*Final Evaluation Report*

# I-270 PREDICTIVE LAYERED OPERATIONS INITIATIVES

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# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF ACRONYMS

| ACRONYM | DEFINITION |
|---|---|
| AI | Artificial Intelligence |
| ANSI | American National Standard Institute |
| ATCMTD | Advance Transportation Congestion Management Technologies Deployment |
| ATMS | Advanced Traffic Management System |
| ATTAIN | Advanced Transportation Technology and Innovation |
| CAD | Computer-Aided Dispatch |
| CCTV | Closed-Circuit Television |
| COVID-19 | Corona Virus Disease of 2019 |
| CRA | Crash Risk Areas |
| CSV | Comma-Separated Values |
| DMS | Dynamic Message Signs |
| EMS | Emergency Medical Services |
| ER | Emergency Response |
| FHWA | Federal Highway Administration |
| GPS | Global Positioning System |
| IMRCP | Integrated Modeling for Road Condition Prediction |
| IBM | International Business Machines Corporation |
| ITS | Intelligent Transportation System |
| KMZ | Keyhole Markup Language |
| MoDOT | Missouri Department of Transportation |
| MSHP | Missouri State Highway Patrol |
| NLP | Natural Language Processing |
| PLOI | Predictive Layered Operations Initiatives |
| RWIS | Road Weather Information Systems |
| RWMP | Road Weather Management Program |
| STIP | Statewide Transportation Improvement Program |
| TMC | Transportation Management Center |
| TSMO | Transportation System Management and Operation |

# EXECUTIVE SUMMARY

The I-270 Predictive Layered Operations Initiative (PLOI) represented the effort by the Missouri Department of Transportation leveraging cutting-edge technologies to improve traffic management and enhance roadway safety along the critical I-270 corridor, while aiming to address congestion and mobility challenges. This effort was completed as a part of the I-270 North Design-Build Project, a large roadway reconstruction project that improved roadway safety and connectivity, particularly in areas of socioeconomic disparity in north St. Louis County, MO.

The I-270 North Project, MoDOT's pursuit within the Statewide Transportation Improvement Program, focused on rebuilding a major portion of the interstate. Through collaborative efforts, MoDOT aimed to achieve project goals including enhancing safety, reliability, and community connectivity, while also emphasizing innovation and workforce diversity. This initiative, funded by an Advanced Transportation and Congestion Management Technologies Deployment (ATCMTD) grant, focused on utilizing three main technologies while being supported by an extensive ITS coverage. The first technologies utilized were predictive analytics models that analyzed a variety of data points, including traffic volumes, weather conditions, and special events, to predict potential crash locations and times. The next technology utilized a video analytics system, and the third technology integrated an Integrated Modeling for Road Condition Prediction (IMRCP) tool that aimed to refine weather and traffic forecasts, intending to decrease weather-related crashes.

The project was initiated in April 2019 with a $2M budget secured by mid-2019 through the ATCMTD grant. A MoDOT task force convened in order to solicit and evaluate vendors that could deliver platforms for the three components of the project. MoDOT selected one vendor for Crash Risk Location Prediction and Incident Identification, another for Advanced Video Analytics and third for Integrated Modeling for Road Condition Prediction (IMRCP). These platforms were procured and by early 2022, all technologies were deployed and integrated into the transportation management efforts of the MoDOT St. Louis District. The initiative aimed to provide real-time, data-driven insights for proactive incident management and crash risk reduction.

The implementation of these transformative technologies was guided by five main goals set in the beginning of the project: (1) Improve safety, (2) Improve MoDOT Emergency Response Time, (3) Reduce Congestion / Improve Mobility, (4) Improve Effectiveness of Real-Time Integrated Transportation Information to the Public, and (5) Improve Return on Investment and Realize Cost Savings.

PLOI was a collaborative effort involving a diverse array of stakeholders across multiple stages of the project. This comprehensive stakeholder team, ranging from the MoDOT Leadership team and Project teams to technology vendors, and supported by WSP USA Inc., played a vital role in every phase of the project. Their collaborative efforts spanned from platform deployment and implementation to functionality validation and outcome evaluation, ensuring the project's success through committed resource management and expert oversight.

