2021-08-03

Analysis of Benefits of an Expansion to UDOT's Incident Management Program

Logan Stewart Bennett
Brigham Young University

Analysis of Benefits of an Expansion to UDOT's

Incident Management Program

Logan Stewart Bennett

A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

Grant George Schultz, Chair
Mitsuru Saito
Dennis Lee Eggett
Gregory Macfarlane

Department of Civil and Environmental Engineering

Brigham Young University

ABSTRACT

Analysis of Benefits of an Expansion to UDOT's
Incident Management Program

Logan Stewart Bennett
Department of Civil and Environmental Engineering, BYU
Master of Science

In 2018 the Utah Department of Transportation (UDOT) funded a study in which data were collected to evaluate performance measures for UDOT's Incident Management Team (IMT) program. After that study was completed, UDOT received funding to expand the size of its IMT program. Additionally, TransSuite, a data source used by the UDOT Traffic Operations Center to log incident-related data, was reconfigured to provide a higher quantity of performance measure data. This study made use of the new data source, in addition to Computer Aided Dispatch logs provided by the Utah Highway Patrol that were used in the first study, to collect performance measure data of the expanded program and measure the impacts of the IMT program expansion. Using these two datasets, a reanalyzed 2018 dataset and a new 2020 dataset, a comparison of performance measures was made. Performance measures studied included those defined as important by the Federal Highway Administration's Focus States Initiative in 2009, namely Roadway Clearance Time, Incident Clearance Time, and Response Time. These performance measures were calculated for IMT responders at 320 incidents in 2018 and 289 incidents in 2020. In addition, data regarding the affected volume associated with incidents, the excess travel time accumulated due to incidents, and the excess user cost associated with incident congestion were gathered. In 2018, 188 incidents were analyzed for these user impacts, and in 2020 144 incidents were analyzed. Statistical analyses were conducted to compare IMT performance between the two years and to determine relationships between performance measures and user impacts. The effects of the COVID-19 pandemic affected traffic volumes during this study, and statistical analyses were adjusted to account for volume differences between the two years. Results indicated that the expansion of the IMT program has allowed UDOT to respond faster to incidents, and respond to a larger quantity of incidents over a larger coverage area and in extended operating hours. Performance of the expanded IMT program has had significant effects in reducing incident-related congestion and its costs.

Keywords: traffic incident management (TIM), incident management team (IMT), performance measures, response time, roadway clearance time, incident clearance time, excess travel time, excess user cost, COVID-19

ACKNOWLEDGEMENTS

I would first like to acknowledge the Utah Department of Transportation (UDOT) for their support in championing this project, as well as the individual members of the Technical Advisory Committee for this study from UDOT and its partners for their guidance and support during the research project, including John Leonard, Jeff Reynolds, Corey Coulam, Kelly Njord, Travis Jensen, Chris Rueckert, and Jeff Nigbur.

Secondly, I would like to thank the members of my graduate committee, Dr. Grant G. Schultz, Dr. Mitsuru Saito, Dr. Dennis L. Eggett, and Dr. Gregory Macfarlane, for the many hours spent meeting with me, instructing me, and guiding me through this research. I am thankful for their friendship and for their trust in me. I have felt less like a student and more like a peer throughout graduate school and this project and I acknowledge and thank them for their role in my professional development.

Thirdly, I would like to thank the other research assistants who have so greatly assisted me in completing this research, namely Mitchell G. Hadfield and Joel Hyer. I wish to thank Mitchell for his tireless and selfless work on the Phase I research that led to this project, and for his continued support after his own project was completed. I would also like to thank Joel for his help in Phase II of this project including his countless hours of data collection and his willing and cheerful attitude throughout the project.

Lastly, I would like to thank my family and friends who have supported me throughout my schooling. Thanks goes to my parents, Scott and Kirsten Bennett, and my siblings, McKay, Jess, Lauren, and Chris, for their constant encouragement and faith in me. I thank my friends Sami Lau, Evan Smith, Max Barnes, Christian Lundskog, and Gina Souriac for attending graduate school with me, for making this stressful time enjoyable, and for keeping me sane.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

1.1 Problem Statement

The Phase I study of the Incident Management Team (IMT) program of the Utah Department of Transportation (UDOT) found that UDOT and the Utah Highway Patrol (UHP) had the data necessary to evaluate incident management performance measures, with the exception of one data point related to incident management activities. That data point was the time when all lanes become open again (T_5) and capacity is restored (Schultz et al. 2019). The UHP maintains the Computer Aided Dispatch (CAD) that contains activities of both UHP officers and UDOT's IMTs at crash sites. UDOT maintains two traffic-related datasets: the Performance Measurement System (PeMS), which collects data from sensors, and Iteris Performance Measurement System (iPeMS, now Iteris ClearGuide), which collects data from probe vehicles. Both datasets help the analyst to estimate the time of incident occurrence and the time of complete incident clearance. UDOT's Traffic Operation Center (TOC) maintains TransSuite data that can be used for the analysis, but during the Phase I study it was found that extracting the T_5 data from TransSuite was difficult. Instead, to accomplish the objective of the study, UHP officers were requested to collect T_5 data from March to August 2018 manually as they assisted crash victims and aided IMTs in clearing congestion. This additional time data made the completion of the study more consistent. Using the data collected in the 6-month period, incident management performance measures were analyzed and user costs due to crashes were estimated under the current IMT program. It was found that decreasing even a few minutes of response time (RT) and roadway clearance time (RCT) would result in a substantial decrease in user costs that would make the IMT program a worthwhile investment.

While the Phase I study was underway, the Utah State Legislature approved funding to expand the operation of the IMT program. The new funding allowed UDOT to increase the number of IMTs, both personnel and equipment, by 12 units. The Phase I study showed that reduction in RT would help UDOT reduce the delay and user costs due to crashes. The expanded IMT program, which began operation in the spring of 2019, provided an opportunity to validate the outcome of the Phase I study using field data. This Phase II study involved the collection of a new set of performance measures data in spring and summer (March to September) 2020 when the new expanded IMT program had been well established. It also involved collection of performance measure data from March to September 2018 using the newly available TransSuite data. This allowed for comparison of IMT performance between the two years to help UDOT evaluate the effectiveness of the IMT program and the impacts of the program expansion.

1.2 Objectives

The following are the objectives selected for the Phase II study of the IMT program. Note that because of the comparative nature of the study, the scope included only IMT activities on freeways or access-controlled highways owned by UDOT because most pre-expansion IMT activities took place on those types of facilities.

- Identify any changes in the way UDOT's IMT program is executed. Any changes that are taking place needed to be identified so that the effects of such changes could be analyzed.
- Analyze the Phase I data including the lane closure data and evaluate if the analysis results could be improved.
- Collect performance measures data of the expanded IMT program.
- Identify the reduction in RCT and incident clearance time (ICT).
- Use statistical analysis methods to evaluate how much improvement the expanded IMT program can achieve over the previous IMT program.

1.3 Scope

A kick-off meeting was held with the UDOT Champion and Research Division representatives to identify members of the Technical Advisory Committee (TAC), the majority of whom had previously worked with the Brigham Young University (BYU) research team in Phase I of the project. TAC members contributed their expertise of UDOT's IMT program and the several data sources to guide the research team in their efforts. The kick-off meeting involved discussion of the possibility of using TransSuite data to aid in performance measurement as a way to collect data for a larger sample of incidents, verify the accuracy of data entries from both UHP and TOC operators, and to evaluate the need for additional training and personnel at the TOC.

A comprehensive literature review on Traffic Incident Management (TIM) and its performance measures was conducted. The research team accessed multiple online sources through the Harold B. Lee Library of BYU, including issues of the *Transportation Research Record: Journal of the Transportation Research Board*, the American Society of Civil Engineers

Journal of Transportation Engineering, and other publications. TIM national analysis reports published by the Federal Highway Administration (FHWA) Office of Operations, such as those written as part of the Every Day Counts Round 4 (EDC-4) initiative, were also reviewed.

A methodology for data collection was modified using the TransSuite database and incidents were analyzed for performance measures, particularly relating to the RT, RCT, and ICT. Performance measure data were collected again for the Phase I time period using this new methodology and new performance measure data were collected for a corresponding time period in 2020. Using the PeMS and iPeMS databases, data relating to incident occurrence and the time when the queue completely dissipated were also collected to evaluate incidents for excess travel time (ETT), affected volume (AV), and excess user cost (EUC). Performance measure and user impact data were reduced and prepared for statistical analyses.

After new datasets were compiled for 2018 and 2020, statistical analyses were performed using Base SAS software (Base SAS 9.4 2013). Significance of relationships between performance measures and user impacts as well as other incident characteristics were determined and quantified through regression analysis. Due to the effects of the COVID-19 pandemic, that affected data collection during the Phase II study, analyses were performed in a way to account for the impact of COVID-19 on traffic volumes, which differed between the two study periods. Comparisons of performance measures and user impacts between the two years were then performed to allow the research team to evaluate the benefits of the expansion to UDOT's IMT program.

1.4 Outline of Report

This report is organized into the following chapters:

1. Introduction
2. Literature Review
3. Data Availability and Collection
4. Data Reduction
5. Results of Statistical Analyses
6. Conclusions and Recommendations

Chapter 2 is a literature review that describes performance measures for IMTs. It also discusses how other states are collecting and using incident management data to improve operations as well as the current state of the practice in Utah given the findings from the Phase I study. Chapter 3 includes details about the expansion to UDOT's IMT program. It discusses the effects of COVID-19 on the data collection process and how data collection was adapted to meet that challenge. Chapter 3 also explains the available data and the process used to collect performance measures and to estimate the ETT, AV, and EUC of incidents. Chapter 4 presents the collected data graphically and numerically. Chapter 5 presents results of the statistical analyses performed. Chapter 6 presents conclusions that were drawn from the results of the analyses. The chapter also contains recommendations for further research.

Included in the Appendices are the incident data compiled by the research team over the course of the project and the results of statistical analyses not included in the body of the report.

2 LITERATURE REVIEW

2.1 Overview

This chapter presents the findings from the literature review conducted to acquire information on TIM performance measures as well as the changes to the TIM program in the state of Utah. This literature review adds to findings from the literature review performed by Schultz et al. (2019) for Phase I of this study to show additional development of TIM performance analysis. In accordance with the conclusions of the FHWA Focus States Initiative (FSI), the performance measures under consideration for TIM are (Owens et al. 2009):

- RCT, defined as the time between the first recordable awareness of the incident by a responsible agency and the first confirmation that all lanes become available for traffic flow.
- ICT, defined as the time between the first recordable awareness of the incident by a responsible agency and the time at which the last responder has left the scene.
- Secondary crashes.

Figure 2-1 shows the timeline of incident response and clearance performed by TIM. These performance measures are used to improve the efficiency and effectiveness of TIM programs by providing standards for data collection and comparison.

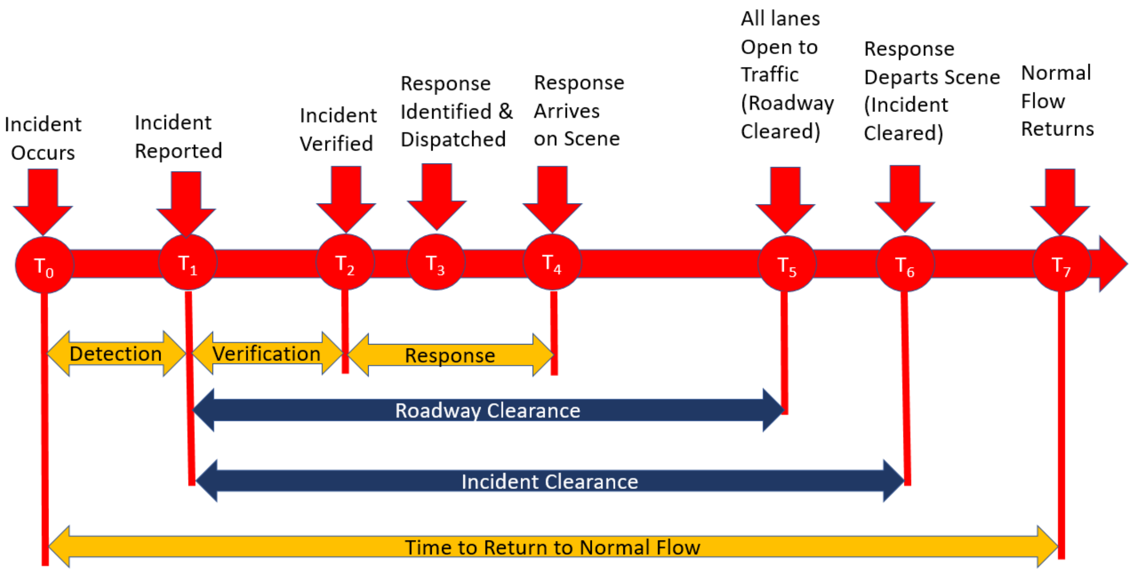


Figure 2-1: TIM timeline (adapted from Conklin et al. 2013).

A key part of the Moving Ahead for Progress in the 21st Century Act (MAP-21 2012) was to invest resources in a TIM performance measurement program. TIM performance has direct impacts on congestion, travel-time, and safety. Investing time and resources into collecting TIM performance measure data will help provide state departments of transportation (DOTs), as well as other state and local response agencies like law enforcement, fire and medical, with objective means for evaluating their incident management programs to improve the performance of U.S. roadway systems. As defined by the National Traffic Incident Management Coalition (NTIMC 2007), benefits of measuring TIM performance include:

- Increasing transparency and accountability.
- Justifying program funding.
- Improving driving conditions and safety.
- Improving communication and coordination between TIM partners.
- Making progress toward the achievement of national goals.

Data sources that are used to analyze TIM performance measures include TOCs, law enforcement, fire and emergency medical services, towing companies, and 511 systems. The data collected by these agencies are used to determine average ICTs and RCTs as well as to track trends throughout the roadway network.

The information in this review was gathered from literature published by state DOTs, national analysis reports published by the FHWA Office of Operations, state DOT TIM-related dashboards, and through FHWA webinars.

The objectives of this literature review are to identify and summarize literature related to TIM to determine protocols of record keeping for TIM performance measures, determine how to develop interagency data-sharing and overcome associated challenges, identify strategies for enhancing current TIM programs, review the current state of the practice in Utah, review the past use of simulation in TIM performance measures analysis. Findings are presented in the following sections.

2.2 Protocols of Record Keeping for Incident Management Performance Measures

Each DOT collects TIM-related data differently due to the variety of data sources available. In 2011, the FHWA encouraged states throughout the U.S. to evaluate their TIM programs and share their analyses and findings. Through this effort, the FHWA was able to examine performance measures that were being collected and how they were being collected (Owens et al. 2009).

Many data sources are emerging as useful sources for gathering and evaluating TIM performance data. According to the National Cooperative Highway Research Program (NCHRP)

Report 904, “Leveraging Big Data to Improve Traffic Incident Management” (Pecheux et al. 2019), some current and emerging methods of collecting and compiling incident data include:

- Collection of data from crash reports.
- Integration of Transportation Management Center (TMC) and safety service patrol (SSP) (i.e., IMT) datasets.
- Integration of TMC and CAD datasets.
- Utilization of crowdsource data and applications that use it, such as Genesis Pulse.
- Utilization of unmanned aerial vehicle technology.

A draft executive summary of the FHWA EDC-4 project reports the national state of the practice of TIM data reporting, including how various methods are being used to gather TIM data elements, namely RCT, ICT, and Secondary Crashes (FHWA 2019). The FHWA reports that using traffic crash reporting:

- Ten states collect ICT.
- Twelve states collect RCT.
- Twenty states collect data that identifies secondary crashes.
- Twenty-four states collect one or more of the three TIM data elements.
- Ten states collect two or more of the three TIM data elements.

The EDC-4 draft executive summary also reports that using data from TMCs:

- Fifteen states collect ICT.
- Seventeen states collect RCT.
- Ten states now count secondary crashes in the TMCs.

- Ten states noted improvements in the quality of TIM data collected in the TMCs.
- Eight states improved TMC training to better handle TIM data.

The EDC-4 draft executive summary reports that using SSP data, the following TIM data accomplishments were noted:

- Two additional states now capture RCT through the SSPs operating in the field.
- One additional new state now captures ICT through SSPs.
- Three additional new states now collect secondary crashes via the SSPs.
- Fourteen states noted improvements in the quality of TIM data obtained by SSPs.
- Eight states improved SSP training to improve TIM data.

Finally, the EDC-4 draft executive summary reports that during the project the following improvements relating to the use of CAD data were made:

- One state demonstrated the use of California Highway Patrol CAD data as a good statewide source of data for ICT (as well as response times).
- Sixteen states have plans to improve CAD integration.

An understanding of how other states gather and use TIM data is helpful in identifying beneficial practices. The NCHRP Report 07-20 by Jodoin et al. (2014) presents the findings from case studies of 14 states that institutionalized the collection and use of TIM performance measure data for improving their TIM programs. In these case studies, examples are provided of how data were collected, analyzed, and reported. In addition to the NCHRP 07-20 report, pertinent TIM-related studies from individual state DOTs have been reviewed to determine the current state of the practice. A summary of TIM activities in Arizona, Minnesota, New York, Colorado, Nevada, Kentucky, and Iowa is presented in the following subsections.

2.2.1 Arizona

The Arizona Department of Transportation (ADOT) uses Traffic and Criminal Software that allows law enforcement and ADOT to share its TIM data electronically (Jodoin et al. 2014). This allows for efficient and uniform data between both agencies. ADOT also partnered with the Arizona Department of Public Safety to conduct a study on the impact of secondary crashes within the state of Arizona (Rensel et al. 2018). The quality of TIM data collected was greatly improved after data recording was made electronic and the location of each crash was documented with global positioning system (GPS) coordinates. TIM data were also used to develop a secondary crash risk model. TIM strategies were evaluated based on effectiveness, the degree of risk presented to IMTs and State Highway Patrol members, and how it would affect the rate of secondary crashes. The components of the formula were a quantification of the effectiveness of the selected TIM strategy used, the percent likelihood of a secondary crash occurring, and the consequential costs of a crash.

2.2.2 Minnesota

The Minnesota DOT (MnDOT) integrated its advanced traffic management system (ATMS) with its CAD system to reduce redundancy, errors, and time associated with manual input of data. MnDOT reports that their ATMS provides more accurate incident start times than before because of collaboration from Minnesota state troopers, 911 dispatchers, and MnDOT TMC operators. The Regional TMC can receive incident start times, officer arrival times, and ICTs directly from state troopers (Jodoin et al. 2014).

2.2.3 New York

The New York State Department of Transportation (NYSDOT) created a program called Highway Emergency Local Patrol (HELP) which assists stranded motorists and vehicles. Each patrol is managed and coordinated by the local TMC to which patrol members report the necessary incident information. The HELP patrolmen are equipped with mobile data terminals that are connected to the TMC to report incident information electronically, including those data elements required for national TIM performance measures (Jodoin et al. 2014). The data collected have allowed NYSDOT to show the effectiveness of the HELP program in reducing delay and increasing safety. A study of the benefits of the HELP program found that implementation of the HELP trucks caused a reduction in total non-recurring congestion of 685,000 vehicle hours per year, a large majority of which came from non-crash-related incidents. That reduction translated into a 32 percent reduction in peak period non-recurring congestion. The program also provided an initial benefit cost ratio of 8.4, considering benefits of safety, ecology, and congestion (Garmen Associates 2000).

2.2.4 Colorado

At the time of the NCHRP 07-20 report in 2014, the Colorado Department of Transportation was working to reorganize its TIM data flow in order to allow TMC operators to focus on incident management rather than on data entry. Their Data Analytics Intelligence System can automatically populate fields of verified incident details such as location and time of incident to facilitate efficient management (Jodoin 2018b).

2.2.5 Nevada

The Nevada Department of Transportation (NDOT) initiated exclusive digital capture of incident data as of November 1, 2018 using the Waycare mobile app. Waycare uses publicly available datasets and crowdsourced data to more quickly and accurately identify incidents while decreasing TIM response times. NDOT reported that using Waycare allows incident information to reach responders an average of 10-12 minutes before 911 calls. While this does not change the response time itself, it does reduce the verification time and facilitate preemptive deployment of troopers to allow responders to report to the scene quicker (Jodoin 2018b).

2.2.6 Kentucky

In 2018 the Kentucky Transportation Center published "Improving the Quality of Traffic Records for Traffic Incident Management" in which all available data sources were evaluated for accuracy, accessibility, and extent of coverage. Data sources included Kentucky State Police (KSP) crash data, TOC incident records, crowdsourced navigation application data, and probe vehicle data.

The KSP crash database covers incidents across the state and provides the most data for determining RCT and the number of secondary incidents, but the accuracy of the data and the amount of detail provided for incidents is limited. There were a number of discrepancies in the incident data that limited its accuracy and detail such as multiple entries for T_1, varied entries for T_5 fluctuating between the time when one or more lanes were opened and when all lanes were opened, instances where RCTs were negative due to the format in which the times were input by KSP operators, and secondary crashes consistently reported as false positives due to the inconsistent definition of a secondary crash. Though there is high level of inaccuracy in the way that secondary crashes are classified, the percentage of correctly classified incidents has gradually increased over time (Souleyrette et al. 2018).

The other data sources evaluated were from the Traffic Response and Incident Management Assisting the River Cities (TRIMARC) TOC, Waze, and HERE. The TRIMARC data covers all performance measures including ICT, includes ample detail on crashes and lane closure data, and is verified to be accurate due to the TOC's effective internal communication. The limiting factor of the TRIMARC data is that its coverage only includes the Louisville metro area, thus the TRIMARC data can only be used for incidents within its geographic coverage. Waze is a crowdsourcing navigation app that provides real time data to users and was useful in providing crash reports for incidents on interstates. The crash reports were used to verify incident times, crash details, queue length, and congested speed. HERE speed data were collected by probe vehicles with GPS connection and were used to verify the effects of incidents based on observed sudden changes in speed.

2.2.7 Iowa

The Iowa DOT launched the Des Moines Metropolitan Area Integrated Corridor Management Program that includes a well outlined TIM blueprint. Priorities included in the blueprint include (Iowa DOT 2019):

- Supporting legislation to advance safety in traffic incidents.
- Developing a statewide TIM multidisciplinary technical working group with representation from several different state agencies.
- Modifying law enforcement crash forms to better track performance measures, working with regional Metropolitan Planning Organizations to guarantee support for TIM.

- Committing to ongoing training at a national level and to developing a TIM Incident Command School.
- Creating a statewide TIM training database.
- Merging incident data with the State Highway Patrol.

2.3 Developing Interagency Data-Sharing

One key to the successful integration of TIM performance measures in incident management is the ability to easily and effectively share data with all responding agencies to facilitate quick incident response and effective incident management. Collaboration is crucial to help reduce clearance times on major roadway networks. This section addresses common data-sharing challenges and considerations as well as factors leading to successful data exchange and integration by observing examples from various DOTs.

2.3.1 Common Data-Sharing Challenges and Considerations

A general list of data-sharing challenges encountered in computing TIM performance measure data includes:

- Cost.
- Inconsistent definitions.
- Data availability.
- Data quality.
- Data completeness.
- Data sharing.
- Data exchange.

- Data integration.
- Appropriate comparisons.
- Timeliness of data.

With inconsistencies existing among the data collected by agencies involved in TIM, identifying when the incident was first reported or when all lanes were available for traffic flow can be difficult.

A typical challenge encountered by DOTs is identifying the times associated with the ICT. Identifying the time of the first recordable awareness and the time the last responder left the scene are often difficult. These times can be reported by different agencies, but without a unified system there can be discrepancies among them, and it can be difficult to determine which represents the correct ICT. A challenge encountered by the Virginia Department of Transportation (VDOT) was:

> "Smart Traffic Center (STC) operators, safety service patrollers, and Transportation Emergency Operations Center (TEOC) managers frequently use variations in nomenclature in describing incident characteristics, and in the interest of time, operators/patrollers often do not enter complete data...While there may be two nearly identical managed incidents, in data terms, they may appear very different and thus will be either analyzed differently or discounted altogether. They are not relatable in the sense that the STCs, safety service patrols, and the TEOC use different formats when capturing information on incidents" (Smith et al. 2005, page 1).

To overcome these challenges, the VDOT Statewide Incident Management Committee came up with three objectives to refine standards for incident performance measures (Smith et al. 2005):

- Establish a common definition of an incident.
- Establish the first of a series of common performance measures for incident management relative to transportation services in Virginia.
- Identify data and information necessary to provide for the calculation of the measures.

In addition to identifying the times associated with an incident, pinpointing exact locations of incidents is also a challenge, as was expressed by the Coordinated Highways Action Response Team (CHART) of the state of Maryland. To better identify incident locations, CHART recommends using precise geographical coordinates obtained from GPS. Using GPS is more convenient and accurate than identifying mile markers along the road. Using GPS to report incident locations would allow CHART and the Maryland Accident Analysis Reporting System to produce more reliable data (Kim and Chang 2012).

One considerable challenge for managing TIM data involves the large volume of data produced daily. "Big Data" comes from a variety of sources including national and international datasets, datasets created by state agencies, crowdsourcing platforms, and social media platforms. Big Data does not have a restrictive schema. Challenges of using Big Data include collecting large amounts of data, identifying which data are important, sharing of data, using common data storage environments, adapting cloud technologies for storage and retrieval, and structuring data for analysis. The use of Big Data could help improve both TIM practices and the understanding of their benefits, though the sizeable data requirements for Big Data tools would likely necessitate established national datasets to analyze TIM data since incidents are not regularly occurring events (Pecheux et al. 2019).

2.3.2 Factors Leading to Successful Data Exchange and Integration

Brooke et al. (2004) reported that interagency exchange of information is the key to obtaining the most rapid, efficient, and appropriate response to highway incidents from all agencies. More and more, such information must be shared across system, organizational, and jurisdictional boundaries.

Similarly, the FHWA FSI on TIM performance measures stated that successful strategies for developing systems of data exchange focus on developing cooperative relationships with all agencies involved. Developing a memorandum of understanding that defines roles, developing outreach materials that document the benefits of TIM performance measures, and establishing cost-sharing agreements are also ways that lead to successful data exchange and integration (Owens et al. 2009). A few examples of agencies that have achieved the goal of data exchange and integration are presented in this subsection.

The city of Austin, Texas built a Combined Transportation, Emergency, and Communications Center (CTECC) which houses the development and implementation of integrated data and communication systems. The CTECC houses the Texas Department of Transportation, the Austin Police Department, the Austin Fire Department, and the Travis County Emergency Medical Services. With all agencies in one building, the CTECC allows for easy communication and data sharing among agencies (Carson 2010).

The Puerto Rico Highway and Transportation Authority (HTA) developed a mobile app called Seguro in 2017 for its Highway Service Patrol operators to use. The app allows for uniform collection of incident details such as operator identification, incident location, incident type, service type, and RT. The app combines data from all operators to create dashboards displaying performance measures and other data analyses, which help the HTA in decision-making, resource allocation, and justification for legislation (Jodoin 2018a).

The Florida Department of Transportation (FDOT) also developed software called Sunguide for its TMCs. Sunguide has full CAD integration and produces performance measure reports. The performance measures are calculated from the CAD data and are displayed on a dashboard to show trends over time, as shown in Figure 2-2 (Jodoin 2018a).

Other solutions to common problems or issues with successful data exchange and integration include (Owens et al. 2009):

- Establishing agreements between law enforcement and DOTs to preclude compromising sensitive data.
- Establishing technical committees to develop common data dictionaries.
- Establishing common timestamps and common geography coordinates for data reporting.
- Identifying and agreeing to a defined standard or standards for data exchange.
- Identifying and agreeing upon methods for integrating text, video, and audio formats for data exchange.
- Identifying and agreeing upon consistent data collection practices within and between agencies.

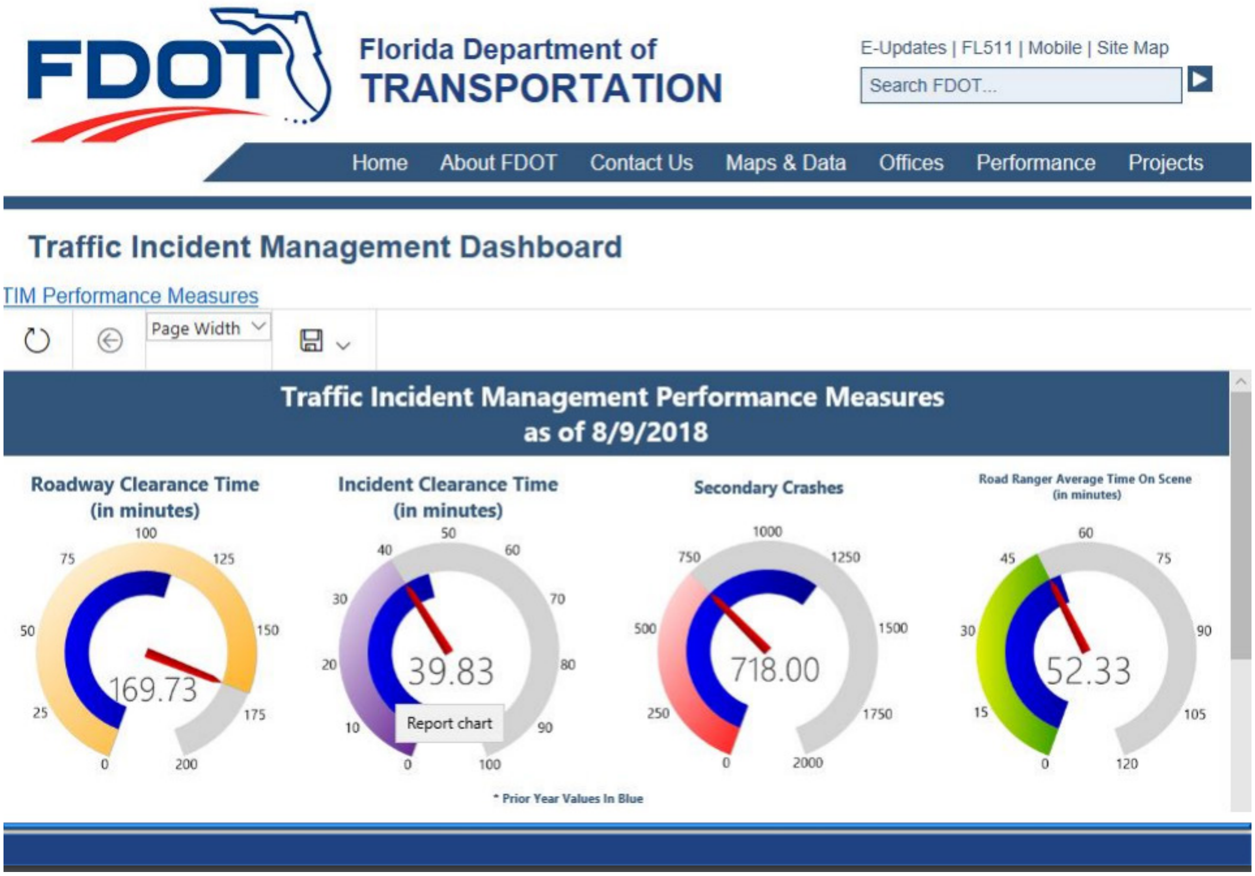


Figure 2-2: FDOT TIM dashboard (Jodoin 2018a).

Collaboration can take place when decision makers from all organizations are made aware of the benefits of sharing collected data. Suggested TIM outreach activities recommended for helping decision makers through this process are conferences and events, structured workshops, personal contact with target agencies, and contacting the press (Owens et al. 2009).

Information regarding successful data exchange is found in the Highway Capacity Manual, which states that an interoperable data exchange system is the most efficient way to perform real-time data exchange. This kind of data exchange can make intelligent transportation systems more effective in gathering and disseminating information (TRB 2010).

Regarding data exchange that utilizes Big Data analytics, Pecheux et al. (2019) clarifies that data must be "open." This means that data must be available in its totality for reuse by anyone for any purpose. Data must be available for redistribution, with permissions for manipulation, reorganization, or combination of the data with any other dataset.

Pecheux et al. (2019) also outlines additional advances that address challenges of data exchange. For instance, to address the issues stemming from variable nomenclature and definitions within TIM, this study developed the Incident Response and Clearance Ontology (IRCO). The goal of IRCO is to provide a uniform way for incident-related data elements to be expressed. Creation of the ontology was made possible with the help of incident responders in a workshop as well as literature describing existing traffic incident-related ontologies. According to the report, "the IRCO attempts to show how the TIM-relevant datasets are related to each other" (Pecheux et al. 2019, page 4).

2.4 Strategies for Enhancing Existing TIM Programs

The NTIMC created the National Unified Goal for TIM, which includes (NTIMC 2007):

- Responder safety.
- Safe, quick clearance.
- Prompt, reliable, interoperable communications.

To achieve these goals, NTIMC set up 18 strategies including (NTIMC 2007):

- TIM partnerships and programs.
- Multidisciplinary national incident management system and TIM training.
- Goals for performance and progress.

- TIM technology.
- Effective TIM policies.
- Awareness and education partnerships.
- Recommended practices for responder safety.
- "Move over" and "slow down" laws.
- Driver training and awareness.
- Multidisciplinary TIM procedures.
- Response and clearance time goals.
- Availability 24/7.
- Multidisciplinary communications practices and procedures.
- Prompt, reliable responder notification.
- Interoperable voice and data networks.
- Broadband emergency communications systems.
- Prompt, reliable traveler information systems.
- Partnerships with news media and information providers.

2.4.1 Information Sharing

In a similar manner, NCHRP Report 520 by Brooke et al. (2004), titled "Sharing Information between Public Safety and Transportation agencies for Traffic Incident Management" lists steps that can be taken to improve TIM programs:

- Establish working-level relationships with responders from every agency that works on incidents in the area of interest.

- Ensure that working-level relationships are supported by standardized operational procedures.
- Create interagency agreements and system interconnections with key agencies involved.
- Institutionalize senior-level relationships among key agencies through a combination of policy agreements, interagency organizations, coordinated budget planning, and other processes to ensure that operational partnerships survive changes in political or managerial leadership.

2.4.2 Safety Service Patrols

SSPs have also been effective in improving TIM. Service patrols can be publicly operated by transportation or police departments or privately operated. The FHWA promotes full-function service patrols on all urban freeways 24/7. The FHWA also encourages the sustainability of service patrols by promoting public agency cost sharing and public/private ownerships (Carson 2010).

2.4.3 Guidance Documents

Shah et al. (2017) reviewed existing methods of evaluating TIM and benefit quantification, then compared the strategies with input from various TIM stakeholder agencies to develop a guidance document. This guidance document can be used to help any TIM-related organization with evaluation and performance measurement.

2.4.4 Laws

Laws can be created to improve TIM. For instance, state Move Over laws require drivers approaching the scene of an incident, where emergency responders are present, to change lanes if possible or to reduce their speed to prevent potential risks to the responders. At the time of her study, Carson (2010) noted that all but two states, Hawaii and New York, had enacted Move Over laws. All 50 states have now enacted these laws (AAA 2021).

Another example is state Driver Removal laws, which are considered as key strategies that allow for quick clearance of non-injury, property damage only (PDO) crashes. PDO crashes account for the majority of crashes that occur on U.S. roadways. These laws encourage drivers involved in incidents to move their vehicle out of the travel lanes. Driver Removal laws help enhance the overall safety of the vehicles involved as well as those approaching the incident. At the time of her study, Carson (2010) noted that about half of U.S. states, including Florida, Georgia, and Texas, for example, had enacted these laws.

2.4.5 Programs

Programs can also be implemented to improve TIM. The NCHRP Report 07-20 by Jodoin et al. (2014) suggests that to improve TIM functionality and efficiency, coalitions should be made with nontraditional partners such as towing contractors, coroners, and those in the trucking industry. These partners, in addition to emergency response and transportation agencies, can cooperate to efficiently decrease clearance times.

Another example of a program that may help improve TIM functionality is the Incident Command System (ICS), implemented by the South Carolina Department of Transportation (SCDOT). ICS is a tactical protocol of unified command and communication for incident management that was developed by the National Incident Management System in the 1970s. The primary functions of ICS agencies are shown in Figure 2-3, which displays the structure of ICS with responsibilities and roles for each agency. SCDOT accomplished a 25 percent reduction in incident duration by implementing these strategies (Ogle et al. 2017).

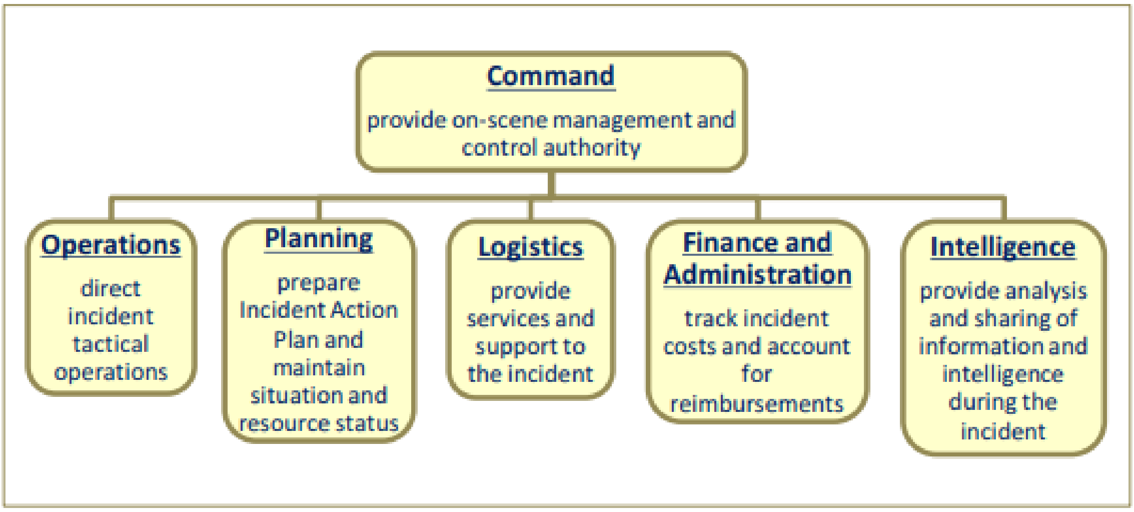


Figure 2-3: Coalition of stakeholder agencies with respected roles in ICS (Ogle et al. 2017).

2.4.6 Enhanced CAD

Enhanced CAD is a system that is continuously updated with emergency vehicle locations to allow for quicker dispatch times. This system uses automatic vehicle location technologies to locate, route, and dispatch the closest emergency vehicles to the scene. This is often referred to as optimized dispatch (Ogle et al. 2017).

2.4.7 Tow Truck owner Incentives

Table 2-1 provides detail into how the Washington State Department of Transportation (WSDOT), the Georgia Department of Transportation (GDOT), and FDOT use incentive-based towing programs.

Table 2-1: Comparison of Three States that Use Incentive-Based Towing (Ogle et al. 2017)

	WSDOT	GDOT	FDOT
Specialized wrecker list for quick clearance?	Major Incident Tow	Towing & Recovery Incentive Program	Rapid Incident Scene Clearance
Separate list for each wrecker category?	No	No	No
Additional training or equipment required?	Yes	Yes	Yes
Required wrecker business hours?	24/7 - 7 days a week	24/7 - 7 days a week	None Established (assume standard 8:00 AM - 5:00 P.M. M-F)
Can passing wrecker respond to accident?	Yes. wrecker would be on a route during peak	No	No
Time allocation wrecker has to arrive on scene?	15 minutes (business hours)	45 minutes (business hours)	60 minutes
Total time allocation for wrecker to clean area?	90 minutes	90 minutes	90 minutes
Incentive bonus?	$2,500	$2,500 standard + $600/$1,000 equipment bonus = $3,500 total	$2,500 standard + $1,000 equipment bonus = $3,500 total
Minimum wrecker requirements?	Two Class C wreckers	Two Class C wreckers and a support vehicle	Once Class C wrecker
Reimbursement for services not rendered?	$600	$600	$600
Penalized for excessive cleanup time?	No	$600 flat or $600/hr.	$600/hr.

FDOT implemented an incentive program for tow-truck owners who work in areas of focus for TIM. Quick response and short clearance times lead to monetary gains for the drivers. Similar to FDOT, other states have started incentive-based programs that reward tow-truck services for their quick response as well as clearance times. Ogle et al. (2017) studied the integration of ICS protocol for effective coordination of multi-agency responses to traffic incidents and analyzed the states' incentive programs. GDOT implemented this incentive-based program in 2008 after which average RCT dropped from 216 to 49 minutes.

2.5 Current State of the Practice in Utah

In 2018, UDOT worked in conjunction with UHP to determine the availability of TIM performance measure data and discovered that elements of the UHP CAD system provided the necessary information to determine performance measures, except the time when all the lanes became open to traffic (T_5 shown in Figure 2-1), which UHP volunteered to collect for a period of 6 months. A study of TIM performance measures in Utah was completed in which data were collected and analyzed to compare performance measures with user costs due to congestion. The cost of congestion due to incidents occurring on interstates in UDOT Regions 2 and 3 was estimated at approximately $58 million per year based on a set of sampled incidents that contained all the necessary data for analysis (1.3 percent of the entire incident data set collected from March to August 2018). A reduction in performance measures, such as RT and RCT, was shown to reduce costs due to congestion (Schultz et al. 2019).

