of using Event Data Recorders (EDRs) for collision investigation?*

The responses were entered via free-form text. Responses were anonymous and participants were asked to confirm that they worked in law enforcement along with their role in investigation (technician and/or analyst). The survey remained open for six weeks between May 1 and June 12, 2020. A total of 16 responses that met the screening criteria were recorded. All respondents worked in law enforcement, and all had experience extracting data from EDRs.

Survey Results

When asked what information they would like recorded automatically during a crash event, video/image data was identified most often (17%) by law enforcement officers. This was followed by vehicle reaction time/performance (i.e., information about automation performance that may contribute to a crash; 12%), speed (10%), driver/passenger video (10%), ADS/driver in control (7%),[5] driver input (5%), and timestamp (5%) data. These results are summarized in Table 4. CAV information most requested by law enforcement.

Table 4. CAV information most requested by law enforcement

Desired information	% Responses
Crash video/image	17%
Automation performance	12%
Speed	10%
In-vehicle video	10%
ADS/driver in control	7%
Driver input	5%
Timestamp	5%

The responses to the other two survey questions were less varied. When asked to provide positive feedback about EDRs, respondents unanimously acknowledged the abundant information and helpful data that EDRs can provide to collision investigation. When asked about possible improvements, responses were less consistent. The most frequent response of the law enforcement officers was the desire for universal cables/single system, identified by 40% of the respondents. This is not surprising, given the high-cost burden of even a basic EDR system. The remaining responses were unique to each respondent.

Additional findings

In addition to the survey results, the officers participating in the interviews and workshop provided several insights about EDRs and CAV data.

- *Camera data*. Officers mentioned GPS and camera data frequently in both settings. This was consistent with the results of the survey. Camera or other visual data would be desirable because physical evidence can disappear rapidly from a crash scene. This is particularly relevant when the investigation changes due to the addition of new information (e.g., a toxicology report). A snapshot that preserves the scene that can be accessed later

[5] Note that this category seems relatively low, given that law enforcement investigations are focused on whether a criminal or civil violation has occurred. As higher levels of automation emerge (i.e., SAE Levels 3+), the question of who is driving becomes critical for law enforcement. This result may indicate low awareness by law enforcement about the changing role of drivers in vehicle automation.

would be helpful. Automated vehicle camera and GPS data could potentially be used in criminal investigations.

- *Data duration*. Most EDR data includes five seconds of data before and following a crash event. A longer data window could show if a driver were driving erratically prior to a crash. The current practice of keeping a 5-second data record may not be sufficient to reveal lane deviations or other aggravating factors that occur prior to a crash. A similarly long record of control inputs would also be helpful.
- *Training*. Participants expressed a need for guidance on how fault should be determined for collisions with AVs when the driver or the vehicle may be responsible for performing the dynamic driving task.
- *Training materials*. Participants indicated that current crash training materials and methods have not kept up with modern technologies. For example, motor vehicle collisions do not generate as much physical evidence as they did in the past. Antilock brakes do not leave the same tire impressions on pavement that are provided in many training examples. Notably, speedometers are driven by stepper motors on some vehicles, meaning that the speedometer will display the speed at the time power was lost. However, this may not be fully covered in training for crash investigators. Training materials also need to account for the fact that many investigations now take place offsite.[6]
- *Driver monitoring*. Biometric markers that are predictive of driver distraction, impairment or fatigue would be helpful during investigations. This entails both access to the data and being able to integrate and interpret biometric data.
- *Delta-V effectiveness*. There is sometimes a need for historic data that is not linked to a collision (i.e., no significant change in delta-V), such as “non-occupant” collisions with pedestrians. EDRs record multiple events, which can make it more challenging to identify the most important crash event in the sequence. Deployment thresholds vary by manufacturer and sometimes by model; this information is not shared with law enforcement.
- *Reports*. Report formats vary among manufacturers, and some are more helpful than others in the courtrooms where they are widely used. For example, Dodge includes helpful user-friendly visualizations and Toyota includes graphs and tables of numbers. Visualizations like those implemented by Dodge are helpful during trials, along with the raw data used for reconstruction.