The deployment of these technologies has demonstrated substantial potential for improvements in crash reduction and emergency response times. For instance, Incident Identification tool had demonstrated to be faster in reducing response times to incidents, on average 10 minutes earlier, by enabling quicker verification of events. Advanced Video Analytics had improved traffic flow monitoring, expanded operators' coverage of cameras and allowed more efficient deployment of resources. IMRCP had capabilities regarding resource management during snow related events, however challenges during implementation and integration of the technology hindered the ability of using all tools available to MoDOT.

The cost-benefit analysis of each technology underscores their value proposition. While initial setup and operational costs are notable, the benefits in terms of lower projected traffic congestion, lower accident rates, and enhanced public safety presented a compelling case for investment. Taking into account the current benefits provided by both incident identification and advanced video analytics, and assuming a cautious approach by estimating Crash Risk Areas' (CRA) crash risk location prediction accuracy at 5%, the overall deployment could potentially achieve a return on investment (ROI) ranging from 6.28X to 7.99X. At the point which Crash Risk Location Prediction accuracy increases to 20%, we would expect a ROI between 7.92X to 16.81X.

Throughout this project, CRA accuracy has continued to improve with a registered accuracy of 10.9% most recently in October 2023. Moreover, these data-driven insights provided by these technologies facilitated more informed decision-making, leading to long-term operational efficiencies and cost savings.

The implementation of these technologies faced various challenges, primarily in the realms of integration and data processing. These constraints were intensified by COVID-19 pandemic, where in-person meetings were not allowed, and training had to be done remotely. This issue directly affected the speed of the integration of technologies along the project. Additionally, limitations on communication between different technological platforms and managing the vast data streams in real time required adaptability. The four-year project proved that clear communication is essential to maintain realistic expectations across all team levels, and prevent misunderstandings about technology capabilities, which significantly impacted the timeline and effectiveness of deploying the technologies. Due to some of these challenges, full use of all technologies was not achieved.

The project recommendations emphasize continuous monitoring, evaluation, and adaptability to ensure effectiveness to meet MoDOT's goals. Key strategies include enhancing law enforcement coordination, engaging MoDOT's entire team, and encouraging stakeholder understanding of the technologies being implemented. The necessity of positive operator feedback, combined with the evaluation of existing and potential data sources, while securing expert support, such as data scientists, are highly recommended. Despite challenges, such as extended implementation delay times due to the pandemic, technologies like Advanced Video Analytics, Crash Risk Area Prediction, and Incident Identification exhibited the ability to enhance transportation management by improving safety, mobility, and traveler information, while IMRCP can improve maintenance decision support when utilized in an area with a significant number of weather events.

Looking forward, the I-270 PLOI proved that these technologies have potential for further advancements. The project's success serves as a blueprint for the expansion of similar technologies across other critical transportation regions. Ongoing development and refinement of predictive models are expected to enhance accuracy and efficiency, offering even greater benefits in terms of safety and mobility. Additionally, the integration of emerging technologies, such as autonomous vehicle communication and smart infrastructure, presents to intensify opportunities to further transformation in roadway operations and safety.

In summary, the I-270 Predictive Layered Operations Initiative serves as evidence of the transformative impact that advanced technologies can have on roadway management. By tackling existing challenges and applying insights gained from the project, it stands as a remarkable achievement.

# 1 INTRODUCTION

The Missouri Department of Transportation (MoDOT) is dedicated to improving safety and reliability on state roadways and in work zones in the State of Missouri. Improving safety and reliability means continuously looking to improve and utilize innovation and changing technology, which relies upon funding and leadership. Missouri had not experienced an increase in gasoline and fuel adjustments for 25 years until October 2021, when a Senate bill came into effect (Modot.org, 2021). To help bridge the gap in funding adjustments, MoDOT applied for the Advance Transportation Congestion Management Technologies Deployment (ATCMTD) under the Fixing America's Surface Transportation (FAST) Act, which helped MoDOT look for ways to supplement their operational capabilities using technologies identified in the I-270 Predictive Layered Operations Initiatives (PLOI). Essentially, PLOI utilized cutting edge technology to improve safety and reliability, while maximizing mobility for vehicles and all modes of transportation. This ATCMTD grant included a suite of three advanced technology applications: Crash Risk Location Prediction & Incident Identification, Advanced Video Analytics, and Integrated Modeling for Road Condition Prediction (IMRCP); all three of these use Transportation System Management and Operation (TSMO) platforms. If these pilots work as theorized, exciting benefits of safety and potential congestion mitigation could revolutionize how to implement smart work zones and enhance all Missouri roadways.

