From Crash to Care:
A Road Towards Improved Safety and Efficiency of Emergency Medical Response

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Academic Abstract

Motor vehicle crashes (MVCs) are a global public health concern. In 2020 alone, there were an estimated 6.76 million police reported crashes in the United States [1]. In the wake of an MVC, those involved may have been inflicted with serious or fatal injuries. Despite large research and development efforts to design vehicles and safety features to help reduce the frequency and severity of MVCs, crashes are, and will continue to be, a reality. In response to MVCs, first responders are tasked to provide crash victims with rapid immediate care and transport them to an appropriate facility. In spite of continued progress in emergency medicine, there are still many operational hurdles that emergency medical technicians need to overcome to perform their duties proficiently. Development and deployment of advanced automatic crash notification (AACN) systems have the potential to reduce the time between a crash and 911 system activation, especially for unseen roadway departures or crashes that render occupants incapacitated. Ultimately, AACN systems may aid first responders and improve MVC patient outcomes, however, these systems only target the earliest elements of an emergency response event.

Therefore, the work contained in this dissertation aimed to identify additional areas for improvement within an emergency response event, specifically MVCs, and propose and/or develop solutions to address them. The first area pertained to emergency medical services (EMS) transportation, which can include responding to and transporting patients from an MVC. Through the analysis of the national EMS Information System database, an existing light vehicle naturalistic driving study, and a pilot ambulance-based naturalistic driving study, this dissertation provides a comprehensive investigation into EMS roadway interactions. The findings of these investigations confirmed that traffic interactions are a common issue and leading cause of EMS delay during response and transport phases. Even when ambulance operators drive with observed “due regard” and utilize emergency lights and sirens appropriate, many drivers were observed to yield the right of way inappropriately or in a delayed manner that resulted in safety critical events on open roadways and in intersections. The second area of improvement pertained to providing EMS with detailed patient information following an MVC. This took shape through the development of a post-crash injury triage system that provides first responders with occupant condition prior to on-scene arrival. The proposed system collects and shares crash occupant respiration rate, heart rate, and mental status through vehicle cabin integrated sensors and a post-crash response operator. This information, and additional vehicle specific crash details, are then populated into post-crash web application that responding agencies can view and interact with to strategically allocate response resources and predevelop transportation plans.

Collectively, the work included in this dissertation identified challenges that EMS face when responding to MVCs, and produced findings that can be used to develop technology, update policies, and innovate in the transportation sector to improve emergency response and post-crash care. The identified safety and efficiency benefits not only apply to emergency respondents but encompass benefits to crash victims and all other road users. Although targeted at MVCs, the findings of this dissertation may also be applicable to many different types of emergencies and can benefit other public safety domains such as law enforcement, fire services, towing, and infrastructure maintenance.
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General Audience Abstract

Motor vehicle crashes (MVCs) are a global public health concern. In 2020 alone, there were an estimated 6.76 million police reported crashes in the United States [1]. In the wake of an MVC, those involved may have been seriously or fatally injured. Despite large research and development efforts to design vehicles and safety features to help reduce the frequency and severity of MVCs, crashes are, and will continue to be, a reality. In response to MVCs, first responders are tasked to provide crash victims with rapid immediate care and transport them to an appropriate facility. In spite of continued progress in emergency medicine, there are still many operational hurdles that emergency medical technicians need to overcome to perform their duties proficiently. Development and deployment of advanced automatic crash notification (AACN) systems have the potential to reduce the time between a crash when a 911 response is started, especially for unseen roadway departures or crashes that render occupants incapacitated. Ultimately, AACN systems may aid first responders and improve MVC patient outcomes, however, these systems only target the earliest elements of an emergency response event.

Therefore, the work contained in this dissertation aimed to identify additional areas for improvement within an emergency response event, specifically MVCs, and propose and/or develop solutions to address them. The first area pertained to emergency medical services (EMS) transportation, which can include responding to and transporting patients from an MVC. Through the analysis of a national database, an existing light vehicle driving study, and a pilot ambulance-based driving study, this dissertation provides a comprehensive investigation into EMS roadway interactions. The findings can be used to better understand EMS roadway interactions and applied to develop innovative ways to improve safety and efficiency for all road users. The second area of improvement pertained to providing EMS with detailed patient information following an MVC. This took shape through the development of a post-crash injury triage system that provides first responders with occupant condition prior to on-scene arrival. The proposed system collects and shares crash occupant respiration rate, heart rate, and mental status, allowing responding agencies to strategically allocate response resources and predevelop transportation plans.

Collectively, the work included in this dissertation identified challenges that EMS face when responding to MVCs, and produced findings that can be used to develop technology, update policies, and innovate in the transportation sector to improve emergency response and post-crash care. The identified safety and efficiency benefits not only apply to emergency respondents but encompass benefits to crash victims and all other road users. Although targeted at MVCs, the findings of this dissertation may also be applicable to many different types of emergencies and can benefit other public safety domains such as law enforcement, fire services, towing, and infrastructure maintenance.
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Attribution

This dissertation contains two published journal papers and two works that were published in conference proceedings. I have been the primary contributor on these works, but other authors have contributed to the final manuscripts. Below are the author contributions to each work.


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1: Introduction

1.0.1 Motivation

Until 2020, motor Vehicle Collisions (MVCs), and the associated number of fatal crashes, had been on a steady decline since the 1970’s [2]. As technology advances, automotive manufacturers have focused vehicle advancement on crash prevention and reduction of crash severity through advanced driver assistance systems (ADAS) (e.g., automatic emergency braking, lane keep assist, and adaptive cruise control). When considering the timeline of a crash event, these safety systems take effect during the pre-crash or crash phase [3]. Although these technologies have led to reported reductions in motor vehicle crashes (MVCs) [3], crashes are still a prevalent issue in transportation and health care. For 2020, the National Highway Traffic Safety Association (NHTSA) reported 38,824 fatal crashes and an estimated 2,282,015 people injured on roadways in the United States [1]. Crashes also carry the burden of high economic loss. A 2023 NHTSA report estimated an economic cost of $340 billion attributed to MVCs that year, including expenditures such as medical care, property damage, lost workplace and household productivity, legal costs, and EMS deployment [4].

When crashes do occur, particularly those of a higher severity, occupants rely on emergency medical services (EMS). Following dispatch to an emergency, EMS must quickly arrive at the scene, rapidly and accurately triage the crash victim(s), and begin treatment. EMS must also select a destination facility properly equipped to provide the most appropriate care. Specifically, selection of a suitable treatment facility is a critical factor for trauma patients. Despite the crucial role EMS plays in emergency response, and for MVCs in particular, post-crash EMS care is underrepresented in research and literature, as little work has been conducted to investigate the intricacies of the multi-capacity role of EMS personnel, identify areas of improvement from the first responder perspective, or address such areas.
Roadway safety campaigns like the National Safety Council’s “Road to Zero” have previously emphasized pre-crash and crash phase efforts to eliminate roadway fatalities and crashes [5]. Building off that foundation, an updated perspective known as the Safe Systems Approach has become a leading point of view [6]. Where previous efforts initially pursued a goal of zero MVCs, the Safe Systems Approach shifts traditional thinking towards a world with zero fatal crashes. A key distinction to note is that, because of this shift in philosophy, the Safe Systems Approach places a strong emphasis on the role of post-crash care. Further, with the publishing of the 2022 National Roadway Safety Strategy [7], and its emphasis on the Safe Systems Approach, there has been increased recognition of the importance of post-crash care and improving this phase of a crash event.

In the context of these strategic shifts and to better address the needs of emergency responders and the post-crash care they provide, this dissertation will (i) identify challenges faced by EMS when responding to MVCs, (ii) investigate highly prevalent issues that need to be resolved, and (iii) develop solutions aimed towards improving the efficiency and safety of emergency response to MVCs. Specially, this investigation will focus on how the identified challenges influence or impact EMS total response time.

1.0.2 Literature Review

In the United States, emergency responders typically consist of law enforcement officers, emergency medical services, fire services, and rescue services. Depending on locality, the extent of these services may vary, and in some locations these services may even be combined (e.g., Fire & Rescue, Fire & EMS). When emergencies happen, the public depends on emergency services to respond rapidly and administer necessary forms of care including, but not limited to, medical care, rescue services, and fire suppression. An emergency response event officially starts when a 911 call is initiated. Next, local public safety answering points (PSAPs) receive the call and dispatch appropriate response services. For motor vehicle crashes, law enforcement, EMS, and/or fire services may be dispatched depending on the nature and
severity of the crash. If necessary, MVC patients will be treated and transferred to a medical facility that is suitably equipped to address their needs.

For emergency medical services in particular, there are seven key stages of an emergency response event for MVCs (Figure 1). The first stage is the crash itself. The second stage is the 911 call, which can be initiated by a crash victim, a bystander, or in some cases the vehicle that crashed. The third stage is EMS dispatch, where a PSAP identifies and successfully sends out the most appropriate EMS resource(s). The fourth stage is EMS response, which starts with an EMS unit accepting the call and ends with the response unit arriving on-scene. The fifth stage is EMS on-scene. The sixth stage is EMS transport starting with the EMS unit leaving the scene and ending once arriving at a treatment facility. The final stage is patient transfer. Depending on the treatment facility case load, the injuries of the crash victims, and many other factors, patient transfer may be quick or may take some time. Situations do exist that deviate from this presented timeline (e.g., patient treatment refusal, advanced EMS care interception), however, this dissertation work will use this seven-stage order of events as a generalized timeline for EMS care following an MVC.

**Emergency Response Timeline**

![Timeline Image]

*Figure 1. A generalized timeline of major events for an emergency medical response to an MVC.*

**Prevalence of Crashes**

The importance of the role EMS plays following an MVC can be best appreciated when considering crash prevalence. For 2019, the National Highway Traffic Safety Association (NHTSA) reported 36,355 fatal crashes in the United States, following a steady decline in fatal crashes since 2016 [1]. With the onset of
the COVID-19 pandemic in 2020, some decrease in fatal crashes due to reduced travel was expected. However, despite an 11% decrease in vehicle miles traveled from 2019 to 2020, NHTSA reported a 6.8% increase in fatal crashes. The resulting 2020 fatality rate per 100 million vehicle miles traveled increased to 1.34, a record high since 2007. In addition to fatal crashes, crash victims can also sustain injuries that can inhibit their ability to work, incur the cost of medical treatment, and in some cases leave them with lifelong injuries that reduce their quality of life.

From a first responder perspective, the National EMS Information System (NEMSIS) is a collection of detailed U.S. EMS activations from years 2009 to present day [8]. The 2019 dataset, for example, contained a total of 36,119,969 activations captured across 47 states and territories, which included 27,925,669 911-initiated responses [9]. Additionally, of the calls that were 911-initiated and in which patient contact was made, the 2019 dataset contained 1,172,727 motor vehicle collisions, which was the second most frequent cause of injury (30.5%). Ultimately, this data shows that motor vehicle crashes are still an important public health issue that needs to be addressed, and that EMS play a large role when crashes occur.

Another component of the relationship between EMS and MVCs involves situations when emergency vehicles themselves are involved in a crash. Emergency vehicle operators are tasked to respond to incidents rapidly, due to the inherently urgent nature of emergencies themselves. There are rules, regulations, and laws which can come from the state, city, town or agency level that are provided to emergency vehicle operators to govern how they drive during emergency response events [10, 11]. Additionally, improvements to emergency vehicle operation and training are topics that are commonly discussed in literature and evaluated through research studies to improve safety [12, 13]. These efforts are usually aimed at improving or supplementing traditional emergency vehicle operator training courses. These laws and guidelines outline the operation of emergency vehicles, even in conditions that are otherwise traditionally unlawful (e.g., high speeds, driving through red lights, driving in the opposite
direction of intended travel), but all require operators to do so with “due regard” for other people, vehicles, and property.

Even under operation with “due regard,” emergency vehicles are still susceptible to crashes due to many factors including operating at high speeds, operation in unsafe locations such as active roadways, and interfacing with complex roadways environments such as intersections [14-17]. This results in emergency vehicle crash involvement. For example, an investigation by the National Safety Council found 180 fatal crashes that involved emergency vehicles in 2020 [18]. These crash fatalities included EMS personnel, drivers and passengers of other vehicles, and pedestrians. Other previous studies that show similar trends have also been conducted on emergency vehicle crashes [19, 20]. Another study conducted a ten year analysis on FARS and GES data revealing that approximately 500 firefighters are involved in crashes each year, of which 1% are fatally injured [21].

Ambulance crashes in particular can involve a wide range of people and carry a unique set of consequences. It is estimated that each year in the U.S. there are 4,500 MVCs involving an ambulance, 1,500 of which result in injury [22]. Beyond the first responders operating the ambulance and those onboard to provide medical treatment, ambulance crashes could also involve patients in or outside of the ambulance, other road users, and pedestrians. It is estimated that there are about 29 fatal ambulance crashes yearly that result in 33 fatalities. Of the yearly fatalities that result from MVCs involving ambulances, a majority (63%) were occupants of other vehicles [22]. Outside the scope of fatalities, general injury is another concern. Smith reports that 84% of EMS providers in the patient compartment were unrestrained and 67% of patients were not fully restrained at the time of the crash, which largely contributes to an increased chance of injury [22]. Finally, the implication that a crash involving an ambulance has on the ongoing emergency response event needs to be considered. When ambulances crash, crucial medical resources and time are lost. If an ambulance crashes on the way to an incident, additional emergency response resources will need to be deployed to the original emergency event as
well as the MVC involving the ambulance. Similarly, if an ambulance crash takes place during the transport phase, additional injury to the patient could be incurred. In the end, MVCs involving ambulances quickly drain available resources to local EMS systems and can lead to delays in patient care.

*The Influence of Time to Definitive Treatment Following Traumatic Injury*

After sustaining an injury, crash victims expect to receive a prompt response from emergency services. Tied to that expectation, it’s not by coincidence that emergency response performance is often evaluated by analyzing response time [23-25]. Commonly, response time is defined as the time interval that either begins from the time a PSAP receives a 911 call or from the time a response unit is dispatched to the time of on-scene arrival [24, 26]. Another way response time is expressed is time to pre-hospital care, but this can be clouded by instances that do not receive prompt 911 calls (e.g., an unwitnessed MVC that left the driver incapacitated). Further, despite its acceptance as an indicative evaluation metric for emergency response performance, using response time alone can oversimplify the complexity of emergency response, as the effects of treatments, delays, and complications that take place during on-scene and transport phases are not well represented. In acknowledgement of this, there has been work published advocating to expand emergency response performance evaluation to take a more holistic approach or utilize a larger variety of evaluation metrics [24, 25].

Response time has, however, been found to have a correlation with crash mortality; longer EMS response times are associated with higher rates of MVC mortality [17, 27-29], despite some evidence to the contrary [30]. Although presented as a generalization for all MVC injuries, this relationship best describes more seriously injured trauma patients. Expanding beyond the time window of response time, a common perception of this relationship has been accepted that for trauma patients to have the greatest chance of survival, they need to receive definitive care within one hour of sustaining their injuries, colloquially termed the “Golden Hour” or “Gold time” [28, 29, 31]. In a study by Ma. et al., on average a response time under 17 minutes led to definitive treatment within the “Golden Hour” threshold [28]. Furthermore,
Tansley et al., found that when predicted travel time of a victim to a trauma center is above thirty minutes, the mortality rate increased by over 60% [32]. These findings have subsequently led to response time and additional time-based standards that agencies and providers aim to meet. In general, agencies strive to have response times for most calls (~90%) between 4-9 minutes, but exact standards may vary by locality or agency [25, 26]. Recent evidence, however, suggests that the relationship between time to definitive care and patient outcomes may be highly dependent on injury type and physiologic condition, thus de-emphasizing the “Golden Hour” as a catch-all rule for all trauma patients [33].

These findings emphasize time as an overarching factor that plays a crucial role throughout all phases of an emergency response event; the time between the crash and 911 activation, response time, the time spent on-scene initially evaluating and treating the patient, and transport time. While EMTs do not want to compromise the quality of care they provide at the cost of quickness, providers still need to maintain efficiency. This tradeoff is complicated by two additional factors that compound the relationship between response time or time to definitive care and MVC mortality: triage accuracy and delay occurrence.

Accurate patient triage is critical when treating trauma patients [34]. Improper patient triage could greatly influence the time to definitive care, resulting in a notable delay, especially if patients require interfacility transfer due to poor initial triaging. Delays, on the other hand, can be experienced at any phase of an emergency response event and can even be present prior to 911 activation [35]. Previous analyses of NEMSIS data showed that MVC patient mortality increased by 3% per each minute of EMS delay [36]. Similar effects were also found for pedestrian fatalities [37].

**Automatic Crash Notifications**

In an MVC, the first step in emergency response is to contact and dispatch emergency services that will address crash victim injuries, maintain traffic flow, and manage hazards that may have resulted from the crash (i.e., fire, debris, or fluid leaks). However, this may not always be possible. For example, there may be a roadside vehicle departure crash that renders the occupant(s) unconscious and unable to contact
emergency services. To better assist crash victims, automatic crash notification (ACN) systems have been developed by automotive manufacturers. An ACN system works by first detecting the crash, then connecting the driver to a PSAP, helping reduce response time and streamline emergency response. Since their inception, ACNs have grown in capability to become advanced automatic crash notification (AACN) systems (Figure 2). These advanced systems detect crashes through more complex means, utilizing vehicle-integrated sensing. In an original ACN system (e.g., OnStar, eCall) the primary trigger for activating an ACN was airbag deployment [38, 39]. AACN systems have expanded beyond just airbag deployment, and now can be initiated through additional mechanisms such as seatbelt pretensioners and kinematic sensors [40-42]. Once a crash is detected and the vehicle is connected to a PSAP, the PSAP may attempt to call the vehicle occupants to determine more information about the crash before dispatching emergency services. Ideally, ACN/AACN systems expedite the activation of 911 by functioning independently from human initiation, directly interfacing with relevant PSAPs, and conveying baseline crash information (e.g., vehicle type, location) [43]. Further improvements to AACN systems in the US may be made possible by the implementation of Next Generation 911 (NG911), an improvement to the current national 911 system that will be digital and capable of communicating more complex information [44, 45].

**Emergency Response Timeline**

![Emergency Response Timeline Diagram]

*Figure 2. A generalized timeline of major events for an emergency medical response to an MVC highlighting the phases that are impacted by the presence of AACN systems.*
Aside from better crash detection mechanisms than its predecessor system, AACNs have the capability to
detect and report an estimated crash type and basic severity. To accompany these improvements, NHTSA
has developed the URGENCY algorithm, a program that estimates occupant injury severity [34, 46]. The
motivation behind URGENCY was to assist first responders that struggled to identify occult occupant
injuries as a result of effective restrain systems [47]. The goal of URGENCY is to compile crash information
in a way that first automatically predicts occupant injury severity and then initiates an emergency
response that is appropriate for the situation. Essentially, the algorithm reduces inconsistencies in
information about the crash and the occupants’ injuries that PSAPs may attempt to collect through
contacting the crashed vehicle. In the case of severe crashes that may require specialized resources (e.g.,
a burn unit, air support), the algorithm may advocate to call specialized resources immediately rather than
after first responders arrive and determine they are needed [47].

There have been multiple studies to evaluate the effectiveness of ACN and AACN systems. Generally,
these studies have shown that ACN/AACN implementation will yield improved MVC mortality outcomes
by way of response time reduction [41, 48-50]. These studies present their findings in reference to MVC
mortality improvements, but MVC related morbidity (e.g., long term effects of non-fatal injuries) need to
also be considered [51]. Current AACN implementation, however, has some shortcomings. First, the exact
type of information provided to PSAPs and/or first responders from AACNs and needed to help reduce
response times is still ill-defined. Additionally, a major issue that impacts the effectiveness of AACN
systems is enrollment. Therefore, an informal scan of known, consumer available AACN systems was
conducted to get an understanding of what activation mechanism options are available, what
communication mechanisms are used, who receives the initial crash notification, and what is required to
enable AACN functionality (Table 1). Overall, the scanned systems were all similar with one exception,
Ford Motor Company’s 911 Assist. Except for Ford’s AACN system, all other surveyed systems require a
paid subscription for the service. This undoubtedly affects enrollment. Recently, crash detection
capabilities have expanded beyond in-vehicle technology, and now may also include cell phones and smart watches, which present new opportunities of real-time crash detection [52, 53]. However, due to the novelty of this application, the effectiveness of personal device crash detection has yet to be explored.

Table 1. A summary of commercially available ACN/AACN services.

<table>
<thead>
<tr>
<th></th>
<th>GM OnStar</th>
<th>Ford 911 Assist</th>
<th>BMW ConnectedDrive</th>
<th>Toyota Safety Connect</th>
<th>Subaru STARLINK</th>
<th>WV Car-Net</th>
<th>Vowlo On Call</th>
<th>Nissan Connect</th>
<th>Chrysler Uconnect</th>
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<tbody>
<tr>
<td><strong>Activation Mechanism</strong></td>
<td>Manual (Occupant activation)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>ACN/AACN Communication Mechanism</strong></td>
<td>Crash Detection</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>ACN/AACN Received by</strong></td>
<td>Service provider call center</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
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<tr>
<td><strong>Public safety access point</strong></td>
<td>X</td>
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<tr>
<td><strong>Enabling Requirements</strong></td>
<td>Requires subscription</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
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<tr>
<td></td>
<td>Requires to be turned on</td>
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1.0.3 Research Objectives

Based on the findings of the literature review, the goal of this dissertation is to identify and address difficulties and challenges that emergency medical services face when responding to motor vehicle collisions. This dissertation is motivated by the lack of EMS-centric research present in current literature, despite the crucial role that EMS plays in post-crash response and care for crash trauma patients and the recent increase in U.S. motor vehicle fatalities. The investigations included within this dissertation also seek to speak to the recent attention placed on post-crash care from the national perspective, in an effort to reduce motor vehicle collisions fatalities by utilizing the Safe Systems Approach. The ensuing investigations in this dissertation aim to:
1. Identify the challenges and difficulties emergency medical technicians encounter when responding to motor vehicle collisions.

2. Investigate the identified challenges and areas of difficulty in Aim 1 to gain qualitative and quantitative understanding of them.

3. Develop proposed solutions aimed at decreasing the total time and/or improving the safety implications of an emergency response to a motor vehicle collision.

4. Identify the type of information that may be utilized by emergency medical technicians to improve the efficiency and safety of the care they provide to crash victims.

5. Identify solutions that could convey desired information to emergency medical technicians and decrease the total time and/or improve the safety implications of an emergency response to a motor vehicle collision.

The overall goal of this dissertation is to provide technology or policy-based solutions that will lead to improvements in the overall time required for effective emergency response to a motor vehicle crash. Proposed solutions will address elements of a generalized emergency response timeline. Additionally, proposed solutions will also provide benefit to non-MVC emergencies.
2: EMT Interviews and Problem Identification

2.0.1 Background

In general, current literature, research, and technology advancement to identify and address the challenges and difficulties faced by EMS personnel responding to vehicular crashes has been limited. However, some areas of current research related to the role and performance that EMS play in post-crash response have been identified. One area encompasses the development of injury prediction metrics based on experimental and observational motor vehicle collision (MVC) kinematics. By combining recorded crash data with retrospective injury diagnosis, injury prediction algorithms have been developed to estimate crash severity and/or injury risk [54-57]. These prediction algorithms are incredibly complex, attributed to the long list of possible factors that affect crashes and occupant injury. Therefore, these algorithms typically use abbreviated injury scale (AIS) scores and body region separation to simplify injury inputs. These injury prediction algorithms could be combined with on-board vehicle sensors or electronic data recorders (EDRs) to output real time data to PSAPs or first responders. These outputs can then be incorporated into AACN systems for application [34, 46, 47, 58, 59]. Current algorithm development investigates prediction accuracy when occupant factors such as age, sex, height, and weight are incorporated. Further influence may also come from occupant medical history. Unfortunately, some of these influential factors are only capable of being included retrospectively, and some have considerable privacy considerations. Additional studies have investigated prolonged recovery from specific injuries sustained from MVCs [51, 60].

Another area of potential interest in the EMS vehicular crash domain concerns formulating better strategies for dispatching and resource optimization of EMS to MVCs [23, 26, 61, 62]. From an urban planning perspective, the question of where to build EMS stations lays the foundation of EMS resource optimization. When well thought out, EMS resource placement or staging will be done in consideration of
key influential factors such as established hospital locations (especially when considering level 1 and 2 trauma center availability), areas of high call volume, and known transportation challenges (e.g., dense, or high-traffic area). Outside of station location, EMS resource optimization shifts toward resource allocation: deciding the quantity or portion of equipment and personnel to preset at each location.

However, in practice, there is not always the foresight and available knowledge to preemptively build emergency response systems this robust. In many cases, cities and towns naturally grow and develop to meet the needs of their residents, building additional resources on an as needed basis, often wherever there is room. Therefore, studies have been conducted to evaluate how reallocation or redesign of EMS resources may lead to improved optimization [61, 62]. This same mentality is also expanded to improving how EMS resources are dispatched, or assigned, to emergencies. For example, a retrospective simulation study was conducted using EMS call data from San Francisco, CA [63]. Findings showed that, in some circumstances, simply assigning the closest immediate EMS resource to an MVC -- particularly if the injuries were non-life threatening -- was not the most appropriate response and could limit overall effectiveness of emergency services if multiple MVCs occurred. Improvement of dispatching practice would then require two key types of information to be readily available to dispatchers: (i) a strong understanding of the capabilities of all EMS resources available (e.g., unit level of care, expected travel time, local call volume) and (ii) a strong understanding of the type and severity of injuries faced by MVC occupants which is often not possible with current technology. Some effort has been made to collect this missing information. For example, the Alabama Public Health Department conducted a three-part study that examined the implementation of an electronic data system, the use of handheld data collection devices, and the development of tools that can predict MVC occupant injury [64]. The study showed success in the collection and implementation of the electronic data and concluded that the data can improve EMS response to MVCs. As mobile technology capabilities have grown considerably since 2005,
it stands-to-reason that many EMS systems now utilize mobile data collection devices (e.g., cell phones, laptops, tablets) to collect more accurate call information than provided by older technologies.

In general, these studies showcase the need for more accurate near-real time information about MVCs, a greater amount of such information, and the potential benefits that would come with that information, but not necessarily which data elements would be most relevant and useful. Consequently, this study was designed to leverage emergency medical technicians (EMTs) interviews about their experiences working with MVCs. The primary objective of these interviews was to identify potential types of information that could improve emergency medical response to MVCs. EMTs were also asked about additional challenges that they face in their responses to these events.

2.0.2 Research Objectives

The primary objective of this study was to collect firsthand data from EMTs to gain a better understanding about what it is like to respond to MVCs. The study had two primary research questions: (1) What challenges and difficulties do EMTs face when responding to motor vehicle collisions? (2) What types of information, if provided to EMTs, could lead to improved MVC EMS response? The study was designed to capture open ended responses from interviewed EMTs and obtain a potentially wide array of information and experience pertaining to MVC response. The results of this study were intended to be used to develop a problem identification use-case for follow up studies.