Schultz et al. (2019) also performed statistical analyses based on the sample of incidents collected and determined relationships between TIM performance measures and user costs in Utah. They found that on average, for each minute delay of RT for IMTs, 0.8 minutes are added to the RCT, 93 more vehicles are affected, 34.6 minutes are added to ETT experienced by users, and $925 is added to the cost of congestion. They analyzed incidents from the dataset collected from March to August 2018 that included the required timestamps to determine IMT response times and created a representative histrogram, shown in Figure 2-4. The histogram and findings demonstrated the potential for UDOT's IMT program to greatly reduce user costs by improving RT.

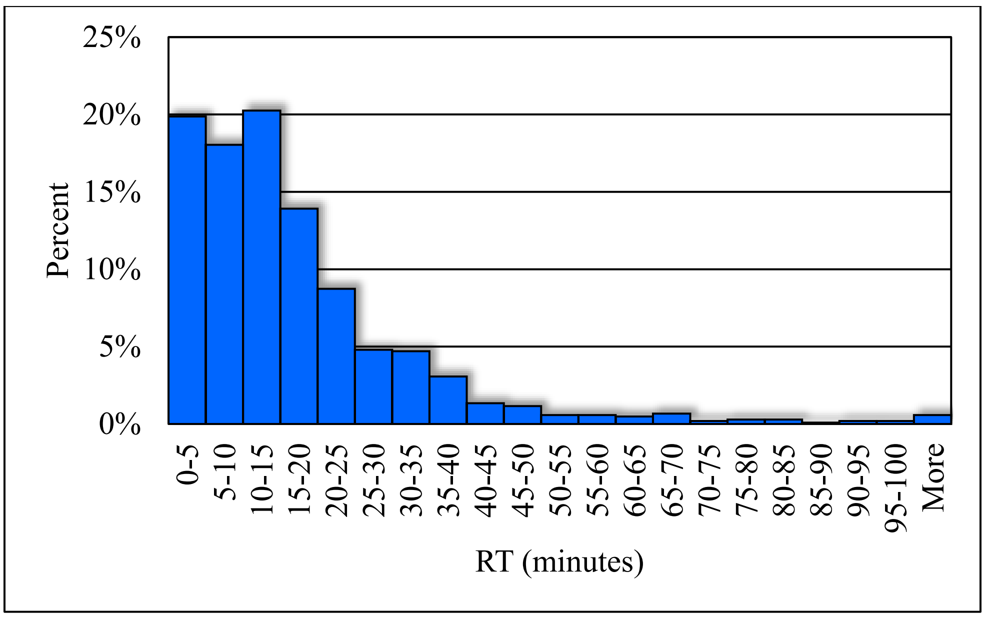


Figure 2-4: Histogram of RTs for first responding IMT using all CAD data.

The Utah State Legislature supplemented the funding of UDOT's IMT program in 2018 to double the fleet size, effectively bringing the total number of staffed teams from 13 to 25. The study of performance measures described in this research paper was initiated in January 2020 to collect performance data to be compared with those found during 2018, with the purpose of analyzing the impacts of the program expansion. The UHP CAD system is used to determine performance measures, and is supplemented with data from the TransSuite database at UDOT's TOC. A comparison of selected incident data between CAD and TransSuite indicated that

TransSuite contained reliable information regarding lane closures that would provide UDOT with the T_5 timestamps necessary to determine when all lanes were available for traffic flow and calculate RCT. This eliminated the need to request that UHP collect T_5, which is not part of incident data routinely collected by UHP.

2.6 Performance Measures Analysis Using Simulation Software

The use of simulation software for incident detection and analysis, advanced transportation management strategy development, demand-forecast modeling, cost-benefit analysis, and other applications have become increasingly common as simulation software and computer technology have advanced to conduct complex, large-scale simulations. Many models relating to traffic incidents have been created with the purpose of predicting incident impacts such as incident duration, delay, traffic diversion to adjacent arterials, and emissions. Other models created, such as those by Pal and Sinha (2002) and Ozbay and Bartin (2003), have focused on TIM strategies to determine optimal fleet sizes, deployment schedules, beat designs, and dispatching policies.

The literature review of a project done by the Texas A&M Transportation Institute called "Planning and Evaluating Active Traffic Management Strategies," defined the roles of simulation software tools and other analytical methods in relation to traffic management as:

> "Microscopic simulation tools rely on car-following and lane-changing theories and simulate the movement of individual vehicles. Mesoscopic simulation tools combine capabilities of both microscopic and macroscopic simulation models considering the individual vehicle as the traffic flow unit, whose movement is governed by the average speed on a link. Macroscopic simulation tools are based on deterministic relationships of

traffic network parameters (speed, flow, density) and simulate traffic on a section-by-section basis" (Kuhn 2014, page 46).

The scope of analyzing TIM performance measures in the state of Utah has been focused on analyzing the real-time performance measures of IMTs on interstates in the most populated part of the state. Because the analysis is expansive, not limited to a few sections of interstate, and would require creating numerous simulation models of different physical layouts with different data needs, simulation tools were considered unsuitable for this study.

The focus of the analysis in this study is not on the direct impact of an incident on traffic flow, the optimization of UDOT's IMT fleet, adjustments to TIM strategies, or on predicting the frequency of future incidents. Rather, the focus has been on the IMT performance measures and the EUC that can be mitigated by the IMTs. UDOT's traffic management programs, including TransSuite, PeMS, and iPeMS, along with the UHP CAD data, were determined to be adequate for the purpose of this study. Despite the inevitable confounding factors involved due to using field data, the research team found this approach most suitable to meet the objectives of the study.

The chosen study approach can include hundreds of field incidents that contain all the necessary performance measures rather than a finite set of incidents limited to a specific region. Thus, a deterministic analysis using real incident data is more realistic than simulation for the purposes of the study. Using IMT performance measures obtained from the field data will allow UDOT not only to verify the changes that will result in EUC but also to conduct similar studies in the future.

2.7 Chapter Summary

This literature review focused on identifying ways states are collecting and using TIM data to evaluate the effectiveness of their TIM programs. It also addressed the changes to the state of the practice of TIM in Utah. Information gathered from case studies of the TIM-related work in other states provides ideas of how to efficiently and effectively gather the data necessary to determine critical performance measures, specifically RCT and ICT.

The studies reviewed were performed by their respective researchers to accurately measure performance of TIM teams and to determine what steps should be taken to improve incident-related communication, responder safety, and traffic clearance tasks. The economic benefits of a TIM program can be analyzed and used to justify future expansion and financial backing of the program. However, Kim et al. (2012) found that "even with the widespread implementation of such programs, effectively minimizing the traffic impact caused by multi-lane blocked incidents remains a critical and challenging issue for most highway agencies."

To accelerate the effective implementation of TIM programs, agencies involved in TIM will need to work together by defining common terms, defining standards of data exchange, and creating effective programs to promote TIM. Further research and data collection of TIM performance measures will make UDOT's TIM program more effective and efficient.

3 DATA AVAILABILITY AND COLLECTION

3.1 Overview

During the Phase I study, data availability for TIM performance measures was established in meetings with representatives from UDOT and UHP. To aid UDOT in measuring performance and evaluating user impacts of its IMT program, one key objective of the Phase I study was to obtain all pertinent incident-related data necessary to determine the performance measures of RT, RCT, and ICT, as well as to analyze the data for the following user impacts:

- ETT: the cumulative excess travel time that users experience over the distance of roadway affected by an incident above the time users would normally spend traveling the same distance of roadway on a day with no incidents.
- AV: the number of vehicles that experienced some measure of delay due to an incident.
- EUC: the dollar value associated with ETT, including the hourly costs of roadway user time and truck delay.

In contrast to Phase I, this study did not involve collection of one dataset to analyze for performance measures and user impacts. Two datasets were collected, for 2018 and 2020, so that comparison of performance measures and user impacts between the two years could be used to determine the effects of the expanded size of UDOT's IMT program. This change in the IMT program size was the primary focus of the study. However, the advent of the COVID-19 pandemic in early 2020 presented additional challenges that the research had to account for in data collection and analysis.

The data collection process used for this Phase II study is similar to that of Phase I (Schultz et al. 2019) with the notable distinction of the use of the UDOT TransSuite database to aid in collecting performance measure data. Because the methodology of data collection has been previously established, the details of the process are left out of this report, and readers are invited to supplement their reading of this chapter with Chapter 3 of Schultz et al. (2019) for a more in-depth understanding of the data collection process and incident analysis. This chapter contains an overview of the changes to UDOT's IMT program from the program expansion, a discussion of data collection considerations caused by the COVID-19 pandemic, a brief discussion of data availability, a discussion on the integration of UDOT's TransSuite database for collecting TIM performance measures, and an overview of the final data collection methodology.

3.2 UDOT IMT Program Expansion

The expansion of UDOT's IMT program was fully effective in spring of 2019 after all additional units were operational. The funding allocated by the Utah State Legislature allowed UDOT to increase the operational budget of the IMT program and expand both operational hours and area of coverage. It also provided for an increase in staffed IMTs from 13 to 25 units. Prior to the expansion, there were 12 full-time teams in UDOT Regions 1, 2, and 3, and one part-time team in St. George in Region 4. The hours of operation of IMT services in Region 2 were increased to 24/7 service, while operations in Regions 1 and 3 are now fully staffed with two morning and afternoon shifts as well as weekend shifts. While dispatching protocol and operations stayed the same after the expansion, the IMT program was able to increase the number of motorist assists and better aid other agencies.

One of the most significant changes of the program expansion was the increase in coverage area for the IMT program. There was a significant increase in the area covered by IMTs in 2020 compared to 2018, as demonstrated by the number of centerline miles covered before and after the expansion. UDOT's IMT program supervisor provided the research team with data relating to the miles covered by IMTs along UDOT interstates and highways before and after the expansion, from which the following figures were created. The raw coverage data provided by UDOT, including the names of roadways, mileposts patrolled, and lengths covered by direction, are included in Appendix A. Figure 3-1 through Figure 3-3 show the centerline miles covered by IMTs on interstates and other state highways in the four regions.

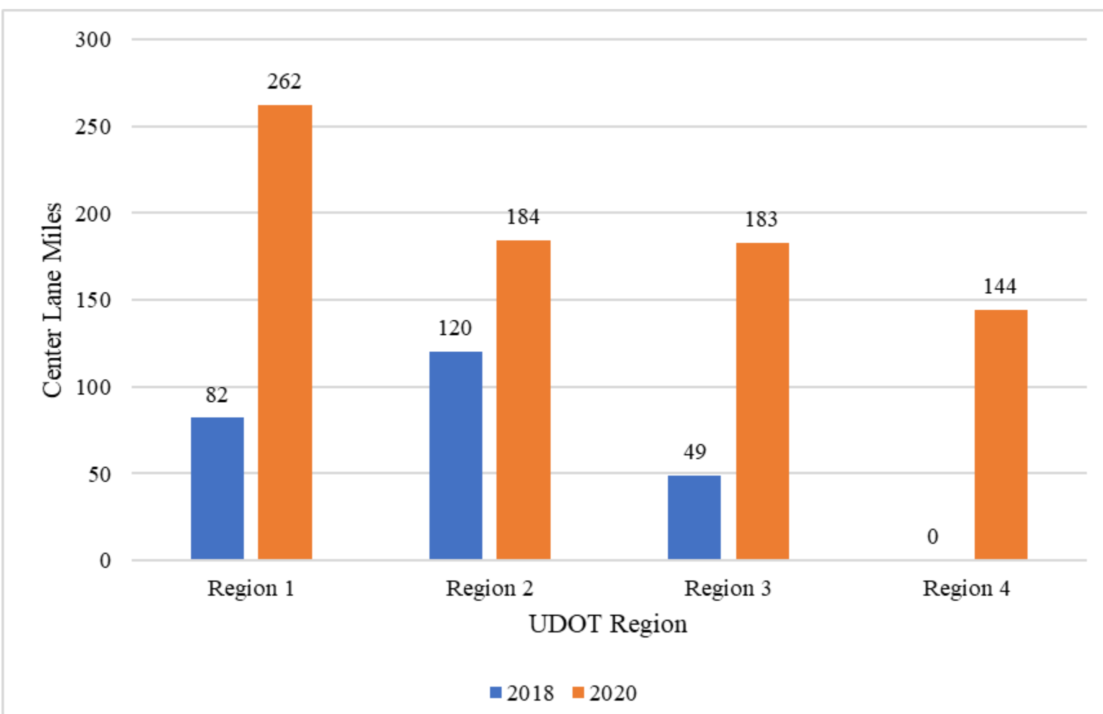


Figure 3-1: Centerline miles covered by IMTs before and after expansion.

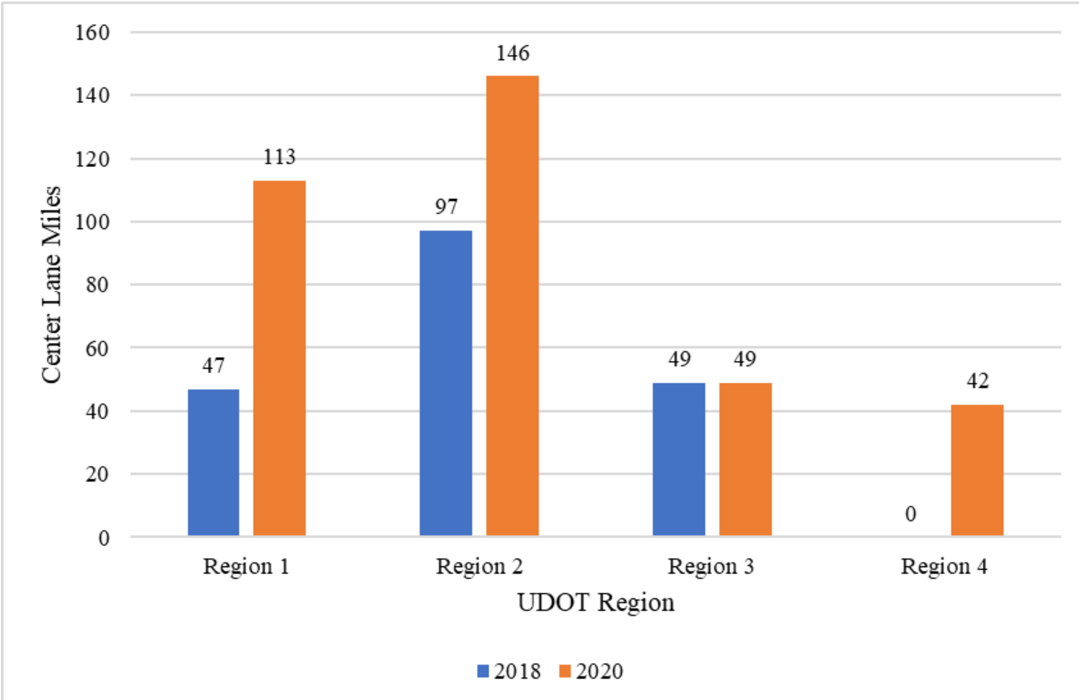


Figure 3-2: Centerline interstate miles covered before and after expansion.

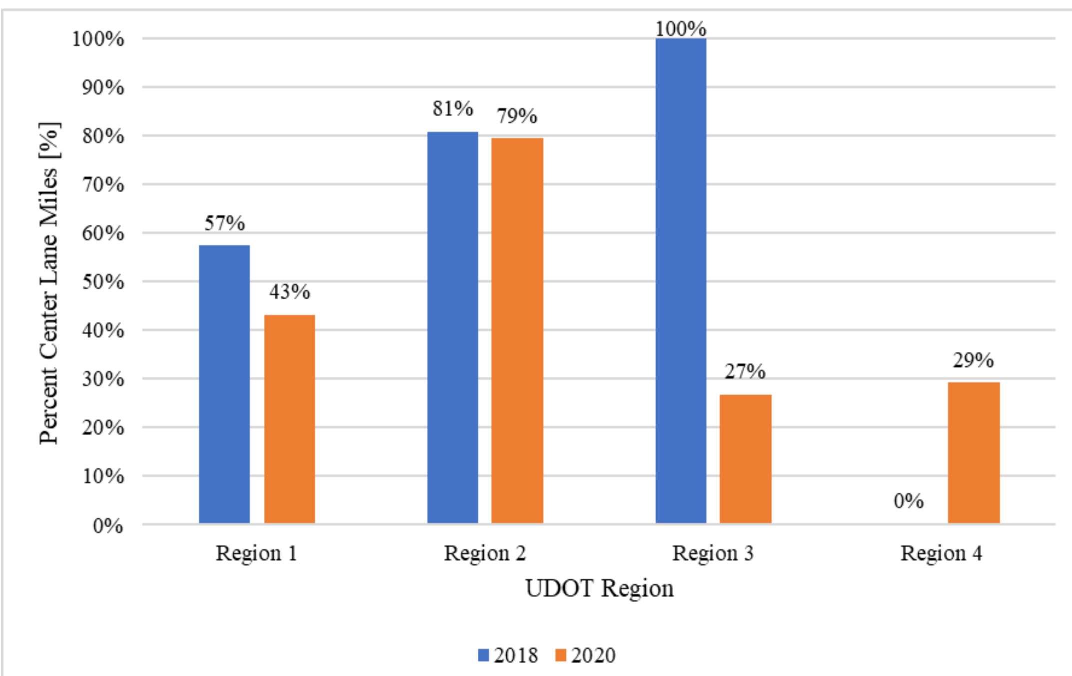


Figure 3-3: Percentage of centerline miles covered by IMTs that are on interstates before and after expansion.

Figure 3-1 shows the total centerline miles covered by year and region. Region 4, covering much of rural southern Utah, was only covered part-time by the IMT fleet in 2018, but was covered by one full-time IMT in the St. George area in 2020. The centerline miles covered in Regions 1 and 3 had a greater increase than Region 2 from 2018 to 2020 primarily because incidents in Region 2 were the primary focus of IMT services prior to the program expansion.

The majority of centerline miles covered by the IMT fleet in 2018 were on interstates. Interstate coverage increased further in 2020 as the IMT coverage area expanded. As shown in Figure 3-2, the centerline interstate miles covered in Region 1 increased significantly from 2018 to 2020 (from 47 to 113). There was a moderate increase in the number of interstate centerline miles covered in Region 2 and there was no increase in Region 3. No miles of interstate were covered full-time in Region 4 until the program expansion, after which 42 miles were covered in 2020. Where interstate miles were already covered, the expansion allowed IMTs to cover additional areas such as state highways.

As seen in Figure 3-3, the proportion of centerline miles covered by IMTs in 2018 that was on interstates was at 81 percent in Region 2 and 100 percent in Region 3. For Region 1, this was 57 percent in 2018, showing that there were some non-interstate roadways covered by IMTs. Due to the major expansion of the IMT coverage area, the majority of centerline miles covered shifted from interstates in 2018 to non-interstate highways in 2020 in all regions except for Region 2. All centerline miles covered in 2018 were still covered in 2020. So, while the number of centerline miles covered on interstates increased between 2018 and 2020 for all regions, the IMT coverage area expanded significantly enough that the majority of centerline miles in 2020 were on state highways instead of interstates.

Figure 3-4 through Figure 3-7 are maps of the IMT coverage areas showing the centerline miles and routes covered in 2018 and 2020.

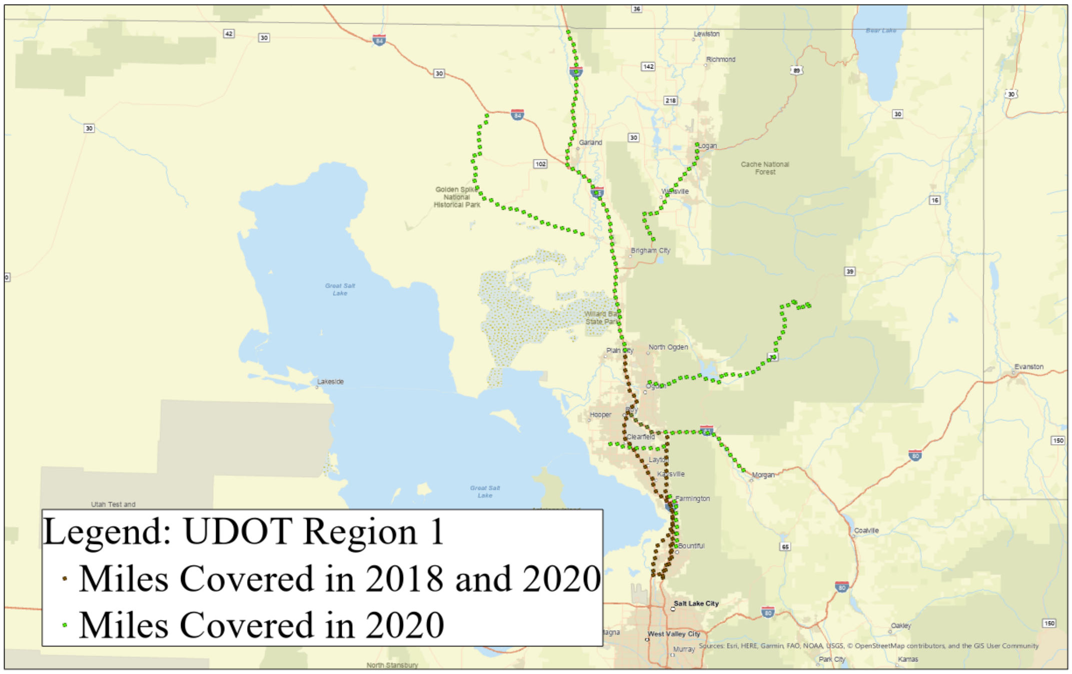


Figure 3-4: Map of IMT coverage area in Region 1 before and after expansion.

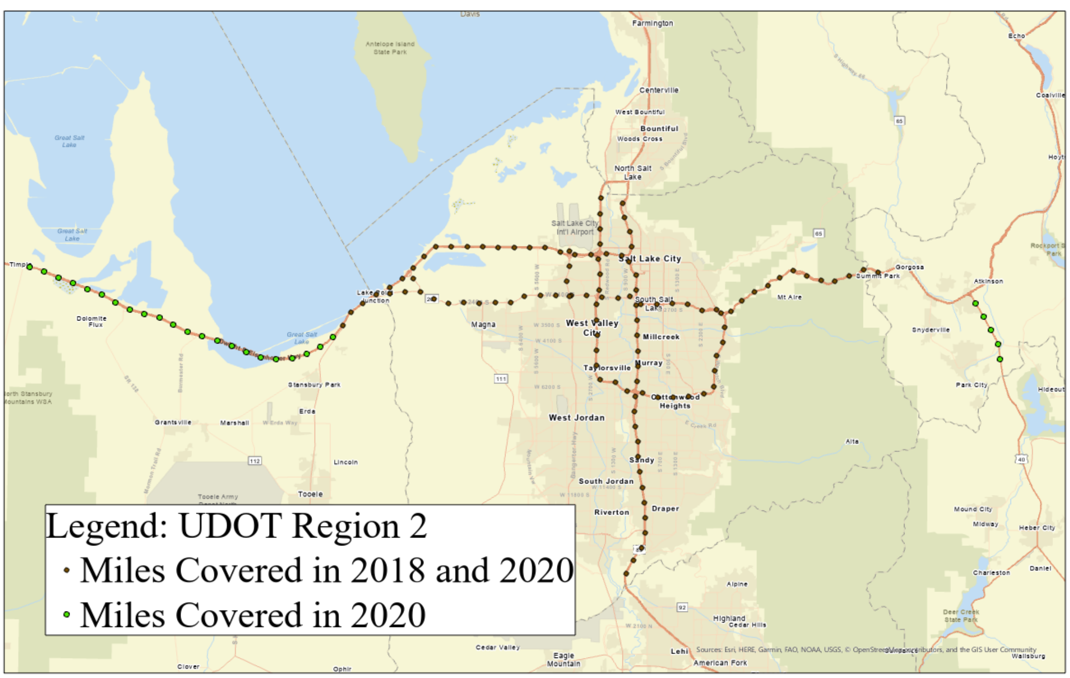


Figure 3-5: Map of IMT coverage area in Region 2 before and after expansion.

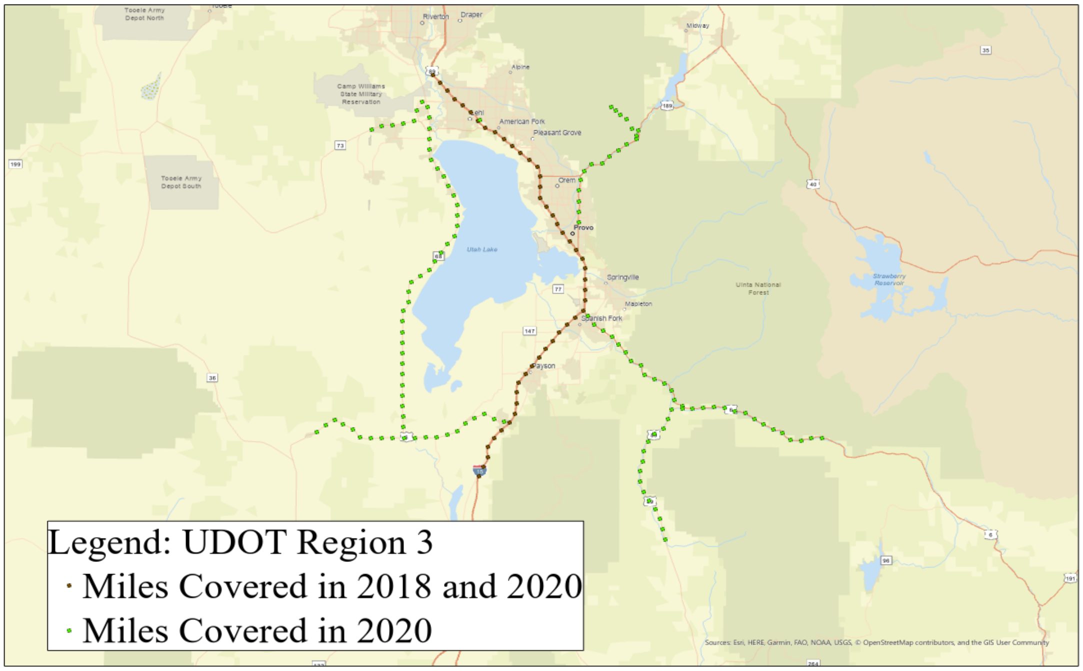


Figure 3-6: Map of IMT coverage area in Region 3 before and after expansion.

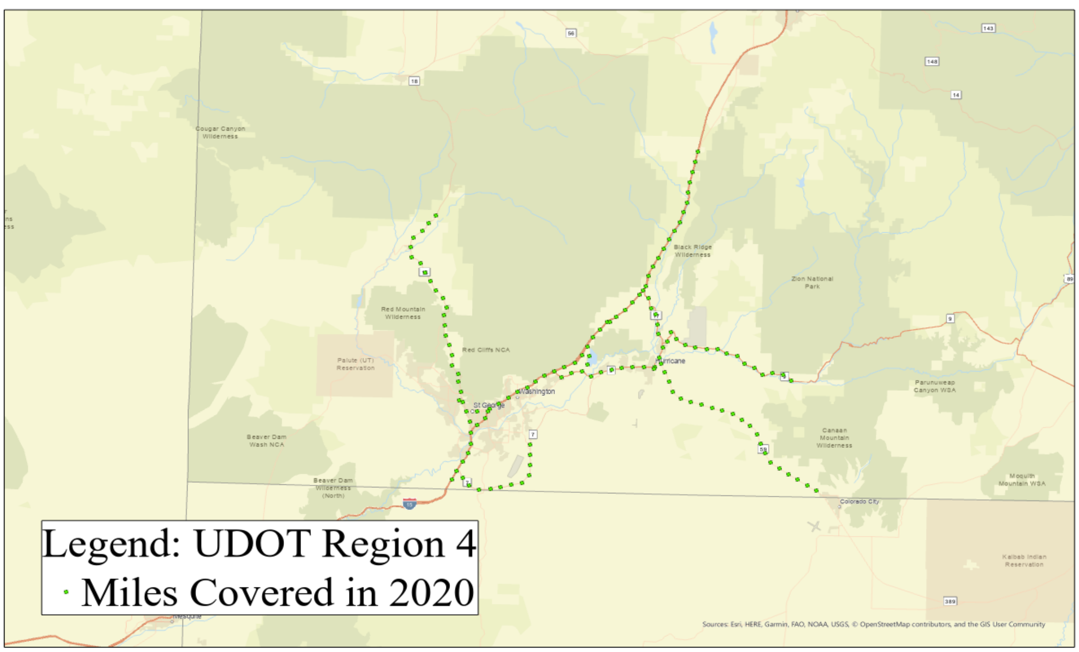


Figure 3-7: Map of IMT coverage area in Region 4 before and after expansion.

In 2018, Region 1 IMT coverage only extended as far north as Weber County, the northern edge of the urbanized part of the Wasatch Front, but had expanded to cover areas in all counties of northern Utah (except Rich County) by 2020. I-15 was previously covered from the southern edge of Region 3 up to the northern edge of Weber County in 2018 but by 2020 was covered all the way up through Box Elder County on Utah's northern border. Many of the centerline miles covered in 2020 that were not covered in 2018 were in rural areas, particularly in canyons. This was true of all regions, but especially for Region 1, which had the largest geographical area and number of centerline miles covered following IMT program expansion.

The increase in centerline miles covered in Region 2 before and after the expansion was not as great as that of other regions because Region 2 was the area serviced the most in 2018. However, there were longer sections of roadway that were covered in 2020 such as I-80 west of Salt Lake City extending towards Tooele County and US-40 east of Salt Lake City in Summit County. Because of its high population and high traffic volumes, Region 2 was the geographical center of IMT coverage area in both 2018 and 2020. IMT coverage area expanded significantly to both the north and south of Region 2 between 2018 and 2020.

Prior to the expansion of the IMT program, I-15 was the only roadway in Region 3 that was covered by IMTs, but after the expansion, several major federal and state highways were added to the original coverage area, many of which were in rural areas, particularly canyons. The vast majority of the IMT coverage area that falls within Region 4 is located in Washington County in the St. George area at the southwest corner of the state. In 2018, this area was covered by one IMT operating part time on the weekends, but in 2020 was covered by a full-time team.

3.3 The Effects of COVID-19 on Data Collection

While data were collected using the new methodology both for the original data collection period in 2018 and a second data collection period in 2020, the advent of the COVID-19 pandemic presented challenges in collecting comparable data. The COVID-19 pandemic caused significant effects on traffic patterns during the 2020 data collection period, the primary effect being a significant decrease in traffic volumes. This resulted in an increase in IMT availability and a change in the typical times of day when incidents occurred. The program expansion allowed for extended coverage hours and an expanded coverage area, but the pandemic elicited additional changes in IMT coverage time and area to adapt to the lower volumes. This section will discuss the reduction in volumes and shifts in traffic patterns and how these changes affected data collection.

3.3.1 Traffic Volume Reduction

The majority of data collected during the 2020 data collection period came after a significant decrease in traffic volumes across the state of Utah which began in March 2020. As seen in Figure 3-8, which shows the difference in average daily traffic volumes by month between 2018 and 2020, traffic volumes on I-15 were reduced in March 2020 by about 25 percent from what they were in March 2018, with around 25,000 fewer vehicles per day. The difference in volumes was most notable in April, with 2020 volumes at approximately 44,000 fewer vehicles per day than in 2018. Due to the drastic reduction in traffic volumes during this period, the data collection periods were adjusted to include more comparable data. The original data collection period included incidents from March to August in both years. Incident data from April were not used in either year due to the large volume differences. Additionally, incidents from the second half of March 2020 were also removed from consideration. Though the months of May and March have similar volume differences between 2018 and 2020, the daily volumes in March began to decrease about halfway through the month in response to restrictions on social gatherings, whereas the daily volumes within the month of May were more even throughout. Therefore, data from the month of May 2020 was included in the analysis. As travel increased and traffic volumes began to increase in the months of May, June, July, and August, the difference between 2018 volumes and 2020 volumes began to decrease, as seen in Figure 3-8. The data collection period was extended to include additional incident data in September, so as to make up for discarded data in April and provide adequate sample sizes for analysis.

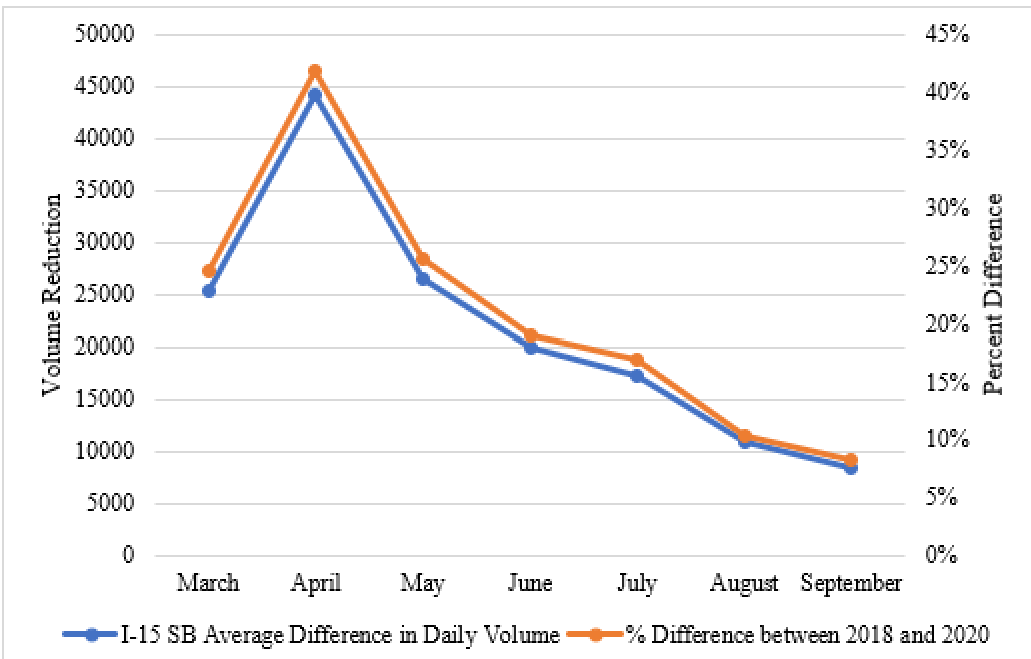


Figure 3-8: Average difference between 2018 and 2020 daily traffic volumes by month on I-15 southbound.

With the reduction in volumes came an associated decrease in the number of incidents logged in the CAD system across the highway system on the segments where IMTs operate. As shown in Figure 3-9, the total number of incidents logged in March 2018 decreased from 1,282 to 699 in March 2020, or about a 45 percent reduction. By contrast, a total of 807 crashes were logged in September 2020 as compared to 943 in September 2018, which represented about a 15 percent reduction, as shown in Figure 3-10. Thus, by September 2020, the difference in the total number of incidents logged between 2018 and 2020 for a given month was significantly lower than it had been earlier in 2020.

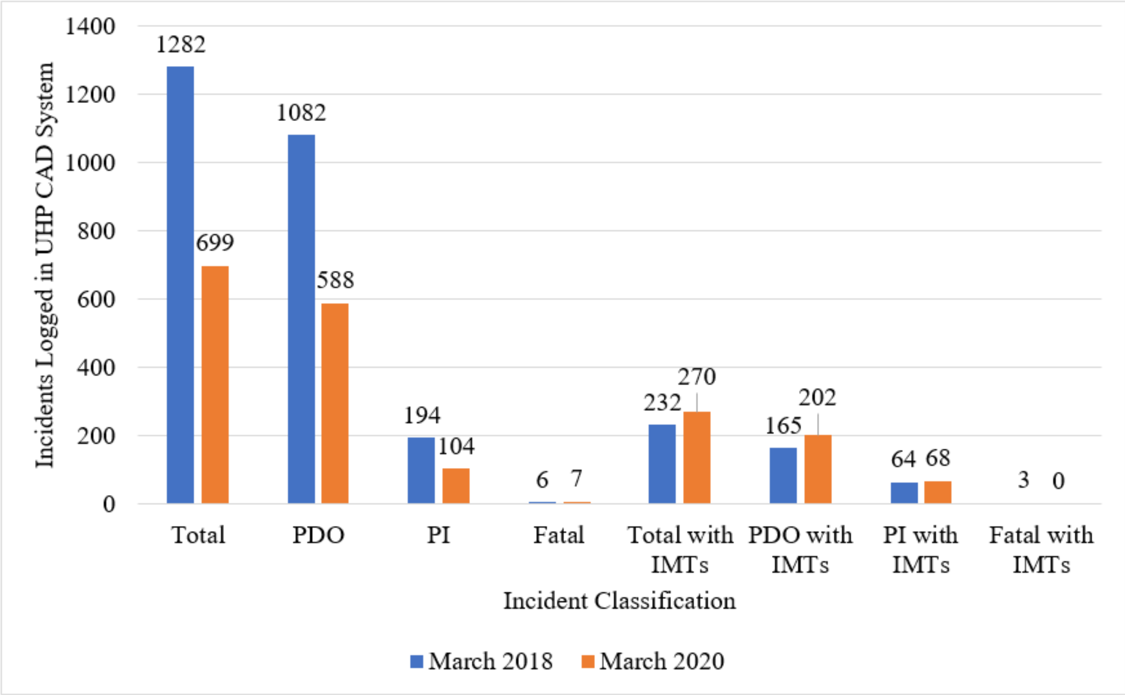


Figure 3-9: Comparison of March 2018 vs. 2020 CAD incident data.

Even though traffic volumes and the number of incidents logged in the CAD system were lower in 2020 than in 2018, the proportions of incidents of differing crash severity types, including Fatal and Incapacitating Injury (FII) incidents, Personal Injury (PI) incidents, and PDO incidents, remained nearly the same between the two years. The percent of FII crashes was 1 percent in both 2018 and 2020. The percentage of PI crashes increased slightly from 27 percent in 2018 to 29 percent in 2020 and the percentage of PDO crashes decreased from 72 percent in 2018 to 70 percent in 2020.

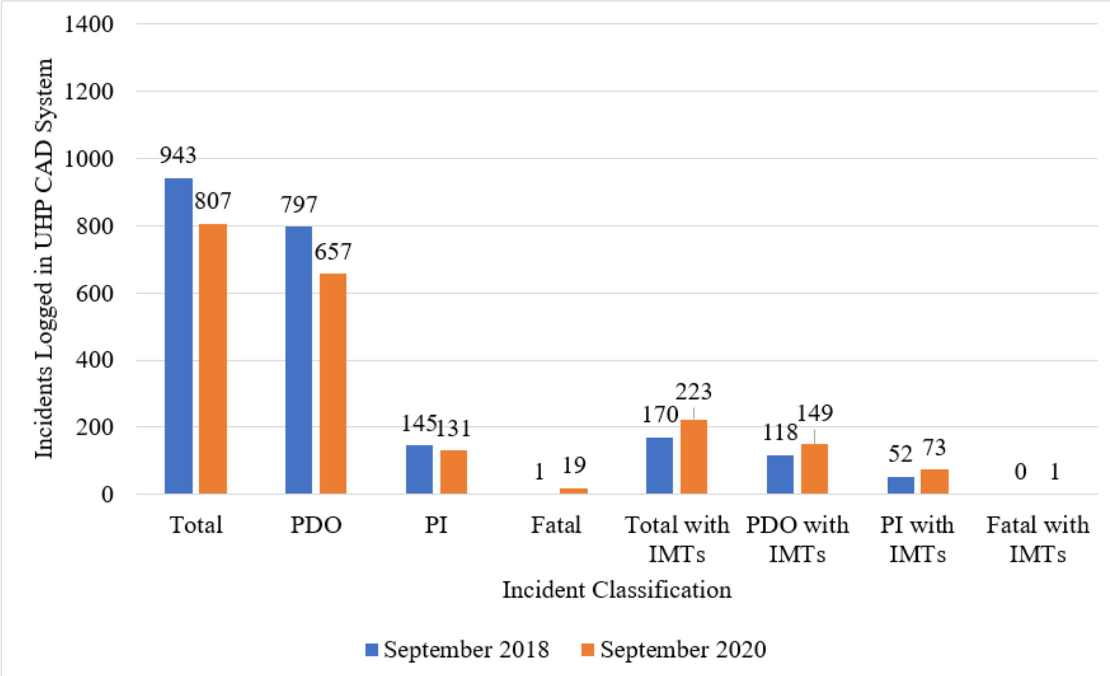


Figure 3-10: Comparison of September 2018 vs. 2020 CAD incident data.

As shown in Figure 3-11, IMTs responded to 38.6 percent of incidents in March 2020, about twice that of the response rate to incidents in March 2018 at 18.1 percent. In September 2020 IMTs responded to 27.6 percent of incidents, compared to the 18.0 percent response rate in September 2018, as shown in Figure 3-12. While the lower traffic volumes and lower number of crashes were a confounding factor in 2020 that increased the normal availability of IMTs, it is likely that the increase in the size of the IMT fleet allowed the IMTs to respond to more incidents independently of the lower volumes. Evidence of this likelihood is given by the fact that as the difference in volumes between 2018 and 2020 decreased month-by-month over the course of 2020, the proportion of incidents with IMTs on scene remained higher in 2020.