This evaluation report serves as a final report, and contains an overview of PLOI, the overall goals for each of the three applications, project timeline, verification process and analysis, data management and collection procedures, evaluation methodology, evaluation of the technologies, and cost benefit analysis. Submission of the evaluation report satisfies the deliverable requirement for the project evaluation plan described in the cooperative agreement.

# 2 OVERVIEW AND BACKGROUND

MoDOT's St. Louis District has a long-standing commitment to TSMO and Intelligent Transportation System (ITS) regional connectivity. The St. Louis District led efforts to create a Transportation Management Center (TMC) in 1999. Customer service has also been a primary focus of MoDOT and the St. Louis TMC; since opening the TMC, MoDOT has implemented a year-round, 24/7 operation. Anyone from the public can contact the TMC and speak with a customer service representative. In addition to the excellent tools within the TMC, MoDOT has installed several TSMO and ITS features throughout its interstate and arterial system, including cameras, dynamic message signs (DMS), traffic detectors, and signals that all are connected and operated through centralized software.

I-270 is the most heavily traveled road of the northern area of St. Louis County, connecting individuals in low-income communities with economic opportunities throughout the region. Although St. Louis County is considered affluent overall, stark disparities exist within the county. North County has poverty rates more than twice as high as the other regions in the county, and much of the area has been designated by the U.S. Department of Housing and Urban Development as a Promise Zone, which are high poverty communities where the federal government partners with local leaders to increase economic activity, improve educational opportunities, leverage private investment, reduce violent crime, enhance public health and address other priorities identified by the community (Hudexchange.info, 2024).

I-270 North Design-Build Project was the single largest project ($278 M) within Missouri's 2019–2023 Statewide Transportation Improvement Program (STIP); MoDOT procured the project using Design-Build project delivery methods in 2019 and was finished in the end of 2023. **Figure 1** outlines the project area, where MoDOT rebuilt 8.6 miles of interstate and interchanges of I-270 through northern St. Louis County.


**Figure 1: I-270 Design-Build Location**

Even with the TSMO and ITS improvements MoDOT has made since 1999, the I-270 North Project was identified to have widespread mobility limitations during construction. The I-270 corridor has a higher crash rate compared to the average of Missouri roadways with identical classifications. Many safety challenges exist within the corridor. Between 2013 and 2018 there were a total of 23 fatal crashes, 97 serious injury crashes, 1,058 minor injury crashes, and nearly 3,015 property damage only crashes. Crashes occurred for a variety of reasons depending on time of day, driver behaviors involved, and crash location. It currently takes an average of 48 minutes to clear a minor crash along the corridor from first notification until all queues are clear. Multi-vehicle crashes take an average of 64 minutes to clear. With over 135,000 vehicles per day, the travel reliability on the corridor was limited and travelers did not have enough information if or when they would meet congestion due to increased demand. Furthermore, the limited alternate routes, including Dunn Road, were inadequate. The six-month closure of the westbound lane of Pershall Road, which functioned as an alternate outer road, exacerbated the traffic difficulties experienced by drivers. MoDOT leadership quickly realized that utilizing advanced TSMO and other innovative solutions during construction could be a huge difference maker to improve safety and reliability in the work zone. For the I-270 North Project, the following project goals were established:

1. Deliver the Project by December 31, 2023, within the program budget of $252 million.
2. Maximize reliability and safety while linking communities for all users.
3. Provide a durable and maintainable transportation network making I-270 a conduit for a prosperous region.
4. Grow and utilize a diverse workforce.
5. Minimize and mitigate impacts to customers through innovation.

MoDOT leveraged the ATCMTD funds to ensure that project goals were met, such as maximizing safety and reliability, especially in the work zones, by having a wide coverage of the interstate system (meeting goal two and goal 5 from the project). MoDOT utilized emerging technology through this pilot project by identifying the following three applications to layer together:

1. Crash Risk Location Prediction & Incident Identification
2. Advanced Video Analytics
3. Integrated Modeling for Road Condition Prediction (IMRCP)

Combining these three technologies created PLOI.