2.0.3 Methods

This study includes structured interviews from 15 EMTs serving in southwest Virginia. The Virginia Tech Institutional Review Board (IRB) approved the protocol for the interviews (IRB #19-848). Each interview was guided by a set of ten questions (Appendix A). The first five questions were focused on identifying issues with dispatching, initial response to incidents, and traveling to and from the scene. Questions six and seven solicited feedback on what information the EMTs felt they needed or wanted in order to
improve response or provide better care. Finally, questions eight through ten addressed recent trends that EMTs may have noticed and the extent to which they receive feedback from medical facilities to which they deliver patients. Participants were first verbally consented and provided with a copy of their consent form. Handwritten notes were taken for each interview, along with an audio recording when consented by the participant. The interviews took place either at the Virginia Tech Transportation Institute (VTTI) in Blacksburg, Virginia or in a private area at the respective EMS station of the interview participant. The interviews generally lasted about 25 minutes, with the longest lasting 35 minutes and the shortest 14 minutes.

After all interviews were completed, the responses to the first seven questions were grouped into thematic categories. This method of quantifying responses was modeled after Terry, et al. [65], who quantified emergency service personnel feedback on how autonomous vehicles should interact with emergency vehicles. To identify the themes that would be used in this study, the notes and recordings of the interviews were first evaluated to extract commonalities. An initial list of themes was drafted based on this exercise. Given the variety in participant experience and his or her ability to articulate topic areas succinctly, each unique thought from each participant was counted only once. A unique thought was identified as an independent topic addressed by the interview participant; these were often preceded and followed by a period of silence as the interview participant thought about their answer, or were preceded by a phrase that signaled a new topic (e.g., “Another issue is…”). To assist with consistency in identification of a unique thought, transcribed notes were typed based on the handwritten notes, and audio recordings when applicable, and were formatted as bullet points, where each bullet point represented a unique thought. The list of themes was then revised into its final form to ensure the themes were overarching and not too vague or too specific. An “Other” category was included to account for all additional unique thoughts shared.
Two interviews were interrupted by emergency calls and were not finished due to subsequent participant unavailability. Completed sections for these interviews were, however, included in the analysis. The EMTs interviewed served in six different locations throughout the southwest Virginia geographical area. Four participants primarily served in urban communities, five primarily served in suburban communities, and six primarily served in rural communities. Many of the participants also volunteered in other states and communities at the time of the interview or previously, contributing to breadth in the feedback received.

2.0.4 Results

The first five interview questions aimed to uncover difficulties EMS personnel have faced during the dispatch, response, and transport phases of emergency response to MVCs, since these practices are not necessarily crash-type dependent. After collecting 14 responses from participants that fully answered this section of the interview, several thematic categories emerged (Figure 3). The most common theme encompassed the difficulties that arise from the inaccuracy or lack of information that is available during the response to an MVC. The second most common theme pertained to difficulties that occur from interactions between EMS vehicles or personnel and other traffic. These difficulties included delay in response time, interactions with unpredictable driver behavior as drivers are approached by an emergency vehicle, and increases in secondary incidents that require EMS attention as a result of road congestion. The third most frequent theme was the mismatch of dispatching and communication technologies. This category encompassed difficulties that arose from too much unnecessary information transmitted over the radio, the poor quality of communication devices that limit the amount of information that can be shared, and agency-to-agency technology incompatibilities or communication delays during mutual aid responses (which are often associated with higher acuity calls). Scene safety, resource allocation and management, and the timely notification of MVC occurrence and/or severity were also prevalent themes mentioned by interviewees. Examples of comments classified in the “Other”
category included helicopter accessibility, hospital staff interactions, and the training of private (e.g., OnStar) dispatchers.

Interview questions six and seven were aimed at developing a list of information that EMS personnel believed would improve the efficiency and level of care when responding to an MVC. Responses from all 15 interview participants were included. Information about vehicles and information about occupants were mentioned most frequently, whereas information about the roadway, while also discussed, was not at the forefront of perceived informational needs (Figure 4).
Further expansion of responses to questions six and seven were made to generate a list of expressed data themes, paired with the identified information source (Figure 5). Desired information that was vehicle-sourced was split into six themes, including an “Other” category. The most mentioned of the themes was data pertaining to vehicle details and location. This included the desire for more accurate vehicle-based transmission of the crash GPS location, the propulsion mechanism of the vehicle (e.g., gas, hybrid, electric), and airbag schematics (e.g., locations and sources of power). The second most prevalent theme was vehicle deformation and extrication, which included the desire to know quantitatively and qualitatively the extent of deformation, particularly of the interior cabin, and whether vehicle extrication would be necessary. The remaining vehicle themes included vehicle kinematics, hazard detection, and rollover detection. The “Other” category for vehicle data included comments on reporting the number of vehicles involved, automating vehicle hazard light activation, and the easy on-scene availability of the aforementioned data elements.

For the second data source of occupant-based information, there were three identified themes (Figure 5). The most common theme for this information source was occupant details and passive safety. This theme mainly encompassed information of how many occupants were in the vehicle at the time of the crash, occupant location, how many of these occupants were belted, and which of these occupants interacted with airbags. The second theme under occupants concerned the victims’ vital signs that are most relevant during an MVC response, especially those that are used in injury severity calculations. Particularly, EMTs were interested in having access to information about the occupants’ heart rate, pulse, respiratory rate, and consciousness. The “Other” category included mentions of a desire to know general occupant injuries and having occupant pre-registration of occupant medical history (e.g., major medical history, allergies, medications) with the vehicle and greater insight on occupant injuries.

The final information source of roadway was divided into three themes (Figure 5). The most common theme was roadway interaction, where EMS personnel would like to have at their disposal a larger
quantity and quality of programmable signs to alert and warn drivers of potential hazards. In addition, the potential for more accurate and precise roadway-based traffic updates for drivers was mentioned. In the roadway improvements theme, EMTs mentioned the development of roadway improvements that may help increase scene safety and reduce the possibility of inappropriate traffic interactions with emergency vehicles. The “Other” category included mentions of better incorporation of helicopter access and better labeled emergency vehicle compliant alternate routes (e.g., bridge heights, roadway weight limits).

Figure 5. Identified themes, paired with the information source, that the interviewed EMTs mentioned when addressing what information they wanted to have to improve the effectiveness and efficiency of vehicle collisions responses.

The last three questions during the interviews were aimed at assessing whether the interviewees observed any injury correlations in particular types of vehicle crashes, gauge how EMS personnel receive feedback about patients they transport and provide participants with the opportunity to comment on anything that they thought would assist the study. Thirteen of the interview participants answered the questions in this section. A vast majority of the interviewees (N=10) indicated having observed correlations between crash types and injury characteristics. However, the relationships mentioned were generally well-known injury mechanisms (e.g., rib injuries experienced by belted occupants). All participants indicated receiving performance feedback from hospital staff, but mainly when they ask for
such feedback. This questioning generally emerged from a particular interest in the outcome of a critical patient or as a self-evaluation tool on the quality of care that was provided. Three of the participants added that they, as leaders in their station, collect such feedback for use in personnel training sessions. Seven participants provided additional comments, but they primarily elaborated or emphasized on previous topics.

2.0.5 Discussion

In general, the interviews revealed some expected and some unexpected results. In the first phase of the interview, it was expected that inaccuracy or lack of information would be mentioned frequently, and this was indeed the most common difficulty expressed (Figure 3). This theme encompassed the hurdles that come with having to plan for all scenarios due to gaps in knowledge about any given MVC. Whether the crash is notified by a bystander, an MVC occupant, or a vehicle service (e.g., ACN systems like OnStar) representative, there is large variability in the quantity and reliability of the information provided. One of the reasons for this observation may be lack of training. As an example, one of the participants mentioned that people are trained to call in emergencies at a young age (often kindergarten) but the process is never again addressed in an educational setting. Another anticipated issue was the timely notification of MVCs and/or estimations of their severities. Interviewees, who stressed the importance of this issue particularly in the context of instances when MVC occupants are unable to summon help by themselves, greatly emphasized this theme. These circumstances can arise because of lack of cellular service, because the vehicle is no longer visible to bystanders or other traffic, or because the occupants are incapacitated. In general, the sooner an incident can be reported, the more effectively the care can be provided [27, 28]. A third anticipated issue was resource allocation and management. Closely linked to receiving timely notifications of MVCs, many participants highlighted that the sooner accurate details can be understood about an MVC, the sooner appropriate resources can be directed to the crash scene. These resources can include extrication tools, the appropriate amount of medical care for the number of patients, or additional
help to clear the scene and reduce traffic congestion. This theme was emphasized by participants who served rural communities, who generally experience longer travel distances—and time—to an MVC. The fourth anticipated issue was scene safety and was commonly expressed by participants who respond to interstate-highway crashes. EMS personnel often rely on the positioning of their vehicles alone to protect themselves and others from injury by other active traffic around the scene. Some participants mentioned that, due to this reason, in their jurisdiction EMTs cannot leave their vehicle to perform care until a second unit is present, despite how long that may take. Depending on the type of MVC, roadside environment, or available resources, strategic placement of EMS vehicles alone may not be an adequate safety measure for emergency responders.

One unexpected issue was the mismatch between dispatching and communication technology. With modern advances in radio and cellular technology, it was surprising to hear accounts of emergency response being hindered by incompatible or limited technologies. For example, one participant mentioned that their department sends a text description of the incident to the onboard computer in their ambulances, but the text provided is limited to 160 characters. This limitation in message size means that important information may be left out or must be provided in separate messages. A second unanticipated issue was the difficulties that arise from traffic interactions while in transit. Interview participants frequently expressed difficulties in interactions with other drivers, which affected their perception of safety and their response time to a crash scene. Both Byrne et al. and Ma et al. indicate that response time is the most critical component out of the entire emergency response chain of events [27, 28]. Drivers that respond incorrectly to approaching emergency vehicles, or simply do not know how to respond, greatly hinder the response process while also increasing the chance of causing another MVC. Difficulties interacting with other drivers are not limited to travel to the scene, but also arise when transporting victims to medical facilities for further treatment. Several participants expressed how difficult it is to pull away from a crash scene, even with lights and sirens activated.
The types of information required by EMS personnel generally followed the expectations, primarily focusing on vehicle and occupants (Figure 4). Ideally, this information would be transmitted to EMS dispatching immediately after the vehicle crash occurred, as this would greatly impact the amount, type, and timeliness of resources sent in response. Interviewees also suggested that the desired information be collected from several independent sources to alleviate the possibility that one failure critically limits system performance. Further, since the vehicle(s) involved are most likely deformed by the crash, redundancy should be built into automated notification systems in case some system elements are compromised.

A more detailed observation into issues related to information about the vehicle suggested several important areas. There was an expectation that information about the vehicle kinematics and presence of a rollover would be mentioned, as it aligned with the necessary inputs for previous predictive injury studies [54-56, 60]. Less expected, however, was the expressed interest in quantifying and conveying the degree of deformation experienced by the vehicle, particularly within the occupant compartment. Several EMTs discussed the possibility that such a measurement could be used to estimate the possibility of entrapment, which would assist with the resource allocation issues mentioned previously. Interviewees were also generally consistent in requesting that information including vehicle make, model, location, propulsion system, airbag location, and instructions on disabling any onboard hazards (e.g., high-voltage systems) be transmitted when a call is dispatched. With the increasing presence of electric and other alternative propulsion vehicles, in addition to manufacturer differences, EMTs struggle to quickly identify the vehicle’s critical components and how to interact with them safely in emergency scenarios. The difficulty associated with identifying and disarming active airbags was also frequently mentioned. Many participants mentioned being aware of cases where other EMTs had been injured or died as a result of accidental airbag activation while responding to an MVC. Interviewees were also interested in being
alerted to the presence of water at the scene (e.g., if the vehicle was in a stream or pond) or fire. These circumstances have great influence on the type of resources required.

In terms of information about the occupants, although it was expected that participants would be interested in metrics to help evaluate the severity of the occupants’ injuries, most interviewees were interested in basic information about the occupants’ attributes and any interaction they may have had with the safety features in the vehicle. This included how many occupants were present at the time of the MVC, where they were sitting, if they were belted, and what airbags they may have interacted with. Several participants mentioned the need to explicitly know if a child occupied a child seat prior to the crash, as sometimes driver shock or incapacitation does not allow crash victims to properly respond to EMT queries related to other vehicle occupants. Extensive searches may then result for potentially ejected children that may not have been present in the vehicle, for example. Additional desired occupant-related information included vitals that could be used to gauge the level of trauma of the occupants. These elements included heart rate, presence of radial pulse, respiratory rate, blood pressure, and an assessment of consciousness. Finally, some interviewees mentioned that some MVCs occur due to sudden onset medical emergencies. Especially with older populations, the ability to associate medical history or conditions with the vehicle they drive may increase the effectiveness of their care.

Two limitations of this study should be considered when interpreting these results. First, although an effort was made to interview EMTs from rural, suburban, and urban communities, all participants resided in the southwest region of the state of Virginia, USA. While, given the experience level of our participants, many had served EMS organizations in other regions of the United States, their responses to this study may be biased to reflect their current operations area. Previous research has suggested that there are meaningful differences in EMS across rural and urban communities [66, 67]. Future work should attempt to examine the congruence of these findings with the experience of EMS personnel in other areas of the United States and other countries. Second, the sample of participants that could be included in this study
was relatively small. Larger samples of participants should be examined in future studies, which may leverage the information obtained in this study into the development of comprehensive surveys that can be answered and analyzed more efficiently than the interview results examined herein.

The findings of this investigation suggest several areas that could benefit from additional research work. First, evaluation of in-service EMS interactions with other traffic should be assessed, and typical conflicts between these vehicles categorized. Results of such analysis may lead to the development of procedures and/or technology candidates that improve traffic interactions between the general driver population and emergency vehicles. Second, approaches for leveraging existing vehicle technology into useful information transmitted through AACN systems should be explored [43, 48-50]. Kinematic data and rollover identification, for example, could be obtained from sources such as EDRs. Information on how many occupants were present, which occupants were belted, and which occupants interacted with deployed airbags, could be retrieved from various integrated sensors in newer vehicles. For example, the weight sensor in seats that trigger the seatbelt warning, if it was extended to the rear seats, could be used to establish the number of occupants, the location of occupants, and which occupants were belted. Pairing of this information with the relay systems that trigger airbags could be used to determine which occupants may have interacted with deployed airbags. Once all this data is collected and processed, the challenge becomes establishing an effective way to communicate the resulting information with the appropriate services, ideally though an AACN system. Finally, new technologies could be leveraged to assist in obtaining some of the desired information. For example, a system that measures the amount of deformation in the occupant compartment and identifies whether any large foreign objects have breached the cabin would be useful in allowing EMTs to expect certain types of injuries and determine the need for extrication tools. On the occupant side, an interactive system could be created that deploys in response to a detected crash and can be used to evaluate the occupants’ vitals and convey them to
responding services. The transmitted information can be further coupled with improved EMS trauma triage training to increase quality of care [68].

2.0.6 Conclusion

The interview responses suggest several areas for improvement related to emergency response to MVCs. In general, information needs to be gathered sooner and with more accuracy. Additionally, the interactions emergency vehicles have with traffic while in transit need to be improved, which would lead to enhancements in both public safety and EMS response times. Advancements in information gathering and transmission would allow resources to be allocated more quickly and precisely. The results of this investigation suggest that vehicle-based information such as precise incident location, deformation measurements, and identification of vehicle hazards would contribute to the better understanding of specific crash circumstances and support the deployment of appropriate tools and personnel. Finally, availability of occupant vitals and early detection of occupant interactions with the vehicle safety systems would be useful elements of information for EMTs. Like the vehicle-based information, availability of these information elements would help identify and distribute resources effectively and rapidly. Some of these information elements are starting to become available through AACNs, the design of which can be informed by the results of this investigation.

Following the conclusion of this study, the most common responses were used to identify follow-up investigations to address the challenges and difficulties faced by EMTs when they respond to MVCs. Follow up investigations that both addressed the collected EMS feedback and could lead to reduced time across multiple phases of an emergency response event were specifically considered. Ultimately, two distinct follow-up investigations were selected as areas of further focus. The first investigation chosen was the development of a taxonomy of harmful traffic interactions experienced by emergency respondents with the intention to generate proposed countermeasures. The studies that comprise this investigation
are included in Chapter 3 and Chapter 4. This investigation primarily addresses transportation related elements of an emergency response (i.e., the response phase and the transport phase), illustrated in Figure 6 under the label “Ambulance NDS”. The label reflects the primary study of the investigation. The second investigation chosen was the development of an interactive injury triage system. The studies that comprise this investigation are included within Chapter 5. These studies focus on early identification and understanding of crash occupant condition, influencing the response and on-scene phases of a generalized emergency response event, illustrated in Figure 6 under the label “Injury Triage System.”

**Emergency Response Timeline**

![Emergency Response Timeline](image)

*Figure 6. A generalized timeline of major events for an emergency medical response to an MVC highlighting the phases that will be impacted by the chosen follow-up investigations.*
3: Emergency Vehicle Interactions Analyzed Through Existing Data Sources

3.0.1 Background

Following a motor vehicle crash (MVC), occupants involved rely on emergency medical services (EMS) to provide immediate medical care as well as transportation to a treatment facility. The role EMS plays becomes increasingly important when considering the relationship between response time and mortality [27, 28]. This relationship is commonly summarized as the “golden hour” – major trauma patients have the best potential outcome when they receive definitive hospital care within one hour after sustaining their injuries [69]. Despite the impact that time can have on the outcome for an MVC occupant, little work has been identified that seeks to improve emergency response times, outside of the work centered on AACN systems, which only focus on early stages of emergency response (Figure 6). Collectively, two investigations were defined by the findings from the EMT interviews summarized in Chapter 2. These investigations seek to improve total call time to MVCs by investigating challenges faced in downstream phases of an emergency response event and develop technology- and/or policy-based solutions. More specifically, both investigations seek to identify and overcome complex obstacles and interactions that EMS encounter within the response, on-scene, and transport phases of an emergency response event. These complex interactions not only present safety challenges for EMS and all other road users but have the potential to significantly delay emergency response. The analyses presented in this chapter aim to explore existing data sources to gain a better understanding of the types of traffic interactions that emergency vehicles have on U.S. roadways with other vehicles, along with the components of emergency response delays, to gain a better understanding of their prevalence and implications for providing effective and timely medical care.
3.1 SHRP 2 Emergency Vehicle Interactions

3.1.1 Research Objectives

The primary objective for this analysis was to investigate the dynamics that surround emergency vehicle interactions with other road users, due to their relevance to emergency response as identified in the EMT interview study [70]. This analysis had two primary research questions: (1) What are the causal factors that lead to harmful or dangerous interactions between emergency vehicles and other roadway traffic? and (2) How prevalent are emergency vehicle takeover events? Per this application, an emergency vehicle takeover event happens when an emergency vehicle crosses paths with another non-stationary vehicle on the road, resulting in the civilian vehicle yielding the right of way. This is an important topic since emergency medical response influences the safety of all road users, the safety of EMS personnel, and the mobility/mortality of the patients that emergency responders are caring for. Ultimately, the topic of emergency response interactions with other road users is widely relevant to roadway users and health care professionals alike.

3.1.2 Methods

The dataset for this analysis was a preexisting subset of the Second Strategic Highway Research Program (SHRP 2) naturalistic driving study (NDS). The protocol and subsequent access to the dataset were approved by the Virginia Tech IRB (#20-183). The data subset was generated using an algorithm to detect strobing effects in the forward video, which often signify the presence of emergency vehicles. The initial dataset included 1625 cases, which were reduced to 1366 events once duplicates were identified and eliminated. Using only the forward video view, each of these events was reduced into a characterization matrix. The matrix allowed for classification of each event as a function of emergency vehicle type, event type, and driver’s response. A text description of each event and associated response was also generated.
To classify driver response to emergency vehicles, the observed response per each event was identified as either “Legal and Safe,” “Legal but Unsafe,” and “Illegal.” These distinctions were made in accordance with a survey of US state driving manuals (Table 2). In a survey of 49 publicly available state driving manuals, although there is minor variation, most states prescribe drivers to yield the right of way to emergency vehicle in active response by yielding and coming to a stop on the right side of the road until the emergency vehicle has safely passed. Interestingly, however, some driver education resources have been found to contradict local laws [71]. All states also instruct drivers to follow the “move over” law, where drivers are required to provide an open lane of travel between themselves and stationary roadside emergency vehicles. If it is not possible to move over (e.g., unsafe to merge, single lane road), drivers are required to slow down below the speed limit and pass with caution. In the analysis, drivers who were observed to blatantly violate the “move over” law or fail to appropriately yield the right of way received a driver response designation of “Illegal.” Some drivers were observed to follow their prescribed behavior but did so in a way that appeared to be unsafe (e.g., moving over at the last second) and received a driver response designation of “Legal but Unsafe.” Ultimately, yield response judgment was made by the author, who has firsthand experience as an EMT and ambulance operator.

Table 2. A summary of US driving manuals’ prescribed responses to emergency vehicles interactions.*

<table>
<thead>
<tr>
<th>Action</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield &amp; stop, to the right</td>
<td>40</td>
</tr>
<tr>
<td>Yield &amp; stop, to the side (unspecified)</td>
<td>5</td>
</tr>
<tr>
<td>Yield, to the right (stop optional or unspecified)</td>
<td>3</td>
</tr>
<tr>
<td>Clear a path &amp; stop, (unspecified side)</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>49</td>
</tr>
</tbody>
</table>

*Driving manual for Mississippi not publicly available

In addition, five event categories were created: “Unknown,” “Stationary Emergency Vehicle,” “Emergency Vehicle Takeover,” “Alternative Traffic Pattern,” and “Other.” Subsequently identified event types were
sorted into eleven unique classifications within the five categories, including an “Unknown” and an “Other” event type. While performing the first iteration of event reduction, however, a few commonalities across events were observed in the “Other” category, and three more event types were created within the “Other” category to represent these cases. Additional events were attributed to these additional event types during a second iteration of data reduction that considered a full dictionary of event types (Table 3).

Table 3. Event types and descriptions used in data reduction of the SHRP 2 emergency vehicle flagged events.

<table>
<thead>
<tr>
<th>Event Category</th>
<th>Event Type</th>
<th>Indicator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unknown</td>
<td>Unknown</td>
<td>0</td>
<td>Unknown or None</td>
</tr>
<tr>
<td>Stationary Emergency Vehicle</td>
<td>Left</td>
<td>1</td>
<td>Stationary Vehicle(s) on the side of the road to the left side of the instrumented vehicle (e.g., traffic stop, roadside assistance, crash, etc.)</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>2</td>
<td>Stationary Vehicle(s) on the side of the road to the right side of the instrumented vehicle (e.g., traffic stop, roadside assistance, crash, etc.)</td>
</tr>
<tr>
<td>Emergency Vehicle Takeover</td>
<td>Passed on Right</td>
<td>3</td>
<td>Emergency vehicle approaches the instrumented vehicle from behind and passes the instrumented vehicle on the right</td>
</tr>
<tr>
<td></td>
<td>Passed on Left</td>
<td>4</td>
<td>Emergency vehicle approaches the instrumented vehicle from behind and passes the instrumented vehicle on the left</td>
</tr>
<tr>
<td></td>
<td>Pullover</td>
<td>5</td>
<td>Emergency vehicle approaches the instrumented vehicle from behind and pulls the instrumented vehicle over</td>
</tr>
<tr>
<td></td>
<td>Opposite Direction</td>
<td>6</td>
<td>Emergency vehicle approaches the instrumented vehicle from the front (opposite the instrumented vehicle direction of travel)</td>
</tr>
<tr>
<td></td>
<td>Following</td>
<td>7</td>
<td>Instrumented vehicle follows an active emergency vehicle (lights activated)</td>
</tr>
<tr>
<td>Alternative Traffic Pattern</td>
<td>Work Zone</td>
<td>8</td>
<td>The emergency vehicle was in place/operating in a work zone</td>
</tr>
<tr>
<td>Manual Traffic Control</td>
<td>9</td>
<td>The emergency vehicle was involved in manual traffic control</td>
<td></td>
</tr>
<tr>
<td>------------------------</td>
<td>---</td>
<td>---------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>10</td>
<td>General classification for other events</td>
<td></td>
</tr>
<tr>
<td>Other: Crossing Path</td>
<td>11</td>
<td>Emergency vehicle is traveling on a crossing path to the instrumented vehicle</td>
<td></td>
</tr>
<tr>
<td>Other: Parking Lot</td>
<td>12</td>
<td>Emergency vehicle is located in a roadside parking lot</td>
<td></td>
</tr>
<tr>
<td>Other: Divided Roadway</td>
<td>13</td>
<td>Emergency vehicle is located on the other side of a divided highway</td>
<td></td>
</tr>
</tbody>
</table>

3.1.3 Results

Results indicated a strong bias in the dataset cases toward stationary roadside events (61%) rather than takeover events (Figure 7). This bias was due in part to the nature of how the dataset was collected since the data was obtained from instrumented passenger vehicles rather than emergency responders. Thus, the observed frequencies of events should not be considered representative of all interactions between roadway traffic and emergency vehicles. However, it is likely that, in general, encounters between roadway traffic and stationary emergency vehicles occur more often than dynamic interactions since traffic flow disruptions are typically reduced as much as possible once an emergency vehicle arrives to a roadside scene. Additionally, a majority of the events captured interactions with single law enforcement vehicles (86%). Comparatively, very few ambulance (< 1%) and fire service (< 1%) interactions were observed. Slightly over 9% of interactions, however, included more than one type of emergency vehicle.
Driver responses observed (i.e., legal vs. legal but unsafe vs. illegal) were overwhelmingly legal and safe. However, there were 48 events where the driver response was identified as “illegal,” and 40 events where the driver response was deemed “legal but unsafe.” The events deemed “illegal” were the most concerning. The large majority of these events (~90%) resulted from the driver failing to obey “move over” laws, which require roadway traffic to provide an open lane of travel between themselves and an emergency vehicle, when passing a stationary emergency vehicle.

3.1.4 Discussion

Initial interest was focused on reviewing the cases that indicated the driver exhibited an “illegal” driving behavior. Only one of the 48 “illegal” cases identified showed an active emergency vehicle takeover event. In that event, a police vehicle passes the instrumented vehicle on the left by crossing the center line of a road. The drivers of the instrumented vehicle and the vehicle ahead failed in that situation to yield the right of way sufficiently fast. It should be noted, however, that it is possible the approaching police vehicle
in this event did not use their lights and sirens until they were too close to the instrumented vehicle, inhibiting them from executing a legal yielding maneuver (the rear video for these cases was not available to the project team). In this event, there was no opposite-direction traffic, but this type of interaction could have adverse safety and response time outcomes if it were to occur in a different setting (e.g., additional traffic, inclement weather, blind turns). Separate interviews with emergency responders have identified reasons or situations where police and other emergency services limit their use of lights and sirens (e.g., avoid frightening drivers, reducing congestion, unintentionally attracting road users to the lights thereby distracting them from the road). However, avoidance or delay of emergency lights and sirens activation may also result in a higher propensity of dangerous interactions between emergency vehicles and other roadway users.

Most of the events with a response classified as “legal but unsafe” involved “move over” law situations. During these unsafe events, however, drivers had ample time to move over and did not do so until they were close to the emergency vehicle, either causing unnecessary congestion around the emergency vehicle or unnecessarily reducing the safety distance buffer between themselves and the emergency vehicle.