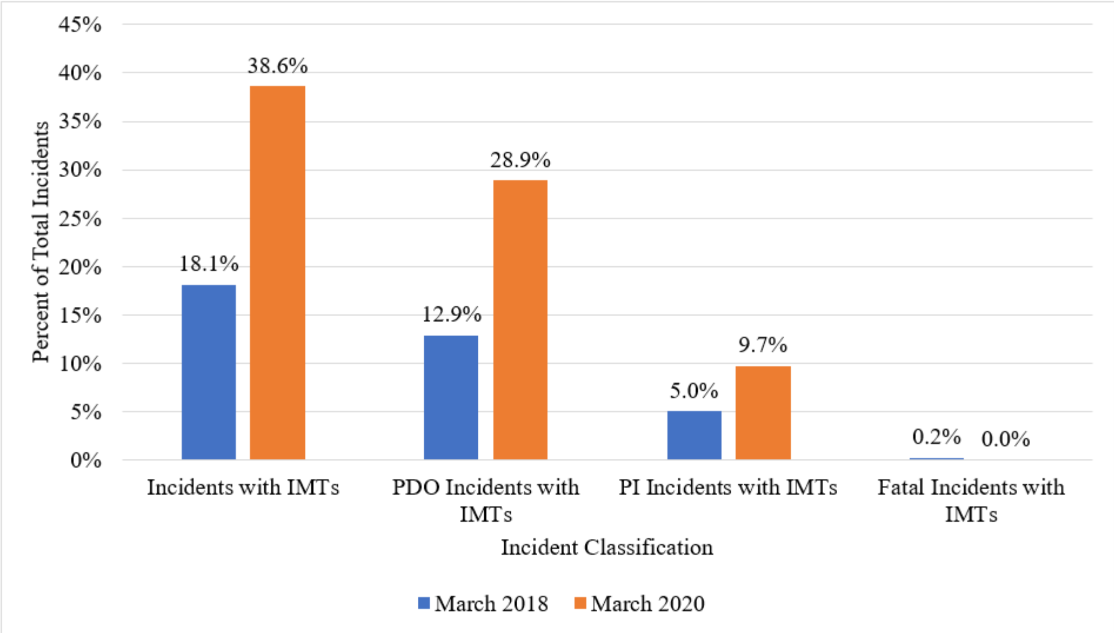


Figure 3-11: Comparison of March incidents with IMTs by year.

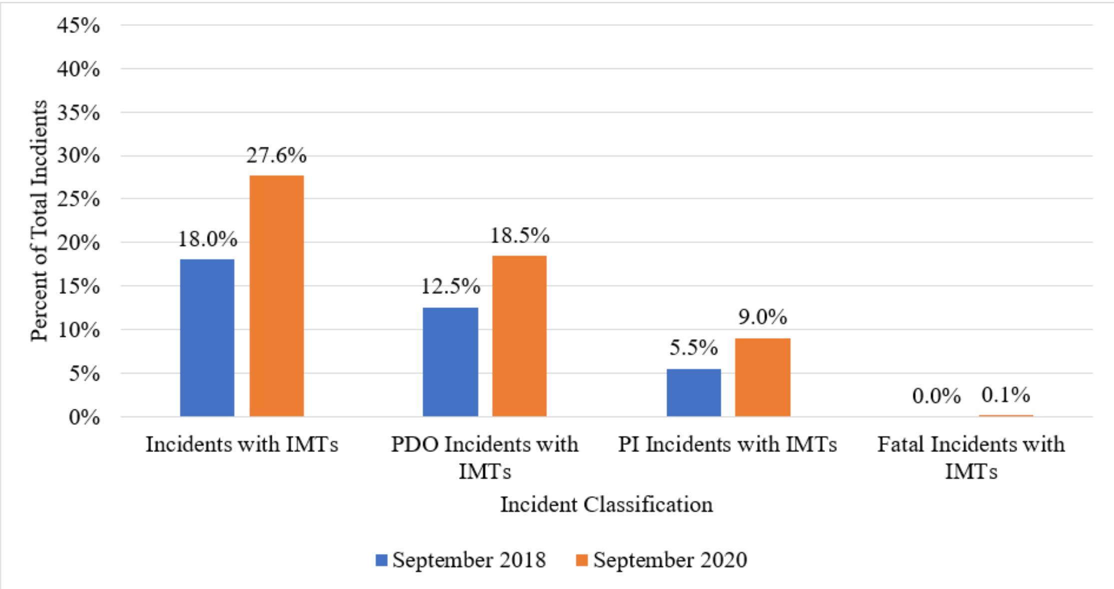


Figure 3-12: Comparison of September incidents with IMTs by year.

Because of the program expansion and reduction in crashes due to the pandemic, more IMTs were able to respond to larger incidents in 2020 than in 2018. Figure 3-13 shows the proportions of incidents in each year with differing numbers of responding IMTs. In both years, the proportion of incidents with only one IMT responding was the same at 60 percent. While the number of incidents with one or two IMTs remained similar in 2018 and 2020, the data show that the number of incidents where three or four teams responded was greater in 2020. Compared to 2018, where a cumulative 5 percent of incidents had three or four IMTs at the scene, in 2020 a cumulative 12 percent of incidents had three or four teams at the scene. This finding may indicate that the greater availability of IMTs in 2020 has allowed the IMT program to send needed teams to incidents that could not be prioritized in 2018 due to limited resources. While the effects are somewhat confounded with the impacts of COVID-19, this trend still indicates that the expanded IMT program has greater flexibility to respond to severe crashes that require a greater number of IMTs without compromising the ability to respond to less severe crashes.

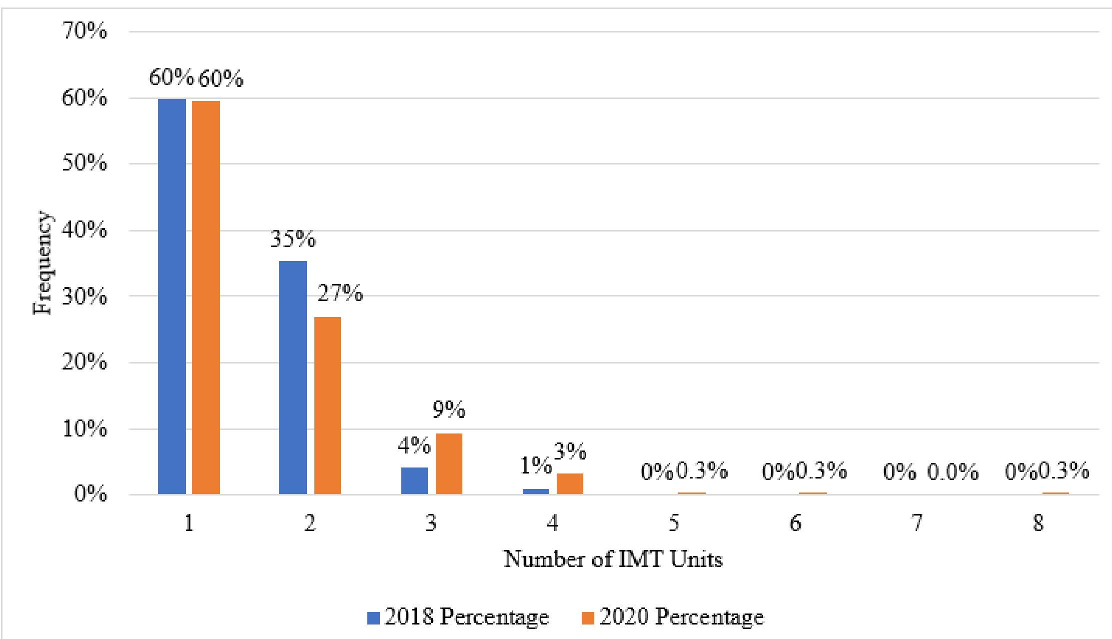


Figure 3-13: Comparison of IMT response distributions by year.

A similar trend was seen in the percentage of incidents with differing numbers of UHP responders, though the number of UHP officers did not increase from 2018 to 2020 as was the case with the IMT program. There was consistently a greater proportion of incidents with more UHP units in 2020 than in 2018, as shown in Figure 3-14. As with the IMTs, the reduction in daily traffic volumes caused an increase in availability for UHP units. Similar to the distribution of responses by IMTs, the percentage of incidents where one and two UHP units responded was not greater in 2020 than in 2018. However, the percentage of incidents with three or more UHP units was consistently greater in 2020 than in 2018.

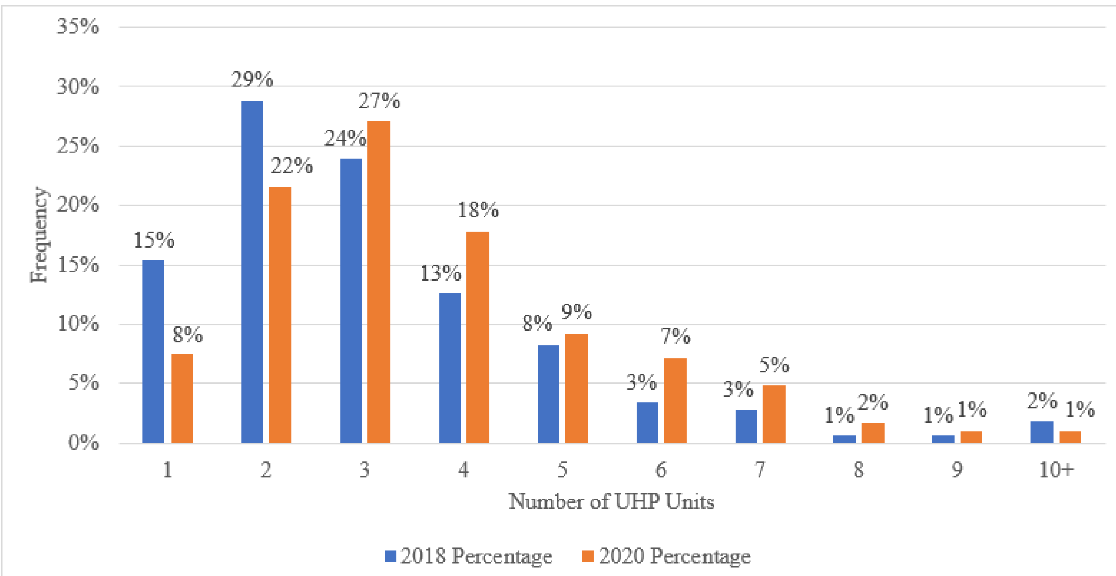


Figure 3-14: Comparison of UHP response distributions by year.

3.3.2 Time of Day of Crashes

There was also a change in the distribution of times of day when incidents occurred during the COVID-19 pandemic. For the purposes of this study, incidents were considered to have occurred during one of five time ranges, as outlined in Table 3-1. As shown in Figure 3-15, there was a significant decrease in the percentage of incidents analyzed that occurred in the AM Peak period, from 27 percent in 2018 to 15 percent in 2020. This decrease was likely due to workforce adjustments such as more people quarantining and working from home instead of commuting to work during the AM Peak period. Patterns of crash frequency stayed about the same for the Afternoon Off Peak and PM Peak periods. However, there was a notable increase in the number of crashes analyzed during the Morning Off Peak and Night Off Peak periods. This increase is likely due to the fact that extended operating hours, with more IMT shifts scheduled during the Morning Off Peak, PM Peak, and Night Off Peak periods, allowed IMTs to respond to more incidents occurring during these times in 2020. The change in the temporal distribution of crashes did not directly affect the data collection process, but the considerations of traffic volumes and extended hours were considered during statistical analysis, which is further explained in Chapter 5.

Table 3-1: Time of Day of Incidents

Morning Off Peak	12:00 A.M. to 6:30 A.M.
AM Peak	6:30 A.M. to 9:10 A.M.
Afternoon Off Peak	9:10 A.M. to 3:50 P.M.
PM Peak	3:50 P.M. to 6:30 P.M.
Night Off Peak	6:30 P.M. to 11:59 P.M.

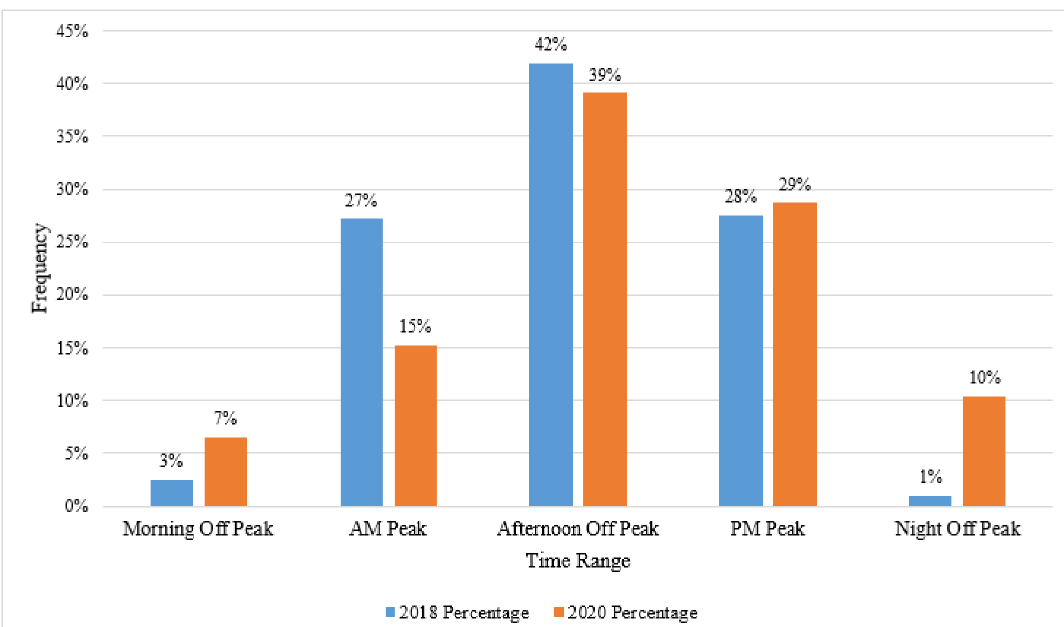


Figure 3-15: Comparison of incidents in differing times of day by year.

3.4 Data Availability

A number of data sources made available by UDOT and UHP provided timepoint data from which performance measures could be determined. These sources also provided facility data such as speed, volume, and travel time from which user impacts could be evaluated. Data collected in this process came from four sources including the UHP CAD System, the UDOT TransSuite database, the UDOT PeMS database, and the UDOT iPeMS database.

Each of these data sources will be briefly explained in the following subsections. With the exception of the UDOT TransSuite database, more details about how each database was used in the data collection process can be found in Chapter 3 of Schultz et al. (2019).

3.4.1 The UHP CAD System

UHP extracted and provided timestamped crash response data for IMT and UHP units from its CAD database. From these timestamped data, times of interest on the TIM Timeline, shown previously in Figure 2-1, were obtained and incident performance measures of RT, RCT, and ICT were determined. CAD files also contain crash severity type broken up into the three categories shown in Table 3-2. The table also correlates these categories of crash severity with the UDOT numeric scale and the KABCO Injury Classification Scale.

The data from CAD files were used to determine RT and ICT of both IMT and UHP units. The limitations of these data come from human error during data entry, whether through missing timestamps or timestamps entered incorrectly. For instance, at times there were multiple timestamps at an incident for a single IMT with the same status code. The occurrence of these types of errors was not frequent and they were addressed on an incident-by-incident basis according to the judgement of the research team.

Table 3-2: Comparison of UHP, UDOT, and KABCO Crash Severity Classifications (Numetric 2018 and NHTSA 2017)

UHP CAD File Crash Severity Type	UDOT Numeric Scale	KABCO Scale	Severity Description
Fatal and Incapacitating Injury (FII)	5	K	Fatal injury: injury that results in death within 30 days of crash
	4	A	Suspected Serious Injury: serious injury not resulting in fatality; incapacitating injury results from the crash
Personal Injury (PI)	3	B	Suspected Minor Injury: minor injury evident at the scene of the crash, not serious injury or fatality
	2	C	Possible Injury: injuries reported but not evident at the scene of the crash
Property Damage Only (PDO)	1	O	No Apparent Injury: the person received no bodily harm

3.4.2 The UDOT TransSuite System

The UDOT TransSuite System was incorporated into the methodology after Phase I when data regarding lane closures (T_5) was reformatted for extraction from the TransSuite database. Because the UDOT TransSuite database was not used in the previous research, the description of this source as well as the justification for its integration into the methodology are given subsequently in Section 3.5.

3.4.3 The UDOT PeMS Database

The PeMS database (UDOT 2018b) made available by Iteris Inc. provided point speed and volume data from radar and loop detectors. These data were used to help determine ETT and AV. Speed data from PeMS were also used to estimate the time an incident took place and the time that traffic flow returned to normal after an incident. Speed contour plots within PeMS helped with spatial analysis and visualization of the magnitude of incidents.

Limitations of PeMS data primarily come from out-of-service detectors. In some instances of severe congestion, such as during an FII crash, speeds were reduced to the point that detectors did not register vehicles passing over them, which made it difficult to get true delay data. An additional issue with PeMS is that data from detectors are available at a granularity of 5 minutes, so incident start time and the time that traffic flow returned to normal cannot be determined to greater than 5-minute accuracy.

3.4.4 The UDOT iPeMS Database

The iPeMS database (UDOT 2018a) made available by Iteris Inc. provided speed and travel time data via real-time and historical traffic data. The database uses probe data collected from cell phone applications and in-vehicle GPS units. The data collected from iPeMS were used to help determine ETT. Specific route segments that can be defined within iPeMS for travel time analysis were created to gather data individual to each incident being analyzed.

One issue with iPeMS probe data used in this study is that the data sampling has variable penetration levels and is therefore not as accurate as raw data provided by the PeMS database. One merit of this probe data over PeMS is that they describe what is happening continuously along the roadway instead of only at detector locations.

3.5 Integration of UDOT's TransSuite Database

During Phase I of the research, UHP collected "C" timestamps that indicated when all lanes at the location of an incident were cleared, which was used as T_5 in the calculation of RCT. At that time, TransSuite data were in an encrypted format that prevented easy extraction for use, but by this Phase II study, TransSuite data were reformatted for extraction from the database. The UDOT TOC provided the research team with TransSuite data, which contained incident lane closure data as a possible alternative to the “C” timestamps collected by UHP to calculate RCT. TransSuite data were integrated with CAD data provided by UHP. This proved to yield a greater number of incidents and a higher percentage of total incidents that were relevant for measuring IMT performance.

The 2018 and 2020 CAD+TransSuite datasets also yielded a greater variety of incidents than the 2018 dataset collected without TransSuite data. The following subsections describe how TIM performance measure data were collected using CAD data, how the use of TransSuite data provided the research team with more performance measure data, and how the validity of using TransSuite data was determined using statistical tools.

3.5.1 Performance Measures Obtained through CAD Data

One of the primary objectives of the Phase I research was to determine the availability of data necessary to collect performance measures defined by the FHWA, namely RCT and ICT. These necessary datapoints are the individual incident timestamps used to calculate performance measures, shown previously on the FHWA Traffic Incident Management Timeline in Figure 2-1.

From the Phase I research, it was determined that the necessary timestamps needed to calculate RCT and ICT were available in UHP’s CAD files (Schultz et al. 2019). In addition, the iPeMS and PeMS databases provided by UDOT were necessary to determine user impacts such as ETT, AV, and EUC. Table 3-3 shows the UHP status codes that corresponded to the necessary timeline elements. UHP did not historically collect the timestamps of status code “C,” corresponding to T_5, but consented to collect them during the 2018 data collection period for the duration of 6 months. With that T_5 data point available, all performance measures of interest to the FHWA were available for the Phase I study.

Table 3-3: UHP Timestamps and Corresponding Times of Interest

Time of Interest	UHP CAD Status Code	Meaning
T_0	---	
T_1 and T_2	"Call Received Time"	Unit notified of incident
T_3	ENRT	Unit en-route to the call
T_4	ARRVD	Unit arrived on scene
T_5	C	All lanes are clear
T_6	CMPLT	Unit cleared the call
T_7	---	

3.5.2 Increase in Relevant Data due to Improvements in TransSuite Data

As previously noted, by Phase II of this research the TOC had reconfigured the TransSuite system and was able to provide the research team with historical incident data for the Phase I data collection period and then for the Phase II data collection period going forward. Analysis of the data collection found that for the 2018 data collection period, TOC operators logged T_5 timestamps for 325 incidents. During the same period, UHP recorded T_5 timestamps for 138 incidents. This meant that more incidents could be analyzed for performance measures if TransSuite data were integrated with UHP CAD files to collect data.

The 2018 CAD dataset yielded a total of 1,216 incidents. Of those incidents, 99.2 percent had ICT, 85.7 percent had RT, 11.3 percent had RCT, 10.6 percent had all three performance measures (ICT, RT, and RCT), and 5.2 percent were able to be analyzed for EUC, as seen in Table 3-4. Incident data valid for the analysis of EUC were the most important since these incidents were the most useful in analyzing the effectiveness of IMT performance. The hope of the research team and members of UDOT was that the addition of TransSuite data to collect T_5 timestamps would increase the number of incidents that contained data for all three performance measures and could therefore be analyzed for EUC.

Table 3-4: Data Funnel for 2018 Data Collecting Using CAD Only

Data Type	Number of Data Points	Percent of Total
Incidents	1216	100.0%
ICT	1206	99.2%
RT	1042	85.7%
RCT	138	11.3%
ICT, RT, and RCT	129	10.6%
Incidents Analyzed for EUC	63	5.2%

The distributions of incidents with IMT performance measures for the 2018 and 2020 CAD+TransSuite datasets are shown in Table 3-5 and Table 3-6, which can be compared to the 2018 CAD dataset shown in Table 3-4. The original 2018 CAD dataset contained data from March to August 2018, whereas the 2018 and 2020 CAD+TransSuite datasets did not include April data and instead included September data, as discussed in Section 3.3.1. However, all datasets had similar numbers of incidents analyzed, with over 1,000 incidents each.

Table 3-5: Data Funnel for 2018 Data Collected Using CAD+TransSuite Data

Data Type	Number of Data Points	Percent of Total
Incidents	1074	100.0%
ICT	1064	99.1%
RT	928	86.4%
RCT	325	30.3%
ICT, RT, and RCT	306	28.5%
Incidents Analyzed for EUC	188	17.5%

Table 3-6: Data Funnel for 2020 Data Collected Using CAD+TransSuite Data

Data Type	**Number of Data Points**	**Percent of Total**
Incidents	1190	100.0%
ICT	1186	99.7%
RT	1007	84.6%
RCT	295	24.8%
ICT, RT, and RCT	280	23.5%
Incidents Analyzed for EUC	144	12.1%

While the 2018 CAD-only and CAD+TransSuite datasets yielded comparable numbers of incidents and similar percentages of the total number of incidents with ICT and RT data, the proportion of incidents with RCT data and those analyzed for EUC were much higher after TransSuite data were introduced. In 2018, the data reanalyzed using TransSuite provided for the analysis of EUC for 188 incidents, or 17.5 percent of the total. This is a 12.3 percent increase in the number of incidents analyzable for EUC from when 2018 CAD data was used alone. The 2020 data obtained from CAD+TransSuite also surpassed data collected in 2018 using only CAD, despite a lower number of crashes recorded in the CAD system, as previously discussed in Section 3.3.1. During the 2020 data collection period, 144 of the 1,190 incidents analyzed for performance measures were able to be analyzed for EUC, or 12.1 percent of the total.

The integration of CAD and TransSuite proved to yield a much more relevant dataset for the analysis of IMT performance. Additionally, the majority of incidents analyzed for EUC in the original CAD-only dataset were also found to be analyzable using the CAD+TransSuite dataset, indicating that analyzable data would not be lost by integrating TransSuite into the methodology. With the increase in the number of analyzable incidents with TransSuite, greater sample sizes of incidents were available for both 2018 and 2020, thus making the results more reliable for statistical analysis.

3.5.3 The Statistical Validity of Using TransSuite

The collection of T_5 timestamps from TransSuite was a viable alternative to using the "C" timestamp previously collected by UHP since the TOC operators collected lane closure data as part of their daily routine, which removed the added responsibility of collecting T_5 from UHP. Though potential for human error exists in both UHP and TOC logs, a two-tailed paired t-test of RCT values analyzed from both sources, calculated using their respective T_5 timestamps, shows that the difference in mean RCTs between the two methods is statistically insignificant with a 95 percent confidence level. Raw TransSuite data were compared with the 172 incidents of the 2018 CAD dataset and the data were reduced to 72 overlapping incidents where at least one IMT was present, both CAD and TransSuite had a valid T_5 timestamp, and the incident did not occur on a road shoulder or exit ramp.

The results of the two-tailed paired t-test are shown in Table 3-7. When the t-statistic (computed) value is less than t Critical two-tail, the difference in means is not significant at the defined confidence level. In this case the t-statistic (computed) is 0.162 and the t Critical two-tail is 1.994; therefore, the difference in means is not significant at a 95 percent confidence level. The difference in the means of CAD RCT and TransSuite RCT is 0.637, indicating that the difference in RCT when T_5 is taken from TransSuite instead of CAD will be small and that the difference in the final results of the statistical analysis on RCT where T_5 is taken from TransSuite will not be significantly different than if T_5 had been taken from CAD. Note that both CAD RCT and TransSuite RCT use T_1 from CAD and that the only value that changes is T_5.

Table 3-7: Two Tailed Paired t-test of RCT Data

Statistic	***CAD RCT***	***TransSuite RCT (TransSuite T5 – CAD T1)***
Mean	54.749	54.112
Variance	1883.734	1625.309
Observations	72	72
Pearson Correlation	0.683	
Hypothesized Mean Difference	0	
df	71	
t Stat	0.162	
P(T<=t) one-tail	0.436	
t Critical one-tail	1.667	
P(T<=t) two-tail	0.872	0.128
t Critical two-tail	1.994	for α = 0.05 given df = 71

Figure 3-16 is a histogram showing a comparison of usable RCT values for the 2018 dataset using both CAD and TransSuite T_5 values. Figure 3-17 is a histogram that shows the difference between the respective RCT values.

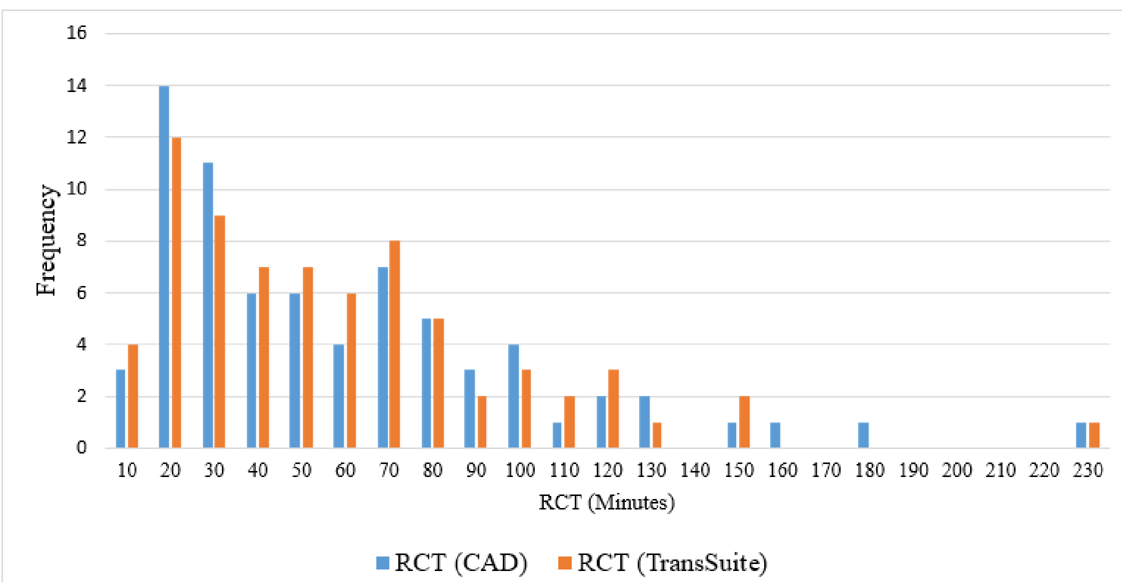


Figure 3-16: Comparison of RCT distributions between CAD and TransSuite.

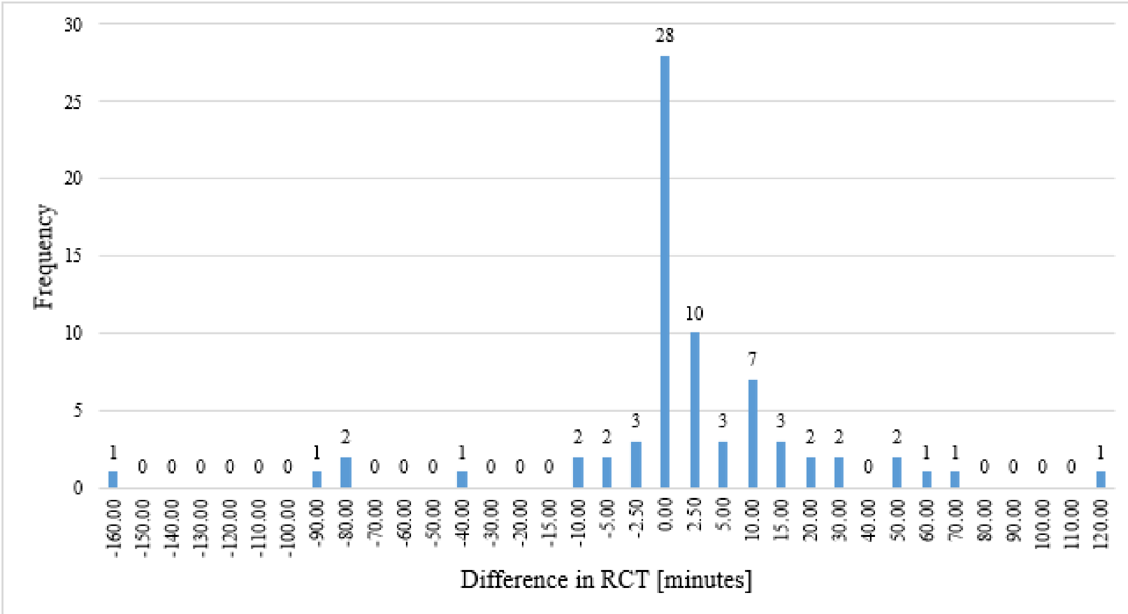


Figure 3-17: Difference between RCTs determined by CAD and CAD+TransSuite.

Figure 3-16 shows frequencies of RCT values both calculated using CAD T_5 and TransSuite T_5 timestamps. The number of incidents with RCTs falling into 10-minute bins is similar between the two data sources. Figure 3-17 shows the frequencies of differences between RCT values for each individual incident analyzed from the 2018 dataset, calculated as the RCT value determined using TransSuite data subtracted from the RCT value determined using CAD data. The majority of RCTs calculated using TransSuite data fall within 5 minutes of those calculated originally from the CAD data. The difference is slightly skewed to the positive side, which indicates that T_5 values as recorded in TransSuite were recorded slightly before those corresponding to the same incident in the CAD file, resulting in slightly shorter RCTs.

As a result of this analysis, TransSuite was considered a viable option for collecting T_5 data for Phase II data collection. Therefore, it was not necessary to request UHP officers to record the "C" timestamps that were provided during Phase I. Nevertheless, the other timestamps that UHP collects in the CAD system were still necessary for determining performance measures and the assistance of UHP officers was essential.

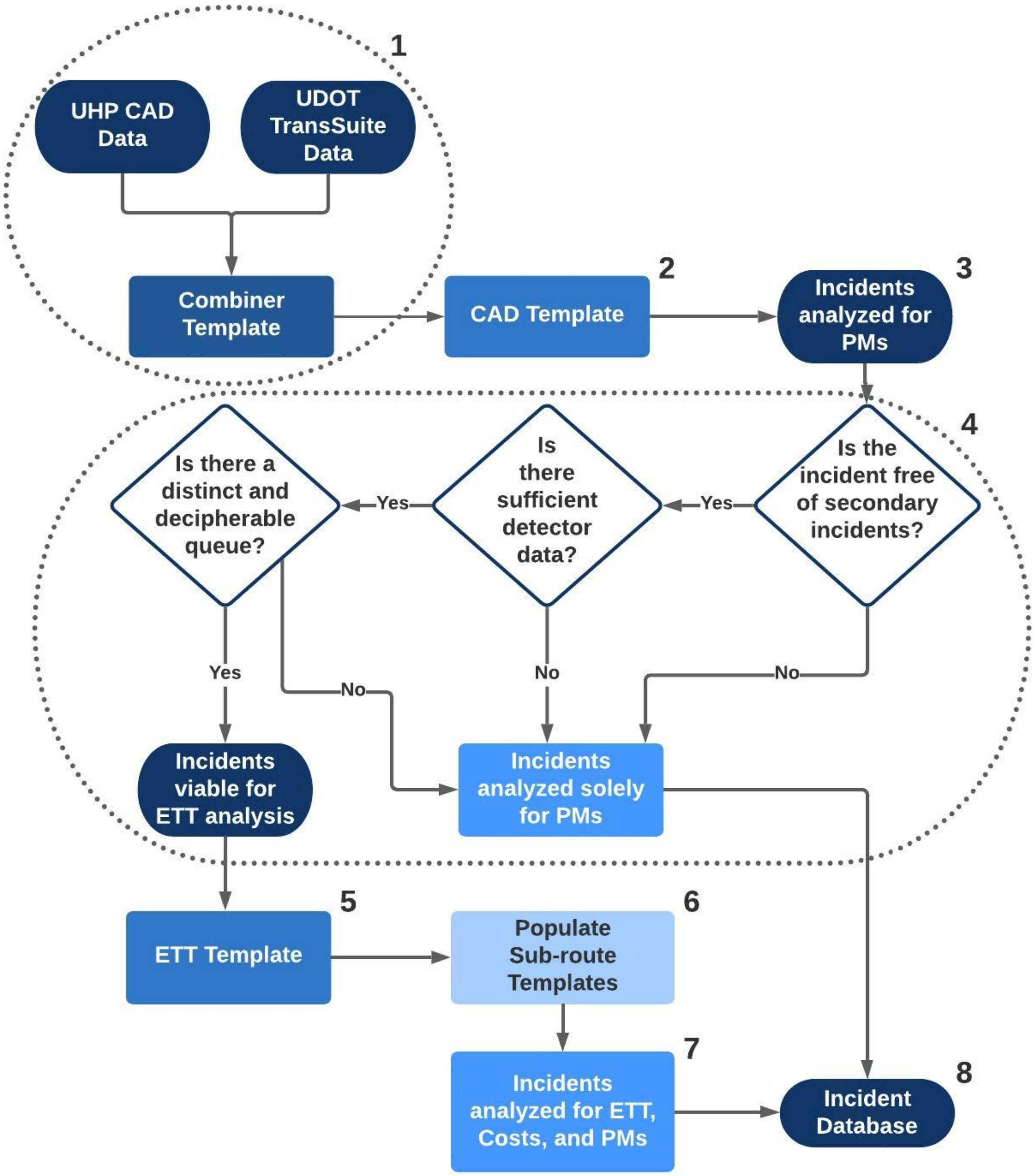
3.6 Data Collection Methodology

As previously mentioned, the data collection methodology used in this study is nearly the same as the methodology described in Schultz et al. (2019), and details about this methodology can be found in that report. The primary difference between the data collection and reduction procedure in this Phase II study and the previous one is that for this phase of research lane closure data from the UDOT TransSuite database was used to determine RCT. In contrast to the Phase I study, performance measure and user impact data were analyzed for two periods. Using an updated methodology, data were collected for comparable data collection periods in both 2018 and 2020, so as to facilitate analysis of differences in performance and impacts of the expansion to UDOT's IMT program.

The data collection and reduction were performed using Microsoft Visual Basic for Applications (VBA) 2019 templates developed by the research team, and a description of each template is presented in this section. The templates were automated to:

- Combine data sources.
- Identify incidents viable for analysis.
- Facilitate data collection.
- Organize collected data for analysis.

The updated methodology used to collect and analyze incident data for the both data collection periods is shown in Figure 3-18.



In this figure, "PMs" refers to "performance measures."

Figure 3-18: Data collection methodology flowchart.

Incidents that had all timestamps necessary to collect all pertinent performance measures (RT, RCT, and ICT) were first identified. Then, from that pool of identified incidents, further investigation was done to determine which incidents were viable for performing user impact analysis. To be used for user impact analysis, incidents must have met the following criteria:

- The incident occurred on an interstate in Utah.
- The incident did not occur on a ramp.
- The incident contained available loop detectors without substantial amounts of missing data on the road segments where the incident occurred.
- The incident had a distinct and decipherable queue, as seen in speed contours provided in the PeMS database.
- The incident did not have secondary incidents.

For each month during the data collection period, from mid-March to the end of September 2020, not including April, the process described by the schematic diagram in Figure 3-18 was followed to collect incident data, which was then stored in an incident database for later analysis. The diagram is numbered by the respective steps that the research team took to collect raw incident data, reduce it to meaningful incidents, then extract and store important information regarding performance measures, user impacts, and other incident characteristics of interest. A brief overview of the process shown in Figure 3-18 will be provided in this section, with subsections corresponding to the numbers in the figure.

3.6.1 Combining CAD and TransSuite Data

At the end of each month the research team received monthly CAD logs from UHP as well as monthly logs of incident data from UDOT's TransSuite database, both as Excel worksheets. Because T_5 timestamps necessary for determining RCT were found in TransSuite while all other timestamps were found in the CAD data, a method was needed to identify matching incidents in the respective logs and combine them. A "Combiner Template" was created in VBA to allow the research team to systematically compare incidents from each respective source. This template allowed the research team to compare incidents based on thresholds in date, time, and location, then identify matches and finally initiate an automated process that would combine timestamps into a single log sheet.

During this step incidents were also vetted by the first two criteria for ETT analysis, and those incidents that did not occur on interstates were discarded. Those that occurred on ramps were marked as viable for performance measures analysis only. After that process was undertaken each month, T_5 timestamps obtained from TransSuite were integrated into the rest of the timestamps found within the CAD data, and performance measures were calculated, as described in Step 2 of the process.

3.6.2 Calculating Performance Measures

The combined incident data gathered in Step 1 were then processed using a separate "CAD Template" created in VBA, which was automated to calculate the performance measures for IMTs and UHP units for each incident using the timestamp data. The VBA script looped through the combined data and created a performance measures template that was populated each time an incident that had the necessary data to calculate RCT, ICT, and RT was identified. This CAD Template also created a file structure for the incidents in each month that could be organized further depending on additional analysis, whether they would be analyzed solely for performance measures, or whether they met criteria to be analyzed for user impacts.

3.6.3 Performance Measures Collected

At this point, all incidents from the raw data that were viable for performance measure analysis had been identified, and performance measures for these incidents had been calculated. Additional steps in the process serve the purpose of identifying which incidents can be further analyzed for user impacts such as ETT, AV, and EUC.

3.6.4 Identifying Incidents Viable for ETT Analysis

The incidents for which performance measures were calculated were individually vetted to determine whether the remaining three criteria for ETT analysis were met. To determine the presence of secondary incidents, sufficient detector data, and a decipherable queue, speed contour plots of each incident were located in the Spatial Analysis reports found in the PeMS database and compared to the combined CAD and TransSuite logs. Detector data were determined to be sufficient by the research team if 85 percent of them were available during the temporal and physical extents of the incident queue, as shown in the speed contour plot.

Examples of how contour plots were used to visualize queues and identify secondary incidents is found in Section 3.5 of Schultz et al. (2019). Incidents that did not meet the criteria mentioned above were entered into an incident database with their respective performance measures.

3.6.5 Preparing Data for ETT Analysis

For each incident that met all five criteria, an "ETT Template" was created in VBA to produce a file structure that would compile all pertinent incident data specific to the incident including travel times, speeds, and volumes for the duration and geographic extent of the incident. To use the ETT template, each incident was compartmentalized into “sub-routes” between facility access points. Detectors in each sub-route were identified in the PeMS database to provide volume data. Each sub-route detector was then paired with a route created in the iPeMS database to provide travel time data.

The timestamps for T_0 and T_7 were also determined by comparing speed contour plots of each incident to speed contour plots of the same location for comparable “normal” days in which incidents did not occur. Once T_0 and T_7 of an incident were determined, along with respective normal days and the subroutes that covered the extent of the queue, the ETT template created a file structure of sub-route templates for data collection of volume and travel time data from PeMS and iPeMS. Examples identifying sub-routes, “normal” days, and T_0 and T_7 can be found in Section 3.6 of Schultz et al. (2019).

3.6.6 Calculating ETT

For each incident, a number of sub-route templates were created by the ETT template. These were populated with travel time data from iPeMS and volume data for each sub-route’s respective PeMS loop detector (verifying an acceptable rate of observed data for each detector and alternating detectors as necessary). The AV of each sub-route was calculated as the cumulative volume that passed through the sub-route during the duration of the incident, from T_0 to T_7. ETT of the subroute was determined as the difference in total travel time experienced by the sub-route’s AV on the day of the incident and the total travel time that same AV would have experienced on normal days. The ETT Template was automated to update with the population of each sub-route template, and total ETT and AV for the incident were then tabulated as the sum of all sub-routes’ ETTs and the largest AV experienced by any one sub-route.

3.6.7 ETT Data Collected

At this point, all incidents viable for ETT analysis had been analyzed for their respective ETT and AV, in addition to performance measures previously determined, and were entered into an incident database with other pertinent incident characteristics.