# 3 PROJECT DESCRIPTION

Through the I-270 PLOI, MoDOT staff had better tools available to share informed and even predictive information and to provide quicker updates to the traveling public. MoDOT's existing extensive ITS coverage along the project corridor should greatly reduce the cost of operations by implementing the I-270 PLOI.

## 3.1 Crash Risk Location Prediction and Incident Identification

The implementation of predictive analytics, more aptly referred to as crash risk location prediction throughout the project, leverages advanced machine learning capabilities. This is achieved through the utilization of models that incorporate multiple complex and dynamic algorithms. This machine learning model took in many data points and used the data points to consider many "if-then" statements, which are conditional statements translated into code language that tells the program what to do with certain pieces of information. Drivers and infrastructure operators must consider and respond to several daily factors and environmental conditions before selecting and implementing appropriate strategies for action. MoDOT deployed a machine learning model that uses many algorithms to arrive simultaneously at multiple answers to very specific questions, and to find overarching trends and conclusions within the answers.

MoDOT procured a machine learning model designed to consider real-time data and historical data when predicting future crashes including traffic volumes, weather forecasts, and special events. This predictive analytics platform included these factors into the model, producing a dynamic map that depicts the increased likelihood of crashes in specific areas at certain times of day and days of the week (**Figure 2**). This could potentially allow law enforcement agencies to identify ranges of time in which the likelihood of a crash is the greatest in a specific area and to increase patrol of that area to prevent and mitigate crashes. This platform also allowed for identifying incidents earlier, improving the speed of incident response. Better incident response leads to a potential of enhanced congestion mitigation and a projected prevention of secondary incidents. This is achieved through lowered speeds and improved driver awareness. In addition to honing enforcement and patrol strategies, MoDOT's traffic crash predictions were attempting to assist other efforts to reduce crashes.