Despite the low number of takeover events in the dataset, some unexpected discrepancies in vehicle behavior were observed. Two types of events of interest were subsequently identified from the dataset. EMTs in previous interviews expressed frustration toward widely varied driver responses to approaching emergency vehicles, usually presented in contrast to prescribed, and presumably predictable, emergency vehicle behavior. The first set of events of interest observed in this study, however, displayed emergency vehicle actions that differed from such prescribed behaviors. One particular event (Figure 8, Panel A) featured a police car passing the instrumented vehicle on the left, then crossing in front of the instrumented vehicle to continue on the roadway. Interestingly, during this event the police car only had its rear-facing lights active, which they turned off as they entered the intersection. This would make it
difficult for the driver of the instrumented vehicle to understand that the approaching police car was in active response and led to a situation of increased risk for both vehicles. Further, the use of rear-facing emergency lights in this situation would fail to properly inform oncoming drivers that the police car was driving in an unexpected way. The second set of events of interest showed instances of both the emergency vehicle and other road users operating in expected ways, yet still led to conflict. In the example presented in Figure 8 (Panel B), a police car was trying to use the right-hand shoulder as an emergency corridor. As the police car progressed forward on the shoulder, a vehicle initially in the right lane tries to yield the right of way by moving into the right shoulder, ultimately stopping the police car rather than allowing it to pass. These events of interest effectively illustrate the need for further study of interactions between roadway users and emergency vehicles to facilitate safer and faster transit, regardless of the situation and the roadway configuration.

Figure 8. Depictions of two unique events interest identified from the SHRP 2 emergency vehicle flagged events. The events feature police cars (PC), the instrumented vehicle (IV) from which the event was captured, and for part B, a primary conflict vehicle (PCV). Part A illustrates an event where an emergency vehicle displayed unexpected behavior. Part B illustrates an event where both the emergency vehicle and other road user operate their vehicles in expected ways, yet still result in a conflict.
This analysis is subject to several limitations and caveats, mainly imposed by the available data. First, all events were coded in context of the driver of the instrumented vehicle. There were several events where other drivers performed unsafe or illegal maneuvers. For consistency, however, these instances were not included in the analysis. Second, the dataset predominantly featured law enforcement vehicles rather than EMS or fire service interactions. Nevertheless, although law enforcement vehicles may be driven in a slightly different manner than fire and rescue vehicles due to personnel roles in an emergency (e.g., law enforcement may attempt to be first on scene) and relative vehicle size, road user yield behavior should still follow the established protocols. Third, since the algorithm that generated the dataset cases was tuned to detect strobing, there is a noticeable bias towards nighttime and/or restricted visibility events. In these circumstances there are typically a smaller number of road users, leading to easier navigation and maneuvering. This, and the high rate of law enforcement vehicles presence in the dataset, may also be contributing to the comparatively low frequency of takeover events observed and to the high frequency of events where driver response was characterized as legal and safe.

3.1.5 Conclusion

Although this analysis was intended to identify attributes of regular road user actions that lead to unsafe interactions with emergency vehicles, there were several instances where the actions of the emergency vehicle led to potentially unsafe situations. Therefore, this analysis emphasizes that emergency vehicle interactions need to be further observed and assessed from both the emergency responder and the typical road user perspectives. The dynamic and high-risk nature of these interactions increases their importance and the safety impact they have on all road users. Originally, it was anticipated that this study would only show other road users “at fault” for impeding emergency response, but it was observed that the behavior of both emergency vehicle operators and other road users can contribute to the current problems. Moreover, this analysis showcased how complex emergency vehicle interactions can be, and the need to thoroughly investigate them to gain a better understanding of causal factors, which in turn
can suggest potential mitigation and/or effective countermeasures. With that motivation, the authors executed a pilot naturalistic driving study featuring two ambulances (Chapter 4). The data collected from that study expands on both road users’ reactions when they are approached or overtaken by emergency vehicles and the behaviors of ambulance operators during emergency response events.

3.2 National EMS Information System Database Delay Analysis

3.2.1 Research Objective

The primary research objective of this analysis was to understand the frequency of delay categories (i.e., dispatch, response, scene, transport) within the U.S. emergency response system. The analysis had five primary research questions: (1) What is the general occurrence of each of the four delay categories that are recorded for emergency response events in the US?; (2) What is the distribution of specific causal factors (i.e., delay types) for the different categories of delays?; (3) How do delay types compare between response modes and transport modes (which are subject to similar delay types)?; (4) How does community density (e.g., rural, suburban, urban) affect each of the delay categories?; and (5) Due to the chronological nature in which delay modes can occur, what is the relationship between subsequent delay categories when multiple modes are present in a single emergency response event?

3.2.2 Methods

Data Source

The data for this analysis came from the NEMSIS database, a large collection of detailed U.S. EMS activations that can include all 50 states and the nation’s territories (depending on yearly enrollment). NEMSIS data encompasses 2009 to the present day [8]. The publicly available database contains deidentified information including patient’s condition, EMS response details, administered medications and treatments, key times throughout the activation event, and other event characteristics. Substantial changes to the database (“Version 3”) were implemented in 2017. The most recent year published is 2021.
The dataset can be obtained by submitting an application through the NEMSIS website (https://nemsis.org/). Specifically, the 2019 NEMSIS dataset was used in this analysis, based on high state participation (47 US states/territories) and a desire to examine data uninfluenced by the COVID-19 pandemic. The 2019 dataset contained 36,119,969 emergency response activations, which included 27,925,669 911-initiated responses [9]. Of the calls that were 911-initiated, and where patient contact was made, the 2019 dataset contained 1,172,727 motor vehicle collisions, which was the second most frequent indicated cause of injury (30.5%).

**Data Processing**

The data was requested through the NEMSIS website and then was originally retrieved on a flash drive containing a series of SAS data files. Each file consisted of a single data table that contained related data elements (e.g., general event data, computation elements, cause of injury). In order to read and manipulate the data, Python was used to first read sections of each file and convert them into multiple parquet files. The parquet files were then merged and read into R for further analysis. The result was a series of tables in R that correspond to each original SAS data file.

The primary NEMSIS tables used in this analysis captured the occurrence of four delay categories: dispatch delay, response delay, scene delay, and transport delay. The initial dataset also included an additional delay category table corresponding to turn-around delay, but this delay element was excluded from the analysis since EMS turn-around takes place after patient transfer. To allow isolation of delay type effects on each delay category, the analysis excluded events where multiple delay types were present within a single delay category. These cases were a small proportion of the overall case population (0.23%, 0.67%, 0.66%, and 0.29% of documented dispatch, response, on scene, and transport delays, respectively).

Further, many cases that exhibited multiple delay types per category contained four or more delay types, likely portraying inaccurate data. Events that reported delays such as “Not Applicable” or “Not Recorded” were also excluded. Only cases that reported delays as “None/No Delay” were counted as non-delay
cases. This resulted in a final population of 26,508,292 cases with defined delay outcomes. Additional NEMSIS tables that provided other relevant information such as the variables “urbanicity” (computed elements table), “response duration” (computed elements table), and “cause of injury” (cause of injury table) were also utilized. Tables were linked through unique event identifiers for each individual activation event.

**Data Analysis**

Research questions one and two, focusing on the frequency of delay categories and distribution of delay types across each category, were addressed by identifying delay frequency across the population of events. First, the frequency of an event having any type of delay was calculated. Next, the relative frequency of each delay category was calculated, followed by determining the frequency of delay types per individual category. Additionally, to examine potential differences in the usage of the delay type “Other” around the country, its use frequency was assessed across U.S. census regions and delay categories.

The third research question aimed to compare and contrast specifically the response and transport delay categories, given the similar nature of their causal factors. This comparison leveraged the changes in call time that occurred in the presence of a delay, statistically assessed through z-tests, and the distribution of delay types, statistically described through chi-square analyses. Significant chi-square tests were supplemented with post-hoc comparison of calculated standardized residuals of the model fit. This comparison allowed identification of specific delay types within a category that were likely to be primary drivers of the statistically significant test. To accomplish this, a Bonferroni corrected p-value ($p = 1.32 \times 10^{-3}$) was first calculated to assess factor level significance. Next, the p-value of each delay type and delay category combination was calculated based on the standardized residuals from the initial chi-square test, which were then compared to the Bonferroni corrected p-value to determine significance. For significant delay type and delay category combinations, positive standardized residuals were interpreted to signify
an increase in observed frequency over what was expected, whereas negative standardized residuals were interpreted as a decrease in observed frequency over what was expected.

The variable “EMSSystemResponseTimeMin” was used to assess response call times. This variable represents the time in minutes from when the response unit was dispatched to the time when the unit arrived on scene. Cases with no recorded time for this variable were excluded. The variable “EMStransportTimeMin” was used for transport call times. This variable represents the time in minutes from when the unit left the scene to the time when the unit arrived at the destination or transfer point. Cases with no recorded time for this variable were excluded. Analysis of the distribution of delay types leveraged delay types that were present in both response and transport categories (e.g., distance, traffic).

The fourth research question, focusing on the influence of community density, was investigated by separating the events within each of the delay categories by delay type and their coded “urbanicity” level (rural, suburban, urban, wilderness, and unknown). To understand how community density may have affected the distribution of delay types throughout each delay category, a chi squared analysis and post-hoc comparison of the calculated standardized residuals was performed for each delay category. First, a Bonferroni corrected p-value (p = 1.25 * 10^{-3}, p = 6.25 * 10^{-4}, p = 5.26 * 10^{-4}, and p = 5.56 * 10^{-4} for dispatch, response, scene, and transport delays, respectively) was calculated to assess factor level significance. Next, the p-value of each delay type and community density level combination was calculated based on the standardized residuals from the initial chi-square test, which were then compared to the Bonferroni corrected p-value to determine significance. For significant delay type and community density level combinations, positive standardized residuals were interpreted to signify an increase in observed frequency over what was expected, whereas negative standardized residuals were interpreted as a decrease in observed frequency over what was expected.
Finally, to address the fifth research question and examine the relationship between all delay modes, two assessments were made. First, a flow map was generated to outline and illustrate the flow of events that experienced one or multiple delay categories. This was accomplished by first sorting all cases that experienced at least one mode of delay by which delay mode was experienced first. Then, each case was assessed to determine if a downstream delay category was also experienced. This assessment was repeated for each case until there were either no more downstream delays or there was a transport delay, which terminated the sequence. Second, total call time was assessed by combining the time span variables “EMSDispatchCenterTimeSec” and “EMSTotalCallTimeMin” to represent the time from PSAP notification to destination arrival. Total call times for events with no delays were then compared to events with one, two, three, and four delay categories present using two-sided z-tests.

Significance for all statistical analyses not requiring Bonferroni adjustments was assessed with a Type I error of 0.05.

3.2.3 Results

General Delay Frequency

Overall, delays in emergency response were frequent, occurring in 8.06% of all NEMSIS events. Chronologically, dispatch delays always occurred first if present, followed by response delays, scene delays, and transport delays. Of the four delay modes, scene delays (4.32%) were the most common, followed by response delays (3.22%), transport delays (1.45%), then dispatch delays (0.57%, Figure 9). The distribution of delay types per each delay category are illustrated in Appendix B. The top three most frequent delay types per each category are listed in Table 4. Note that, when examining each of the four delay categories, the “Other” delay type was either the most or second-most commonly reported delay type. The high prevalence of the delay type “Other” prompted an additional analysis to better understand usage (Table 2). The analysis revealed that the use of “Other” as a delay type was most common in scene
delays and from states located in the South Atlantic division (i.e., Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia).

![Figure 9. Relative occurrence of each delay category.](image)

Table 4. Delay categories and their color-coded three most common delay types.

<table>
<thead>
<tr>
<th>Delay Category</th>
<th>Most Common Delay Type</th>
<th>Second-Most Common Delay Type</th>
<th>Third-Most Common Delay Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dispatch</td>
<td>Other</td>
<td>High Call Volume</td>
<td>No EMS Vehicle Available</td>
</tr>
<tr>
<td>Response</td>
<td>Distance</td>
<td>Other</td>
<td>Traffic</td>
</tr>
<tr>
<td>Scene</td>
<td>Other</td>
<td>Staff Delay</td>
<td>Patient Access</td>
</tr>
<tr>
<td>Transport</td>
<td>Distance</td>
<td>Other</td>
<td>Traffic</td>
</tr>
</tbody>
</table>
Comparison of call times across the response and transport delay categories showed a significant increase in response time ($z = 92.31$, $p<0.001$) when considering response events with no delay (Mean [$M$]=17.07 minutes, Standard Deviation [SD]=60.95) compared to events with response delay (M=20.55 minutes, SD=31.85). Similarly, a significant increase in transport time was observed ($z = 231.5$, $p<0.001$) when considering transport events with no delay (M=18.78 minutes, SD=22.16) and events with transport delay (M=31.67 minutes, SD=33.88).

Response and transport delay categories had 12 shared delay types (Figure 10). In addition, response delays included another four unique delay types, and transport delays included another three unique delay types. Overall, response delays outnumbered transport delays at a ratio greater than 2:1. However, when adjusted to proportionality of delay category, transport delays were more prevalent in many of the
most frequent shared delay types (Figure 11). The distribution of delay types between response and transport delay categories was significantly different \( \chi^2 (18, N = 1236132) = 109723, p < 0.01 \). Post-hoc comparison was then made using the Bonferroni corrected p-value and directionality derived from the chi-square standardized residuals (Figure 12), which showed significant differences between all the shared delay types in the response and transport delay categories. Observations of increase or decrease in observed frequency over what was expected, however, varied between delay categories.

Figure 10. Frequency of delay type distribution across response and transport delay categories.
Figure 11. Proportion of delay types compared between response and transport delay categories. Only delay types that occurred in 1% or more of the delays in each of the categories are shown.

Figure 12. Differences observed in delay type frequency between response and transport delay categories.
Each of the four delay categories and the distribution of their delay types were then further split by community density (i.e., rural, suburban, urban, wilderness, and unknown) and assessed based on frequency (Appendix C) and relative proportion (Appendix D). Significant differences in delay type frequency by community density were observed for dispatch delays ($\chi^2 (28, N = 150162) = 3382.6, p < 0.01$), response delays ($\chi^2 (60, N = 852746) = 118755, p < 0.01$), scene delays ($\chi^2 (72, N = 1146042) = 21963, p < 0.01$), and transport delays ($\chi^2 (56, N = 383386) = 18237, p < 0.01$). Post hoc analyses results showed that most delay types, across all four delay categories, had significantly different prevalence based on community density. The greatest level of distinction was observed for urban communities, which differed from both suburban and rural communities. More specifically, for dispatch delays, most of the delay types showed a significant decrease in the number of cases observed when other community densities were compared to the expected values for the “urban” group (Figure 13). The main exception to this trend, however, was the “high call volume” delay type, which showed a significant increase from the expected values in urban settings. Additionally, a significant increase in observed values of “other” dispatch delays occurred in rural areas, whereas the three other defined community levels exhibited a significant decrease.
Figure 13. Differences observed in delay type frequency across urbanicity levels for dispatch delay category cases. Delay types are sorted from most (top) to least (bottom) frequent.

A similar trend was observed for response delays, where the “urban” and “unknown” groups generally showed a significant decrease in observed values for most delay types while “suburban,” “rural,” and “wilderness” groups showed a significant increase (Figure 14). Noteworthy exceptions to this generalization included the “distance” and “scene safety” delay types, which showed significant increases in observed values for “urban” environments, and the “traffic” delay type, which showed significant increases in observed values for “unknown” environments.
For scene delay types (Figure 15), due to a generally greater resource availability in urban environments, it was expected that resource-dependent delay types would be less common in urban settings. The “Patient Access,” “Extrication,” Triage/Multiple Patients,” “Awaiting Ground Unit,” “Awaiting Air Unit,” “Mechanical Issue-Unit, Equipment, etc.,” and “Vehicle Failure of this Unit” delay types met this expectation. In contrast, delay types such as “Distance,” “Language Barrier,” and “Traffic” were expected to occur more frequently in urban environments. Observations from the data matched these expectations. Exceptions to these set expectations included the delay types “Staff Delay,” “Safety-Patient,” and “Safety-Crew/Staging” which, contrary to the expectation of no environment impact, were found to have a significant increase in observed values over what was expected in urban settings.
Figure 15. Differences observed in delay type frequency across urbanicity levels for scene delay category cases. Delay types are sorted from most (top) to least (bottom) frequent.

Finally, for transport delays (Figure 16), delays due to distance in urban cases were found to be less prevalent than in more rural settings, as expected but in contrast to observations in the response delay category. On the other hand, the “Other” and “Traffic” delay types were found to show a significant increase from expected values in urban settings, again, in contrast with response delay category observations. The distributions of other delay types for the transport delay category matched expectations based on the different community density categories that were examined.
Figure 16. Differences observed in delay type frequency across urbanicity levels for transport delay category cases. Delay types are sorted from most (top) to least (bottom) frequent.

Inter-Delay Relationships

The chronological analysis of delays showed substantial differences in the likelihoods of subsequent delay categories once a particular category was present (Figure 17). Inputs A, F, J, and M in the figure represent the percentage of cases that experience a specific delay category first, which is why input A is 100% (all EMS activations that experienced a dispatch delay must start in dispatch delay). Outputs B, G, K, and N represent the percentage of cases that do not experience a downstream delay from their current delay category, which is why output N is 100% (all EMS activations that experienced a transport delay must end in transport delay). Finally, cases that experience additional downstream delay categories are expressed with transitions (labeled C, D, E, H, I, and L) that feature two percentages. The first percentage quantifies the cases that are output from the upstream delay category. The second percentage quantifies the cases...
that are input into the downstream delay category. Notably, the flow map illustrates that over 50% of cases that experience a transport delay also experience at least one other delay category. These other categories are generally either a response or a scene delay.

Figure 17. Flow map depicting the relationship between delay categories by illustrating the percentage of cases that experience one, two, three, or four categories of delay and the relationships between subsequent delay categories.

Total call times increased ($z = 148.18, p<0.001$) when considering events with no delay ($M=76.04$ minutes, $SD=86.03$) compared to events with only one category of delay experienced ($M=89.65$ minutes, $SD=63.37$). These increases were larger as events with two delay categories ($z = 123.94, p<0.001; M=107.61$ minutes, $SD=70.13$), three delay categories ($z = 86.66, p<0.001; M=126.89$ minutes, $SD=76.88$), and four delay categories ($z = 12.10, p<0.001; M=102.56$ minutes, $SD=95.68$) were considered (Figure 18). It is noteworthy that the total call time when four delay categories were present tended to be smaller than when two or three delay categories were present, an unexpected finding.
Figure 18. Distribution of total call time with no delay reported (maroon) compared to increasing number of delay categories (orange). Plot A shows the distribution of when only one delay category is present, followed by two (plot B), three (plot C), and all four delay categories (plot D). The mean time of each distribution is indicated by the vertical dashed lines. Note that the distributions associated with delays (in orange) were layered in front of the no delay distributions (in maroon), which produces variations in the color of the two distributions when they overlap.

3.2.4 Discussion

General Delay Frequency

Analysis of the general frequency in which EMS experience delays confirmed that delays are a relevant issue in emergency response. The analysis identified that 8.06% of the fully documented cases in the dataset included some type of delay—more than 2 million cases nationwide. When considering the individual delay frequencies of the four delay categories, the relatively low number of dispatch delays present in the dataset was unsurprising. Dispatch center staff are often trained to work with callers to quickly identify the source of the emergency call and leverage their resources to best meet community needs (e.g., multi-lingual staff in diverse communities, geographic familiarity with the call area) and efficiently dispatch necessary resources. Additionally, 911 dispatching has been greatly improved by
enhanced 911 services, where cellular callers can have their calling location pinpointed using GPS, expanding upon capabilities of traditional landlines use [72, 73]. This was further supported by the delay type distribution found in the dataset for the dispatch delay category, where the largest defined contributions to the dispatch delays did not arise from errors or problems in dispatching, but rather from times of high call volumes, unavailable units, and unknown circumstances coded as “other.” In contrast to the relatively low frequency of dispatch delays, a much greater frequency of on-scene delays was expected, mainly due to factors like secondary resource procurements (e.g., additional staff/ higher levels of pre-hospital care, extrication equipment) and on-scene patient treatment (e.g., diabetes related treatments, cardiopulmonary resuscitation). This expectation was supported by the delay type distribution found in the dataset.

Prevalence and causal factors for the response and transport delay categories were expected to be similar due to their similar nature. However, the analysis revealed that response delays (3.22%) occurred more than twice as frequently as transport delays (1.45%). Three possible reasons may explain this difference in prevalence. First, an emergent response bias, which is a product of how emergency calls are generally handled. In many cases, 911 calls are considered critical until on-scene personnel can evaluate the extent of the emergency at hand, ultimately adjusting the perceived severity of the call as needed. This is often accompanied by EMS agencies establishing shorter time span goals for the response phase compared to the transport phase [25, 26]. Even with the common use of emergent driving (active lights and/or sirens) during the response phase, these shorter time spans may ultimately result in a more stringent evaluation criterion being used to determine whether a response delay (vs. a transport delay) was present in a particular response. Second, patients receive treatment during the transport phase. Since transported patients are being monitored and receiving treatment while under EMS care, agency-set transport time goals are often relaxed compared to response time goals. Third, presence of non-transport cases. Transport may not have been ultimately performed due to patient refusal (before or after treatment), on-
scene transfer of care, or when patients may have been declared deceased on-scene. Additional investigation is necessary to determine the contributions of each of these factors to the observed difference in frequency between response and transport delays.

Several analyses also indicated the need to improve data specificity, namely, clearly define when the “Other” delay type should be used. As defined by the NEMSIS dictionary, “Other” is to be used to capture any delay causality beyond the predetermined list of delay types. In practice, as indicated by the results, the use of “Other” is quite frequent (representing either the most or second-most commonly reported delay type in each category) and represents a major roadblock in gathering useful information from NEMSIS. Results indicated that the use of “Other” as a delay type was most prevalent in certain types of delays and/or geographical regions, suggesting that additional training in proper input of records may be needed. In the short term, however, perhaps EMS reports that select “Other” could be required to submit a free text entry to describe the delay. Those entries could be reviewed periodically and either modified to fit within one of the predefined delay types or used to add missing delay types.

*Response vs. Transport Delays*

Differences between response and transport delays were present in call times and in the prevalence of specific delay types. Although experiencing a response delay or a transport delay were both shown to significantly increase call time for that specific phase of a response (vs. no delay), the presence of a transport delay increased that call time by a larger magnitude than observed when a response delay was present. Analysis of delay types observed across both response and transport delay categories showed that, for most of the shared delay types, cases associated with transport delays generally exceeded the expected values. Notably, however, three delay types did not follow this pattern: “distance,” “directions/unable to locate,” and “route obstruction.” Seeing less transport delay cases than expected for “directions/unable to locate” and “route obstruction” is logical, as ambulance operators should be much more familiar with the route to and location of the treatment facilities they service, as compared to
emergency call locations that tend to be arbitrary. For the “distance” delay type, the emergent response bias and established agency-set time objectives, previously mentioned, may also be at play. Since goal transport times are often lengthier than those in the response phase, a more forgiving window exists before the phase may be deemed delayed, which translates into a lower likelihood that distance would become a delay factor. Interestingly, however, in the presence of non-delay conditions, the mean response and transport times were found to be very similar. When considering factors like resource availability and access, this finding may be useful in evaluating the efficiency associated with where agencies and treatment facilities are located. Whereas the finding that the average non-delayed response and transport times are similar suggests that agency resources and destination/treatment facilities are properly spaced within the community, the significantly higher portion of response delay cases due to “distance” than expected suggests that improvements in this area are still possible.

*Delay Type by Community Density*

Community density substantially modified the distribution of delay types across the four delay categories. When considering dispatch delays, the general trend showed that for “urban” coded cases there was a significant decrease in the number of cases observed (versus cases expected) compared to the other community density types. Most likely, this effect is a result of the overall high frequency of cases coded as “urban” (observable in Appendix C). Likewise, it was observed (and expected) that the delay type “high call volume” would show increased observed cases (versus cases expected) since urban locations are more densely populated and therefore more likely to experience instances of high call volume. An interesting observation, however, is the significant increase in observed values for “other” dispatch delays in rural areas. One reason for this may be a mismatch in documentation methods or technology. Many agencies in the U.S. use one of several popular online, subscription-based applications to integrate their documentation (e.g., EMS EHR, Omnigo, ImageTrend), but financial resources to access these may be limited in rural communities. Ultimately, the lack of these applications may lead to alternate
documentation that does not translate appropriately when compiled at the national level. Alternately, the observation of increased observed prevalence in “other” dispatch delays may be influenced by distinct dispatching practices utilized by rural communities.

A similar trend was observed for response delays, where the “urban” and “unknown” groups generally showed a significant decrease in observed cases (versus expected cases) compared to the other environments. One exception to this observation was the relatively high prevalence of the “distance” delay type in urban settings. This was a surprising finding, as intuitively it was not expected that delay due to distance would be a common issue in urban communities, where locations are generally geographically closer to one another. Limited by the data available within the dataset, it was not possible to draw further insights on these cases that could indicate causal factors for the relatively large prevalence of distance delays in urban settings. Considering the sizable contribution that these urban cases make within the dataset, however, future research efforts should further examine urban delays due to distance. The second exception was for the “scene safety” delay type. These are often events that are deemed dangerous (e.g., hazardous materials present, acts of violence, fires). To establish readily available medical care while reducing the likelihood of injuring or incapacitating EMS personnel, EMTs are often staged near, but not at, dangerous scenes. Likely due to population and associated resource density, it is more common for these types of events to take place in urban and suburban environments. The last exception for response delays is the “traffic” delay type which unexpectedly showed a significant increase in observed values for only “unknown” cases. Throughout the entire dataset, very few delays were coded to have occurred in an “unknown” community density outside of response delays due to traffic. Thus, these findings may be an artifact of the data collection process or may have been unintentionally introduced during the deidentification process the dataset goes through before release. Nevertheless, this finding further justifies the need to specifically investigate emergency responder traffic interactions.
The distribution of scene delay types did not seem to vary substantially along with community density. This finding may be due to the increased granularity of delay types compared to other delay categories. Nevertheless, given that urban communities generally possess a greater quantity and quality of relevant resources (e.g., personnel, equipment), it could be expected that resource-dependent delay types would be less common in urban settings, as seen in the distribution of the “Patient Access,” “Extrication,” Triage/Multiple Patients,” “Awaiting Ground Unit,” “Awaiting Air Unit,” “Mechanical Issue-Unit, Equipment, etc.” and “Vehicle Failure of this Unit” delay types. Further, some delay types were expected and found to occur more frequently in an urban environment. These delay types included “Distance,” “Language Barrier,” and “Traffic.” One important exception to this resource-based expectation, however, was the delay type “Staff Delay.” This result was somewhat unexpected as urban EMS agencies are more likely to have 24-hour staff, be less dependent on off-site, on-call personnel than their rural and suburban counterparts, and/or have better localization of resources within the community. It is possible, however, that in the context of an on-scene delay this finding may include secondary staff delays such as awaiting advanced life support following patient contact, particularly if required treatment is beyond the scope of those first on scene. Additional delay types that did not match expectations included “Safety-Patient” and “Safety-Crew/Staging,” which were observed more frequently in urban settings. These delays are generally due to EMS personnel awaiting law enforcement arrival to secure the patient(s) and/or the scene to ensure safety before triage and treatment begin. The observed increase of these scene delay cases due to safety in urban settings may be caused by particular challenges introduced by the more complex urban environment. For example, in a city it would be much more difficult to secure a set geographic area than in a more open, less dense community. Further, very specialized (i.e., limited availability and/or geographically distant) personnel may be required to help eliminate certain hazards more common in urban areas. Additionally, in rural areas, due to less available public safety personnel, EMS may be better trained or permitted to secure scenes and contain hazards.
Lastly, the most interesting observations made regarding transport delays involved characterizing whether the distributions of the top three delay types shifted in the transport delay category in contrast with the response delay category. When considering urban environments, the significant decrease in observed delays due to distance met expectations. This finding suggests a more favorable distribution of treatment facilities in urban environments compared to suburban and rural locations, at least in reference to where emergency events are taking place. In contrast, for urban environments, the “Other” and “Traffic” delay types were found to show a significant increase from expected values. Speculating about reasons for this observation in “Other” delay type cases is difficult due to the vaguely defined nature of this variable level. For “Traffic,” on the other hand, non-critical patients (which make up the majority of transport patients) are taken to the hospital in non-emergent fashion. That makes these patients subject to regular traffic flow, and such flows would be expected to be denser (and lead to delays more often) in urban settings. The distribution of other delay types for the transport delay category was generally unremarkable and met expectations.

