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ANALYSIS OF BENEFITS OF UDOT'S EXPANDED INCIDENT MANAGEMENT TEAM PROGRAM

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RESEARCH

Keeping Utah Moving

Utah Department of Transportation - Research Division
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DISCLAIMER

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16. Abstract

In 2019, the Utah Department of Transportation (UDOT) funded a research study evaluating the performance measures of UDOT's expanded Incident Management Team (IMT) program. The number of IMTs patrolling Utah roadways increased from 13 to 25 between 2018 and 2020. Crash data were collected from the Utah Highway Patrol's Computer Aided Dispatch database and from the UDOT TransSuite database to compare IMT performance measures between the two years and to evaluate the benefits of the expanded IMT program. However, these data were compromised due to the effects of the COVID-19 pandemic. This study collected data for 2022 using the same methodology as the Phase II study to compare IMT performance measures in 2022 with those of 2018 after traffic volumes had returned to a similar level as those of pre-pandemic levels. There were 283 and 307 incidents for the years of 2018 and 2022, respectively, that were analyzed for IMT performance measures which include response time, roadway clearance time, and incident clearance time. There were 172 and 236 incidents for the years of 2018 and 2022, respectively, that were analyzed for the user impact categories of affected volume, excess travel time, and excess user costs. Results of the statistical analyses conducted on the 2018 and 2022 datasets show that IMTs can respond more quickly to incidents in a larger coverage area with significantly reduced user impacts. The expanded IMT program is also able to respond to more incidents, including those of high severity, while significantly decreasing congestion.

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LIST OF ACRONYMS

ATIS	Advanced Traveler Information System
AV	Affected Volume
AVO	Average Vehicle Occupancy
BYU	Brigham Young University
CAD	Computer-Aided Dispatch
CCTV	Closed Circuit Television
ETT	Excess Travel Time
EUC	Excess User Costs
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FII	Fatal and Incapacitating Injury
FSI	Focus States Initiative
HOV	High-Occupancy Vehicle
ICT	Incident Clearance Time
IHC	Individual Hourly Cost
IMT	Incident Management Team
ITS	Intelligent Transportation System
Ln	Natural Log
NCHRP	National Cooperative Highway Research Program
PDO	Property Damage Only
PI	Personal Injury
RT	Response Time
RCT	Roadway Clearance Time
THC	Truck Hourly Cost
TIM	Traffic Incident Management
TOC	Traffic Operations Center
UDOT	Utah Department of Transportation
UHP	Utah Highway Patrol
VBA	Visual Basic for Applications

VMS	Variable Message Sign
VMT	Vehicle Miles Traveled

EXECUTIVE SUMMARY

In 2019, the Utah Department of Transportation (UDOT) funded a research study to evaluate the performance measures of an expanded Incident Management Team (IMT) program. The number of IMTs patrolling Utah roadways increased from 13 to 25 between 2018 and 2020. Crash data were collected from the Utah Highway Patrol's (UHP) Computer-Aided Dispatch (CAD) database and from the UDOT TransSuite database for 2018 and 2020. Data were collected to compare IMT performance measures between the two years and to evaluate the benefits of the expanded IMT program. However, these data were compromised due to the effects of the COVID-19 pandemic.

Because of the impacts caused by the COVID-19 pandemic, one of the recommendations from the research was to collect data in a future year without the impacts of COVID-19. The research presented in this report collected data for 2022 using the same methodology as the previous research to compare IMT performance measures in 2022 with those of 2018 after traffic volumes had returned to a similar level as those of pre-pandemic levels. There were 283 and 307 incidents that were analyzed for the years of 2018 and 2022, respectively, for the IMT performance measure categories of response time (RT), roadway clearance time (RCT), and incident clearance time (ICT). RT improved by 7 percent between 2018 and 2022 with significant reductions for all crash types. RCT was overall longer in 2022 than in 2018. While there was no statistically significant difference in the least squares means of the natural log (Ln) of RCT between 2018 and 2022, there was an 18 percent difference in the back-transformed Ln RCT for personal injury (PI) crashes. IMT ICT was shown to improve by 10 percent, demonstrating that IMTs are completing their work faster in 2022 than in 2018.

There were 172 and 236 incidents for the years of 2018 and 2022, respectively, that were analyzed for the user impact categories of affected volume (AV), excess travel time (ETT), and excess user costs (EUC). The AV of the median property damage only (PDO) and PI crashes in 2022 decreased by over 20 percent from that of 2018. The ETT and EUC of the median PDO crash decreased by over 40 percent between 2018 and 2022, and the ETT and EUC of the median PI crash decreased by over 50 percent between 2018 and 2022. The back-transformed least squares means of Ln ETT for the number of IMTs that responded to a given crash were significantly lower in 2022 than in 2018. This demonstrates that IMTs responded to smaller incidents in 2022 than in 2018 due to there being more teams available.

The time for which the speed of traffic was significantly below normal during an incident was reduced by 15 percent for PDO crashes and 7 percent for PI crashes between 2018 and 2022 which reflects the work of IMTs in user impacts. The IMT program is able to respond to incidents over a larger geographic area more quickly in 2022 than in 2018 and has the resources to respond to crashes of greater severity at a lower cost in 2022 than in 2018 without compromising its ability to respond to other crashes. This study recommends conducting further research on optimizing the number and location of IMTs on Utah roadways to strategically allocate UDOT’s resources to benefit the greatest number of roadway users for the lowest system-wide cost.

1.0 INTRODUCTION

1.1 Problem Statement

Non-recurring congestion accounts for a large portion of congestion taking place on interstate highways along the Wasatch Front. To help offset the impacts caused by non-recurring congestion, the Utah Department of Transportation (UDOT) has implemented an Incident Management Team (IMT) program to achieve the following benefits: 1) increased driver and responder safety, 2) congestion relief, 3) effective preparation for larger-scale emergencies and disasters, 4) public resources well spent to improve the public's life, and 5) reduced emissions caused by the delays created by incident-induced congestion. To evaluate the effectiveness of the IMT program in the state, Brigham Young University (BYU) researchers evaluated crashes to estimate performance measures and user costs of the IMT program. BYU conducted research on data collected in 2018 concluding that a potentially significant reduction in excess user costs (EUC) caused by congestion due to crashes could be achieved by reducing some of the incident performance measures, including response time (RT), roadway clearance time (RCT), and incident clearance time (ICT) (Bennett et al., 2021; Hadfield et al., 2021; Schultz et al., 2019). As the research team was nearing completion of the 2018 study, the Utah Legislature allocated additional funding to expand the IMT program by 12 units, from 13 to 25 total.

To evaluate the impacts of the expanded IMT program, both in terms of personnel and equipment, BYU and Avenue Consultants conducted a Phase II study that collected data in the summer of 2020, after the expanded IMT program had been established. The Phase II study of the UDOT IMT program integrated UDOT's Traffic Operations Center (TOC) TransSuite data with the Utah Highway Patrol (UHP) Computer-Aided Dispatch (CAD) data to analyze the effectiveness of IMTs. One challenge encountered in the 2020 study was that traffic patterns during the summer of 2020 were altered due to the impacts of the COVID-19 pandemic. To account for the effects of the pandemic, the research team collected traffic data and adjusted the data based on the differences in volume from 2018 to 2020. The results of the 2020 evaluation showed a shift towards shorter RT in 2020. Statistical analysis accounting for discrepancies in volumes between the data collected in 2018 and 2020 indicated significant benefits of the IMT program's expansion, particularly in terms of increased consistency. The expansion of the IMT program was shown to provide more consistent services with similar levels of performance on wider geographic and temporal scales; however, one of the outcomes of the 2020 research was a slightly longer overall RCT, possibly due to added precautions caused by the pandemic (Bennett et al., 2022; Schultz et al., 2021). IMT ICTs were shown to have improved.

The Phase II study demonstrated that the expansion of the IMT program improved the quality of service and expanded the range of the service provided on roadways in Utah. Because of the impact caused by the COVID-19 pandemic, a follow-up study was recommended to verify the extent of the results of the Phase II study, without the impact of the pandemic, by collecting 2022 incident data using the same methodology as Phase II and in the same 6-month period used to compare with 2018 incident data from Phase I and Phase II. The result of the Phase III study is documented in this report.

Performance measures collected for this study are consistent with previous studies and include RT, RCT, and ICT. User impacts for the same category of incidents including excess travel time (ETT), affected volume (AV), and EUC also decreased significantly from 2018 to 2020, though the extent of the lower user costs is inconclusive due to the effects of the COVID-19 pandemic. The extent of the effectiveness of the post-expansion IMT program needed to be verified by collecting and analyzing 2022 incident data to be compared with 2018 incident data. Traffic volumes observed on Utah interstates in 2022 have been verified to have returned to similar levels as those of pre-pandemic traffic volumes.

1.2 Objectives

The objective of this study was to evaluate performance measures of the UDOT IMT program without the impacts of the COVID-19 pandemic using the same data sources, methodology, and study area as the Phase I and Phase II studies to identify changes in the expanded program. While the expanded IMT program coverage area is larger than that of the study area, the IMT activity area for this study is limited to Utah and Salt Lake Counties to be consistent with the Phase I and Phase II studies. The Phase III study period included the months of March through August to be consistent with the data collected for the same time period in 2018.

1.3 Scope

The scope of the project includes completing a literature review of new developments and studies completed within the Traffic Incident Management (TIM) field between 2019 and 2022. The primary sources accessed for the literature review were the Transportation Research Board: Transportation Research Information Database and the American Society of Civil Engineers: Journal of Transportation Engineering.

The existing methodology from Phase II was used to collect performance measures of 2022 crashes by integrating the UHP CAD and UDOT TransSuite data. Traffic data for the crashes identified were then extracted from the UDOT PeMS (UDOT 2023a) and Clear Guide (formerly iPeMS) (UDOT 2023b) databases to analyze the data for user impacts using the same script and methodology as Phase II. After new datasets were compiled for 2018 and 2022, 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. 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 the UDOT IMT program.

1.4 Outline of Report

This report is organized into the following chapters:

1. Introduction
2. Literature Review
3. Methodology
4. Data Reduction
5. Results of Statistical Analyses
6. Conclusions
7. Recommendations and Implementation

Chapter 2 is a literature review that describes new findings on IMT performance measures, user impacts due to crashes, and other miscellaneous topics related to incident management. Chapter 3 explains the methodology including available data, the process used to collect performance measures, and the process of estimating 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. Chapter 7 provides recommendations and implementation for the research.

2.0 LITERATURE REVIEW

2.1 Overview

This chapter presents the findings from the literature review of TIM performance measures, the user impacts of crashes, and other miscellaneous topics related to TIM that have occurred between 2019 and 2022.

2.2 Performance Measures

The performance measures considered in this study are RT, RCT, and ICT in accordance with the conclusions of the Federal Highway Administration (FHWA) Focus States Initiative (FSI) (Owens et al., 2009). Unless otherwise noted, these performance measures refer to those of IMTs as opposed to those of other responders. Each of these measures will be discussed in the following sections.

2.2.1 Response Time

RT is defined as the time from when an incident has been verified to have occurred to when the IMT responders arrive on scene of the crash. Effective communication and use of technology are key factors in decreasing RT. The National Cooperative Highway Research Program (NCHRP) released a report titled, “A Development of Guidelines for Quantifying Benefits of Traffic Incident Management Strategies,” that references a study that was completed by the National Traffic Incident Management Coalition. The study reported that multiple agencies have experienced significant decreases in RT due to the implementation and integration of Intelligent Transportation System (ITS) technologies such as TOC closed circuit television (CCTV) footage, speed detectors, and traffic counters. The San Antonio TransGuide ITS system, which integrates TOC CCTV footage with the agency’s communications network, decreased RT in the San Antonio area by 20 percent during its first year of implementation. Monroe County, New York, implemented an ITS traffic camera system that led to decreasing incident verification times by over 50 percent and reducing RT between 5 to 12 minutes per incident (Shah et al., 2022).

2.2.2 Roadway Clearance Time

RCT is 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. The State of Georgia implemented a Towing and Recovery Incentive Program in which professional heavy-duty towing companies were paid bonuses for clearing large commercial vehicle incidents in 90 minutes or less. This has reduced RCT for large commercial vehicle incidents from 269 minutes to 94 minutes (Shah et al., 2022). This demonstrates the effectiveness of monetary bonuses as a tactic in improving TIM performance measures.

2.2.3 Incident Clearance Time

ICT is defined as the time between the first recordable awareness of an incident by a responsible agency and the time at which the last responder has left the scene. A study conducted on the performance measures of the Florida Road Rangers, a freeway service patrol provided by the Florida Department of Transportation (FDOT), showed that average ICT decreased by 25 percent for the incidents that the Road Rangers responded to as opposed to the incidents responded to by other agencies. Crash data were taken from FDOT's Sun Guide Database, which included the geographic location, RT, and ICT of an incident. Incident detection data from the Sun Guide Database came from the following sources: 1) Road Rangers (IMTs), 2) ITS services (including CCTV, Florida 511 probe vehicles, Waze data, and Transportation Management Centers), and 3) Florida Highway Patrol units. Over 28,000 incidents were analyzed in a statistical model to estimate an average ICT. Quantile regression was used to account for the outlying incidents with very high ICT that would otherwise make the dataset right skewed (or skewed towards higher ICT outlier values). Some of the incident characteristics that were related to ICT were incident severity, detection method, shoulder blockage, lighting conditions, time of day, whether the crash occurred on a weekday or weekend, and whether towing was involved (Salum et al., 2020).

The research by Salum et al. (2020) demonstrates the positive impacts of having a dedicated freeway service patrol, or IMT fleet, on decreasing incident duration. This is similar to the UDOT TIM Phase I and Phase II studies, which integrated crash data from two different data sources to analyze the RT, RCT, and ICT of IMTs (Schultz et al., 2021; Schultz et al., 2019).

The methodology of these two studies will be discussed in Chapter 3. The same methodology used in Phase II will be used in this, the Phase III research, with the exception of accounting for changes in volume that came about as a result of the COVID-19 pandemic.

2.3 User Impacts

The primary user impact considered in TIM research is EUC, defined as the financial cost incurred because of excess time spent in traffic caused by incidents on the roadway. Research has been done to quantify the costs due to congestion that are borne by drivers, companies, and communities. A research study completed by the Virginia Transportation Research Council, called, “Cost of Congestion Due to Incidents on Freeways,” developed a methodology to assign costs to incidents. Incident congestion costs were calculated for each link of the network within the study area by estimating: 1) travelers’ value of time, 2) incident probability (both of primary and secondary incidents) of the network, and 3) delay due to an incident (Lan et al., 2021). Travelers’ value of time was estimated using parameters such as Virginia’s average hourly wages for each category of vehicle, US average hourly wages for each category of vehicle, FHWA average occupancy of vehicle estimates, and traffic flows from a travel demand model. The function used to determine the value of time is shown in Equation 2-1.

$$\boldsymbol{VoT = \frac{PL_1}{PL_0} \times \frac{INC_1}{INC_0} \times \sum(R_i \times HE_i \times AO_i \times F_i)} \qquad \textbf{(2-1)}$$

Where:

VoT	=	travelers’ value of time
PL_1	=	prevailing price level at time of analysis
PL_0	=	baseline price level at time when value-of-time values were estimated
INC_1	=	prevailing income level at time of analysis
INC_0	=	baseline income level at time when value-of-time values were estimated
R_i	=	ratio of the value of time for travelers in traffic category *i* and hourly earnings for travelers in traffic category *i*
HE_i	=	average hourly earnings of travelers in traffic category *i*

AO_i	=	average occupancy of vehicles in traffic category i as a fraction of total throughput
F_i	=	flow on route under study
i	=	subscript that indexes the categories of traffic.

A primary incident probability was determined for each link using the mean distributions of the Virginia Department of Transportation's crash data. Secondary incident probability was determined using a mathematical model developed in a previous study based on I-66 crash data. The probability of each incident type was multiplied by the final congestion costs due to the delay of an incident (Lan et al., 2021).

Incident durations and delay were determined for each segment of the network based on crash type, location within the network, and the time of day as well as the day of the week of the incident. Given the type of incident, lane closures, and subsequent flow, volumes were estimated using traffic data from multiple sources. Traffic delay was divided by the incident duration to give a delay per incident minute for incident type and vehicle type. The value of time function was used given vehicle types and delay per incident minute to calculate a cost for incidents on the network (Lan et al., 2021).

Findings from the study indicate that congestion costs increased as the number of lane closures increased. Areas within the network with higher traffic volumes (i.e., urban areas) experienced a greater cost increase as compared to suburban and rural areas. The cost also varied depending on the crash type, location of the incident, and time of day as well as the day of the week. The authors recommend adapting the methodology to fit local conditions as costs can vary substantially (Lan et al., 2021). Thus, the results of this study can be applicable to optimizing the number of IMTs in each location of the network.

2.4 Miscellaneous Topics

The miscellaneous topics discovered in the literature review include secondary crashes, incident classification, hours of TIM operation, and traffic management during freeway incidents.

2.4.1 Secondary Crashes

Secondary crashes (or incidents) are defined in the FHWA FSI as any unplanned crashes beginning at the time of detection of the primary incident where a collision occurs either within the incident scenes or within the queue, including the opposite direction, which result from the original incident (Owens et al., 2009). Secondary crashes exacerbate congestion due to the primary incident and can compromise traffic safety.

The NCHRP “Development of Guidelines for Quantifying Benefits of Traffic Incident Management Strategies” report equates delay reduction from safety service patrols to crash reduction, meaning that the presence of freeway service patrols, or IMTs, reduces the number of secondary crashes due to lower ICT and incident duration times (Shah et al., 2022). In a study referenced in the NCHRP report by Karlaftis et al. (1999), a logistical regression model was developed to predict the probability of the occurrence of a secondary crash based on the characteristics of the primary incident. The results suggest that the likelihood of a secondary incident is reduced by 18.5 percent during the winter and 36.3 percent during other seasons. This assumes that IMTs are involved in clearing the crash and that their presence decreases incident duration by about 10 minutes on average, thus reducing the likelihood of a secondary incident (Shah et al., 2022).

Shah et al. (2022) noted that the factors that have the greatest impact on the severity of secondary crashes are visibility, number of lanes blocked, and primary incident duration. It was also concluded that secondary crashes occur more frequently during peak periods on urban freeways with the most common crash type being rear-end collisions. This study also assumed a linear correlation between the number of secondary crashes and incident duration (Shah et al., 2022).

2.4.2 Incident Classification and Type

Shah et al. (2022) reference a study completed by the Center for Advanced Transportation Technology that collected incidents and identified multiple variables that could be used to further classify incidents such as whether or not it was a single vehicle collision, debris was present, the vehicle involved was disabled, a crash occurred, a vehicle fire occurred, a

HAZMAT spill occurred, the incident occurred in a work zone, and if weather was related to the cause of the crash (Shah et al., 2022). Including these incident characteristics provides a wide range of factors in analyzing crash data to better understand the effects of individual characteristics on incident duration. Quantifying the number of incidents that correspond to each type can also help responders to be better prepared in responding to crashes.

2.4.3 TIM Operating Hours

Shah et al. (2022) references a study that compares estimated cost-benefit ratios of TIM programs that operate during daytime hours only and 24 hours a day (Latoski et al., 1998). The case study roadway segments used to quantify both programs included a 16-mile segment of I-80 and an 8-mile segment of I-65 in Lake County, Indiana, where the I-65 segments were covered by IMTs only during peak hours. The case study for the daytime-only program was conducted for the full year of 1995 and the 24-hours program was conducted from June to December of 1996. The factors that were quantified monetarily to compare the two programs were delay due to crashes, reduction in secondary crashes, operating costs, fuel consumption, and changes in vehicle miles traveled (VMT). In addition to these factors, the TIM program costs that were considered are annual investment costs, employee salary and benefits, overhead costs, and maintenance costs (Shah et al., 2022).

The daytime-only program compared to base conditions had an effectiveness ratio of 4.7:1 and the 24 hours program compared to base conditions had an effectiveness ratio of 13.3:1, thus making the 24-hours program 2.8 times more effective than the daytime-only program (Shah et al., 2022). This demonstrates the cost-effectiveness of extending TIM operating hours, providing benefits not only to road users but also to state Departments of Transportation and other agencies.

2.4.4 Traffic Management During Incidents

In addition to preventing crashes, an important aspect of incident management is the response of traffic to an incident, the diversion of traffic from major roads where incidents occur frequently onto other roads, and optimizing signal timing during incidents to allow the network to continue to move traffic in spite of congestion. Crash diversion can be accomplished through

Variable Messaging Signs (VMS) and other Advanced Traveler Information System (ATIS) technologies to warn drivers before approaching the incident of the anticipated delays.

Multiple studies have yielded various diversion rates of traffic during incidents due to different forms of VMS and other ATIS technologies. Diversion rates have been estimated through survey responses, logit models, algorithms based on incident characteristics, as well as predicted driver response, loop detectors, and Bluetooth data. A research article titled, "Data and Modeling Support of the Management of Diversion Routes During Freeway Incidents," reviewed the state of the practice and noted that while studies each have their own unique parameters, most of the results from surveys, logit models, and algorithms concluded that a significantly higher percentage of drivers (over 40 percent in most studies) would divert their route in an incident after receiving messages through VMS, whereas according to loop detector and Bluetooth data, only 4 percent to 27 percent would divert their route (Tariq et al., 2022). This indicates that factors such as driver familiarity with a route and other incident-specific factors discouraging drivers to divert may play a larger role in an actual event than previously anticipated.

A UDOT study conducted by Utah State University that evaluated VMS messages and their effect on traffic diversion rates provided the following characteristics associated with higher diversion rates: 1) the number of miles to the crash in the VMS message, 2) the lane in which the crash occurred (left, middle, or right) in the VMS message, 3) shorter distances between VMS devices and the incident location, 4) nighttime conditions, and 5) high traffic volumes. Higher diversion rates were seen during the morning peak hour and lower rates were seen during the evening peak hour (Acharya and Mekker, 2022).

Tariq et al. (2022) estimated diversion rates by using a clustering and cumulative volume analysis. Clustering volume analysis is completed by taking loop detector data for set time periods during an incident where cars were grouped in clusters known as k-means clusters, which are part of an empirical method developed for volume analysis of vehicle clusters. Only days that did not have rain or adverse weather were used for analysis. Normal days were chosen that did not have any crashes or adverse weather present and their volumes were clustered and quantified. The cumulative volume of both incident and normal days was taken by summing the clustered volumes (Tariq et al., 2022).

The average cumulative volume was found for the normal days and the difference was found between this and the cumulative volume of the incident days as shown in Figure 2-1. After the crash is cleared, congestion dissipates, and traffic speed increases; if no diversion has occurred on the roadway, then the cumulative volume of the roadway will be the same as that of the normal days. If diversion has occurred, then the cumulative volume will be lower than the normal days. Therefore, the diversion rate is found by taking the difference in cumulative volume of the normal and incident days and then dividing this by the volume of the normal days as shown in Equation 2-2. The normal days and cumulative volume analysis were included in the methodology of UDOT TIM Phase I and II, which is discussed in Chapter 3.