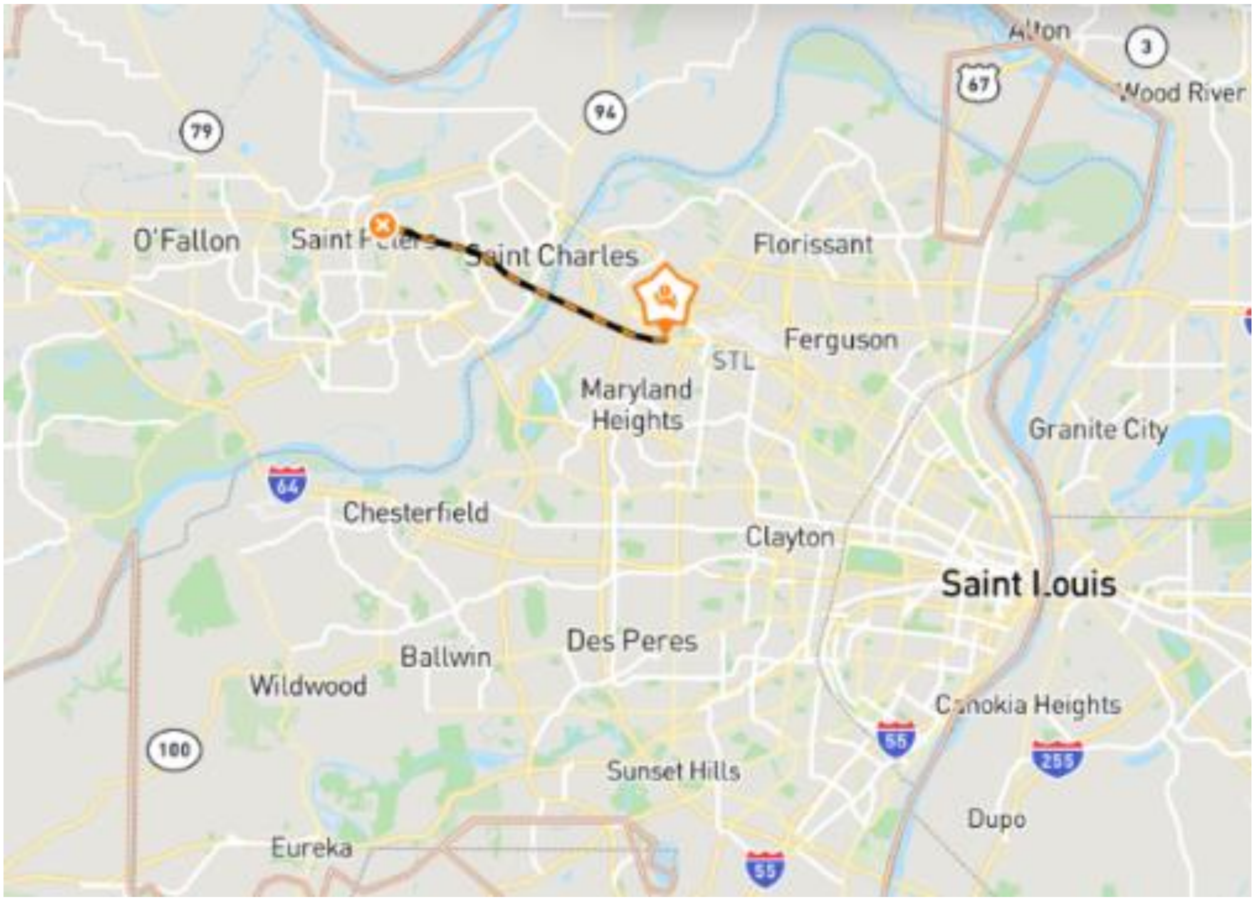


**Figure 2: Sample Crash Risk Area (CRA) Map from Crash Risk Location Prediction Portal**

The model's data collection and predictions helped and will continue to help providing data for public safety campaigns and assist engineers in identifying areas where a roadway redesign may reduce crashes. Through the implementation of an integrated platform, with the primary technology being Crash Risk Location Prediction & Incident Identification, complemented by the addition of Advanced Video Analytics and IMRCP within the I-270 PLOI, MoDOT had the goal of delivering real-time information to the public; however, integration issues between the different technologies prevented this goal from being achieved.

As MoDOT's model continues to collect crash data, its efficiency will potentially increase as crash trends may become more observable over time with a growing body of information. Combining several large series of data is crucial for a machine learning model to draw conclusions that are complex enough to aid in successful practical applications. For example, crashes may significantly increase each Friday night in certain areas directly following a major sporting event that occurs nearby to those areas. The I-270 PLOI predictive model considered several factors before it predicted an increase in crashes in areas nearby, such as a sporting event. The machine learning model may consider the area's proximity to the sporting event, the time of year and day of the week it is considering, the time of day, whether a sporting event is completed, the weather, the visibility, the complexity of the roadway it is considering, current and projected traffic volumes, the history of crashes in the specific area, and other relevant factors.

MoDOT deployed a predictive analytics platform capable of using complex algorithms to draw nuanced conclusions from traffic, weather, and incident data to better inform Missouri's deployment of state enforcement, winter maintenance, and incident response resources. Where other machine learning systems have been deployed for highway crash and incident analytics purposes, other states' Department of Transportation (DOT) program managers have noted beneficial effects, such as successfully predicting crashes and equipping patrol officers to forestall crashes. The State of Tennessee, for instance, recorded a decrease in traffic crashes 20% below the average (National Institute of Justice, 2024). Based on these results and factoring in the presence of active work zones, MoDOT predicts the number of incidents along I-270 North will decrease by similar percentages. **Figure 3** represents the Federal Highway (FHWA) Timeline of Traffic Incident Management, which is a visual representation of the entire process of traffic incident management procedures from when the incident occurs until normal traffic conditions return. The timeframe from when an incident occurs (T0) to when the incident is reported (T1), is considered the time of crash detection. The I-270 PLOI allowed quicker detection identification, which enabled a faster response and clearance of an incident by shortening the time between the incidence occurrence (T0) and verification of the incident (T2). Based on the results from the Nevada DOT predictive analytics pilot project, it is predicted the detection time will be improved anywhere between zero to ten minutes. The I-270 PLOI would enable better positioning of emergency response vehicles, resulting in a reduction in response time (T2 to T3).