3.6.8 Storing Incident Data for Analysis

All incidents, both those that were analyzed only for performance measures and those also analyzed for ETT and AV were entered into an incident database that contains details about each incident such as date, time, time of day, location, crash type, number of IMTs and UHP units at the scene, number of lanes at bottleneck, and number of lanes closed. For those incidents analyzed for ETT and AV, the percentage of trucks on the roadway during the incident was entered using the Automated Vehicle Classification report found within PeMS.

Average Vehicle Occupancy (AVO) data were also entered for each incident dependent on time and location as detailed in Schultz et al. (2015). EUC was determined using the ETT of each incident in conjunction with the incident's respective truck percentage, AVO, and hourly costs of truck time and individual time as outlined in Ellis (2017). More details regarding how EUC was calculated in this study can be found in Section 3.6 of Schultz et al. (2019). Readers interested in the incident data collected in these incident databases may reach out to the authors.

This methodology was used to create 2018 and 2020 databases of incidents and their performance measures, user impacts, and other incident characteristics such as the number of IMTs and the number of lanes closed. The research team then compared performance measure and user impact data from the two years using data reduction and statistical analyses.

3.7 Chapter Summary

The IMT program expansion has allowed UDOT to provide TIM services to a much larger coverage area and at more times of the day. The number of centerline miles covered by the IMT program increased from 251 in 2018 to 773 in 2020. This represents an increase of 552 centerline miles, or 208 percent. The expansion now allows IMTs to patrol many other state routes in Regions 1, 2, and 3 in addition to the interstate routes. Additionally, Region 4 now has a full-time, fully-staffed team in Washington County that operates during peak periods (not 24/7). The data indicate that more IMTs are now available for each incident, meaning that the higher number of resources allows the program to more efficiently respond to crashes as needed. IMTs are now able to respond to smaller incidents and motorist assists that might not have been able to be prioritized with fewer resources in 2018.

Both UDOT and UHP provided the research team with data sources to collect data regarding performance of UDOT's IMT program. The addition of the TransSuite database to the data collection methodology allowed the research team to analyze a higher proportion of performance measure and user impact data than when CAD was solely used. Data were analyzed for both 2018 and 2020 from March through September (with the exception of April 2020) such that a comparison of performance measures between the two years could be performed. However, the COVID-19 pandemic caused changes in traffic patterns in 2020, particularly a reduction in traffic volumes, which necessitated consideration of the effect of volume changes in statistical analyses. With more IMTs in 2020, UDOT was able to adjust IMT coverage areas and IMT shifts to adapt to the needs presented by the COVID-19 pandemic.

4 DATA REDUCTION

4.1 Overview

With the methods described in Chapter 3, CAD and TransSuite data were integrated to obtain performance measures and user impact data. This chapter presents the raw data that were reduced for the analysis of the UDOT IMT program. It contains a comparison between the incident data collected in 2018 and 2020, reduced performance measures, and user impacts of the 2018 and 2020 data collection periods. The performance measures for which data were collected are RT, RCT, and ICT and the user impacts for which data were collected are AV, ETT, and EUC. It should be noted that this study focused on performance of UDOT's IMTs, although UHP-related data were also collected and analyzed. For the purposes of this report, all references to ICT and RT denote IMT ICT and IMT RT, respectively, whereas RCT values are the same for both IMTs and UHP units.

4.2 Incident Data Collected

The integration of TransSuite data with CAD data provided much more relevant data for the analysis of IMT performance measures than with CAD data only. The distribution of incidents that contained relevant performance measures from the 2018 and 2020 CAD+TransSuite integrated datasets were shown previously in Table 3-5 and Table 3-6, respectively. The impacts of COVID-19 included slight reductions in the number of incidents observed within the UHP CAD logs. However, with the addition of TransSuite data, adequate samples of performance measure data were still able to be collected. In 2018, 28.5 percent of the incidents collected contained all three performance measures of interest, and this number was only slightly smaller in 2020 at 23.5 percent. In 2018, 17.5 percent of the incidents were able to be analyzed for EUC, and in 2020 12.1 percent of incidents were analyzed for EUC.

4.3 Performance Measures

IMT performance measure data including RT, RCT, and ICT were collected for the 2020 data collection period and compared with 2018 IMT performance measure data. The box plots shown in Figure 4-1 and Figure 4-2 were prepared based on incident data where at least one IMT responded to an incident and show the ranges of RT, RCT, and ICT based on crash type.

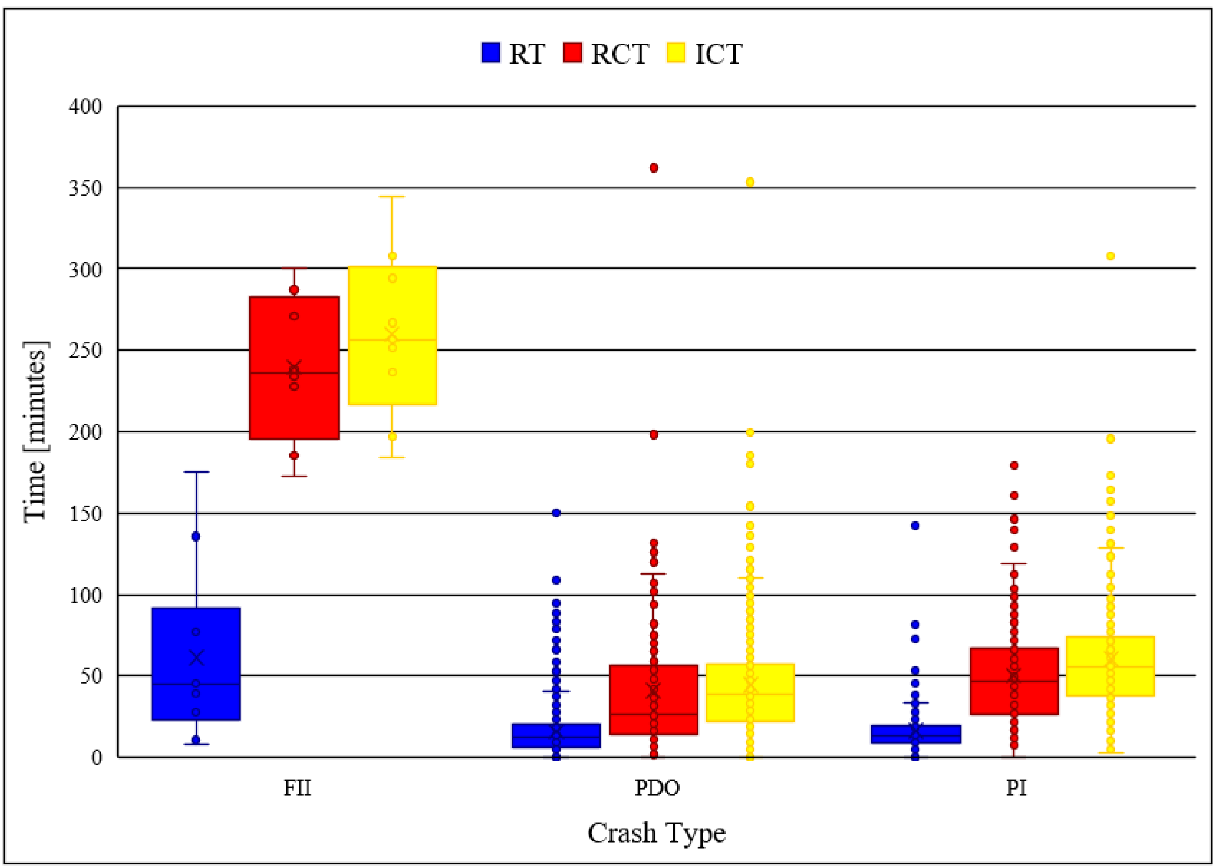


Figure 4-1: Boxplot showing spread of 2018 IMT performance measures by crash type.

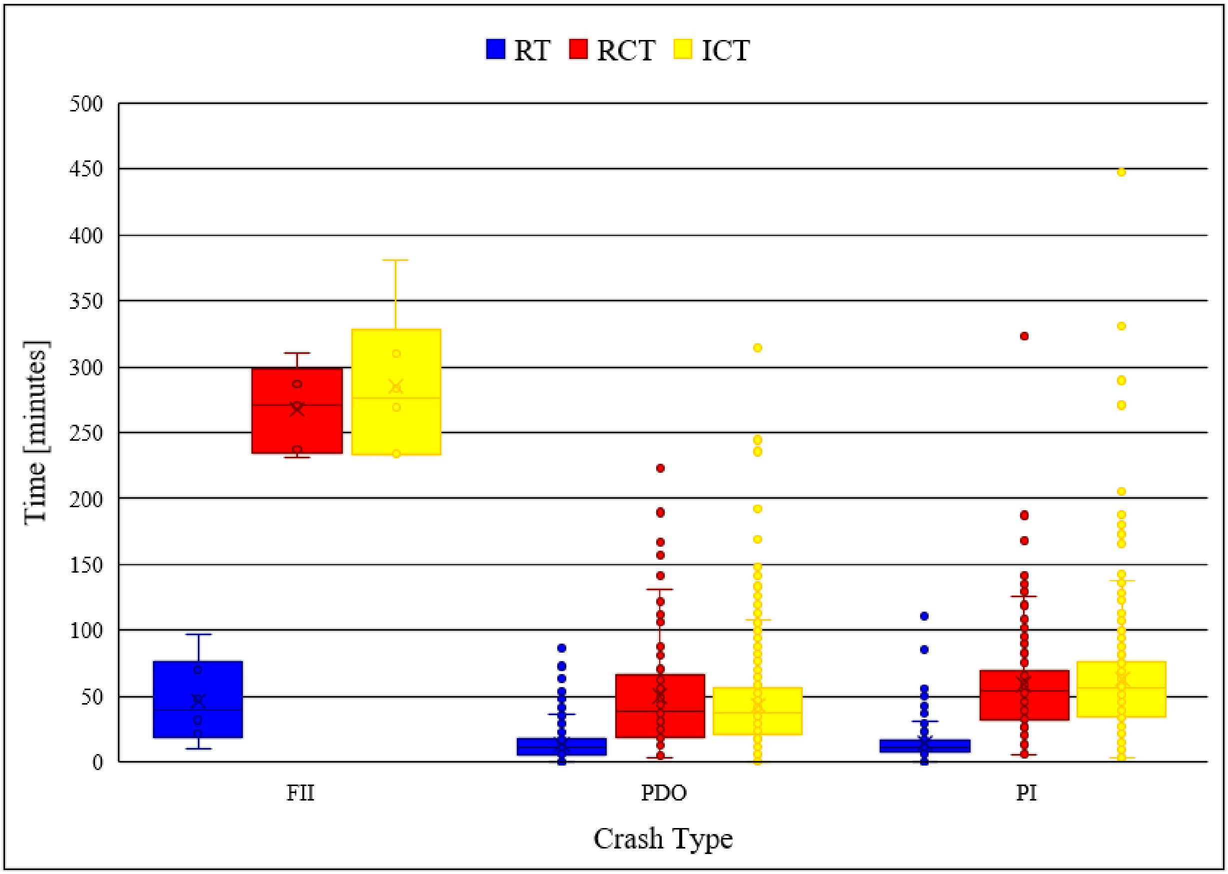


Figure 4-2: Boxplot showing spread of 2020 IMT performance measures by crash type.

In general, RT values got shorter from 2018 to 2020. As shown in Figure 4-3 and Figure 4-4, the percentage of incidents that IMTs responded to within 15 minutes of a crash occurring increased from 58.8 percent in 2018 to 65.9 percent in 2020, for a difference of 7.1 percent, or a 12.1 percent improvement from 2018 to 2020. As previously discussed in Section 3.2, the IMT program expanded to cover a much larger area in 2020. The improvement to response times in 2020 shows that IMTs are able to respond faster to incidents with an expanded fleet, even over a larger area. This is one clear indication of how the program expansion has helped to improve IMT performance in 2020.

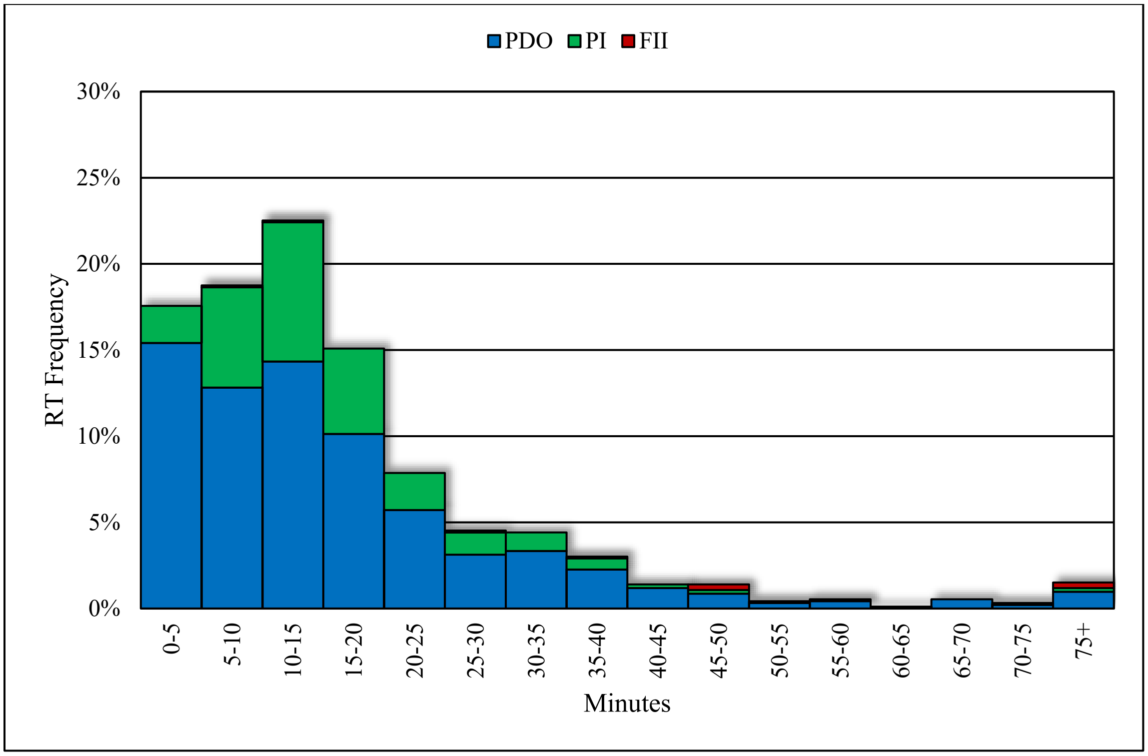


Figure 4-3: 2018 distribution of RT.

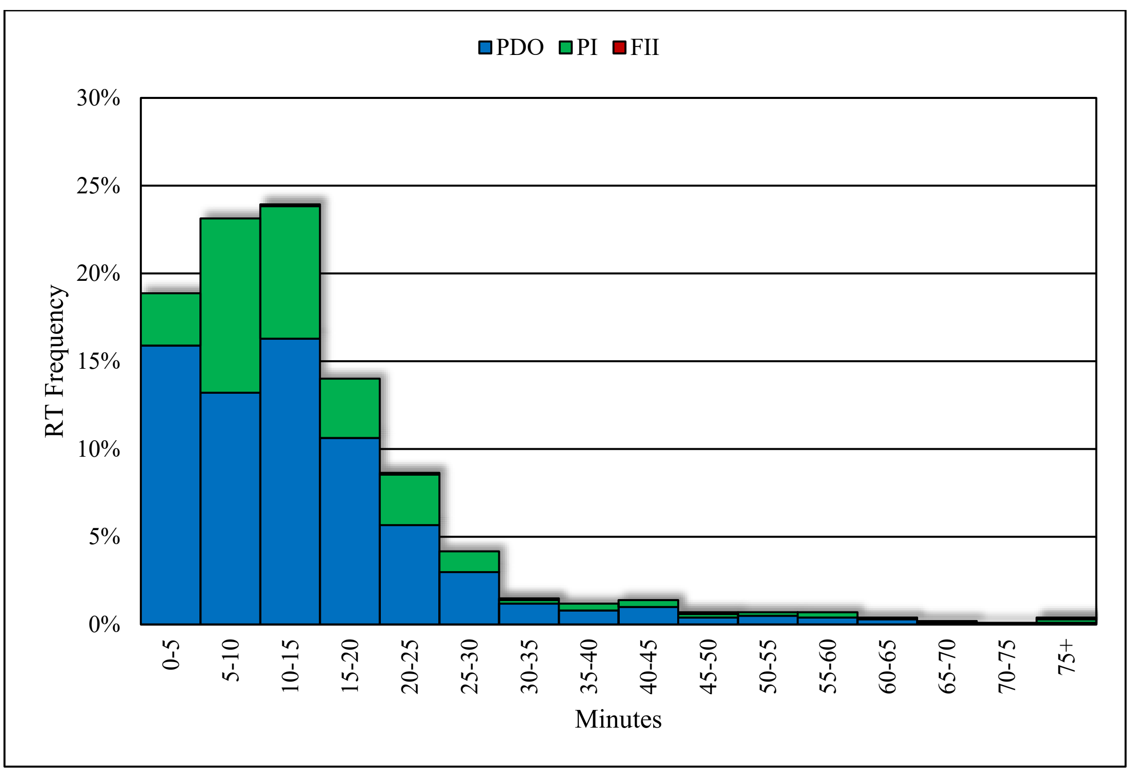


Figure 4-4: 2020 distribution of RT.

There was an increase in IMT RCT values from 2018 to 2020. As shown in Figure 4-5 and Figure 4-6, the percentage of incidents for which IMTs were able to clear the roadway within 45 minutes of a crash occurring decreased from 55.7 percent in 2018 to 46.4 percent in 2020, for a difference of 9.3 percent, or a 16.7 percent decrease from 2018 to 2020. One potential cause for longer IMT RCT expressed by IMT leadership was the additional focus that IMTs put on personal safety due to COVID-19 as they responded to incidents.

ICT remained about the same between 2018 and 2020. As shown in Figure 4-7 and Figure 4-8, there was a minor increase in the percentage of incidents from which IMTs were able to clear the scene in less than 45 minutes, from 52.0 percent in 2018 to 53.5 percent in 2020, for a difference of 1.5 percent, or a 2.9 percent improvement from 2018 to 2020.

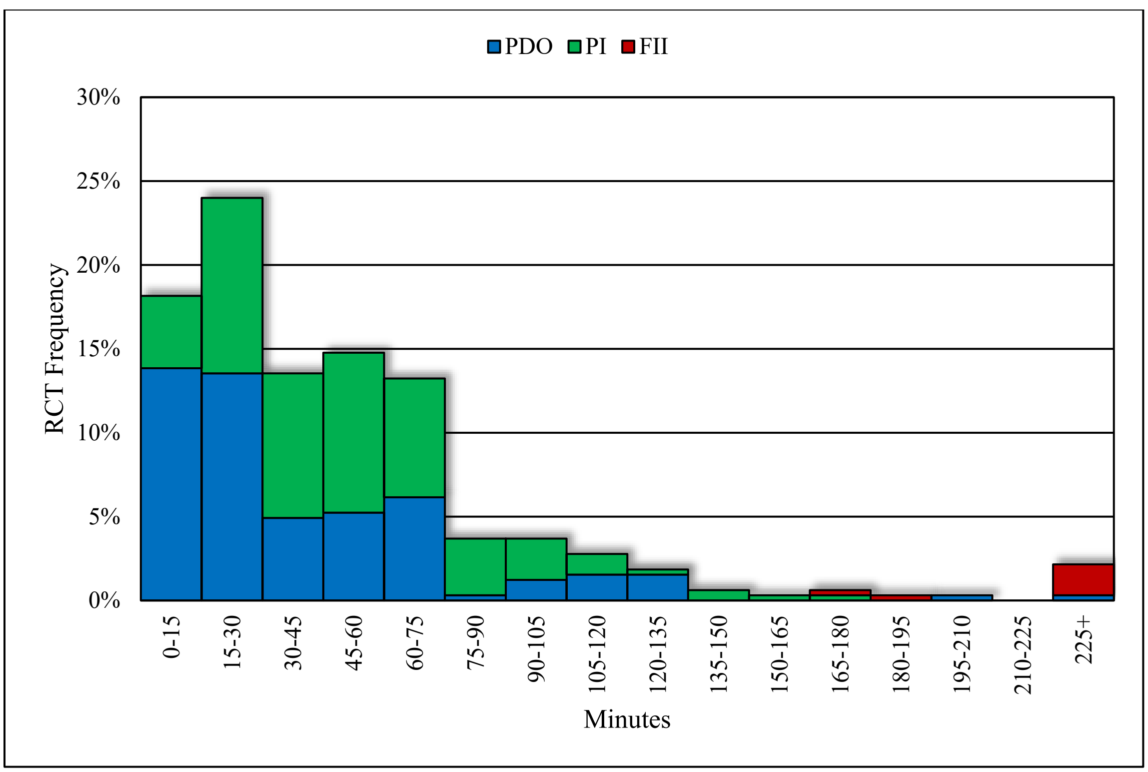


Figure 4-5: 2018 distribution of RCT.

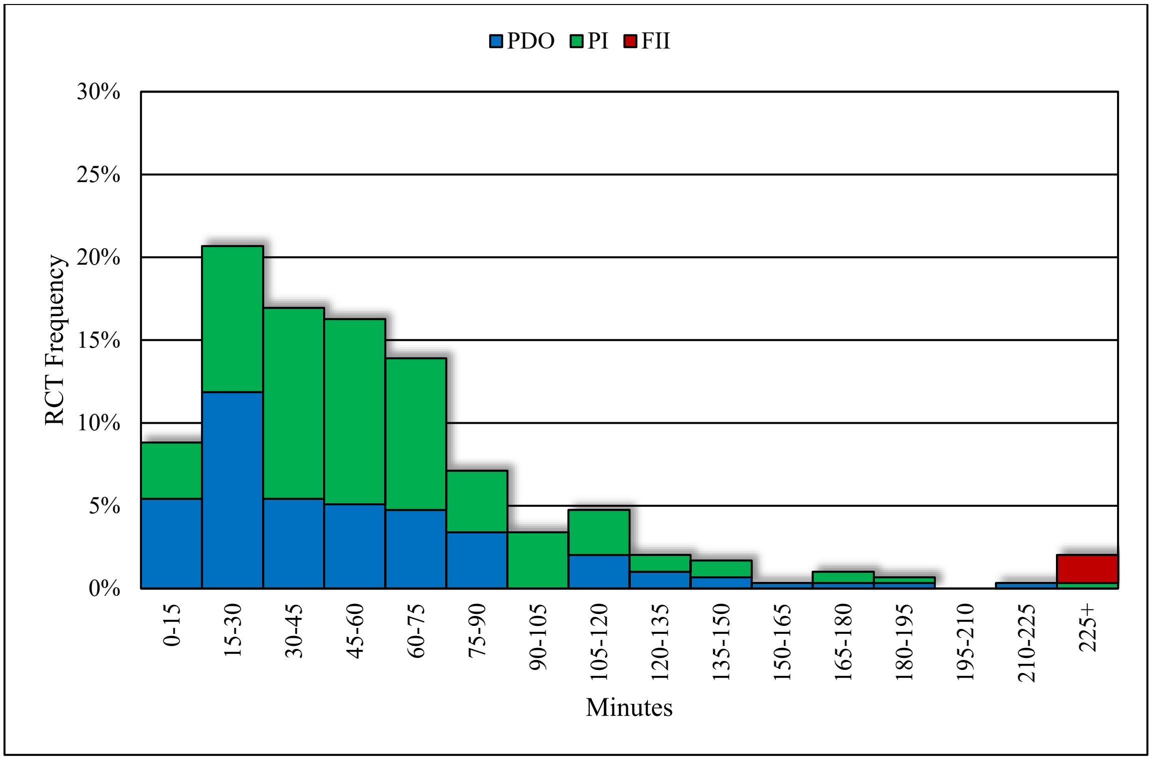


Figure 4-6: 2020 distribution of RCT.

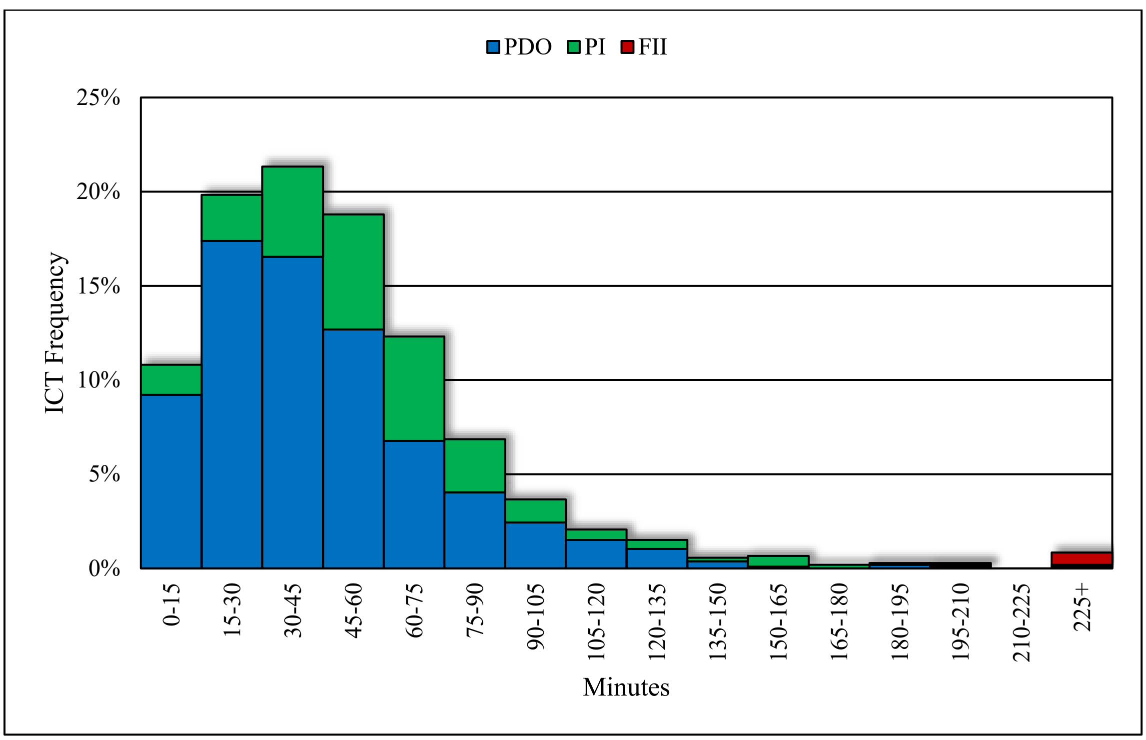


Figure 4-7: 2018 distribution of ICT.

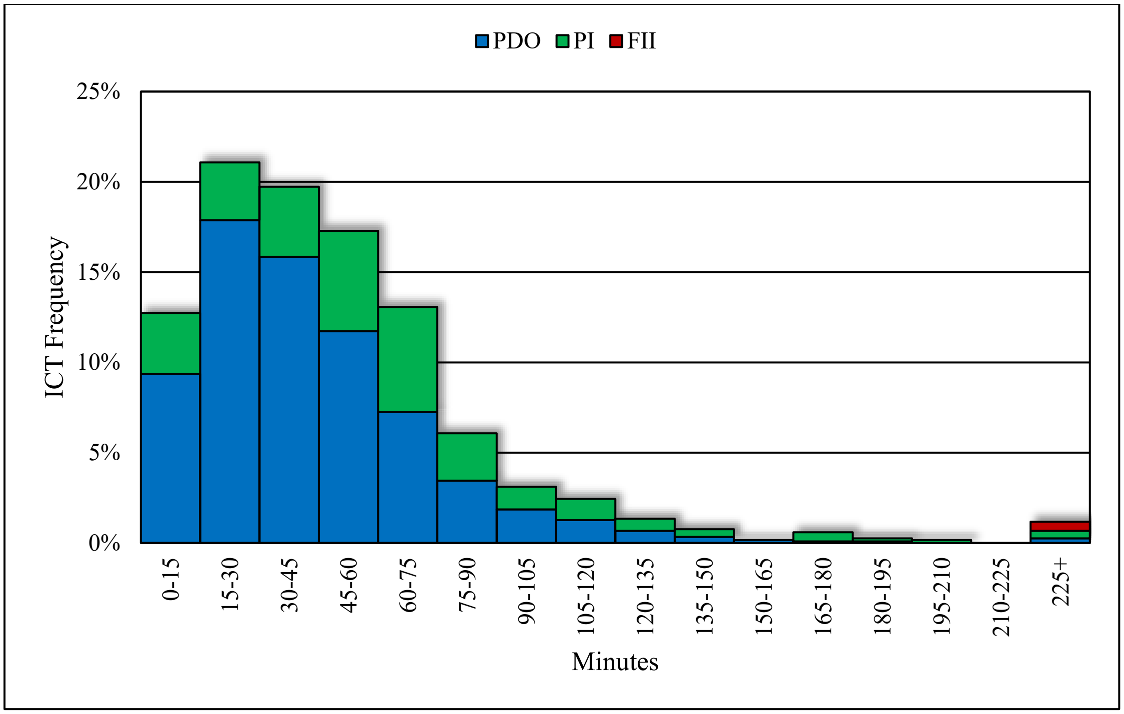


Figure 4-8: 2020 distribution of ICT.

Overall, IMT performance was well maintained between 2018 and 2020. IMTs were able to respond to incidents faster in 2020 in spite of an expanded coverage area. RCT values were slightly longer in 2020 than in 2018, and this is likely due to precautions taken by IMT personnel with regards to the COVID-19 pandemic. ICT values were almost identical between both years. These results indicate that with the expanded program, UDOT is able to provide IMT services of similar quality at a much larger scale, over a larger coverage area and at more times of the day, as well as to more incidents.

4.4 User Impacts

The user impacts measured in this study were AV, ETT, and EUC, all of which were significantly lower in 2020 than in 2018 due to the effects of COVID-19. Consequently, the trends of each measure of user impact between 2018 and 2020 were essentially the same. The trend in each performance measure vs EUC illustrates the decrease in costs to roadway users due to traffic incidents. Figure 4-9 through Figure 4-14 are scatter plots showing the relationships between performance measures and EUC in both 2018 and 2020.

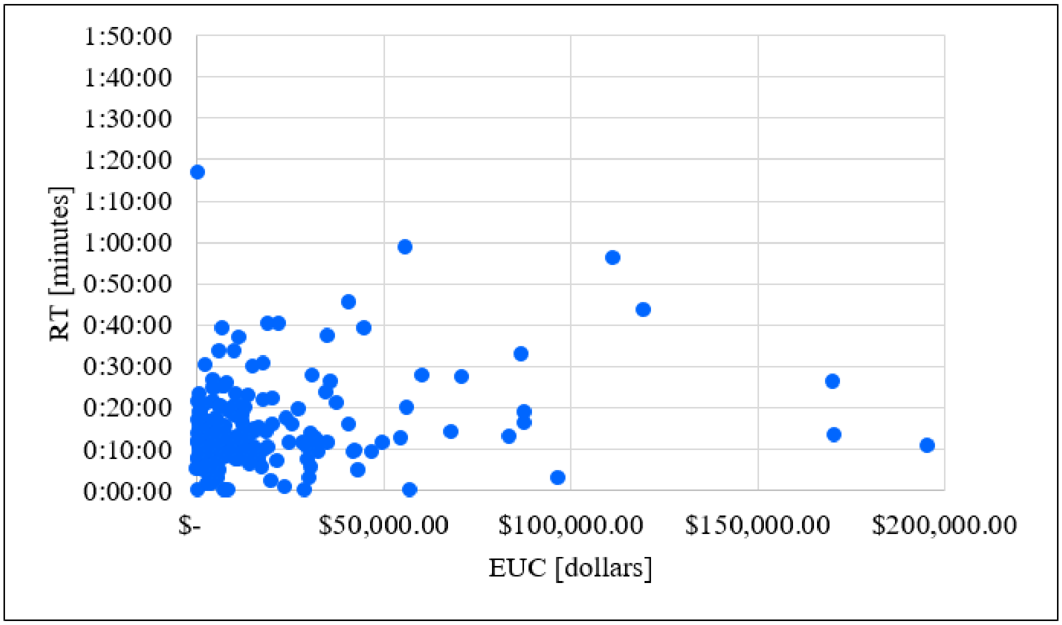


Figure 4-9: 2018 RT vs. EUC.

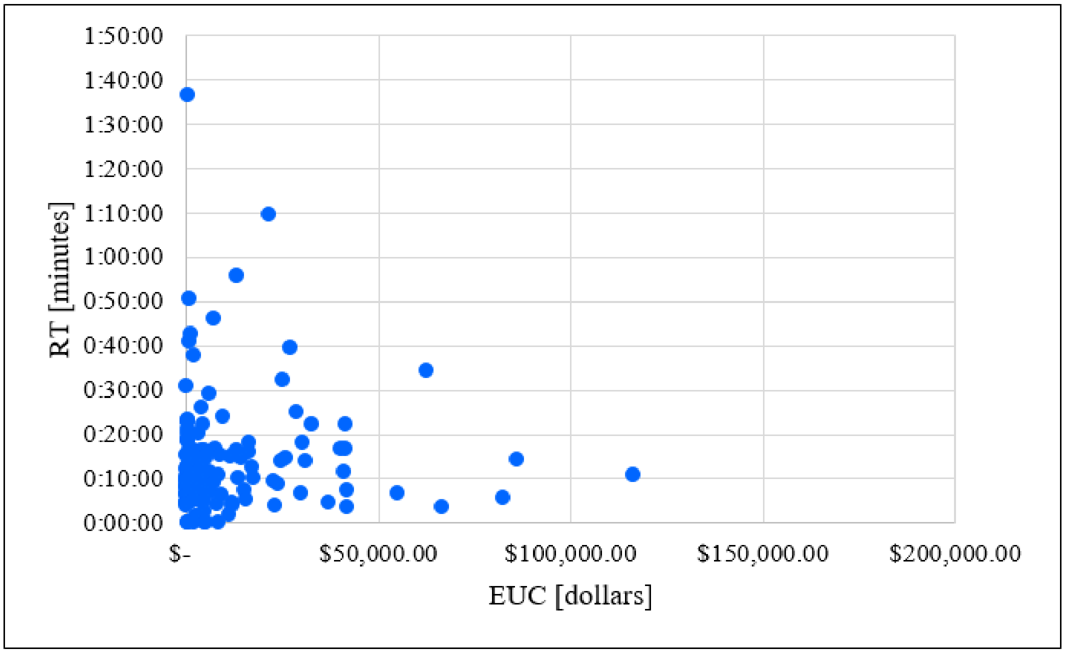


Figure 4-10: 2020 RT vs. EUC.

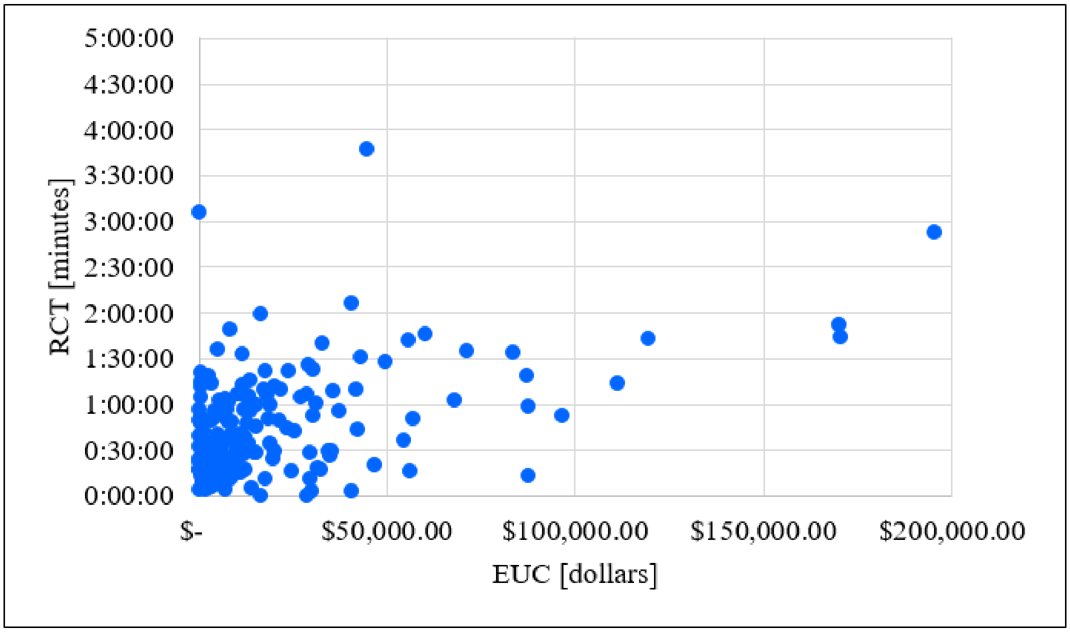


Figure 4-11: 2018 RCT vs EUC.

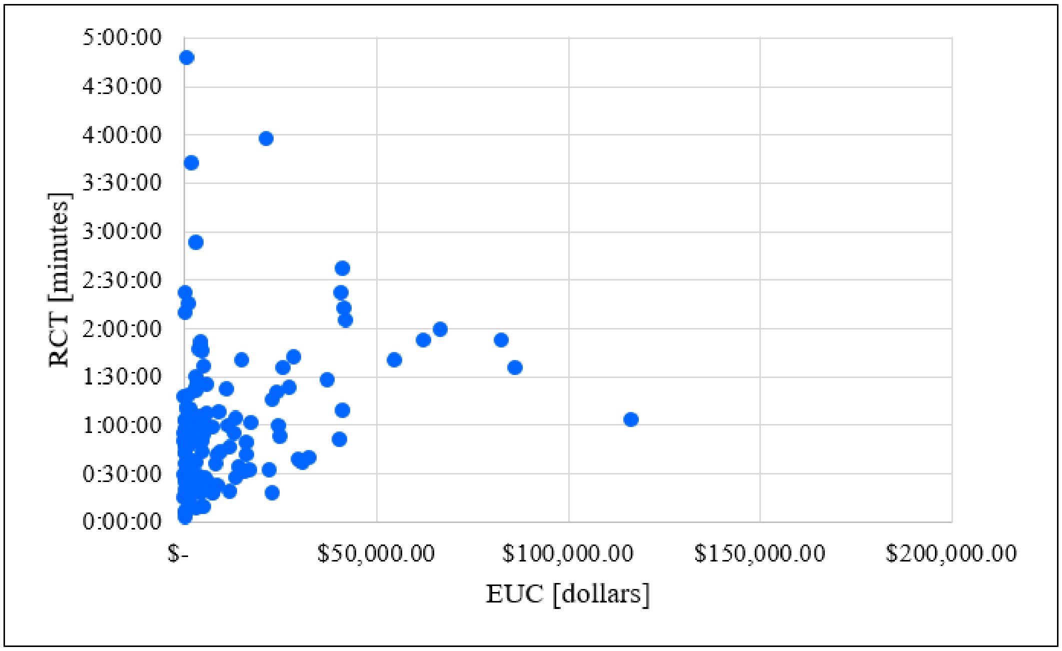


Figure 4-12: 2020 RCT vs. EUC.

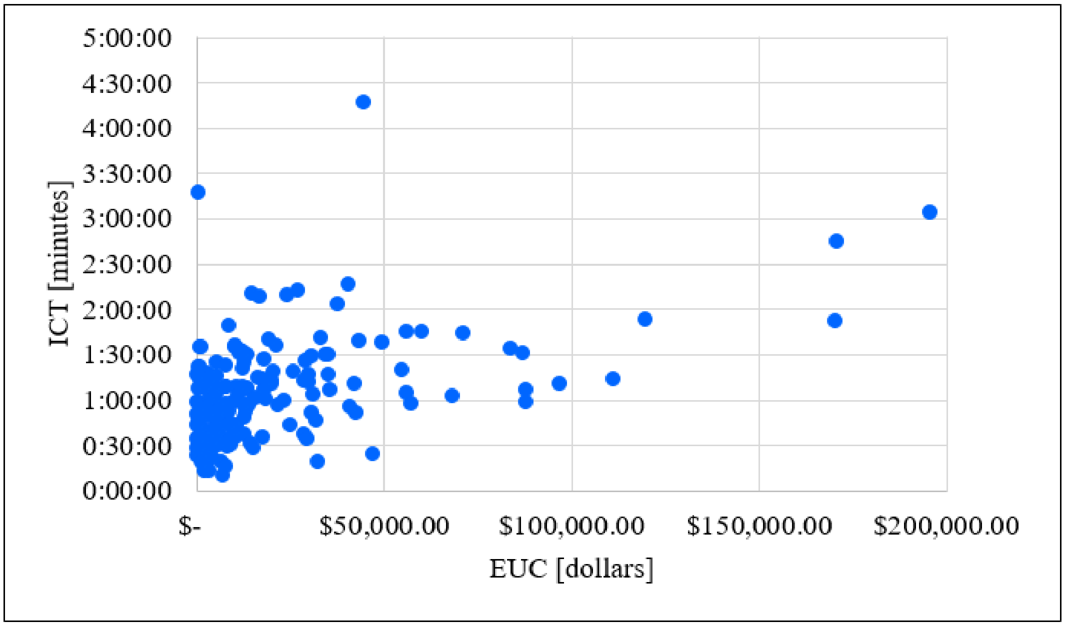


Figure 4-13: 2018 ICT vs. EUC.