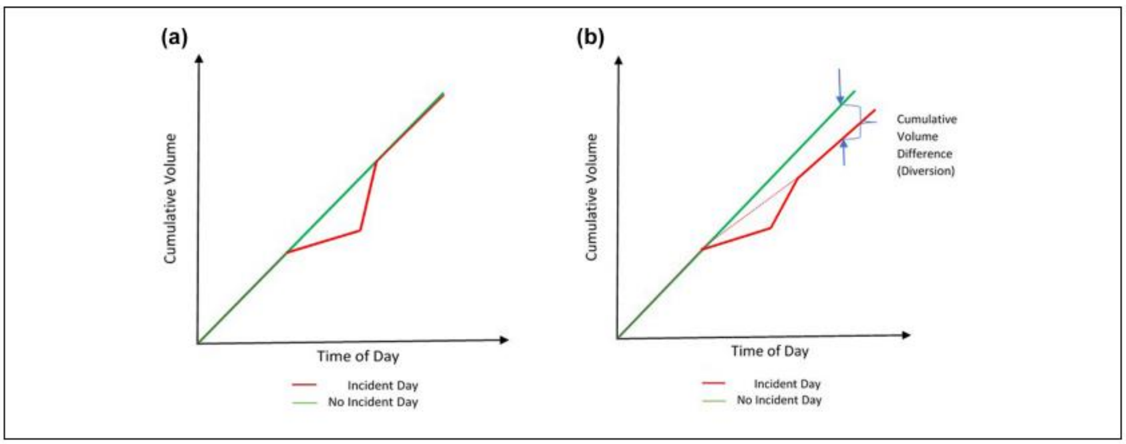

Figure 2-1 Cumulative volume comparison when a) diversion does not occur and b) when diversion does occur (Tariq et al., 2022).

$$\boldsymbol{Diversion\ Rate = \frac{Cumulative\ Vol.\ of\ Normal\ Day - Cumulative\ Vol.\ of\ Incident\ Day}{Cumulative\ Vol.\ of\ Normal\ Day}} \quad \textbf{(2-2)}$$

The average diversion rate for incidents both before and after 7:00 am with 1 or 2 lanes blocked was approximately 5 percent. The 50th percentile diversion rates were slightly lower than the average diversion rates, showing that the dataset is slightly right skewed with more higher diversion rates as outliers than lower diversion rates. In general, the more lanes blocked, the higher the diversion rate. The upper bound of diversion is 22 percent before 7:00 am, making between 20 percent and 25 percent the upper limit of diversion that can generally be expected. It was noted that the capacity of the off-ramps is already between 80 percent and 90 percent of capacity at peak periods and that they likely are a limiting factor on the diversion rate of an exit. The authors recommend that transportation agencies install sensors in off-ramps to better understand diversion rates (Tariq et al., 2022). UDOT maintains a system of off-ramp loop detectors on all off-ramps on the urban Wasatch Front, which is a unique and accurate tool for measuring traffic performance.

Diversion rates are important to understand when developing signal timing plans along alternative routes of a corridor in the event of a crash. This involves reallocating green time of signal phases at intersections that fall along these alternative routes to dissipate traffic when heavy congestion is present. One study by Zhou (2008) showed that a 10 percent diversion rate from freeways to parallel corridors using adaptive signal timing caused minimal delays to the parallel corridors. CORSIM was used to model crashes on a freeway and to see the effects of different diversion rates on the network adjacent and parallel to the freeway. Different diversion rates were modeled ranging from 5 percent to 25 percent in increments of 5 percent. The research found the optimal rate for the network to be 10 percent, which yielded minimal delays to the parallel corridors.

Another study by Tian et al. (2002) showed that adaptive signal timing between a freeway and arterial reduced travel time between 8 percent and 25 percent. This study developed specific algorithms based on the Genetic Algorithm, a commonly used algorithm for optimizing signal timing in intersections, to optimize signal timing using the yielded diversion rates (Tariq et al., 2022). Thus, planning for and developing traffic management plans and signal timing along routes with frequent congestion is an important supplementary aspect of incident management.

2.5 Summary

From the literature reviewed in this study, some ways of improving IMT performance measures include the use of technology to better coordinate incident response and offering monetary incentives for tow truck drivers or other professionals clearing crashes. The methodology that UDOT has used previously to quantify TIM performance measures and EUC is similar to that used by other states in more recent studies. The presence of IMTs and other freeway service patrols on roadways helps decrease incident duration and the likelihood of secondary crashes occurring, especially during peak hours when congestion is heaviest. TIM program service hours operating on a 24-hour basis instead of a daytime-only basis not only reduce delay for roadway users but also are more effective when program and operating costs are considered. Understanding the diversion rates of traffic during incidents can prove useful for developing and optimizing special signal timing plans to alleviate congestion on roadways where incidents occur frequently.

3.0 METHODOLOGY

3.1 Overview

Consistent with the scope of the Phase II study to quantify the benefits associated with the expansion of the UDOT IMT program, a key objective of this study was to quantify the performance measures of RT, RCT, and ICT in addition to quantifying the following user impacts:

1. 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. For this study, ETT was measured in hours.
2. AV: the number of vehicles that experienced some measure of delay due to an incident.
3. EUC: the dollar value associated with ETT, including the hourly costs of roadway user time and truck delay.

Data were collected for 2018 and 2022 so that a comparison of performance measures and user impacts between the two years could be used to determine the effects of the expanded size of the UDOT IMT program. The methodology of this project was developed during Phase I and modified during Phase II to integrate TransSuite data with UHP CAD data that was the original sole data source for crash data in Phase I. All other parts of the methodology are the same with the exception of not needing to account for low volumes due to COVID-19 as in the Phase II study. The reader is invited to read Chapter 3 of both the Phase I and Phase II reports for more details on the methodology (Schultz et al., 2021; Schultz et al., 2019). This chapter provides a summary of the changes in the data collection period and IMT coverage area as well as key aspects of the methodology described in the previous two reports.

3.2 Changes in Data Collection Period and IMT Coverage Area Since Phase I

Consistent with Phase I, it was originally anticipated that the study period for the Phase II study would be for the months of March through August of 2020, which was the same month range analyzed for 2018 during the Phase I study. However, due to the COVID-19 pandemic, the data for the month of April 2020 and the last part of March 2020 had to be discarded due to the artificially low traffic volumes that were experienced at the beginning of the pandemic. While volumes were still significantly below normal, those for May 2020 and of subsequent months in 2020 were considered to be high enough to complete the study, and data were collected for the month of September for both 2018 and 2020 to make a full 6-month comparison and use the same months in 2018 as 2020 (Schultz et al., 2021).

The Phase III study used data from March through August of 2018 and 2022 to be consistent with the original study period of Phase I. The data collection methodology and process were the same for Phase III as for Phase II except that the effects of the low traffic volumes due to COVID-19 did were not accounted for in the statistical analysis in Phase III as they were in Phase II. The 2018 data analyzed in Phase II for the months of March through August were able to be reused, and 2022 data were collected for this same time period according to the methodology summarized in this report.

Consistent with Phase I and Phase II, the study area was limited to mainline interstates in Utah and Salt Lake Counties that made up the majority of the original coverage area of IMTs before the program expansion, though IMTs began to cover outside of these areas after the program expansion. The miles covered by IMTs in both 2018 and 2020 (pre-program expansion) are compared with those that began to be covered in 2020 (post-program expansion) in Figure 3-1, Figure 3-2, Figure 3-3, and Figure 3-4 (Schultz et al., 2021). The areas in each figure are the four UDOT regions, extending from Region 1 at the northern end of the state to Region 4 at the southern end of the state. Region 2 had a moderate increase in the number of lane miles covered by IMTs, while Region 1 and Region 3 had significant increases in the number of lane miles covered by IMTs. Region 4 was not originally covered by IMTs in 2018 but was covered in 2020 after the program expansion.

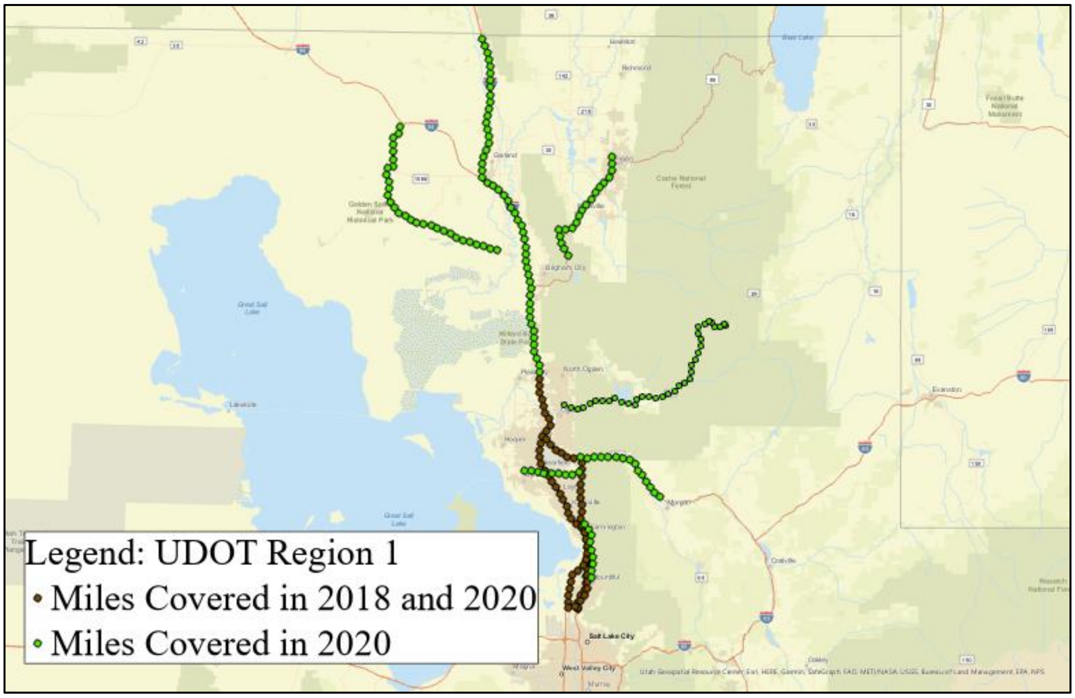

Figure 3-1: Map of IMT coverage area in UDOT Region 1 before and after expansion (Schultz et al., 2021).

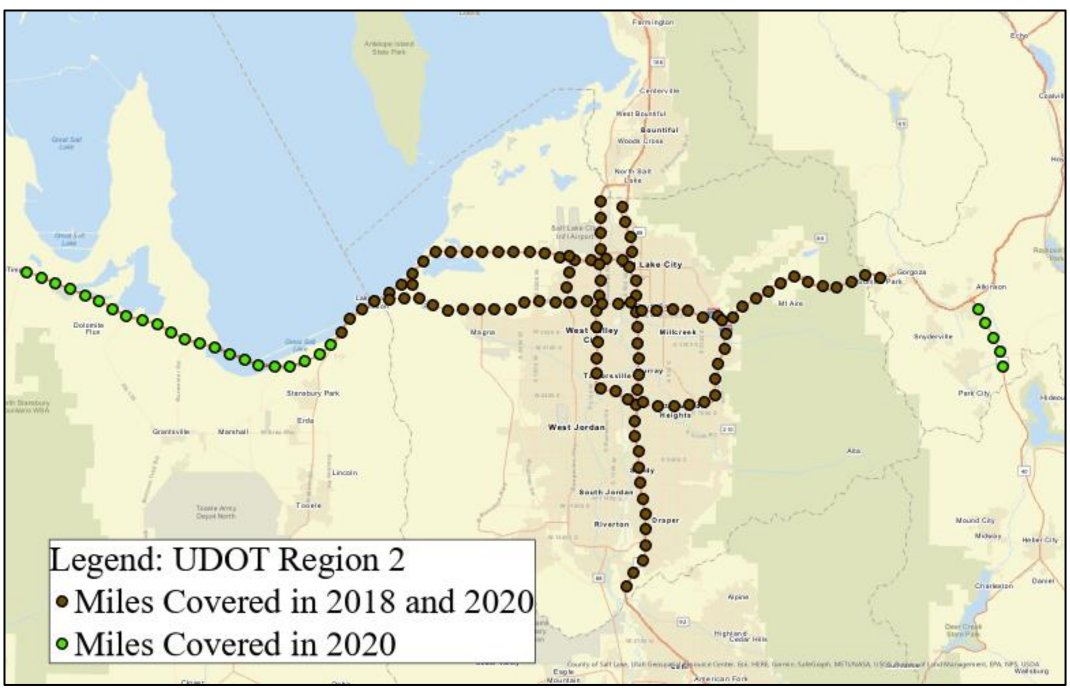

Figure 3-2: Map of IMT coverage area in UDOT Region 2 before and after expansion (Schultz et al., 2021).

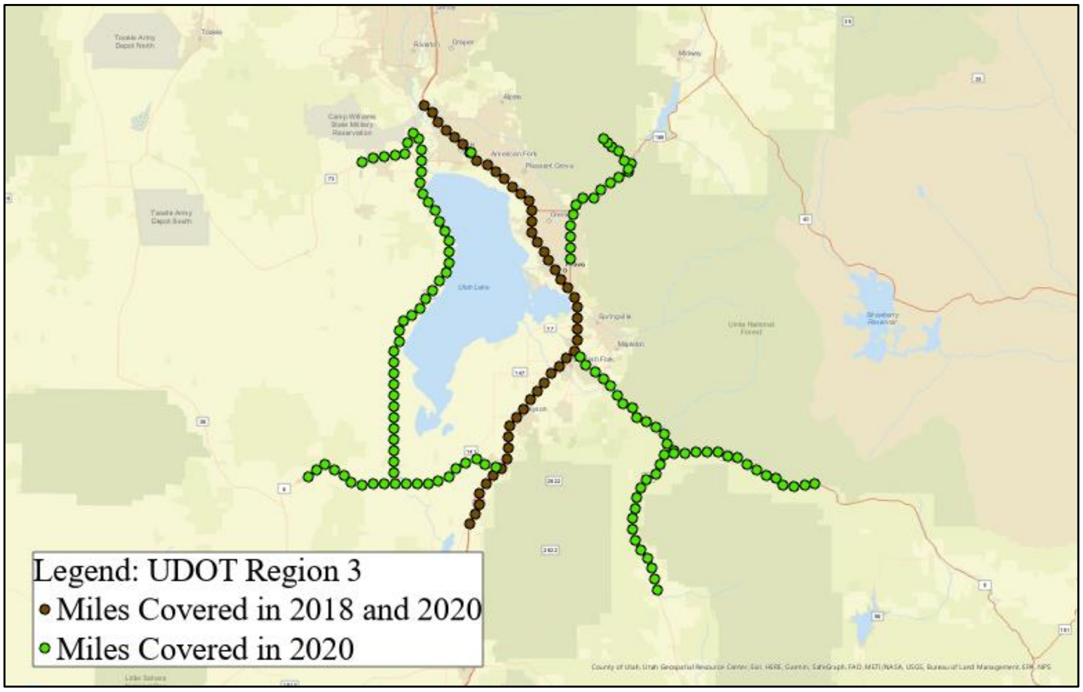

Figure 3-3: Map of IMT coverage area in UDOT Region 3 before and after expansion (Schultz et al., 2021).

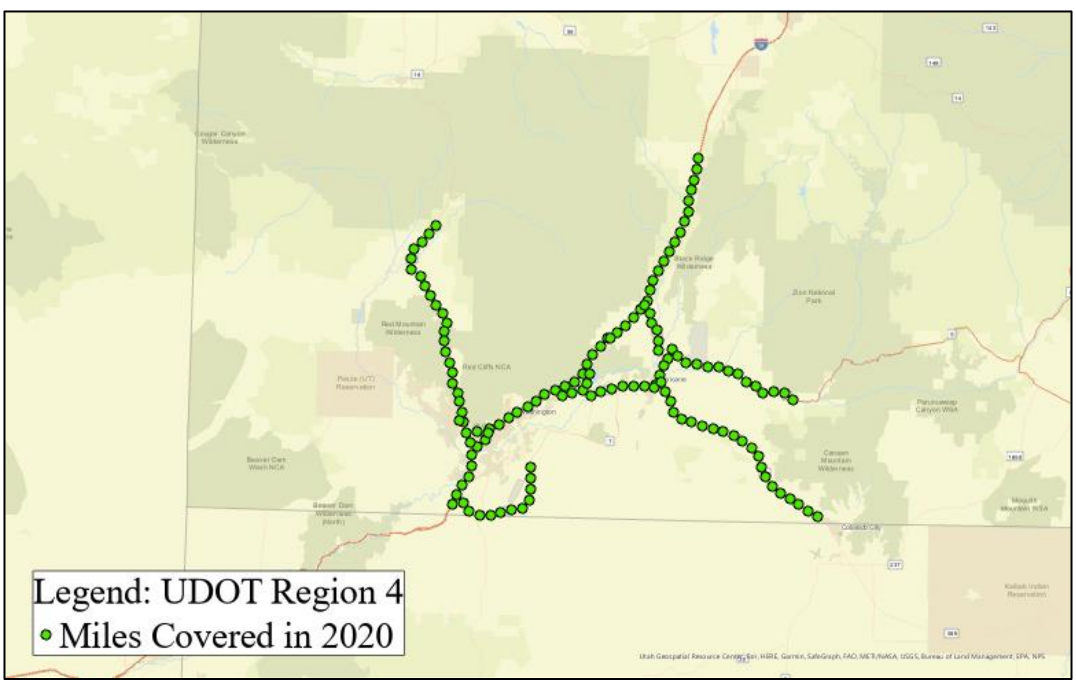

Figure 3-4: Map of IMT coverage area in UDOT Region 4 before and after expansion (Schultz et al., 2021).

3.3 Data Collection Methodology

IMT performance measures were determined from the UHP CAD and UDOT TransSuite incident data, and user impacts were determined from PeMS and Clear Guide traffic data for each incident with the necessary characteristics. The process for how data sources were integrated to obtain IMT performance measures and the process for how user impacts were calculated are explained in Chapter 3 of the Phase I study (Schultz et al., 2019) and in Chapter 3 of the Phase II study (Schultz et al., 2021).

3.3.1 Performance Measures

Crash data were primarily obtained from the UHP CAD data, which includes the timestamps of IMTs and UHP teams for each incident response. UHP provided the research team with a version of the data with confidential information redacted. The crash types included in the CAD data are Property Damage Only (PDO), Personal Injury (PI), and Fatal and Incapacitating Injury (FII). Figure 3-5 shows the timestamps required to calculate RT, RCT, and ICT. The timestamps needed for calculating performance measures are T_1, T_4, T_5, and T_6. T_1 corresponds with the time when the incident was reported. T_2 was assumed to be equal to T_1 due to most incidents being reported by UHP officers who patrol for crashes that are then verified by TOC personnel. T_4 is the time at which responders arrived at the incident location. T_5 corresponds with the time when all lanes of traffic were cleared, and T_6 corresponds with the time when first responders left the site. RT, RCT, and ICT are calculated by taking the difference of T_4, T_5, and T_6 with T_1, respectively.

The CAD data were adequate to determine the performance measures of RT and ICT for most incidents but not for RCT. UHP collected the T_5 timestamp during Phase I to allow the research team to determine RCT values, but it was later discovered that the UDOT TransSuite database, which contains the lane closures and openings for incidents recorded by TOC operators, were available and could be used in place of the T_5 timestamps collected by UHP. A paired t-test was conducted on the RCTs of crashes in the CAD dataset that were collected as part of Phase I and those of the TransSuite dataset (TransSuite T_5 – CAD T_1) that were identified to be the same crashes as those in the CAD dataset. The t-test demonstrated that there is no statistically significant difference between the CAD RCT and TransSuite T_5 – CAD T_1.

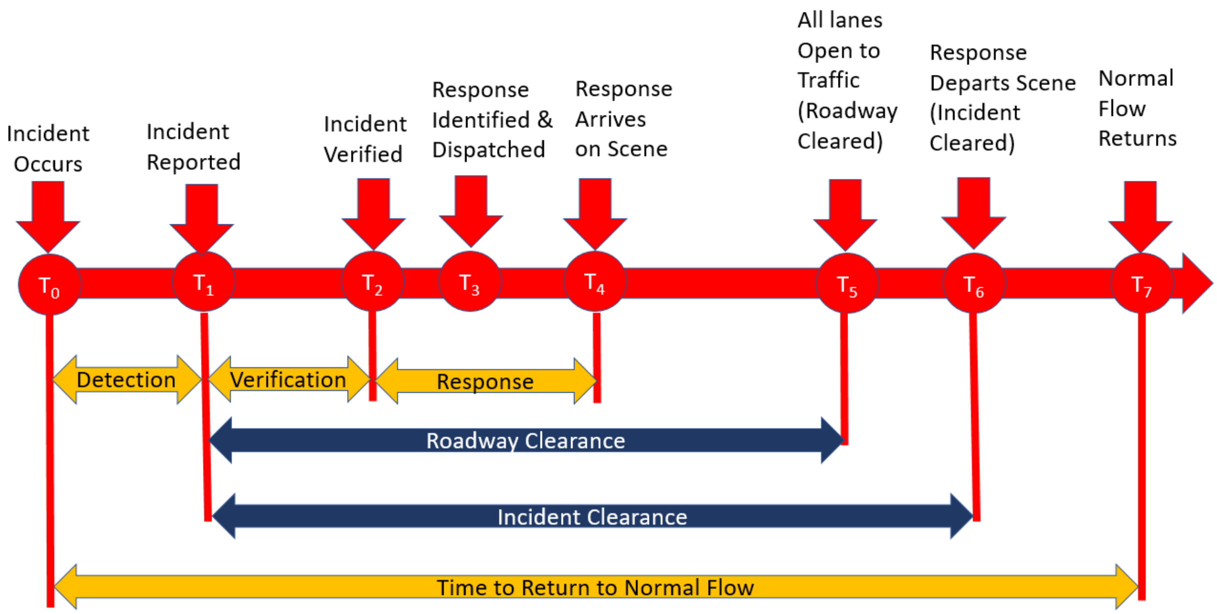

Figure 3-5: TIM timeline (adapted from Conklin et al., 2013).

Phase II and Phase III integrated TransSuite data with crashes that were identified to be the same as those in the CAD data, which increased the total number of usable incidents of the 2018 dataset with all performance measures by 58 percent and those that were able to be analyzed for EUC by 66 percent. Table 3-1 summarizes the percent increase in 2018 incidents after the integration of CAD and TransSuite. Note that these are the numbers of incidents analyzed in Phase II that had an adjusted data collection period because of COVID-19. Therefore, the number of incidents shown will differ somewhat from those in Table 4-1 used for the Phase III analysis.

Table 3-1: Percent Increase in 2018 Dataset After Integrating CAD and TransSuite Data

Data Type	2018 CAD Only Dataset	2018 CAD and TransSuite Combined Dataset	Percent Increase
Incidents with RT, RCT, and ICT	129	306	137%
Incidents Analyzed for User Impacts	63	188	198%

Crash incidents in the CAD and TransSuite datasets were integrated using an Excel Visual Basic for Applications (VBA) script that identified all CAD and TransSuite incidents that occurred within 15 minutes of one another. The research team then verified whether a pair of incidents were the same. Another VBA script was then used to identify all incidents that could be analyzed for performance measures. The requirements for an incident to be analyzed for performance measures include having at least one IMT respond, having one or more lanes of traffic closed during the incident, having all necessary timestamps for the given incident contained within the CAD data, and not occurring on a ramp. The performance measures data from CAD and TransSuite were integrated for each incident and incidents were then able to be evaluated for user impacts.

3.3.2 User Impacts

In addition to the requirements described previously for incidents to be analyzed for performance measures, the requirements for an incident to be evaluated for user impacts were that there was a decipherable queue, there were no secondary incidents whose queue affected that of the incident being evaluated, and that there were sufficient traffic data to perform the analysis. The traffic data included as part of the analysis were speed and volumes taken from the PeMS database and speed and average travel time for individual routes taken from the Clear Guide (previously iPeMS) database. The PeMS data are collected through loop detectors and the Clear Guide data are collected through probe data taken from cell phone applications and in-vehicle GPS units.

The general process for calculating user impacts of incidents where IMTs are present requires establishing a baseline of normal traffic conditions to compare with incident traffic conditions. Therefore, three days with normal traffic conditions for the same time period and location as the incident are chosen to compare with incident traffic conditions. As shown previously in Figure 3-5, T_0 is the time at which an incident occurs and T_7 is the time at which traffic conditions return to normal. The difference between T_7 and T_0 represents the amount of time which the average speed of traffic was significantly below normal and roadway users experienced significant delays.

The exact time at which an incident occurred was not contained in the data and the PeMS speed and volume data have a limited granularity of 5 minutes. Therefore, T_0 was determined to be the first 5-minute increment for which the average speed of traffic was reduced significantly below normal, and T_7 was determined to be the first 5-minute increment for which the average speed of traffic returned to within the same threshold of normal traffic. For the purposes of this study, the threshold of normal traffic conditions was within 20 mph of the average speed of the average of normal days. In cases where incidents did not have a reduction in speed of 20 mph or more, a lower difference in the average speed of traffic was determined by the research team. While this process introduces subjectivity to the analysis process, the threshold of within 20 mph of traffic was meant to be a conservative estimate.