Investigators also commented on the usefulness of third-party tools for investigation. Specifically, investigation tools currently made by Berla (www.berla.co) can be used to access a vehicle’s infotainment system to gather GPS, vehicle event, mobile phone and media data. These data elements can be used during criminal investigations to determine whether a person (via a connected mobile device) was at a specific location at the time of an event, as indicated by a GPS. However, Berla systems and the training to use them can be expensive and few agencies have them. Furthermore, Berla is not authorized by manufacturers and can require destructive examinations of vehicles (e.g., removing parts of the dash or removing head units). GM’s Onstar technology can perform similar functions to Berla, according to the officers interviewed.

[6] Compounding this issue is that agency budgets are limited, resulting in few well-trained officers.

Survey Discussion

Law enforcement responses to the first survey question contained multiple references to information that is typically captured by the environmental sensors of CAVs. Specifically, the responses of video/image data and driver/passenger video can be provided from the information that is collected and captured by environmental sensors. The recommended comprehensive environmental sensor from the literature synthesis (comprised of the combination of camera and LiDAR technologies) would provide a complete and user-friendly depiction of the environment both around and within the vehicle. Additionally, the results of the survey indicate that law enforcement officers acknowledge the power of the information that can be gathered from an EDR, and the desire for a universal cable for all EDRs was confirmed. Overall, more consistency was observed within the in-person survey results compared to the online survey results. This is likely due, in part, to the overview of ADS technology that was provided as part of the workshop. The presentation may have influenced the results as the in-person participants had a similar baseline understanding of the technology, while the background of the online respondents was unknown.

A possible limitation of this study is the number of survey responses. The survey was distributed to law enforcement agencies in 10 different states and kept open for five weeks. Recruitment emails were sent by other law enforcement officers in the hopes that there would be a higher response rate if recruitment was performed by a peer. At the end, the survey response was limited, which may have skewed the conclusions of the survey data. However, when comparing the survey data to the expert interviews and related efforts performed by other groups (see Related Work), there is some overlap.

The law enforcement responses were also influenced by their EDR experience and exposure to ADAS technology. Most recommendations addressed shortcomings with existing EDR data (speed errors, hardware issues), lack of available information about ADAS features (ADAS features in vehicles), and exposure to related technology (e.g., cameras and the Berla system). It is possible that, with additional training and exposure to ADS systems, the law enforcement would have more recommendations for system improvements. This highlights the need for additional training in ADAS and ADS topics for law enforcement.

General Discussion

Crash reconstruction is changing rapidly with more pre-crash information becoming available through various sensors. There is an opportunity to leverage the large-scale data being collected and stored in connected and automated vehicles. The review of literature on sensors being used in CAVs shows that range, pedestrian detection, and steering control are important issues with regards sensor capabilities. The results from the survey of law enforcement confirm the desire and need for data from visual sensors, along with information about the state of the automation. There is also broad support for uniform, streamlined methods for accessing objective data following a crash.

The results of this research are based on the insights provided by a comprehensive literature review and interviews with law enforcement who conduct crash investigations. The data gathered from the interviews are valid as substantial efforts went into carefully documenting the interview data. Additionally, the findings are based on input from key stakeholders, i.e., law enforcement, who are critical for the generation of future safety data.

This research also contributes by answering a fundamental question about crash investigations i.e., what new data to use for CAV involved collisions. Clearly, LiDAR and radar data combined with camera data provides keys to pre-crash contributing factors. Strategies for mitigating these factors are important for future research. This research will likely impact stakeholders, especially law enforcement and crash investigators by motivating the application of a data-driven approach to crash investigations. This research can be used to support the collection of ADS data, developing appropriate protocols to analyze the new data from LiDARs and cameras and mandate to include ADS data along with EDR reports.

Related Work

This research project is consistent with previous recommendations advocating for law enforcement officer input in the design of automated data collection tools to assist in crash reconstruction. To the best of our knowledge, this current effort remains the only attempt at this research. However, there have been some similar projects taking place in the U.S. and abroad that are relevant and could influence future work. Those efforts are summarized in this section.