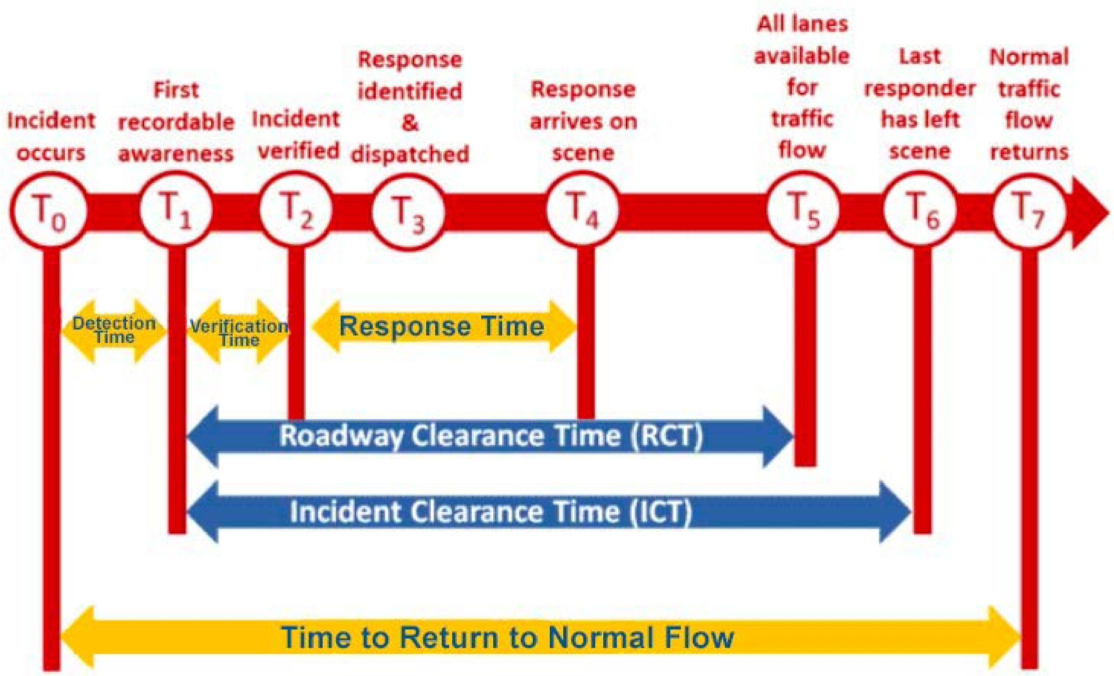


**Figure 3: FHWA Timeline of Traffic Incident Management**

## 3.2 Advanced Video Analytics

Video analytics systems can analyze live Closed-Circuit Television (CCTV) camera feeds to identify events and conditions in real-time. Video analytics applied to roadway systems can be used to collect traffic data such as volume, speed, and vehicle classification, or to detect incidents and unusual conditions to create and send alerts.

The I-270 North corridor has had about 3,500 crashes within the 15-mile segment in the last five years beginning from 2018. It currently takes an average of 48 minutes to clear a minor crash along the corridor from first notification until all queues are cleared. Multi-vehicle crashes take an average of 64 minutes to clear. Incidents are typically discovered by human monitoring of CCTV camera streams or by reports from the public, law enforcement, or emergency responders. The St. Louis TMC typically has about five TMC staff members to monitor approximately 650 cameras in the region while concurrently working on tasks. Because of this, there can be a significant delay between when a crash or other incident occurs and when it is discovered by the TMC. This increases the time to respond to and clear incidents which leads to an increase in congestion and queue lengths. The longer non-recurring congestion is present on the roadway, the more likely it is that a secondary crash could occur. According to MoDOT crash data, approximately 4.2% of all crashes throughout the interstate corridors in the Saint Louis District were observed to be secondary crashes (2018-2023). A study made in Virginia identified that the likelihood of a secondary crash increases by 2.8% for each minute the primary incident continues to be a hazard (Khattak et al., 2012).

The I-270 North corridor has 23 CCTV cameras available for live viewing of video streams. As a result of this ATCMTD grant, MoDOT procured a video analytics system which can utilize existing camera infrastructure, minimizing hardware costs. The video analytics system is set up to allow TMC staff, as well as internal and external project staff, to receive notifications of potential issues. The video analytics system was used to identify incidents and dangerous conditions more quickly than is currently possible due to staffing and technological limitations. Shorter times between an incident’s occurrence and the responders’ dispatch time can reduce the impact of the incident on congestion and queue lengths; this should lead to a potential reduction in secondary incidents and improve system travel reliability.