The volume of vehicles that diverted to other routes due to congestion caused by an incident was not quantified as part of the AV of an incident. To accurately quantify AV with some vehicles diverting and exiting the roadway during the incident, the section of the roadway that was affected by the crash was segmented into links (called subroutes) between ramps. The AV of each subroute was measured as the sum of the volume of vehicles between T_0 and T_7 for the incident day, and the AV of the incident was taken to be the maximum AV of all subroutes affected by the crash. For cases when severe crashes occurred and traffic was diverted to other routes, the incident was not quantified. The ETT of an incident was found by calculating the ETT for each 5-minute increment between T_0 and T_7 for the incident and average of normal days. The hours of ETT for each 5-minute increment were found by multiplying the average travel time of the subroute by the volume of vehicles at that loop detector. The ETT of an incident was then calculated by taking the difference between the sum of the ETT for each 5-minute increment between T_0 and T_7 for the incident and average of normal days.

The EUC is the sum of the cost of travel time for passenger vehicles and trucks. Costs due to the ETT of passengers and trucks are the only factors considered in this analysis, and the costs of excess fuel burned, property damage of a crash, injuries if sustained during the crash, and the impacts of motor vehicle emissions on public health are not included in this study, making EUC values for this study a conservative estimate. To account for the difference in cost of travel time for trucks from that of passenger vehicles, the percentage of trucks in traffic was obtained from PeMS, and separate hourly costs were used for passenger vehicles and trucks. The percentage of trucks in traffic (Truck%) for this study was based on the percentage of vehicles that were 30 ft or longer while those that were less than 30 ft were passenger vehicles. The percentage of trucks was taken from the same loop detector as that of the AV of the incident.

The individual hourly cost (IHC) was estimated to be \$17.81 and the truck hourly cost (THC) was estimated to be \$53.69 based on a study by the Texas A&M Transportation Institute (Ellis, 2017). While these values are outdated for 2022 user impacts data, the same values were used as those for 2018 data during Phase I and Phase II to make a valid comparison without the effects of inflation as a confounding factor. The EUC formula also includes an average vehicle occupancy (AVO) factor to account for the time of multiple passengers per vehicle. THC has an incorporated AVO of 1.14, thus it does not require an external AVO factor in the EUC formula. IHC is multiplied by an AVO factor calibrated to the given interstate, direction of travel, and time of day for which the incident occurred. These AVO values were obtained from Schultz et al. (2015) and, while the values are somewhat outdated for 2022 data, were used to be consistent with 2018 data values. The formula for EUC is shown in Equation 3-1.

$$\boldsymbol{EUC = ETT * ((1 - Truck\%) * AVO * IHC + Truck\% * THC)} \quad \textbf{(3-1)}$$

To summarize, the steps for analyzing an incident for user impacts are as follows:

1. Identify the queue of the incident being evaluated using PeMS speed data.
2. If the incident meets the requirements to be analyzed for user impacts, choose three normal days to average the respective speed data to serve as a base comparison for the day with the incident.
3. Find the difference in the average speed of traffic between the average of three normal days and the incident day.
4. Determine T_0 and T_7 by identifying the times at which the average speed of traffic is reduced to 20 mph or more below normal and returns to within 20 mph of normal, respectively.
5. Create subroute sheets for the subroutes affected by the incident queue.
6. Obtain Clear Guide speed data and average travel time data for each respective subroute, and obtain PeMS volume data from the corresponding loop detector of each given subroute.

7. Use the VBA script within each subroute sheet to upload and process the Clear Guide and PeMS data for the given subroute to calculate AV and ETT between T_0 and T_7.
8. Calculate ETT of each subroute by taking the difference of the sums of ETT for the incident and normal days of each subroute.
9. Calculate the total ETT for the incident by summing the ETT for each subroute.
10. Take the maximum AV of all subroutes as the AV of the incident.
11. Record AV and total ETT in the incident database.
12. Find the percentage of trucks in traffic for the loop detector that had the maximum AV of all subroutes for the incident.
13. Calculate EUC using Equation 3-1.

3.4 Summary

IMT coverage area increased significantly between 2018 and 2020 along with the number of IMT units. Some regions that had not been covered previously in 2018 began to be covered in 2020. The methodology for this study is like that of the Phase II analysis except that the impacts of COVID-19 were not accounted for because traffic volumes in 2022 had returned to normal relative to those in 2018. TransSuite lane closures data were integrated with those of the UHP CAD data to calculate IMT performance measures of RT, RCT, and ICT. IMT performance measures were calculated by taking the difference between the UHP timestamps corresponding to RT and ICT with T_1. RCT was calculated by taking the difference between TransSuite T_5 when all lanes were cleared and CAD T_1. The integration of TransSuite data yielded approximately a 200 percent increase in crashes that could be analyzed for performance measures and user impacts as compared to the UHP CAD data used in Phase I.

User impacts of AV, ETT, and EUC were calculated as explained in this chapter. AV accounted for vehicles in the queue that were affected by congestion that occurred between T_0 and T_7, or during the time period when traffic experienced congestion, but did not account for vehicles that diverted from their route. AV was determined by dividing the roadway affected by an incident into links called subroutes to find the maximum volume that occurred on any subroute that was affected by the incident. ETT was calculated by finding the difference between the travel time for the average of normal days and that of the incident day. EUC was calculated as a function of ETT, the percentage of trucks in traffic, AVO, and the individual hourly costs for passengers and trucks taken from Ellis (2017). The methodology is meant to produce conservative estimates of the effects of delay due to an incident that roadway users encounter, and the goal of this study was to obtain data to compare the effectiveness of IMTs between 2018 and 2022 (or before and after the expansion of the IMT program).

4.0 DATA REDUCTION

4.1 Overview

This chapter provides the results of the raw data that were collected using the methodology described in Chapter 3. The performance measures for which data were collected are RT, RCT, and ICT, and the user impacts are AV, ETT, and EUC. Although UHP data were collected, this study focuses on IMTs, and, unless otherwise noted, these performance measures refer to those of IMTs. Therefore, RT and ICT values referred to in this section of the paper are for IMTs. RCT was essentially the same for IMTs and UHP teams. A comparison is made between 2018 and 2022 data to compare the amount of usable data yielded from the CAD and TransSuite integrated incident data, performance measures of IMTs, and the user impacts of the crashes responded to by at least one IMT.

4.2 Incident Data Collected

With the data integrated from the CAD and TransSuite databases, many more incidents were able to be analyzed than if the TransSuite database was not able to be used to supplement CAD data as reported in Chapter 3. The 2018 and 2022 datasets both yielded similarly sized data sets which can be seen in Table 4-1 and Table 4-2. The 2018 and 2022 datasets had 1,097 and 1,526 incidents for which IMTs were present, respectively. Of those total incidents for which IMTs were present, 99 percent or more had ICTs in both years, 83 percent or more of incidents had an RT, 21 percent or more had an RCT, 20 percent or more had all three performance measures listed above, and 15 percent or more were able to be analyzed for EUC and other user impacts in addition to all performance measures. This shows that the percentage of usable data becomes progressively less descending through each data type. While the 2022 dataset had lower percentages of incidents for each data type, its larger sample size made it comparable to that of the 2018 dataset.

Table 4-1: 2018 Incident Data Points by Type

Data Type	Number of Data Points	Percent of Total
Incidents	1,097	100%
ICT	1,089	99%
RT	944	86%
RCT	305	28%
ICT, RT, and RCT	283	26%
Incidents Analyzed for User Impacts	172	16%

Table 4-2: 2022 Incident Data Points by Type

Data Type	Number of Data Points	Percent of Total
Incidents	1,526	100%
ICT	1,520	100%
RT	1,272	83%
RCT	319	21%
ICT, RT, and RCT	307	20%
Incidents Analyzed for User Impacts	236	15%

The crash distribution by type is shown in Table 4-3 and Table 4-4 for 2018 and 2022, respectively. As shown in the table, FII crashes made up less than 1 percent of the total for both years. PI crashes made up 26 percent of the total in 2018 and increased to 34 percent of the total in 2022. PDO crashes made up 74 percent of the total in 2018 and decreased to 66 percent of the total in 2022. While the distribution of each crash type is comparable between 2018 and 2022 datasets, there is a shift in the data to a higher percentage of PI crashes in 2022 showing that injury crashes were more prevalent in 2022 compared to 2018.

Table 4-3: 2018 Crash Distribution by Type

Crash Severity Type	Crashes	Percent of Crashes
FII	10	<1%
PI	280	26%
PDO	807	74%
Total	1,097	100%

Table 4-4: 2022 Crash Distribution by Type

Crash Severity Type	Crashes	Percent of Crashes
FII	9	<1%
PI	512	34%
PDO	1,005	66%
Total	1,526	100%

In addition to the crash type distribution shifting to a higher percentage of PI crashes, it can be seen from Figure 4-1 and Figure 4-2 that the crash frequency increased from 2018 to 2022. The month in 2022 with the lowest number of crashes during the data collection period (July) had 223 crashes, which was higher than the highest month in 2018 (March) with 209 crashes. The distribution of crashes by type for each month is approximately the same for each respective year. While the reasons for why crash rate and severity have increased between 2018 and 2022 are not clear, the COVID-19 pandemic may have influenced driver behavior. The reasons for this are outside the scope of this study.

It should be noted that comparisons and analysis results shown hereafter for FII crashes may be skewed and not representative due to the small sample size of crashes in both years. These data alone can only be inferred for the time and geographic area of the data collection period.

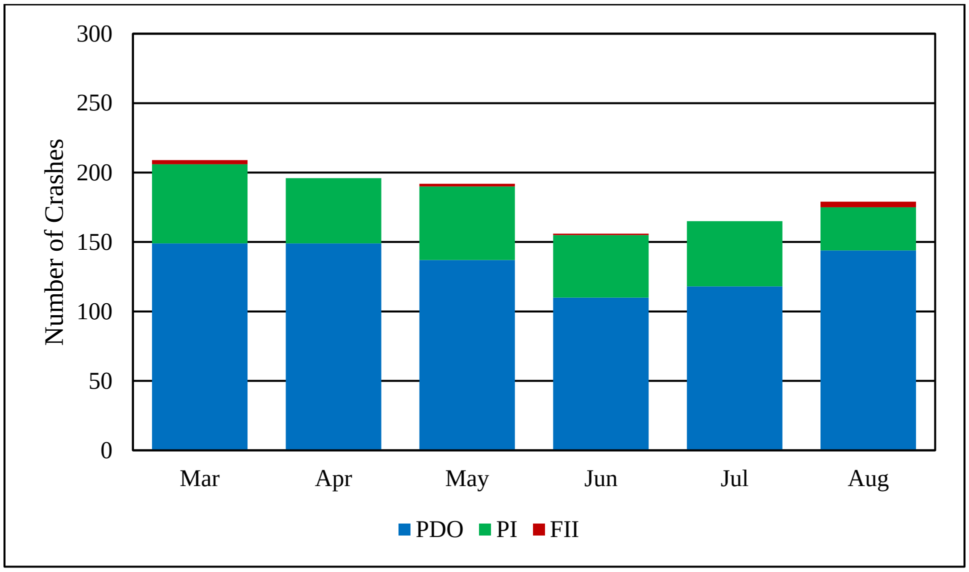

Figure 4-1: 2018 crash type by month.

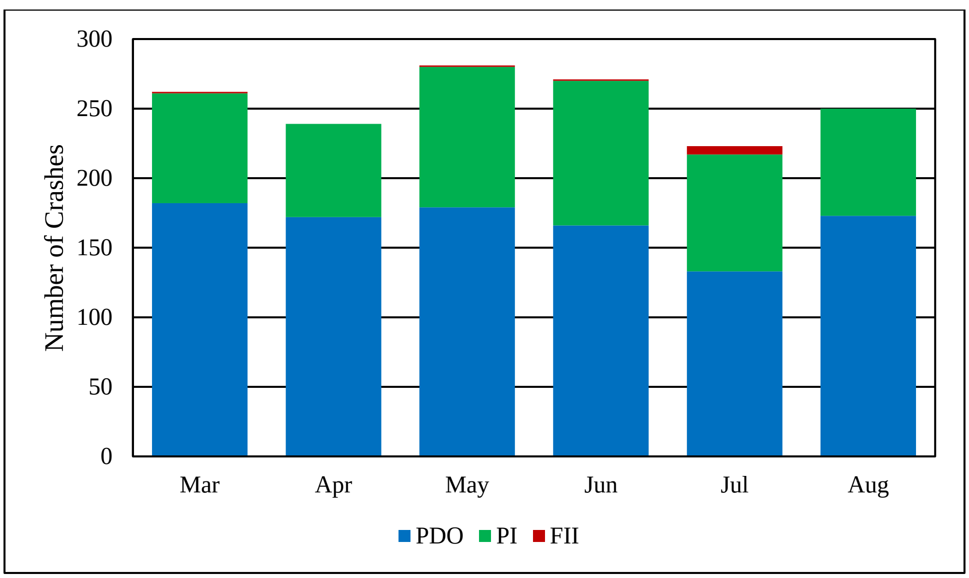

Figure 4-2: 2022 crash type by month.

4.3 Performance Measures

The performance measures of RT, RCT, and ICT by crash type that were collected for the 2018 and 2022 datasets are compared in Figure 4-3 and Figure 4-4 with boxplots of the 2018 and 2022 datasets, respectively. While the crash data have several large outliers in performance measures and other parameters, it can be noticed that the magnitude of the extreme outliers in 2022 is generally lower than that of the outliers in 2018. While the difference in performance measures for PDO and PI crashes between 2018 and 2022 is not obvious due to the large scale of the times of performance measures, Figure 4-3 and Figure 4-4 primarily show a decrease in RT for FII crashes.

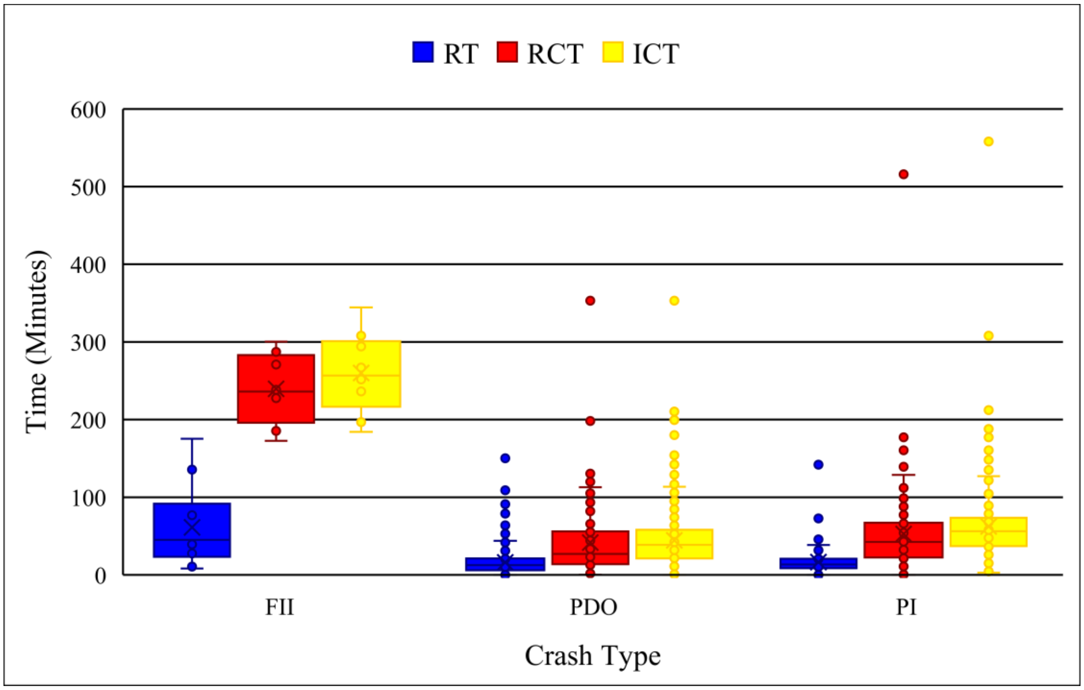

Figure 4-3: Boxplot of 2018 performance measures.

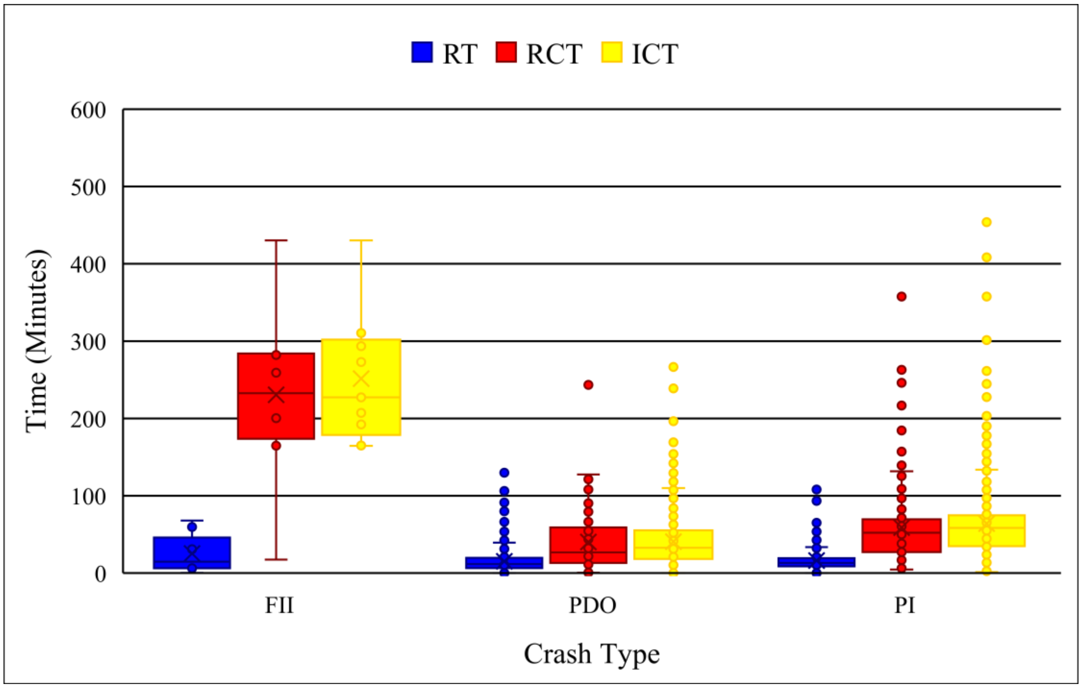

Figure 4-4: Boxplot of 2022 performance measures.

Histograms of RT are shown in Figure 4-5 and Figure 4-6 for 2018 and 2022, respectively. The distribution of RT shifted from 58 percent of incidents responded to within the first 15 minutes of a crash in 2018 to 62 percent in 2022 for a difference of 4 percent and an improvement of 7 percent. The peak that occurs in the first three bins, or the first 15 minutes of a crash, is higher in 2022 than in 2018, showing that IMTs are generally responding faster in 2022 than in 2018. These results are as expected due to the increased number of IMTs patrolling Utah roadways in 2022 where more IMTs increase the availability of units to respond to more crashes. Results show that units can respond to incidents overall more quickly in 2022 than in 2018 despite the increase in geographic coverage area of IMTs.

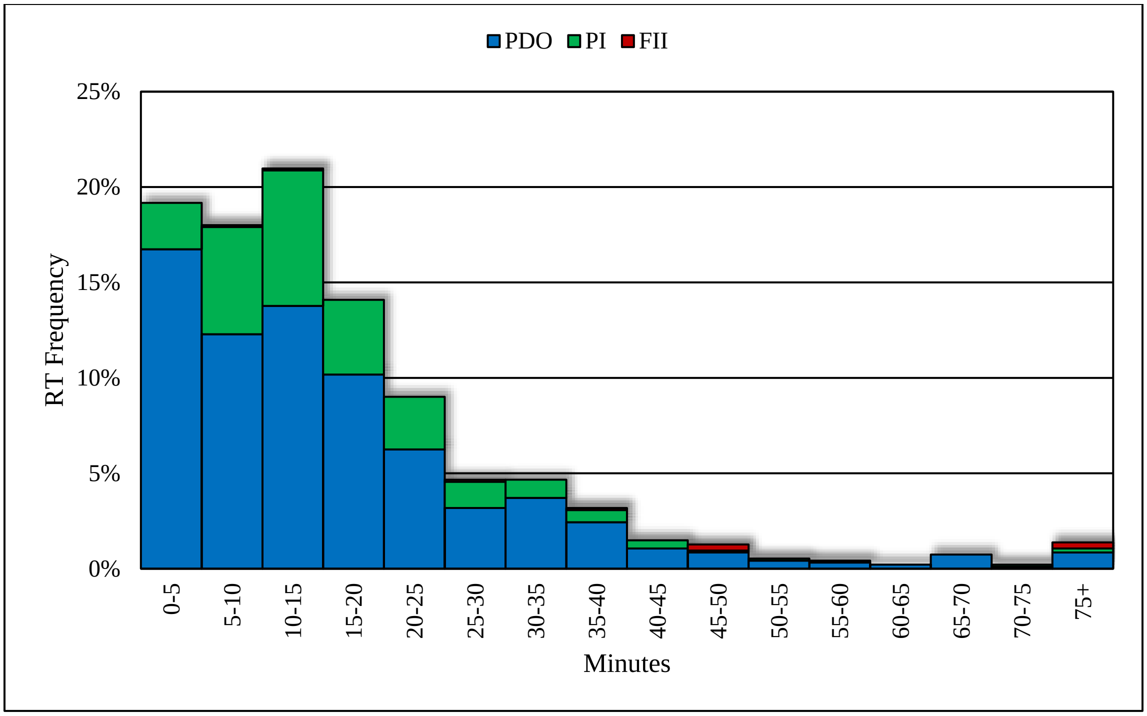

Figure 4-5: 2018 distribution of RT.

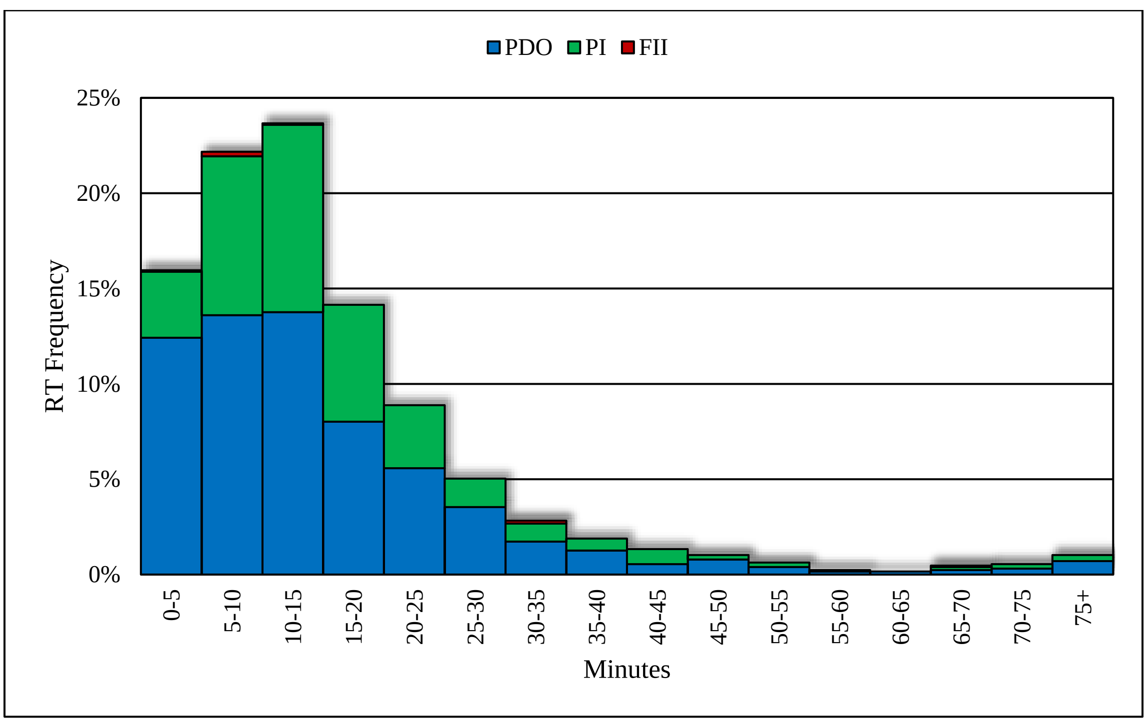

Figure 4-6: 2022 distribution of RT.