SAE Automated Driving System Data Logger (J3197)

The SAE Automated Driving System (ADS) Data Logger recommends data elements for SAE Levels 3-5 (i.e., automated driving systems) that can describe the events of a crash or near-crash (SAE, 2020). The recommended practice provides definitions for the data elements, recommends a minimum set of data elements, and specifies a record format for motor vehicles. The data elements in the ADS data logger come from vehicle sensors, such as cameras and LiDAR, that track driving information when there is no driver actively performing the driving task. In this sense, the ADS sensors would provide the eye-witness account in the absence of a human driver. The ADS Data Logger would not be intended as a replacement to an EDR; rather, the two would operate in conjunction with traditional reconstruction methods (e.g., analysis of physical evidence) for a more comprehensive crash reconstruction.[7]

Like the EDR, the ADS Data Logger would record information leading up to a collision. This would include ADS operational data and information about the crash environment. Operational data includes details about the triggering even and ADS-requested control, such as acceleration and braking. Environmental information includes navigation information, such as location and heading, and details about the roadway, such as roadway geometry and vehicle lane position. A strength of the ADS data logger would be the inclusion of an "annotated image" obtained from one or more cameras, which would include a snapshot of the crash scene with labels and bounding boxes describing identified object in the area.

While the ADS Data Logger would be designed to record a data snapshot in parallel with the EDR (based on the delta-V), it would also be available for other triggering events so it could also be used in the event of crashes where another vehicle was not involved, such as a collision with a

[7] Note that integrating different datasets (with no common timestamp) for analysis is going to be challenging for crash investigations. Addressing this will be a major issue in CAV supplemented crash investigations.

pedestrian. The authors acknowledge that ADS technology is still a work in progress, and the ADS Data Logger is subject to change as the technology evolves.

Data Storage System for Automated Driving (DSSAD)

The Data Storage System for Automated Driving (DSSAD) is part of the World Forum for Harmonization of Vehicle Regulations (WP.29) framework document on automated/autonomous vehicles. The WP.29 framework identifies principles for the safety and security of ADAS and ADS vehicles. The DSSAD is one of serval principles within the framework developed by the international working group.

The DSSAD reports two key fields, summarizing the status of the vehicle's automated system and who was in control at a specific point in time. A limitation of the EDR.is that one would still need to associate the record with the actual crash event, requiring datasets to be combined with the EDR data. Unlike the EDR, the DSSAD would provide continuous storage due to the limited size of the data involved. The data would then be able to be provided by request, rather than following a triggering event. This would not only allow an investigator to determine who was in control during a severe collision, but also following a collision with a smaller vehicle or pedestrian, a traffic offense, or an unsafe maneuver.

The DSSAD would include a timestamp along with interactions between the driver and the system (i.t., who/what was requested to be in control and who/what was in control), including the fields needed to record the automated vehicle data in MMUCC-compliant crash reports. The specific recommended fields include the date and time, on/off status of the automation, the transition request, and the time of the takeover/transition.

Vehicle Control History (VCH)

The vehicle control history (VCH) is a specialized EDR that has been available in many Toyota vehicles since 2013. The VCH continuously monitors vehicle systems and driver inputs for system events including lane departures, strong/emergency braking, antilock brake activation, sudden steering, sudden acceleration. Along with each event, the VCH stores the vehicle speed, engine RPM, throttle, acceleration, and steering angle. These values are stored 5 seconds before and 5 seconds after the event, along with the odometer reading and a timestamp. This is somewhat different from the EDR as the date are recorded for more types of events, and the data include driver and automation control responses.

Collects data by monitoring for certain triggers related to vehicle systems and driver inputs. A crash event is not required to trigger a VCH event. The VCH triggers based on system-related events (lane departure, pre-collision braking, or ABS activation) and driver-related events (sudden braking, sudden steering, sudden acceleration). The VCH stores data such as vehicle speed, engine RPM, throttle opening, acceleration, and steering for 5 seconds prior to an event and 5 seconds after an event. For each event, the associated ignition cycle, date and timestamp according to the GPS system, event triggered, and odometer are recorded." VCH has a total of 26 triggers, such as electronic stability control (ESC) activation or sudden accelerator presses. The system also has a large amount of storage (by contemporary standards), which can be used to establish driving patterns well before the event in question.