**Inter-Delay Relationships**

Naturally, it is expected that as the number of delays experienced during an emergency response event increase, so will the event duration. Analyses of the flow map generated in this investigation indicate that more than 50% of emergency response events that experience a transport delay include additional delays from the other delay categories, particularly the response and scene delay categories. The compounding of these delays significantly increased the total call time, with the exception of cases when all four delay categories were present. One reason for this exception could be the relatively small frequency of cases that experienced all four delay categories (N=6,470). Further, these observations may include inaccurate data. Considering that these events are documented to have experienced four different delays, it seems unlikely that the total emergency response time would fall below a 60-minute interval.
3.2.5 Conclusion

With the intention of reducing emergency response delays to improve overall efficiency and care, the findings of this study present helpful insight to direct improvement efforts. From the perspective of frequency alone, targeting scene delays could be a strong first step as they were, at about 45% of all documented delays, the most frequent. To achieve this, the findings suggest that working towards reducing staff delays and expediting patient access would best service this phase of an emergency response event. Direct improvement efforts towards delay types prominent in urban communities would also have a sizeable impact, since they comprise most of the case population. Care should be taken, however, to ensure that improvements in urban communities do not come at the cost of neglecting suburban and rural areas.

It is also important to find ways to address multiple components of emergency response delays at once. Due to the frequent observed coupling of transport delays with other delay categories, one way to tackle emergency response delays could be to concentrate on transport delays. Consequently, a reduction in the prevalence of transport delays would also yield a sizable reduction in the number of events that experience multiple delay categories, resulting in improved total emergency response times. Focusing on transport delays may also lead to response delay improvements, since these two delay categories shared delay types in more than 90% of their case volume. Specifically, directing research to better understand and address distance and traffic related delays would substantially reduce the frequency of delays in these two categories.

Ultimately, emergency response delays are a serious issue that invokes safety concerns for both emergency responders and their patients. For emergency responders, delays can lead to backlogged patients, added stress in potentially dangerous environments, or present additional hazards. For patients, delays result in increased time to definitive care which could lead to higher chances of morbidity and
mortality. The findings of this study can be used to help direct future research to best address and improve emergency response delays. Due to the fact that this study captured data from across the U.S., additional research should be conducted to verify delay type relevance on a local scale before potential solutions are implemented.
4: Ambulance Naturalistic Driving Study

4.0.1 Background

In a previous study (Chapter 2), EMTs were interviewed about their experiences while responding to vehicular crashes. Some EMTs expressed concern about their traffic interactions with other road users when in active emergency response, noting that other drivers can react in unpredictable and unsafe ways. Although there exists published work that investigates the adverse implications of longer emergency response times on patient outcomes as well as the crash risk associated with emergency driving, limited work has been found that identifies and analyzes specific challenges that emergency responders encounter when traveling to and from emergency calls [17, 74]. To understand the baseline of the prescribed response that regular drivers should exhibit when encountering an emergency vehicle, a survey of US driving manuals was conducted. The survey showed that although variation between states exists, most US drivers are taught to yield the right of way by merging to the right side of the road when they are approached by an emergency vehicle. An initial research investigation of naturalistic data collected from the SHRP 2 research project (Chapter 3.1) was conducted to gain greater insights on first-hand emergency vehicle interactions. Due to the low frequency of emergency response events observed, and the fact that videos were collected from the perspective of average road users, a majority of the emergency vehicle interactions in that dataset involved stationary emergency vehicles responding to roadside events (e.g., traffic stops and roadside assistance) and did not provide sufficient insight into the dynamics and variability associated with takeover events. Additionally, all videos were forward-facing, and, during an emergency vehicle takeover event originating behind the instrumented vehicle, there was no view of the emergency vehicle approach. These videos did, however, highlight several complex scenarios that should be further investigated (e.g., when a highway emergency corridor is utilized by emergency vehicles).
To better understand the type of complex scenarios that emergency vehicles encounter during active response and the type of reactions that road users have when faced with an emergency vehicle, this study instrumented two ambulances to participate in a six month long naturalistic driving study. The participating ambulances were instrumented to directly collect all interactions with other road users as a means to provide detailed insight into the types of scenarios ambulance operators navigate every day. Additionally, this understanding can lead to the development of engineering solutions to improve safety and reduce response times surrounding these interactions, ultimately leading to decreased crashes and improved mortality and morbidity outcomes for patients being assisted by these emergency services.

4.0.2 Research Objectives

The primary objective of this research study was to evaluate how traditional road users (e.g., other vehicles, pedestrians, and bicyclists) respond when an ambulance in active emergency response crosses their path. This was accomplished by collecting high-quality naturalistic data from real-world settings while ambulance operators navigated to and from emergency calls. Specifically, this research effort sought to answer four key research questions: (1) How do other road users react when approached by an ambulance in active emergency response in real-world settings?; (2) How are ambulance operators reacting to other road users?; (3) What conditions may lead to unsafe or confusing interactions with other road users?; and (4) What data elements can be collected to be used as inputs to a safety benefits model that considers these interactions? A secondary objective of this study was to compile a dataset of naturalistic driving ambulance data, as this study is the first of its kind.

4.0.3 Methods

Recruitment and Instrumentation

The Virginia Tech IRB approved the protocol for this study (IRB #21-540). Participating EMS agencies were recruited through both private and public safety points of contact. Eligibility requirements for candidate
participating agencies were self-identification as a 911 transport agency and service to a high call-volume area. Additionally, agencies which were within driving range of Virginia Tech (5-6 hours) and non-volunteer-based were preferred due to logistical constraints. This study included naturalistic driving data from two ambulances, one located in North Carolina and the other in Virginia. Once an EMS agency agreed to support the study and instrumentation permission was obtained, ambulance operators within that agency that were known to drive the candidate ambulance were contacted to anticipate their general level of interest in the study. Once a sufficient number of operators were anticipated to participate, the driver recruitment phase began. Any driver who was employed by the participating agency and was approved to operate an agency ambulance was eligible to participate in the study. All eligible participants also needed to be 18 years of age or older and speak English. Drivers who had interest in participating in the study were then scheduled for an intake meeting where they completed the study consent process and the demographics and pre-study questionnaire (Appendix E). Participants were compensated if permitted by the agency of employment. A total of 18 consented drivers participated in the study. Answers to the participant demographics questionnaire were summarized using JMP (version 16.0.0).

The two participating agencies had some notable differences in enrollment, vehicle type, and service area. Agency 1’s ambulance was a 2019 Chevrolet Express (van body) and had six consented drivers throughout the data collection period (from May 2022 to January 2023). This vehicle was continuously in service during data collection and rotated between urban, suburban, and rural stations within the agency’s run area. The Agency 1 ambulance operated within a county of approximately 850 square miles and served an estimated population of 1.15 million residents. Geographically, Agency 1’s service area was centered around a major urban city and included many less densely populated communities that surrounded the city. Agency 2’s ambulance was a 2019 Ford F-450 (truck body) and had 12 consented drivers throughout the data collection period (from September 2022 to April 2023). This vehicle was also continuously in service during data collection but was assigned to a single station, where it predominantly served the
same communities throughout the study period. The Agency 2 ambulance operated within a county of approximately 251 square miles and served an estimated population of 97,000 residents. Although Agency 2’s run area surrounded an urban center, like Agency 1, that urban center was not included in the agency’s jurisdiction. Thus, Agency 2’s run area predominantly included suburban and rural communities that surrounded the urban center.

A VTTI flexDAS data acquisition system was used to collect continuous video and vehicle data from all vehicle drivers any time the vehicle was turned on and in motion. A digital still image was taken of each participating driver’s face during the consent process to ID the correct participant in the videos during subsequent data processing. All recorded data pertaining to non-participating drivers was excluded from any processing or analysis. While the ambulance was active, the flexDAS collected continuous video of the drivers’ face, an over-the-shoulder view of the driver, the ambulance accelerator and brake pedals, the forward roadway, the rear roadway, and the left and right sides of the ambulance. Cameras were placed and directed in such a way as to prevent capturing patient information to the extent possible. The flexDAS also collected continuous vehicle data including vehicle speed, longitudinal and lateral acceleration, steering data, GPS location, emergency light use, and emergency siren use. Both ambulances were instrumented with forward-facing radar units that collected data about leading objects and vehicles throughout the study, however, only the Virginia ambulance could be additionally instrumented with a rear-facing radar. As an additional means to limit the collection of patient information, the flexDAS was also configured to go into standby mode (i.e., stop writing a data file) anytime the vehicle speed was at 0 mph for five minutes or longer, and resume data collection (i.e., begin writing a new data file) following a pause once the vehicle speed reached 5 mph.

Data Summaries

Following the end of data collection there were a total of 8,044 data files. All files were initially processed to meet VTTI’s variable standardization requirements. Files were then retained for analysis if they showed
ambulance operation by consented drivers, had a duration of three minutes or greater, and captured data for a distance of at least one mile. The remaining files were considered trips for the purpose of the analysis. Next, trips were either classified as non-emergent or emergent, where any trip that included the use of emergency lights and/or sirens for any portion of time was classified as emergent. Only those drivers who had both non-emergent and emergent data were considered for further data analysis, which resulted in the removal of one consented driver (Driver 7). This resulted in 2,520 total trips, of which 926 were emergent. A dataset summary was then generated to capture the number of trips, mileage, and duration for both non-emergent and emergent trips per driver. The dataset was also assessed for agency-specific distributions of trip duration, trip distance, and the time of day the trip took place.

**Kinematic Analysis**

Next, the distribution of vehicle kinematics was assessed. Kinematics is the study of measurements that express how objects move, including metrics like velocity and acceleration. Initially, each trip was assessed across four speed metrics of interest: minimum speed, maximum speed, mean speed, and standard deviation of speed. Each metric was analyzed using a random effects mixed General Linear Model in JMP (version 16.0.0) that accounted for effects due to agency and trip type (non-emergent vs. emergent). Significance was assessed for the main effects and two-way interactions with an alpha of 0.05. Tukey HSD *post hoc* tests were conducted to further assess any significant effects.

Kinematic analysis also included identification and assessment of events of interest, comprised of instances with high-magnitude longitudinal acceleration, lateral acceleration, or yaw rate. Traditionally, kinematic events of interest are identified by applying accepted metric threshold values, or “trigger” values, that are often associated with safety critical events as defined in past naturalistic driving studies [75]. However, since the driving style associated with ambulances, particularly during emergent responses, was anticipated to exhibit what is normally classified as aggressive driving for traditional road users, suitable threshold values needed to be first identified. During preliminary data analysis, several
threshold values (±0.3 g through ±0.5 g in 0.05 g steps for acceleration; ±3 deg/s through ±10 deg/s in 1 deg/s steps for yaw) were evaluated against the dataset for each metric of interest to identify values with appropriate sensitivity. This preliminary assessment included comparing the size of each threshold’s event subset and video verification of potential events. Following the initial assessment, the resulting threshold values were identified: 0.4 g for positive longitudinal acceleration (experienced from forward acceleration), -0.4 g for negative longitudinal acceleration (experienced from hard braking), ±0.4 g for lateral acceleration (experienced from left and right turns), and ±5 deg/s for yaw rate (also experienced from left and right turns, but further requiring a swerving maneuver with both steering and counter-steering). These determined thresholds were applied for each metric following the same approach as Kim et. al., [76]. The frequency of incidents, grouped by driver and trip type, were then used to determine incident prevalence by calculating a rate in terms of events per 100 miles traveled (EPHMT). Rates for each of the four kinematic events of interest were analyzed using a random effect mixed General Linear Model in JMP (version 16.0.0) that accounted for effects due to agency and trip type. Significance was assessed for the main effects and two-way interactions with an alpha of 0.1. The type I error value was increased from 0.05, as used in the speed analysis, to account for a decrease in confidence from a reduced number of data points. Tukey HSD post hoc tests were conducted to assess any significant effects. Finally, to contextualize findings and evaluate overall driver behavior, all flagged kinematic events of interest were summed per driver and trip type, converted to EPHMT, then converted to rate ratios (emergent/non-emergent) for each driver.

Roadway Use Analysis

The final component of data analysis included evaluation of emergency vehicle operation and interactions in the context of roadway infrastructure. This was accomplished first through a map-matching process using the recorded GPS coordinates collected from the instrumented ambulances. Raw GPS data was sampled at 10 Hz. The data was then down-sampled to 1 Hz, and input into a local instance of the Valhalla
map-matching platform. The Valhalla platform snaps the route, inferred from the GPS breadcrumbs, to an OpenStreetMaps map. This process also leveraged GPS coordinate timestamps to improve accuracy. Key data elements including posted speed limit, road classification (i.e., motorway, trunk, primary, secondary, tertiary, residential, unclassified, or service), and instances of intersection crossing (i.e., simple or complex) were derived from the map data.

To further investigate speeding behavior, known posted speed limits were compared to recorded vehicle speeds. For each trip, the mileage traveled with known speed limits was calculated. Only trips with more than 50% mileage of known speed limits were considered for analysis. This resulted in a total of 2,322 consented trips, where 826 were emergent. The proportion of mileage spent speeding was calculated for each trip using four speeding thresholds: any speed in excess of the speed limit, in excess of 5 mph over the speed limit, in excess of 10 mph over the speed limit, and in excess of 15 mph over the speed limit. Based on a large prevalence of instances where drivers exceeded the speed limit by small amounts, the 10 mph or greater threshold was viewed as the most appropriate indicator of speeding behavior for this study population. Speeding behavior was then analyzed using a random effect mixed General Linear Model in JMP (version 16.0.0) that accounted for effects due to agency and trip type. Significance was assessed for the main effects and two-way interactions with an alpha of 0.05. Tukey HSD post hoc tests were conducted to assess any significant effects.

Consented trips were also separated into proportions of each road classification level travelled. Only trips that had defined road classifications for the entire length of the trip were considered. This resulted in a total of 2,444 consented trips, of which 890 were emergent. Trips associated with each of the eight road classes were then analyzed in the previously defined statistical model. A follow-up analysis was then conducted to assess speeding behavior in the context of road classification, without considering the effects of agency. To do this, the proportion of distance traveled in excess of 10 mph over the speed limit was determined for each road class traveled within each trip. Speeding behavior was then analyzed using
a random effect mixed General Linear Model in JMP (version 16.0.0) that accounted for effects due to road class and trip type. Significance was assessed for the main effects and two-way interactions with an alpha of 0.05. Tukey HSD post hoc tests were conducted to assess any significant effects.

Known road classes were also used to assess video data for traffic interactions. For this analysis, trip files were separated by the determined road class, then divided into 21-second-long segments (a standard duration for baseline video annotation at VTTI). For each road class, 50 randomly selected segments were pulled from the emergent trip subset of the data. Some segments lasted less than 21 seconds due to loss of video data but were still considered; these segments were infrequent and not anticipated to affect the findings. Each video was manually assessed for traffic interactions and considered direction of travel, vehicle type (e.g., light vs. heavy), time of day (e.g., day vs. night), and the presence of adverse weather elements (e.g., rain, snow). To be considered as a vehicle interaction, the other vehicle needed to be adjacent to the instrumented ambulance, and not separated by a barrier (e.g., raised median on a divided roadway). Additionally, if the video footage contained a large traffic queue (usually caused by a crash at the intended response destination), only the first 20 vehicle interactions were considered to avoid inflating the findings artificially.

For each documented interaction, yield response of the other road user was categorized as “appropriate,” “inappropriate,” or “appropriate but delayed” similar to the study described in Chapter 3.1. In general, “appropriate” responses were assigned to vehicles that yielded the right of way quickly and maximizing their capability (e.g., used the entire shoulder; Figure 19). Although rightward yielding is generally preferred (Table 2, Chapter 3), if ample space was provided to the overtaking emergency vehicle, leftward yielding was also deemed appropriate. Similarly, “appropriate but delayed” responses were assigned to vehicles that either delayed their yielding behavior such that it required the ambulance operator to make a noticeable adjustment, or to vehicles that did not yield using the full extent of the roadway (Figure 20). Finally, “inappropriate” responses were assigned to vehicles that failed to yield (Figure 21). Yield response
distinction was made using all relevant video angles to best understand the extent of the interaction. The evaluation considered factors such as visibility (e.g., line of sight between the vehicles, weather), estimated travel speed of other vehicles, and roadway layout (e.g., shoulder presence). Ultimately, yield response judgment was made by the author who has firsthand experience as an EMT and ambulance operator. The yield responses were then categorized in the context of safety as “safe” (corresponding to “appropriate” yield behavior) and “safety critical” (corresponding to “inappropriate” and “appropriate but delayed” yield behavior). The rates of occurrence for these levels were then used to characterize the traffic interactions.

Figure 19. Drivers of vehicles on both sides of the two-lane road yield to their respective right-side shoulders to provide a path for the emergent ambulance. All pictured drivers were deemed to have responded appropriately.
Figure 20. Drivers on a motorway attempt to clear a path for the emergent ambulance. The driver of the light-colored vehicle on the left was deemed to have an “appropriate but delayed” response. Although the light-colored vehicle did yield, they had ample time to merge into the right lane (which would have been the preferred response due to the small left side shoulder) and did not come fully to a stop, which made overtaking the vehicle more challenging for the ambulance. Before passing the light-colored vehicle, the ambulance operator had to come to a stop and wait for more room to open on the right in order to drive around the light vehicle and pass them on the right.

Figure 21. The driver of the blue pickup truck in the left lane was deemed to have responded “inappropriately.” The blue truck was the sole occupant of the left lane for some time as the ambulance approached it. There was ample opportunity for the blue truck to merge into the right lane, but the driver did not execute that maneuver. Once the ambulance caught up to the blue truck, the ambulance operator was forced to brake and use the left shoulder to maneuver around the blue pickup truck.
Finally, traffic interactions at and within the intersections were specifically investigated. This analysis only considered emergent intersection travel. Intersections of interest were then flagged if traversing the intersection was approximated to last longer than 2 seconds based on GPS timestamps. No motorway intersections were flagged due to overall low prevalence and rapid crossing when present. The list of identified events across all road classes was then randomized. The first 100 intersections were then manually assessed for traffic interactions using video footage. There was no standardized video duration associated with evaluating intersection interactions. Rather, video and data from each intersection were assessed from intersection approach through intersection exit, with exact start and stop points determined by the author’s judgement. The yield response of the other road user(s) was the primary focus of the analysis, documented in the same way as for the roadway interactions but considering some additional variables (e.g., road class, traffic control device present, relative direction of travel, vehicle type, time of day, and the presence of weather). To be considered as a vehicle interaction, other vehicles either needed to be adjacent to the instrumented ambulance within the roadway segment leading into or out of the intersection or had the potential to disrupt the passage of the ambulance (e.g., a passenger car on a perpendicular roadway with a green traffic light).

4.0.4 Results

Data Summaries

With the exception of the reported number of miles driven in the past year and the reported number of weekly driving hours, the answers to the demographics questionnaire showed similar results between the agencies (Table 6). If any question was left unanswered by at least one driver, the total number of respondents for that question is indicated in the table. The number of trips per driver ranged from 9 to 394. The number of miles driven were also totaled for each driver and trip type, ranging between 11 and 1,780 for emergent trips and 56 to 2,270 for non-emergent trips (Table 7). Of the data collected, 36.7% of
trips were emergent (corresponding to 36.1% of captured miles driven and 35.3% of driving duration; Figure 22).

Table 6. Drive demographic summary.

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</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>4</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>2</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>38.5 (12.37)</td>
<td>33.25 (8.62)</td>
<td></td>
</tr>
<tr>
<td>Use of corrective lenses when driving</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>3</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>3</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>Use of hearing aid when driving</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>6</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>Number of motor vehicle crashes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>1.67 (2.07)</td>
<td>1.33 (1.97)</td>
<td></td>
</tr>
<tr>
<td>Number of years experience driving an ambulance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>12.67 (10.56)</td>
<td>10.04 (9.74)</td>
<td></td>
</tr>
<tr>
<td>Number of years at current agency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>4.67 (4.89)</td>
<td>7.41 (7.86)</td>
<td></td>
</tr>
<tr>
<td>Are you involved in new driver training (n=17)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>0</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>6</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Number of miles driven in the past year (n=14)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>16,825 (3,431)</td>
<td>2,935 (3,417)</td>
<td></td>
</tr>
<tr>
<td>Number of average duty hours per week</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>51.67 (9.09)</td>
<td>57.5 (20.30)</td>
<td></td>
</tr>
<tr>
<td>Number of average driving hours per week</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>32.83 (11.46)</td>
<td>26.83 (15.21)</td>
<td></td>
</tr>
</tbody>
</table>
Table 7. Trip summary by driver and trip type.

<table>
<thead>
<tr>
<th>Agency</th>
<th>Driver</th>
<th>Trip Type</th>
<th>Number of Trips</th>
<th>Mileage (mi)</th>
<th>Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Non-Emergent</td>
<td>233</td>
<td>2115.3</td>
<td>4573.4</td>
</tr>
<tr>
<td>Agency 1</td>
<td></td>
<td>Emergent</td>
<td>161</td>
<td>1780.9</td>
<td>3493.6</td>
</tr>
<tr>
<td></td>
<td>Driver 2</td>
<td>Non-Emergent</td>
<td>150</td>
<td>1274.2</td>
<td>2553.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>117</td>
<td>1011.0</td>
<td>2007.2</td>
</tr>
<tr>
<td></td>
<td>Driver 3</td>
<td>Non-Emergent</td>
<td>200</td>
<td>1903.8</td>
<td>3890.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>127</td>
<td>1340.2</td>
<td>2516.3</td>
</tr>
<tr>
<td></td>
<td>Driver 4</td>
<td>Non-Emergent</td>
<td>77</td>
<td>744.2</td>
<td>1462.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>15</td>
<td>180.2</td>
<td>335.3</td>
</tr>
<tr>
<td></td>
<td>Driver 5</td>
<td>Non-Emergent</td>
<td>251</td>
<td>2270.9</td>
<td>4609.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>105</td>
<td>1049.8</td>
<td>2003.0</td>
</tr>
<tr>
<td></td>
<td>Driver 6</td>
<td>Non-Emergent</td>
<td>9</td>
<td>56.2</td>
<td>132.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>6</td>
<td>36.5</td>
<td>95.8</td>
</tr>
<tr>
<td></td>
<td>Driver 8</td>
<td>Non-Emergent</td>
<td>19</td>
<td>158.0</td>
<td>358.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>1</td>
<td>16.8</td>
<td>17.8</td>
</tr>
<tr>
<td></td>
<td>Driver 9</td>
<td>Non-Emergent</td>
<td>121</td>
<td>1025.1</td>
<td>2075.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>67</td>
<td>356.5</td>
<td>774.9</td>
</tr>
<tr>
<td></td>
<td>Driver 10</td>
<td>Non-Emergent</td>
<td>37</td>
<td>401.9</td>
<td>714.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>26</td>
<td>198.7</td>
<td>335.3</td>
</tr>
<tr>
<td></td>
<td>Driver 11</td>
<td>Non-Emergent</td>
<td>7</td>
<td>73.0</td>
<td>129.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>2</td>
<td>11.7</td>
<td>26.0</td>
</tr>
<tr>
<td></td>
<td>Driver 12</td>
<td>Non-Emergent</td>
<td>94</td>
<td>711.4</td>
<td>1631.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>53</td>
<td>326.6</td>
<td>724.2</td>
</tr>
<tr>
<td></td>
<td>Driver 13</td>
<td>Non-Emergent</td>
<td>34</td>
<td>340.3</td>
<td>653.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>5</td>
<td>33.4</td>
<td>75.7</td>
</tr>
<tr>
<td></td>
<td>Driver 14</td>
<td>Non-Emergent</td>
<td>18</td>
<td>137.4</td>
<td>294.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>10</td>
<td>86.0</td>
<td>173.5</td>
</tr>
<tr>
<td></td>
<td>Driver 15</td>
<td>Non-Emergent</td>
<td>119</td>
<td>1215.4</td>
<td>2198.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>114</td>
<td>919.7</td>
<td>1738.6</td>
</tr>
<tr>
<td></td>
<td>Driver 16</td>
<td>Non-Emergent</td>
<td>93</td>
<td>749.8</td>
<td>1509.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>42</td>
<td>234.9</td>
<td>502.5</td>
</tr>
<tr>
<td></td>
<td>Driver 17</td>
<td>Non-Emergent</td>
<td>50</td>
<td>339.7</td>
<td>756.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>30</td>
<td>164.8</td>
<td>393.9</td>
</tr>
<tr>
<td></td>
<td>Driver 18</td>
<td>Non-Emergent</td>
<td>82</td>
<td>760.7</td>
<td>1476.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Emergent</td>
<td>45</td>
<td>311.8</td>
<td>639.3</td>
</tr>
</tbody>
</table>
For trip duration (Figure 23) in Agency 1, emergent trips (which were less frequent overall) followed roughly the same distribution as the non-emergent trips recorded. This same trend generally held true for Agency 2, with the exception of emergent trips lasting 7-12 minutes, which nearly doubled the number of non-emergent trips that spanned that time range. Similarly, for trip distance (Figure 24) in Agency 1, the emergent trips followed the same distribution as the non-emergent trips. While there was also general alignment in the distributions for Agency 2, there were two noteworthy distinctions. First, emergent trips under four miles outnumbered non-emergent trips. Second, there were two very large spikes in non-emergent trip distance, one centered around eight miles and one centered around 17 miles. With respect to trip time-of-day, both agencies showed mid-day peaks in call volume from about 10AM to 3PM; Agency 1 showed an additional nighttime peak from about 8PM to 2AM (Figure 25).
Figure 23. Trip duration by agency with overlap between the non-emergent and emergent distributions. Note that emergent trip data (in orange) was layered in front of the non-emergent trip data (in maroon), which produces variations in the color of the two distributions when they overlap.