Histograms of RCT are shown in Figure 4-7 and Figure 4-8 for 2018 and 2022, respectively. Nineteen percent of incidents had all lanes of traffic cleared within the first 45 minutes in 2018. This decreased to 13 percent in 2022 for a difference of 6 percent and a 32 percent change. Comparing the percentage of incidents responded to within the first 75 minutes, the results were similar with 27 percent in 2018 and 20 percent in 2022 for a difference of 7 percent and a 26 percent change, showing an increase in RCT between 2018 and 2022. It is apparent that there is a higher percentage of PI incidents in 2022 than in 2018, and the increased crash rate and severity of crashes in 2022 could be a contributing factor to the decrease in RCT. A more detailed analysis of performance measures is done by crash type in Section 5.4.

It was found that some RCT values were greater than their respective ICT values, which conceptually is invalid because IMTs should not have left the crash site before the roadway was cleared. It was assumed that because CAD timestamps are reported by UHP teams that are on site during an incident and the other data points come from the CAD dataset, the CAD data would be more reliable in this case than TransSuite data. In these cases, the ICT value of the incident was substituted for the RCT value. The RCT values that were greater than their respective ICT values were usually within 10 minutes or less of the ICT value, so the potential error could have also been due to TOC operators having multiple incidents to watch and other urgent tasks that could have kept them busy until they detected that the incident had been cleared from CCTV footage. It is also possible that IMTs and UHP officers reported leaving the site sooner than they actually did. This effect of replacing RCTs with their respective ICT in cases where RCT was greater than ICT only shifted the distribution of RCT from the unmodified data values by about 1 percent, so the effects of crashes with this discrepancy were considered to be insignificant.

Histograms of ICT are shown in Figure 4-9 and Figure 4-10 for 2018 and 2022, respectively. IMTs cleared the crash and left the crash site within 45 minutes for 61 percent of incidents in 2018 and for 67 percent of incidents in 2022, making the difference 6 percent and the improvement 10 percent. IMTs being on the site of a crash for less time overall is a significant improvement for UDOT’s IMT program.

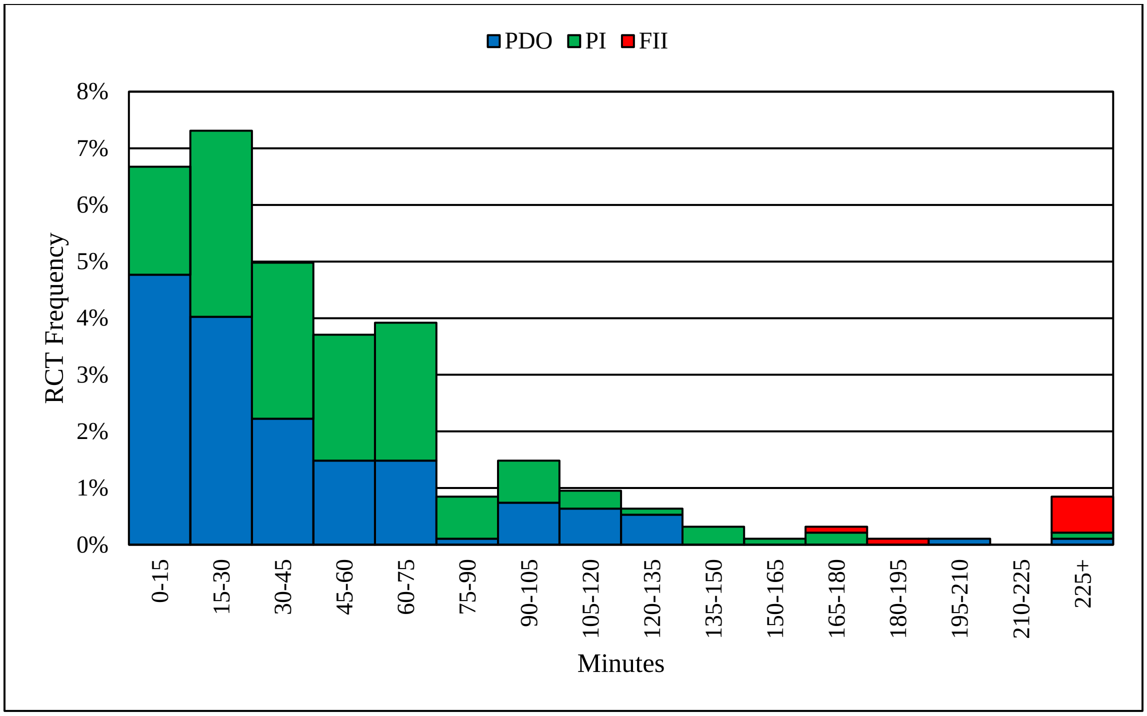

Figure 4-7: 2018 distribution of RCT.

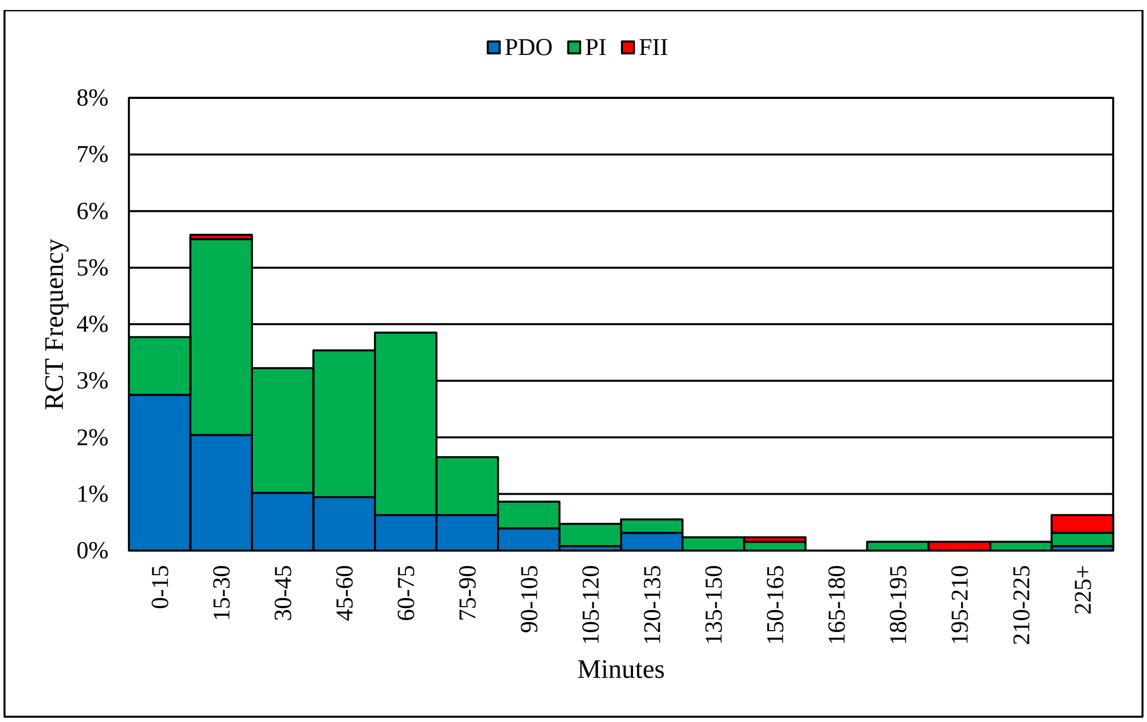

Figure 4-8: 2022 distribution of RCT.

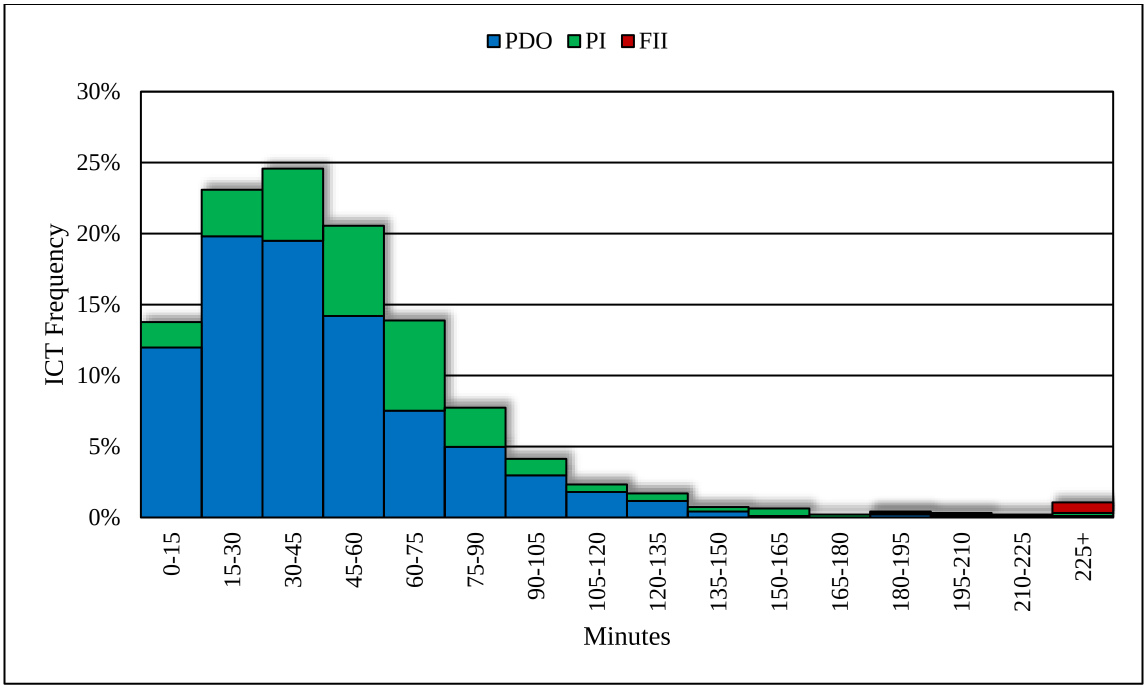

Figure 4-9: 2018 distribution of ICT.

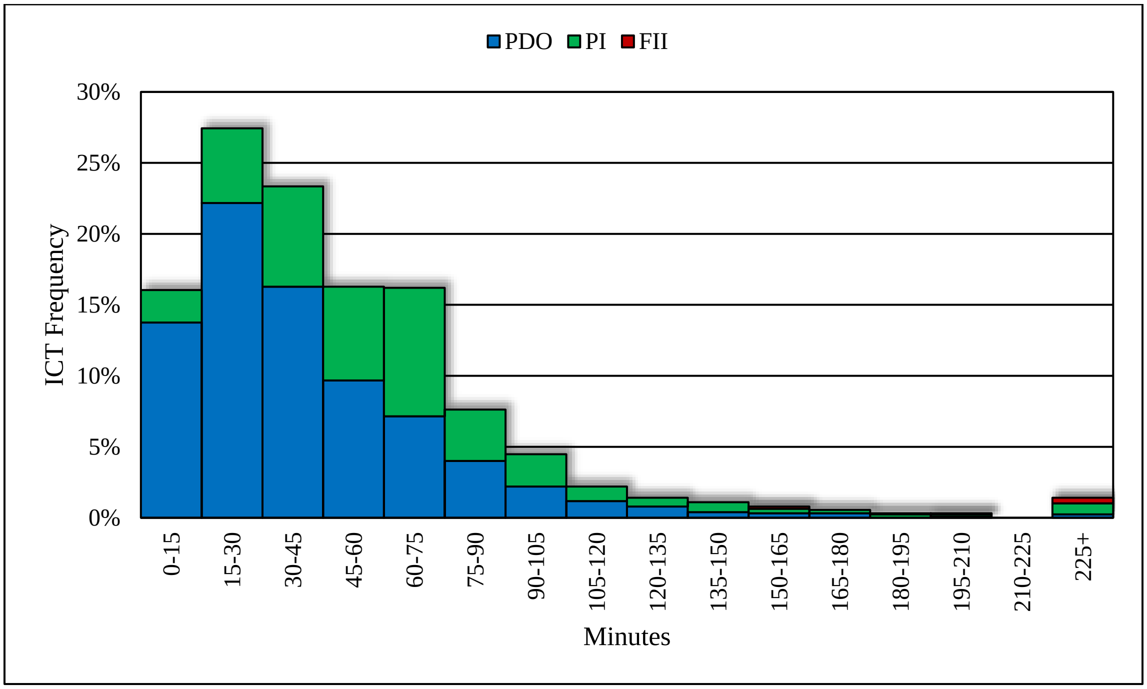

Figure 4-10: 2022 distribution of ICT.

4.4 User Impacts

The user impacts of AV, ETT, and EUC had a right-tailed distribution like that of the performance measures where the distribution was skewed towards crashes with higher values, so it was determined that taking the median of user impacts rather than the average would be a more statistically valid comparison for preliminary results. Incidents were grouped by crash type and by year, and the median was taken for each user impact. The results and percent reductions from 2018 to 2022 are shown in Table 4-5, Table 4-6, and Table 4-7.

The percent reduction was positive for each user impact and each crash type except for the AV of FII crashes. However, the sample size of FII crashes that were able to be analyzed for user impacts in 2018 and 2022 was very small with only 2 FII incidents in 2018 and 6 FII incidents in 2022 out of 172 and 236 incidents that could be quantified for user impacts in each year, respectively. Therefore, the results of FII crashes are highly skewed due to the small sample size. Despite the highly skewed results such as the 93 percent reduction in ETT and EUC for FII crashes between 2018 and 2022, it can be noted that the work of IMTs appears to decrease the extreme delay experienced in 2018 FII crashes due to there being more IMTs in 2022 to respond to high severity incidents without compromising the ability of the fleet to respond to other incidents.

Table 4-5: Median User Impacts for PDO Crashes

User Impact	2018	2022	Percent Reduction
AV [Vehicles]	6,635	5,027	24%
ETT [Hours]	340	184	46%
EUC [$]	$8,269.75	$4,757.91	42%

Table 4-6: Median User Impacts for PI Crashes

User Impact	2018	2022	Percent Reduction
AV [Vehicles]	6,933	5,518	20%
ETT [Hours]	493	231	53%
EUC [$]	$12,752.58	$6,215.59	51%

Table 4-7: Median User Impacts for FII Crashes

User Impact	2018	2022	Percent Reduction
AV [Vehicles]	6,495	7,897	-22%
ETT [Hours]	3,601	253	93%
EUC [$]	$97,899.53	$6,615.98	93%

For PDO and PI crashes, AV was reduced by 24 percent and 20 percent between 2018 and 2022, respectively, showing significant decreases in the number of vehicles that were affected by incidents to which IMTs responded. There was an even greater decrease in ETT and EUC for PDO and PI crashes with reductions of 46 and 42 percent, respectively, for PDO crashes and 53 and 51 percent, respectively, for PI crashes. Thus, the increased fleet size of IMTs reduced the total amount of time for which all roadway users are stuck in traffic by almost half between 2018 and 2022 based on the median of all incidents by crash type. AV appears not to have as high of a reduction which could be because when a crash occurs, many vehicles are affected initially, but the number continues to grow only at a steady rate depending on the flow of traffic. However, while ETT and AV are related, ETT increases at a greater rate over time as the number of vehicles in the queue increases and the average travel time of traffic decreases. For that reason, ETT has a higher variability from crash to crash while AV is more static, though it also does increase with time. EUC is a function primarily of ETT, thus the two variables are highly correlated.

The percent differences between user impacts of PI and PDO crashes for their respective years are shown in Table 4-8. While the difference in AV of PI and PDO crashes is not large for the year 2018 at 4 percent and 2022 at 10 percent, PI crashes delayed users more than PDO crashes in 2018 relative to 2022 with percent differences of 45 percent and 26 percent in 2018 and 2022, respectively. PI crashes were also more expensive than PDO crashes in 2018 relative to 2022 with percent differences in EUC of 54 percent and 31 percent for 2018 and 2022, respectively. This shows that the contrast between the user impacts of incidents with injuries and without injuries was less in 2022 than in 2018. From these results, it can be deduced that a larger fleet of IMTs decreases the impact of injury crashes on traffic due to having more units to better manage crashes with higher severity.

Table 4-8: Percent Difference Between User Impacts of PI and PDO Crashes

User Impact	2018	2022
AV	4%	10%
ETT	45%	26%
EUC	54%	31%

4.5 Summary

There were a comparable number of incidents with all relevant performance measures and ones that could be analyzed for user impacts in both the 2018 and 2022 datasets. The crash rate increased between 2018 and 2022, and the crash distribution shifted from being 26 percent PI crashes in 2018 to 34 percent in 2022. The vast majority of incidents that were not PI crashes were PDO crashes with less than 1 percent of FII crashes for both years. IMT performance measures that were quantified in this study are RT, RCT, and ICT; and user impacts that were quantified in this study are AV, ETT, and EUC.

RT improved by about 7 percent between 2018 and 2022 where more incidents of all those responded to by IMTs were responded to within the first 15 minutes of a crash. This is significant especially due to the larger coverage area of IMTs in 2022 than in 2018 before the program expansion had occurred. RCT shifted to longer times in 2022 from 2018 with a percent difference of about 32 percent where the percentage of incidents that were cleared in the first 45 minutes decreased from 19 percent in 2018 to 13 percent in 2022. One possible reason for this is the higher crash frequency and shift in crash distribution to PI crashes making it difficult to clear more crashes with a higher severity. ICT improved by 10 percent showing that IMTs are still finishing work on site and leaving the site more quickly in 2022 than in 2018.

User impacts had significant reductions between 2018 and 2022 in almost all cases for PDO, PI, and FII crashes. For PDO and PI crashes, AV is reduced by 20 to 24 percent, and ETT and EUC are reduced by 42 to 53 percent. These are significant reductions in both the number of vehicles affected by an incident and the time cost time for which passengers in those vehicles (including trucks) are stuck in traffic. This can be attributed to the increase in fleet size allowing IMTs to respond to more crashes in a broader geographic area than was possible before the program expansion. The difference in ETT and EUC between PI crashes and PDO crashes decreased between 2018 and 2022, showing that having more IMTs to respond to PI crashes with potentially higher severity decreases the severity of the delay on traffic.

5.0 RESULTS OF STATISTICAL ANALYSIS

5.1 Overview

Statistical regression analyses were performed on the 2018 and 2022 datasets described in Chapter 4 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 AV, ETT, and EUC, were evaluated against a number of incident characteristics to determine any meaningful relationships between them. Due to the right skew of the performance measures and user impacts data (i.e., towards higher times and quantities), a natural log (Ln) transformation was performed for analyzing the dataset to ensure that the outliers did not affect the results of the data. This process and the interpretation of the data is described later in this chapter. The incident characteristics that were analyzed against performance measures and user impacts include:

- The number of IMTs responding to the scene
- The number of UHP teams 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 ratio of lanes closed to lanes at the bottleneck
- The time of day when the incident occurred

The following two time-related parameters were also analyzed against performance measures and user impacts:

- T_7-T_0: The total time for which the average speed of traffic was significantly below normal
- T_7-T_5: The time from after all lanes of the road are cleared to when the average speed of traffic returns to within the range of normal

The following sections describe the statistical significance levels assumed for the data and the process of data transformation. The least squares means of the performance measures of RT and RCT are presented by crash type and by year. The results of a regression analysis conducted analyzing the impact of each incident characteristic as well as the year and crash type with IMT and UHP performance measures is then presented. A similar regression analysis conducted on user impacts versus all performance measures, incident characteristics, and time-related parameters is discussed. The focus of these analyses was to identify relationships of practical significance that help answer the questions of whether the 2022 IMT program is more effective than the 2018 program, which variables have the greatest impact on performance measures and user impacts, and which factors, if any, caused the changes in performance measures and user impacts between 2018 and 2022.

5.2 Statistical Significance of Data

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: Scale of Statistical Significance

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

In this table and all subsequent tables, “ns” means “not significant”

Due to the high variability of crash data, there are some parameters with non-significant p-values that are still of practical significance and that indicate potential trends in the data that cannot be proven due to the variability of the data. Thus, an important distinction between statistical significance and practical significance is that not all relationships that are statistically significant have as much practical significance, and not every relationship that is not statistically significant does not have practical significance. Not all statistically significant relationships analyzed here provide direct answers to the research questions of whether the expanded IMT program is more effective in 2022 than before the expansion in 2018, which variables have the greatest impact on performance measures and user impacts, and which factors, if any, caused the changes in performance measures and user impacts between 2018 and 2022.

5.3 Data Transformation

The assumptions of multiple linear regression are that the data 1) is approximately linear when visualized with a fitted line, 2) is normally distributed, 3) has a constant variance (as well as standard deviation) around the fitted line, and 4) is independent, or has data points that are all independent of one another. To meet these assumptions, the performance measures of RCT and ICT as well as the user impacts of ETT, AV, and EUC were transformed by taking the natural log of the data. This was necessary to ensure that the outliers of each variable did not skew the results of the regressions analysis.

Many parameters in this analysis contain outliers that cause the data distribution to be right-tailed, or skewed toward higher values, rather than normally distributed, which has an approximately bell-curved shape. Figure 5-1 and Figure 5-2 show histograms of 2022 RCT and 2022 Ln RCT, respectively, which are shown as examples to demonstrate the need for natural log transformation on RCT and other variables. The untransformed RCT has a right-tailed skew, but the shape of the Ln RCT distribution is corrected to be approximately normal after the natural log transformation.

Figure 5-3 and Figure 5-4 display scatterplots of RCT vs. RT and Ln RCT vs. RT, respectively. Many of the points with higher RCT values in the untransformed scatterplot show upwardly diverging RCT values that increase with RT, which is a sign of non-constant variance. With the exception of a couple of outlying data points with a low Ln RCT value, the natural log transformation of the Ln RCT vs. RT scatterplot corrects this issue. The linear fit of the data is also improved slightly.

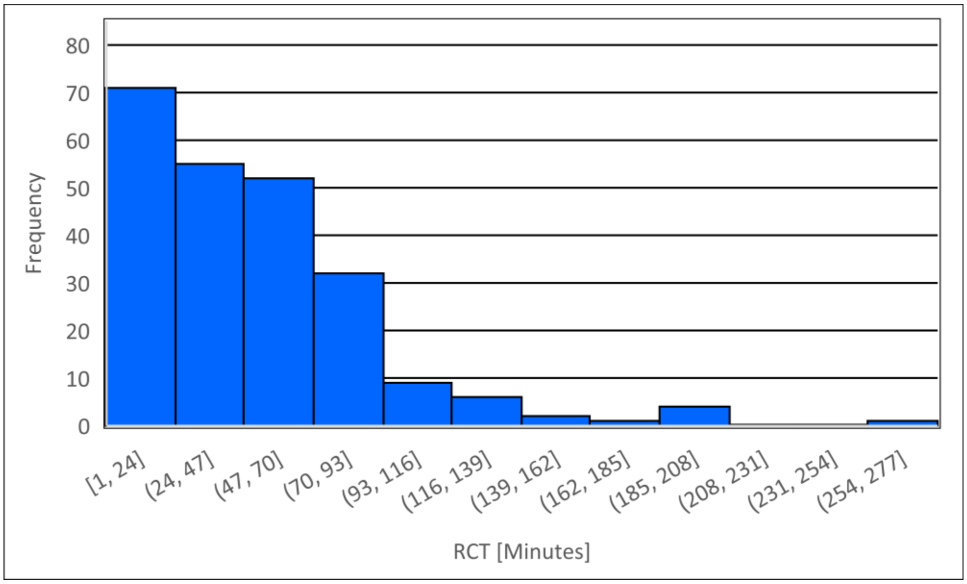

Figure 5-1: Distribution of untransformed RCT.