Advanced Automatic Collision Notification (AACN) system

The Advanced Automatic Collision Notification (AACN) is a system being explored by Toyota and Bosch to help the vehicle driver and passengers following a severe crash (Iyoda et al., 2016). The

AACN transmits the delta-V and seatbelt data to a data center following a crash. These data elements are then used to estimate the severity of the crash, which is then forwarded to local hospitals and first-responders to inform the dispatch of an ambulance or helicopter to the crash scene for a faster response.

In addition to its support of the vehicle occupants, the AACN is also noteworthy because it includes an automated data upload to a cloud storage system following a crash without the use of additional hardware and software on site. This is a significant advantage over current EDR technologies, which require additional hardware, numerous cables, and a technician with specialized training.

EDR Data Archiving

An issue during the workshop with law enforcement was that EDR data files are not generally stored in a central data repository. However, a representative sample of EDR images are included in the Crash Investigation Sampling System (CISS). CISS is part of NHTSA's crash data collection program and represents a randomly selected sample of U.S. crash reports in which at least one passenger vehicle was towed from the crash scene. 2512 CISS records included EDR files (approximately 94% of CISS crash reports) in 2018. An online tool to view cases, data files and other CISS resources are available online: [https://www.nhtsa.gov/crash-data-systems/crash-investigation-sampling-system.](https://www.nhtsa.gov/crash-data-systems/crash-investigation-sampling-system)

EDR files imaged using the Bosch CDR kit during an investigation can be automatically attached to a CISS crash file through CISSWeb, the data entry software used to populate CISS (Mynatt et al., 2017). When files are not available electronically, a technician will manually transcribe the information into the database from a pdf. EDR data elements are maintained in six relational tables in CISS (Figure 5 [Radja, Noh & Zhang, 2020]).

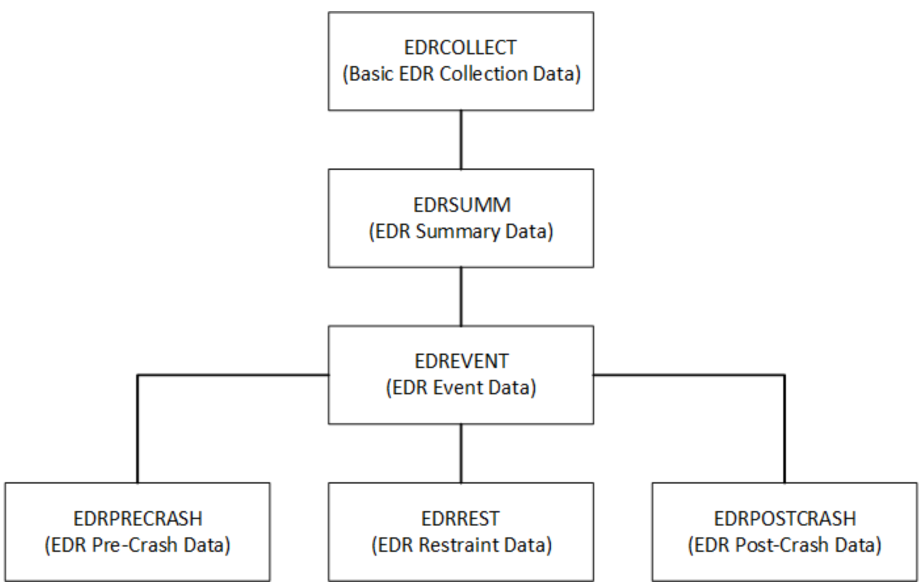

Figure 7. EDR Data Files included in the NHTSA Crash Investigation Sampling System (CISS)

The EDRCOLLECT table includes information about the method used by an investigator to download the EDR data and whether the download was successful. EDRSUMM includes information about the data file, such as the CDR version and the size of the EDR file. The remaining tables, EDREVENT, EDRPRECRASH, EDRREST and EDRPOSTCRASH include the EDR data, including fields outlined in CFR Title 49 Part 563.