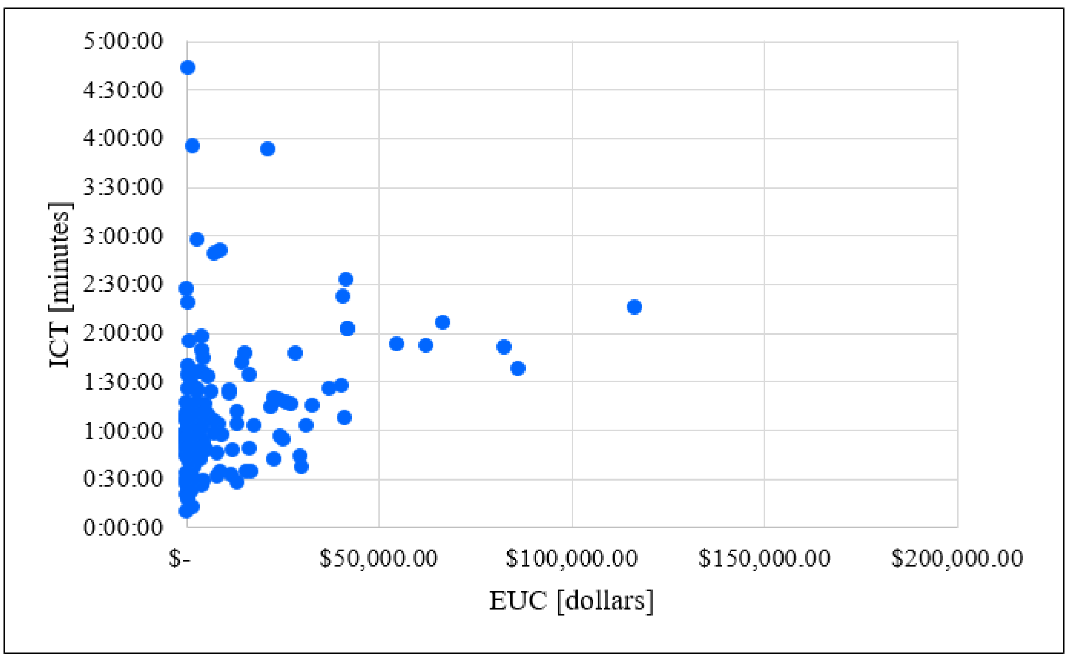


Figure 4-14: 2020 ICT vs. EUC.

For each scatter plot, the 2020 data points are grouped more closely together than those of the 2018 dataset. There are fewer extreme outliers in 2020 (as defined by the number of cases approaching $200,000.00) when compared to the 2018 data. Less scattering of data points in the 2020 plots suggests greater consistency in IMT performance in 2020 than in 2018. In the 2020 scatterplots, particularly RCT and ICT, there appears to be a trend of fewer large EUC outliers paired with more large performance measure outliers than in their respective 2018 scatterplots. This suggests that incidents required a longer time for the queue to grow in 2020 to incur the same EUC as in 2018. The inverse of this relationship is the cost per minute of RT, RCT, or ICT, resulting in a lower cost in 2020 than in 2018 per added minute of each respective performance measure that roadway users were stuck in traffic.

A lower cost per added minute of RT, RCT, or ICT in 2020 than in 2018 suggests that IMTs were more efficient in 2020 after the fleet was expanded, but these results cannot be interpreted outside of the context of low traffic volumes in 2020 caused by COVID-19. Because EUC is proportional to AV and ETT, the same relationships and trends for each performance measure vs EUC and cost per added minute of each performance measure exist for AV and ETT as EUC. A statistical analysis that accounts for the reduction in EUC due to the change in traffic volumes in 2020 is presented in Chapter 5.

The average EUC compared to the number of IMTs that responded to an incident appears to be a dependent relationship in 2018, and somewhat independent in 2020, as shown in Figure 4-15. While EUC generally increased with the number of IMTs that responded in 2018, this trend is only somewhat applicable in 2020 and for incidents with one, two, and three teams.

For incidents in 2020 with four teams present, EUC was lower than for those where one, two, or three teams were present. This trend is different from that of 2018, where the EUC for incidents with four teams was exponentially higher than the EUC of those incidents with one, two, or three teams. The EUC for incidents where four teams responded in 2018 was likely high due to the fact that there were fewer staffed IMTs before the expansion. However, the data trend is also potentially exaggerated due to a small sample size of incidents with four teams responding, with only three such incidents analyzed in 2018 and nine such incidents analyzed in 2020. The trend is also potentially exaggerated due to the severity and higher traffic volumes associated with incidents where four IMTs were required.

Though the EUC was relatively low in 2020, these data show that EUC was fairly consistent in 2020 compared to 2018, where the value of EUC fluctuated greatly depending on the number of IMTs that were required at the incident. It is likely that this trend in consistent values is linked to the program expansion and to the reduction in traffic volumes. Statistical analyses in Chapter 5 investigate these possibilities.

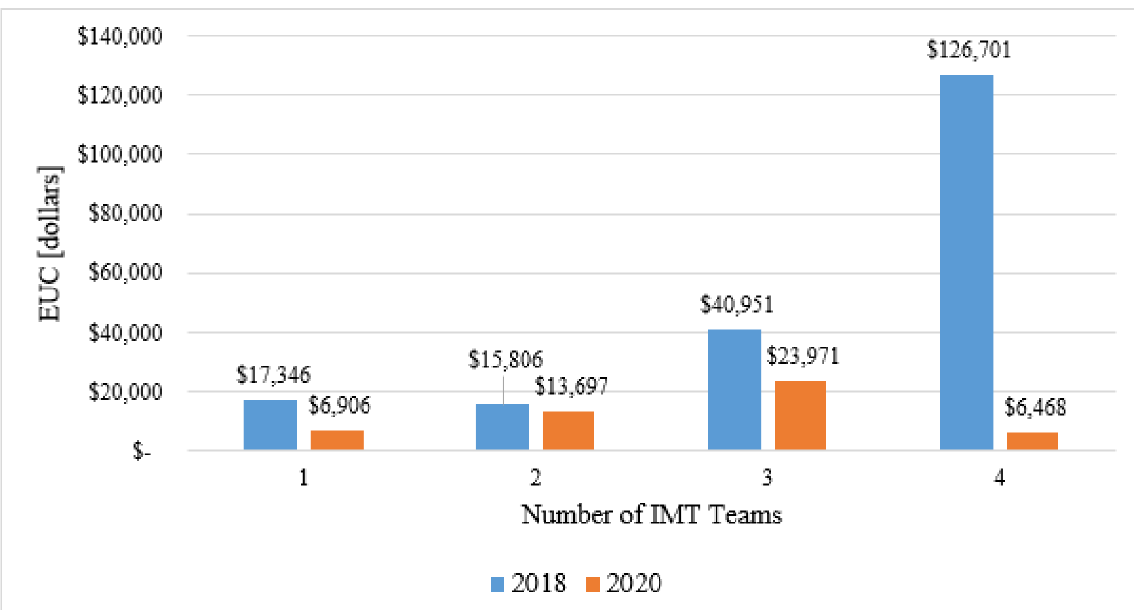


Figure 4-15: Comparison of average EUCs by number of responding IMTs.

The reductions in user impacts from 2018 to 2020 were apparent, partially due to the improvement in IMT performance and partially due to the effects of COVID-19. As shown in

Table 4-1, the averages of AV, ETT, and EUC were reduced by 28 percent, 43 percent, and 44 percent respectively between 2018 and 2020.

Table 4-1: Reductions in User Impacts Between 2018 and 2020

Performance Measure	2018 Average	2020 Average	% Reduction
AV [vehicles]	7,642	5,467	28%
ETT [minutes]	759.50	429.65	43%
EUC [$]	$19,532.78	$10,906.69	44%

The difference in EUC estimates between 2018 and 2020 was also stark for each individual crash type as shown in Table 4-2 and Table 4-3, respectively. It should be noted that these estimates of EUC can be considered conservative since they do not account for the cost of lost time for diverted traffic, rather just those vehicles that join the incident queue. The difference in EUC estimates and percent difference in EUC estimates between 2018 and 2020 are shown in Table 4-4 and Table 4-5.

The sample size of incidents able to be measured for EUC for PI and PDO incidents was greater in 2020 by 22 percent and 7 percent, respectively, but the sample size of incidents able to be measured for EUC for FII crashes was greater in 2018 by 40 percent, high due to a small sample size for both 2018 and 2020. Estimates for FII crashes were not included because only three were analyzed for EUC in 2018 and two in 2020, and these EUC values varied greatly.

Estimates for PI and PDO costs are more reliable and provide a more consistent baseline estimate of EUC accrued during each data collection period because these crash types occur much more frequently. Despite the higher number of incidents for which data were collected in

2020, the cost estimate over 6 months was still lower than that of 2018 due to the significantly lower average costs per crash in 2020.

Table 4-2: 2018 EUC Estimates

Crash Type	**Average Cost per Crash**	**Number of Crashes in 6 months**	**Cost Estimate over 6 months**
FII	-	10	-
PI	$ 20,610	285	$5,873,850
PDO	$ 16,576	779	$12,912,704
	Total	1,074	$18,786,554

Table 4-3: 2020 EUC Estimates

Crash Type	**Average Cost per Crash**	**Number of Crashes in 6 months**	**Cost Estimate over 6 months**
FII	-	6	-
PI	$11,759	347	$4,080,373
PDO	$9,597	837	$8,032,689
	Total	1,190	$12,113,062

Table 4-4: Differences in EUC Estimates Between 2018 and 2020

Crash Type	**Difference in Average Cost per Crash**	**Difference in the Number of Crashes in 6 Months**	**Difference in Cost Estimate over 6 months**
FII	-	4	-
PI	$8,851	-62	$1,793,477
PDO	$6,979	-58	$4,880,015
	Total	-116	$6,673,492

Table 4-5: Percent Difference in EUC Estimates Between 2018 and 2020

Crash Type	Percent Difference in Average Cost per Crash	Percent Difference in the Number of Crashes in 6 Months	Percent Difference in Cost Estimate over 6 Months
FII	-	40%	-
PI	43%	-22%	31%
PDO	42%	-7%	38%
	Total	-	36%

The difference in average cost per crash between 2018 and 2020 for PI and PDO crashes was $8,852 and $6,979, respectively, which equates to 43 percent and 42 percent, respectively. The difference in cost estimates over 6 months for PI and PDO crashes was $1,793,696 and $4,879,770, respectively. This equates to 31 percent and 38 percent respectively. Without accounting for the lower traffic volumes in 2020, EUC was significantly lower by crash type in 2020 than in 2018. When excluding FII crashes, PDO crashes accounted for the majority of the total costs due to the number of PDO crashes. The difference in total costs between 2018 and 2020 was $6,673,465, which equates to a 36 percent reduction.

4.5 Chapter Summary

With the methodology using CAD+TransSuite data, adequate incident data was able to be collected. In 2018, 1,074 incidents were analyzed for performance measures, with 28.5 percent of the incidents containing all three performance measures and 17.5 percent of the incidents meeting criteria to be analyzed for EUC. Of 1,190 incidents analyzed for performance measures in 2020, 23.5 percent contained all three performance measures and 12.1 percent met criteria to be analyzed for EUC.

For IMT performance measures, RT was lower in 2020 than in 2018, indicating that IMTs could consistently respond more quickly to incidents over a larger coverage area in 2020. IMT RCT slightly increased in 2020 compared to 2018, potentially due to the IMTs' increased focus on safety and increased coordination with UHP units at incidents. The difference in ICT between 2018 and 2020 was negligible.

User impacts were significantly lower in 2020 than in 2018. The cost per crash for PI and PDO crashes was lower by 43 percent and 42 percent, respectively, in 2020 than in 2018. The cost estimate over 6 months was $6,673,465 lower in 2020 than in 2018, equivalent to a decrease of 36 percent. The decrease in user impacts is likely influenced by improvements in IMT performance as a result of the program expansion. However, the results may still be biased due to the low traffic volumes in 2020 caused by the COVID-19 pandemic. These differences will be accounted for in the statistical analyses in Chapter 5.

5 RESULTS OF STATISTICAL ANALYSES

5.1 Overview

Statistical regression analyses were performed on the 2018 and 2020 datasets described in the previous chapter with the primary purpose of comparing the results of the two years. Analyses of the performance measures RCT and ICT, as well as the user impacts ETT and EUC, were run against a number of incident characteristics to determine any meaningful relationships between them. The incident characteristics used in the analyses include:

- The number of IMTs responding to the scene.
- The number of lanes in the roadway at the location of the bottleneck
- The number of lanes closed by IMT responders at the location of the incident
- The available lanes at the bottleneck (defined as the number of lanes closed at the incident location subtracted from the lanes in the roadway at the location of the bottleneck).
- The time of day when the incident occurred.

RCT and ICT were also analyzed against RT. User impacts were analyzed against RT, UHP RT, RCT, ICT, and UHP ICT performance measures. This study focused on performance of UDOT's IMTs, although UHP-related data were also analyzed. As mentioned previously, all references to ICT and RT in this report denote IMT ICT and RT, respectively. Analyses of UHP related data are included in Appendix C.

Since analyses of performance measures were run against incident characteristics for RCT and ICT but not for RT, the numbers of incidents analyzed for performance measures differ slightly from what appear in Table 3-5 and Table 3-6. Those tables show that in 2018 and 2020 there were respectively 306 and 280 incidents collected from CAD+TransSuite data that contained values of all three performance measures. However, the numbers of incidents analyzed for ICT and RCT are higher since it was not necessary to contain RT data for most of these analyses. Incidents were preferably collected that had all three performance measures available, but since there were fewer incidents with T_5 timepoints, some incidents that contained RCT values were still added to the incident database but not RT values, for instance, to ensure adequate sample sizes of RCT data. It should be noted that in most analyses of performance measures in this section, the standard error is greater in 2020 than in 2018, due to the fact that 320 incidents were analyzed for performance measures in 2018 and 289 incidents were analyzed for performance measures in 2020.

Statistical analyses of the RCT and ICT performance measures were performed for 320 incidents in 2018 and 289 incidents in 2020. The statistical analyses on performance measures made use of all incidents that had the required ICT or RCT values available, which is why the numbers of incidents analyzed for performance measures are greater than the number of incidents collected with all three performance measures. The

The analyses assumed a significance level, α, of 0.05. However, significance for the respective tests is shown by means of an asterisk scale denoted in Table 5-1 (Ramsey and Schafer 2013). Significance will be denoted in all analyses found in this chapter by means of these asterisks. In general, p-values ≤ 0.05 denote that a relationship may be considered significant, whereas p-values > 0.10 denote that a relationship may be considered not significant. However, p-values may suggest a significant relationship if they lie between 0.05 and 0.10.

Table 5-1: Significance Scale Notation

P-value	Significance	Evidence
$p \leq 0.0001$	****	Conclusive
$0.0001 < p \leq 0.01$	***	Convincing
$0.01 < p \leq 0.05$	**	Moderate
$0.05 < p \leq 0.10$	*	Suggestive
$p > 0.10$	ns	No evidence

In this table and all subsequent tables, "ns" means "not significant".

It should be noted that statistical significance does not always coincide with practical importance. There may be relationships that are shown to be significant that do not have much practical meaning to UDOT. There also may be relationships that are shown to be not significant statistically but still hold practical importance. For instance, an analyzed value of ETT of 300 minutes could potentially be reported as not significant due to the wide range of ETT values in the dataset. However, in reality 300 minutes of ETT is a substantial amount of time cost to the user. For that reason, practical importance should always be considered in conjunction with the significance reported here. Relationships included in this section are those that the research team deemed being practically important or of use in understanding the effects of the program expansion on performance measures and user impacts.

Due to the structure of the data collected and the added factor of the volume difference between 2018 and 2020 triggered by the COVID-19 pandemic, the statistical analyses for performance measures and user impacts were performed differently. As described previously in Section 3.3, the effect of COVID-19 on vehicular volumes had a greater impact on ETT and EUC than was initially expected. It was important to account for the volume difference when analyzing the user impacts so the results could uniquely reflect the change in the size of the IMT program between the two years. To accomplish this, a regression comparison of user impacts between 2018 and 2020 was performed to account for the volume difference. More details about this direct analysis will be provided in Section 5.3.

For the performance measure data, regression analyses were performed separately for the 2018 and 2020 data and then results were compared side-by-side. The research team assumed that the work performed by IMTs would not be directly affected by the queue size, or would more likely be affected by the nature and magnitude of crashes. This assumption allowed all incidents for which performance measures were collected to be included in the analysis even if they were not analyzed for user impacts, since volumes were only collected for those incidents that met certain criteria, as described in Chapter 3. The results of analyses on performance measures and user impacts will be described in the following sections.

5.2 Performance Measures

Analyses were run for both RCT and ICT. However, in most instances the RCT and ICT were highly correlated. This was the case both for 2018 and 2020, as shown in Figure 5-1 and Figure 5-2, which depict both the RCT and ICT for the incidents collected in each year. It can be seen from the figures that both performance measures tend to fall in the same range of minutes for the majority of incidents. For that reason, only the results of analyses for RCT are included in this section. Results for ICT are included in Appendix B.

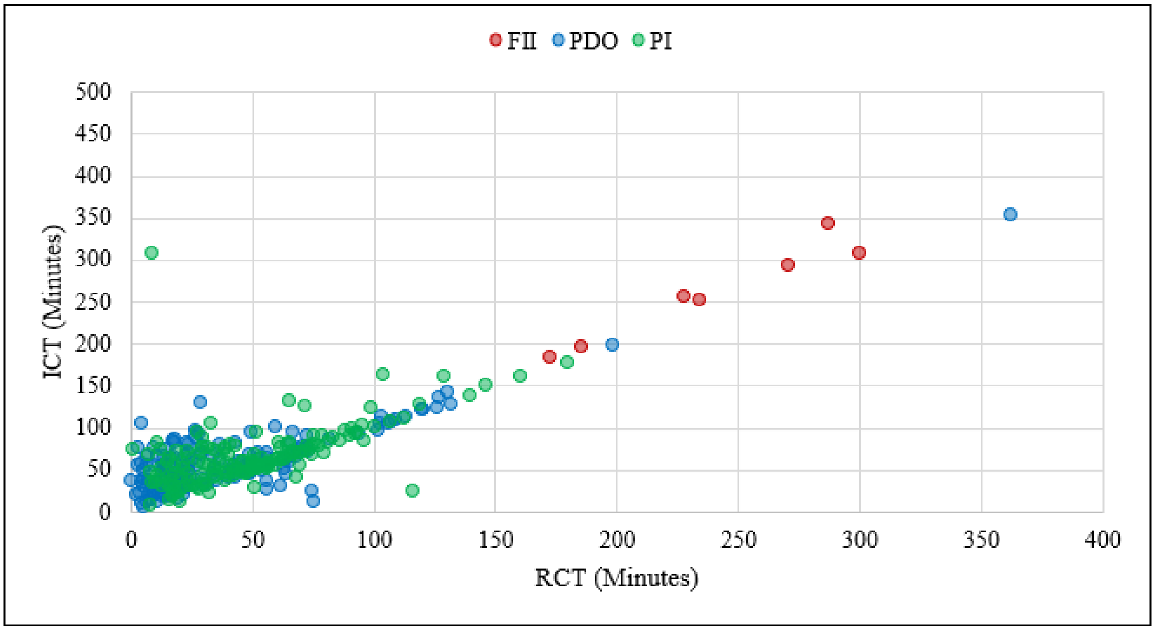


Figure 5-1: Linear relationship between RCT and ICT in 2018.

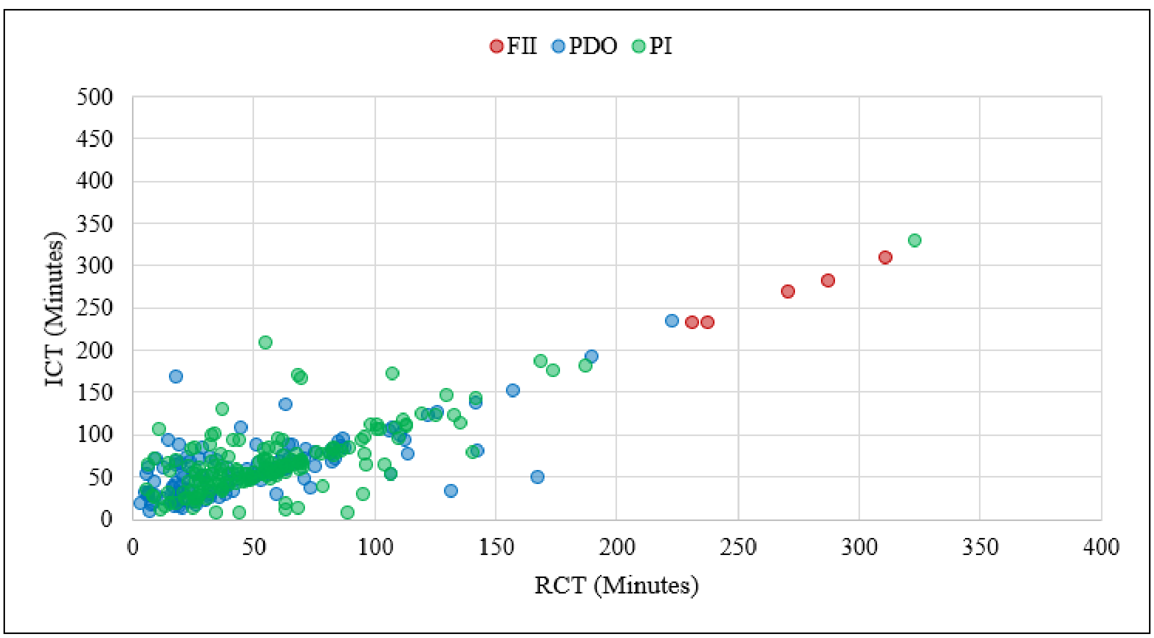


Figure 5-2: Linear relationship between RCT and ICT in 2020.

This section includes results of statistical analyses performed on RCT against a number of incident characteristics, including the number of IMTs responding to the scene, the number of lanes at the location of the bottleneck, the number of lanes closed by IMT responders, and the time of day when the incident occurred. An analysis was also performed on RCT against RT. The performance measures were analyzed to test for the fixed effects of each incident characteristic and for crash type, since severity is directly related to the on-scene requirements of the IMTs.

5.2.1 RCT vs. Number of IMTs

Table 5-2 and Table 5-3 show results for the analysis of RCT versus the number of IMTs responding to the scene.

Table 5-2: Significance of RCT vs. Number of IMTs

Are RCT values dependent on the number of IMTs?	Year	p > |t|	Significance
	2018	0.0195	**
	2020	<0.0001	****

Table 5-3: Analysis of RCT on Number of IMTs

Number of IMTs	Year	Mean RCT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
1	2018	104.21	93.90	114.53	5.24	191	314	<0.0001	****
	2020	121.05	109.43	132.68	5.90	172	280	<0.0001	****
2	2018	114.50	104.28	124.71	5.19	113	314	<0.0001	****
	2020	122.17	108.95	135.39	6.72	78	280	<0.0001	****
3	2018	131.18	108.82	153.54	11.37	13	314	<0.0001	****
	2020	148.36	131.47	165.26	8.58	27	280	<0.0001	****
4	2018	110.69	68.49	152.89	21.45	3	314	<0.0001	****
	2020	121.84	95.38	148.30	13.44	9	280	<0.0001	****
5	2020	177.00	104.26	249.74	36.95	1	280	<0.0001	****
6	2020	126.63	53.86	199.40	36.97	1	280	0.0007	***
8	2020	390.07	317.33	462.81	36.95	1	280	<0.0001	****

Note that in this table and in all that follow, SE refers to the standard error and DF refers to the degrees of freedom.

Table 5-2 describes the effect that the number of IMTs has on the RCT. The p-values in this table indicate the significance of the regression model. In this case low p-values indicate a good fit of the model, meaning that there is a significant difference in RCTs between incidents with differing numbers of IMT responders, both for 2018 and 2020. Table 5-3 shows estimates for the mean RCT by number of IMTs for both 2018 and 2020. The p-values in this table are not indications of model significance, but rather of the significance of individual estimates within the model. In this case, the low p-values associated with the estimated means, or model coefficients, all indicate that the estimates are significantly different from zero. The distinction between p-values of the regression models and of the model estimates is carried throughout the chapter. Tables following the general format of Table 5-2 provide p-values that indicate the significance of the regression models themselves, and tables fallowing the general format of Table 5-3 provide p-values that indicate the significance of model coefficients.

Table 5-3 also shows adequate sample sizes of incidents with one, two, and three IMTs in both 2018 and 2020. For incidents with four, five, six, and eight IMTs at an incident, the sample sizes are smaller and therefore the estimates are less reliable since smaller sample sizes tend to have a larger distribution than larger samples and are also typically more affected by outliers.

There was only one case each of incident scenarios where five, six, or eight IMTs responded to the scene in 2020, and none in 2018. Even though the estimates may be less reliable, the fact that UDOT's IMT program was capable of sending larger numbers of IMTs to incidents when needed is a good indication of the added flexibility and capability of the program after the expansion. It is likely that incidents occurred in 2018 for which five or more IMTs would have been beneficial, but the resources were either not available or spread too thinly to be of use when the need arose.

For both 2018 and 2020, there is a generally positive trend between the number of IMTs responding to the scene and the RCT for the incident. This can be seen clearly in Figure 5-3. The positive trend is a somewhat expected result, as the number of IMTs is likely related to severity of the incident. Values of RCT may be somewhat higher due to extraneous circumstances related to the COVID-19 pandemic, as discussed in Section 4.3. This consideration is at play in all the analyses of RCT in this section.

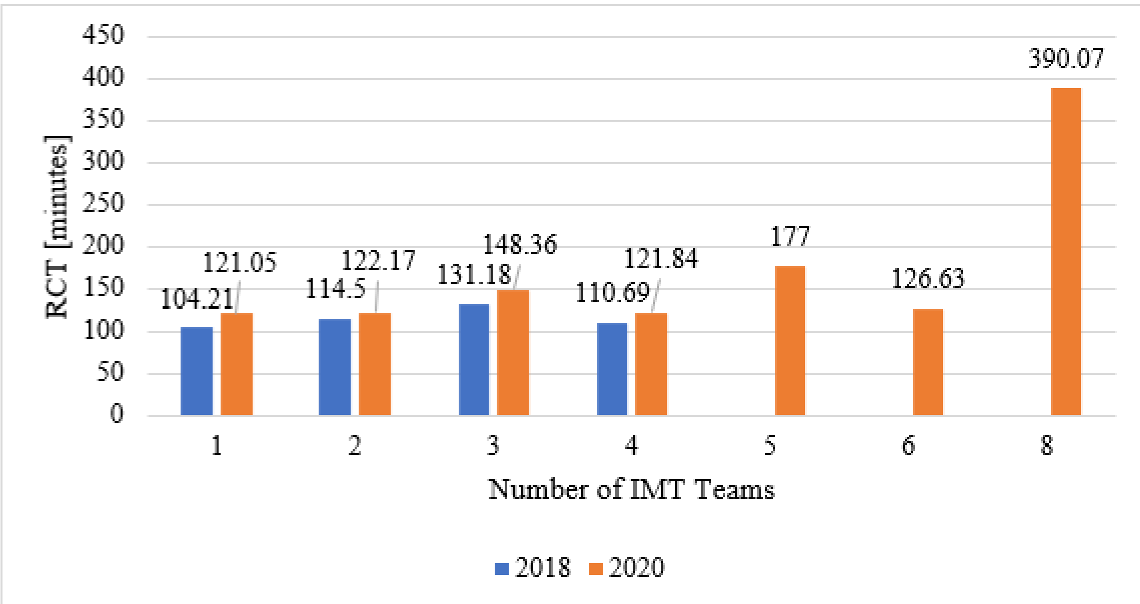


Figure 5-3: RCT vs. number of responding IMTs.

5.2.2 RCT vs. Number of Lanes at Bottleneck

Table 5-4 and Table 5-5 show results for the analysis of RCT versus the number of lanes in the direction corresponding to the crash at the location of the bottleneck. For example, if an incident occurred on an eight-lane freeway in the northbound direction, then there would be four lanes at the bottleneck.

Table 5-4: Significance of RCT vs. Number of Lanes at Bottleneck

	Year	p > |t|	Significance
Are RCT values dependent on the number of lanes at the bottleneck?	2018	0.411	ns
	2020	0.0765	*

Table 5-5: Analysis of RCT vs. Number of Lanes at Bottleneck

Lanes at Bottleneck	Year	Mean RCT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
1	2018	---	---	---	---	---	---	---	---
	2020	98.80	74.66	122.93	12.23	20	181	<0.0001	****
2	2018	124.33	69.25	179.40	27.91	1	182	<0.0001	****
	2020	130.57	101.46	159.68	14.75	4	181	<0.0001	****
3	2018	101.69	86.20	117.17	7.85	18	182	<0.0001	****
	2020	130.82	110.27	151.38	10.42	19	181	<0.0001	****
4	2018	92.74	79.08	106.41	6.93	39	182	<0.0001	****
	2020	137.57	117.76	157.37	10.04	31	181	<0.0001	****
5	2018	89.36	77.53	101.19	5.99	59	182	<0.0001	****
	2020	126.33	107.50	145.15	9.54	39	181	<0.0001	****
6	2018	93.19	80.64	105.75	6.36	64	182	<0.0001	****
	2020	127.64	111.13	144.15	8.37	73	181	<0.0001	****
7	2018	83.70	62.80	104.60	10.59	9	182	<0.0001	****
	2020	137.42	97.71	177.13	20.12	4	181	<0.0001	****

Table 5-4 indicates that in 2018 there was not any significant relationship between the number of lanes at the bottleneck and the RCT. In 2020 there is a suggestive but inconclusive relationship, indicating that the mean RCT from at least one lane configuration is different from the others. This result is likely due to the fact that for 2020 there is a low mean RCT for incidents with one lane at the bottleneck whereas the mean RCTs in 2020 for all other lane configurations are somewhat consistent.

There were no analyzed instances of crashes occurring at locations with only one lane at the bottleneck in 2018, which in this case would comprise single-lane freeway connector ramps.

Adequate samples are present for situations where three, four, five, and six lanes are present at the incident bottleneck, while less reliable results may be drawn from one, two, and seven-lane bottleneck situations. Table 5-5 indicates that the estimated means are significantly different from zero. Figure 5-4 provides a visual comparison of trends in mean RCTs by lane configuration for 2018 and 2020.

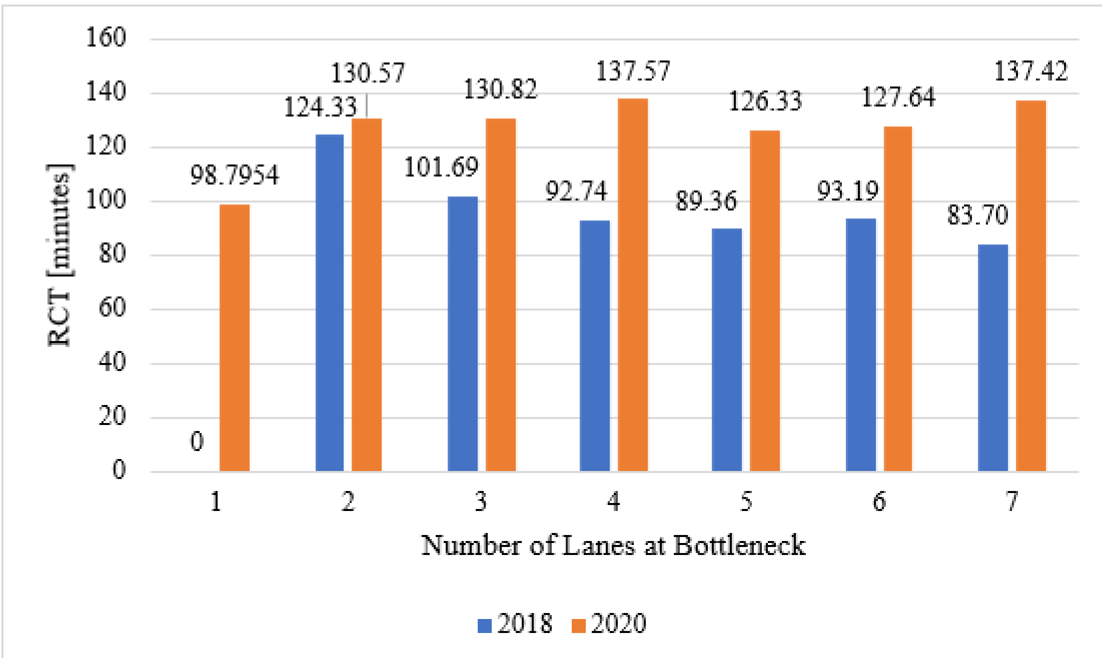


Figure 5-4: RCT vs. number of lanes at the bottleneck.

In Figure 5-4 there is a somewhat downward trend for 2018 RCT as the number of the lanes at the bottleneck increases. This could be due to a number of reasons. Higher speeds in less congested areas away from the urban centers, such as where two or three lanes exist at the bottleneck, could lead to more severe incidents that require more clearance work. This trend could also emphasize the fact that the urban areas of Regions 2 and 3 were the focus of IMT work prior to the expansion, whereas the larger program in 2020 may be more capable of reaching and clearing incidents more on the periphery of these urban areas. The RCTs are higher overall in 2020, likely because of COVID-19, but RCT values are also more stable across the range of bottleneck lane numbers in 2020 than in 2018, indicating that the expanded program is more flexible in responding to incidents as needed.

5.2.3 RCT vs. Number of Lanes Closed

Table 5-6 and Table 5-7 show results for the analysis of RCT versus the number of lanes closed by IMTs. The number of lanes closed is an indication of the magnitude of an incident.

Table 5-6: Significance of RCT vs. Number of Lanes Closed

	Year	p > |t|	Significance
Are RCT values dependent on the number of lanes closed?	2018	0.0159	**
	2020	0.0001	****

Table 5-7: Analysis of RCT vs. Number of Lanes Closed

Lanes Closed	Year	Mean RCT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
1	2018	103.42	91.89	114.96	5.86	170	312	<0.0001	****
	2020	111.66	97.90	125.42	6.99	127	255	<0.0001	****
2	2018	106.33	93.99	118.66	6.27	82	312	<0.0001	****
	2020	128.26	114.10	142.42	7.19	75	255	<0.0001	****
3	2018	119.87	106.26	133.48	6.92	50	312	<0.0001	****
	2020	132.13	115.27	148.99	8.56	37	255	<0.0001	****
4	2018	116.32	94.66	137.97	11.01	13	312	<0.0001	****
	2020	137.89	118.75	157.03	9.72	21	255	<0.0001	****
5	2018	147.24	110.47	184.01	18.69	4	312	<0.0001	****
	2020	214.16	157.96	270.36	28.54	2	255	<0.0001	****
6	2018	61.53	-14.07	137.12	38.42	1	312	0.1103	ns
	2020	112.52	33.74	191.30	40.00	1	255	0.0053	***

Table 5-6 indicates that there is a significant relationship between RCT and the number of lanes closed for both 2018 and 2020. Table 5-7 indicates that there were adequate sample sizes of incidents for which one, two, three, or four lanes were closed, with much smaller samples of incidents with five or six lanes closed. Trends in the data can be seen in Figure 5-5.

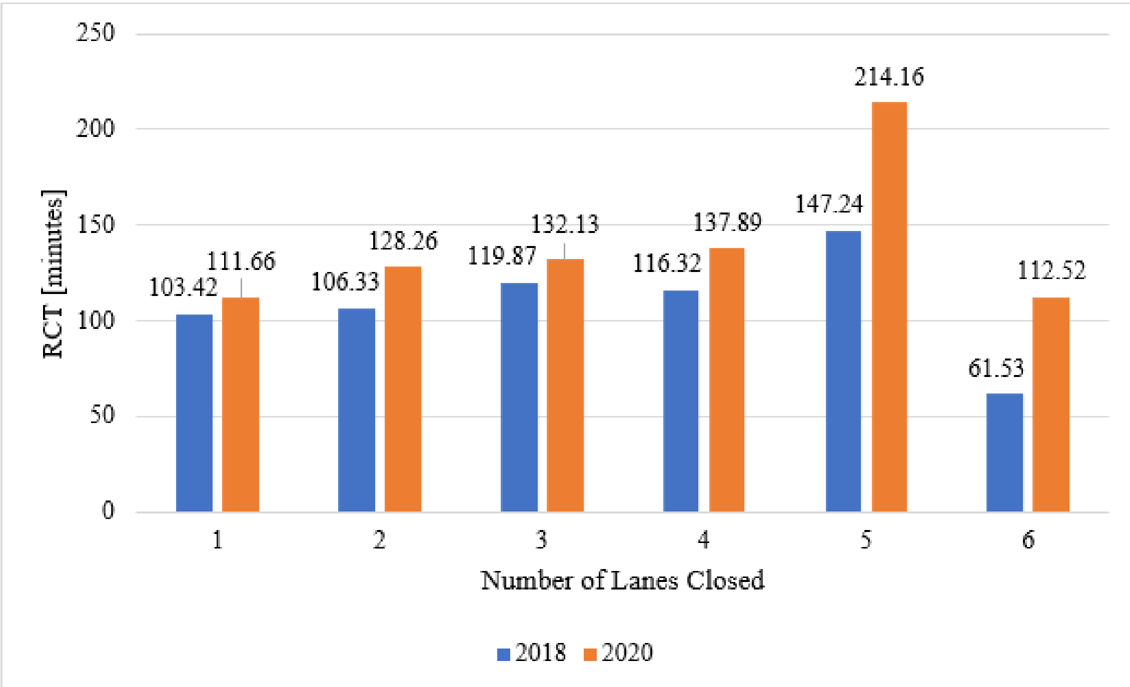


Figure 5-5: RCT vs. number of lanes closed.

There is a slight upward trend in RCT as the number of lanes closed increases, which is an expected result given that lane closures require more work from the IMTs.

5.2.4 RCT vs. Number of Available Lanes

An analysis of RCT was also performed in relation to the number of available lanes. However, this parameter ignores the temporal aspect of IMT work. For instance, an incident may have different lanes closed at different times, such as is the case of the incident shown in Figure 5-6. The analysis performed on available lanes considers the number of lanes closed for at least some period of time at some point during the incident. For instance, in Figure 5-6, the available lanes for this incident would be three, though for a large part of the incident duration there were four lanes available. For that reason, the number of available lanes may not be a helpful factor to consider in all scenarios.

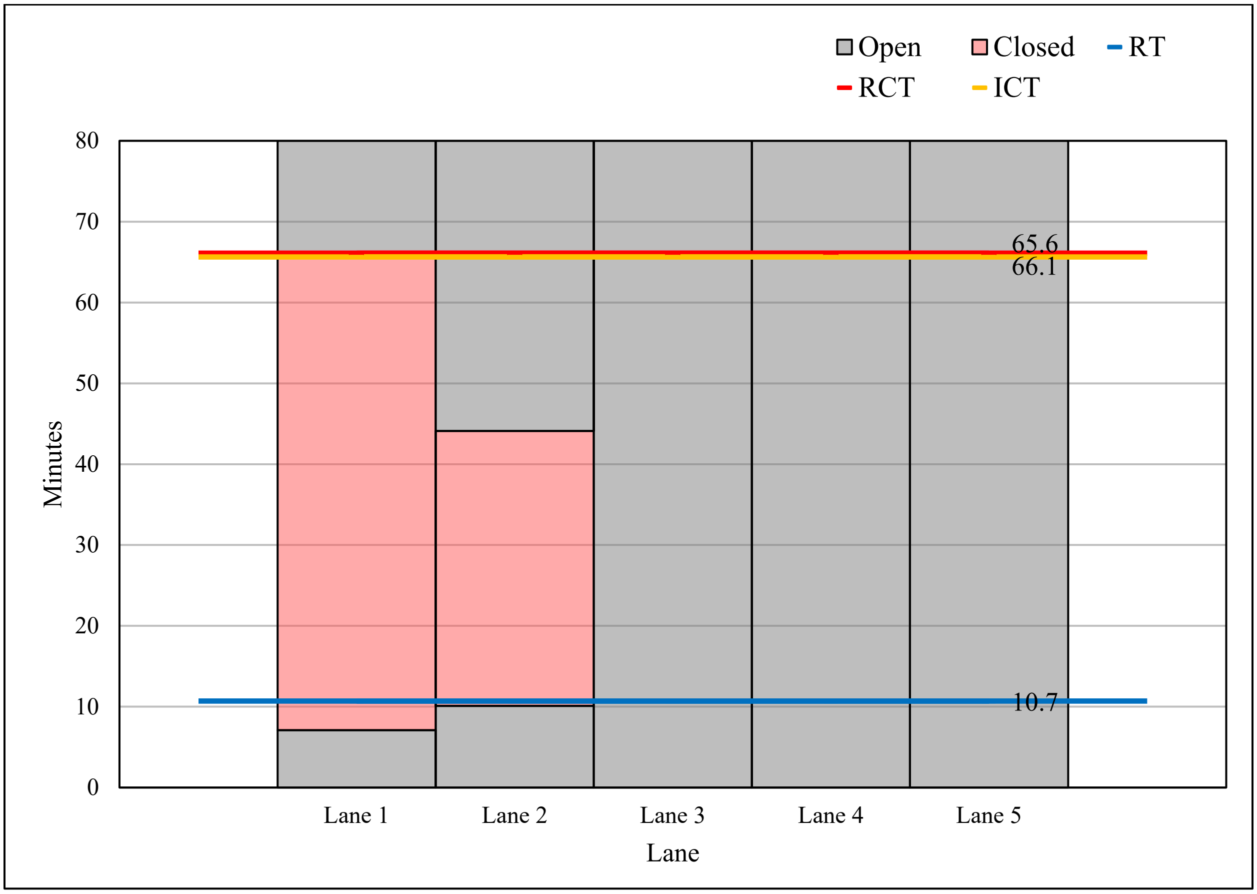


Figure 5-6: Incident visualization showing time length of lane closures.