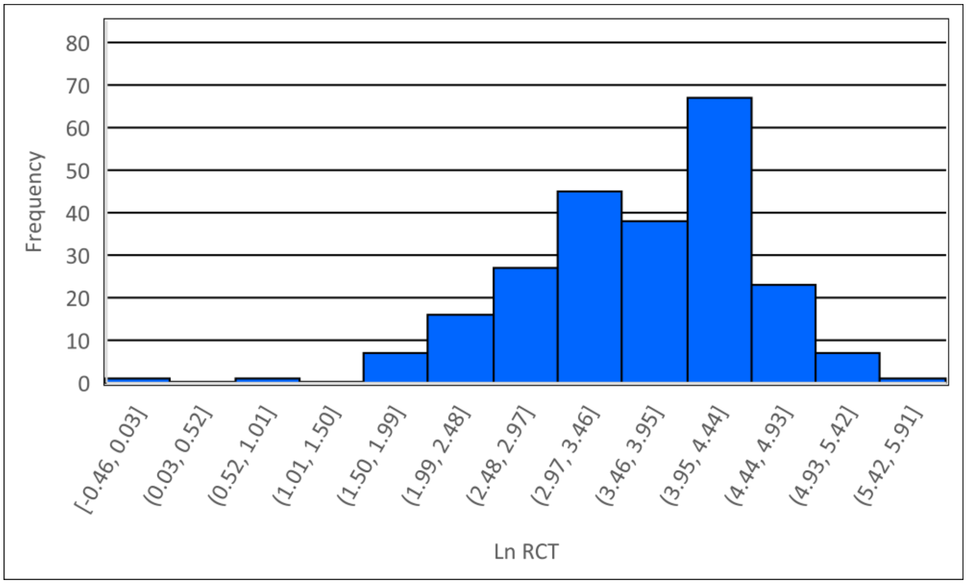

Figure 5-2: Distribution of Ln RCT.

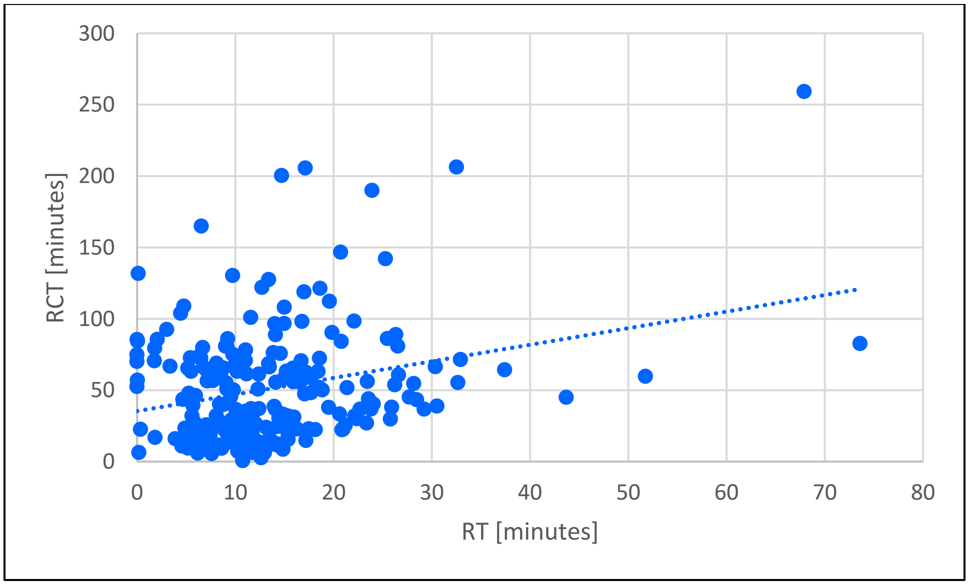

Figure 5-3: Untransformed RCT vs. RT.

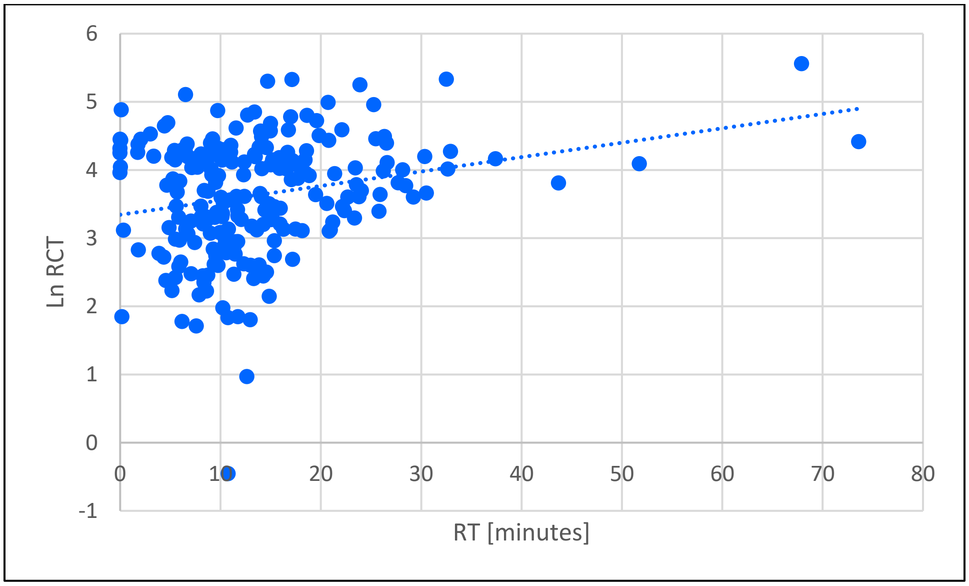

Figure 5-4: Ln RCT vs. RT.

Consistent with the methodology discussed in Chapter 3, secondary incidents were only quantified if their queues did not overlap with that of the primary crash. Thus, the assumption that all data points are independent is met. The natural log transformation of variables helps to meet the other assumptions of linear regression that ensure that the upper outliers of each variable will not skew the overall trend in the data results.

5.4 Analysis of Performance Measures by Crash Type and Year

Least squares means were calculated for RT and Ln RCT and grouped by crash type to perform a more detailed comparison of the differences in these performance measures between 2018 and 2022. The results for the RT least squares means are shown in Table 5-2, and the back-transformed Ln RCT least squares means are shown in Table 5-3. Note that due to the natural log transformation, the standard error is measured as a percentage rather than a value in minutes. RT was reduced for all crash types between 2018 and 2022 and is at least suggestively statistically significant for all except PI crashes. The reduction in RT of FII crashes is 48 percent, showing that IMTs responded to FII crashes in 2022 in almost half the time of that in 2018. Note that the results of FII crashes are potentially skewed due to the small sample size. While the adjusted p-value for the RT of PI crashes is not statistically significant, the percent reduction of 28 percent is still high enough to be a notable improvement.

The back-transformed least squares means of Ln RCT values in 2018 and 2022 were reduced for FII and PDO. However, the differences in least squares means were not statistically significant for these crash types or for PI crashes. Because the percent difference in RCT for PDO crashes is less than 1 percent and the percent standard error is 11 percent, the percent difference between the two years cannot be guaranteed to be positive. The back-transformed least squares means of Ln RCT were shown to have increased by 18 percent. While this increase is also not statistically significant, it shows that the increase in 2022 was primarily due to PI crashes, though the results could be due to chance because of variability in the data.

Table 5-2: RT Least Squares Means by Crash Type

Crash Type	2018 RT [min]	2022 RT [min]	Percent Reduction	Standard Error [min]	Adjusted P value
FII	53.5	27.8	48%	7.0	0.0037
PI	17.4	12.5	28%	1.6	0.8025
PDO	15.9	13.9	13%	1.8	0.0775

Table 5-3: Back-Transformed Ln RCT Least Squares Means by Crash Type

Crash Type	2018 RCT [min]	2022 RCT [min]	Percent Reduction	Percent Standard Error	Adjusted P value
FII	235.2	179.3	24%	55%	0.9897
PI	38.5	45.3	-18%	10%	0.4987
PDO	27.0	26.8	<1%	11%	1.000

Some variables required natural log transformation to meet the assumptions of linear regression due to the right-tailed skew of the data toward higher values. The reduction in least squares means of RT from 2018 to 2022 shows improvement in performance despite the change for PI crashes not being statistically significant, though the result is still valuable. Least squares means of Ln RCT were also reduced from 2018 and 2022 for FII and PDO crashes, though Ln RCT values for PDO crashes were relatively unchanged and the percent standard error was 11 percent, meaning that the percent difference in PDO crashes could not be guaranteed to be positive due to the standard error causing the percent difference to include zero. Thus, there is no conclusive evidence of any change or improvement in RCT for PDO crashes. The least squares means of Ln RCT for PI crashes increased by 18 percent between 2018 and 2022, and, while this change was also not statistically significant, the decrease in RCT between 2018 and 2022 appears to be due to PI crashes.

5.5 Statistical Analysis of Performance Measures

The regression analysis of performance measures is described in the following subsections. Included throughout are the processes of analysis, tables of regression model results, and interpretations of those results. The purpose was to identify relationships of practical significance that help answer the questions of whether the 2022 IMT program is more effective than the 2018 program, which variables have the greatest impact on performance measures, and which factors, if any, caused the changes observed in performance measures between 2018 and 2022.

5.5.1 Introduction

IMT performance measures consisting of Ln RCT, Ln IMT ICT, and Ln UHP ICT were modeled through linear regression to analyze the effects of each incident characteristic on IMT performance measures as well as the performance measures of IMT RT and UHP RT. The incident characteristics analyzed in addition to IMT RT and UHP RT were the number of IMTs, number of UHP teams, number of lanes at the bottleneck, number of available lanes, number of lanes closed, and time range. The models in this report are grouped by independent variables (i.e., incident characteristics) with three models for each of the performance measures mentioned previously grouped in one table.

Since analyses of performance measures were run against incident characteristics for RCT and ICT but not for RT, the number of incidents analyzed for different performance measures and combinations of them differ slightly from what appeared previously in Table 4-1 and Table 4-2. Because some incidents did not have an RT but did have an RCT and ICT, the sample sizes of some relationships experienced minor changes based on the performance measure analyzed. As stated previously, for each invalid RCT value that was higher than its respective ICT value, the RCT value was set equal to its ICT value if the ICT value was valid.

Each statistical model was originally analyzed with an incident characteristic variable, year variable, *incident characteristic*year* interaction variable, and crash type variables for each crash type. In addition to these variables, the adjusted R squared value for each model was included to indicate the strength of correlation of the dependent and independent variables of the model which is adjusted based on the number of data points in the dataset to prevent the value from potentially increasing based on the number of data points. The variables in each model can be back-transformed and interpreted by taking e^x of the natural log values.

The incident characteristic variable represents the rate of increase in the given performance measure per increase of 1.0 of the given incident characteristic. Note that because each dependent variable is a performance measure with a natural log, that the coefficients of the performance measure or incident characteristic variable do not represent a linear slope but rather a multiplicative difference. The year variable is termed *year 2018* where crashes in year 2022 are the reference case, and the coefficient of the *year 2018* variable of a given model represents the difference in intercept (or percent difference from the reference case) of the fitted line between 2018 and 2022 crash data. The *incident characteristic*year* interaction variable represents the difference in performance measure or incident characteristic variable, or rate of change, between 2018 and 2022 crash data for the given model. The crash type variables included are FII crashes and PDO crashes with PI crashes as the reference case.

After viewing the models for each incident characteristic with all variables included, the *incident characteristic*year* interaction variable was removed for the majority of models due to it only being statistically significant for one model and, in some cases, affecting the statistical significance of the incident characteristic and year variables.

Some of the trends for each variable are described here to provide a summary and interpretation of the values of variables that are general to most models. Model-specific analysis and interpretation are provided hereafter. The majority of incident characteristics had a statistically significant relationship with each performance measure modeled as a dependent variable. Only a few models had a statistically significant *year 2018* variable, and most were for Ln RCT models. While it was not statistically significant in the majority of cases, the *year 2018* variable did not have an adverse effect on most models and was kept to compare the difference between performance measures in both years based on the given incident characteristic.

The *year 2018* variable for the Ln RCT models, though statistically insignificant for the majority of models, was typically negative except for one model with an *incident characteristic*2018* interaction variable. As shown in Table 5-4, the range of coefficient values for the year 2018 for Ln RCT models without interaction variables was -0.0606 to -0.1449, which back-transform using an e^x transformation to values reflecting differences in RCT of between -6 percent and -13 percent between 2018 and 2022. These values are fairly consistent with the differences in RCT observed previously. The *year 2018* variable for Ln IMT ICT models fluctuated in whether it was positive or negative but was consistently below an absolute value of 0.0339, which back-transforms to a percent difference of about 3 percent in IMT ICT (both positive and negative) between 2018 and 2022. Ln UHP ICT models were negative for all models without an *incident characteristic*year* interaction variable and had a range for the *year 2018* variable of -0.0386 to -0.0788, which back-transform to percent differences of -4 to -8 percent between 2022 and 2018 UHP ICT values. While these trends are not statistically significant and indicate variability within the data, they do show that IMT and UHP performance measures have similar values between 2018 and 2022, and Ln RCT as well as Ln UHP ICT values are somewhat longer in 2022 than in 2018. Note that the majority of the *year 2018* variable coefficients of performance measures models were not statistically significant, and that these ranges are meant to be an approximate comparison to reflect general trends.

Table 5-4: Range of Typical Coefficient Values for Difference Between 2018 and 2022 Performance Measures of Linear Regression Models

Year 2018	**Ln RCT**		**Ln IMT ICT**		**Ln UHP ICT**	
	Coefficient	Difference	Coefficient	Difference	Coefficient	Difference
Lower	-0.0606	-6%	-0.0149	-1%	-0.0386	-4%
Upper	-0.1449	-13%	0.0339	3%	-0.0788	-8%

The majority of crash type variables in all models were statistically significant. Table 5-5 displays the range of typical values of coefficients and their respective back-transformed percent differences with the reference case of PI crashes. Note that there are exceptions to the ranges shown because these are ranges for typical values, and there may be outliers in individual models. FII crashes typically have RCT values of over 200 percent greater than those of PI crashes, showing that FII crashes typically have clearance times of three times longer than the reference case of PI crashes. The same is true for IMT ICT and UHP ICT values; the high end UHP ICT percent difference is over 500 showing that UHP ICT values may be up to 6 times higher for FII crashes than for PI crashes.

Table 5-5: Range of Typical Coefficient Values for Crash Types of Performance Measures Linear Regression Models

Crash Type	**Range**	**Ln RCT**		**Ln IMT ICT**		**Ln UHP ICT**	
		Coefficient	**Percent Difference**	**Coefficient**	**Percent Difference**	**Coefficient**	**Percent Difference**
FII	Lower	1.15	216%	1.15	216%	1.55	371%
	Upper	1.65	421%	1.35	286%	1.80	505%
PDO	Lower	-0.35	-30%	-0.08	-8%	-0.13	-12%
	Upper	-0.45	-36%	-0.17	-17%	-0.21	-19%

*Note that PI crashes are the reference case

The percent difference in RCT values for PDO crashes was 30 to 36 percent lower than those of PI crashes, showing that PI crashes require 1.42 to 1.57 times longer to clear than PDO crashes. IMT ICT and UHP ICT are also significantly lower for PDO crashes than PI crashes, though not by as much as the difference in RCT for PDO crashes. The adjusted R squared values typically range from 0.10 to 0.25 for the Ln RCT and Ln IMT ICT models and slightly higher for the 0.15 to 0.30 for the Ln UHP ICT models. This indicates that while there is not a strong correlation present between any performance measure and incident characteristic that a noticeable correlation is still present, and that the variability in the data simply is not explained by the model. Crash data is inherently variable, and there are many factors including human behavior that make each crash unpredictable in nature; therefore, general trends in relationships between variables are still practically significant though the adjusted R squared values may not be high.

5.5.2 Performance Measures vs. IMT RT

The IMT RT variable is statistically significant for each performance measures model, and the coefficient value for each model shown in Table 5-6 is very low at 0.0001 or 0.0002. These back-transform to values of 0.01 percent and 0.02 percent of an increase in performance measures for every added second of IMT RT, or 0.6 percent and 1.2 percent increase for every added minute of IMT RT. The scatterplot in Figure 5-5 visualizes the linear model of Ln RCT vs. IMT RT. Note that, in addition to the slope of the fitted line being quite low, the intercept is fairly high with a coefficient value of 7.7130, which back-transforms to 2,237 seconds, or 37.3 minutes. This indicates that Ln RCT is not largely affected by increases in IMT RT and that RCT is likely to be within a threshold of values with minor variability due to IMT RT. The initial model run with an *IMT RT*2018* interaction variable had a very low coefficient for this value that was not statistically significant, showing that there was no significant rate of change of performance measures due to any difference in IMT RT between 2018 and 2022.

Table 5-6: Regression Models of Performance Measures vs. IMT RT

Independent Variables	Dependent Variables		
	Ln RCT	Ln IMT ICT	Ln UHP ICT
IMT RT	0.0002****	0.0002****	0.0001***
Year 2018	-0.1258*	-0.0110 ns	-0.0788*
FII Crash	1.1790****	1.1940****	1.6140****
PDO Crash	-0.4301****	-0.1724***	-0.2108****
Intercept	7.7130****	8.086****	8.6700****
Adj R Squared	0.20	0.20	0.27

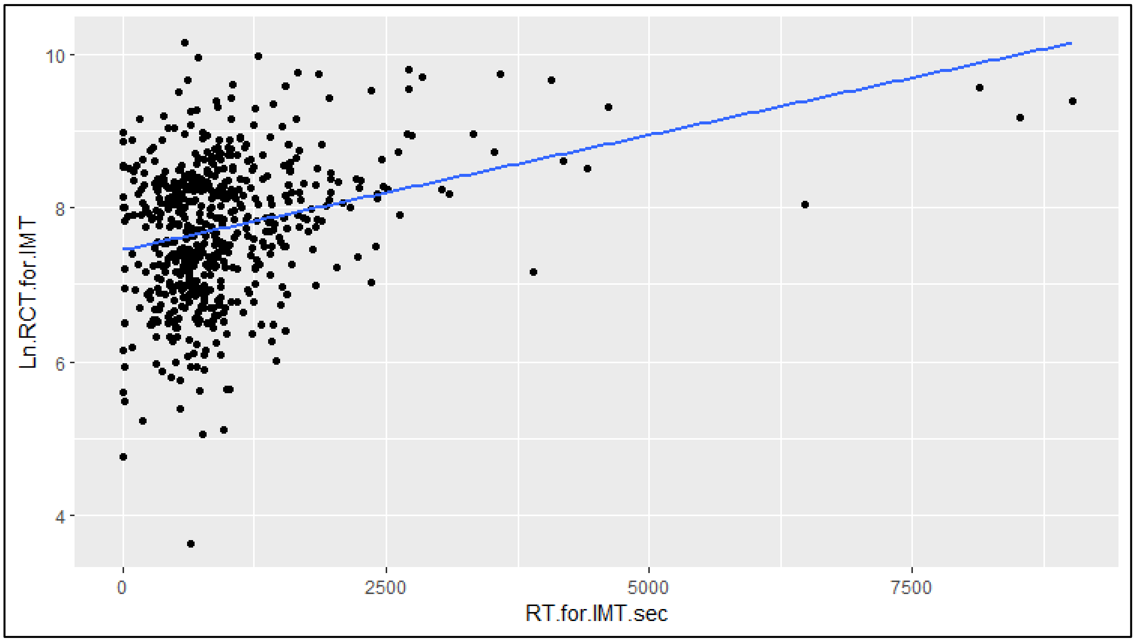

Figure 5-5: Scatterplot of regression model of Ln RCT vs. IMT RT.

5.5.3 Performance Measures vs. UHP RT

The performance measure models for UHP RT are shown in Table 5-7 which indicate that the UHP RT variable is only suggestively statistically significant with the Ln RCT and Ln IMT ICT and not statistically significant with Ln UHP ICT. UHP units typically respond to crashes quickly regardless of the severity of the crash or its clearance times. Similar to IMT RT, the coefficients for the UHP RT models are all very low, indicating that an increase of a few minutes will not have a significant increase on performance measures.

Table 5-7: Regression Models of Performance Measures vs. UHP RT

Independent Variables	Dependent Variables		
	Ln RCT	Ln IMT ICT	Ln UHP ICT
UHP RT	0.0001*	<0.0001*	<0.0001 ns
Year 2018	-0.0832 ns	0.0161 ns	-0.0617 ns
FII Crash	1.5860****	1.4380****	1.7940****
PDO Crash	-0.4359****	-0.1520***	-0.2020****
Intercept	7.8010****	8.1330****	8.7220****
Adj R Squared	0.15	0.13	0.25

5.5.4 Performance Measures vs. Number of IMTs

The relationship between the number of IMTs and performance measures is statistically significant for each model as shown in Table 5-8. The multiplicative increases in each performance measure per added IMT for each performance measure model are given by the coefficient values of 0.2428, 0.2348, and 0.0931 for the Ln RCT, Ln IMT ICT, and Ln UHP ICT models, respectively. These values back-transform to a 27 percent, 26 percent, and 10 percent increase in each respective performance measure per added IMT that responds to the crash. While the adjusted R squared values of 0.18, 0.19, and 0.26 indicate that there is variability in the data, this trend shows that there are significant increases in performance measures for each added IMT, particularly for IMT performance measures. It is likely that the percent increase for the Ln UHP ICT is lower than the other models because UHP officers are more likely to stay at the site of a crash for a longer period of time than IMTs due to the additional duties of aiding crash victims and occasionally escorting them off-site.

Table 5-8: Regression Models of Performance Measures vs. Number of IMTs

Independent Variables	Dependent Variables		
	Ln RCT	Ln IMT ICT	Ln UHP ICT
Number of IMTs	0.2428****	0.2348****	0.0931***
Year 2018	-0.0867 ns	0.0098 ns	-0.0639 ns
FII Crash	1.4131****	1.2499****	1.7264****
PDO Crash	-0.4191 ****	-0.1450***	-0.2040****
Intercept	7.5039****	7.8286****	8.5994****
Adj R Squared	0.18	0.19	0.26

5.5.5 Performance Measures vs. Number of UHP Teams

The number of UHP teams is the incident characteristic with the strongest correlation with performance measures, as shown by the adjusted R squared values in Table 5-9. The number of UHP teams can be inferred to correlate with the amount of time and work required to clear a roadway. The coefficient values for the *number of UHPs* variable for the Ln RCT, Ln IMT ICT, and Ln UHP ICT models are 0.1411, 0.1305, and 0.1170, respectively, which back-transform to percent increases in performance measures of 15, 14, and 12 percent, respectively, for each added UHP team. The number of UHP teams also correlates well with performance measures due to there being many more of them available to respond to crashes than IMTs. Greater numbers make this variable more ideal for being interpreted as a continuous variable that can be interpolated along a line while still fitting the data as shown in Figure 5-6.