CISS provides an example of how crash data recorded and stored by a vehicle can be maintained in a database. A relational structure is required to maintain the hierarchy of data tables needed to organize the large amount of data. This includes the metadata describing the data download, equipment used and file size, airbag and seat belt status, and summary information about the crash (e.g., maximum Delta-V), as well as the time-series data recorded immediately prior to and following the crash (i.e., the pre- and post-crash data elements). EDR tables in CISS can become quite large, including over 500,000 pre- post-crash data records describing the 2,512 EDR records in 2019. Replacing or adding annotated image or video data to those crash records would require substantial file storage space.

CISS includes only a fraction of EDR files downloaded by crash investigators annually; however, as the CISS Analytical User's Guide indicates, not every EDR file can be automatically uploaded to CISS and some need to be manually entered from pdf files. This demonstrates there are still some obstacles to reliably uploading EDR files, even when experienced investigators are involved in the process.

Future Research and Next Steps

The results of related work and the surveys of law enforcement show there is a need for data collection and analysis protocols that investigation teams could follow to obtain, download, and analyze CAV data. At a minimum this would include performance of the driving task by an automated system as well as storing visual representations of a crash scene. While analysis of CAV involved crashes can yield important new insights, CAV crashes will require police to deal with complexities of new automation and communication technologies and disengagements (whether human-initiated or ADS-initiated) of the ADS during collisions. Therefore, a new dimension of disengagements emerges as salient in CAV crashes. The literature has shown that in current AV testing, humans are disengaging more than ADS. And where ADS disengage, software and hardware & planning discrepancies are the important reasons. These require continued research, along with involving more stakeholders that are involved in the crash reconstruction process and new technology testing programs at the state level.

One finding of the current work was that the inclusion of stakeholders in the EDR and CAV discussion should extend from law enforcement officers to professional crash investigators. Law enforcement officers may not work with EDRs on a regular or extensive basis, and collision investigation is a relatively small portion of law enforcement. However, professional crash investigators may have more extensive expertise and experience with EDRs and the outputs of EDRs. Extending the survey to professional crash investigators would allow for more refined and specific results. In addition, the contributions from the law enforcement officers participating in the workshop and those responding to the online survey suggest there is a need to incorporate CAV technology concepts in law enforcement training. This was supported by anecdotal comments from the officers following the workshop, but not formally recorded as part of data collection. Future efforts should address this topic directly and determine which CAV topics would benefit officers now and in the future.

On the other hand, simulation platforms provide capability to generate synthetic data for early evaluation of CAV sensors and their potential capabilities in accident reconstruction. Synthetic

Sensor Data Generation is the task of producing synthetic data under simulation that has the characteristics of real data that might be collected on an actual vehicle driving on public roads. One of the platforms that is being promoted by the USDOT is CARLA, which can simulate different CAV sensors such as LiDAR, radar, and cameras. Future research can utilize these rich data sources to develop appropriate protocols to harness this information in crash investigations.

This project can be expanded to incorporate commercial motor vehicle (CMV) fleets. Heavy CMVs are equipped with data-recording engine control modules called HV-EDRs. While these are not intended for use as EDRs, HV-EDRs can reveal information about vehicle conditions and driver inputs leading up to a crash. Furthermore, CMV fleets have found significant benefits to using active safety technology such as collision mitigation braking (CMB) and forward collision warning (FCW). These systems often can record rich datasets related to a collision event, but few agencies have the training and equipment to access the data. Finally, CMV fleets are highly interested in vehicle automation to reduce driver-associated costs, therefore CMV fleets will be one of the earliest large-scale deployments of automation. Future research should be conducted to investigate 1) the feasibility of investigators obtaining HV-EDR data, 2) the feasibility of investigators obtaining CMB/FCW data, and 3) large-scale automation in CMV fleets.