Figure 24. Trip distance by agency with overlap between the non-emergent and emergent distributions. Note that emergent trip data (in orange) was layered in front of the non-emergent trip data (in maroon), which produces variations in the color of the two distributions when they overlap.
Kinematic Analysis

When analyzing the effects that agency and trip type had on the speed metrics of interest, minimum speed was found to be uninfluenced (Table 8). Maximum speed was found to be affected by trip type, where the mean emergent maximum speed ($M = 64.9 \text{ mph}$, Standard Error [SE] = 0.90 mph) was significantly larger than the mean non-emergent maximum speed ($M = 58.2 \text{ mph}$, SE = 0.87 mph). For mean trip speed, the interaction between agency and trip type was found to be significant (Table 9). Agency 1’s mean speed was observed to increase when transitioning from non-emergent trips ($M = 28.1 \text{ mph}$, SE = 0.69 mph) to emergent trips ($M = 29.5 \text{ mph}$, SE = 0.75 mph), whereas Agency 2’s mean speed decreased when transitioning from non-emergent trips ($M = 29.0 \text{ mph}$, SE = 0.60 mph) to emergent trips ($M = 26.9 \text{ mph}$, SE = 0.69 mph). Finally, both the agency and trip type main effects were found to be significant for the standard deviation of speed. For the agency main effect, Agency 1 showed a larger mean standard deviation ($M = 21.1 \text{ mph}$, SE = 0.87 mph) than Agency 2 ($M = 18.7 \text{ mph}$, SE = 0.87 mph). For the trip type
main effect, emergent trips showed a larger standard deviation (M = 21.4 mph, SE = 0.87 mph) than non-emergent trips (M = 18.3 mph, SE = 0.87 mph).

Table 8. Statistical significance summary for speed metrics of interest. Non-significant effects were left blank.

<table>
<thead>
<tr>
<th>Speed Metric</th>
<th>Detected Effects</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum Speed</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Maximum Speed</td>
<td>-</td>
<td>Emergent &gt; Non-emergent</td>
</tr>
<tr>
<td>Mean Speed</td>
<td>-</td>
<td>See Table 9</td>
</tr>
<tr>
<td>Standard Deviation Speed</td>
<td>Agency 1 &gt; Agency 2</td>
<td>Emergent &gt; Non-emergent</td>
</tr>
</tbody>
</table>

Table 9. Mean trip speed for the interaction effect between Agency and Trip Type. Similar levels are indicated by shared Tukey HSD levels. Means are reported in miles per hour.

<table>
<thead>
<tr>
<th>Interaction Level</th>
<th>Tukey HSD Levels</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agency 1, Emergent</td>
<td>A, B</td>
<td>29.52</td>
</tr>
<tr>
<td>Agency 2, Non-Emergent</td>
<td>A, C</td>
<td>29.03</td>
</tr>
<tr>
<td>Agency 1, Non-Emergent</td>
<td>C, D</td>
<td>28.10</td>
</tr>
<tr>
<td>Agency 2, Emergent</td>
<td>B, D</td>
<td>26.93</td>
</tr>
</tbody>
</table>

Longitudinal acceleration kinematic events were evaluated at a peak acceleration threshold value of 0.4 g (Table 10) but no events were captured at this magnitude. Lowering the threshold to 0.3 g did not yield any valid events either. Incidence rates of longitudinal deceleration (i.e., braking) events were significantly affected by the agency and trip type main effects. For the agency main effect, Agency 1 had higher mean incident rates (M = 0.69 EPHMT, SE = 0.20 EPHMT) than Agency 2 (M = 0.23 EPHMT, SE = 0.15 EPHMT). For the trip type main effect, emergent trips had higher mean incident rates (M = 0.69 EPHMT, SE = 0.16 EPHMT) than non-emergent trips (M = 0.23 EPHMT, SE = 0.16 EPHMT). At this threshold, several of the flagged kinematic events resulted from safety critical events, such as a near-crash where a motorist traveling at a high rate of speed crossed paths with an ambulance that was clearing and traversing a large intersection (Figure 26). For lateral acceleration, the agency main effect, trip type main effect, and their interaction were found to significantly affect the observed incident rate. Analysis of the interaction effect
(Table 11) indicated that, while for both agencies the emergent driving incident rates more than doubled non-emergent rates, the incident rates for Agency 1 were about ten times larger than the rates for Agency 2 across both trip types. For yaw, only the main effect of trip type was significant; emergent trips had a larger rate of yaw events ($M = 0.11$ EPHMT, $SE = 0.04$ EPHMT) than non-emergent trips ($M < 0.01$ EPHMT, $SE = 0.04$ EPHMT). Finally, the driver rate ratios for all kinematic events of interest showed that a larger proportion of Agency 1 drivers exhibited signs of aggressive driving during emergent trips (ratios $> 1$) compared to Agency 2 drivers (Table 12).

Table 10. Statistical significance summary for incidence rates of different kinematic events. Non-significant effects were left blank.

<table>
<thead>
<tr>
<th>Kinematic Event of Interest</th>
<th>Agency</th>
<th>Trip Type</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive Longitudinal Acceleration</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Negative Longitudinal Acceleration</td>
<td>Agency 1 &gt; Agency 2</td>
<td>Emergent &gt; Non-emergent</td>
<td>-</td>
</tr>
<tr>
<td>Lateral Acceleration</td>
<td>Agency 1 &gt; Agency 2</td>
<td>Emergent &gt; Non-emergent</td>
<td>See Table 11</td>
</tr>
<tr>
<td>Yaw</td>
<td>-</td>
<td>Emergent &gt; Non-emergent</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 26. Near crash event detected using the -0.4g longitudinal acceleration threshold.
Table 11. Lateral acceleration event rates for the interaction between Agency and Trip Type. Similar levels are indicated by shared Tukey HSD levels.

<table>
<thead>
<tr>
<th>Interaction Level</th>
<th>Tukey HSD Levels</th>
<th>Mean Rate (EPHMT)</th>
<th>Std Error (EPHMP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agency 1, Emergent</td>
<td>A</td>
<td>3.09</td>
<td>0.77</td>
</tr>
<tr>
<td>Agency 1, Non-Emergent</td>
<td>B</td>
<td>1.24</td>
<td>0.77</td>
</tr>
<tr>
<td>Agency 2, Emergent</td>
<td>B</td>
<td>0.32</td>
<td>0.57</td>
</tr>
<tr>
<td>Agency 2, Non-Emergent</td>
<td>B</td>
<td>0.08</td>
<td>0.57</td>
</tr>
</tbody>
</table>

Table 12. Driver rate ratios of aggregated kinematic events of interest. "*" corresponds to drivers with no non-emergent kinematic events of interest.

<table>
<thead>
<tr>
<th>Driver</th>
<th>Rate Ratio (emergent /non-emergent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Driver 1</td>
<td>2.31</td>
</tr>
<tr>
<td>Driver 2</td>
<td>3.92</td>
</tr>
<tr>
<td>Driver 3</td>
<td>1.56</td>
</tr>
<tr>
<td>Driver 4</td>
<td>3.44</td>
</tr>
<tr>
<td>Driver 5</td>
<td>3.97</td>
</tr>
<tr>
<td>Driver 6</td>
<td>*</td>
</tr>
<tr>
<td>Driver 7</td>
<td>0.00</td>
</tr>
<tr>
<td>Driver 8</td>
<td>8.05</td>
</tr>
<tr>
<td>Driver 9</td>
<td>2.02</td>
</tr>
<tr>
<td>Driver 10</td>
<td>*</td>
</tr>
<tr>
<td>Driver 11</td>
<td>2.18</td>
</tr>
<tr>
<td>Driver 12</td>
<td>*</td>
</tr>
<tr>
<td>Driver 13</td>
<td>*</td>
</tr>
<tr>
<td>Driver 14</td>
<td>*</td>
</tr>
<tr>
<td>Driver 15</td>
<td>6.28</td>
</tr>
<tr>
<td>Driver 16</td>
<td>*</td>
</tr>
<tr>
<td>Driver 17</td>
<td>*</td>
</tr>
<tr>
<td>Driver 18</td>
<td>*</td>
</tr>
</tbody>
</table>

Roadway Use Analysis

Speeding behavior varied across agency, trip type, and the interaction between these two factors. Analysis of the interaction effects (Table 13) showed that, while emergent driving led to approximately twice as much distance traveled speeding at more than 10 mph over the speed limit for both agencies, Agency 2's speeding prevalence was much larger than Agency 1's across all trip types (Figure 27).
Table 13. Speeding (>10 mph) proportion for the Agency X Trip Type interaction levels. Similar levels are indicated by shared Tukey HSD levels.

<table>
<thead>
<tr>
<th>Interaction Level</th>
<th>Tukey HSD Levels</th>
<th>Mean Proportion of Distance Spent Speeding</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agency 2, Emergent</td>
<td>A</td>
<td>0.57</td>
<td>0.04</td>
</tr>
<tr>
<td>Agency 2, Non-Emergent</td>
<td>B</td>
<td>0.28</td>
<td>0.02</td>
</tr>
<tr>
<td>Agency 1, Emergent</td>
<td>B</td>
<td>0.22</td>
<td>0.02</td>
</tr>
<tr>
<td>Agency 1, Non-Emergent</td>
<td>C</td>
<td>0.08</td>
<td>0.02</td>
</tr>
</tbody>
</table>

The proportions of use for the eight road class levels defined in the map-matching process showed a significant effect of agency for nearly all the most common road classes (i.e., trunk, primary, secondary, tertiary, and residential; Figure 28). For Agency 1, secondary roads were the most traveled, with a general trend of decreased prevalence as road classes both increased (moving towards motorway) and decreased (moving towards residential) in size and complexity. On the other hand, for Agency 2, primary roads were
the most traveled, followed by a general trend of decreased prevalence as road classes decreased (moving towards residential) in size and complexity. Agency 2 showed very limited use of motorway or trunk roads. Differences due to trip type or the interaction between trip type and agency were much less common. The only significant trip type main effect and significant interaction effects were found for residential roads, where Agency 2 emergent use (15%) was much larger than Agency 2 non-emergent, Agency 1 emergent, and Agency 1 non-emergent use (6%, 6%, and 4%, respectively).

Figure 28. Prevalence of roadway use across all road classes, separated by agency. Road classes decrease in size and complexity from left to right. Road classes with a "*" denote a significant main effect from agency level.

Analysis of speeding behavior in the context of trip type and road class revealed significance for both main effects (trip type and road class) and their interaction. Similar to the earlier speeding analysis, emergent trips were once again found to have a significantly higher proportion of speeding prevalence (M = 0.27, SE = 0.016) than non-emergent trips (M = 0.15, SE = 0.012). For the road class main effect, post hoc analysis grouped speeding prevalence by road type into three groups (Table 14). The first group with the highest proportion of speeding prevalence contained primary roads. The next group contained motorway, trunk, secondary, and service roads, which exhibited a moderate proportion of speeding prevalence. The final group, with the lowest proportion of speeding prevalence, contained tertiary, residential, service, and unclassified roads. Finally, the interaction between road class and trip type showed that although
speeding is more prevalent for emergent trips across all road classes, some road classes experience increased tendency of emergent speeding than others (Figure 29).

Table 14. Speeding (>+10 mph) proportion for the road class main effect. Similar levels are indicated by shared Tukey HSD levels.

<table>
<thead>
<tr>
<th>Road Class</th>
<th>Tukey HSD Levels</th>
<th>Mean Proportion of Distance Spent Speeding</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motorway</td>
<td>B</td>
<td>0.27</td>
<td>0.01</td>
</tr>
<tr>
<td>Trunk</td>
<td>B</td>
<td>0.26</td>
<td>0.01</td>
</tr>
<tr>
<td>Primary</td>
<td>A</td>
<td>0.35</td>
<td>0.01</td>
</tr>
<tr>
<td>Secondary</td>
<td>B</td>
<td>0.26</td>
<td>0.01</td>
</tr>
<tr>
<td>Tertiary</td>
<td>C</td>
<td>0.15</td>
<td>0.01</td>
</tr>
<tr>
<td>Residential</td>
<td>C</td>
<td>0.16</td>
<td>0.01</td>
</tr>
<tr>
<td>Service</td>
<td>B, C</td>
<td>0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>Unclassified</td>
<td>C</td>
<td>0.14</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Figure 29. Speeding proportion across all road classes separated by emergent and non-emergent trips.

Most observed traffic interactions during emergent periods took place on primary roads, followed by trunk, tertiary, secondary, motorway, and residential roads (Table 15). The prevalence of safety critical interactions ranged from 1.0% to 8.5% amongst the different road classes. Overall, there were 588 observed traffic interactions in these sampled observation periods, where 3.74% were deemed safety
critical. For intersections specifically, the greatest number of observed interactions took place at intersections on secondary roads, followed by primary, tertiary, trunk, then residential roads (Table 16). The prevalence of safety critical interactions ranged from 6.9% to 50% between the different road classes. Overall, there were 130 observed traffic interactions at intersections, where 13.85% were deemed safety critical. Limited interactions were observed with pedestrians and cyclists and were therefore not reported.

<table>
<thead>
<tr>
<th>Road Class</th>
<th>Interactions</th>
<th>Safety Critical Interactions (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motorway</td>
<td>59</td>
<td>8.47</td>
</tr>
<tr>
<td>Trunk</td>
<td>135</td>
<td>4.44</td>
</tr>
<tr>
<td>Primary</td>
<td>190</td>
<td>1.05</td>
</tr>
<tr>
<td>Secondary</td>
<td>89</td>
<td>7.87</td>
</tr>
<tr>
<td>Tertiary</td>
<td>100</td>
<td>1.00</td>
</tr>
<tr>
<td>Residential</td>
<td>15</td>
<td>6.67</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>588</strong></td>
<td><strong>3.74</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Road Class</th>
<th>Interactions</th>
<th>Safety Critical Interactions (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trunk</td>
<td>16</td>
<td>25.00</td>
</tr>
<tr>
<td>Primary</td>
<td>33</td>
<td>9.09</td>
</tr>
<tr>
<td>Secondary</td>
<td>58</td>
<td>6.90</td>
</tr>
<tr>
<td>Tertiary</td>
<td>19</td>
<td>26.32</td>
</tr>
<tr>
<td>Residential</td>
<td>4</td>
<td>50.00</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>130</strong></td>
<td><strong>13.85</strong></td>
</tr>
</tbody>
</table>

4.0.5 Discussion

*Data Summaries*

The distributions of the driver demographics between both participating agencies were comparable, even when considering the relatively small sample size of drivers. For example, the sample of drivers from Agency 1 was slightly older and had a larger range in age than Agency 2, but the age in both agencies
centered around early middle-age. The main differences observed between agencies were for the reported number of miles driven in the past year and number of average driving hours per week. For both of these metrics, the mean of Agency 1 driver responses was larger, with a smaller standard deviation, than for Agency 2. This finding may be a result of differences in the operating domain of each agency/vehicle. Agency 1 covers a geographical area about four times greater than Agency 2, and additionally serves a population about 10 times larger than that of Agency 2. This ultimately results in Agency 1 experiencing a much higher call volume than Agency 2, as supported by the approximated call volume values gathered from administrative points of contact within each agency during agency recruitment. Although it can be assumed that each of the agencies scale their staff and fleet to accommodate their relative jurisdictions and call volumes, it is not unreasonable to expect that Agency 1 drivers would drive longer and further than drivers in Agency 2.

Trip summaries by driver and trip type confirmed a larger prevalence of non-emergent driving than emergent driving, which was an expected result of the study. This is reflective of an emergent response bias, where many 911 calls are considered critical until arrival on-scene, where call acuity can be fully and accurately assessed. Consequently, many calls that elicit an initial emergent 911 response may then be followed first by a non-emergent transport to a treatment facility, then by another non-emergent trip back to the station or local staging point. Although this pattern can be interrupted by occurrences like patient refusals or back-to-back calls, the anticipated 2:1 non-emergent to emergent ratio is supported by the collected data, where just over one third of trips were emergent.

The relationship between non-emergent and emergent trips was further compared by exploring the distribution of trips by trip duration and trip distance, split by agency due to anticipated differences. For the most part, emergent trips followed the same distribution as non-emergent trips, with a few exceptions specific to Agency 2. In trip duration metrics for Agency 2, emergent trips lasting 7 to 12 minutes largely outnumbered non-emergent trips. This may be a result of the proximity the Agency 2 ambulance has to
particular regions of high call volume in their run area. One reason that an exception like this was not observed for the Agency 1 ambulance may be that it rotated to different stations within the agency’s run area, alleviating any potential proximity bias. Furthermore, for Agency 2, non-emergent trips centered around 8 and 17 miles in length largely outnumbered emergent trips. This is likely due to the proximity of the two main treatment facilities in Agency 2’s run area to the station; these distances perfectly align with the distances between the Agency 2 station and the local hospital (Lv. II trauma center) and the regional hospital (Lv. I trauma center). Once again, similar exceptions are not observed for Agency 1, likely as an effect of the truck rotating stations. Non-emergent and emergent trip distributions were also compared by time of day, where both agencies showed midday increases in trip volume. However, Agency 1 also showed an additional increase in trip volume at nighttime, likely as a result of a much larger urban center with a more prominent night life.

Kinematic Analysis

Significant differences in maximum speed between non-emergent and emergent trips were observed from the data collected. This was an expected finding since emergency vehicle operators are permitted to violate speed limits, with the intention of reducing travel time, when operating emergent and under “due regard.” For mean speed, however, it was expected for there to either be no change or at most a small increase in magnitude from non-emergent trips to emergent trips. Although Agency 1 showed such an increase, Agency 2 showed a decrease. Agency 2’s decrease in mean speed from non-emergent to emergent trips may be related to its interstate proximity and that the interstate serves as a main artery of their run area and provides a direct path to the regional hospital. Although Virginia law allows emergent driving in excess of the speed limit by up to 20mph (but limited to 80mph), frequent use of the interstate (with posted speed limits ranging 60-70mph), especially if frequently used for non-emergent trips, could have caused this shift. This effect could have been compounded if Agency 2 had consistently used local roads when traveling to calls (where most emergent calls take place) and/or to transport patients to the
hospitals and then used the interstate when returning to the station. Finally, for the standard deviation of speed a larger variation was expected during emergent driving due to the ability to exceed the speed limit. This expectation was confirmed by the data. Agency 1 also exhibited a larger variation in speed than Agency 2, which could be attributed to how their ambulance rotated locations and may have been utilized on a wider variety of roadways.

For the kinematic events of interest, it was expected to not find any events with large-magnitude positive longitudinal accelerations, considering the weight of an ambulance and how that weight influences its ability to increase speed rapidly. Even when the threshold was reduced to 0.3 g, only four events were identified, all of which took place at low speeds and on steep inclines and are indicative of slope effects on the instrumentation that collected this metric.

Across all kinematic event types, it was expected that emergent trips would exhibit higher rates of incidence than non-emergent trips. This was based on the assumption that even if most ambulance operators are well trained and can appropriately operate an ambulance safely under “due regard,” characteristics of emergent driving would still resemble “aggressive” driving behaviors that result in elevated kinematic profiles. Since ambulance operators typically drive at or above the speed limit while driving emergent, they may need to brake harder to slow down or come to a stop in those circumstances, take turns faster or more aggressively, and make more dynamic maneuvers to pass efficiently through traffic-controlled intersections or around other road users (especially if said road users fail to appropriately yield the right of way). This expectation was supported by the data collected, as events with large magnitude negative longitudinal acceleration (hard braking events), lateral acceleration, and yaw were all found to have a significantly higher incidence rate during emergent driving.

Although it was not expected for the agency to have a significant effect on kinematic events of interest, Agency 1 was found to have significantly higher kinematic event incidence rates for both negative
longitudinal acceleration and lateral acceleration. This behavior may be partially due to differences between the two instrumented ambulances. Agency 1’s vehicle was lighter, and gas powered, compared to Agency 2’s heavier diesel-powered truck. This difference may give Agency 1 drivers more maneuverability and by extension the capability to drive in such a way that hard braking and turning are less hazardous or disadvantageous than they would be in a heavier and bulkier ambulance. It should be noted, however, that random video reduction of flagged hard braking events yielded multiple instances in which Agency 1 drivers overshot and missed turns. These instances may be due to driver error or poor integration of navigation equipment. Additionally, due to the large prevalence of kinematic events within Agency 1, rate ratios of incidence rates based on trip type were calculated for each driver to better discern driving behavior amongst drivers and agencies. This comparison revealed that both agencies included drivers that operated the ambulances much more aggressively than others under emergent conditions. This finding, however, applied to a larger proportion of Agency 1 drivers compared to Agency 2. Although this could be a reflection of vehicle maneuverability as previously mentioned, it could also be partly a function of individual driver behavior or roadway infrastructure.

Roadway Use Analysis

To better understand driver behavior, speeding prevalence was investigated utilizing GPS coordinate map-matching to compare vehicle speed with known posted speed limits. As expected, speeding prevalence was significantly higher during emergent trips than non-emergent trips. Interestingly, however, Agency 2 showed a significantly higher incidence of speeding (by a factor of more than two across both emergent and non-emergent trips) than Agency 1. This becomes an important observation when taking into account that Agency 1 drivers showed higher incidence rates of kinematic events of interest, suggesting that elevated speeds may not have served as the primary reason for the observed agency effects on kinematic event incidence rate.
The dataset was then evaluated to understand prevalence of the different road classes traveled. Although all eight levels were analyzed, the results of interest focus on the six most common road classes (i.e., motorway, trunk, primary, secondary, tertiary, and residential). This evaluation was meant to quantify the types of roads that each agency operates on. Significant differences in road class use were detected between the agencies for five of the six main road classes. Not only did the agencies differ in road class use, but they each showed unique trends in the context of roadway complexity traversed. On one hand, as road complexity increased, Agency 1 showed a gradual increase in road class use that peaked at secondary roads, then gradually decreased. This trend may be a result of how the Agency 1 ambulance rotated between stations, serving a larger assortment of communities. For Agency 2, however, peak road use took place on primary roads followed by a steady decrease as road complexity decreased, with a noticeable minimal use of motorways and trunk roads. Some of the differences in road class utilization between the agencies may be a function of the accuracy of road classification within the map-matching process, which is noted to be limited by the definitions associated with each road class. This is especially relevant for neighboring classes, where, for example, some motorways could also be defined as trunk roads, or some tertiary roads could perhaps be better defined as secondary roads. More likely, however, detected differences between agencies are a result of different roadway and community infrastructure associated with each jurisdiction, which justify the incorporation of agency as a model effect across variables of interest. Significant differences in road class use for trip type were only detected for residential roads, which was driven by emergent utilization from Agency 2, although Agency 2 did have a larger residential road use overall.

A follow up analysis of speeding behavior in context road classification was also conducted under the assumption that road classes across agencies were similar, despite differences in agency locations. As expected, the analysis supported the earlier finding that speeding is more prevalent in emergent driving than non-emergent driving. Significant differences in speeding based on road class, however, were also
detected and modulated the extent of the significant differences due to trip type. This finding revealed higher distance-based proportions of speeding for the larger and more complex road classes (e.g., motorways) than the smaller and simpler ones (e.g., residential roads). This was an unsurprising finding since larger and more open roadways are already designed for and facilitate higher speeds. In contrast, smaller roads (e.g., tertiary, residential) may be more likely to contain elements, such as frequent traffic control devices (e.g., stop signs) or windy paths, that make speeding more difficult. The significant interaction between road class and trip type did reveal an interesting finding, where the magnitude of increased speeding prevalence between emergent and non-emergent trips varied considerably between the different road classes. For example, the difference in the proportion of speeding on primary roads between the two trip types was 0.28, where for residential roads it was only 0.05. Understanding that emergent speeding is considerably more prevalent on certain road classes than others could be a key element when trying to understand the types of interactions that occur between emergent emergency vehicles and other road users.

Road classes were also assessed through video reduction, via random sampling, to understand the types of traffic interactions that were taking place during emergent driving. The assessed data sample revealed primary roads to have the highest frequency of interactions, but one of the lowest frequencies of safety critical events. Motorways, however, which were found to have a relatively low frequency of traffic interactions, were associated with the highest frequency of safety critical events. This relationship is most likely a result of a combined effect between roadway complexity and motorist use frequency. For example, motorways are typically large, multilane roads that can accommodate large volumes of motorists. Therefore, due to the larger amounts of available space, drivers can more easily yield out of the way of the emergency vehicle, even to a degree that would eliminate the interaction all together (e.g., moving two lanes to the right). However, when traffic flow is disrupted (for example, due to a crash), the large volume of motorists quickly overwhelms the roadway and results in limited available space to yield...
and more difficult conditions to effectively detect emergency vehicles. Thus, it is understandable that although only a moderate number of interactions were observed on motorways, there was still a relatively high number of safety critical interactions. In a similar vein, residential roads revealed a low number of interactions, yet still saw a relatively high percentage of safety critical interactions. Here, the higher rate of safety critical interactions may be reflective of less available space to yield or to surprise encounters based on restricted views due to trees, houses, or other objects. Hence, it appears that road class may influence the types of interactions that emergency vehicles have with other road users, but additional effects (e.g., traffic volume, number of lanes, shoulder presence) should be considered to fully capture the relationship.

Intersections were also analyzed using random sample video reduction that considered road class, although road class was not the target element of the analysis. Through 100 intersections, 130 traffic interactions were observed. About one in every eight of these interactions was deemed safety critical. Most of these safety critical interactions captured motorists traveling perpendicular to the approaching ambulance. Another commonly observed situation arose from other motorists trying to turn in the intersection at the same time as the ambulance (either to “beat” it or misinterpreting its intended direction and thinking they were clear to proceed). Although a smaller sample of videos was used in the intersection analysis compared to the total combined road class sample, the rate of overall safety critical interactions appeared to be consistent and not strongly dependent on specific situations. Therefore, when comparing the total proportion of safety critical interactions from the road class analysis to the intersection analysis, ambulance operators appear to be approximately three times more likely to experience a potentially dangerous or hazardous vehicle interaction in an intersection than on an open roadway segment. This was an expected finding, as most emergency vehicle crashes occur in intersections [14-16]. However, further understanding the progression of these hazardous roadway interactions may lead to innovative and effective solutions to this crash problem. For example, improvements to emergency
vehicle dispatching and routing to avoid high-conflict intersections could reduce the frequency of potentially harmful vehicle interactions. Only several interactions were observed with pedestrians at intersections and were therefore not considered in the analysis. This was predominantly an effect of the research approach as it was not centered on trying to find these interactions.