Table 5-9: Regression Models of Performance Measures vs. Number of UHP Teams

Independent Variables	**Dependent Variables**		
	Ln RCT	Ln IMT ICT	Ln UHP ICT
Number of UHPs	0.1411****	0.1305****	0.1170****
Year 2018	-0.0651 ns	0.0338 ns	-0.0469 ns
FII Crash	0.5130**	0.4598**	0.9309****
PDO Crash	-0.3447****	-0.0777 ns	-0.1336***
Intercept	7.3701****	7.7195****	8.3251****
Adj R Squared	0.22	0.24	0.35

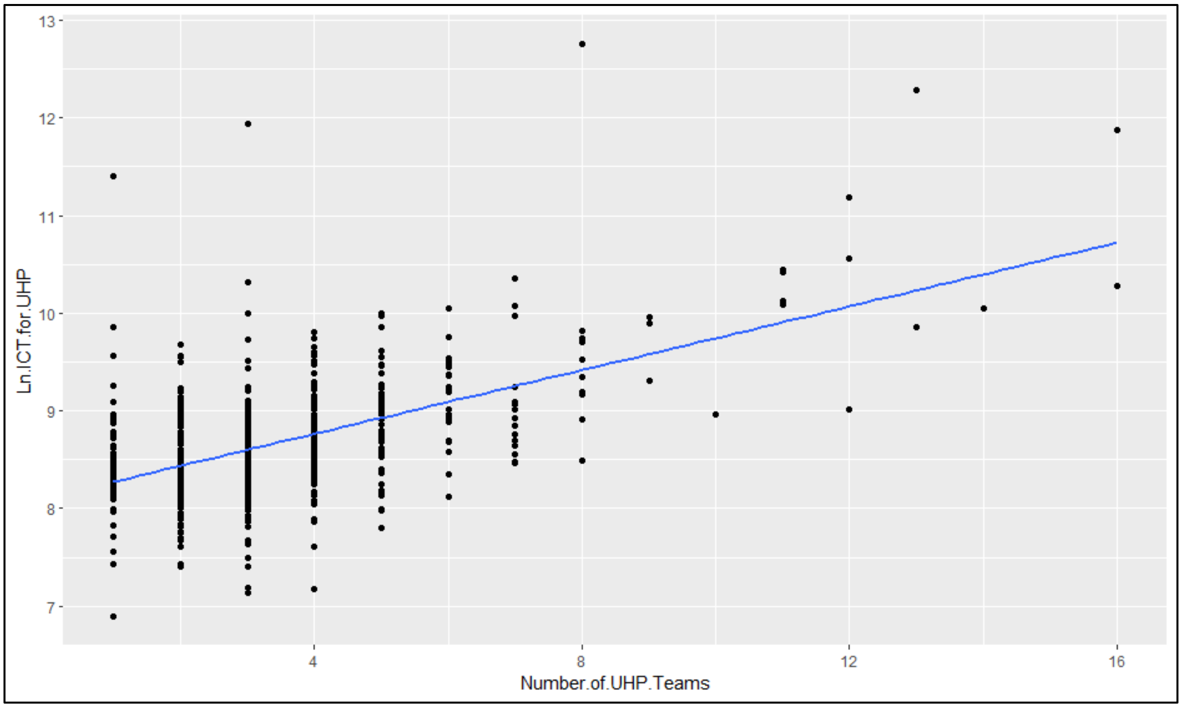

Figure 5-6: Scatterplot of regression model of Ln UHP ICT vs. number of UHP teams.

5.5.6 Performance Measures vs. Number of Lanes at Bottleneck

The number of lanes at the bottleneck represents the total number of lanes of a roadway at the site of a crash. The statistical models in Table 5-10 indicate that there was not a statistically significant relationship between the independent variable of number of lanes at the bottleneck and performance measures. The coefficients of this variable are all low values that indicate that each added lane makes little difference on performance measures. The value for IMT performance measures is positive while that for Ln UHP ICT is negative, indicating that there is obscurity to the number of lanes at the bottleneck being used as a variable to predict performance measures. It is logical to conclude that the amount of time required to clear a roadway is not affected by the number of lanes on the roadway. The *lanes at bottleneck*2018* interaction term was included due to the statistically significant difference in rate of change in performance measures based on number of lanes at the bottleneck between years 2018 and 2022. The coefficient value -0.1684 indicates that RCT increases at a rate of 11 percent slower in 2018 than the reference year of 2022 which results in a negative rate of change of Ln RCT in 2018, or that RCT decreased for each additional lane at the bottleneck in 2018 whereas Ln RCT in 2022 as well as other performance measures in either year had relatively flat fitted lines, or low rates of change of performance measures per added lane at the bottleneck.

Table 5-10: Regression Models of Performance Measures vs. Number of Lanes at Bottleneck

Independent Variables	Dependent Variables		
	Ln RCT	Ln IMT ICT	Ln UHP ICT
Number of Lanes at Bottleneck	0.0355 ns	0.0247 ns	-0.0227 ns
Year 2018	0.7286**	0.1515 ns	0.0189 ns
Lanes at Bottleneck*2018	-0.1684**	-0.0308 ns	-0.0112 ns
FII Crash	1.6356****	1.3166****	1.6626****
PDO Crash	-0.4328****	-0.1111*	-0.1720***
Intercept	7.6524****	8.0280****	8.8340****
Adj R Squared	0.16	0.09	0.17

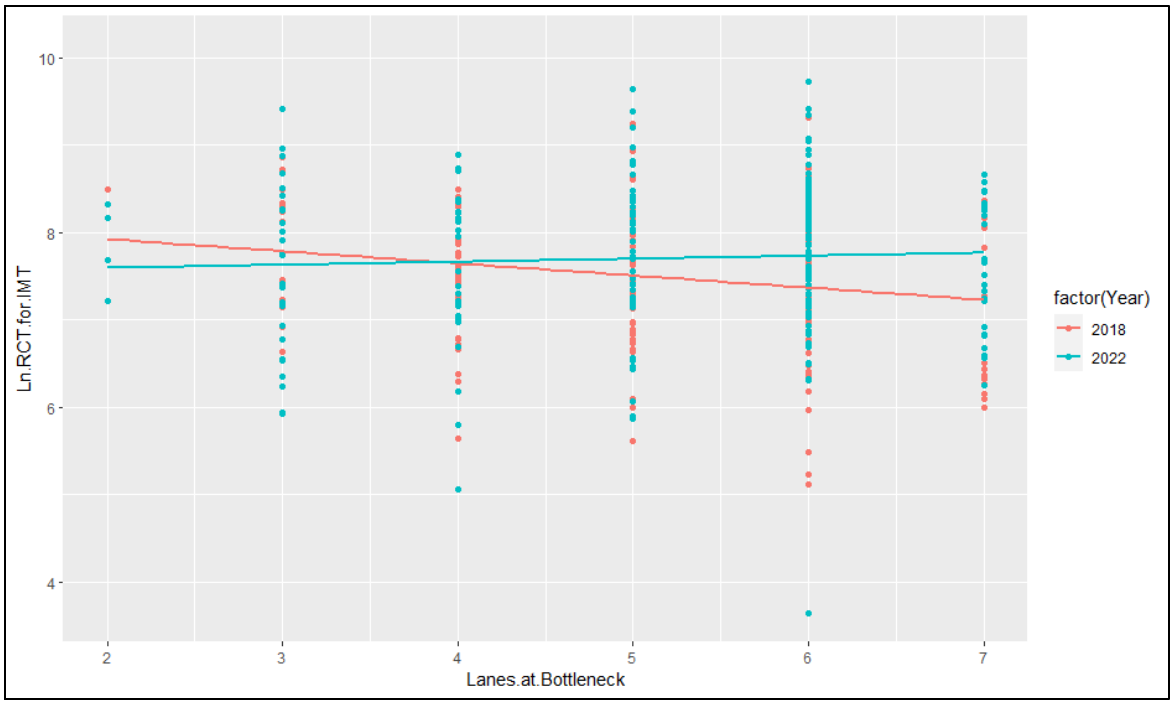

Figure 5-7: Scatterplot of regression model of Ln RCT for IMT vs. number of lanes at bottleneck.

5.5.7 Performance Measures vs. Number of Available Lanes

The number of available lanes is the difference between the number of lanes at the bottleneck and the number of lanes closed. The correlation between performance measures and the independent variable of *number of available lanes* is shown to be negative for each model in Table 5-11, which indicates that a roadway with more available lanes during the crash requires less time to clear per added lane. The coefficients of -0.0788, -0.0522, and -0.0539 back-transform to 8, 5, and 5 percent lower clearance times per added lane for the Ln RCT, Ln IMT ICT, and Ln UHP ICT models, respectively. Crashes with more available lanes (and consequently fewer lanes closed) typically have much less blockage and are likely to require less time to clear as a result.

Table 5-11: Regression Models of Performance Measures vs. Number of Available Lanes

Independent Variables	**Dependent Variables**		
	Ln RCT	Ln IMT ICT	Ln UHP ICT
Number of Available Lanes	-0.0788***	-0.0522***	-0.0539***
Year 2018	-0.1449*	-0.0149 ns	-0.0408 ns
FII Crash	1.4984****	1.2374****	1.5870****
PDO Crash	-0.4239****	-0.0998*	-0.1637***
Intercept	8.0910****	8.3227****	8.8870****
Adj R Squared	0.16	0.11	0.19

Table 5-12 shows that the relationships between performance measures and the number of lanes closed were all statistically significant. The coefficient values for the number of lanes closed variable for the Ln RCT, Ln IMT ICT, and Ln UHP ICT models were 0.1309, 0.1211, and 0.0823, respectively, which back-transform to 14, 13, and 9 percent increases in performance measures per added lane closed, respectively. Similar and inversely to the number of available lanes relationship, the greater the number of lanes closed, the more likely that the required clearance time will be high due to greater crash severity.

Table 5-12: Regression Models of Performance Measures vs. Number of Lanes Closed

Independent Variables	**Dependent Variables**		
	Ln RCT	Ln IMT ICT	Ln UHP ICT
Number of Lanes Closed	0.1309***	0.1211****	0.0823***
Year 2018	-0.0606 ns	0.0271 ns	-0.0386 ns
FII Crash	1.5335****	1.2044****	1.7713****
PDO Crash	-0.3656****	-0.0913*	-0.1826****
Intercept	7.5501****	7.9075****	8.5526****
Adj R Squared	0.17	0.16	0.27

5.5.8 Performance Measures vs Time Range

Due to time range being a categorical variable, the medians of the non-logged performance measures were taken and compared by time range between 2018 and 2022, and the results are shown in Table 5-13. The change in time range distribution is minor for most time range categories except the night off-peak which shifted from having 1 percent of crashes to which IMTs responded in 2018 to 10 percent of crashes to which IMTs responded in 2022. Minor decreases occurred in the AM peak and afternoon off-peak periods of 5 percent and 6 percent, respectively. The categories with the largest differences in RCT, IMT ICT, and UHP ICT were those with small sample size that could be easily swayed including the morning off-peak, which increased in all performance measures from 2018 to 2022, and the night off-peak, which decreased from 2018 to 2022 by a factor of over 3 in each performance measure. The AM peak saw moderate increases in each performance measure between 2018 and 2022 while the PM peak stayed almost the same between 2018 and 2022 with a slight increase in RCT and a slight decrease in UHP ICT. The afternoon off-peak, which had the largest percentage of the total sample, had a moderate increase in RCT and UHP ICT and a slight decrease in IMT ICT.

Table 5-13: Median Values of Performance Measures by Time Range

Performance Measure	Time Range									
	Morning Off-Peak		AM Peak		Afternoon Off-Peak		PM Peak		Night Off-Peak	
Year	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**
RCT [min]	192	271	29	53	42	52	30	33	198	48
IMT ICT [min]	197	283	50	68	67	63	56	56	235	65
UHP ICT [min]	227	285	81	89	87	93	82	81	277	94
Sample Size	7	4	75	64	124	111	94	103	4	33
Percent Total for Respective Year	2%	1%	25%	20%	41%	35%	31%	33%	1%	10%

5.6 **Statistical Analysis of User Impacts**

The regression analysis of user impacts is described in the following subsections. Included throughout are the processes used for analysis, tables of regression model results, and interpretations of those results. The purpose was to identify relationships of practical significance that help answer the questions of whether the 2022 IMT program is more effective than the 2018 program, which variables have the greatest impact on user impacts, and which factors, if any, caused the changes observed in user impacts between 2018 and 2022.

5.6.1 Introduction

Similar to the analysis of performance measures, statistical models were created for each user impact against each performance measure and incident characteristic to investigate the effect of each variable, individually, on user impacts. Models are grouped by independent variables (i.e., performance measures and incident characteristics) with three models in each group presented in one table. The Ln ETT and Ln EUC models consistently had very similar results due to EUC being a function of ETT.

Each statistical model was originally analyzed with a performance measure or incident characteristic variable, year variable, *performance measure variable*year* interaction variable, and crash type variables for each crash type. In addition to these variables, the adjusted R squared value for each model was included to indicate the strength of correlation of the dependent and independent variables of the model which is adjusted based on the number of data points in the dataset to prevent the value from potentially increasing based on number of data points. The variables in each model can be back-transformed and interpreted by taking e^x of the natural log values with the exception of the performance measure or incident characteristic and *performance measure*2018* variables for models that have a natural log variable for both dependent and independent variables which require a 2^x back-transformation.

The performance measure or incident characteristic variable represents the rate of increase in the given user impact per increase in performance measure or incident characteristic. Note that because each user impact is a natural log variable, the coefficients of the performance measure or incident characteristic variable do not represent a linear slope but rather a multiplicative difference. The year variable is termed *year 2018* where crashes in year 2022 are the reference case, and the coefficient for the year 2018 variable of a given model represents the difference in intercept of fitted line between 2018 and 2022 crash data. The *performance measure*year* interaction variable represents the difference in performance measure or incident characteristic variable, or rate of change, between 2018 and 2022 crash data for the given model. The crash type variables included are FII crashes and PDO crashes with PI crashes as the reference case.

After viewing the models for each performance measure or incident characteristic with all variables included, the *performance measure*year* interaction variable and crash type variables were removed for groups of models for which no model of the three user impacts in each group had a coefficient that was statistically significant. Removing these variables made minor improvements, if any, to the adjusted R squared values and, in many cases, changed the result of the year 2018 variable to being statistically significant whereas it was not previously. This was done acknowledging that there was no clear difference between the rate of change of user impacts based on the performance measure or incident characteristic variable for 2018 and 2022 crash data as well as after consideration that no valuable information was being lost by removing the variable in spite of it not being statistically significant.

Some of the trends for each variable are described here to provide a summary and interpretation of the values of variables that are general to most models. Model-specific analysis and interpretation are provided later in this section. The performance measure or incident characteristic variable and *year 2018* variables were always statistically significant for at least one of the three models of user impacts in each group. The range of coefficients for the *year 2018* variable for Ln AV models without *performance measure*year* interaction variables was 0.1331 to 0.2698, which back-transform to a range of 9 percent to 21 percent more vehicles affected by crashes in 2018 than in 2022 with most models being in the 17 percent to 20 percent range. The range of coefficients for the year 2018 variable for Ln ETT and Ln EUC models without *performance measure*year* interaction variables was 0.5101 to 0.8122, which back-transform to a range of 42 percent to 76 percent higher impacts in 2018 than in 2022 with models being in the 65 percent to 70 percent range. Because these models do not have an interaction variable reflecting the change in rate, the *year 2018* variable for these statistical models reflect differences in user impacts in a similar range between those of PDO and PI crashes for reductions in median user impacts described previously in Section 4.4.

Only a few models had statistically significant *performance measure*year* interaction variables. Because these models have interaction variables, the value of the year 2018 coefficient for a given model is relative and may differ significantly from those of other models without interaction variables. For those models with crash type variables included, the coefficients for FII crashes were typically negative, indicating that FII crashes typically had lower user impacts than the reference case, or PI crashes. Note that this is despite the very small sample size of FII crashes and that not all FII crash variables in each model were statistically significant. PDO crash variables were not statistically significant for the majority of models, and the coefficient values were inconsistent among models with some indicating greater or lesser user impacts than the reference case of PI crashes. For this reason, the performance measure or incident characteristic and year 2018 variables are given greater attention in this analysis.

Note that while the intercepts of each model are relative to the other variables in the model due to varying rates of change of performance measures and incident characteristic variables, Ln AV models typically have significantly greater intercept values than Ln ETT and Ln EUC models which are typically more variable. The coefficients for performance measure or incident characteristic variables are nearly always greater in the Ln ETT and Ln EUC models than Ln AV models. This represents AV being highly impacted at the beginning of a crash, where there is a high number of vehicles within the vicinity of the crash that are initially affected. The rate at which Ln AV increases is not nearly as high as Ln ETT and EUC representing that the hours and cost in time of a crash do not increase as much until more vehicles have been in the queue for a longer period of time.

5.6.2 User Impacts vs. Ln RCT

RCT is the total time required to clear all lanes of traffic and is shown to have a significant impact on user impacts. The majority of all regression variables in the models for user impacts vs. Ln RCT were statistically significant as shown in Table 5-14. The Ln RCT coefficients for the Ln AV, Ln ETT, and Ln EUC models are 0.4370, 1.0585, and 1.0677, respectively, which back-transform to rates of change of 35 percent in AV, 108 percent in ETT, and 109 percent in EUC for every 100 percent increase in RCT. Note that these are for the reference case of year 2022 crashes. The coefficient values of the *Ln RCT*year 2018* interaction variable for Ln AV, Ln ETT, and Ln EUC were -0.2301, -0.3041, and -0.3040, which back-transform to differences in rates of change of -15 percent, -19, and -19 percent from the reference case of year 2022, respectively.

Table 5-14: Regression Models of User Impacts vs. Ln RCT

Independent Variables	**Dependent Variables**		
	Ln AV	Ln ETT	Ln EUC
Ln IMT RCT	0.4370****	1.0585****	1.0677****
Year 2018	2.0337***	3.2022**	3.2090**
Ln IMT RCT*2018	-0.2301***	-0.3041*	-0.3040*
FII Crash	-0.6354**	-1.6774**	-1.6417**
PDO Crash	0.1654**	0.2316 ns	0.2196 ns
Intercept	5.0963****	-3.1691***	0.0173 ns
Adj R Squared	0.17	0.22	0.17

The year 2018 variable coefficients are positive and adjust the fitted line of user impacts vs. Ln RCT for 2018 crashes to begin at a higher point than the fitted line for 2022 crashes. However, the 2022 fitted line has a higher slope than the 2018 fitted line. The scatterplot shown in Figure 5-8 visualizes the Ln ETT vs. Ln RCT model where the 2018 fitted line remains above the 2022 fitted line for the whole range of both 2018 and 2022 datasets. With significantly lower user impact values for 2022 crashes and a greater slope of the 2022 fitted line, or a greater rate of change of user impacts based on Ln RCT in 2022, this suggests that the magnitude of user impacts is more dependent on RCT in 2022 than in 2018. The difference in least squares means of Ln RCT between 2018 and 2022 crashes in Table 5-3 indicates that crashes were not cleared any more quickly overall in 2022 than in 2018, therefore the increased fleet size and work of IMTs while a given roadway is being cleared are plausible reasons for the reduction in user impacts between 2018 and 2022.

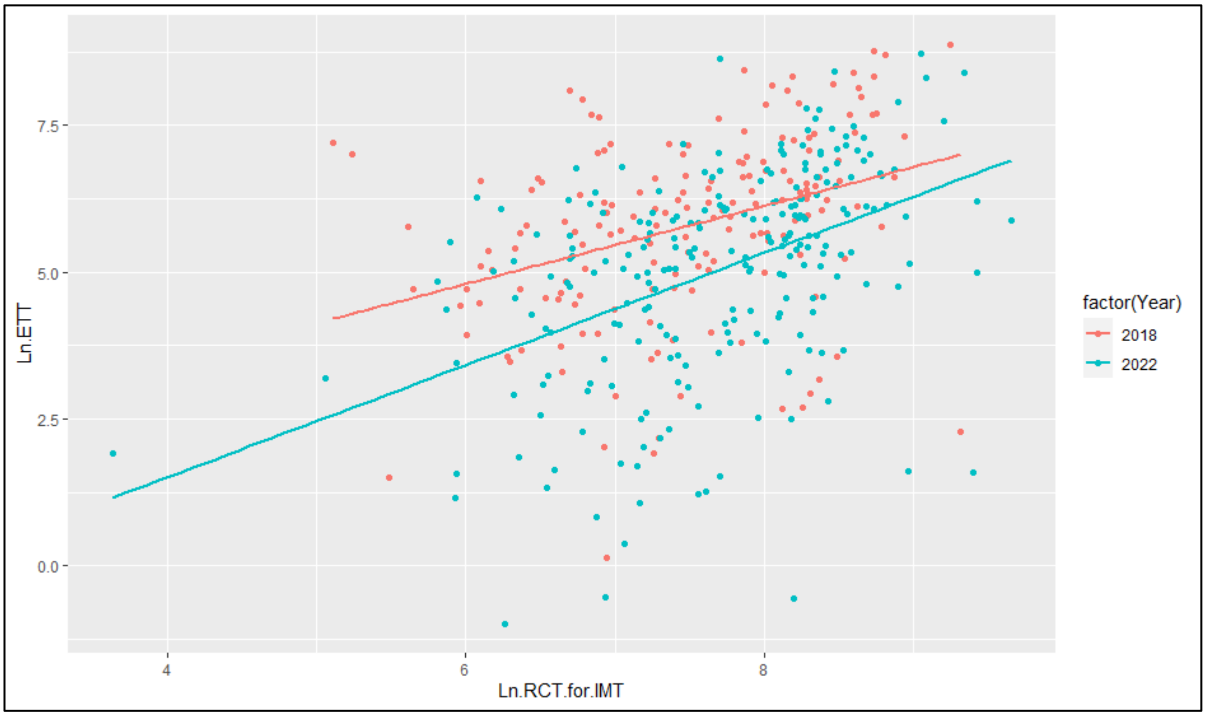

Figure 5-8: Scatterplot of regression model of Ln ETT vs. Ln RCT.

Both FII crash and PDO crash variables were statistically significant for the Ln AV model, and only the FII crash variable was statistically significant for the Ln ETT and Ln EUC models. The coefficient of the FII crash type variable for the Ln ETT model is -1.6774 which back-transforms to 535 percent fewer hours of ETT for FII crashes than PI crashes. This suggests that the magnitude of user impacts for PI crashes was significantly higher than that of FII crashes.

5.6.3 User Impacts vs. Ln IMT ICT

The user impacts vs. Ln IMT ICT models are shown in Table 5-15. The Ln IMT ICT variable was statistically significant for each model of user impacts, and the coefficients were found to be 0.4424, 1.1880, and 1.2060 for Ln AV, Ln ETT, and Ln EUC, respectively. These coefficients back-transform to similar rates of change as the Ln RCT models of a 36 percent increase in AV, 128 percent increase in ETT, and 131 percent increase in EUC per 100 percent increase in IMT ICT. The *Ln IMT ICT*2018* interaction variable in the initial models demonstrated low rates of change that were not statistically significant, suggesting that IMT ICT is not as likely to be a major cause for the significant decrease in user impacts between 2018 and 2022 as the change due to the work of IMTs during a crash.

Table 5-15: Regression Models of User Impacts vs. Ln IMT ICT

Independent Variables	**Dependent Variables**		
	Ln AV	Ln ETT	Ln EUC
Ln IMT ICT	0.4424****	1.1880****	1.2060****
Year 2018	0.2506***	0.7933****	0.7700****
FII Crash	-0.6270**	-1.6837 **	-1.6560**
PDO Crash	0.0639 ns	-0.0550 ns	-0.0689 ns
Intercept	4.9018****	-4.5760****	-1.4637 ns
Adj R Squared	0.13	0.19	0.19

5.6.4 User Impacts vs. Ln UHP ICT

The user impacts vs. Ln UHP ICT models are shown in Table 5-16. The UHP ICT variable was statistically significant for each model of user impacts with coefficients of 0.2542, 0.9196, and 0.9381 for Ln AV, Ln ETT, and Ln EUC, respectively. These coefficients back-transform to a 19 percent increase in AV, 89 percent increase in ETT, and 91 percent increase in EUC per 100 percent increase in UHP ICT. These relationships have somewhat lower rates of change than Ln RCT and Ln IMT ICT and also have higher intercepts, indicating that user impacts are not affected nearly as much by UHP ICT as other variables. In addition, the adjusted R squared values of the Ln UHP ICT models are lower than the Ln RCT and Ln IMT ICT models for each respective user impact. Because UHP units may need to stay at a crash site for long periods of time after the crash has been cleared or to escort crash victims off of the crash site, UHP ICT data had many outliers and may not always proportionally reflect the degree to which roadway users were affected by a crash as well as other variables.