Conclusion

While current EDRs provide effective supplemental information that supports physical evidence, CAV sensor data can serve as an automated witness that can accurately preserve the scene of a crash event. The ability to record, report, and store accurate crash data would benefit future investigators, safety researchers, and manufacturers by improving the reliability of crash reports. This study assessed law enforcement stakeholder perspectives on how this increasingly available CAV data can be leveraged to improve crash investigation procedures. As part of this effort, we performed a supplementary literature review to identify which sensors are commonly included in CAV research to compare with the data collected from law enforcement.

Key findings of this research include:

- The literature on CAV sensors shows that functional range, pedestrian detection, and steering control are the most important capabilities
- The recommended environmental sensor combination includes camera and LiDAR technologies, which can provide a complete and visually descriptive depiction of the environment both outside and inside the vehicle
- Compared to other individual sensors, LiDAR is the most robust environmental sensor based on the identified limitations
- Law enforcement officers unanimously agreed that the abundant information and helpful data are the best advantage of modern EDRs
- The most common improvement recommendation to EDRs was the use to universal cables or other common system for accessing the data
- The two most recommended pieces of information by law enforcement included camera data and information about automation performance
- The results of the law enforcement surveys are consistent with similar efforts to develop guidelines for reporting crash data for CAVs

These findings suggest that EDR data can be expanded to include CAV data as modern vehicles are integrating increasingly automated systems, such as ADAS and Toyota Techstream (which stores pre-crash images and vehicle control data). Furthermore, the survey findings regarding the number of cables needed, the need for training, and easier to interpret CDR reports reveal that access to EDR data can be further standardized. Because understanding how to use EDR access systems requires training in physics and vehicle technologies, developing a well-trained crash investigator currently requires large direct (training and hardware) and indirect (time away from duty) investments from an agency.

The main objective of this work was to explore how law enforcement could contribute to the design of future crash reconstruction. A key element of the project is the use of safe systems approach incorporating key stakeholders, data collection processes, technological capabilities, and deriving information from data. It is expected that the results of this work can help improve crash reconstruction procedures when combined with the opinions of other crash reconstruction experts. It will be important to understand the perspectives of other key stakeholders, such as crash reconstruction experts, to design a useful dataset that will not only help in future reconstruction efforts, but also help researchers improve the safety of the vehicles involved. An additional lesson from this research is the need to educate traffic safety professionals, including law enforcement, of the functions and limitations of CAV technology so they can be better prepared to address the variety of new challenges that will continue to emerge as automated vehicles appear on the roadways in larger numbers.

ADAS technology continues to enter the market, and broad development and testing continues to move CAV with higher automation levels closer to deployment. CAV technology is evolving, and developers still have an opportunity to communicate their intentions to stakeholders in the transportation community and accommodate their needs in future designs through participatory development or updated policies. Postponing law enforcement involvement would likely leave new onerous challenges to law enforcement instead of providing innovative tools that could ultimately improve road safety.

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Appendix A: Law Enforcement Survey

The University of North Carolina Highway Safety Research Center (HSRC) is conducting research to better understand how vehicle event data recorders (EDRs) could be improved with new automated vehicle data.

New vehicle technologies like adaptive cruise control and lane departure warnings are designed to assist the driver, but they also collect detailed data about the vehicle and objects in the immediate area that could be useful for collision reconstruction. As technology gets more advanced, it may also be possible to automatically collect new information about the vehicle, its location, the environment and even the driver.

Thinking of the future of collision investigation, what are the **top thre**e pieces of information (that are not available today) you would most like to get from a vehicle automatically after a collision?

1) ______________________
2) ______________________
3) ______________________

What do you like most about the **current process** of using EDRs for collision investigation?

____

What could be improved about the **current process** of using EDRs for collision investigation?

____

Do you work in law enforcement?

a) Yes
b) No

What is your role in collision investigation?

a) Technician
b) Analyst
c) Both
d) None
e) Other (please specify) ____________

Appendix B: Literature Review References

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