Table 5-8 and Table 5-9 show results for the analysis of RCT versus the number of lanes available at the location of the incident. Figure 5-7 shows a visual representation of the results.

Table 5-8: Significance of RCT vs. Number of Available Lanes

	Year	p > |t|	Significance
Are RCT values dependent on the number of available lanes?	2018	0.0118	**
	2020	0.0321	**

Table 5-9: Analysis of RCT on Number of Available Lanes

Available Lanes	Year	Mean RCT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
0	2018	108.08	90.93	125.23	8.69	8	181	<0.0001	****
	2020	112.89	92.22	133.57	10.48	30	180	<0.0001	****
1	2018	90.94	75.34	106.54	7.91	17	181	<0.0001	****
	2020	133.23	109.66	156.79	11.94	22	180	<0.0001	****
2	2018	95.39	80.46	110.31	7.57	27	181	<0.0001	****
	2020	137.08	115.68	158.47	10.84	25	180	<0.0001	****
3	2018	92.45	79.46	105.44	6.58	57	181	<0.0001	****
	2020	129.10	108.46	149.75	10.46	45	180	<0.0001	****
4	2018	80.93	67.47	94.38	6.82	45	181	<0.0001	****
	2020	115.89	94.96	136.82	10.61	41	180	<0.0001	****
5	2018	77.76	62.86	92.66	7.55	27	181	<0.0001	****
	2020	107.01	83.93	130.09	11.70	24	180	<0.0001	****
6	2018	77.92	55.20	100.64	11.52	7	181	<0.0001	****
	2020	103.60	49.05	158.14	27.64	2	180	0.0002	***

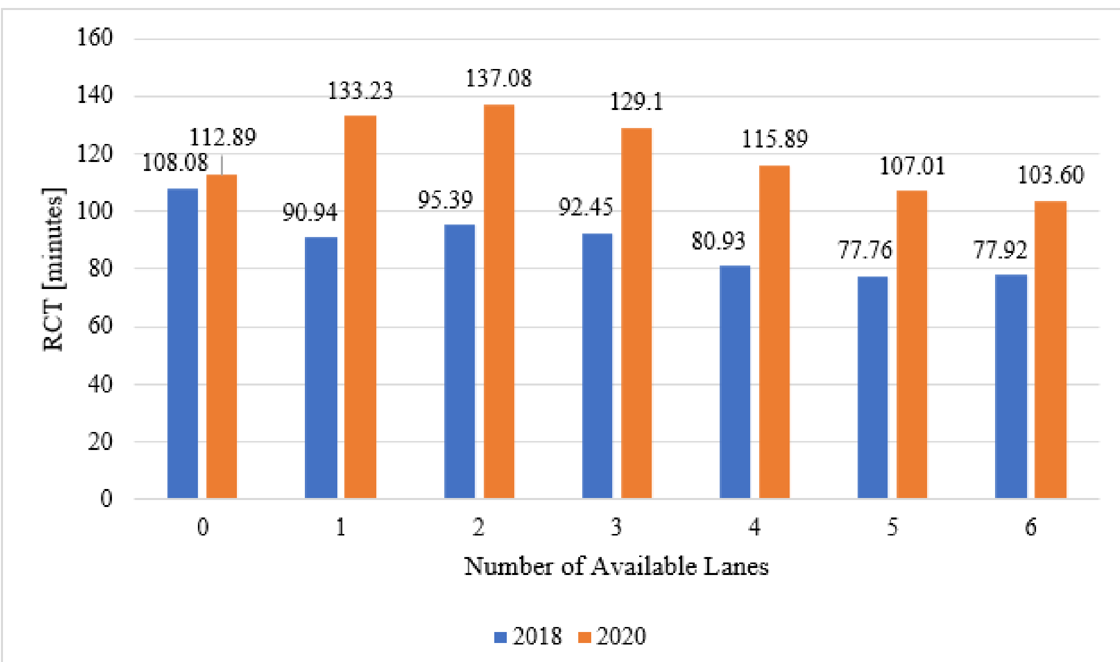


Figure 5-7: RCT vs. number of available lanes.

Table 5-8 indicates that there is a significant relationship between RCT and the number of available lanes both in 2018 and in 2020. There is a somewhat even spread of samples with the respective number of lane closures.

Those incidents with zero available lanes are those in which all lanes of the roadway must be blocked off. For these incidents it is expected that there will be significant delay, though lower delay may actually be shown for the duration of the incident due to the fact that volumes passing the bottleneck are zero during the time when all lanes are closed. Drivers may also be warned in advance of the shutdown and take detours. The trend of lower RCTs as the number of available lanes increases is an expected result, since a lower number of lane closures generally means less work for the IMTs to perform.

5.2.5 RCT vs. Time of Day

Incidents were organized into bins depending on the time that the incident occurred since different times of day experience different travel patterns. IMT members' work shifts also fluctuate over the course of the day. The bins for the respective times of day considered were previously shown in Table 3-1 and are shown again in Table 5-10 for convenience. Table 5-11 and Table 5-12 show results for the analysis done of RCT versus the time of day of the incident. Figure 5-8 shows a visual representation of the results.

Table 5-10: Time of Day of Incidents

Morning Off Peak	12:00 A.M. to 6:30 A.M.
AM Peak	6:30 A.M. to 9:10 A.M.
Afternoon Off Peak	9:10 A.M. to 3:50 P.M.
PM Peak	3:50 P.M. to 6:30 P.M.
Night Off Peak	6:30 P.M. to 11:59 P.M.

Table 5-11: Significance of RCT vs. Time of Day

Are RCT values dependent on the time of day?	**Year**	**p > |t|**	**Significance**
	2018	<0.0001	****
	2020	0.002	***

Table 5-12: Analysis of RCT vs. Time of Day

Time of Day	Year	Mean RCT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
Morning Off Peak	2018	155.61	130.05	181.18	12.99	8	313	<0.0001	****
	2020	150.65	130.17	171.13	10.41	19	282	<0.0001	****
AM Peak	2018	85.64	72.35	98.93	6.76	87	313	<0.0001	****
	2020	118.60	101.85	135.35	8.51	44	282	<0.0001	****
Afternoon Off Peak	2018	95.80	83.71	107.88	6.14	134	313	<0.0001	****
	2020	128.99	114.91	143.06	7.15	113	282	<0.0001	****
PM Peak	2018	84.44	71.17	97.70	6.74	88	313	<0.0001	****
	2020	113.43	99.08	127.79	7.29	83	282	<0.0001	****
Night Off Peak	2018	188.53	146.33	230.73	21.45	3	313	<0.0001	****
	2020	126.16	109.71	142.60	8.36	30	282	<0.0001	****

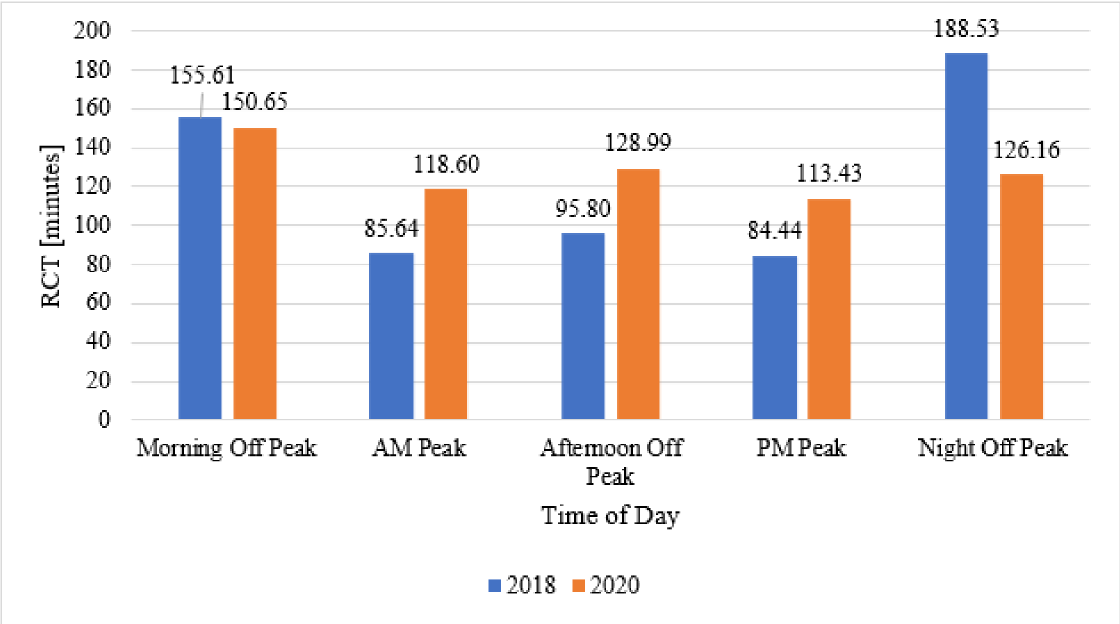


Figure 5-8: RCT vs. time of day.

The statistics in Table 5-11 indicate that in both 2018 and 2020 there is a significant relationship between RCT and time of day when the incident occurs. Table 5-12 shows adequate samples in 2018 and 2020 for AM Peak, Afternoon Off Peak, and PM Peak periods. Much lower samples were found in the Morning Off Peak and Night Off Peak. However, it should be noted that the sample size of incidents serviced by IMTs during these periods was much greater in 2020 than in 2018. In 2018, eight analyzable incidents occurred during the Morning Off Peak period and three occurred during the Night Off Peak. The 2020 Morning Off Peak sample more than doubled to 19, while the Night Off Peak increased tenfold to 30. This is a clear indication that there is a need for IMT services outside of previously established operating hours, and that the program expansion has allowed UDOT to meet those needs.

Figure 5-8 clearly shows larger RCTs for incidents that occur in the off-peak periods, particularly the Morning and Night Off Peaks. This result could be explained in a number of ways. Off peak periods are likely less congested, which may lead to higher speeds and more serious crashes, requiring more extensive clean-up efforts. However, this analysis accounted for crash type, so this should not be the primary explanation. It is more likely that a lower number of units on patrol outside of the peak periods results in longer RT before beginning to clear the roadway. As previously stated, AV may not have a sizeable impact on the performance of IMTs, since the queue length does not directly affect the work that IMTs perform.

Given this context, the difference between 2018 and 2020 is likely representative of the ability of the IMT program to reach more incidents in a timely manner after the program expansion. RCTs are much more consistent in 2020 regardless of the time of day when the incidents occur when compared with 2018.

5.2.6 RCT vs. RT

An analysis was also run comparing the RCTs in 2018 and 2020 to the distribution of RTs for each year. Table 5-13 is a statistical output that shows the solution for fixed effects of the regression analysis run on RT and crash type for the 2020 dataset. Table 5-14 shows a summary of the results of the analysis of RCT versus RT.

Table 5-13: Solution of Fixed Effects for Regression of RCT vs. RT and Crash Type

Effect	Crash Type	Estimate	Lower	Upper	SE	DF	t Value	p > |t|	Significance
Intercept		52.87	44.23	61.53	4.39	271	12.04	<0.0001	****
Crash Type	FII Crash	189.61	150.82	228.41	19.71	271	9.62	<0.0001	****
Crash Type	PDO Crash	-8.45	-18.28	1.36	4.99	271	-1.7	0.0912	*
Crash Type	PI Crash	0	.	.	.	.	.	.	.
RT		0.50	0.09	0.91	0.21	271	2.43	0.0159	**

Table 5-14: Analysis of RCT on RT

Year	Mean RCT per minute RT	Lower	Upper	SE	Sample Size	p > |t|	Significance
2018	0.82	0.56	1.07	0.13	303	<0.0001	****
2020	0.50	0.09	0.91	0.21	275	0.0159	**

Table 5-13 gives an example of the full regression, in this case on the 2020 dataset. The significance shown in the table indicates whether or not each variable has a significant effect on the RCT estimate after all other variables are held constant, or fixed. An equation for this regression can be drawn from the fixed effects as shown in Equation 5-1:

$$RCT\ (minutes) = 52.87 + 189.61 * FII\ Crash - 8.45 * PDO\ Crash + 0.50 * RT(minutes), \tag{5-1}$$

where PI Crash is a reference level and where both FII Crash (yes = 1, no = 0) and PDO Crash (yes = 1, no = 0) are indicator variables.

Table 5-14 indicates that after accounting for crash type, there is still a significant effect of RT on RCT for both 2018 and 2020. For 2018, each added minute of RT translates to about 0.8 minutes of added RCT. For 2020, this value is about 0.5 minutes of RCT per minute of RT. This analysis is statistically significant but the results are expected since both RT and RCT begin at T_1, so the analysis may not be of great practical importance on its own.

However, fewer minutes of RCT per minute of RT in 2020 could be due to a couple of reasons. This result would occur if there were equal RCTs in 2018 and 2020 with longer RTs in 2020, or if there were equal RTs in 2018 and 2020 with shorter RCTs in 2020. It has been shown, however, that both of these scenarios are not the case. The program expansion has shifted the distribution of RT towards quicker responses, and other analyses have shown that RCT is slightly larger on average in 2020 than in 2018. A likely explanation is that the expanded program is now able to service a number of smaller incidents that may not have been prioritized in 2018 with fewer resources available compared to 2020. This regression shows that RCT cannot be described solely by crash type, but that RT also has an effect on the time it takes to clear the lanes at the scene of the incident.

5.3 User Impacts

The results of the statistical analyses performed on the user impacts gathered in 2018 and 2020 are shown in this section. Analyses were run for both ETT and EUC. Because the EUC is calculated as a function of ETT, these two values are very well correlated. However, results are shown separately since it is beneficial to see impacts of incidents in terms of both time and cost.

This section includes results of statistical analyses of ETT and EUC versus a number of incident characteristics, including the number of IMTs responding, the number of lanes at the location of the bottleneck, the number of lanes closed by IMT responders, and the time of day when the incident occurred. These characteristics were all included as indicator variables. Analyses of ETT and EUC were also performed against the performance measures RT, RCT, and ICT, which are continuous variables.

All analyses of user impacts were adjusted for crash type, as was the case with the performance measures analysis. However, it was also necessary to adjust the analyses of user impacts for volumes, given the volume difference between 2018 and 2020 caused by COVID-19. While the regression analysis of performance measures was done separately for the 2018 and 2020 datasets and the results compared side by side, a direct regression of the two years was necessary to account for the volume difference in the user impacts analysis.

These analyses of user impacts were run to test for the fixed effects of each incident characteristic like the performance measures analyses, but accounted for more than simply crash type. Whereas t-tests were run on the performance measure data to compare the means of performance measures for 2018 and 2020, F-tests are used on the user impact data to compare the variances of each user impact for 2018 and 2020. These F-tests are appropriate for the regression analyses being performed on the user impact data.

Regression of each incident characteristic was adjusted for the fixed effects of crash type as well as AV, year, and the interaction between year and the incident characteristic. Inclusion of the interaction term between the year and each incident characteristic allowed the research team to obtain an estimate of the unique effect of the program size on the user impacts and evaluate the benefits of the program expansion.

5.3.1 ETT and EUC vs. Number of IMTs

Table 5-15 and Table 5-16 are statistical outputs that show the fixed effects of the regression analyses of ETT and EUC versus the number of IMTs responding to the scene, respectively, for both 2018 and 2020 combined.

Table 5-15: Fixed Effects for Regression of ETT vs. Number of IMTs

Effect	Num. DF	Den. DF	F Value	p > F	Significance
AV	1	323	187.68	<0.0001	****
Crash Type	2	323	3.16	0.0436	**
Year	1	323	46.18	<0.0001	****
Number of IMTs	3	323	19.76	<0.0001	****
Year * Number of IMTs	3	323	18.92	<0.0001	****

In this table and all that follow, Num. DF and Den. DF refer to numerator and denominator degrees of freedom, respectively.

Table 5-16: Fixed Effects for Regression of EUC vs. Number of IMTs

Effect	Num. DF	Den. DF	F Value	p > F	Significance
AV	1	323	178.22	<0.0001	****
Crash Type	2	323	3.15	0.0442	**
Year	1	323	48.33	<0.0001	****
Number of IMTs	3	323	20.60	<0.0001	****
Year * Number of IMTs	3	323	19.90	<0.0001	****

The tables show results of F-tests performed to show whether each effect had an impact on ETT and EUC after accounting for the effect of all other variables. For instance, with p-values < 0.0001, it is shown that the AVs associated with incidents have a significant effect on the ETT and EUC, all other variables held constant. This result demonstrates the expected relationship between the size of the queue and the travel time added due to the incident. Both ETT and EUC for the crash type effect also have a significant impact after adjusting for all other variables. All other fixed effects can be interpreted in a similar manner.

The focus of these analyses, however, is the interaction term between the incident characteristic and year, which by holding all other effects constant describes the difference in ETT and EUC between 2018 and 2020 due to the program size. Table 5-15 and Table 5-16 show with conclusive evidence (p-value < 0.0001) that there is a difference in ETT and EUC between 2018 and 2020 depending on the number of IMTs after accounting for the volume difference caused by COVID-19. The expansion of the IMT program does have an effect on ETT and EUC, even after removing the effect of the difference in traffic volumes in 2018 and 2020.

Therefore, to focus on the effects of the program expansion on IMT operations, the additional analyses in this section will focus solely on the effect of the interact term on user impacts, following the format of Table 5-17 and Table 5-18, which show the significance of program size on the incident characteristic. Estimates that follow are the least squares averages of ETT and EUC for each incident characteristic and are the estimates solely attributed to the interaction term, which indicates the effects of program size.

Table 5-17: Significance of IMT Program Size vs. ETT for Number of IMTs

Does the difference in ETT between 2018 and 2020 depend on the number of IMTs, after accounting for volume differences?	**p > F**	**Significance**
	<0.0001	****

Table 5-18: Significance of IMT Program Size vs. EUC for Number of IMTs

Does the difference in EUC between 2018 and 2020 depend on the number of IMTs, after accounting for volume differences?	**p > F**	**Significance**
	<0.0001	****

Table 5-19 and Table 5-20 respectively show summarized results for the analyses of ETT and EUC versus the year and the number of IMTs responding to the scene. Scenarios with one, two, three, and four responding IMTs are included in this analysis because there were no such instances in 2018 where more than four IMTs responded, and those instances in 2020 did not meet criteria to be analyzed for ETT and EUC.

Table 5-19: Analysis of IMT Program Size vs. ETT for Number of IMTs

Number of IMTs	Mean ETT for 2018	Mean ETT for 2020	Difference in Means	Sample Size	SE	p > |t|	Significance
1	774.89	722.62	52.69	189	106.86	0.625	ns
2	816.56	879.16	-62.60	111	134.70	0.642	ns
3	1401.50	906.41	495.08	23	314.28	0.116	ns
4	4399.96	771.37	3628.60	11	483.49	<0.0001	****

Table 5-20: Analysis of IMT Program Size vs. EUC for Number of IMTs

Number of IMTs	Mean EUC for 2018	Mean EUC for 2020	Difference in Means	Sample Size	SE	p > |t|	Significance
1	$20,100	$19,027	$1,073	189	$2,484	0.7060	ns
2	$21,483	$22,834	-$1,351	111	$3,585	0.707	ns
3	$36,464	$23,415	$13,049	23	$8,364	0.12	ns
4	$119,293	$20,080	$99,213	11	$12,867	<0.0001	****

Table 5-19 and Table 5-20 show similar results. The sample size for incidents with four IMTs was small, with three and eight such incidents in 2018 and 2020, respectively. These incidents had a large spread of AV and ETT values, and thus the ETT and EUC estimates from the interaction term may not be reliable. Interpretation of cases where one, two, or three IMTs responded are safer to interpret. The difference in means between the two years is the mean of 2020 subtracted from the mean of 2018, so a positive difference indicates that ETT and EUC were reduced in 2020. The different effects of year on ETT and EUC between 2018 and 2020 can best be seen visually, as shown in Figure 5-9 and Figure 5-10.

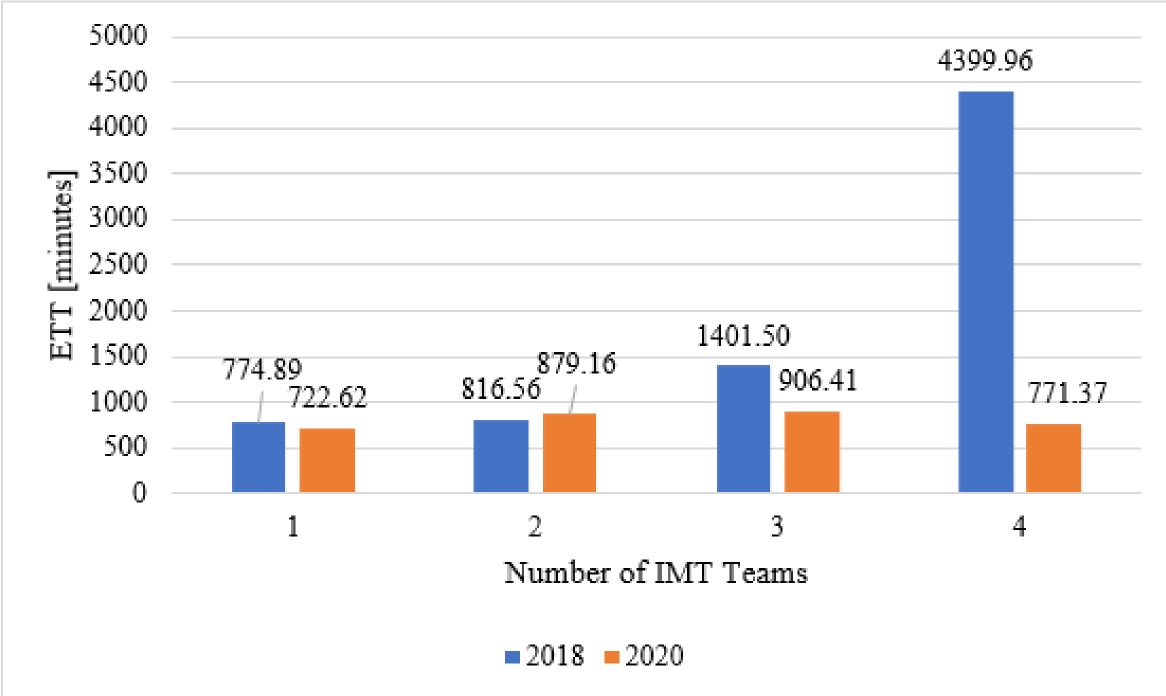


Figure 5-9: Estimates of ETT vs. year and number of IMTs.

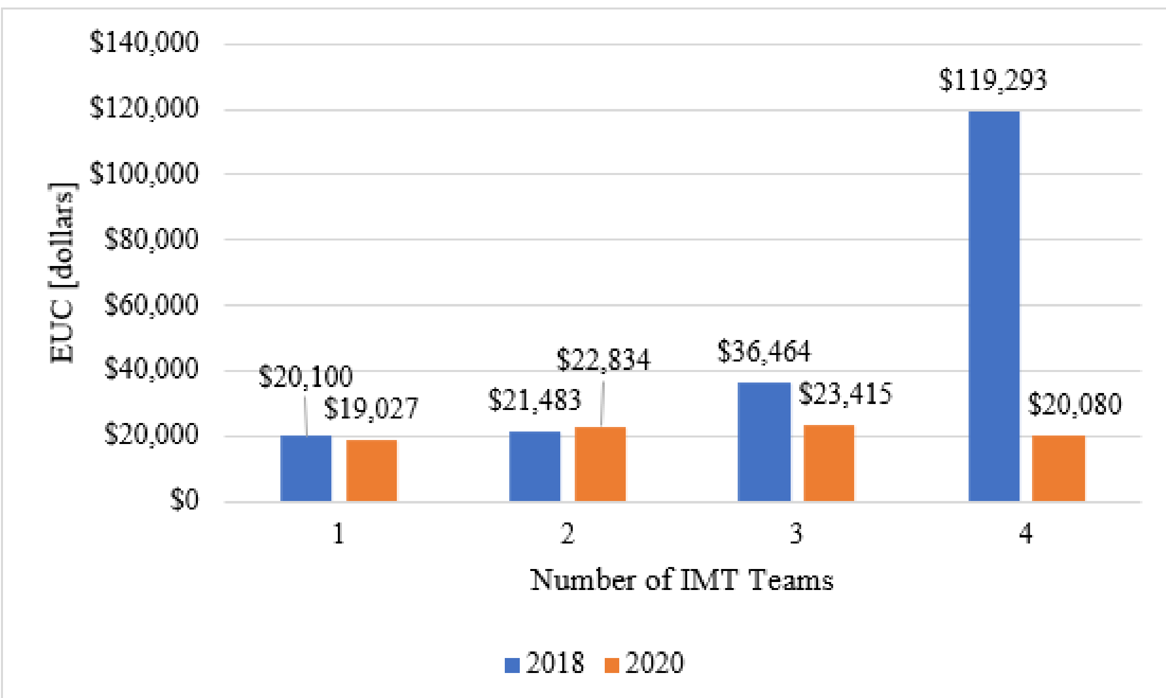


Figure 5-10: Estimates of EUC vs. year and number of IMTs.

The figures indicate that regardless of the number of IMTs in the program, IMTs are able to similarly respond to incidents where one or two teams are required. Where three or four IMTs are required at the scene, the program is shown to be capable of responding to incidents in such a way that results in lower ETT and EUC. This could be due to a number of components, including the sample size of these types of crashes. For instance, in the 2018 sample there were 10 incidents with three or four IMTs present, whereas in 2020 there were 24 such incidents. However, it should be reiterated that the difference in volumes between 2018 and 2020 has already been accounted for in the fixed effects.

The estimates of EUC shown in Table 5-20 and Figure 5-10 represent the impact of program size after accounting for all other fixed effects. Having a greater number of IMTs available does have direct benefits in reducing ETT and EUC. Additionally, ETT and EUC are much more consistent in 2020 than in 2018, indicated by the fact that their respective values stay largely the same regardless of the number of teams responding. Having more IMTs does not mean that the program can necessarily clear all incidents faster, but it does provide the capability of clearing all incidents more consistently. This pattern of consistent ETT and EUC is corroborated in the analysis of ETT and EUC versus the number of lanes closed.

5.3.2 ETT and EUC vs. Number of Lanes at Bottleneck

Statistical analysis proved that there was no relationship between ETT or EUC and the number of lanes at the bottleneck, as indicated in Table 5-21 and Table 5-22.

Table 5-21: Significance of IMT Program Size vs. ETT for Lanes at Bottleneck

	p > F	Significance
Does ETT between 2018 and 2020 depend on the number of lanes at the bottleneck, after accounting for volume differences?	0.8237	ns

Table 5-22: Significance of IMT Program Size vs. EUC for Lanes at Bottleneck

	p > F	Significance
Does EUC between 2018 and 2020 depend on the number of lanes at the bottleneck, after accounting for volume differences?	0.8779	ns

The fact that the number of lanes at the bottleneck has no significant effect on ETT or EUC indicates that incidents are not served better by the expanded program than the program in 2018 based on roadway geometry alone. It is more likely that crash severity has a greater impact on accrual of ETT and EUC at an incident.

5.3.3 ETT and EUC vs. Number of Lanes Closed

Table 5-23 through Table 5-26 show results for the analysis of ETT and EUC versus the number of lanes closed by IMTs at the location of the incident. The effect of program size on ETT and EUC with respect to the number of lanes closed is shown in Table 5-23 and Table 5-24. Estimates of the differences in ETT and EUC between the two years for each respective number of lanes closed are shown in Table 5-25 and Table 5-26.

Table 5-23: Significance of IMT Program Size vs. ETT for Lanes Closed

	p > F	Significance
Does ETT between 2018 and 2020 depend on the number of lanes closed, after accounting for volume differences?	<0.0001	****

Table 5-24: Significance of IMT Program Size vs. EUC for Lanes Closed

Does EUC between 2018 and 2020 depend on the number of lanes closed, after accounting for volume differences?	p > F	Significance
	<0.0001	****

Table 5-25: Analysis of IMT Program Size vs. ETT for Lanes Closed

Lanes Closed	Mean ETT for 2018	Mean ETT for 2020	Difference in Means	Sample Size	SE	p > |t|	Significance
1	756.42	867.77	-111.35	140	123.84	0.369	ns
2	1045.46	1023.20	22.2575	104	137.01	0.871	ns
3	1393.61	1068.48	325.12	61	183.04	0.077	*
4	2688.21	862.73	1825.48	25	286.36	<0.0001	****
6	-217.87	943.58	-1161.45	2	1044.5	0.2670	ns

Table 5-26: Analysis of IMT Program Size on EUC for Lanes Closed

Lanes Closed	Mean EUC for 2018	Mean EUC for 2020	Difference in Means	Sample Size	SE	p > |t|	Significance
1	$20,307	$22,913	-$2,606	140	$3,313	0.432	ns
2	$27,509	$27,463	$46	104	$3,666	0.99	ns
3	$36,054	$27,502	$8,552	61	$4,897	0.082	*
4	$72,462	$22,809	$49,653	25	$7,662	<0.0001	****
6	-$7,119	$25,200	-$32,319	2	$27,946	0.248	ns

Table 5-23 and Table 5-24 indicate with conclusive evidence that even after accounting for the difference in volumes between 2018 and 2020, the number of lanes closed causes ETT and EUC to differ significantly for different IMT program sizes.

Data analyzed in 2018 included instances of incidents with one, two, three, four, five, and six lane closures. In 2020, no incident was analyzed with five lane closures, and therefore the analysis here does not include a difference in ETT or EUC for that scenario. Generally, there was an adequate sample of incidents with fewer lanes closed. Few incidents were analyzed in either year for which six lanes were closed, and the results shown in Table 5-25 and Table 5-26 are therefore not representative of the reality of those scenarios. The p-values from these tables also indicate that estimates of ETT and EUC for incidents where one, two, and six lanes are closed are not very significant in their magnitude, especially when compared with the very low p-values associated with ETT and EUC for incidents where four lanes were closed.

The negative ETT and EUC in 2018 for incidents with six-lane closures indicates that drivers gained time due to the incident. This is likely related to the fact that a complete closure of the roadway removes congestion beyond the bottleneck, and travel times after closure may actually improve for the vehicles trapped in the queue, especially where recurring congestion would exist otherwise. This was the case in some instances, but is not the norm. Relationships given in the tables are represented visually in Figure 5-11 and Figure 5-12.

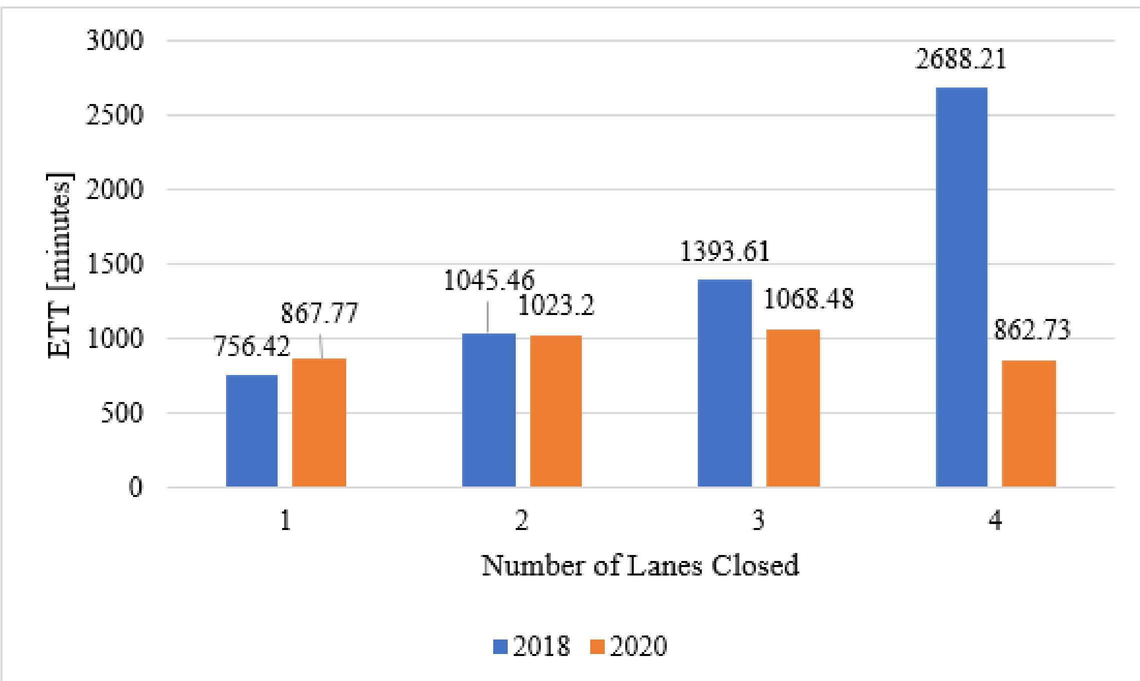


Figure 5-11: Estimates of ETT by program size and number of lanes closed.

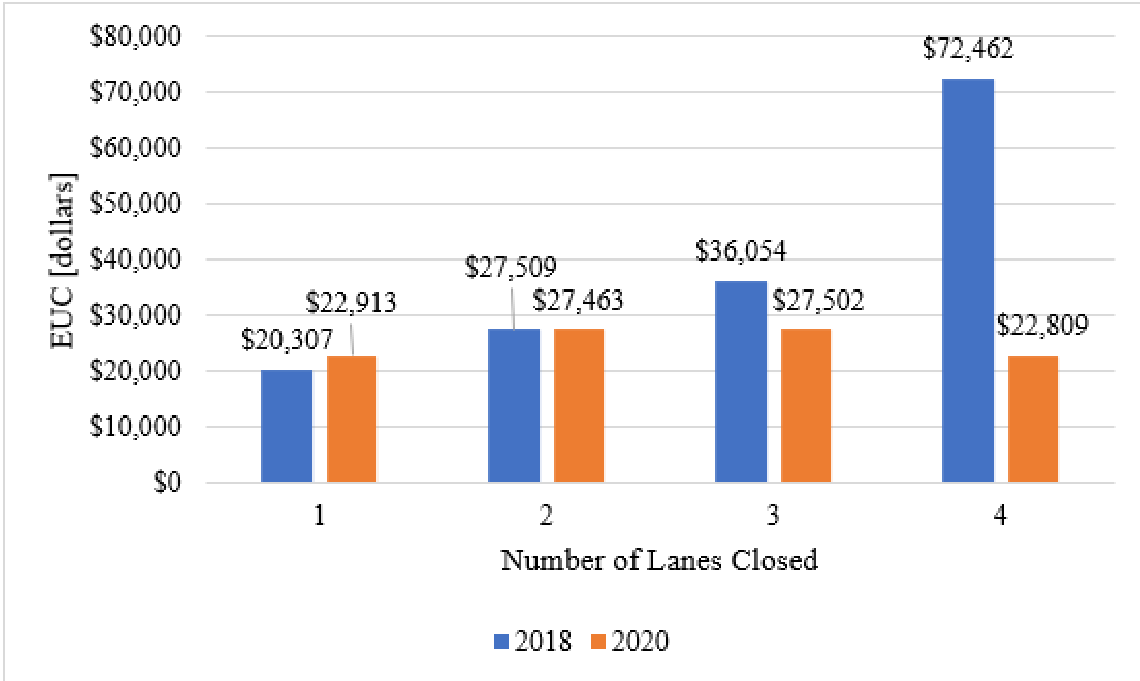


Figure 5-12: Estimates of EUC by program size and number of lanes closed.

It is important to evaluate the differences in ETT and EUC from both years. It appears that where one lane was closed, ETT values were slightly larger in 2020 than in 2018 after accounting for AV. The values of RCT were shown to be slightly higher in 2020 than in 2018. However, in spite of this there is a generally positive trend in the difference in ETT and EUC between 2018 and 2020 as the number of lanes closed increases. This can be seen clearly in Figure 5-11 and Figure 5-12.

A similar trend to what was seen in the analysis of the number of IMTs at the scene of an incident is seen in this analysis. Where one or two lanes are closed, the values of ETT and EUC are similar before and after the program expansion. However, where three or four lanes are closed, the ETT and EUC values are much lower in 2020 than in 2018. Again, the consistency of ETT and EUC is much greater in 2020 than in 2018. Regardless of the number of lanes closed, the values of ETT in 2020 were all within roughly 200 minutes of each other and the values of EUC in 2020 were all within roughly $4,700 of each other, whereas in 2018 ETT and EUC increased with the number of lanes closed. The difference indicates again that the expanded program is capable of providing a much more consistent service.

5.3.4 ETT and EUC vs. Number of Available Lanes

Statistical analysis proved that program size caused no difference in ETT or EUC based on the number of available lanes at the bottleneck, as indicated in Table 5-27 and Table 5-28.

Table 5-27: Significance of IMT Program Size vs. ETT for Number of Available Lanes

Does ETT between 2018 and 2020 depend on the number of available lanes, after accounting for volume differences?	**p > F**	**Significance**
	0.2624	ns

Table 5-28: Significance of IMT Program Size vs. EUC for Number of Available Lanes

Does EUC between 2018 and 2020 depend on the number of available lanes, after accounting for volume differences?	**p > F**	**Significance**
	0.2669	ns

Similar to the analysis of the number of lanes at the bottleneck, the number of available lanes does not necessarily indicate the severity of an incident. This could explain the fact that the number of available lanes does not significantly affect ETT or EUC for different program sizes, especially when these analyses are adjusted for crash type.

5.3.5 ETT and EUC vs. Time of Day

Table 5-29 through Table 5-32 show results for the analysis of the effect of program size on ETT and EUC for incidents occurring at different times of day.

Table 5-29: Significance of IMT Program Size vs. ETT for Time of Day

Does ETT between 2018 and 2020 depend on the time of day, after accounting for volume differences?	**p > F**	**Significance**
	0.4174	ns

Table 5-30: Significance of IMT Program Size vs. EUC for Time of Day

Does EUC between 2018 and 2020 depend on the time of day, after accounting for volume differences?	**p > F**	**Significance**
	0.3698	ns

Table 5-29 and Table 5-30 show that the statistical analyses did not indicate any significant effect of program size on the difference between 2018 and 2020 values of ETT or EUC for different times of day. Where differences between the two years are small, it still may be beneficial to include estimates of ETT and EUC for each respective time of day to aid in understanding the need for IMT services throughout the day.

Table 5-31 and Table 5-32 show the results of total ETT and EUC analyzed from the entire dataset of 2018 and 2020 incidents together, meaning that these are not simply estimates from the interaction term. This analysis does not distinguish differences in ETT between 2018 and 2020, but analyzes patterns of ETT across the time of day for both years. Figure 5-13 and Figure 5-14 show visual representations of those results.

Table 5-31: Analysis of ETT vs. Time of Day

Time of Day	Mean ETT	Lower	Upper	Sample Size	SE	p > |t|	Significance
Morning Off Peak	463.16	-244.25	1170.58	5	359.57	0.199	ns
AM Peak	1214.95	867.89	1562.01	76	176.41	<0.0001	****
Afternoon Off Peak	1356.27	1037.45	1675.08	135	162.05	<0.0001	****
PM Peak	1295.44	972.6	1618.28	100	164.09	<0.0001	****
Night Off Peak	920.17	99.4179	1740.92	18	417.18	0.028	**

Table 5-32: Analysis of EUC vs. Time of Day

Time of Day	Mean EUC	Lower	Upper	Sample Size	SE	p > |t|	Significance
Morning Off Peak	$11,634	-$7,199	$30,466	5	$9,572	0.225	ns
AM Peak	$31,124	$21,885	$40,363	76	$4,696	<0.0001	****
Afternoon Off Peak	$36,941	$28,454	$45,428	135	$4,314	<0.0001	****
PM Peak	$34,058	$25,463	$42,652	100	$4,368	<0.0001	****
Night Off Peak	$24,776	$2,926	$46,625	18	$11,106	0.026	**

Morning Off Peak and Night Off Peak periods have lower sample sizes and higher standard errors. As a result, the estimates for these periods may be less reliable. It was previously established that the sample size of incidents serviced by IMTs during these periods was greater in 2020 than in 2018. This provided more data from which user impacts could be analyzed. Of the eight and 19 respective incidents analyzed for performance measures during the Morning Off Peak period in 2018 and 2020, two incidents from 2018 and three incidents from 2020 met the criteria for subsequent analysis. Of the three and 30 respective incidents analyzed for performance measures in 2018 and 2020, one incident from 2018 and 17 incidents from 2020 met the criteria for subsequent analysis.