Table 5-16: Regression Models of User Impacts vs. Ln UHP ICT

Independent Variables	**Dependent Variables**		
	Ln AV	Ln ETT	Ln EUC
Ln UHP ICT	0.2542***	0.9196****	0.9381****
Year 2018	0.2513***	0.8122****	0.7894****
FII Crash	0.0642 ns	-1.8154**	-1.7877**
PDO Crash	-0.3026 ns	-0.0154 ns	-0.0283 ns
Intercept	6.2917****	-2.9111**	0.1867 ns
Adj R Squared	0.05	0.11	0.11

5.6.5 User Impacts vs. IMT RT

Similar to the relationship of Ln IMT RCT vs. IMT RT, the IMT RT in the model for each user impact has a very low rate of change. IMT RT coefficients for each user impact model are <0.0001, 0.0003, and 0.0003 for Ln AV, Ln ETT, and Ln EUC, respectively, as shown in Table 5-17. The back-transformed value of the IMT RT coefficient of the Ln ETT and Ln EUC model is a 0.03 percent increase in ETT per added second of IMT RT, or 1.8 percent increase in ETT per added minute of IMT RT. Like the Ln IMT RCT vs. IMT RT model, each user impact model has a relatively high intercept with a very low coefficient of rate of change of user impact based on IMT RT. This demonstrates that IMT RT, individually, does not have a significant effect on user impacts, and that IMT RT is likely to fall within a certain threshold which is largely inconsequential in its effect on user impacts.

Table 5-17: Regression Models of User Impacts vs. IMT RT

Independent Variables	**Dependent Variables**		
	Ln AV	Ln ETT	Ln EUC
IMT RT	<0.0001 ns	0.0003*	0.0003***
Year 2018	0.2397***	0.7096****	0.6816***
Intercept	8.4400****	4.8239****	8.0737****
Adj R Squared	0.03	0.05	0.05

The IMT RT variable for the Ln ETT and Ln EUC models are both at least suggestively statistically significant but not for the Ln AV model, showing that there is not a strong correlation between the user impacts and IMT RT alone. The IMT RT variable originally was not statistically significant for any user impacts model before removing the *IMT RT*year 2018* variable. This along with each crash type variable were removed from the initial model to produce a cleaner model. While there was a statistically significant difference in IMT RT between years 2022 and 2018 that showed that IMT RT was shorter in 2022 than in 2018, the *IMT RT*year 2018* variable not being statistically significant reflects that the change in IMT RT between the two years does not seem to have a significant effect on user impacts.

5.6.6 User Impacts vs. UHP RT

The user impacts vs. Ln UHP RT models are shown in Table 5-18. The UHP RT variable is not statistically significant in the Ln AV model and only suggestively statistically significant in the Ln ETT and Ln EUC models. Similar to IMT RT, the coefficient values for this variable are very low suggesting that UHP RT makes little to no difference on user impacts. Because there are many UHP teams that consistently respond to crashes in a short time period regardless of the magnitude of the effects of the crash, UHP RT is a variable that is not idealized to have a large variance or correlate significantly with user impacts which may have a much larger variance.

Table 5-18: Regression Models of User Impacts vs. UHP RT

Independent Variables	**Dependent Variables**		
	Ln AV	Ln ETT	Ln EUC
UHP RT	<-0.0001 ns	-0.0003*	-0.0003*
Year 2018	0.2531***	0.7499***	0.7236***
Intercept	8.5120****	5.1760****	8.4265****
Adj R Squared	<0.01	0.05	0.04

5.6.7 User Impacts vs. Ln T_7-T_5

T_7-T_5 represents the time from when all lanes of the roadway have been cleared to when traffic conditions have returned to normal relative to regular traffic patterns. The median values of T_7-T_5 were taken for both 2018 and 2022 data by crash type, and the results are shown in

Table 5-19. The percent differences in T_7-T_5 between 2018 and 2022 for PDO, PI, and FII crashes were -54, -54, and -30 percent, respectively. This demonstrates that the work of IMTs decreases the amount of time required for the effects of a crash to dissipate after being cleared by over half. This is a potentially significant factor in the decrease of user impacts of crashes between 2018 and 2022.

Table 5-19: Median T_7-T_5 Values by Year and Crash Type

Year	Crash Type		
	PDO	PI	FII
2018 [min]	28	24	10
2022 [min]	13	11	7
Percent Difference	-54%	-54%	-30%

The user impacts vs. Ln UHP ICT models are shown in Table 5-20. Ln T_7-T_5 has a stronger correlation than most other variables with user impacts with R squared values of 0.30 for Ln AV, 0.19 for Ln ETT, and 0.20 for Ln EUC. The coefficients of the Ln T_7-T_5 variable for the Ln AV, Ln ETT, and Ln EUC models are 0.2510, 0.4516, and 0.4505, respectively. These back-transform to rates of change of 19 percent, 37 percent, and 37 percent per 100 percent increase in T_7-T_5, respectively, and are applicable to the reference case of year 2022 crashes.

Table 5-20: Regression Models of User Impacts vs. Ln T_7-T_5

Independent Variables	Dependent Variables		
	Ln AV	Ln ETT	Ln EUC
Ln T_7-T_5	0.2510****	0.4516****	0.4505****
Year 2018	-1.1494***	-1.4140 ns	-1.4160 ns
Ln T_7-T_5*2018	0.1730***	0.2544*	0.2515*
FII Crash	-0.3937 ns	-0.4135 ns	-0.3659 ns
PDO Crash	-0.1035 ns	-0.4665***	-0.4878***
Intercept	6.9421****	2.4266***	5.6974****
Adj R Squared	0.30	0.19	0.20

Unique to most models, the year 2018 variable coefficients are not significant for the Ln ETT and Ln EUC models. The coefficients for each model are also negative, indicating that the fitted line for user impacts vs. Ln T_7-T_5 begins at a lower value and is not consistent enough to be statistically significant as shown in Figure 5-9. The positive coefficients for the *Ln* T_7-T_5*2018 variable in each model indicate that the rate of increase in user impacts for crashes in year 2018 is higher than that of 2022 crashes. The values of the coefficients of the *Ln* T_7-T_5*2018 variable are 0.1730, 0.2544, and 0.2515 for Ln AV, Ln ETT, and Ln EUC, which back-transform to differences in the rate of change between 2018 and 2022 of 13 percent, 19 percent, and 19 percent, respectively. This indicates that while the difference in user impacts based on Ln T_7-T_5 may not be consistent between 2018 and 2022, the impact of the time for traffic to return to normal after a crash being cleared was greater for 2018 crashes than 2022 crashes, or that 2018 was more sensitive to the effects of time. While the reason for this cannot be inferred from these models, this suggests that the effects of crashes dissipated more quickly due to the work of IMTs in 2022 than in 2018, as was demonstrated previously.

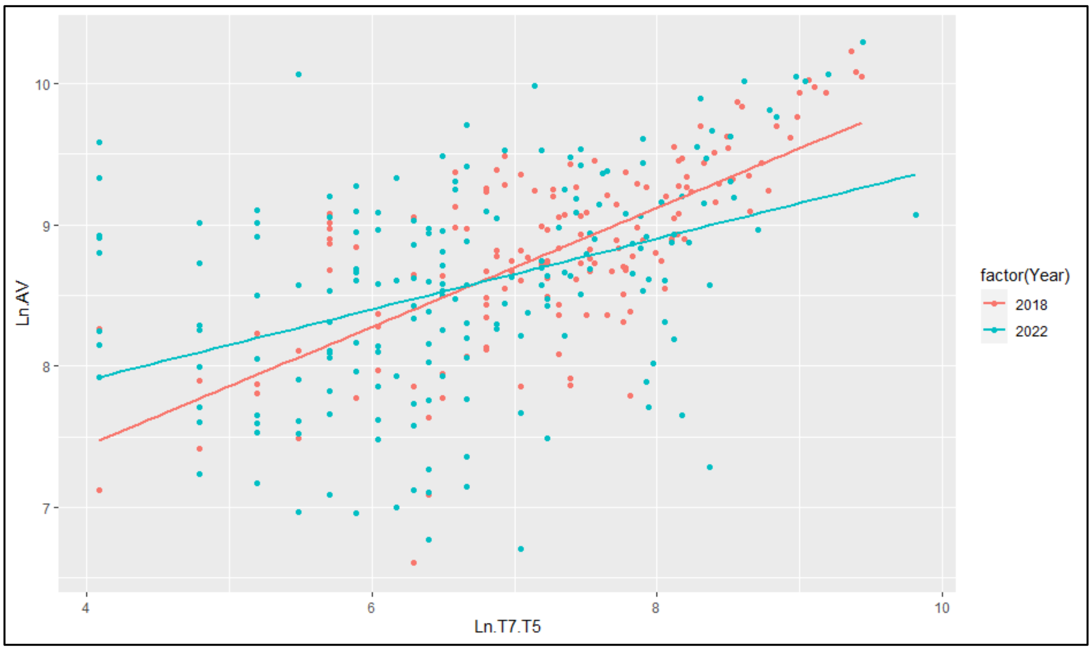

Figure 5-9: Scatterplot of regression model of Ln AV vs. Ln T_7-T_5.

The difference in user impacts based on Ln T_7-T_5 and crash type was not statistically significant for FII crashes but was for PDO crashes in some models. The negative coefficients for each crash type variable suggest that the reference case of PI crashes had greater user impacts than FII crashes and likely did have higher user impacts than PDO crashes except for Ln AV.

5.6.8 User Impacts vs. Ln T_7-T_0

Ln T_7-T_0 is the total time for which the speed of traffic was significantly impacted based on an average of normal days and may be termed the duration of the effects of an incident. The correlation of Ln T_7-T_0 with user impacts is the strongest based on adjusted R squared values of 0.65 for Ln AV and 0.55 for both Ln ETT and EUC as shown in Figure 5-10. Nearly all variables were highly statistically significant except for PDO crashes, indicating more consistent trends in the data for the difference in user impacts between years and some crash types as shown in Table 5-21.

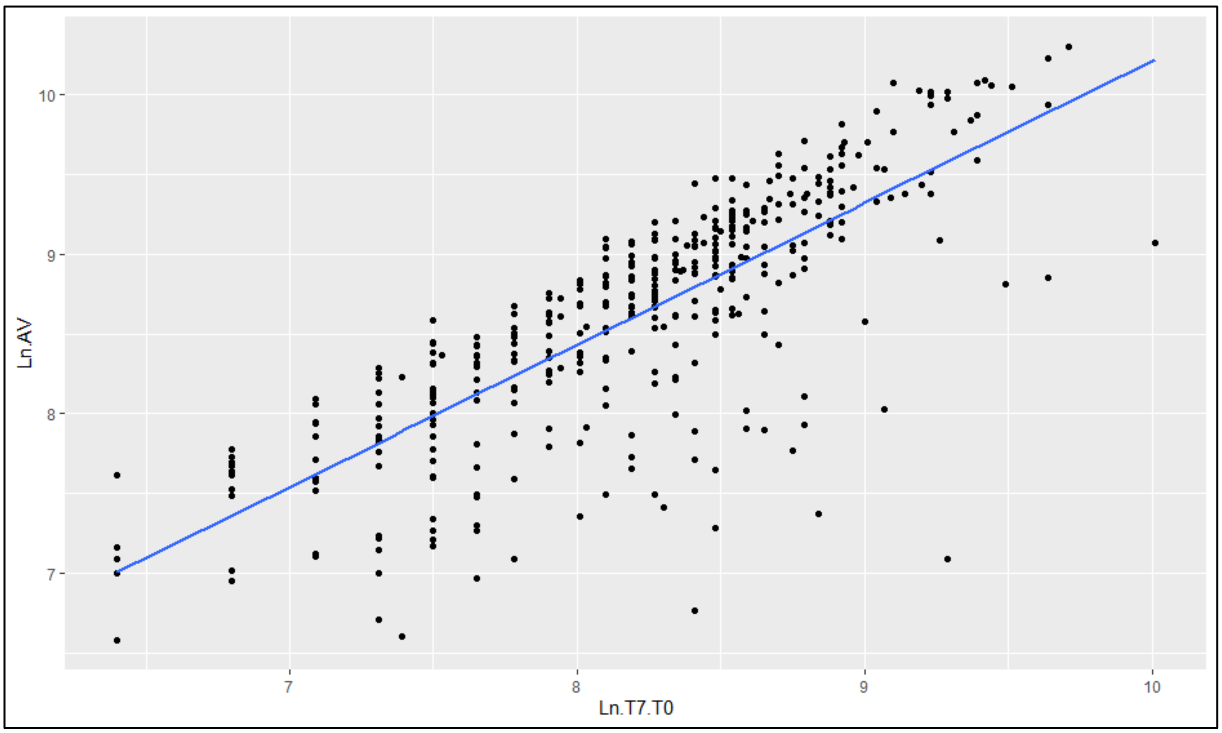

Figure 5-10: Scatterplot of regression model of Ln AV vs. Ln T_7-T_0.

Table 5-21: Regression Models of User Impacts vs. Ln T_7-T_0

Independent Variables	Dependent Variables		
	Ln AV	Ln ETT	Ln EUC
Ln T_7-T_0	0.9286****	1.9898****	2.0006****
Year 2018	0.1331***	0.5352****	0.5101****
FII Crash	-0.9862***	-2.1399 ****	2.100****
PDO Crash	0.1365****	0.0784 ns	0.0640 ns
Intercept	0.8925***	-11.2114****	-8.0407****
Adj R Squared	0.65	0.55	0.55

The coefficients for the Ln T_7-T_0 variable were 0.9286 for Ln AV, 1.9898 for Ln ETT, and 2.0006 for Ln EUC. These coefficients back-transform to rates of increase of 90 percent, 297 percent, and 300 percent per 100 percent increase in T_7-T_0, respectively. The duration of the effects of a crash are correlated with the degree to which roadway users are impacted by those crashes. Interestingly, the *Ln T_7-T_0*2018* interaction variable in each initial model was not statistically significant for any user impact. The coefficient value for this variable in each user impacts model was low, indicating that the difference in the rate of change of user impacts based on T_7-T_0 between 2018 and 2022 was minimal, and p-values were all over 0.60. Thus, regardless of the duration of a crash, user impacts do not increase at a different rate based on the duration of a crash between 2018 and 2022.

The median values of T_7-T_0 were taken by crash type for years 2018 and 2022 to compare differences between the two years. The values for this are shown in Table 5-22. T_7-T_0 values are lower in 2022 than in 2018 by 15 percent for PDO crashes and 7 percent for PI crashes, while they are 3 percent higher for FII crashes. This demonstrates that, while RCT is longer in 2022 than in 2018, there is an overall reduction in the amount of time that the effects of a crash last for in 2022. This is a significant factor in the decrease in user impacts.

Table 5-22: Difference in Median Values of T_7-T_0 by Year and Crash Type

Year	Crash Type		
	PDO	**PI**	**FII**
2018 [min]	65	70	167
2022 [min]	55	65	172
Percent Difference	-15%	-7%	3%

Using the regression models for user impacts vs. Ln T_7-T_0, values were obtained to approximate the user impacts for the median T_7-T_0 values for 2018 and 2022 which are shown in Table 5-23. For this comparison, the reference case of PI crashes was used. With the model calibrated to the conditions of both respective years, the differences in AV, ETT, and EUC are 22 percent, 98 percent, and 93 percent, respectively. Note that these percent differences in user impacts are nearly the same as for the median user impacts of PI crashes shown previously in Table 4-6. The values yielded from the model indicate that a difference of 8 percent in the time that the speed of a Utah interstate-highway affected by a crash is significantly below normal for a PI crash results in almost half of the total delay that all roadway users experience. While RCT is no shorter in 2022 than in 2018, the work of IMTs clearing crashes reduces the time for which the speed of traffic is significantly below normal, which difference leads to significantly reduced user impacts.

The reduction in Ln T_7-T_0 between 2018 and 2022 is evident from the median T_7-T_0 values in Table 5-22, and the overall reduction in user impacts reflected by the year variable is indicated by the year 2018 coefficients for each user impacts model in Table 5-21. These coefficients are 0.1331, 0.5352, and 0.5101 for Ln AV, Ln ETT, and Ln EUC, which back-transform to 14 percent, 71 percent, and 67 percent, respectively, representing the percent difference in user impacts with 2022 crashes. When the values of these coefficients are compared with those shown previously in Table 4-6, it is evident that the majority of the reduction in user impacts is due to the change in the work of IMTs between 2018 and 2022 rather than the 5-minute reduction in T_7-T_0 for PI crashes.

Table 5-23: Predicted Difference in User Impacts Between PI Crashes in 2018 and 2022 Based on Ln T_7-T_0 Regression Models

Year	Median T_7-T_0 for PI Crashes [min]	Median T_7-T_0 for PI Crashes [sec]	AV [vehicles]	ETT [hours]	EUC [$]
2018	70	4,200	6,456	374	9,510
2022	65	3,900	5,276	189	4,923
Difference	5	300	1,180	185	4,587
Percent Difference	7%	7%	18%	49%	48%

5.6.9 User Impacts vs. Ratio of Lanes Closed to Lanes at Bottleneck

The "lane ratio" refers to the ratio of lanes closed during a crash to the total lanes at the bottleneck where the larger the ratio, the more lanes that are closed and the higher that the user impacts would be expected to be. The number of lanes closed for this variable was taken as the greatest number of lanes closed during RCT. As shown in Table 5-24, the lane ratio variable was statistically significant for the Ln ETT and Ln EUC models but not for the Ln AV model. This variable is obscure in the Ln AV model due to the negative coefficient value which indicates the opposite trend of what would be expected, though this is also reflected by its very low adjusted R squared value of 0.02.

The values of the lane ratio coefficient for the Ln ETT and Ln EUC models are 1.7445 and 1.7422, which back-transform to a 472 and 471 percent increase, respectively, per increase of 1.0 in the ratio of lanes closed to lanes at the bottleneck. Because the applicable range of the ratio is limited to between 0 and 1.0, a better increment of interpretation would be in tenth points, for which the coefficient is divided by 10 and then back-transformed by taking e^x. These yield a 19 percent increase for both Ln ETT and Ln EUC per increase of 0.1 in the ratio of lanes closed to lanes at the bottleneck. The *lane Ratio*2018* interaction variable not being statistically significant in the initial model indicates that there is not a statistically significant difference in rate of change of user impacts between 2018 and 2022 based on the proportion of lanes closed.

Table 5-24: Regression Models of User Impacts vs. Ratio of Lanes Closed to Lanes at Bottleneck

Independent Variables	Dependent Variables		
	Ln AV	Ln ETT	Ln EUC
Lane Ratio	-0.0168 ns	1.7445****	1.7422****
Year 2018	0.2477***	0.7507****	0.7248***
Intercept	8.5216****	4.3298****	7.5844****
Adj R Squared	0.02	0.09	0.09

5.6.10 User Impacts vs. Number of IMTs

The number of IMTs was the total number of IMTs that responded to a crash at any time. The number of IMTs that responded to a crash is one of the primary variables that changed between 2018 and 2022 due to the program expansion. The models for this incident characteristic are shown in Table 5-25. The coefficient values for the number of IMTs variable of the Ln AV, Ln ETT, and Ln EUC models were 0.1178, 0.5346, and 0.5385, which back-transform to an increase of 13, 71, and 71 percent in user impacts, respectively, per added IMT that responds to a crash. IMTs confirmed in a meeting with the research team that, typically, one unit will respond to a crash initially depending on the size of the crash, and then more will respond to help if necessary. This indicates that the number of IMTs is a reactionary variable, where the number of IMTs increases with user impacts due to more severe crashes requiring more units to clear whereas less severe crashes can be cleared with one or two teams.

Table 5-25: Regression Models of User Impacts vs. Number of IMTs

Independent Variables	Dependent Variables		
	Ln AV	Ln ETT	Ln EUC
Number of IMTs	0.1178**	0.5346****	0.5385****
Year 2018	0.2488***	0.7561***	0.7302***
Intercept	8.3363****	4.2297****	7.4775****
Adj R Squared	0.04	0.09	0.08

The differences in user impacts by number of IMTs between 2018 and 2022 are significant as shown in Table 5-26, which show the median hours of ETT per number of IMTs that responded to a crash for each year. Interestingly, the sample size of incidents for a given number of IMTs per crash remained the same proportional to the total number of crashes between 2018 and 2022. Incidents with one IMT had a median value of 341 hours of ETT in 2018 but only about half of that in 2022 with a median value of 165 hours of ETT. The median number of hours of ETT when two IMTs were present is very similar between the 2 years with 387 hours in 2018 and 349 hours in 2022. This shows that with more IMTs in 2022 that teams could respond to more crashes as well as to those of lower severity; the median crash that a single IMT responded to in 2022 was half the size of that of 2018. With more teams on the road in 2022, the IMT program had the resources to send multiple IMTs to crashes that were not as severe as those in 2018 without neglecting other crashes. The number of IMTs added to the fleet between 2018 and 2020 (over double) is almost proportional to the approximate difference in user impacts between 2018 and 2022 (a little less than double depending on the crash type as shown previously in Table 4-5, Table 4-6, and Table 4-7).

Table 5-26: Median Hours of ETT and Sample Size of Incidents by Number of IMTs

	Number of IMTs							
	1		2		3		4	
Year	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**
Median ETT Value [hours]	341	165	387	349	1,211	348	6,355	1,087
Sample Size	100	139	57	72	10	18	3	4
Percent Total for Respective Year	59%	60%	34%	31%	6%	8%	2%	2%

5.6.11 User Impacts vs. Number of UHP Teams

The number of UHP teams was shown to be statistically significant for predicting Ln ETT and Ln EUC but not Ln AV as shown in Table 5-27. While the number of UHP teams is correlated with Ln ETT and Ln EUC, the correlation is not strong with adjusted R squared values of only 0.07 and 0.06, respectively. The number of UHP teams may vary from incident to incident due to differing needs at the site of each crash that are independent of the severity of the crash. Because there are many more UHP teams than IMTs, the number of UHP teams that respond to each crash is more flexible than for IMTs. The coefficient values of the Ln ETT and Ln EUC variables are 0.1508 and 0.1542, which back-transform to rates of change of 16 and 17 percent increases in user impacts, respectively, per added UHP team.

Table 5-27: Regression Models of User Impacts vs. Number of UHP Teams

Independent Variables	Dependent Variables		
	Ln AV	Ln ETT	Ln EUC
Number of UHPs	0.0202 ns	0.1508***	0.1542***
Year 2018	0.2531***	0.7912****	0.7662***
Intercept	8.4446****	4.5167****	7.7585****
Adj R Squared	0.03	0.07	0.06

5.6.12 User Impacts vs. Number of Available Lanes

The number of available lanes is the difference between the number of lanes at the bottleneck of a crash and the number of lanes closed during the crash. The coefficients for the user impacts models of the number of available lanes are shown in Table 5-28. The coefficients of the number of available lanes variable for the Ln ETT and Ln EUC models are both negative, indicating that these user impacts decrease with more available lanes. However, the coefficient for the Ln AV model is positive, indicating that even with more available lanes to allow traffic to continue to flow, there are more vehicles affected by the crash when more lanes are available. Because AV does not account for some vehicles being affected by delay more than others, it is logical to assume that more lanes of traffic being available still allows more vehicles to pass through the site of a crash. Vehicles are inevitably delayed by a crash regardless of the number of vehicles delayed, though the degree of delay experienced by roadway users when more lanes are available is not nearly as high as when fewer lanes are available. Hence, AV is the number of affected vehicles and ETT as well as EUC are a measure of the degree to which roadway users were affected by a crash. While these models are indicative of an important phenomenon, the low adjusted R squared value for each model indicates that they are not ideal for predicting user impacts.

Table 5-28: Regression Models of User Impacts vs. Number of Available Lanes

Independent Variables	Dependent Variables		
	Ln AV	Ln ETT	Ln EUC
Number of Available Lanes	0.0599**	-0.1428**	-0.1425**
Year 2018	0.2525***	0.7399***	0.7140***
Intercept	8.3224****	5.4979****	8.7506****
Adj R Squared	0.04	0.06	0.05

5.6.13 User Impacts vs. Number of Lanes Closed

The effect of one lane being closed can be very significant to traffic and safety. The coefficient values for the models of the user impacts vs. number of lanes closed is shown in Table 5-29. The values of these coefficients for the Ln AV, Ln ETT, and Ln EUC models are 0.1179, 0.5687, and 0.5664, respectively, which back-transform to an increase in user impacts of 13, 77, and 76 percent, respectively, per additional lane closed. While there are many other factors that influence the user impacts of an incident, the number of lanes does have a significant correlation relative to other incident characteristics for predicting Ln ETT and Ln EUC.