Throughout the data reduction process, there were common themes and behaviors of other road users that were observed and noted. One such behavior, and seemingly most prevalent, was a reluctance or delay to yield the right of way. This was observed in both the roadway and intersection analysis. Several drivers waited until the ambulance was very close before they yielded, causing the ambulance operators to have to brake to navigate around these vehicles rather than pass them more smoothly. The behavior was also present in traffic queues, both on roadways and when leading into an intersection. In these situations, nearly all drivers would remain in static formation until one person made the first effort to clear a path. After that, most drivers would then emulate the maneuver of that first driver. This delayed yield behavior sometimes resulted in vehicles yielding on the left side of the road, even when yielding to the right would have been more accessible and safer, requiring the ambulance operators to brake and swerve to get around safely. In some of these cases, delayed yielding behavior may be due to reduced ability to see or hear the approaching emergency vehicle. To combat this, connected vehicle technology may be utilized to generate in-vehicle alerts to drivers informing them of an approaching emergency vehicle, thus allowing for a larger time window to yield, or at least prepare to yield [77]. For example, just as emergency vehicles are equipped with lights and sirens that can be activated during emergent responses, they could also be equipped with the ability to emit radio signals to other vehicles, for example in a 100-yard radius, to inform other road users that there is a nearby emergency vehicle. In the simplest form, this would result in an alert light (similar to a check engine light) appearing on the dashboard or display of nearby vehicles indicating the presence of an emergent emergency vehicle. Signal strength and subsequent alert distribution could also be scaled to emergency vehicle speed to help ensure the range
of vehicles alerted is appropriate. Functionality of a conceptually similar feature has been proven by the company HAAS Alert, which produces aftermarket signal distribution devices for public safety service and signal receivers for private vehicles [78]. HAAS Alert has also partnered in the past with Chrysler (for select Chrysler, Jeep, Dodge, and Ram vehicles) and Waze (a mapping and navigation service), making similar services more accessible for drivers.

Another commonality in observed behaviors is that emergency vehicle turns are particularly confusing for other drivers. This mostly pertains to intersection traversals but also encompasses other elements of roadway travel. From the video footage viewed, ambulance drivers often choose the “path of least resistance” to get to an intersection. This may mean using a turn lane that has fewer vehicles in it even if the ambulance is not turning, or driving on the wrong side of the road to bypass queued traffic. These interactions can be further complicated by elements such as changing traffic lights, blocked line of sight for other road users, or non-compliant drivers who do not want to yield the right of way. On several occasions, ambulance operators were also observed to add to the confusion by choosing to drive in an unintuitive way, causing other road users to change yielding routes that lead to the ambulance coming to a hard and brief stop before returning to the intended route. A generalized solution in these situations is difficult to generate since intersection crossing events can greatly differ from one another; the “correct” approach in each of these events is subject to change based on vehicle types involved, initial driver reactions, and possible “escape” or “exit” routes, to name just a few influencing factors. Ultimately, emergency vehicle emergent intersection crossings need to be further studied to better understand the prevalence of specific driver reactions and how to further improve them.

Although nearly 750 hours of consented trips were captured in this study, the results are only based on two ambulances and the ambulance operators that agreed to participate in the study. Despite this, the data does portray many of the transportation-related difficulties that EMTs expressed in the interviews described in Chapter 2. Nonetheless, the two participating agencies do not effectively represent all U.S.
EMS agencies, and a larger data collection effort will be needed to better capture more representative data. The random sampling approach for video reduction of roadway and intersection interactions was an effective approach to gain an understanding of the dataset but limits confidence in the results. Additional data reduction efforts could be applied to a larger portion, or the entirety, of the dataset to better define the types of interaction ambulance operators are having with other road users. Another limitation of this approach is the subjectiveness of interpreting if a vehicle was truly displaying appropriate vs. inappropriate behavior. These judgments, however, were made utilizing multiple video perspectives and considered factors like emergency vehicle speed, estimated interaction vehicle speed, visibility, and the author’s first-hand experience as an ambulance operator.

4.0.6 Conclusion

The work described in this chapter was a pilot study that served as the first of its kind to capture point-of-view ambulance operation through a naturalistic driving study. The primary goal of this study was to capture interactions that ambulance operators have with other road users, with a particular interest in emergent driving. Additionally, the data collected in the study was assessed to understand how ambulances are being driven under different conditions and roadway environments. Although it was expected that the emergent driving would be associated with factors like larger maximum speed and increased instances of hard braking, the results of the study quantitatively contextualize the findings in comparison to non-emergent driving. Further, the dataset captured events deemed safety critical that illustrate confusing and/or dangerous interactions that occur between emergency vehicles and other road users. These events reinforce the understanding that intersections are particularly dangerous for emergency vehicles while driving in emergent fashion, even when the use of emergency lights and sirens is present. The dataset also captures the complex yielding structure that surrounds traffic queues formed around crash sites and the intersections that pose unique challenges for first responders to traverse through.
Although the data captured in this study is limited to the two participating agencies and the drivers that consented into the study, each agency’s relative geographical operational area and call volume were considered during recruitment. Agency 1’s ambulance operated continuously throughout the length of the study and captured data from urban, suburban, and rural environments based on station rotation. Agency 2’s ambulance was also in continuous service and able to capture multiple use environments but favored suburban and rural communities. The enrollment of both agencies helped capture a wide variety of emergency vehicle use that supports generalizable findings. Nevertheless, there were expected differences between the agencies, which were reflected in the findings for many of the analyses. Therefore, if future studies can recruit additional agencies and vehicles from other parts of the country and expand the dataset, it could help minimize the impact of agency-specific effects and allow researchers to address broader questions surrounding generalized emergency vehicle operation. Still, this dataset is anticipated to be useful in answering questions about emergency vehicle operation well beyond the initial scope of this study.
5: Motor Vehicle Crash Injury Triage

5.1 Injury Assessment and Triage Practices

5.1.1 Literature Review

Injury Severity Prediction Algorithms

Over the last two decades, there have been notable efforts to develop and utilize injury severity prediction algorithms with a generalized focus on improving vehicle safety. A large subset of these efforts seeks to better understand and model the relationship between MVCs and associated occupant injuries directly through algorithm development and evaluation [41, 42, 46, 54-57, 59, 79, 80]. These algorithms are typically developed using publicly available crash data, from sources such as the National Automotive Sampling System Crashworthiness Data System (NASS CDS) and Crash Injury Surveillance System (CISS) [41, 56, 57, 59, 79, 80]. Other studies have used similar data sources from other countries, such as the German In-Depth Accident Study (GIDAS) and on-board crash pulse recorders (CPR) or Electronic Crash Recorder (ECR)—similar to event data recorders (EDRs) used in the U.S. [54, 55].

Despite differences in data sources, most injury severity prediction algorithms define injury outputs by using injury scores assigned to the crash data following victim treatment. One type of injury score used is the abbreviated injury scale (AIS), which is a seven digit coding lexicon used to denote injuries and their severity [81]. Severity is ranked from 1, defined as “minor,” to 6, defined as “non-survivable.” Patients who have their injuries classified with AIS scores can also be represented by maximum AIS (MAIS) score, which is simply the severity value of the most severe injury a patient had sustained. A third scaling system used is the injury severity score (ISS). ISS is first determined by assigning each sustained injury to one of six body regions (i.e., head & neck, face, chest, abdomen, extremity, external) and its corresponding AIS score. Then, the three most severely injured regions have the top injury severity value squared and
summed. This results in an overall ISS that can range from 1 to 75, since patients with any injury severity value of 6 are excluded.

Depending on the intended application of the developed algorithm and initial data source, variations of injury scales and score ranges may be utilized. For example, a study by Stigson et al. considered MAIS 2+ for their model [55]. Injury risk models can also be further differentiated by isolating body regions. For example, Weaver et al. developed a total of 40 injury risk curves (where some addressed a specific injury [n=23] and the others included multiple injuries encompassed within body-region-specific AIS 2+ through 5+ scores [n=17]) [56]. Other work exclusively considered MVC injuries for specific populations (e.g., pediatric [41, 57]). Inputs to predictive injury severity algorithms can also vary based on data source and intended application. Commonly, vehicle-centric and kinematic data is included in model development with variables such as delta-V, impact speed, belt use, rollover occurrence, and vehicle type [41, 42, 46, 54-57, 59, 80]. Additional vehicle-centric inputs such as post-crash deformation values, crash configuration, impact angle, and objective energy equivalent speed (OEES) have also been identified [41, 54, 55]. Occupant-based inputs are also included in these models, including factors like age and sex. Such inputs have been shown to influence injury susceptibility, which has improved algorithm accuracy [41, 46, 55, 59, 80]. Related work has also been conducted that focuses on prolonged recovery and long-term impairment [51, 60, 82].

Despite the proven accuracy in injury predictability these algorithms have shown, there are some key limitations that hinder their overall usefulness. One limitation is model specificity. Although some development has taken place to generate more highly-specific models, namely the work by Weaver et al. [41, 56], many of the published models encapsulate a wide variety of injuries and the severity variations of such injuries [54, 55, 57, 59]. Due to the complexity of these prediction algorithms, reducing output variability makes the development task more manageable but may dilute accuracy. A further consideration then becomes the accuracy of current injury scoring metrics [34]. For example, two unique
injuries may be classified with an AIS severity of 3, but they are inherently associated with significantly different mortality rates, treatment time sensitivity, and injury predictability/detection. Another major limitation is data availability. Injury severity estimation algorithms are developed and evaluated retrospectively. Several variables that are used by these algorithms are often unknown at the time of the crash and/or are not currently captured by available technology (e.g., occupant age or sex). AACN systems like OnStar or systems tied into the anticipated NG911, however, may allow AACN operators or crash response coordinators the ability to access such data in the near future. Nevertheless, despite the possible availability and inclusion of some occupant-centric measures, an additional limitation is that these algorithms do not consider occupant physiology. One final limitation to consider is the real time capability and application of these algorithms. Well-established systems like OnStar and URGENCY have been proven capable of real time injury prediction by utilizing EDR outputs on a quasi-real time basis; however, delivery of injury prediction to EMS has not generally been put into practice [59]. This is only compounded by effective system use, considering OnStar and other similar services require a paid subscription. Hence, the meaningful application of injury prediction algorithms seems dependent on further integration into AACN systems [83].

*Triage Accuracy*

Triage is the process of briefly assessing patient injuries in order to assign the patient an injury severity level and treatment preference, which are then used to determine care and transport. When patients receive traumatic injuries, as is frequently seen in MVCs, they rely on the trauma system to provide care. Beyond pre-hospital care, the trauma system in the U.S. features trauma centers differentiated by level, ranging from Level I (most capable) to Level IV [84]. Level I trauma centers are defined by their capability of providing general and specialized care, across a wide variety of practices, at all times. Level I trauma centers are also differentiated by their required involvement in research and education. Level II trauma centers often have similar capabilities to those of Level I facilities, but they tend to be limited in some
specialized practices or programs. Nevertheless, both Level I/II trauma centers can provide definitive care for all patients. On the other hand, Level III/IV trauma centers can still treat and care for trauma patients, but most major trauma patients will need to be transferred to a Level I or II facility for definitive care once stabilized. Due to facility location and available EMS resources, patients who are known to need Level I/II resources may still be initially brought to lower-level treatment centers. Receiving treatment at a trauma center, particularly one of higher-level designation, has been shown to dramatically improve trauma patient survivability [85]. MacKenzie et al., for example, report risk of death to be 25 percent lower when patients are treated at a Level I trauma center compared to a non-trauma center [85]. Not all trauma patients, however, should be brought to Level I/II trauma centers. To reduce both mortality and morbidity following major trauma, advanced medical resources need to be preserved for patients whose injuries require them [40, 68]. To help combat this, triage practices have been set to help not overwhelm major trauma centers with patients who may be able to receive the care they need at a lower-level facility [86]. This is accomplished by evaluating triage guidelines to identify the proportion of patients that are under- triaged or over- triaged, then modifying those parameters to accommodate trauma center ability. Today, common goals are set to less than 5% and between 25%-35% for under- triage and over- triage, respectively [80].

Ultimately, patients need to be brought to facilities that are capable of treating their injuries. This relationship is often denoted as the “right care” at the “right place” at the “right time” [34, 87]. Therefore, accuracy in injury triage is another crucial aspect of post-crash care. Initial triage (and reassessment) by EMS determines pre-hospital treatment, activation of advanced resources (e.g., advanced life support, air transportation), speed of transport, and definitive treatment facility selection [68]. Although these decisions can be influenced by additional factors like response delay, extent of vehicle entrapment, or the influence of other medical conditions, initial occupant triage sets the course for the remainder of pre- hospital care (and definitive care in many cases) [68, 87]. To maintain consistency and efficiency in patient
Triage, triage protocols like the Field Triage Guidelines for Injured Patients (FTG) have been established and amended over time[68, 86]. The FTG is set up to quickly identify if a patient needs to be brought to a trauma center by evaluation of patient physiology, anatomy, mechanism of injury, and other special considerations. Although the FTG is commonly used, a review of studies that investigate FTG accuracy have shown under-triage values as high as 80% and over-triage values in excess of 60%, which is greatly influenced by population demographics [86]. Field triage protocol effectiveness can also be affected by EMS compliance. Although it is noted that EMS provider judgement may be capable of providing useful perspective outside of practiced triage protocol, the quality of such judgment and the ensuing effectiveness is still unknown [68]. Further, a study by VanRein et al. found EMS triage compliance to range between 38% and 72%, yet still result in high rates of under-triage [68]. Finally, pre-hospital triage accuracy can be greatly affected by the presence of occult injuries, or injuries that are difficult to detect, as detection is influenced by physical and available technology limitations [87].

With increasing technological capabilities, the role of AACN systems needs to be addressed when considering pre-hospital triage capability and accuracy. In 2008, the Center for Disease Control (CDC) formed an expert panel to discuss and evaluate the role of AACNs in MVC response and how to leverage them to better triage crash victims [40]. The panel, and successive published report, greatly emphasized the importance of appropriately triaging crash victims. The recommendations made by the expert panel included: what information should be transmitted following the crash that could be used to predict the ISS score, criteria for the AACN provider to contact the vehicle occupants to further evaluate occupant risk, criteria for the AACN provider to escalate contacting the vehicle occupants to PSAPs, criteria for the AACN provider to relay crash information to PSAPs, and additional information for the AACN provider to relay to PSAPs when available. A majority of the information that the panel suggested being obtained and transmitted by the AACN system was centered around vehicle-centric data (including delta-V, principal direction of force, the number of impacts, seatbelt usage, and vehicle type). The CDC recommendations
also include the collection of several occupant metrics (e.g., age, injuries, number of occupants), intended to be obtained from verbal communication with the occupants, although acquiring that information may not always be possible. As highlighted earlier, these data elements are commonly used in injury risk prediction algorithms, which can be integrated into AACN systems [34, 46, 54-56, 88].

Collectively, studies that investigate pre-hospital triage accuracy and effectiveness call for refinement to triage protocols, increased compliance, and better integration into AACN systems to facilitate improvements in MVC mortality and morbidity [34, 40, 68, 87]. Changes to the triage process currently in place would require systemic cooperation from a variety of stakeholders. Additionally, these studies accentuate the need for more accurate near-real time information about MVCs, a greater amount of such information, and the potential improvements to triaging that would follow.

5.1.2 Injury Triage System Development

The experiences of EMS personnel and their ability to understand the mortality and morbidity risks associated with different injuries are critical to MVC post-crash care. This analysis aims to enhance MVC triage by developing an interactive, in-vehicle triage system. This system will allow for earlier assessment of the general condition of vehicle occupants by transmitting pertinent vital measurements to EMS prior to on-scene arrival. The system will effectively triage a crash victim immediately following a crash and continue to monitor the victim's vitals, allowing for earlier physiological trend monitoring. Ideally, this system will reduce the time spent on-scene through earlier activation of secondary resources and enable EMS to preemptively develop a transport plan.

5.1.3 Research Objectives

The objective of this work was to outline the necessary requirements and technology needed to develop an interactive injury triage system. A literature review was conducted to address the primary research question: What accepted injury triage protocol should be used as the foundation for the development of
an interactive, post-crash injury triage system? This review identified widely accepted triage protocols, their inputs (e.g., required physiological vital sign measurements), and their limitations.

5.1.4 Protocol Selection

Triage is a necessary first step in treating patient injuries. Triage allows EMS to gain a better understanding of the physiologic and physical status of a patient and their injuries, with the intention to identify treatment and transportation options. Typical triage practices first evaluate patients for life threatening conditions, often referred to as the ABCs (i.e., airway, breathing, and circulation). Patients with life threats that are not immediately resolvable are categorized as critical. Once life threats have been ruled out and/or addressed, patients undergo an evaluation of vital metrics. Agencies may use triage protocols to outline expected patient interactions to make sure patients are well evaluated before beginning treatment. Triage protocols have also been generated for instances, such as mass casualty incidents (MCIs), where there may be a high volume of patients that need to be evaluated. These triage protocols enable EMS to distribute resources with the goal of saving the highest number of lives by prioritizing patients with life-threatening injuries. In the absence of MCI triaging, treatment order would be random and could result in wasted supplies, inefficient care, and a higher number of casualties. Due to the complexity of emergency scenarios in which an MCI can occur, different triage protocols have been developed to cater to variable situations and patient populations. Such protocols include “Guidelines for Field Triage of Injured Patients,” written by the Centers for Disease Control (CDC); Sort, Assess, Lifesaving interventions, Treatment and/or Transport (SALT); and Simple Triage and Rapid Treatment (START). Some protocols target specific emergencies while others are general in application. For example, the CDC’s guidelines feature instructions which cover a wide range of scenarios including falls, crashes, and burns, with insight on how to treat vulnerable victims (e.g., pregnant patients, pediatrics, and geriatrics) [89].
Most triage protocols follow a simple algorithm to classify a victim under a certain severity code or category. Several studies have been conducted to compare and contrast triage methods. One study compared START versus SALT triage outcomes and found the differences to be minimal and non-influential on clinical outcome [90]. Another triage protocol comparative study indicated that using a Sacco Score yielded most accurate triage outcomes due to the measure’s accuracy in predicting victim mortality [91]. The Sacco Score is generated by evaluating patient respiration, pulse, and motor response and is typically utilized for patients suffering from blunt or penetrating trauma [92]. A study by Cross & Cicero, in contrast, indicated that the START protocol excelled at pediatric triage and suggested that a triage approach developed by the Fire Department of New York was better suited for adult application [91]. While the procedures and steps each protocol follows differ slightly, the goal of each method is the same: to streamline resource distribution and treatment to minimize patient death and injury effects. An additional study reviewed twenty different triage protocols [93]. That study concluded that there is no triage system that performs consistently better than others, but recommended that triage protocol development, selection, and application be based upon the local environment, intended use, and available resources.

Therefore, primarily due to its commonality and prevalence, the START protocol (Figure 30) was selected to serve as the foundational algorithm for development of the in-vehicle, post-crash injury triage system in this work. The START algorithm consists of metrics that are evaluated to determine the triage category (“minor,” “delayed,” “immediate,” “deceased”) the patient falls into [94, 95]. The first metric evaluated in the protocol is respiration rate. If patients are not respirating, their airway is repositioned and reevaluated. If the patient is still not respirating, they are labeled “deceased.” If respirations resume following airway repositioning or if the patient was initially respirating at a rate higher than 30 breaths per minute (brpm), they are labeled “immediate.” If the patient is respirating at a rate of less than 30 brpm, the triage proceeds to the second evaluation metric, perfusion. Perfusion is assessed by evaluating presence of the radial pulse (or capillary refill). Absence of a radial pulse or prolonged capillary refill results
in the patient being labeled “immediate.” If a radial pulse is present or capillary refill is under two seconds, the patient is then evaluated using the last metric, mental status. Mental status is assessed by gauging patient responses to command prompts. It is important to note that the START protocol is intended to be used to quickly triage multiple patients, especially in MCIs. The implementation of this protocol as the foundation for the injury triage system serves primarily to identify a baseline of influential vital measurements that are commonly used to make pre-hospital treatment decisions. Therefore, when applied to post-crash assessment in this application, some deviation from the strict protocol algorithm will be needed to best suit crash victim needs. For example, in the event that a patient was evaluated as nonbreathing, it is unlikely, barring obvious signs of death, that they will be immediately assumed deceased by responding EMS. Rather, they will be reassessed on-scene and provided initial treatment. Additionally, it is expected that this injury triage system will evaluate patient mental status beyond the scope of simple command prompts. Instead, the system will evaluate patient alertness and, if conscious, their orientation to person, place, time, and event.

![START Triage Algorithm](image)

*Figure 30. START Triage Algorithm [90].*
5.2 Respiration

5.2.1 Research Objectives

The first objective for the development of the respiration component of the injury triage system was to identify technologies that could capture occupant respiration rate. To accomplish this, a literature review was guided by the research question: What devices are capable of detecting accurate respiration rate and may be suitable for vehicle integration? The findings of this review then led to the selection of candidate technologies. The second objective of this work was then to evaluate how well candidate technologies were able to obtain occupant respiration rate when integrated into the vehicle cabin. Experimentation and developed solutions were guided by the following research questions: (1) What is the precision and accuracy of the respiration rate detection systems in a vehicle setting?; and (2) How is the precision and accuracy of the respiration rate detection systems affected by environmental factors?

5.2.2 Technology Selection

The first metric assessed in the START protocol algorithm is respiration. Respiration can be evaluated for both rate and quality. Respiration rate is determined by counting the number of breaths an individual takes within a minute, resulting in a quantitative measurement of respirations per minute. Respiration quality is expressed as a qualitative expression (e.g., normal, shallow, irregular) used to assist in describing breathing effort. In a clinical setting, respiration rate and quality are measured by visual inspection from the clinician. Due to the time sensitivity EMTs face when triaging victims, respirations are often counted for a shorter period (i.e., 10 or 15 seconds) then scaled by a suitable multiplier to estimate the measurement over a one-minute window. However, for patients with irregular respirations, shorter assessment windows may not be the most appropriate for evaluation. Overall, visual inspection proves efficient and effective in determining patient respiration rate. The main objective of this review, however, is to identify alternate methods to capture respiration rate that can be integrated into a vehicle to assess
crash victim condition. Identified alternate methods were classified as active or passive. Active detection methods were defined as requiring direct input from the patient or other individual(s) to take measurements, such as a physician counting respirations. Passive detection systems, in contrast, may function without direct input, which may better suit applications for crash victim triage, especially when victims may be seriously injured or unconscious. For this reason, passive detection systems were primarily sought and reviewed. Ideally, methods for this application should also be activated immediately following a crash and provide constant occupant monitoring to assist in establishing vital sign trends. Finally, in-vehicle sensors should be integrated such that the hardware is robust enough to maintain functionality following a crash, not be bothersome or distracting to the occupant, and be capable of providing accurate measurements.

The first detection methods identified utilize sound to monitor and measure respiration rate. One study by Arlotto et al. used an ultrasonic transmitter and receiver to measure the difference in frequency between a person’s breath and ambient air surrounding the point of interest (i.e., the nose and mouth region) [96]. The intended application of the study was to monitor respiration rate of individuals sleeping. To accommodate intentionally quiet environments, a high frequency sound wave (40 kHz) was used. The received signal was then processed to filter out disruptions that were due to movement and background noise. Limitations associated with this study include the large size of the hardware used, unconscious patient application, and sound frequency limitations due to the distance needed to appropriately receive the refracted sound waves. Alternatively, another study used ultrasound to determine respiration rate by targeting the chest of the patient [97]. This study utilized a smartphone speaker and microphone to emit a 20 kHz sound at the target’s chest, receive the reflected sound at the same source, then determine respiration rate from the detected superposition that resulted from chest movement. The results of the study showed that this method was able to estimate an accurate respiration rate. Compared to the first ultrasonic respiration rate detection method, this application uses much smaller equipment, making it
applicable in more dynamic environments. Finally, a third study was identified that estimated respiration rate by analyzing audio samples collected from a wearable microphones (i.e., Apple AirPods) [98]. This study was able to successfully estimate respiration rate, but there are some considerable limitations that need to be considered for in-vehicle application based on original experimental design. The study focused on estimating respiration rate surrounding different stages of exercise. Respiration frequency and intensity, however, increase with exercise, resulting in louder respirations that are not necessarily characteristic of MVC patients. Also, experimentation with this approach did not consider ambient noise. Lastly, in a vehicle with multiple patients, the method may have difficulty differentiating respirations between passengers depending on factors like proximity, quality of respiration, and environmental noise.

The second set of detection methods for respiration rate used imaging. One such imaging study used a single RGB camera, centered at the pit of the neck, that recorded video of the subject [99]. Once recorded, pixels around the area of interest were split into RGB components, then postprocessed to show trends in respirations. The trends were analyzed, and stronger signals were used to create frequency and time intervals between each breath, ultimately yielding a respiration rate. The goal of this study was to develop a method of contactless monitoring, which could be applied in at-home settings. The single laptop camera used allowed for easy transport and required minimal space, which was considered valuable in non-clinical situations. However, the camera needed to be able to continuously target the area of interest – if the camera was stationary, the patient needed to be still as well. Additionally, this study required some manual input to indicate where the pit of the neck was on the recorded video. The researchers of this approach concluded that future work would be needed to evaluate other influential factors like lighting and clothing. A second imaging-based method to detect respiration rate used a method called “Eulerian Video Magnification” to enhance video [100]. This process allowed for simple video data to be processed in a way that could detect extremely subtle changes in color (expressed in reference to changes skin color as a result of circulation) and low amplitude motion (e.g., movement due to respiration). This was
achieved by analyzing color variation in a single pixel over time, then processing that color variation for rate detection. Although this study did not focus on respiration rate detection, application of the methodology could be passively used in a vehicle-based setting.

A third technique to detect respiration rate by evaluating thermal changes was used in a study by Boccanfuso & O’Kane [101]. In this study, temperature at the philtrum (the region in between the upper lip and the bridge of the nose) was monitored by an infrared (or thermal) sensor. This application could detect respiration by sensing changes in temperature as a result of exhalation, then processed that data into a respiration rate. The intended application for this study was for use in physical therapy rehabilitative robotics and socially assistive robotics. To accommodate these conditions, the study used a pan-tilt platform, camera, and facial recognition software to detect (and target) the point of interest. This allowed application of the approach in dynamic tasks. Future work was proposed to evaluate performance when potentially limiting factors are present, like the presence of perspiration. Although the equipment used was relatively small, the need to have both the camera and infrared sensor does make the overall setup larger than some of the single sensor alternatives.

The final respiration rate detection method identified used the pressure sensor in a vehicle seat [102]. This seat sensor system included a fluid-filled bladder and a pressure transducer. The seat sensor output voltage readings that were filtered and processed to generate estimated respiratory rate. The same approach and technology were also used with different filtering and processing parameters to estimate heart rate detection. Compared to other identified passive detection techniques, this approach used sensors already integrated into the vehicle. Most current vehicles feature seat sensors in the front seats, but future expansion to the rear seats is within reason. Despite this method’s detection accuracy and vehicle setting relevance, past work has only been completed in laboratory settings, without the influence of vehicle and environmental factors.
Of these candidate methodologies and technologies that could be used to passively detect respiration rate, three candidates were selected to be evaluated for integration into the proposed injury triage system. Selection criteria consisted of anticipated ease of sensor integration into the vehicle, respiration rate detection accuracy in the laboratory (as reported in the relevant original studies), and the ability to continuously track respiration rate. Passive sensing technologies were preferred due to their ability to assess occupants without direct input. The first candidate method and technology selected was application of ultrasonics to the chest [97]. The second method and technology selected was the application of thermal sensing to the upper lip [101]. Finally, the third method and technology selected was the processing of voltage outputs from vehicle seat pressure sensors [102].