While the occurrence of incidents at these time periods can also be influenced by other factors such as differing traffic volumes, construction conditions, etc., the data indicate that the expanded IMT program is more capable of reaching incidents at these times of day. The extended operating hours and coverage area of the IMT program have direct benefits to roadway safety and operations.

Lower values of ETT and EUC during the Morning and Night Off Peaks are expected, since these times have lower traffic volumes. The results indicate that the greatest average values of ETT and EUC do not occur during a peak period at all, but rather in the middle of the day during the Afternoon Off Peak. However, the AM and PM Peak periods still have high average ETT and EUC values. This data may be beneficial in helping make IMT allocation-related decisions.

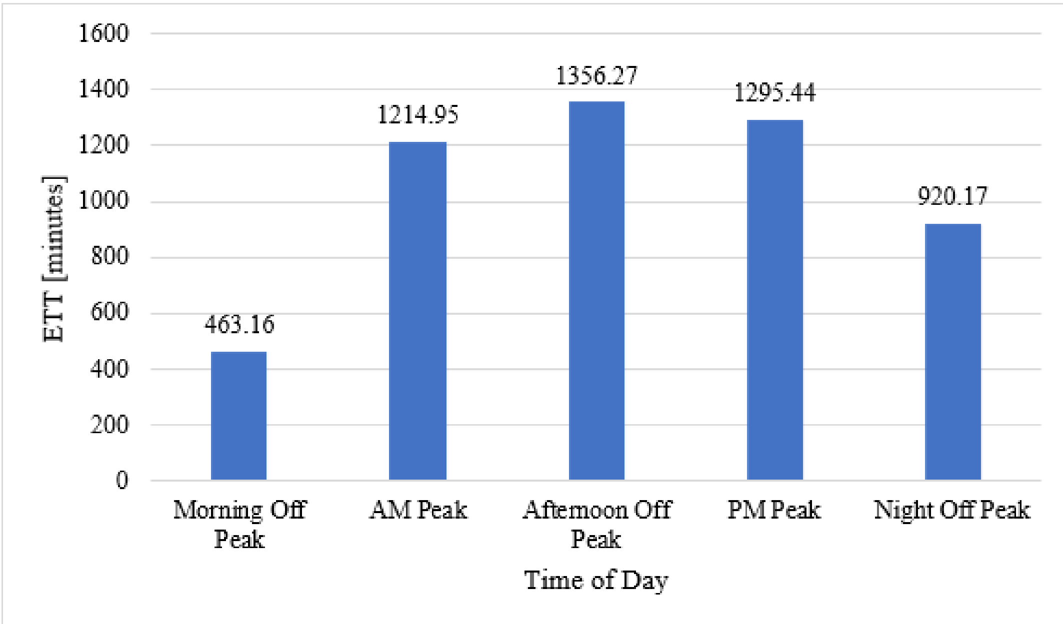


Figure 5-13: Estimates of ETT vs. time of day.

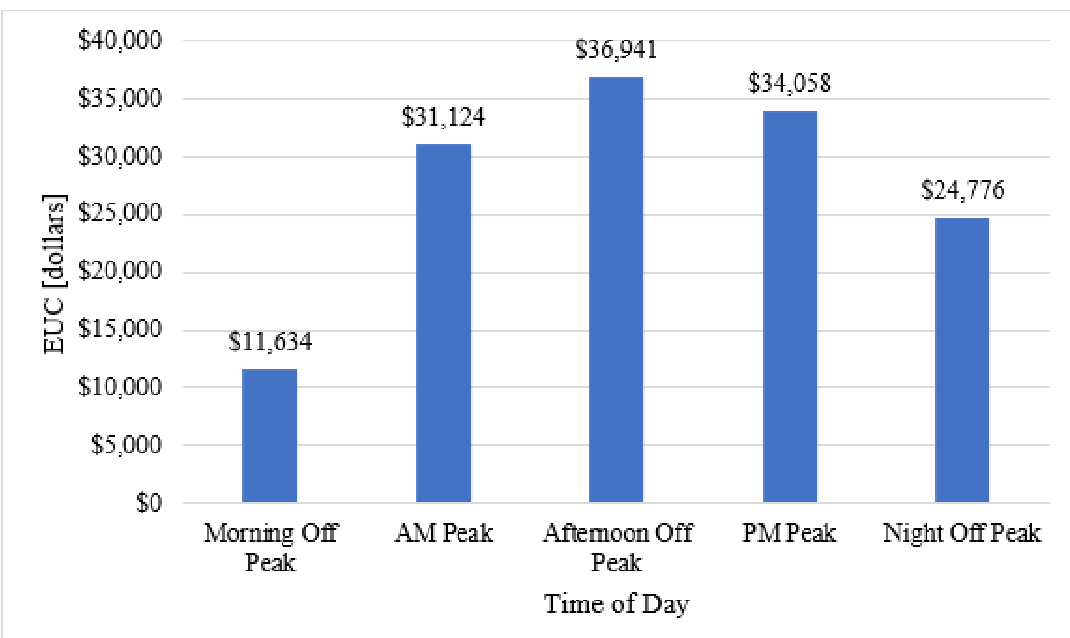


Figure 5-14: Estimates of EUC vs. time of day.

5.3.6 ETT and EUC vs. RT

Table 5-33 and Table 5-34 are statistical outputs that show the fixed effects of the regression analyses of ETT and EUC versus RT, as well as the solutions to the fixed effects. As previously established, these analyses were performed on the entire dataset of 2018 and 2020 incidents combined so that differences in volume between the two years could be accounted for in the regression.

Table 5-33: Fixed Effects for Regression of ETT vs. RT

Effect	Num. DF	Den. DF	F Value	p > F	Significance
AV	1	321	163.82	<0.0001	****
Crash Type	2	321	8.94	0.0002	***
Year	1	321	1.10	0.295	ns
RT	1	321	0.05	0.83	ns
RT * Year	1	321	4.07	0.0446	**

Table 5-34: Fixed Effects for Regression of EUC vs. RT

Effect	Num. DF	Den. DF	F Value	p > F	Significance
AV	1	321	153.44	<0.0001	****
Crash Type	2	321	8.80	0.0002	***
Year	1	321	1.14	0.2873	ns
RT	1	321	0.00	0.9593	ns
RT * Year	1	321	4.13	0.043	**

The p-values in Table 5-33 and Table 5-34 indicate the significance of the effect of each respective variable in explaining the ETT and EUC, respectively. Both AV and crash type have significant effects on ETT and EUC when all other variables are held constant. This result is expected since ETT is directly related to AV, and severity of an incident may determine throughput at the bottleneck and growth of the queue.

It appears in both cases that year alone and RT alone do not have significant effects on ETT or EUC, and cannot explain either of the user impacts. However, as in previous analyses on user impacts, the focus of these analyses is the interaction term between year and the incident characteristic, in this case RT. With all other variables held constant, this interaction term describes the effect of the program size in each respective year, since all other differences between the years are considered in the other variables in the analysis. The analyses provide moderate evidence of a statistical difference in ETT and EUC due to the difference in IMT program size in 2018 and 2020. The effects of program size on ETT and EUC are further described in the statistical outputs shown in Table 5-35 and Table 5-36.

Table 5-35 and Table 5-36 provide estimates for the effects of each variable on ETT and EUC, respectively. The p-values of the intercepts are not significant, which is a good indicator that ETT and EUC are adequately explained by the variables in the regression models.

Table 5-35: Solution for Fixed Effects for Regression of ETT vs. RT

Effect	Crash Type	Year	Estimate	Lower	Upper	SE	DF	t Value	p > |t|	Significance
Intercept			-98.45	-333.70	136.81	119.58	321	-0.82	0.41	ns
AV			0.13	0.11	0.14	0.01	321	12.80	<.0001	****
Crash Type	FII Crash		1450.16	673.62	2226.69	394.71	321	3.67	0.0003	***
Crash Type	PDO Crash		-152.71	-323.34	17.93	86.73	321	-1.76	0.0793	*
Crash Type	PI Crash		0.00	-	-	-	-	-	-	-
Year		2018	-144.76	-416.24	126.73	137.99	321	-1.05	0.2950	ns
Year		2020	0.00	.	.	.	.	.	.	.
RT			-8.20	-18.92	2.52	5.45	321	-1.50	0.1334	ns
RT * Year		2018	14.66	0.36	28.97	7.27	321	2.02	0.0446	**
RT * Year		2020	0.00	-	-	-	-	-	-	-

Table 5-36: Solution for Fixed Effects for Regression of EUC vs. RT

Effect	Crash Type	Year	Estimate	Lower	Upper	SE	DF	t Value	p > |t|	Significance
Intercept			-3010.56	-	3279.6	3197.22	321	-0.94	0.3471	ns
AV			3.25	2.73	3.77	0.26	321	12.39	<.0001	****
Crash Type	FII Crash		39262	18499	60025	10553	321	3.72	0.0002	***
Crash Type	PDO Crash		-3724.33	-8286.8	838.14	2319.06	321	-1.61	0.1093	ns
Crash Type	PI Crash		0.00	-	-	-	-	-	-	-
Year		2018	-3932.23	-	3326.6	3689.62	321	-1.07	0.2873	ns
Year		2020	0.00	-	-	-	-	-	-	-
RT			-202.98	-489.65	83.68	145.71	321	-1.39	0.1646	ns
RT * Year		2018	394.93	12.44	777.42	194.42	321	2.03	0.0430	**
RT * Year		2020	0.00	-	-	-	-	-	-	-

Equations for the regressions on ETT and EUC can be drawn from the fixed effects as shown in Equation 5-2 and Equation 5-3:

$$ETT\ (minutes) = -98.45 + 0.13 * AV + 1450.16 * FII\ Crash - 152.71 * PDO\ Crash - 144.76 * year - 8.20 * RT(minutes) + \mathbf{14.66} * (\boldsymbol{year} * \boldsymbol{RT}) \tag{5-2}$$

$$EUC\ (\$) = -3010.56 + 3.25 * AV + 39262 * FII\ Crash - 3724.33 * PDO\ Crash - 3932.23 * year - 202.98 * RT(minutes) + \mathbf{394.93} * (\boldsymbol{year} * \boldsymbol{RT}), \tag{5-3}$$

where PI Crash is a reference level and where FII Crash (yes = 1, no = 0), PDO Crash (yes = 1, no = 0), and year (2018 = 1, 2020 = 0) are indicator variables.

The interaction terms in each equation have been bolded as they describe the quantifiable benefits of the larger program size. These results indicate that after accounting for the respective effects of AV, crash type, and year, each extra minute of RT that occurred due to the smaller fleet size in 2018 equated to an increase in ETT of 14.66 minutes. To phrase this result differently, it could be said that for every minute of RT saved by program expansion in 2020, 14.66 minutes of ETT were saved. Similarly, for each minute of RT reduced by program expansion in 2020, $394.93 were saved.

Yearly time savings and costs savings can be determined using the data collected paired with the estimates from the interaction term. Median RT values for 2020 were previously shown in Figure 4-4 to be between 10-15 minutes. UDOT's Traffic Management Division Operations Engineer reported to the research team that the IMT program was able to respond to roughly 9,000 incidents in the year after the expansion. Given this information, time savings and cost savings can be estimated. For instance, if IMTs can respond to the majority of incidents within 15 minutes, with savings of 14.66 minutes of ETT per minute of RT and over 9,000 incidents responded to, this amounts to roughly 1,979,100 minutes, or 32,985 hours, of ETT saved in 2020 due to the program expansion, with a 95 percent confidence interval from 810 to 65,183 hours. The same assumptions of 15-minute RT and 9,000 incidents, coupled with savings of $394.93 of EUC per minute of RT, amounts to roughly $53,315,550 of EUC saved in 2020 due to the program expansion, with a 95 percent confidence interval from $1,679,400 to $104,951,700.

Since the interaction terms in these regression models describe the benefits specific to the program expansion, summarized results for all following analyses will be presented as shown in Table 5-37 and Table 5-38. Positive differences in means indicate savings in 2020.

Table 5-37: Analysis of IMT Program Size vs. ETT for RT

Difference in Means [minutes]	Lower	Upper	Sample Size	SE	p > F	Significance
14.66	0.36	28.97	328	7.27	0.0446	**

Table 5-38: Analysis of IMT Program Size on EUC vs. RT

Difference in Means	Lower	Upper	Sample Size	SE	p > F	Significance
$394.93	$12.44	$777.42	328	$194.42	0.0430	**

5.3.7 ETT and EUC vs. RCT

Table 5-39 and Table 5-40 show results of the interaction terms for the analyses of ETT and EUC versus the RCT.

Table 5-39: Analysis of IMT Program Size vs. ETT for RCT

Difference in Means [minutes]	Lower	Upper	Sample Size	SE	p > F	Significance
10.45	6.37	14.52	334	2.07	<0.0001	****

Table 5-40: Analysis of IMT Program Size vs. EUC for RCT

Difference in Means	Lower	Upper	Sample Size	SE	p > F	Significance
$277.13	$167.86	$386.39	334	$55.54	<0.0001	****

The interaction terms for these analyses also provide conclusive evidence of benefits to ETT and EUC from the program expansion. For each minute of RCT in 2020, about 10.45 minutes of ETT were saved when compared with 2018, as well as $277.13 of EUC. It has been shown in the previous analysis of performance measures that values of RCT were somewhat consistent between 2018 and 2020. This analysis on user impacts indicates that while the time to clear the roadway of incidents may be similar after the expansion, having more IMTs performing that work does have direct benefits in reducing the time and costs associated with incident congestion.

5.3.8 ETT and EUC vs. ICT

Table 5-41 and Table 5-42 show results of the interaction terms for the analyses of ETT and EUC versus ICT.

Table 5-41: Analysis of IMT Program Size vs. ETT for IMT ICT

Difference in Means [minutes]	Lower	Upper	Sample Size	SE	p > F	Significance
9.85	5.59	14.11	334	2.17	<0.0001	****

Table 5-42: Analysis of IMT Program Size vs. EUC for IMT ICT

Difference in Means	Lower	Upper	Sample Size	SE	p > F	Significance
$265.36	$151.37	$379.36	334	$57.95	<0.0001	****

Figure 5-1 and Figure 5-2 previously showed the strong correlation in both 2018 and 2020 between RCT and IMT ICT. This correlation is evidence that IMTs are able to leave the scene of an incident soon after finishing their responsibilities to clear the roadway. The results of the analyses introduced in this section are therefore quite similar to the previous analyses of RCT. For each minute of IMT ICT in 2020, about 9.85 minutes of ETT as well as $265.36 of EUC were saved when compared with 2018.

5.4 Chapter Summary

The side-by-side comparison of the 2018 and 2020 performance measure analyses reveal a number of things about the expansion of UDOT's IMT program. First, there were slightly wider confidence intervals in 2020 than in 2018 across most analyses. While there were 320 incidents analyzed for performance measures in 2018 and 289 in 2020, the larger confidence intervals in 2020 would indicate that there is a greater spread of RCTs in 2020 than in 2018. This does not mean that the work of the IMTs has become less efficient. Rather, it reflects the fact that the expanded program has been able to service a wider range of incidents, both on geographic and temporal scales.

The effects of COVID-19 must be jointly considered with the effects of the program size for these analyses. It is possible that slightly higher RCTs in 2020 than in 2018 are due to precautions taken by IMT personnel at the scene of incidents to prevent potential exposure to the virus. This possibility was corroborated by discussions with the IMT program manager. Traffic volumes have been proven to be lower in 2020 than in 2018, as was discussed in Chapter 3, and this may have implications on the compounding effects of congestion experienced by roadway users, particularly ETT and EUC. However, it was assumed that queue size does not directly affect the work performed by IMTs although it directly affects ETT and EUC calculations, so analyses on performance measures were not adjusted directly for AV.

Similar levels of RCT and ICT performance were seen for 2018 and 2020. One important distinction is that the RCTs in 2020 were more consistent. The time required by IMTs to clear incidents fluctuated less in 2020 than in 2018 regardless of the characteristics of the incidents such as location, time, or severity. This consistency is a mark of the flexibility that the expanded program has to respond to incidents as needed. Overall, similar levels of performance on a wider geographic and temporal scale are a promising result for the increased capabilities of the IMT program after the expansion.

The statistical regression analyses on both ETT and EUC demonstrate the impacts that the expansion to UDOT's IMT program has had on its ability to prevent incident-related congestion. Analyses indicated in some cases that an interaction term between the year and an incident characteristic, which described the effect of the program size, had a significant effect on ETT and EUC. This was true when analyzing incidents by the number of IMTs that responded and when analyzing incidents by the number of lanes that were closed. Notable is the fact that values of ETT and EUC were found to be much more consistent in 2020 than in 2018, which indicates added flexibility in the larger program. Having more IMTs does not mean that the program can necessarily clear all incidents faster, but it does provide the capability of clearing all incidents more consistently.

Regression analyses were also performed on ETT and EUC against a number of performance measures. Because AV is directly related to ETT and EUC, an interaction term was used to describe the effects of the program size before and after the expansion, after accounting for volumes in 2018 and 2020. In all cases where performance measures reflected IMT activity, the size of the program was shown to be significant in reducing congestion-related travel time and costs. Table 5-43 and Table 5-44 summarize the differences in ETT and EUC due solely to the program expansion. Positive differences indicate time and costs savings in 2020. Visual representations of the data are shown in Figure 5-15 and Figure 5-16. The bars shown represent the 95 percent confidence interval of the means and the whiskers represent the standard errors.

Table 5-43: Summary of Analyses of ETT vs. Performance Measures

Performance Measure	Difference in Mean ETT per Minute of Performance Measure	Lower	Upper	SE
RT	14.66	0.36	28.97	7.27
RCT	10.45	6.37	14.52	2.07
IMT ICT	9.85	5.59	14.11	2.17

Table 5-44: Summary of Analyses of EUC vs. Performance Measures

Performance Measure	Difference in Mean EUC per Minute of Performance Measure	Lower	Upper	SE
RT	$394.93	$12.44	$777.42	$194.42
RCT	$277.13	$167.86	$386.39	$55.54
IMT ICT	$265.36	$151.37	$379.36	$57.95

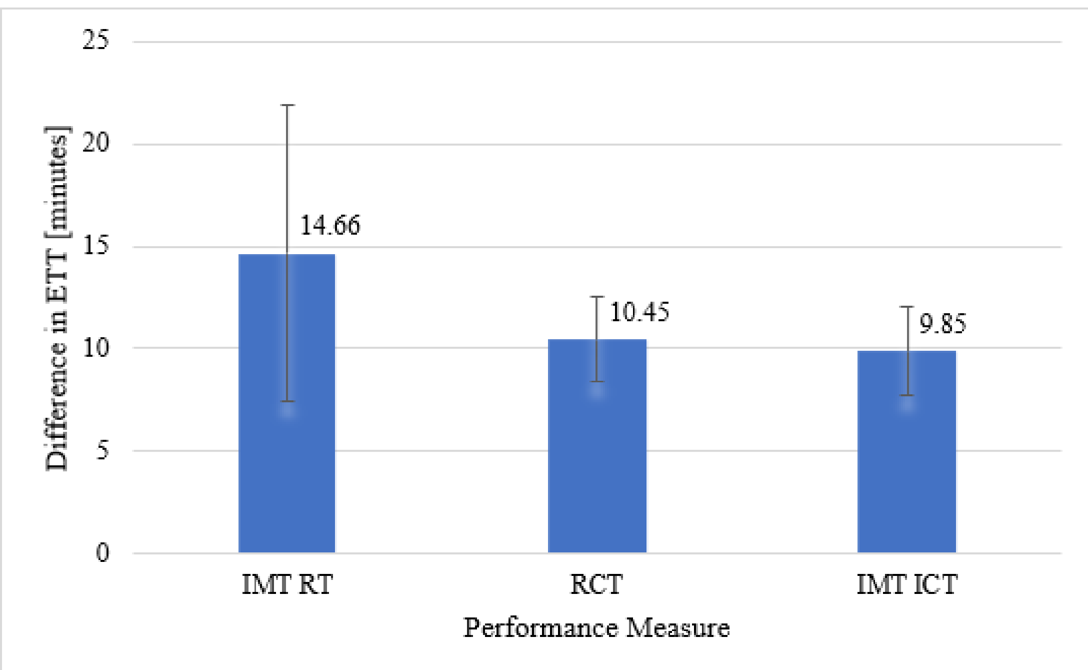


Figure 5-15: Summary of analyses on ETT by performance measures.

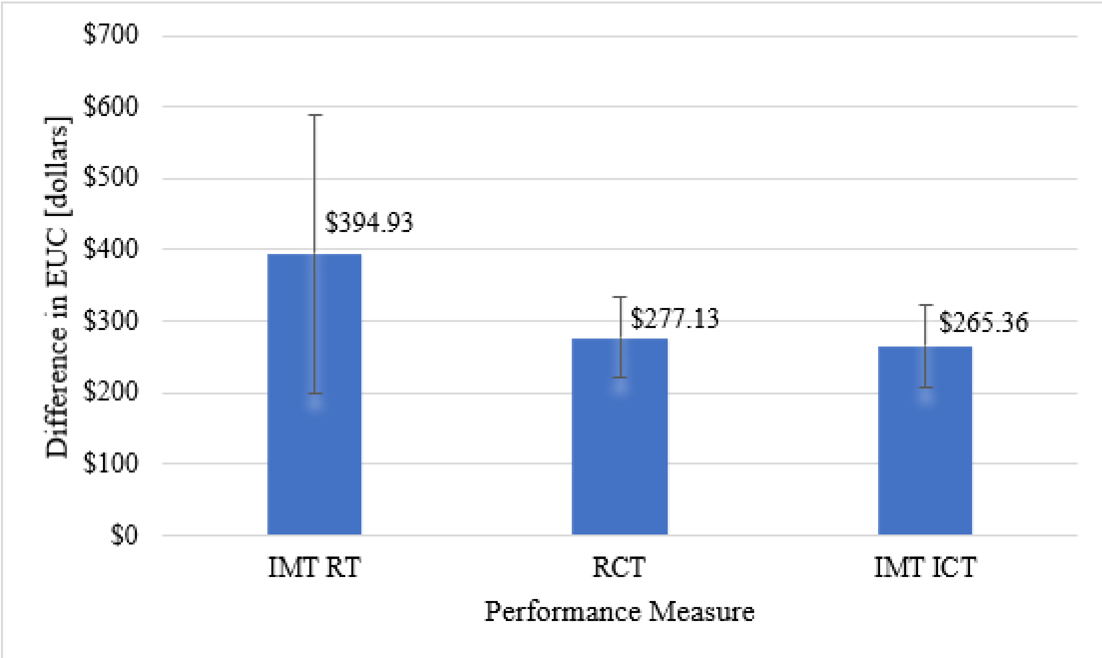


Figure 5-16: Summary of analyses on EUC by performance measures.

The results indicate that the reduction in RT due to the program expansion has had the greatest benefit to reductions in ETT and EUC. For each minute of RT in 2020, 14.66 minutes and $394.93 less are accrued than in 2018. While these amounts may seem trivial, the savings per minute of RT aggregated over the course of a year do add up quickly to represent a huge monetary benefit of the expanded program. Considering the distribution of RTs in 2020 and the number of incidents that the expanded program is capable of responding to in a year, the IMT program expansion has saved roughly 32,985 hours (95 percent confidence interval from 810 to 65,183 hours) of ETT and $53,315,550 (95 percent confidence interval from $1,679,400 to $104,951,700) of EUC.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Summary

The purpose of this study was to evaluate the impacts of the expansion to UDOT's IMT program that occurred in 2018. Objectives included identifying changes in IMT program operations, reanalyzing Phase I (2018) data with new methods, collecting a second dataset of IMT performance measures in 2020, and analyzing the datasets to determine benefits of the expansion. Performance measure data were collected using timestamps from UHP's CAD system as well as TransSuite data provided by UDOT. A second set of data was collected between March 1, 2020 and September 30, 2020, excluding the second half of March and April due to the effects of COVID-19 on traffic volumes. Phase I data were reanalyzed using the TransSuite data and expanded to match the dates analyzed in 2020. Statistical analyses were performed to evaluate relationships between performance measures, incident characteristics, and user impacts. Comparison of results for 2018 and 2020 were then done to evaluate the impacts of the program expansion. This chapter describes the findings from the study, limitations and challenges, recommendations drawn from the study, and recommendations for future research.

6.2 Findings

The findings from this study can be split into observations from data reduction and the results of statistical analyses on the collected data. The tables and figures included in this section are from previous sections of this report, but are shown again for reference.

6.2.1 Data Reduction

The raw data collected over the course of the two years revealed a number of helpful observations regarding the performance of the program after the 2018 expansion. First, the use of TransSuite data provided a much higher number of incidents with timestamps logged for all performance measures. Table 6-1 and Table 6-2, respectively, show the data funnels of performance measure data collected in 2018 using only CAD data and of the reanalyzed 2018 data using CAD and TransSuite data together.

Table 6-1: Data Funnel for 2018 Data Collected Using CAD Data Only

Data Type	Number of Data Points	Percent of Total
Incidents	1216	100.0%
ICT	1206	99.2%
RT	1042	85.7%
RCT	138	11.3%
ICT, RT, and RCT	129	10.6%
Incidents Analyzed for EUC	63	5.2%

Table 6-2: Data Funnel for 2018 Data Collected Using CAD+TransSuite Data

Data Type	Number of Data Points	Percent of Total
Incidents	1074	100.0%
ICT	1064	99.1%
RT	928	86.4%
RCT	325	30.3%
ICT, RT, and RCT	306	28.5%
Incidents Analyzed for EUC	188	17.5%

The number of incidents analyzed overall using CAD and TransSuite data was slightly less than when only CAD data were used, but both the number and percentage of incidents with all three performance measures calculated were much higher, with a jump from 129 to 306 incidents once TransSuite was incorporated into the methodology, or an increase from 10.6 percent to 28.5 percent of all incidents. This higher number of incidents with data for all performance measures meant a higher sample of incidents from which user impacts could be analyzed, with a jump from 63 to 188 incidents.

The addition of TransSuite data provided for a much more comprehensive analysis of the incidents for which data were collected. The ability to analyze more incidents was also likely a product of the fact that there was a greater percentage of incidents in 2020 that had IMT responders. Even with slightly lower numbers of incidents in the CAD data in 2020 than in 2018, there were consistently higher numbers of incidents with IMTs responding.

Observation of the distributions of RT values for each year showed a shift towards lower RTs in 2020. While values of RCT and IMT ICT were similar in 2018 and 2020, the shift in RT is beneficial, as shown by the distributions in Figure 6-1 and Figure 6-2.

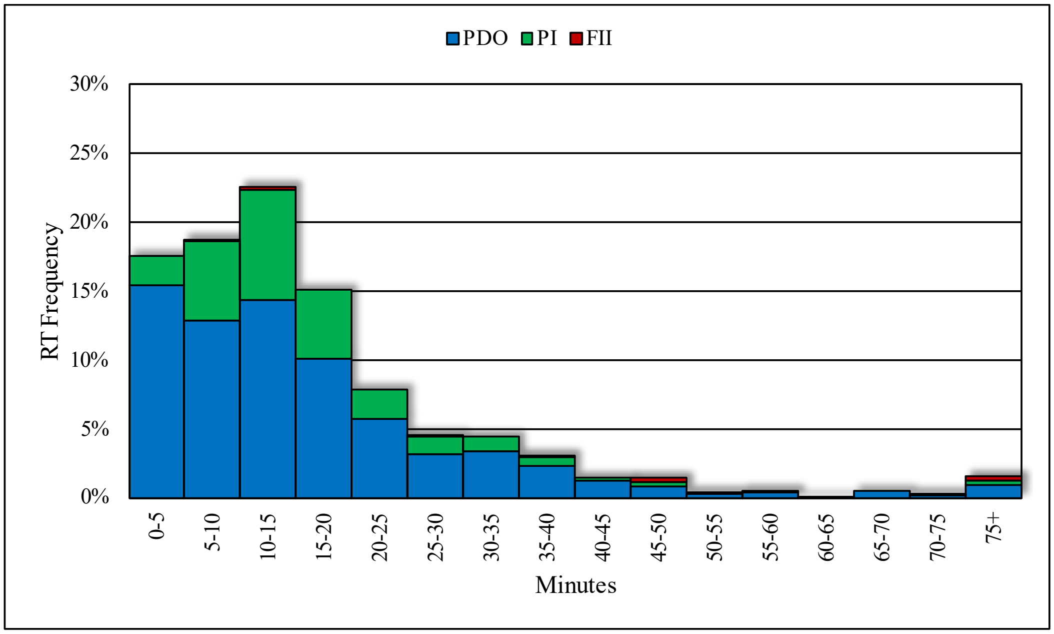


Figure 6-1: 2018 distribution of RT.

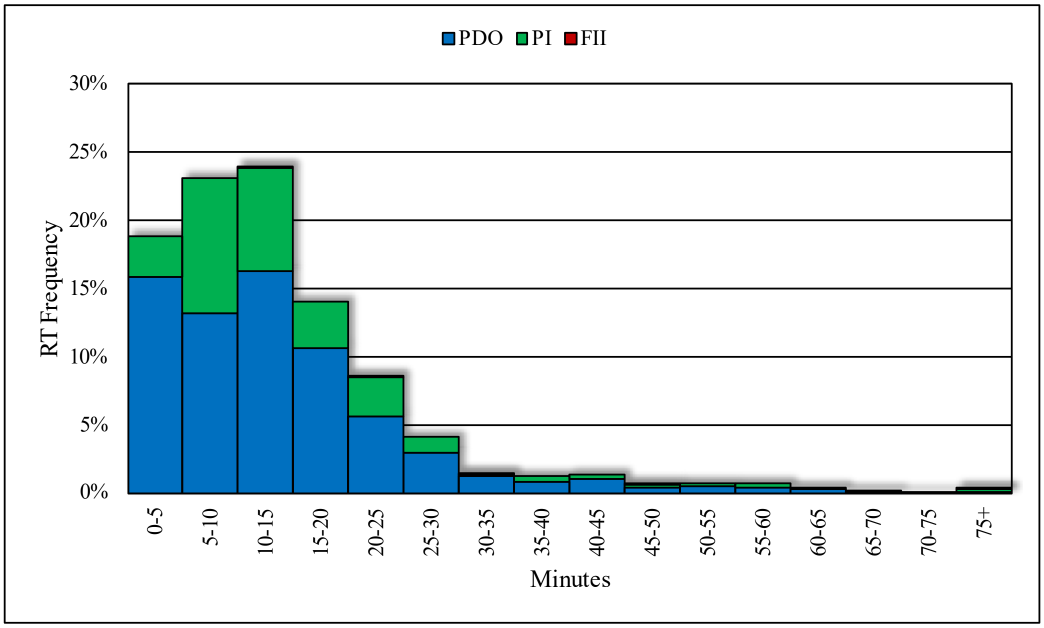


Figure 6-2: 2020 distribution of RT.

The proportion of incidents responded to within the first 15 minutes after verification of the incident increased from 58.8 percent in 2018 to 65.9 percent in 2020, a difference of 7.1 percent, or a 12.1 percent improvement. This is an indication of the expanded program's ability to reach incidents faster with more units on the road. Results from the statistical analyses would suggest that this shift provides a monumental benefit to Utah drivers in terms of ETT and EUC. Those results will be summarized in Section 6.2.2.

The advent of the COVID-19 pandemic in Utah created a reduction in traffic volumes that affected user impacts felt by drivers. The effects on traffic volume were most notable in March and April of 2020, after which traffic volumes slowly resumed normal levels. Analysis of incidents during 2018 and 2020 provided insights into the effects of lower traffic volumes on the AV, ETT, and EUC associated with incidents. Reductions in AV, ETT, and EUC from 2018 to 2020 were identified, as shown in Table 6-3.

Table 6-3: Reductions in User Impacts Between 2018 and 2020

User Impacts	2018 Average	2020 Average	% Reduction
AV [vehicles]	7642	5467	28%
ETT [minutes]	759.50	429.65	43%
EUC [$]	$ 19,532.78	$ 10,906.69	44%

On average, the AV of incidents was reduced 28 percent from 2018 to 2020. This reduction in AV may have had a larger effect on queue growth and dissipation than originally expected. This possibility is corroborated by the associated reductions of ETT and EUC from 2018 to 2020 of 43 percent and 44 percent, respectively. It is also possible that the larger IMT program in 2020 was able to provide service to smaller incidents that would not have been prioritized before the expansion. However, the reduction in volumes caused by COVID-19 is significant enough that this is the likely explanation for the reductions shown. This trend in the raw data was considered by the research team and statistical analyses were run in a way to address this volume reduction, as described in Chapter 5.

Estimates of EUC accrued due to incidents over the course of the data collection periods for 2018 and 2020 must be considered in the context of the volume reduction discussed. However, it should be noted that these estimates of EUC do not include the congestion associated with diverted traffic nor do they account for the portion of incidents analyzed outside of the CAD+TransSuite dataset used in this study.

Though 1,074 and 1,190 incidents were respectively analyzed in 2018 and 2020 by this method, the UDOT Traffic Management Division Operations Engineer indicated that in 2018 the IMT program was able to respond to around 4,500 incidents, and the program expansion allowed this amount to go up to around 9,000 incidents in 2020. For these reasons it is reasonable to assume that the estimates shown are conservative. Table 6-4 and Table 6-5 show the estimated costs associated with congestion from incidents analyzed over the 6-month study period for each year.

Table 6-4: 2018 EUC Estimates

Crash Type	Average Cost per Crash	Number of Crashes in 6 Months	User Cost Estimate over 6 Months
FII	-	10	$ -
PI	$ 20,610	285	$ 5,873,850
PDO	$ 16,576	779	$ 12,912,704
	Total	1074	$ 18,786,554

Table 6-5: 2020 EUC Estimates

Crash Type	Average Cost per Crash	Number of Crashes in 6 Months	User Cost Estimate over 6 Months
FII	-	6	$ -
PI	$ 11,759	347	$ 4,080,373
PDO	$ 9,597	837	$ 8,032,689
	Total	1190	$ 12,113,062

6.2.2 Statistical Analyses

The results of statistical analyses of the performance measures collected in 2018 and 2020 indicated that performance between the two years is roughly the same for RCT and ICT. Given a larger coverage area and extended operating hours, the IMT program is more capable of providing quality service at a larger geographic and temporal scale. Performance measures were also more consistent after the program expansion, which could be a sign of greater flexibility of the IMT program to prioritize incidents as needed with more units.

Statistical analyses of the user impacts of ETT and EUC also indicated that the effects of congestion are much more consistent after the program expansion than before. A combined look at the results of performance measure and user impact analyses indicates that while the IMT program cannot necessarily clear all incidents faster, it can clear them consistently with similar clearance times.

It was also proven that the expansion had direct benefits in reducing ETT and EUC for specific IMT performance measures. Regression analyses accounted for differences in traffic volumes between the years and crash type to evaluate the effects attributed solely to the greater size of the IMT program in 2020.

When compared to 2018, each minute of RT reduced in 2020 translated on average to:

- ETT savings of 14.66 minutes.
- EUC savings of $394.93.

When compared to 2018, each minute of RCT reduced in 2020 translated on average to:

- ETT savings of 10.45 minutes.
- EUC savings of $277.13.

When compared to 2018, each minute of ICT reduced in 2020 translated on average to:

- ETT savings of 9.85 minutes.
- EUC savings of $265.36.

These savings only refer to the portion of congestion costs related directly to program size. These reductions in ETT and EUC accumulate into sizeable savings of roughly 32,985 hours (95 percent confidence interval from 810 to 65,183 hours) and $53,315,550 (95 percent confidence interval from $1,679,400 to $104,951,700), respectively.

6.3 Limitations and Challenges

Over the course of the study a number of confounding variables and discrepancies in the data had to be addressed. One discrepancy came from the fact that PeMS provides separate volume data for mainline stations and HOV lanes. The research team decided not to use the volumes from the HOV lanes since these lanes act as a separate facility. However, TransSuite included a number of incidents that occurred in the HOV lane, which were not analyzed in Phase I. Because the 2018 data were reanalyzed using TransSuite, these incidents were still analyzed during both data collection periods, but the volumes in the HOV lanes were still not used. This decision was justified based on the fact that estimates of ETT and EUC are conservative and only include traffic in the queue that does not divert to other routes.

Additionally, TransSuite also indicates that shoulders must sometimes be blocked and then cleared. The research team chose to ignore the timestamps pertaining to shoulders to simplify the data collection process, though this could potentially have affected the relationship of RCT with ETT given that the shoulder still affects roadway performance.

There were some instances of incidents for which values of RCT were greater than ICT, indicating that the lanes were completely cleared after the last IMT had already left the scene of the incident. In other cases, the RT value was greater than the RCT value, indicating that the roadway was cleared before IMTs even arrived. Discussion with the TOC manager pointed out that there is potential for slight errors in the data reporting process. Sometimes IMTs may preemptively indicate that they are clearing the scene. At other times, UHP responders may assess the scene before IMTs arrive, and if vehicles involved in the incident are able to evacuate the lanes, UHP officers may mark the lanes as open before an IMT begins other clean-up duties. These cases are not frequent, and the research team chose not to eliminate incidents with these seeming inconsistencies.

The greatest challenge faced during the course of the study was the global COVID-19 pandemic. In particular, the shifting patterns of quarantine and telecommuting created large reductions in traffic volumes in 2020. This volume reduction was very apparent in the data collected, particularly the spread of the ETT and EUC values for each respective year. In some instances, statistical analyses were performed in such a way that the effects of the traffic volume were fixed, so that other variables could be evaluated independently. However, this was not possible for all analyses and causality was confounded by the existence of both program size differences and volume differences between the two years.

Additionally, raw values of EUC were calculated directly from the AV for each incident, meaning that a direct comparison of the raw values of EUC accrued over each data collection period was confounded by the volumes. The research team investigated whether normalizing values of EUC by AV was possible, but found that the effect of the volume reduction could not be removed due to the process used to determine EUC. Ultimately, analyses were able to be performed to account for this issue.

6.4 Recommendations

The data collection process for IMT performance measures is simpler and more comprehensive with the addition of TransSuite data used to collect T_5 timestamps for the UHP CAD system. The methodology used in this study could be used as a basis for an eventual integration of these two data sources, so that UDOT can develop an automated dashboard of TIM performance. Institutionalization of this data collection could also be a tool used to gauge current performance against program goals and objectives.

It is recommended that UDOT develop a schedule of yearly performance evaluation so that goals for RT, RCT, and ICT can be met and adjusted. Over time this will increase the accountability of the program and improve its performance. Additionally, a dashboard relating performance of the IMT program could be a beneficial tool in communicating the benefits of the program to legislators.

It is also recommended that training for TIM activities and protocol be developed so that all parties involved in incident management can improve their understanding and ability to perform TIM activities. The research team is aware of the formation of the Utah Traffic Incident Management Coalition and suggests that, in the case of the institutionalization of performance measure data collection, best practices of data collection be developed as part of the training regimen.

6.5 Future Research Recommendations

A third phase of this research is recommended so that the performance of the expanded program can be analyzed without the effects of COVID-19. As previously explained, the difference in volumes between 2018 and 2020 precluded some types of analysis. Additionally, the estimates of benefits to ETT and EUC presented in this paper are specifically related to the program expansion, and it is likely that improvements to performance measures going forward would be quantitatively different given the establishment of a larger program. Ideally, performance measures can continue to be collected to allow UDOT to continually monitor performance and adjust IMT procedures. Where the collection of user impacts such as ETT and EUC requires a more manual approach, it is suggested that the third phase of this study be pursued to collect a new dataset without the confounding factor of abnormal traffic volumes.

Further investigation into the use of results from these studies to create a business case is recommended. An in-depth analysis of user impacts, program costs, IMT activity, and IMT coverage could be investigated to determine what other quantifiable benefits IMT program improvements may have.

REFERENCES

American Automobile Association (AAA). (2021). “Digest of Motor Laws.” < https://drivinglaws.aaa.com/tag/move-over-law/> (May 24, 2021).

Base SAS 9.4. (2013). 100 SAS Campus Drive Cary, NC 27513-2414, USA: SAS Institute.

Brooke, K., Dopart, K., Smith, T., and Flannery, A. (2004). NCHRP Report 520: “Sharing Information between Public Safety and Transportation Agencies for Traffic Incident Management.,” Transportation Research Board. Washington DC. pg.1-19.

Carson, J. (2010). “Best Practices in Traffic Incident Management.” <https://ops.fhwa.dot.gov/publications/fhwahop10050/fhwahop10050.pdf> (Apr. 11, 2019).

Conklin, C., Bahler, S., Belmore, K., Hallenbeck, M., Ishimura, J., Schnell, G., Clark, J., Curley, C., Kandarpa, R., Hill, D., and But, A. (2013). “Transportation Management Center: Data Capture for Performance and Mobility Measures Guidebook.” <https://www.its.dot.gov/research_archives/data_capture/pdf/data_capture_reference_manual.pdf> (Apr. 11, 2019).

Ellis, D.R. (2017). “Value of Delay Time for Use in Mobility Monitoring Efforts.” Texas Transportation Institute (TTI). College Station.

Federal Highway Administration (FHWA). (2019). “Every Day Counts Round 4 (EDC-4) Innovation: Using Data to Improve Traffic Incident Management.” [Unpublished draft Executive Summary]. Provided by Paul Jodoin, May 1, 2020.

Garmen Associates. (2000). “H.E.L.P. Benefit Assessment Final Report.” Prepared for the New York State Department of Transportation.