Table 5-29: Regression Models of User Impacts vs. Number of Lanes Closed

Independent Variables	**Dependent Variables**		
	Ln AV	Ln ETT	Ln EUC
Number of Lanes Closed	0.1179***	0.5687****	0.5664****
Year 2018	0.2464***	0.7833****	0.7600****
FII Crash	-0.3194 ns	-1.3904**	-1.3351*
PDO Crash	0.0300 ns	-0.1189 ns	-0.1353 ns
Intercept	8.2704****	3.9598****	7.2235****
Adj R Squared	0.05	0.15	0.15

5.6.14 User Impacts vs. Time Range

Due to time ranges being a non-numeric and non-continuous variable, the median value of user impact and sample size of crashes that occurred in each time range was taken rather than creating linear regression models. The results for 2018 and 2022 are shown in Table 5-30. The sample size of incidents in each time range category stays within 5 percent between 2018 and 2022 for the morning off-peak, AM peak, and night off-peak; however, there is an 8 percent decrease in crashes that fall within the afternoon off-peak between 2018 and 2022 as well as a 9 percent increase in the number of crashes that fall within the night off-peak. While these sample sizes only include those that were analyzed for user impacts, this demonstrates a minor shift toward crashes occurring later in the day in 2022 from that of 2018 which had a higher percentage of crashes occur in the AM peak and afternoon off-peak periods.

Table 5-30: Median User Impact Values of Crashes by Time Range

User Impact	Time Range									
	Morning Off-Peak		AM Peak		Afternoon Off-Peak		PM Peak		Night Off-Peak	
Year	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**
AV [vehicles]	10,927	4,223	5,865	6,969	7,626	5,310	6,880	5,780	10,581	1,977
ETT [hours]	2,209	197	295	258	492	186	443	283	2,211	17
EUC [$1000]	57.25	5.17	6.52	6.01	13.37	4.93	11.26	7.05	56.89	0.44
Sample Size	2	2	42	46	72	80	52	81	2	24
Percent Total for Respective Year	1%	1%	25%	20%	42%	34%	31%	35%	1%	10%

The decrease in user impacts between 2018 and 2022 is larger for some time categories than others with the exception of AV for the AM peak period which increases between 2018 and 2022. The reason for this is unknown and perhaps is due to greater traffic volumes in 2022; however, ETT and EUC are slightly lower for this time category in 2022 than in 2018. Thus, user impacts appear to be somewhat unchanged for the AM peak period. There are very large decreases in user impacts between 2018 and 2022 for the morning off-peak and night off-peak, and there are not as extreme yet still significant differences between 2018 and 2022 user impacts for the afternoon off-peak and PM peak periods.

5.7 Conclusions

IMT performance measures and user impacts were analyzed to determine whether the IMT program was more effective in 2022 than in 2018 as well as to find relationships of practical significance to better understand factors affecting performance measures and user impacts that changed between 2018 and 2022. The natural log was taken for all performance measures, user impacts, and time parameters to allow the right-skewed data to meet the assumptions of linear regression. The least squares means of IMT RT shown previously in Table 5-2 indicate that IMT RT decreased between 2018 and 2022 for each crash type, particularly for FII crashes which decreased by 48 percent. This shows that IMTs can maintain a more consistent response time for all crash types. The back-transformed least squares means of Ln RCT shown previously in Table 5-3 show that, while none of the relationships are statistically significant enough for the results to be conclusive, PI crashes are primarily the cause for longer RCT in

2022 than in 2018. RCT remained relatively unchanged for PDO crashes and decreased by 24 percent for FII crashes.

The regression analysis showed that the year 2018 variable was not statistically significant for most performance measures models due to there not being a large, consistent difference in performance measures between 2018 and 2022. FII crashes, if predicted along a fitted least squares line would have RCT values of over 3 times longer than the reference case of PI crashes and UHP ICT values of up to 6 times higher than PI crashes. PDO crashes were predicted to be 30 to 36 percent lower than PI crashes, as shown previously in Table 5-5.

While IMT RT had a statistically significant relationship with each performance measure and user impact, it was shown to have a very low rate of change of 1.2 percent increase in RCT per added minute of RT and a high intercept, indicating that IMT RT does not have a large impact on performance measures and that performance measures and user impacts are likely to fall within a loose threshold as shown previously in Figure 5-5. This same trend also applies to the relationship of user impacts vs. IMT RT. The performance measures relationship with the strongest correlation was Ln UHP ICT vs. Number of UHP Teams with an adjusted R squared value of 0.35. While UHP ICT did not have a strong correlation with user impacts relative to other independent variables, it was the performance measure that best correlated with the effects of incident characteristics on the required clearance time. The number of UHP teams was the independent variable in the performance measures regression models that best reflected the time and effort that it took responders to clear crashes.

The time-range analysis showed that the majority of crashes occur in the afternoon off-peak period followed by the PM peak and AM peak periods. The distribution of the percentage of crashes by time period shifted in 2018 from 41 percent of crashes in the afternoon off-peak period to only 35 percent in 2022, and from 1 percent in the night off-peak in 2018 to 10 percent in 2022. This shows that IMTs responded to more crashes in the night off-peak in 2022 than in 2018, likely due to the increased number of units as well as that the program had changed to 24-7 operation hours. The median RCT value decreased from 198 minutes to 48 minutes, showing that IMTs were able to clear crashes that occurred during the night off-peak three times more quickly in 2018 than 2022. This shows that the IMT program was significantly more consistent in 2022 than in 2018. User impacts decreased significantly for almost all time-range categories, particularly for the morning off-peak and night off-peak.

While almost no performance measures models had a statistically significant *incident characteristic*year 2018* interaction variable (the variable indicating a difference in the rate of increase of a variable between 2018 from the reference year of 2022), the user impacts models that had significant *performance measure*year 2018* interaction variables were the Ln RCT and Ln T_7-T_5 models. The *Ln RCT* variable from the Ln RCT models indicated that AV increased by 35 percent and ETT as well as EUC increased by over 108 percent for a 100 percent increase in RCT; the *Ln RCT*year 2018* variable indicated that these rates of change were 15 percent and 19 percent lower in 2018 than in 2022, respectively. The rate of change of user impacts is lower in 2018 than in 2022, showing that crashes in 2022, while still having significantly lower user impacts than in 2018, are more sensitive to the impact of the length of RCT. This shows that RCT, though not shorter overall in 2022 than in 2018, has a greater effect on 2022 crashes than on those in 2018, which indicates that there is a positive change in the work of IMTs.

The median values were taken for T_7-T_5 and T_7-T_0, and they were grouped by year and by crash type. T_7-T_5 was reduced from 2018 to 2022 by 54 percent for PDO and PI crashes, showing that the time that traffic needed to return to normal after being cleared was 54 percent lower in 2022 than in 2018. The medians of T_7-T_0 were reduced by 15 and 7 percent for PDO and PI crashes, respectively, between 2018 and 2022. Note that even though the percent difference is not as high as for the medians of T_7-T_5 that this is because the time after a crash is cleared is significantly shorter than the total time for which the speed of traffic was significantly below normal. These results indicate that IMTs significantly reduced the amount of time for which roadway users are impacted by crashes between 2018 and 2022, particularly the portion of after a crash is cleared, which was a primary cause for the significant decrease in user impacts. Note that the Ln AV vs. Ln T_7-T_0 relationship had the strongest correlation of all user impacts models and all models in general with an adjusted R squared value of 0.65.

The median hours of ETT per number of IMTs that responded to an incident decreased significantly between 2018 and 2022 for most medians of ETT per number of IMTs. The median hours of ETT for one IMT in 2022 was half that of 2018, showing that with more IMTs in the program that the median crash severity to which one IMT responded was significantly lower in 2022 than in 2018. IMTs were not spread as thin in 2022 as in 2018, so the median hours of ETT for when three or four IMTs responded to a crash were over 3 times lower in 2022 than in 2018.

6.0 CONCLUSIONS

6.1 Summary

The purpose of this study was to estimate and compare IMT performance measures and user impacts for the years of 2018 and 2022 to analyze the benefits of the IMT program expansion that occurred between 2018 and 2020 to evaluate the added benefits of an expanded program to public safety, congestion relief, and flexibility of responders. Crash data were obtained from UHP CAD data and integrated with that of the TransSuite lane closure data. Data were collected for March through August of 2022 and data for the same time period in 2018 were used to compare with that of 2022.

The performance measures collected were RT, RCT, and ICT, and the user impacts collected were AV, ETT, and EUC. The methodology for this study was the same as that of the Phase II study except that the research team did not need to account for the significant difference in volumes due to COVID-19 (Bennett et al., 2022; Schultz et al., 2021). Data were reduced to produce general results, and a statistical analysis was conducted on the data using linear regression. The findings are summarized by performance measures and user impacts, and limitations and challenges encountered during the study are presented.

6.2 Findings

The findings for performance measures describe the changes and improvements in IMT activity as well as relationships of significance that were presented in Chapter 4 and Chapter 5. Overall improvements were shown for RT and ICT. The findings for user impacts demonstrate significant reductions in each user impact between 2018 and 2022.

6.2.1 Performance Measures

RT was shown to improve overall with an increase in the proportion of incidents that were responded to within the first 15 minutes of an incident by 7 percent. The statistical analysis showed that reductions in RT for FII, PI, and PDO crashes were 48, 28, and 13 percent, respectively, as summarized in Table 6-1. Results for RCT were shown to be longer overall in

2022 by a difference of approximately 32 percent within the first 45 minutes. While there was no statistically significant difference in the least squares means of Ln RCT between 2018 and 2022, there was an 18 percent increase in the back-transformed Ln RCT for PI crashes alone between 2018 and 2022, as shown in Table 6-2. The percent differences for FII and PDO crashes were 24 percent and less than 1 percent, respectively, though the results were not statistically significant. This indicates that the increase in RCT was likely due primarily to a higher percentage of PI crashes. This is logical due to the increased crash frequency in 2022 and minor shift in crash distribution to a higher percentage of PI crashes. ICT was shown to have improved overall between 2018 and 2022 with IMTs leaving the site of a crash within the first 45 minutes of a crash for 61 percent of incidents in 2018 and 67 percent of incidents in 2022. This difference of 6 percent equates to a relative percent difference and improvement of 10 percent more incidents in 2022 than in 2018, demonstrating that IMTs are completing their work faster in 2022 than in 2018 despite RCT being overall longer.

Table 6-1: RT Least Squares Means by Crash Type

Crash Type	2018 RT [min]	2022 RT [min]	Percent Reduction	Standard Error [min]	Adjusted P value
FII	53.5	27.8	48%	7.0	0.0037
PI	17.4	12.5	28%	1.6	0.8025
PDO	15.9	13.9	13%	1.8	0.0775

Table 6-2: Back-Transformed Ln RCT Least Squares Means by Crash Type

Crash Type	2018 RCT [min]	2022 RCT [min]	Percent Reduction	Percent Standard Error	Adjusted P value
FII	235.2	179.3	24%	55%	0.9897
PI	38.5	45.3	-18%	10%	0.4987
PDO	27.0	26.8	<1%	11%	1.000

Regression models of performance measures vs. IMT RT showed that while IMT RT had a statistically significant relationship with the IMT performance measure that it did not have a significant impact on performance measures and user impacts due to its low slope of fitted line and high intercept, meaning that an increase in IMT RT will have a minor impact on performance measures and user impacts; most incidents fall within a general threshold of performance measure or user impacts values irrespective of IMT RT. The Ln UHP ICT vs. Number of UHP Teams relationship was shown to have the strongest correlation of all performance measure models, and the *Ln UHP ICT* and *number of UHP Teams* variables were shown to be the dependent and independent variables amongst all performance measures models that had the strongest correlations with other variables. The distribution of the percentage of crashes by time period shifted in 2018 from 42 percent of crashes in the afternoon off-peak period to only 34 percent in 2022, and from 1 percent in the night off-peak in 2018 to 10 percent in 2022. This shows that IMTs responded to more crashes in the night off-peak in 2022 than in 2018, likely due to the increased number of units as well as that the program had changed to 24-7 operation hours. The median RCT value for the night off-peak period decreased by a factor of 3, showing that the IMT program eliminated severe outliers in performance measure values between 2018 and 2022 and showed greater consistency.

6.2.2 User Impacts

User impacts were shown to have decreased significantly from 2018 to 2022 with reductions of 24 and 20 percent for AV of PDO and PI crashes, over 42 percent for the ETT and EUC of PDO crashes, and over 51 percent for ETT and EUC of PI crashes as shown in Table 6-3, Table 6-4, and Table 6-5. Table 6-5 shows that while the sample size of FII crashes was very small, thus skewing the general results to extreme values, FII crashes were shown to have reductions of 93 percent for ETT and EUC between 2018 and 2022. This demonstrates great benefits for the state of Utah with the expansion of the IMT program where the cost to roadway users due to delay in 2022 is almost half that of 2018. The contrast between PI and PDO crashes is also less in 2022 than in 2018, showing that having more IMTs available to respond to crashes decreases the effect of higher severity crashes on user impacts.

Table 6-3: Median User Impacts for PDO Crashes

User Impact	2018	2022	Percent Reduction
AV [Vehicles]	6,635	5,027	24%
ETT [Hours]	340	184	46%
EUC [$]	$8,269.75	$4,757.91	42%

Table 6-4: Median User Impacts for PI Crashes

User Impact	2018	2022	Percent Reduction
AV [Vehicles]	6,933	5,518	20%
ETT [Hours]	493	231	53%
EUC [$]	$12,752.58	$6,215.59	51%

Table 6-5: Median User Impacts for FII Crashes

User Impact	2018	2022	Percent Reduction
AV [Vehicles]	6,495	7,897	-22%
ETT [Hours]	3,601	253	93%
EUC [$]	$97,899.53	$6,615.98	93%

Regression models of user impacts vs. Ln RCT had a statistically significant *Ln RCT* variable as well as *Ln RCT*year 2018* interaction variable. This indicates a difference in the slopes of the fitted lines between 2018 and 2022 crashes of 15 percent lower AV per 100 percent increase in RCT in 2018 vs. 2022, and 19 percent lower of both ETT and EUC per 100 percent increase in RCT in 2018 vs. 2022. Figure 6-1 shows that while the least squares fitted line for Ln ETT vs Ln RCT in 2018 is located above that of 2022, the 2022 fitted line has a higher slope and is more sensitive to change in Ln RCT than that of 2018. While RCT is overall longer in 2022, the impact of RCT on user impacts is greater in 2022 than in 2018. T_7-T_5 reflects the median amount of time required for traffic to return to normal after a crash has been cleared. The median values of T_7-T_5 for each year and crash type shown in Table 6-6 include a 54 percent decrease between 2018 and 2022 for PDO and PI crashes. This along with a related significant decrease in T_7-T_0, or the total time for which the speed of traffic is significantly below normal, show that the work of IMTs resulted in an overall shorter amount of time for which roadway users were significantly impacted by a crash, showing that the work of IMTs during a crash in 2022 and the reduced T_7-T_5 and T_7-T_0 are the primary causes for the significant reduction in user impacts between 2018 and 2022.

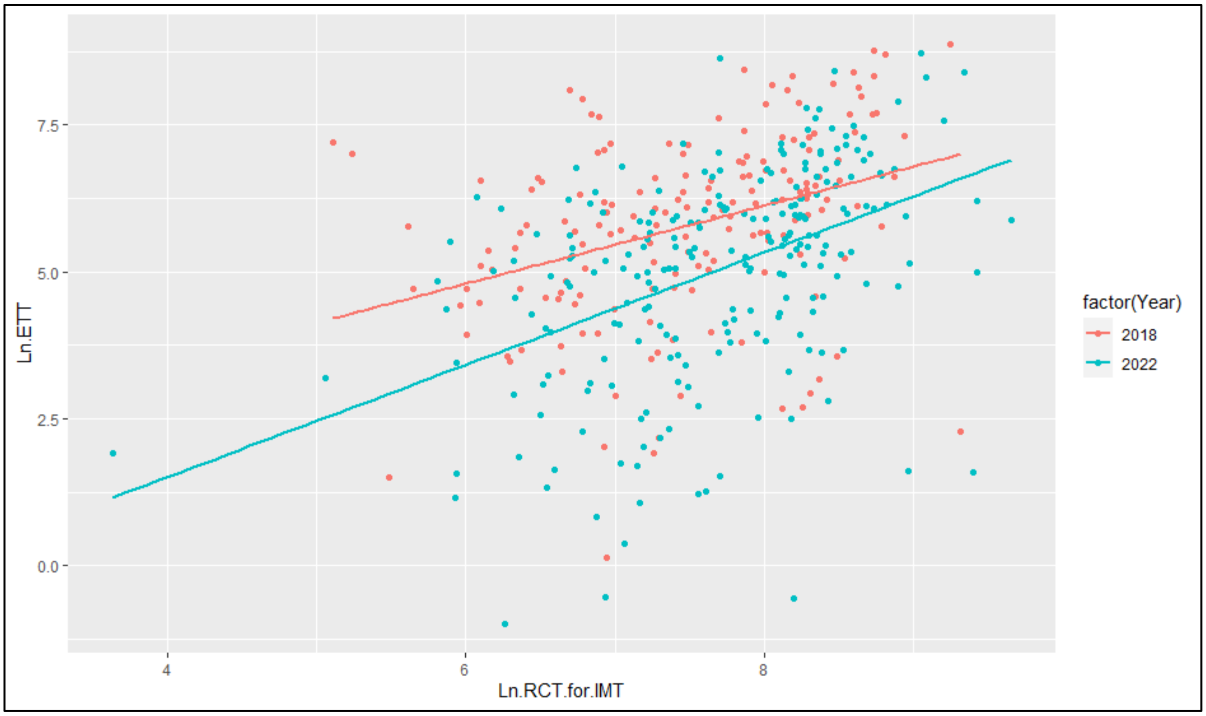

Figure 6-1: Scatterplot of regression model of Ln ETT vs. Ln RCT.

Table 6-6: Median T_7-T_5 Values by Year and Crash Type

Year	Crash Type		
	PDO	PI	FII
2018 [min]	28	24	10
2022 [min]	13	11	7
Percent Difference	-54%	-54%	-30%

The median hours of ETT per number of IMT decreased significantly between 2018 and 2022. As shown in Table 6-7, incidents with one IMT had a median ETT value of 341 hours in 2018 and 165 hours in 2022 for a reduction of about half between 2018 and 2022. With a larger fleet in 2022, more IMTs were able to respond to crashes systemwide, which significantly decreased the median values of user impacts as well as the user impacts per crash which IMTs responded to. The expanded resources of the IMT program in 2022 allow IMTs not to be spread too thin and to maintain a consistent degree of service provided to Utah roadways.

Table 6-7: Median Hours of ETT by Crash Type and Number of IMTs

	Number of IMTs							
	1		2		3		4	
Year	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**	**2018**	**2022**
Median ETT Value [hours]	341	165	387	349	1,211	348	6,355	1,087
Sample Size	100	139	57	72	10	18	3	4
Percent Total for Respective Year	59%	60%	34%	31%	6%	8%	2%	2%

6.3 Limitations and Challenges

One limitation of this study is that the volumes of high-occupancy vehicle (HOV) lanes were not used since these are intended to be a separate facility. TransSuite data still included lane closures for HOV lanes, which were used because the closure of the HOV lane still had a large impact on adjacent lanes of traffic. ETT and EUC are also intended to be conservative estimates that do not include the delay experienced by roadway users outside of the interstates that may have been affected by traffic being diverted. Other costs not included in this study were that of property damage directly due to the crash, injuries, and those due to the effects of emissions released by motor vehicles on human health. Though TransSuite included the lane closures of incidents that occurred on shoulders, these data were not included for analysis, though they still have an indirect effect on traffic.

One potential source of error was the case when TransSuite data occasionally reported T_5 (the time when lanes were cleared) after T_6 (the time which IMTs had left the scene of the crash), thus making RCT greater than ICT, which is invalid. While it is possible that IMTs and UHP teams reported T_6 early, it was also seen that TransSuite operators who were likely busy with other tasks at the same time as watching a given incident on CCTV camera footage may have reported lane closures late in some cases. While most RCT values that were greater than their respective ICT values differed by less than 10 minutes, it was believed that UHP CAD data was more accurate than TransSuite data in these cases.

Another discrepancy in the data collected was that some incidents had loop detectors that did not have data available at the time of the incident for a given subroute. In this case, an adjacent loop detector was used that was not in the subroute due to there not being another alternative, and it was assumed that volumes for an adjacent detector would not differ significantly with those of the subroute itself if a detector had been available. One potential source of error was the effect of diversion and lower volumes that would cause a minor discrepancy. It was also assumed that loop detector data with a percentage observed of 85 percent or higher would be adequate for data collection.

The items during data collection that required engineering judgment to determine and thus introduced a degree of subjectivity were determining the values of T_0 and T_7 of an incident, whether a secondary incident had a significant impact on traffic as well as if it should be discarded, and how much of a given queue was the result of a crash rather than due to randomized congestion. While efforts and coordination were made for researchers to be consistent in how these parameters were determined, there were cases found from data collected in both 2018 and 2022 where T_0 had been determined differently by different researchers. For most incidents, a significant reduction in speed due to an incident occurs within approximately 5 minutes of T_1, therefore T_0 and T_1 are usually close together. In some cases where T_0 did not occur until 10 or 15 minutes after IMTs had arrived on scene and begun to close lanes, T_0 had been marked in some instances as being equal to T_1 and in other instances as the time when the significant decrease in speed occurred a while after T_1.

It was determined that T_0 was most accurately represented as the time when a significant decrease in speed occurred even if it occurred a while after T_1, so incidents were sorted through to correct this issue. While most queues primarily extended upstream of the bottleneck of an incident, some had significant congestion that extended downstream of the incident. Because of the confounding of queues that may occur more often downstream of an incident, it was determined during Phase II that only one subroute downstream of the subroute of the bottleneck should be quantified. This issue was also corrected for incidents that had been analyzed prior to this decision being made when all incidents were examined for these issues. The cost estimates and results provided in this study are meant to provide UDOT with conservative estimates and a better understanding of the relationships between user impacts and incident parameters.

7.0 RECOMMENDATIONS AND IMPLEMENTATION

7.1 Recommendations

One post-2020 change in IMT protocol that was identified was that IMTs stay on site with a crash victim until a tow truck arrives, whereas IMTs previously would respond to other crashes after clearing one. No recommendations are made currently for changes in IMT protocol. It has been well established in the Phase III study as well as the Phase II study that IMTs provide significant benefits to roadway users affected by incidents and that the costs to implement the program expansion were arguably well worth the benefits seen by roadway users early after implementation. Determining the optimal number of IMTs and the areas that IMTs should cover to increase effectiveness of resources would best help UDOT to allocate funds strategically to benefit the greatest number of roadway users for the lowest system-wide cost.

7.2 Implementation

The results of this research will be implemented through the UDOT Traffic Management Division by continuing to evaluate and request funding for additional IMT units as appropriate to benefit the traveling public. The Traffic Operations Group: Incident Management Team program will also collect information on how many total incidents occur on Utah highways and how many of those are responded to by IMTs. This additional data will help with future planning and will guide IMT program administrators in requesting additional funding. Additional data will also be collected on secondary crashes to determine if IMT units are successful in reducing secondary crashes. Future research could be conducted based on the results of this preliminary data collection to determine if there is a reduction in secondary crashes with IMT response. The implementation will also take into consideration the results of ongoing research to identify where future IMT units could be staged to provide the best possible impact to the traveling public. The results of this research provide great value to the citizens of the state of Utah by illustrating the benefits provided by the IMTs on Utah roadways.

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