5.2.3 Methods

All three of the selected systems were integrated into a 2015 Ford Taurus. The ultrasonic respiration detection system utilized a Dell™ desktop speaker to emit a sinusoidal, ultrasonic signal (20 kHz), paired with a Blue Yeti™ microphone to record the reflected and ambient signals at 48 kHz sampling frequency using a built-in sound recorder app on a Windows laptop. The thermal respiration detection system, which recorded changes in air temperature associated with exhalation, utilized an infrared (IR) thermometer (Melexis™ MLX90614) with a 17-bit analog-to-digital converter (ADC) mounted on an adjustable pan-tilt platform and aimed at the subjects’ philtrum. Signals from this sensor were sampled over an inter-integrated circuit (I2C) bus at 5 Hz and processed using an Arduino Uno™ board. Finally, the pressure-based detection system leveraged an already existing fluid bladder embedded in the front passenger seat, which serves as a component of the on-board “occupant classification system.” The pressure sensor connected to the bladder was replaced with an analog pressure sensor (OEM part number 12228430), similar to the approach of Wusk and Gabler [102]. This pressure sensor signal was sampled at 100 Hz using a microcontroller (Raspberry Pi™ RP2040) with a 12-bit ADC.
This study was approved by the Virginia Tech IRB (#22-991). Four experimental factors were considered: (1) occupant weight (between subjects), (2) cabin temperature (within subject), (3) occupant clothing weight (within subject), and (4) environmental sound (within subject). Each of these factors had three levels. Weight classes for participants were centered at 54.4kg (120lbs), 79.4kg (175lbs), and 116.1kg (256lbs), with an allowable range of ± 6.8kg (15lbs), which captured an adult weight range from a 10th percentile female to a 90th percentile male. A total of six participants were included in the study, two from each weight class. Of the participants, two identified as female and the remaining four as male, with an age range of 21 to 26 years (M = 23.33, SD = 1.97). The cabin temperature levels were 15.6°C (60°F), 20°C (68°F), and 24.4°C (76°F). Participants brought their own upper body clothing for the experiment, including a t-shirt (lightweight), sweatshirt (midweight), and an outdoor jacket (heavyweight). Finally, environmental sound was added using the vehicle’s radio, with noise levels of 40dB, 60dB (normal conversation volume), and 80dB. Participants underwent a total of 27 four-minute trials combining all the cabin temperature, clothing, and sound levels. Participants were instructed to breathe normally through each trial and were permitted to use their cellphones to help them to not think about breathing, resulting in moderate respiration rates (approximately 12 – 18 brpm). A respiration belt (Vernier™ Go Direct™) worn by the participants provided the benchmark respiration rate.

Output signals from the audio recording, IR thermometer, and pressure sensor were filtered in the 0.1 – 0.5 Hz range using a zero-phase finite impulse response (FIR) bandpass filter (stopband attenuation = 60dB, steepness = 0.85; Figure 31) to capture respiration rates within the range of 6 to 30 brpm, as the expected normal breathing rate was 12 to 18 brpm [103]. The respiration belt signal obtained from the device manufacturer’s software did not require any additional filtering. Signals from each sensor were visually inspected for integrity in the time and frequency domains. Next, a peak detection and filtering algorithm was constructed and applied to obtain timestamps for the occurrence of each signal peak (corresponding to peak inhalation) in each dataset (Figure 32). This process included smoothing the data
by merging two successive peaks within 250ms of each other into one peak to account for signal noise. Processed signals from all three tested sensors and the output from the respiration belt were then synchronized based on recorded universal time stamps (Figure 33). Respiration rate for each sensor and device was then calculated by counting the number of peaks present in a 30-second sliding window (using a step size of 1 second across a 230-second trial period). Finally, the mean and standard deviation of the respiration rates were calculated for each sensor and trial. These two metrics were then analyzed using a random effect mixed General Linear Model in JMP version 16.0.0. Significance was assessed for the main effects and two-way interactions with an alpha of 0.05. Tukey HSD post hoc tests were conducted to assess any significant effects.

![Magnitude and phase response plot](image)

*Figure 31. Magnitude and phase response plot for the applied 0.1 – 0.5 Hz zero-phase finite impulse response bandpass filter.*
Figure 32. Steps of signal processing for respiration rate detection using the seat sensor output as an example, sampled over 2 minutes. The first plot (top) shows the raw data collected. The second plot (middle) shows the data after initial filtering. The third plot (bottom) shows the filtered signal with smoothed peak detection.

Figure 33. Sampled synced signal outputs from all three tested sensors and the respiration belt.
5.2.4 Results

Across the three test sensors, the mean respiration rates from the IR and pressure sensors were not significantly different from the mean respiration rate recorded from the respiration belt ($M = 21.2$ brpm, $M = 18.9$ brpm, $M = 21.1$ brpm, respectively, Table 17). The mean respiration rate from the ultrasound sensor ($M = 16.4$ brpm), however, was significantly different from the mean respiration rate from the respiration belt. All sensor means had a standard error of $0.64$ brpm. The in-vehicle temperature and sound levels also showed statistical significance. For temperature level, the $15.6^\circ C$ ($M = 18.8$ brpm) condition yielded a significantly lower mean respiration rate than the $20^\circ C$ and $24.4^\circ C$ conditions ($M = 19.7$ brpm and $M = 19.6$ brpm, respectively), albeit all three levels were within $1$ brpm of one another and had a standard error of $0.18$ brpm. For sound level, the $40$ dB ($M = 19.0$ brpm) condition resulted in a lower mean respiration rate that then tended to plateau at higher sound levels ($M = 19.7$ brpm and $M = 19.5$ brpm), where all levels had a standard error of $0.14$ brpm.

Table 17. Summary of significant effects for mean respiration rate. Non-significant effects were left blank.

<table>
<thead>
<tr>
<th>Experimental Factor</th>
<th>Detected Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor</td>
<td>Belt Truth &amp; IR &amp; Pressure &gt; Ultrasound</td>
</tr>
<tr>
<td>Temperature</td>
<td>$24.4^\circ C$ &amp; $20^\circ C &gt; 15.6^\circ C$</td>
</tr>
<tr>
<td>Weight</td>
<td>-</td>
</tr>
<tr>
<td>Clothing Weight</td>
<td>-</td>
</tr>
<tr>
<td>Sound</td>
<td>$80$ dB &amp; $60$ dB &gt; $40$ dB</td>
</tr>
</tbody>
</table>

For the standard deviation of respiration rate, significant effects were found for the sensor type, sound level, and clothing weight main effects (Table 18). Significant effects were also found for the interactions between sensor type and sound level, sensor type and clothing weight, and weight and clothing weight. For the sensor type main effect, both the pressure and ultrasonic sensors were found to have standard deviation of mean respiration rate not significantly different from that of the respiration belt ($M = 2.3$ brpm, $M = 2.0$ brpm, $M = 2.1$ brpm, respectively). The mean standard deviation in respiration rate from the IR sensor ($M = 2.7$ brpm), however, was found to be significantly different. All sensor means had a
standard error of 0.11 brpm. For the sound level main effect, the mean standard deviation of respiration rate at 40 dB (M = 2.1 brpm) was found to be lower than that of the louder conditions (M = 2.2 brpm and M = 2.4 brpm), where all levels had a standard error of 0.05 brpm. For the clothing weight main effect, the heavyweight condition (M = 2.1 brpm) had significantly lower standard deviation than the lightweight and midweight conditions (M = 2.3 brpm and M = 2.3 brpm), where all levels had a standard error of 0.02 brpm. Interpretation of the significant interactions did not yield additional insights related to the efficacy of the sensors.

Table 18. Summary of significant effects for the standard deviation of mean respiration rate. Non-significant effects were left blank.

<table>
<thead>
<tr>
<th>Experimental Factor</th>
<th>Detected Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor</td>
<td>Belt Truth &amp; Pressure &amp; Ultrasound &gt; IR</td>
</tr>
<tr>
<td>Temperature</td>
<td>-</td>
</tr>
<tr>
<td>Weight</td>
<td>-</td>
</tr>
<tr>
<td>Clothing Weight</td>
<td>Lightweight &amp; Midweight &gt; Heavyweight</td>
</tr>
<tr>
<td>Sound</td>
<td>80 dB &amp; 60 dB &gt; 40 dB</td>
</tr>
</tbody>
</table>

5.2.5 Discussion

As the purpose of the study was to evaluate the effectiveness of the various passive sensing systems in a vehicle cabin setting, it was unsurprising that the main effect associated with sensor type was found to be significant. The experimental design of this study was structured in such a way that would test the basic limits of the selected sensors by including conditional variation targeted at the sensory input for each system (e.g., weight variation for the pressure sensor). Therefore, these findings serve as a foundation in understanding the limitations of these sensor systems in a vehicle-based setting but will require further research and development before purposeful application. For instance, these findings expand the work of Wusk and Gabler [102] by considering additional sensors and introducing noise due to vehicle vibration, which was speculated to influence pressure sensor performance. Nevertheless, similar sensor accuracy was observed between Wusk and Gabler [102] and the current work.
Among the tested sensor systems, the pressure sensor was found to best match the accuracy and precision of the respiration belt. Further, since the pressure sensor system utilizes components already present in many vehicles, it presents a solution that would add little if any cost when integrated into the vehicle fleet. Based on these findings, it is our recommendation that the embedded pressure sensor system be further investigated and developed for real time respiration rate assessment and integration into a post-crash injury triage application. The data obtained by this system could also be applied and in other open areas of research, such as to further enhance or develop injury prediction algorithms by supporting the future acquisition of occupant-specific vital metrics (e.g., weight) or for rear seat child occupant detection. Future work should address limitations in the approach used for this proof-of-concept work, including lack of consideration of crash victim self-initiated motion and changes in occupant posture, as these factors have the potential to introduce artifacts in the measured signals.

5.3 Perfusion

5.3.1 Research Objectives

The first objective for the development of the perfusion component of the injury triage system was to identify technologies that could capture occupant pulse rate and/or heart rate. To accomplish this, a literature review was guided by the research question: What devices are capable of detecting accurate perfusion and may be suitable for vehicle integration? The findings of this review then led to the selection of candidate technologies. The second objective of this work was then to evaluate how well candidate technologies were able to obtain occupant perfusion when integrated into the vehicle cabin.Experimentation and developed solutions were outlined by the following research questions: (1) What is the precision and accuracy of the perfusion detection systems in a vehicle setting?; and (2) How is the precision and accuracy of the perfusion detection systems affected by environmental factors?
5.3.2 Technology Selection

Following respiration rate assessment, the next metric in the START protocol is perfusion assessment. Perfusion is defined as the flow of blood through the circulatory system, which is driven by the pumping of the heart. The circulation of blood through the body allows for gas exchange, where red blood cells deliver oxygen to the body’s organs and transport carbon dioxide out of the body. Simply, perfusion can be assessed by evaluating pulse. Like respiration, pulse can also be evaluated for both rate and quality. When the heart contracts, it creates a pressure that forces blood through the circulatory system. For arteries near the skin surface, these changes in blood volume that result from pressure changes cause expansion. Thus, by applying an external force to the artery walls (e.g., a finger), pulse can be palpated.

Pulse rate is determined by counting the number of pulses, or beats, that occur in a one-minute window, commonly reported as beats per minute (bpm). Like respiration rate, pulse rate can be evaluated across a shorter time window and extrapolated but, for patients with an irregular pulse, evaluating across a full one-minute window may be more appropriate [104, 105]. Perfusion can also be expressed as a qualitative expression (e.g., normal, weak, irregular).

Although heart rate and pulse rate are closely related and often interchanged, they are technically different. This difference may best be explained by observing the signal used to determine heart rate. True heart rates are often obtained by electrocardiogram (ECG) which captures the electrical signals in the heart. In an ECG, each “pulse” is actually composed of multiple peaks and troughs, denoted in order with the letters “P,” “Q,” “R,” “S,” and “T” [106]. Therefore, due to a medical complication or injury, there could be a significant difference between heart rate and pulse rate. For example, following a traumatic injury to the right upper arm, a person’s heart rate may be 110 bpm, but the pulse rate in the right hand may be 60 bpm and weak, indicating poor perfusion. If it is suspected that perfusion may be compromised, providers may compare pulse rates from multiple body sites. In many situations, however, heart rate serves as a suitable surrogate for pulse rate.
Many factors can affect the performance of the circulatory system, including traumas commonly experienced by MVC victims. Assessing a person’s perfusion is a quick first step in identifying if there may be an issue with the circulatory system (e.g., decrease in cardiac output, blood loss). In a clinical setting, perfusion is commonly evaluated either by manual palpation or using a pulse oximeter (usually applied to a fingertip), and pulse quality is determined from manual palpation. There are multiple locations in the body that can be used to assess pulse (e.g., radial artery on the wrist, brachial artery on the upper arm, carotid artery on the neck, femoral artery on the thigh, popliteal artery on the calf, and the dorsalis pedis arteries on the feet). Due to ease of access, carotid, radial, and dorsal pedis palpation are commonly used to quickly assess perfusion [107]. In trauma assessment, utilization of the radial pulse provides a certain advantage. Due to further distance from the heart, radial pulse assessment may enable emergency responders to get a better understanding of whole-body perfusion compared to, for example, assessing carotid pulse a few inches away from the heart. Due to anatomical differences in pediatrics, perfusion in children may be evaluated using capillary refill time (CRT) [108]. CRT is measured by placing enough pressure on the bed of the nail, or other location, to force out most of the blood, then removing pressure and counting how many seconds it takes for the blood to return.

As expressed earlier for respiration detection systems, this inquiry is directed at identifying perfusion detection systems that are passive, can be activated immediately, provide constant occupant monitoring, and are physically robust, easily integrated, and accurate.

Several imaging-based detection methods were identified for contactless detection of perfusion. The first is photo-plethysmography (PPG) imaging. PPG monitoring is a widely applied method that uses light to measure subdural blood volume and behavior. Most applications that utilize PPG (e.g., pulse oximeters, smart watches) require the sensors to be very close to or touching the skin; however, contactless applications of PPG have been identified. One such application utilized a camera and near infrared LEDs to measure pulse rate (in the cheek) and transmit the measurements to a smartphone [109]. The main
goal of that application was to increase subject trackability and reduce error in measurement caused by subject motion. In the application, the processing unit separates the PPG signal from the raw data and calculates the pulse after filtering for lighting changes. Another study that used contactless PPG imaging did so with the intention to compare the results against laser speckle contrast analysis, which is a well-known perfusion monitoring technology [110]. This study utilized an RGB camera and a light ring to collect data for further processing to generate a perfusion map of the hand. The experimentation included several tests to change perfusion behavior and evaluate perfusion measurement and accuracy. The researchers of this approach concluded that contactless PPG imaging could provide adequate perfusion measurements. This method is conceptually similar to the previously mentioned method of “Eulerian Video Magnification” for respiration rate detection, which could also be used to determine heart rate [100, 111].

Another method of imaging-based contactless perfusion measurement is laser speckle contrast analysis (LASCA) [110]. In this application, LASCA was performed using an infrared laser as a light source and a monochromatic infrared camera to capture the video. LASAC is a well-known perfusion monitoring technology and was used in this study as a validation metric against contactless PPG imaging. As expected, LASCA monitoring proved robust across experimentation trials and capable of providing accurate perfusion measurements.

A third method identified for perfusion detection was the same in-vehicle pressure sensor utilized in the respiration detection experimentation [102]. Under different data filtering parameters, the original study by Wusk & Gabler [102] was also able to successfully assess the heart rate of seated occupants in a laboratory setting. As mentioned before, this approach utilizes sensors already present in the vehicle.

Finally, the use of radar and ultrasound technology were also identified as methods of contactless perfusion detection [112]. Ultrasound technology can be used to evaluate pulse rate as it can measure
blood flow velocity. Pulse rate can then be extrapolated by monitoring for cyclic changes in flow rate. As a relatively less expensive and contactless alternative, this Shi et al. study examined the application of radar technology to assess pulse rate from observing cyclic changes in vessel diameter. Radar detection was applied using a continuous radar signal towards the subject and reflected back by the skin of the neck (mostly focused on the carotid artery). Changes in relative displacement were calculated and converted into a pulse rate. The study demonstrated similar performance between the ultrasound and radar detection methods. However, the radar detection was very sensitive to body movement, which can cause discrepancies in pulse rate readings and calculations.

Similar system considerations to those used for respiration rate detection were applied to select perfusion detection methodologies and technologies for experimental evaluation. Of the identified systems that could be used to passively detect perfusion, PPG imaging and LASCA were initially selected to be evaluated for integration into the proposed injury triage system. However, due to the success of the seat integrated pressure sensor, and the substantial cost of the imaging equipment needed for PPG and or LASCA monitoring, the following study solely investigates the ability of the pressure-based seat sensor system to accurately monitor occupant heart rate in a vehicle setting. The main caveat with this approach is that pressure sensor system will target heart rate rather than pulse rate.

5.3.3 Methods

This study was approved by the Virginia Tech IRB (#23-575). The experimental design for this study was largely based on the one used for the evaluation of respiration rate detection technologies. Experimentation took place in the same 2015 Ford Taurus. The pressure sensor system (housed within the front passenger seat) utilized the same analog pressure sensor (OEM part number 12228430) that replaced the factory component for this make and model. This pressure sensor signal was sampled at 100 Hz using a microcontroller (Raspberry Pi™ RP2040) with a 12-bit ADC.
The experimental design of this study was structured in consideration of the results of the respiration rate detection experimentation, ultimately having this study consider the following experimental factors: (1) occupant weight (between subjects), (2) occupant clothing weight (within subject), and (3) occupant motion (within subject). Each of these factors had three levels. Weight classes for participants were centered at 54.4kg (120lbs), 79.4kg (175lbs), and 116.1kg (256lbs), with an allowable range of ± 6.8kg (15lbs), which captured an adult weight range from a 10th percentile female to a 90th percentile male. A total of six participants were included in the study, two from each weight class. Of the participants, three identified as female and the remaining three as male, with a captured age range of 20 to 35 (M = 25.33, SD = 4.82). Participants brought their own upper body clothing for the experiment, including a t-shirt (lightweight), sweatshirt (midweight), and an outdoor jacket (heavyweight). Finally, occupant motion was assessed at the levels of still, infrequent motion (movement every 30 seconds), and moderate motion (movement every 15 seconds). For both the infrequent and moderate motion trials, participants were instructed to move their upper body to face one of two target images (alternating each time) in the vehicle when they heard a timed chime, then return to their normal resting position (i.e., seated with eyes forward). The target images were of the Hokie Bird™ placed on the bottom right corner of the front passenger window and the bottom left corner of the rear driver’s side window. Participants underwent a total of 9 five-minute trials combining all the clothing weight and occupant motion levels. Participants were instructed to sit in a comfortable position and follow basic commands, resulting in moderate heart rates (approximately 60 – 90 bpm). A heart rate monitor (Polar H10™) worn by the participants provided the benchmark heart rate.

Output signals from the pressure sensor were filtered in the 0.6 – 3.5 Hz range using a zero-phase finite impulse response (FIR) bandpass filter (stopband attenuation = 60dB, steepness = 0.85; Figure 34) to capture heart rates within the range of 36 – 210 bpm, as the expected normal adult heart rate is 60 – 100 bpm [103]. The outputs obtained from the heart rate sensor used for benchmark did not require any
additional filtering and were provided as point measures of heart rate sampled at 10 Hz. Signals from both sensors were visually inspected for integrity in the time and frequency domains. Although independently collected, data from the pressure sensor and heart rate sensor were synced using the file timestamps. Next, a peak detection algorithm was used on the pressure sensor data to identify all peaks in the dataset that served as inputs to the heart rate calculation. When the heart pumps blood, it pushes blood out twice per cycle; once to the lungs to enable gas exchange, then once to the rest of the body to deliver oxygenated blood. Therefore, to eliminate signal noise that may have resulted from the heart’s two pumps per cycle, the data was smoothed by merging two successive peaks within 50ms of each other into one peak. Heart rate was then calculated by counting the number of merged peaks present in a 30-second sliding window (using a step size of 1 second across a 290-second trial period) then multiplying by a factor of 2. Finally, the mean and standard deviation of the collected heart rates were calculated for each trial for both the heart rate sensor and pressure sensor.

![Figure 34. Magnitude and phase response plot for the applied 0.1 – 0.5 Hz zero-phase finite impulse response bandpass filter.](image-url)
Figure 35. Steps of signal processing for heart rate detection using the seat sensor output as an example, sampled over 20 seconds. The first plot (top) shows the raw data collected. The second plot (middle) shows the data after initial filtering. The third plot (bottom) shows the filtered signal with smoothed peak detection. The large spike in the signal is due to a signal noise, such as the participant shifting their weight in the seat.

First, to evaluate the pressure sensor accuracy against the heart rate sensor as a benchmark, a paired t-test was performed in JMP (version 16.0.0). Significance was assessed with an alpha of 0.05. This test did not assume equal variances. Next, the calculated means and standard deviations for the heart rate sensor and pressure sensor system were analyzed in context of the experiment’s independent variables using a random effect mixed General Linear Model in JMP (version 16.0.0). Significance was assessed for the main effects and two-way interactions with an alpha of 0.05. Tukey HSD post hoc tests were conducted to assess any significant effects.

5.3.4 Results

From the paired t-test, mean heart rate collected from the pressure sensor (M = 75.3 bpm) did not significantly differ from the mean benchmark heart rate (M = 72.9 bpm), t(53) = -2.0, p = 0.05. The pressure sensor, however, overestimated mean heart rate by 2.4 bpm. Secondary analysis from the linear model found the only significant main effect to be occupant motion (Table 19). The mean heart rate for the middle condition of infrequent movement (M = 74.0 bpm) was found to be statistically similar to both the
still condition (M = 75.6 bpm) and the moderate movement condition (M = 72.5 bpm), but the still condition was found to be significantly different from the moderate motion condition. Additionally, the interaction between occupant weight and sensor type and the interaction between occupant motion and sensor type were also found to be significant. Interpretation of these interactions revealed that the patterns observed appeared to be an artifact of the pressure sensor’s overestimation of heart rate, which was then amplified by variations within occupant weight and motion, respectively.

Table 19. Summary of occupant motion main effect

<table>
<thead>
<tr>
<th>Level</th>
<th>Tukey HSD Levels</th>
<th>Mean (bpm)</th>
<th>Std Error (bpm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Still</td>
<td>A</td>
<td>75.75</td>
<td>0.58</td>
</tr>
<tr>
<td>Infrequent</td>
<td>A, B</td>
<td>73.96</td>
<td>0.58</td>
</tr>
<tr>
<td>Moderate</td>
<td>B</td>
<td>72.55</td>
<td>0.58</td>
</tr>
</tbody>
</table>

For the standard deviation of heart rate, significant main effects were found for sensor type and clothing weight (Table 19). For the sensor type main effect, the pressure sensor showed significantly larger standard deviation (M = 4.83 bpm, SE = 0.11 bpm) than the benchmark (M = 3.86 bpm, SE = 0.11 bpm). For the clothing weight main effect, the mean heart rate for the middle condition of midweight clothing (M = 4.36 bpm, SE = 0.01 bpm) was found to be statistically similar to both the lightweight (M = 4.07 bpm, SE = 0.01 bpm) and the heavyweight condition (M = 4.61 bpm, SE = 0.01 bpm), but the lightweight condition was found to be significantly different than the heavyweight condition. There were no significant interactions detected.

Table 20. Summary of significant effects for the standard deviation or heart rate detection. Non-significant effects were left blank.

<table>
<thead>
<tr>
<th>Experimental Factor</th>
<th>Detected Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor</td>
<td>Pressure &gt; HR Sensor</td>
</tr>
<tr>
<td>Weight</td>
<td>-</td>
</tr>
<tr>
<td>Clothing Weight</td>
<td>Heavyweight ≥ Midweight ≥ Lightweight,</td>
</tr>
<tr>
<td></td>
<td>Heavyweight ≠ Lightweight</td>
</tr>
<tr>
<td>Motion</td>
<td>-</td>
</tr>
</tbody>
</table>
5.3.5 Discussion

Considering the primary goal of this study, to assess whether the pressure sensor system would suffice as an accurate method of heart rate detection in a vehicle setting, it was important to observe a lack of statistical difference between the pressure sensor heart rate estimates and the ground truth. This finding helps justify further development of a seat-based pressure sensor system. Not only did this study validate the application of this system for heart rate monitoring, but in combination with success of this system at respiration rate detection in the previous study and the ability to provide other fundamental occupant metrics (e.g., seat occupancy, size/weight), the pressure sensor system becomes a strong contender as an innovative post-crash vehicle occupant status assessment tool.

As expected, larger variation in pressure-sensor-derived heart rate was observed compared to that of the benchmark device. This is most likely a result of several factors. First, pre-study benchtop testing indicated that the pressure sensor does not map pressure to output voltage in a linear fashion and that sensitivity decreases at both output extremes. This likely influenced the accuracy of results for light and heavy weight participants. Second, unlike the data from the benchmark device, data from the pressure sensor needed to be filtered and processed. Some steps of data processing may have contributed to the larger variability observed. Third, the pressure sensor system was very sensitive to how participants sat. The most accurate readings were collected when participants were seated all the way back, had their upper legs resting on the seat, and their feet on the vehicle floor. Due to differences in participant size, however, this ideal seating position was not always achieved and may have introduced additional variability.

To best inform future development of the pressure sensor system for post-crash heart rate detection, the results of this study need to be contextualized within the applied signal processing. The signal processing algorithm was optimized to be most accurate for the middle conditions of occupant weight and motion. The implication of this decision becomes evident in the context of the main effect associated with
occupant motion, where the middle condition was found to be similar to both ends of the tested range, but the end conditions significantly differed from one another. This artifact is then amplified within the significant interaction between occupant motion and sensor type where, on average, the still and infrequent motion conditions overestimated, and the moderate motion condition underestimated, heart rate compared to the benchmark, with the infrequent motion condition displaying the smallest difference. Similarly, although the occupant weight main effect was not found to yield significantly different responses on its own, the interaction between occupant weight and sensor type was found to be significant. For this interaction, on average, the lightweight condition underestimated, and the midweight and heavyweight conditions overestimated, heart rate compared to the benchmark, with the midweight condition exhibiting the smallest difference. To improve upon this limitation, a dynamic data processing model could be developed and applied to optimize signal processing across several different occupant weight ranges and motion intensities. This model would first detect and distinguish an occupant’s weight and degree of motion, then apply signal processing algorithms specialized for that occupant and their motions.

5.4 Mental State

5.4.1 Research Objectives

The first objective for the development of the mental state component of the injury triage system was to identify procedures and protocols that are used to evaluate mental status. To accomplish this, a literature review was guided by the research question: What protocols are used to evaluate patient mental status? The findings of this review then led to the selection of a preferred approach. The second objective of this work was to evaluate how to collect and share crash occupant mental status information. A study was conducted, comprised of first responder focus groups, to answer one primary research question: How
can crash occupant mental status evaluation data be best collected and shared with emergency responders?

5.4.2 Methodology Selection

The final metric in triaging a patient while following START protocols is to evaluate mental status. Unlike the previously investigated metrics, mental status evaluation does not have a quantitative measurement associated with it. Rather, patients are often asked questions and/or instructed to follow commands where their answers and reactions dictate their mental status scoring. A patient’s mental status can be evaluated by several different evaluation tools. The first evaluation that is often employed is gauging level of consciousness. A person’s gross level of consciousness is often categorized using the acronym AVPU which stands for “alert,” “verbal,” “painful,” and “unresponsive” [113]. A person is scored as “alert” if they can respond or react spontaneously and independently. An “alert” person can also be identified by spontaneous eye movement and the ability to communicate freely when addressed. A person is scored as “verbal” if they are only able to respond or react to verbal stimuli, which usually takes the form of calling their name or prompting them with simple commands. A person is scored as “painful” if they are only able to react or respond to painful stimuli, which may often include rubbing their sternum or applying pressure to the fingernail bed. Finally, a person is scored as “unresponsive” if they cannot function independently and do not respond to verbal or painful stimuli.