Iowa Department of Transportation (Iowa DOT). (2019). “Des Moines Metropolitan Area Integrated Corridor Management (ICM): Program-Level Concept of Operations.”

Jodoin, P., King, J., and Pecheux, K. (2014). NCHRP Report 07-20: “Guidance for Implementation of Traffic Incident Management Performance Measures.,” Transportation Research Board. Washington DC. <http://nchrptimpm.timnetwork.org/> (Apr. 11, 2019).

Jodoin, P. (2018a). "Collection, Analysis, and Use of Data to Improve Traffic Incident Management (TIM): Innovative Examples from Successful States." A webinar presented by the FHWA.

Jodoin, P. (2018b). EDC-4 TIM Data Western Regional Workshop. Salt Lake City, UT. October 31, 2018.

Kim, W., Franz, M., and Chang, G. (2012). "Enhancement of Freeway Incident Traffic Management and Resulting Benefits." Maryland State Highway Administration Report SP009B4Q.

Kim, W. and Chang, G. (2012). "Review and Enhancement of CHART Operations to Maximize the Benefit of Incident Response and Management." Maryland State Highway Administration Report SB009B4U. pp.8-10, 20, 46-50, 55.

Kuhn, B. (2014). "Planning and Evaluating Active Traffic Management Strategies." NCHRP Project 03-114. Literature review presented by Texas A&M Transportation Institute, Battelle, Kimley-Horn and Associates, Inc., and Constance Sorrell. < http://onlinepubs.trb.org/onlinepubs/nchrp/docs/NCHRP03-114_LiteratureReview-Revised.pdf> (April 11, 2019).

Moving Ahead for Progress in the 21st Century Act (MAP-21), (2012). Pub. L. No. 112-141 USC.

National Highway Traffic Safety Association (NHTSA). (2017). "MMUCC Guideline: Model Minimum Uniform Crash Criteria, 5th Edition." <https://crashstats.nhtsa.dot.gov/Api /Public/Publication/812433> (Apr. 11, 2019).

National Traffic Incident Management Coalition (NTIMC). (2007). "National Unified Goal for Traffic Incident Management." <http://timnetwork.org/wp-content/uploads/NUG-Unified-Goal-Nov07.pdf> (Apr. 11, 2019).

Numetric. (2018). "UDOT SafeMap." <https://udot.numetric.com> (Apr. 11, 2019).

Ogle, J., Chowdhury, M., Huynh, N., Davis, J, and Xie, Y. (2017). "Integration of the Incident Command System (ICS) Protocol for Effective coordination of Multi-Agency Response to Traffic Incidents." <http://www.scdot.scltap.org/wp-content/uploads/2017/06/SPR-699-FHWA-SC-17-07.pdf> (Apr. 11, 2019).

Owens, N.D., Armstrong, A.H., Mitchell, C., and Brewster, R. (2009). "Federal Highway Administration Focus States Initiative: Traffic Incident Management Performance Measures Final Report." <https://ops.fhwa.dot.gov/publications/fhwahop10010/ fhwahop10010.pdf> (Apr. 11, 2019).

Ozbay, K. and Bartin, B. (2003). "Incident Management Simulation." *Simulation*, 79(2), 69-82.

Pal, R. and Sinha, K.C. (2002). "Simulation Model for Evaluating and Improving Effectiveness of Freeway Service Patrol Programs." *Journal of Transportation Engineering*, 128(4).

Pecheux, K.K., Pecheux, B.B., Carrick, G. (2019). "Leveraging Big Data to Improve Traffic Incident Management." NCHRP Research Report 904. <https://doi.org/10.17226/25604> (Jul. 28, 2021).

Ramsey, F., and Schafer, D. (2013). *The Statistical Sleuth: A Course in Methods of Data Analysis.* CENGAGE, Boston, MA.

Rensel, E., Rafferty, P., Yorks, C. (2018). "Traffic Incident Management and Reducing Secondary Crashes in Arizona." Report No. FHWA-AZ-18-740, Arizona Department of Transportation, Phoenix.

Schultz, G.G., Mineer, S.T., Hamblin, C.A., Halliday, D.B., Groberg, C.C., and Burris, M.W. (2015). "I-15 Express Lanes Study Phase II: Recommendations." Report No. UT-15.03, Utah Department of Transportation, Salt Lake City.

Schultz, G.G., Saito, M., Hadfield, M.G., Bennett, L.S., and Eggett, D.L. (2019). "Analysis of Performance Measures of Traffic Incident Management in Utah." Report No. UT-19.01, Utah Department of Transportation, Salt Lake City.

Shah, V., Hatcher, G., Greer, E., and Fraser, J. (2017). NCHRP Report 03-108: "Guidance on Quantifying Benefits of TIM Strategies.," Transportation Research Board. Washington DC.

Smith, B., Evans, M., and Babiceanu, S. (2005). "Development of Incident Data Collection Standards for Virginia Department of Transportation Freeway Operations." <http://www.virginiadot.org/vtrc/main/online_reports/pdf/05-cr19.pdf> (Apr. 11, 2019).

Souleyrette, R., Chen, M., Zang, Xu., Green, E.R., Sagar, S. (2018). "Improving the Quality of Traffic Records for Traffic Incident Management." Report No. KTC-18-22/SPR18-567-1F, Kentucky Transportation Center, Lexington.

Transportation Research Board (TRB). (2010). "Highway Capacity Manual, 2010 Ed." Washington, DC.

Utah Department of Transportation (UDOT). (2018a). "Iteris Performance Measurement System" (iPeMS). <https://udotdemo.iteris-pems.com/> (Apr. 11, 2019).

Utah Department of Transportation (UDOT). (2018b). "Iteris Performance Measurement System" (PeMS). <https://udot.iteris-pems.com/> (Apr. 11, 2019).

LIST OF ACRONYMS

ADOT	Arizona Department of Transportation
ATMS	Advanced Traffic Management System
AV	Affected Volume
AVO	Average Vehicle Occupancy
BYU	Brigham Young University
CAD	Computer-aided Dispatch
CHART	Coordinated Highways Action Response Team
CTECC	Combined Transportation, Emergency, and Communications Center
DOT	Department of Transportation
EDC-4	Every Day Counts Round 4
ETT	Excess Travel Time
EUC	Excess User Cost
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FII	Fatal and Incapacitating Injury
FSI	Focus States Initiative
GDOT	Georgia Department of Transportation
GPS	Global Positioning System

HELP	Highway Emergency Local Patrol
HTA	Highway and Transportation Authority
ICS	Incident Command System
ICT	Incident Clearance Time
IMT	Incident Management Team
iPeMS	Iteris Performance Measurement System
IRCO	Incident Response and Clearance Ontology
KSP	Kentucky State Police
MnDOT	Minnesota Department of Transportation
NCHRP	National Cooperative Highway Research Program
NTIMC	National Traffic Incident Management Coalition
NDOT	Nevada Department of Transportation
NYSDOT	New York State Department of Transportation
PDO	Property Damage Only
PeMS	Performance Measurement System
PI	Personal Injury
RCT	Roadway Clearance Time
RT	Response Time
SCDOT	South Carolina Department of Transportation
SSP	Safety Service Patrol
STC	Smart Traffic Center
TAC	Technical Advisory Committee
TEOC	Transportation Emergency Operations Center

TIM	Traffic Incident Management
TMC	Transportation Management Center
TOC	Traffic Operations Center
TRIMARC	Traffic Response and Incident Management Assisting the River Cities
UDOT	Utah Department of Transportation
UHP	Utah Highway Patrol
VBA	Visual Basic for Applications
VDOT	Virginia Department of Transportation
WSDOT	Washington State Department of Transportation

APPENDIX A. EXPANDED IMT COVERAGE AREAS

The figures and maps shown in Section 3.2 show the centerline miles covered by IMTs in both 2018 and 2020 in the four UDOT regions. Data about IMT coverage areas before and after the program expansion were provided to the research team by UDOT's IMT program supervisor and included the names of roadways, mileposts patrolled, and lengths covered by direction. Those data are provided here, in Table A-1 through Table A-7. It should be noted that the centerline miles provided in the body of the report do not consider the directionality of the lengths covered, and the totals are therefore half of what appear in the tables here. This was done to avoid confusion between the miles covered by IMTs and the total number of roadway miles in the respective regions, which are not reported by direction. As was discussed in the body of the report, Region 4 did not have any full-time IMTs stationed there until after the program expansion, which is why center miles for Region 4 are only given for the post-expansion program.

Table A-1: Region 1 Centerline Miles Covered Prior to Program Expansion

Section Description	Beginning Milepost	Ending Milepost	Length [miles]
I-15 Davis County (Northbound)	312.0	349.0	37
I-15 Davis County (Southbound)	349.0	312.0	37
US-89 (Northbound)	383.0	406.0	23
US-89 (Southbound)	406.0	383.0	23
SR-87/Legacy Pkwy (Northbound)	0.0	12.0	12
SR-87/Legacy Pkwy (Southbound)	12.0	0.0	12
I-215 (Northbound)	26.0	30.0	4
I-215 (Southbound)	30.0	26.0	4
I-84 (Eastbound)	81.0	87.0	6
I-84 (Westbound)	87.0	81.0	6
Total			164

Table A-2: Region 2 Centerline Miles Covered Prior to Program Expansion

Section Description	Beginning Milepost	Ending Milepost	Length [miles]
I-15 (Northbound) Main Flow	286.0	313.0	27
I-15 (Southbound) Main Flow	313.0	286.0	27
I-80 (Eastbound)	99.0	140.0	41
I-80 (Westbound)	140.0	99.0	41
I-215 (Northbound)	0.0	29.0	29
I-215 (Southbound)	29.0	0.0	29
SR-201 (Eastbound)	0.0	17.0	17
SR-201 (Westbound)	17.0	0.0	17
SR-202 (Northbound)	0.0	3.0	3
SR-202 (Southbound)	3.0	0.0	3
SR-154/Bangerter Hwy (Northbound)	21.0	24.0	3
SR-154/Bangerter Hwy (Southbound)	24.0	21.0	3
Total			240

Table A-3: Region 3 Centerline Miles Covered Prior to Program Expansion

Section Description	Beginning Milepost	Ending Milepost	Length [miles]
I-15 (Northbound) Main Flow	239.0	288.0	49
I-15 (Southbound) Main Flow	288.0	239.0	49
Total			98

Table A-4: Region 1 Centerline Miles Covered After Program Expansion

Section Description	Beginning Milepost	Ending Milepost	Length [miles]
I-15 Davis County (Northbound)	312.0	400.0	88
I-15 Davis County (Southbound)	400.0	312.0	88
US-89 (Northbound)	383.0	406.0	23
US-89 (Southbound)	406.0	383.0	23
SR-87/Legacy Pkwy (Northbound)	0.0	12.0	12
SR-87/Legacy Pkwy (Southbound)	12.0	0.0	12
I-215 (Northbound)	26.0	30.0	4
I-215 (Southbound)	30.0	26.0	4
I-84 (Eastbound)	81.0	102.0	21
I-84 (Westbound)	102.0	81.0	21
SR-105 (Northbound)	0.0	2.0	2
SR-105 (Southbound)	2.0	0.0	2
SR-106 (Northbound)	0.0	10.0	10
SR-106 (Southbound)	10.0	0.0	10
SR-193 (Northbound)	0.0	17.0	17
SR-193 (Southbound)	17.0	0.0	17
SR-91 (Northbound)	10.0	28.0	18
SR-91 (Southbound)	28.0	10.0	18
SR-39 (Northbound)	7.0	43.0	36
SR-39 (Southbound)	43.0	7.0	36
SR-83 (Northbound)	0.0	31.0	31
SR-83 (Southbound)	31.0	0.0	31
Total			524

Table A-5: Region 2 Centerline Miles Covered After Program Expansion

Section Description	Beginning Milepost	Ending Milepost	Length [miles]
I-15 (Northbound) Main Flow	286.0	313.0	27
I-15 (Southbound) Main Flow	313.0	286.0	27
I-80 (Eastbound)	77.0	167.0	90
I-80 (Westbound)	167.0	77.0	90
I-215 (Northbound)	0.0	29.0	29
I-215 (Southbound)	29.0	0.0	29
SR-201 (Eastbound)	0.0	17.0	17
SR-201 (Westbound)	17.0	0.0	17
SR-202 (Northbound)	0.0	3.0	3
SR-202 (Southbound)	3.0	0.0	3
SR-154/Bangerter Hwy (Northbound)	21.0	24.0	3
SR-154/Bangerter Hwy (Southbound)	24.0	21.0	3
US-40 (Eastbound)	0.0	15.0	15
US-40 (Westbound)	15.0	0.0	15
Total			368

Table A-6: Region 3 Centerline Miles Covered After Program Expansion

Section Description	Beginning Milepost	Ending Milepost	Length [miles]
I-15 (Northbound) Main Flow	239.0	288.0	49
I-15 (Southbound) Main Flow	288.0	239.0	49
US-6 (Eastbound)	141.0	201.0	60
US-6 (Westbound)	201.0	141.0	60
SR-189 (Northbound)	3.0	15.0	12
SR-189 (Southbound)	15.0	3.0	12
SR-73 (Eastbound)	31.0	36.0	5
SR-73 (Westbound)	36.0	31.0	5
SR-68 (Northbound)	0.0	34.0	34
SR-68 (Southbound)	34.0	0.0	34
SR-85 (Eastbound)	0.0	3.0	3
SR-85 (Westbound)	3.0	0.0	3
SR-92 (Eastbound)	22.0	27.0	5
SR-92 (Westbound)	27.0	22.0	5
US-89 (Northbound)	298.0	313.0	15
US-89 (Southbound)	313.0	298.0	15
Total			366

Table A-7: Region 4 Centerline Miles Covered After Program Expansion

Section Description	Beginning Milepost	Ending Milepost	Length [miles]
I-15 (Northbound) Main Flow	0.0	42.0	42
I-15 (Southbound) Main Flow	42.0	0.0	42
SR-17 (Northbound)	0.0	6.0	6
SR-17 (Southbound)	6.0	0.0	6
SR-9 (Northbound	0.0	27.0	27
SR-9 (Southbound)	27.0	0.0	27
SR-59 (Northbound)	0.0	23.0	23
SR-59 (Southbound)	23.0	0.0	23
SR-7 (Northbound)	0.0	11.0	11
SR-7 (Southbound)	11.0	0.0	11
SR-18 (Northbound	0.0	24.0	24
SR-18 (Southbound)	24.0	0.0	24
SR-228 (Northbound)	0.0	2.0	2
SR-228 (Southbound)	2.0	0.0	2
SR-318 (Northbound)	0.0	2.0	2
SR-318 (Southbound)	2.0	0.0	2
SR-34 (Eastbound)	0.0	4.0	4
SR-34 (Westbound)	4.0	0.0	4
SR-8 (Eastbound)	0.0	3.0	3
SR-8 (Westbound)	3.0	0.0	3
Total			288

APPENDIX B. STATISTICAL RESULTS OF ICT

This appendix includes results of statistical analyses of ICT versus a number of incident characteristics, including the number of IMTs responding, the number of lanes in the roadway at the location of the bottleneck, the number of lanes closed by IMT responders, and the time of day when the incident occurred. An analysis was also performed of ICT versus RT. The analyses tested for the fixed effects of each incident characteristic and for crash type, since severity is directly related to the on-scene requirements of the IMTs. The results are similar to those found in Section 5.2, as values of RCT and ICT were very well correlated. Numeric results are shown here, and explanation of results is limited to those analyses where the results differed from those in Section 5.2.

B.1 Performance Measures

B.1.1 ICT vs. Number of IMTs

Table B-1 and Table B-2 show results for the analysis of ICT versus the number of IMTs responding to the scene. The results are shown visually in Figure B-1.

Table B-1: Significance of ICT vs. Number of IMTs

	Year	p > |t|	Significance
Does ICT depend on the number of IMTs?	2018	0.0008	***
	2020	<0.0001	****

Table B-2: Analysis of ICT vs. Number of IMTs

Number of IMTs	Year	Mean ICT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
1	2018	119.46	108.35	130.57	5.65	191	314	<0.0001	****
	2020	125.11	109.43	132.68	5.90	172	280	<0.0001	****
2	2018	136.80	126.08	147.52	5.45	113	314	<0.0001	****
	2020	133.58	108.95	135.39	6.72	78	280	<0.0001	****
3	2018	142.46	119.67	165.25	11.58	13	314	<0.0001	****
	2020	157.83	131.47	165.26	8.58	27	280	<0.0001	****
4	2018	135.01	92.54	177.48	21.59	3	314	<0.0001	****
	2020	130.95	95.38	148.30	13.44	9	280	<0.0001	****
5	2020	159.73	104.26	249.74	36.95	1	280	<0.0001	****
6	2020	122.19	53.86	199.40	36.97	1	280	0.0007	***
8	2020	394.43	317.33	462.81	36.95	1	280	<0.0001	****

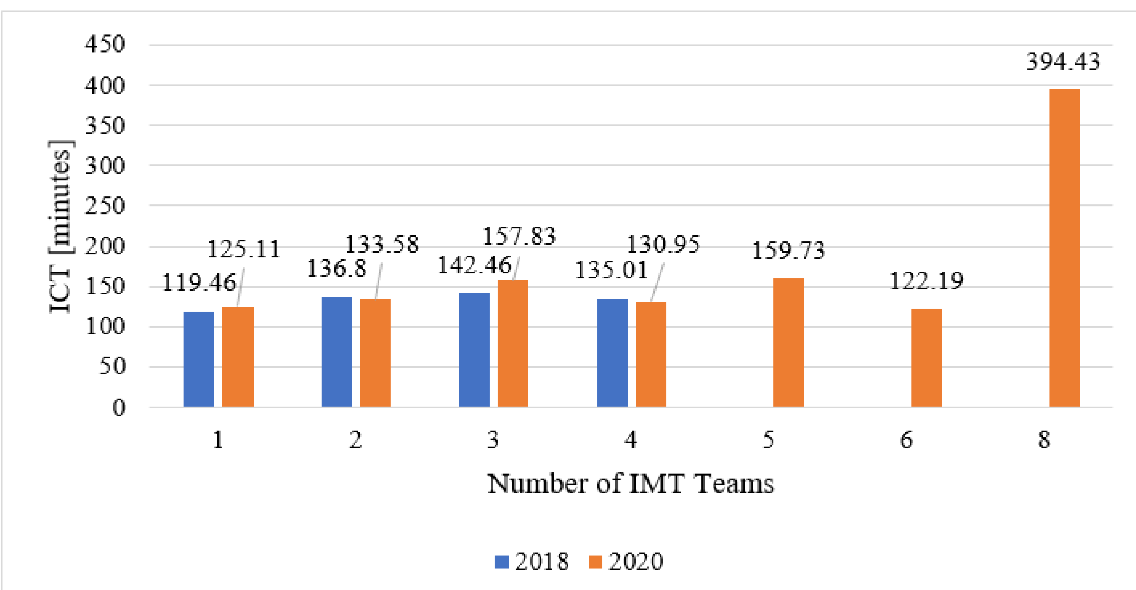


Figure B-1: ICT vs. number of responding IMTs.

B.1.2 ICT vs. Number of Lanes at Bottleneck

Table B-3 and Table B-4 show results for the analysis of ICT versus the number of lanes in the direction corresponding to the crash at the location of the bottleneck. The results of the analysis are shown visually in Figure B-2.

Table B-3: Significance of ICT vs. Number of Lanes at Bottleneck

<table>
<tr><td colspan="4"></td></tr>
<tr><td rowspan="3">Does ICT depend on the number of lanes at the bottleneck?</td><td>Year</td><td>p > |t|</td><td>Significance</td></tr>
<tr><td>2018</td><td>0.318</td><td>ns</td></tr>
<tr><td>2020</td><td>0.0605</td><td>*</td></tr>
</table>

Table B-4: Analysis of ICT vs. Number of Lanes at Bottleneck

<table>
<tr><td colspan="10"></td></tr>
<tr><td>Lanes at Bottleneck</td><td>Year</td><td>Mean ICT [minutes]</td><td>Lower</td><td>Upper</td><td>SE</td><td>Sample Size</td><td>DF</td><td>p > |t|</td><td>Significance</td></tr>
<tr><td rowspan="2">1</td><td>2018</td><td>---</td><td>---</td><td>---</td><td>---</td><td>---</td><td>---</td><td>---</td><td>---</td></tr>
<tr><td>2020</td><td>105.84</td><td>82.16</td><td>129.51</td><td>12.00</td><td>20</td><td>181</td><td><0.0001</td><td>****</td></tr>
<tr><td rowspan="2">2</td><td>2018</td><td>129.27</td><td>74.17</td><td>184.37</td><td>27.93</td><td>1</td><td>182</td><td><0.0001</td><td>****</td></tr>
<tr><td>2020</td><td>122.87</td><td>94.31</td><td>151.43</td><td>14.48</td><td>4</td><td>181</td><td><0.0001</td><td>****</td></tr>
<tr><td rowspan="2">3</td><td>2018</td><td>120.26</td><td>104.77</td><td>135.76</td><td>7.85</td><td>18</td><td>182</td><td><0.0001</td><td>****</td></tr>
<tr><td>2020</td><td>142.05</td><td>121.88</td><td>162.21</td><td>10.22</td><td>19</td><td>181</td><td><0.0001</td><td>****</td></tr>
<tr><td rowspan="2">4</td><td>2018</td><td>110.33</td><td>96.66</td><td>124.01</td><td>6.93</td><td>39</td><td>182</td><td><0.0001</td><td>****</td></tr>
<tr><td>2020</td><td>140.89</td><td>121.46</td><td>160.32</td><td>9.85</td><td>31</td><td>181</td><td><0.0001</td><td>****</td></tr>
<tr><td rowspan="2">5</td><td>2018</td><td>106.10</td><td>94.26</td><td>117.93</td><td>6.00</td><td>59</td><td>182</td><td><0.0001</td><td>****</td></tr>
<tr><td>2020</td><td>136.03</td><td>117.56</td><td>154.50</td><td>9.36</td><td>39</td><td>181</td><td><0.0001</td><td>****</td></tr>
<tr><td rowspan="2">6</td><td>2018</td><td>115.39</td><td>102.83</td><td>127.96</td><td>6.37</td><td>64</td><td>182</td><td><0.0001</td><td>****</td></tr>
<tr><td>2020</td><td>137.51</td><td>121.31</td><td>153.71</td><td>8.21</td><td>73</td><td>181</td><td><0.0001</td><td>****</td></tr>
<tr><td rowspan="2">7</td><td>2018</td><td>114.16</td><td>93.25</td><td>135.07</td><td>10.60</td><td>9</td><td>182</td><td><0.0001</td><td>****</td></tr>
<tr><td>2020</td><td>129.14</td><td>90.18</td><td>168.10</td><td>19.74</td><td>4</td><td>181</td><td><0.0001</td><td>****</td></tr>
</table>

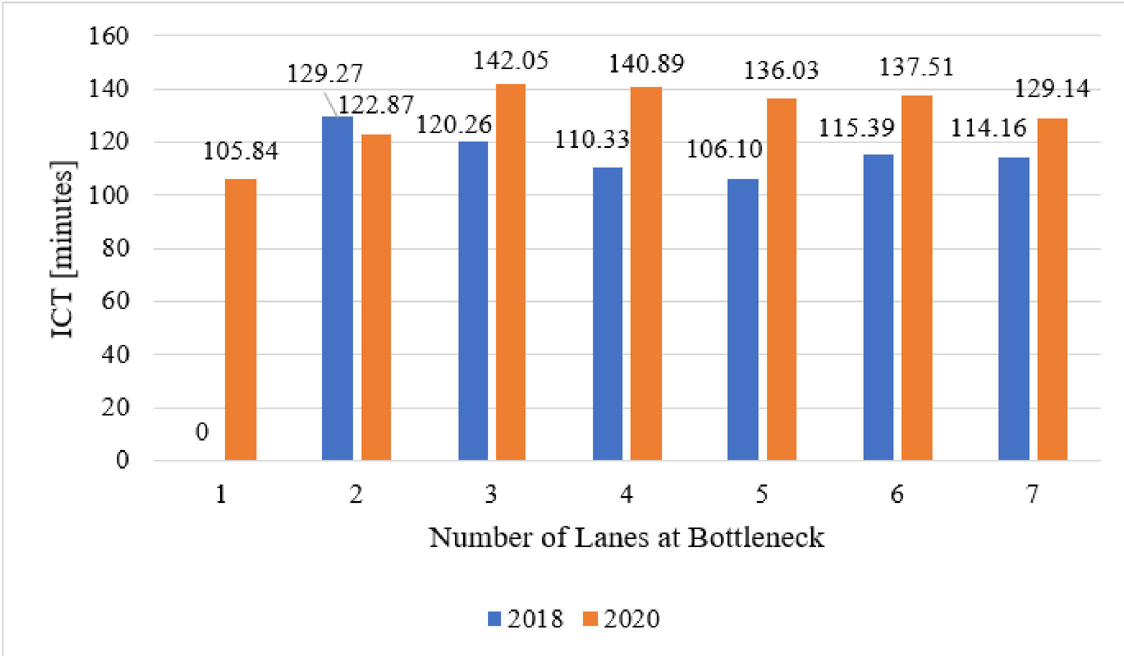


Figure B-2: ICT vs. number of lanes at the bottleneck.

B.1.3 ICT vs. Number of Lanes Closed

Table B-5 and Table B-6 show results for the analysis of ICT versus the number of lanes closed by IMTs at the location of the incident. The number of lanes closed is an indication of the magnitude of an incident. The results of the analysis are shown visually in Figure B-3.

Table B-5: Significance of ICT vs. Number of Lanes Closed

Does ICT depend on the number of lanes closed?	**Year**	**p > |t|**	**Significance**
	2018	0.0429	**
	2020	<0.0001	****

Table B-6: Analysis of ICT vs. Number of Lanes Closed

Lanes Closed	Year	Mean ICT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
1	2018	124.98	112.32	137.64	6.43	170	312	<0.0001	****
	2020	116.32	103.00	129.64	6.76	127	255	<0.0001	****
2	2018	125.64	111.98	139.30	6.94	82	312	<0.0001	****
	2020	136.72	123.01	150.42	6.96	75	255	<0.0001	****
3	2018	137.84	123.35	152.33	7.36	50	312	<0.0001	****
	2020	134.79	118.47	151.11	8.28	37	255	<0.0001	****
4	2018	136.18	113.78	158.59	11.39	13	312	<0.0001	****
	2020	146.86	128.33	165.38	9.40	21	255	<0.0001	****
5	2018	165.54	127.90	203.18	19.13	4	312	<0.0001	****
	2020	219.89	165.50	274.27	27.62	2	255	<0.0001	****
6	2018	68.37	-9.41	146.14	39.53	1	312	0.0847	*
	2020	99.68	23.44	175.92	38.71	1	255	0.0106	**

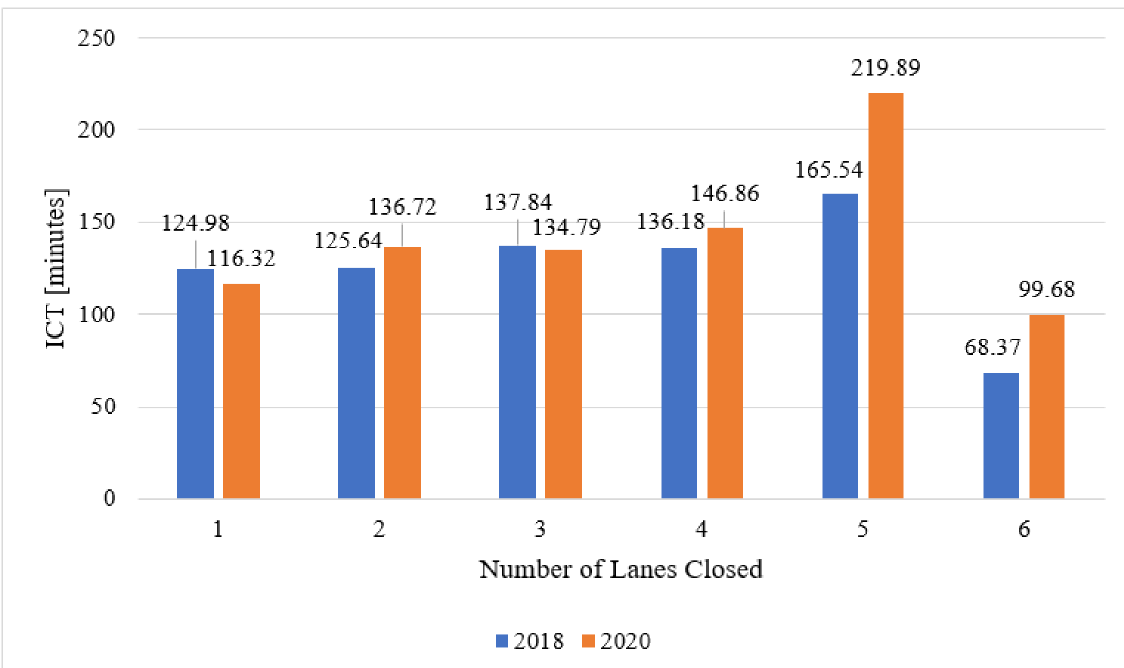


Figure B-3: ICT vs. number of lanes closed.

B.1.4 ICT vs. Number of Available Lanes

An analysis of ICT was also performed on the number of available lanes. Table B-7 and Table B-8 show results for the analysis of IMT CT versus the number of lanes available at the location of the incident. Figure B-4 shows a visual representation of the results.

Table B-7: Significance of ICT vs. Number of Available Lanes

	Year	p > |t|	Significance
Does ICT depend on the number of available lanes?	2018	0.0373	**
	2020	0.0086	***

Table B-8: Analysis of ICT vs. Number of Available Lanes

Available Lanes	Year	Mean ICT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
0	2018	126.51	109.17	143.85	8.79	8	181	<0.0001	****
	2020	115.77	95.65	135.89	10.20	30	180	<0.0001	****
1	2018	104.90	89.13	120.67	7.99	17	181	<0.0001	****
	2020	136.37	113.43	159.30	11.62	22	180	<0.0001	****
2	2018	116.13	101.04	131.22	7.65	27	181	<0.0001	****
	2020	147.23	126.41	168.06	10.55	25	180	<0.0001	****
3	2018	110.33	97.20	123.46	6.65	57	181	<0.0001	****
	2020	133.78	113.68	153.87	10.18	45	180	<0.0001	****
4	2018	98.80	85.19	112.40	6.89	45	181	<0.0001	****
	2020	122.36	101.99	142.73	10.32	41	180	<0.0001	****
5	2018	103.27	88.21	118.34	7.63	27	181	<0.0001	****
	2020	120.39	97.93	142.86	11.38	24	180	<0.0001	****
6	2018	113.88	90.91	136.85	11.64	7	181	<0.0001	****
	2020	78.65	25.56	131.74	26.90	2	180	0.0039	***

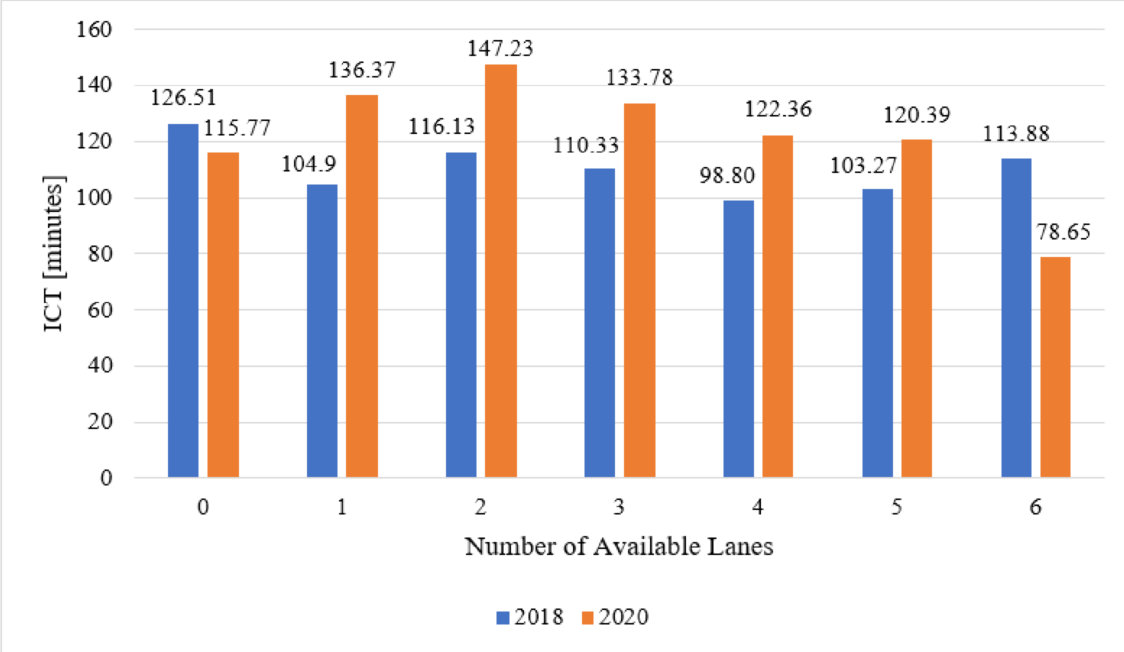


Figure B-4: ICT vs. number of available lanes.

B.1.5 ICT vs. Time of Day

Table B-9 and Table B-10 show results for the analysis of ICT versus the time of day of the incident. Figure B-5 shows a visual representation of the results.

Table B-9: Significance of ICT vs. Time of Day

Does ICT depend on the time of day?	**Year**	**p > |t|**	**Significance**
	2018	<0.0001	****
	2020	0.1028	ns

Table B-10: Analysis of ICT vs. Time of Day

Time of Day	Year	Mean ICT [minutes]	Lower	Upper	SE	Sample Size	DF	p > |t|	Significance
Morning Off Peak	2018	168.38	140.79	195.96	14.02	8	313	<0.0001	****
	2020	139.60	119.02	160.18	10.46	19	282	<0.0001	****
AM Peak	2018	105.21	91.28	119.14	7.08	87	313	<0.0001	****
	2020	140.70	123.87	157.53	8.55	44	282	<0.0001	****
Afternoon Off Peak	2018	117.74	105.05	130.44	6.45	134	313	<0.0001	****
	2020	138.18	124.04	152.32	7.18	113	282	<0.0001	****
PM Peak	2018	107.83	93.90	121.76	7.08	88	313	<0.0001	****
	2020	125.62	111.19	140.04	7.33	83	282	<0.0001	****
Night Off Peak	2018	206.15	162.77	249.53	22.05	3	313	<0.0001	****
	2020	125.77	109.24	142.29	8.40	30	282	<0.0001	****

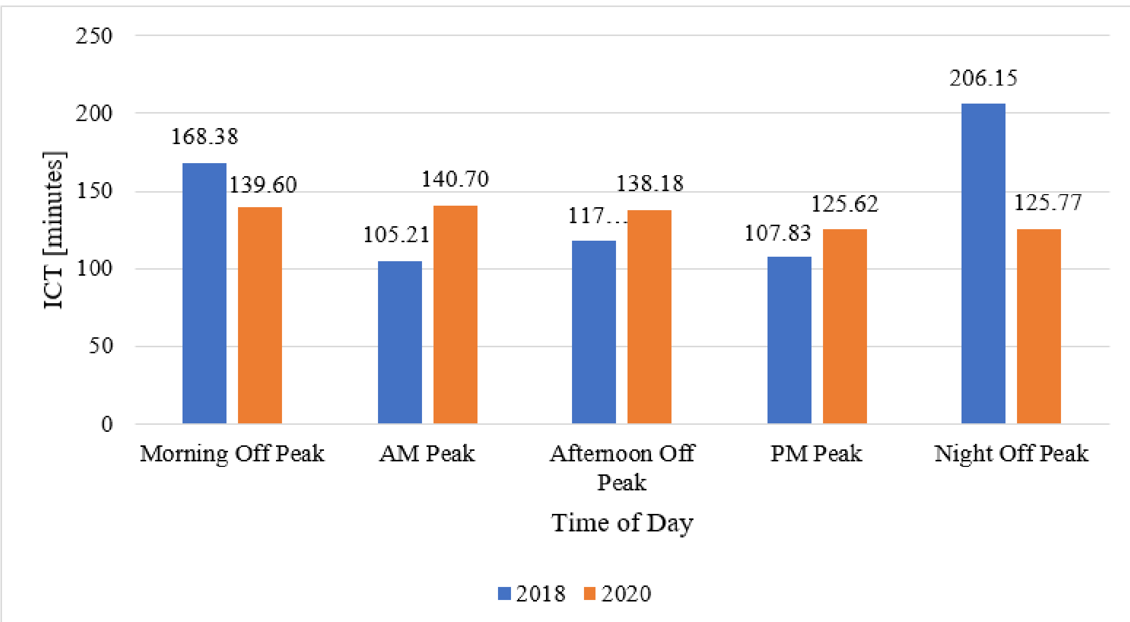


Figure B-5: ICT vs. time of day.

The statistics in Table B-9 indicate that time of day did not have a significant effect on ICT in 2020. This is different from the results of the analysis of RCT versus time of day in Section 5.2.5 of the report. In 2020 RCT values varied at different times of day, which could be indicative of fluctuations in congestion patterns at peak and off-peak periods that would affect incident queueing patterns. However, as Table B-9 indicates, the time it took for IMTs to leave the scene was fairly consistent across all times of day in 2020. While incidents at times of day were consistently cleared more quickly, IMTs tended to stay at the scene for similar amounts of time, which could be due to additional responsibilities and clean-up required after lane clearance.

One observation from the results shown in Table B-10 and Figure B-5 is that in 2020 IMTs were able to leave the scene of the incident much more consistently than in 2018. Before the program expansion, IMTs tended to stay at the scene of crashes in the off-peak periods for longer amounts of time. However, with addition of more IMTs, they have been able to fulfill their duties, leave the scene, and get to safety faster during those times. The consistency of performance is one of the greatest advantages that the statistical results in this report have shown, and that result of consistency is substantiated in this analysis as well.

B.1.6 ICT vs. RT

An analysis of ICT against the distribution of RT for each given year in 2018 and 2020 was also performed. Table B-11 shows a summary of the results of this analysis.

Table B-11: Analysis of ICT vs. RT

Year	Mean ICT per minute RT	Lower	Upper	SE	Sample Size	p > |t|	Significance
2018	0.84	0.56	1.11	0.14	302	<0.0001	****
2020	0.56	0.16	0.96	0.20	275	0.0058	***

Table B-11 indicates that after accounting for crash type, there is still a significant effect of RT on ICT for both 2018 and 2020. For 2018, each added minute of RT translates to about 0.84 minutes of added ICT. For 2020, this value is about 0.56 minutes of ICT per minute of RT. This result shows that ICT cannot be described solely by crash type, but that RT also has an effect on the time it takes IMTs to leave the scene of the incident.

APPENDIX C. STATISTICAL RESULTS OF UHP PERFORMANCE

The purpose of this study was to evaluate the effects of UDOT's IMT program after the 2018 expansion. For that reason, the data reduction and analysis in the report focus on performance measures of IMTs and the user impacts associated with IMT performance. However, performance measure data were collected for UHP teams and analyses were also conducted on UHP performance. A brief overview of practical findings is shown here.

C.1 User Impacts

Analyses of the effects of UHP performance on user impacts were conducted, with the following results.

C.1.1 ETT and EUC vs. UHP RT

Table C-1 and Table C-2 show results of an analysis of ETT and EUC versus UHP RT.

Table C-1: Significance of IMT Program Size vs. ETT for UHP RT

Does ETT between 2018 and 2020 depend on UHP RT, after accounting for volume differences?	**p > F**	**Significance**
	0.4199	ns

Table C-2: Significance of IMT Program Size vs. EUC for UHP RT

Does EUC between 2018 and 2020 depend on UHP RT, after accounting for volume differences?	p > F	Significance
	0.5178	ns

The tables indicate that there is not a significant relationship between the time it takes UHP units to respond to an incident and the amount of ETT or EUC that are accrued. This is likely due to the fact that UHP consistently responds quickly to incidents. According to the 2018 incident data collected, UHP units arrived within the first 15 minutes about 84 percent of the time. This increased to about 88 percent of the time in 2020.

C.1.2 ETT and EUC vs. UHP ICT

Table C-3 and Table C-4 show results of the interaction terms for the analyses of ETT and EUC versus UHP ICT.

Table C-3: Analysis of IMT Program Size vs. ETT for UHP ICT

Difference in Means [minutes]	Lower	Upper	Sample Size	SE	p > F	Significance
1.70	0.37	3.03	334	0.68	0.0122	**

Table C-4: Analysis of IMT Program Size vs. EUC for UHP ICT

Difference in Means	Lower	Upper	Sample Size	SE	p > F	Significance
$46.79	$11.29	$82.28	334	$18.04	0.0099	***

The analyses show that there is a significant effect of the program expansion on ETT and EUC in terms of the UHP ICT. While significant, the effect is smaller than those from previous analyses of ICT. This is likely due to the fact that UHP responders have additional duties that they must complete before officially clearing the incident, such as additional paperwork and the occasional responsibility to escort crash victims to the hospital. For each minute of UHP ICT saved in 2020, about 1.70 minutes of ETT and $46.79 of EUC were saved when compared with 2018.