A second evaluation tool to evaluate mental status is to assess a person’s orientation. Orientation can only be assessed on “alert” patients and covers four categories: person, place, time, and event. Simple questioning is used to collect responses (e.g., What is your name?; Can you tell me where you are right now?; What is today’s date?; What were you doing today?). Orientation is commonly reported as alert and oriented times the degree of orientation. For example, an alert patient oriented to person, place, and event but not time would be denoted “A&O x 3”.
Finally, the Glasgow Comma Scale (GCS) can also be used to evaluate mental status. GCS is determined by evaluating a person's eye-opening response, verbal response, and motor response. The scale has a maximum combined score of 15 and a minimum combined score of 3 [114]. Eye-opening response is scored on a continuous scale of 1 to 4 points with a score of 4 corresponding to spontaneous eye opening and a score of 1 corresponding to no eye opening. Verbal response is scored on a continuous scale of 1 to 5 points with a score of 5 corresponding to full orientation and a score of 1 corresponding to no verbal response. Finally motor response is scored on a continuous scale of 1 to 6 with a score of 6 corresponding to the ability to fully obey commands and complete movements and a score of one corresponding to no motor response. GCS is often conveyed as the total score the patient received. In some circumstances, however, the GCS may be portrayed as each individual response score to better describe the patient's condition.

Of the three mental status evaluation tools listed, AVPU with orientation was selected as the method of interest for this application. Although the more intricate point system used in the GCS may allow for a more detailed evaluation of mental status, evaluation is a bit more involved than for the other evaluation tools. This would make application of the GCS to appropriately assess motor response particularly challenging in a contactless in-vehicle environment. More specifically, these evaluation tools are anticipated to be employed using one- or two-way audio/visual conversations between the crash occupants and an automated system or crash detection system operator, supported by an AACN or NG911 system.

5.4.3 Methods

This study used the output of six focus groups sessions that captured responses from 18 EMTs who practice in southwest Virginia. The study protocol was approved by the Virginia Tech IRB (#23-1058). Each focus group session was guided by a series of prompts and follow up questions (Appendix EF). The first
half of the prompts described an automated system that would interact with crash occupants to collect mental status metrics. These questions also probed ways in which the mental status information could be provided to first responders. The second half of the prompts described a human-based system that would perform the same tasks as the automated system but could also be capable of additional assessments. Each session also allotted time for participants to suggest other methods for collecting and/or sharing crash occupant mental status metrics that were not previously discussed and that they felt would be effective. Participants were informed prior to the start of each session that participation in the focus groups implied consent to have notes taken on their responses and group discourse. Typed notes were taken throughout each session. Each session took place at the participants’ EMS station. Sessions lasted between 15 and 30 minutes, depending on the number of participants. Focus groups were limited to a maximum of five participants at a time. The smallest session included two participants and the largest session included five. Following the conclusion of all the focus groups, the session notes were used to summarize participant responses.

5.4.4 Results

For the first half of the focus groups sessions, participants were asked to envision an automated system that would interact with crash occupants to gather mental status information. About half of the participants commented positively about the proposed system, indicating they believed it would be able to gather sufficient information from crash occupants to then be used to determine their mental status. The remaining half of participants, however, were not in favor of the automated system. The primary concern, expressed by nearly all opposed participants, was how accurately the automated system could collect data. Additional concerns included the system’s ability to discern responses between multiple occupants, differentiate direct responses from discourse, and appropriately interpret incorrect versus unintended responses.
When presented with the possibility of receiving audio-recorded responses to the mental status evaluation questions, nearly all participants favored this approach. Participants indicated this would allow them to leverage occupant voices and background noises to generate a pre-assessment of occupant condition. About half of the focus group participants also stated that it would allow them to potentially interpret incorrect versus unintended responses, an important distinction that would likely be an area of concern with automated system outputs. Of the few participants who were not in favor of this method, the main concerns surrounded audio clarity, the length of time needed to listen to all responses, and challenges associated with language barriers. Participants were less favorable towards letting the automated system transcribe responses, as only half responded positively to this data sharing method. Although most participants agreed that transcribed responses could be quickly read, many drew concerns surrounding transcription accuracy. When ultimately asked for method preference, however, all participants indicated that they would want both the audio recorded and transcribed responses available, stating that combined use could provide the best information about patient condition and compensate for anticipated issues with both methods.

For the second half of the focus groups sessions, participants were described a human-operated system that would interact with crash occupants. Nearly all participants indicated an immediate preference for a human-based system over the automated one. These participants believed that a human operator could overcome many of the anticipated challenges expected from an automated system. Some of these reasons included the ability to interpret responses, repeat or clarify questions, and potentially calm occupants to gather more accurate responses. A few participants, however, were starkly opposed to the human-operated system, mainly citing poor experiences with emergency medical dispatchers where gathered information was grossly inaccurate.

Mental status data collected from the human-operated system was first proposed to participants to be shared with first responders in the form of transcribed notes, where the system operator would dictate
crash occupant responses. About three-quarters of the participants were in favor of receiving transcribed responses. Many of these participants expressed their interest was based on anticipated enhanced clarity, as compared to the “speech-to-text” style transcriptions that would be available from the automated system. One of the opposed participants, however, voiced strong concerns surrounding human dictation quality. Human-collected mental status data was also proposed to be shared via annotation of responses, still providing typed responses, but condensing the length and specificity. Only about half of the participants were in favor of receiving annotated responses. Of those in favor, half of them elaborated that annotated responses could be more efficient to read but indicated concern about reducing accuracy at the cost of efficiency and about the ill effects that operator inexperience could have on the quality of the annotations. Only about half of the participants were interested in receiving both transcribed and annotated responses, whereas the remaining half were evenly split on their preference for the transcribed or annotated responses.

At the end of each session, participants were able to express additional ideas for other ways mental status information could be collected or shared. Most participants did not have additional ideas to share. Several participants stated they would be interested in also receiving audio recorded responses from the human-operated system. Several others stated they would be interested in potentially receiving a video feed from the cabin to be able to better see occupants and their condition.

5.4.5 Discussion

When considering the overall responses from the focus group sessions, a vast majority of the participants were not only in favor of a human-operated system but preferred it to the automated one. This was an expected finding due to anticipated challenges associated with an automated system and benefits associated with a human-based one, most of which were expressed by the participants throughout the focus group sessions. For this reason, participants were first introduced to the automated system, to limit
their bias and be able to gather as much feedback as possible without prejudice. Successful implementation of such a system could be possible through AACN systems or even anticipated Enhanced 911 abilities.

When it comes to the methods of sharing occupant mental status, there were several unanticipated findings. The first, and most noteworthy, was the overwhelming number of participants that requested all methods of sharing mental status to be available. The main caveat associated with this request was that information be provided in a non-overwhelming way, where the data could be easily sorted and parsed to best match the needs of the first responder user. The general widespread interest in receiving audio recordings of occupant responses was also unanticipated. This was expected to be viewed as a time-consuming and chaotic way of receiving mental status information, yet many of the participants thought hearing crash occupant voices would be quite telling about their condition and allow them to better judge the correctness of responses. Even more so, the request for audio recordings to be available even within the human-operated system speaks to its perceived usefulness within the participant population.

5.5 Rescue Application Development

A key component of successful implementation of the proposed post-crash injury triage system is effective data delivery to relevant first responders. Although there is potential for this information to be shared through local dispatchers and computer aided dispatch (CAD) notes, these methods would not appropriately accommodate the volume and quality of the proposed data. An alternative approach to existing channels of communication could take the form of a 3rd party web-based application (“app”) that first responders could access to view the collected post-crash data. Through a collaborative effort with an ongoing automated driving system (ADS)-related project funded by the Federal Highway Administration (Agreement No. 693JJ32040003), a web-based application was designed and developed to share advanced vehicle and occupant-specific crash data with first responders. A large portion of the data that
may be shared through this app is collected from vehicle-integrated sensors. Additional data can be incorporated by way of an automated post-crash assessment program, a fleet manager (e.g., personnel that oversee a fleet vehicle’s use), or an AACN operator (e.g., OnStar dispatcher). The development of this application was in accordance with a project scenario that encompassed first responder interactions with an ADS equipped vehicle following a crash. The application assumes vehicle capability to send AACNs following the detection of an MVC. Included within that crash alert will be a unique vehicle crash event identifier, (e.g., a four-digit number) that can be used to link relevant first responders with data received directly from the crashed vehicle. The app also contains a searchable repository of “Rescue Sheets,” defined by the International Organization for Standardization (ISO 17840-3), which serve as quick reference guides on vehicle subsystems relevant to extrication and handling activities following a crash [115]. The application was developed on an Android tablet platform, but it could be modified to work with other wireless devices such as laptops or cell phones, which are also commonly used for EMS call reports and documentation. Screenshots of this application, recorded from a live demonstration, can be found in Appendix G.

Upon application start up, first responders will be able to enter the vehicle crash event identifier or manually search for a vehicle’s “Rescue Sheet.” If a vehicle crash event identifier is entered, the user will be automatically linked to the supported crash data and be able to toggle between the four main tabs (i.e., Occupant, Vehicle, Map, and Rescue Sheets). All users will initially be brought to the Occupant tab, which provides a bird’s-eye view of the occupant compartment. Based on integrated vehicle sensors, this tab will be continuously populated with seat occupancy status (e.g., unoccupied, occupied, left the vehicle, ejected, unknown), belt status at the time of the crash, occupant respiration rate, and occupant heart rate. Additionally, more occupant details such as name, age, gender, and mental status can be collected and populated on this tab through an aforementioned, automated post-crash assessment program or through human administrators. Occupants who present potentially dangerous parameters of
interest will be flagged (e.g., with a red outline around the seating position) to direct first responders to crash occupants who may be at a greater mortality risk. Defined occupant parameters that will be flagged include respiration rates outside the range of 12 to 20 brpm, heart rates outside the range of 60 to 110 bpm, sustained rapid changes in respiration rate or heart rate, any mental status worse than alert and fully oriented (A&O x 4), unbelted occupants, and ejected occupants (externally or in-cabin). Finally, users can also click on occupied, or once occupied, seats to view time series data of the respiration and heart rates, administrator notes, and occupant-specific airbag interactions.

The Vehicle tab primarily contains information on general crash details and vehicle sub-systems. The initial view of the Vehicle tab provides the vehicle year, make, and model, as well as a bird’s-eye view of the entire vehicle with crash details that include the primary direction of impact, the vehicle speed at impact, and the crash acceleration in units of gravity. In the top right corner of the screen are rollover and airbag status messages. The left side of the screen lists indicated hazards (noted with relevant icons) that can be tapped to provide brief descriptions. Some hazards will be populated based on vehicle sensor information (e.g., a battery icon if battery temperature or integrity are assessed as potentially dangerous) while others will be dependent on a rescue app administrator that can view the crash and/or live video (e.g., a hazmat icon if a truck involved in the crash may have spilled hazardous materials). At the bottom of the screen are toggleable sub-systems that can be turned on and off on the two-dimensional vehicle model to show their relative location. Examples of these sub-systems include high voltage wires, vehicle controls, and the fuel system. A switch in the top right corner of the screen allows the user to change the vehicle model to a movable three-dimensional view to provide increased accessibility to the sub-system location information.

The final two tabs are the Map tab and the Rescue Sheet tab. In the Map tab window, the user is directed to a map with a crash icon pinned at the crash location, with an approximate one-mile radius view. A brief crash description is also provided next to the crash icon. Once loaded, the user can scroll the map, zoom
in, or zoom out. The user can also switch from the standard street view to a satellite view. This map is not intended to route first responders, rather, it is intended to provide location data without disrupting the navigation services while responding. The Rescue Sheet tab serves as a quick launch to the specific “Rescue Sheet” document for the open event vehicle. This document contains many of the sub-systems viewable in the Vehicle tab, while providing additional information. The documentation itself helps streamline rapid response, especially when first responders may be unfamiliar with the vehicle or any of the embedded sub-systems. Having the documentation accessible through its own designated tab helps first responders who have the unique vehicle crash event identifier avoid searching for the relevant documentation.

5.6 Conclusion

The development of a post-crash injury triage system would provide first responders with detailed information that can be used to improve efficiency within the response and on-scene components of an emergency response event, specifically for an MVC. Knowledge about post-crash occupant physiologic condition can be used to properly direct emergency response resources early in the response phase and begin development of a transport plan. These benefits could lead to time reductions throughout the emergency response event and help local emergency response organizations in optimizing how they allocate personnel. Although the sensing systems needed to capture respiration rate, heart rate, and mental status need to be robust enough to maintain functionality after a crash, redundancy (through further development and refinement of tested systems, and/or the additional incorporation of other alternatives) can be utilized to help ensure data consistency and quality. A prime example of the need for redundancy would be in the wake of a rollover crash. Although the presence of a rollover is often used as a standalone high injury risk indicator resulting in widespread emergency response resource deployment, if the vehicle does not come to rest back on all four tires and occupant weight is not on the seat, the pressure sensor will not be able to accurately assess respiration or heart rate. The ability to collect this
type of information also opens the opportunity to incorporate it into existing injury risk models to improve specificity and outcome accuracy. This could be potentially accomplished through recording post-crash occupant vital metrics on vehicle EDRs for later retrospective analysis.

Finally, the work outlined in this chapter directly addresses the call for more detailed information, specific to the crash occupants, expressed from the EMT interviews described in Chapter 2. Further, the design and development of the post-crash rescue application expands the breadth of both the quality and quantity of the information that can be shared effectively with first responders. In the context of crash occupants, the rescue app not only allows for continuous vital status updates and history, but can also convey occupancy status, belt use, airbag interactions, and additional information that may be available from a rescue application operator. In the context of the vehicle, the rescue app allows for effective communication of crash details, vehicle characteristics, and hazard detection, which was also discovered to be desired information from the EMT interviews. The framework of the rescue application could also be used to lay the foundation for incorporating this type of post-crash information into the upcoming NG911 system.
6: Conclusion

Global efforts to reduce MVC frequency and severity currently stand at the forefront of vehicle safety research. Although progress in traffic safety improvements has generally been steady, and the transportation sector will keep innovating to meet the shared goal of “road to zero,” mortality and morbidity associated with MVCs will continue to be a relevant topic in transportation safety for many years to come. Thankfully, recently adopted perspectives such as the Safe Systems Approach highlight the important role that post-crash care plays towards the challenging goal of zero roadway fatalities. The work conforming this dissertation presents a series of projects aimed at addressing concerns and difficulties faced by EMTs while responding to MVCs, with the intention of identifying solutions to improve the safety and efficiency of post-crash care. More specifically, the projects explored in this dissertation target later phases of emergency response events that are not currently the focus of post-crash care advancement. In combination, the findings of these studies can lead to sizable improvements in reducing time to definitive care, namely within the response, on-scene, and transportation phases of an emergency response event.

On the topic of emergency vehicle traffic interactions, which was explored and investigated in Chapters 3 and 4, the results were found to support that dangerous and confusing interactions between emergency vehicles and other road users are a common and major concern. Through the exploratory analysis of the NEMSIS database, traffic was found to be a leading cause of EMS delay, highlighting the prevalence and consequences of these difficult interactions. However, further investigation into traffic interactions using the SHRP2 NDS dataset revealed that these challenging exchanges are not caused solely by civilian motorists but in some instances may have been originated by the emergency vehicle operator. These results motivated the ambulance NDS study, which once again supported claims of commonplace confusing and dangerous emergency vehicle traffic interactions. The ambulance NDS study successfully captured complex traffic interactions which were identified through applying kinematic threshold triggers.
and random sampling video reduction. Collectively, these findings showcase that the use of emergency vehicle lights and sirens are not sufficient when trying to reduce conflicts between emergency vehicles and other road users, and may need to be paired with new technology to foster safer and more efficient emergent driving.

To provide first responders with a greater quality and quantity of crash relevant information, a post-crash injury triage system was developed. This system was scoped to capture triage relevant vitals including respiration rate, heart rate, and mental status. Several studies, described through Chapter 5, were conducted to test the effectiveness of capturing said metrics via passive sensors that could be integrated into the vehicle cabin. Following testing and data analysis, the application of a pressure sensor system embedded into the vehicle seat showed to be the most capable of accurately monitoring occupant respiration rate and heart rate; though, further development will be needed to improve robustness and versatility of this sensing technology. First responders were also presented with several methods for collecting and sharing crash occupant mental status information through a series of focus groups. The summary of those sessions identified a human post-crash operator (similar to an OnStar operator) being the preferred method of data collection. The sessions also revealed that first responders were in favor of receiving audio recorded responses, transcribed responses, and annotated responses, but preferred the ability to receive all options rather than just one. Ultimately, a post-crash rescue application was developed to incorporate occupant vital metrics of interest, and additional occupant- and vehicle-centric crash details, to provide first responders with an effective way to view high quality crash relevant information.

The findings of the work presented in the study are two-fold, as they present information that can be used to directly benefit both first responders and other road users. From the first responder perspective, a better understanding of traffic interactions can directly lead to efficiency advances, contributing to reduced time to definitive care, but also reducing the potential for secondary crashes during emergent
response. Likewise, the development of an in-vehicle post-crash injury triage system presents the opportunity for first responders to streamline and optimize resource allocation, once again contributing to reduced time to definitive care, but also presents an opportunity to collect crash occupant data that can be used to further develop injury risk prediction algorithms and vehicle safety systems. Ultimately, the findings of the work presented in this dissertation possess the potential to be paired with emerging technologies in vehicle connectivity to provide first responders with safer transportation equipment, more detailed information surrounding the crashed vehicle, and important medical information about the vehicle occupants. Thus, when combined together, the findings of this dissertation provide detailed information and solutions to address challenges faced throughout all phases of emergency response event to an MVC (Figure 36).

**Figure 36.** A generalized timeline of major events for an emergency medical response to an MVC, highlighting the technological solutions, both existing and proposed in this dissertation, that will cover challenges throughout an emergency response event.
Appendices
Appendix A

EMT Interview Questions

Phase 1: General Feedback

1. What are problems you experience when being dispatched to a call (e.g., communication, technology, interpretation)?

2. What is the difference in information that comes from a person calling in the emergency vs. a system like OnStar?

3. What are problems you experience when attending to an incident? This is aimed more at issues with processes or other general topics, not crash-specific problems.

4. What are problems you experience in transit to and arrival at an emergency facility?

5. What are some aspects of the current dispatching/travel system that work really well?

Phase 2: Needs and Wants

6. What information do you wish you had from dispatching that you currently do not? Please list as many as come to mind. For each of these:
   a. Do you feel that this piece of information is more of a need than a want?
   b. How would the additional information be useful?
   c. When would the information be useful?

7. What technology, or tools, would help smooth out the process of responding to emergency situations?

Phase 3: Injury Relationships

8. Do you see any correlations between vehicular crash types and injury characteristics?
   a. If yes, how would you explain the relationship in your own words

9. Do you ever receive (or ask for) any feedback from hospital staff related to patients you bring in after a vehicular crash?
   b. If not, why not?
   c. Is/Would such feedback useful to you? How?

10. Is there anything these questions may not have led to that you feel is relevant to an EMT’s response to vehicular crashes?
Appendix B

Delay Type Frequencies Across All Delay Categories

Delay type frequencies are shown for dispatch delays, response delays, scene delays, and transport delays in Figure B1, Figure B2, Figure B3, and Figure B4, respectively. To emphasize relative frequencies within each delay category, the y-axes on each of the graphs are scaled differently. Therefore, care should be taken when examining frequencies across the different figures.

Figure B1. The overall frequency of dispatch delay types.

Figure B2. The overall frequency of response delay types.
Figure B3. The overall frequency of scene delay types.

Figure B4. The overall frequency of transport delay types.
Appendix C

Community Density Distributions per Delay Type Across All Delay Categories

Community density distributions by delay type are shown for dispatch delay, response delay, scene delay, and transport delay categories in Figure C1, Figure C2, Figure C3, and Figure C4 respectively. To emphasize relative frequencies within each delay category, the y-axes on each of the graphs are scaled differently. Therefore, care should be taken when examining frequencies across the different figures.

Figure C1. Distribution of cases sorted by community density across dispatch delay types.

Figure C2. Distribution of cases sorted by community density across response delay types.
Figure C3. Distribution of cases sorted by community density across scene delay types.

Figure C4. Distribution of cases sorted by community density across transport delay types.
Appendix D

Community Density Proportions per Delay Type Across Urbanicity Factors

Proportional community density distributions by delay type are shown for dispatch delay, response delay, scene delay, and transport delay categories in Figure D1, Figure D2, Figure D3, and Figure D4 respectively.

Figure D1. Proportion of cases by dispatch delay types across community density levels.

Figure D2. Proportion of cases by response delay types across community density levels.
Figure D3. Proportion of cases by scene delay types across community density levels.

Figure D4. Proportion of cases by transport delay types across community density levels.
Appendix E

<table>
<thead>
<tr>
<th>Demographics Questionnaire</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. What is your gender? ______________</td>
</tr>
<tr>
<td>2. What is your age? ______________</td>
</tr>
<tr>
<td>3. Do you wear corrective lenses while driving? ______________</td>
</tr>
<tr>
<td>4. Do you wear a hearing aid while driving? ______________</td>
</tr>
<tr>
<td>5. How many motor vehicle accidents have you been in? ______________</td>
</tr>
<tr>
<td>6. How long have you been driving an ambulance for? _____ years</td>
</tr>
<tr>
<td>7. How long have you driven for your current agency? _____ years</td>
</tr>
<tr>
<td>8. Do you train drivers for your agency? ___ Yes ___ No</td>
</tr>
<tr>
<td>9. About how many miles have you driven on duty in the last year? ______________</td>
</tr>
<tr>
<td>10. How many hours are you typically on-duty per week? ______________</td>
</tr>
<tr>
<td>11. How many hours are you typically driving per week? ______________</td>
</tr>
</tbody>
</table>
Appendix F

Focus Group Framework and Questions

Before we begin, I would like to remind everyone that participation in this focus groups is voluntary. By remaining and participating in the session, you are consenting to have notes taken on your responses to the presented questions and group dialogue that may follow. If at any time you decide you no longer wish to participate, you may excuse yourself from the session. Any noted responses up to that point will be retained. If you must leave due to an emergency call, you may follow up with me to complete the series of questions if you’d like. This session will last between 15-30 minutes.

Project overview

The research team is developing a post-crash, injury triage system. The intention and design of this system is to capture crash occupant’s respiration rate, heart rate, and mental status, then provide those metrics to EMS prior to their on-scene arrival. This data is anticipated to be provided to first responders through third party applications but may also be available through computer aided dispatch (CAD) notes. The goal of this focus group will be to discuss several methods for collecting and sharing crash occupant mental status. Several systems will be described. Please provide your impressions of these systems and how well you think you would interact with them.

Automated Systems

The first system we will talk about is an automated system. Following the detection of a crash, this system will be activated. The automated system will first start by interacting with the driver, then proceed to the other vehicle occupants, if present, by identifying the seat they are occupying. The automated system will attempt to establish each occupant’s level of consciousness and degree of orientation through simple questioning.

1. How do you feel about automated-based system?

Since the system is automated responses will be recorded, not interpreted. One method of recording responses would be audio recording. Alternately, audio recoded responses could be transcribed (e.g., converted to text).

2. What do you think about audio recording occupant responses?

3. What do you think about transcribing occupant responses?
4. How would you feel if you were provided with both audio recorded and transcribed responses?

**Human Controlled Systems**

The second system we will talk about is a human controlled system. Following the detection of a crash, this system will be activated, and a person will be connected to the vehicle through an audio and/or video connection. It is anticipated that future vehicles that would have this technology would be owned by a fleet service, and in that case a fleet manager or operator would be the person connected with the vehicle. Alternately, a connection could be made with advanced automatic crash notification service operators (similar to how OnStar operators call vehicles that were involved in crashes). In both circumstances, the person connected to the vehicle will briefly talk to the crash occupants to establish each occupant’s level of consciousness and degree of orientation through simple questioning.

5. How do you feel about a human-based system?

Since the responses are being collected by a human, crash occupant responses can be recorded but also interpreted to provide clearer data. Therefore, responses could more easily and accurately be transcribed (e.g., converted to text). Additionally, responses could be annotated, where the crash response operator could simply indicate their interpreted level of consciousness and orientation (e.g., Driver is A&Ox3).

6. What do you think about a crash response operator transcribing occupant responses?

7. What do you think about a crash response operator annotating occupant responses?

8. How would you feel if you were provided with both transcribed and annotated responses?

Final thoughts

9. Is there another method of collecting or sharing occupant mental status that you can think of that was not discussed that you would be interested in?
Appendix G

Rescue App Screenshots

Figure G1. Starting page of the web-based rescue application. Users can either enter a specified unique vehicle crash event identifier or search the repository for “Rescue Sheets.”
Figure G2. The Occupant tab within the rescue app. In this window the user can see overall vehicle occupancy status, belt use status, occupant details (e.g., age, gender) occupant respiration rate, occupant heat rate, and occupant mental status.
Figure G3. Additional occupant information is available for all seated, or once seated occupants. By tapping on the seat in the Occupant tab, this window will pop up to show occupant specific airbag interaction status, rescue app administrator entered notes, and times series data of respiration rate and heart rate.
Figure G4. The Vehicle tab within the rescue app. In this window the user can see crash details and where pertinent sub-systems are within the vehicle. In addition to the many sub-systems, users can also see crash details, quick reference status conditions (e.g., rollover and airbag detection), and hazard detection.
Figure G5. Within the Vehicle tab, users can also view a 3D model of the vehicle to better understand the location of the displayed sub-systems.
In the Map tab, the user gets access to a pinned crash location in google maps. The users can scroll the map, zoom in/out, and change to satellite view.

Figure G6. In the Map tab, the user gets access to a pinned crash location in google maps. The users can scroll the map, zoom in/out, and change to satellite view.
INTRODUCTION

The emergency response procedures for F-150 Hybrid vehicles are similar to those for traditional gasoline-powered vehicles, with special considerations for the high-voltage electrical system components. These vehicles use an electric motor in addition to a conventional gasoline engine to power the vehicle.

WARNING: ALWAYS ASSUME THE VEHICLE’S HIGH-VOLTAGE SYSTEM IS POWERED UP! Before accessing the vehicle make sure that any external power supply is disconnected (e.g., electric charger, electric tools). Failure to follow these instructions may result in serious personal injury or death.

HYBRID ELECTRIC VEHICLE IDENTIFICATION

Identification using vehicle characteristics

1. "POWERBOOST" emblem on front door
2. Under-hood Orange High-Voltage cables

Publication Date: 10/2022

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Figure G7. In the Rescue Sheet tab, the user gets automatically directed to the specific “rescue sheet” document for the vehicle involved in the crash.
References


[8] NHTSA Office of EMS. NEMSIS.


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