## 3.3 Integrated Modeling for Road Conditions Prediction

Missouri's roadways are subject to a range of threats to the continuity of safe and efficient operations. Work zones can further increase roadway vulnerability to changing conditions. The Midwest's variable and frequently severe weather creates challenges in all four seasons. Heavy and persistent rainfall causes flooding risks along both the state's major rivers and small streams. Winter snow-and-ice storms can occur between October and May. These kinds of events, combined with congestion and work zones in the major urban areas, can create compounded operational risks. Slight variations in conditions can have major impacts when rain is falling near freezing temperatures. The complexity of these challenges led the FHWA's Office of Operations Road Weather Management division to design and develop a predictive analytics tool known as the Integrated Modeling for Road Condition Prediction (IMRCP) to inform operational decision making relative to changing traffic and road conditions. The Kansas City urban area was selected by FHWA as a test site for IMRCP, due in part to its central midwestern location with year-round complex weather patterns.

With the ATCMTD initiative, MoDOT proposed to expand the operational reach of its IMRCP capabilities to the I-270 North corridor. The high-quality road-weather information provided by the IMRCP is capable of being exported to external systems through an automated process; this data could greatly improve the accuracy of crash predictions provided by the I-270 PLOI.

MoDOT proposed to use ATCMTD and state matching funds to incorporate IMRCP into predictive analytics to provide more accurate and complete coverage of road and traffic conditions for all seasons on the I-270 North corridor. Including the IMRCP with the main Predictive Analytics model will enable operators to prepare for severe weather events with more advance warning, thus providing travelers with more information and routing options. In addition, MoDOT can better plan for the effective treatment of roadways, both prior to storms and as weather conditions are predicted to change. Improved winter operations efforts can help reduce weather-related crashes. **Table 1** describes the technology deployed for each of the PLOI applications.

**Table 1: Technology Deployed**

| No. | Technologies Deployed for PLOI Application |
|---|---|
| 1 | Predictive Analytics for Crash Risk Location Prediction & Incident Identification |
| 2 | Advanced Video Analytics |
| 3 | Predictive Analytics for Weather Conditions (IMRCP) |

## 3.4 Goals and Objectives

The goals and objectives of PLOI reflect the overarching program purpose of the ATCMTD grant: to improve safety, efficiency, system performance, and infrastructure return on investment. The following sections outline the goals and objectives associated with each tool and methodology.

### *3.4.1 Predictive Analytics and Incident Identification*

MoDOT intended to use this service to predict the location and timing of future highway incidents in relationship to the confluence of factors related to infrastructure condition, direction of travel, weather and precipitation, direction of sunlight, driver behavior, volume, and the occurrence of special events. In addition, it also provided a tool that uses multiple sources to identify crashes and incidents throughout the study area.

### *3.4.2 Advanced Video Analytics*

MoDOT intended to use the incident detection and notification capabilities of video analytics throughout St. Louis region, including St. Louis City, St. Louis County, and St. Charles County to identify and thus respond to incidents and crashes more quickly. Video analytics was used to identify dangerous conditions such as stopped vehicles, slowed traffic, debris in roadway, wrong-way vehicles, and pedestrians on the interstate.

### *3.4.3 Integrated Modeling for Road Conditions Prediction*

MoDOT intended to use this platform to integrate historical traffic and road-weather event data with real- time data to enable operational event forecasting that predicts changing traffic and road conditions up to eight hours in the future. This ability to “time travel” also enabled looking back in time for performance measurement and after-action reviews. Elements of the forecast included atmospheric and road weather conditions, hydrology, traffic demand and management strategies, work zones, winter maintenance operations, incidents, and special events. **Table 2** summarizes the overarching PLOI’s goals, objectives by platform, and associated anticipated outcomes.

**Table 2: Summary of I-270 PLOI Goals, Objectives by Application, and Anticipated Outcomes**

(blue-IMRCP; yellow-Crash Risk Location Prediction & Incident Identification; orange-Advanced Video Analytics)

| Goals | Technology | Objectives | Anticipated Outcomes |
|---|---|---|---|
| **Improve Safety** | IMRCP | Develop an operations and maintenance plan to prepare for weather issues identified in the IMRCP | Reduce serious injury and fatal crashes related to weather conditions. |
| | | | Reduce total crashes related to weather conditions. |
| | Crash Risk Location Prediction & Incident Identification | Send emergency responders to predicted safety concern areas | Reduce total projected crashes (including secondary crashes) by getting responders to a safety concern area prior to crashes occurring |
| | | Send emergency responders to identified traffic incidents | |
| | | Utilize other ITS devices (DMS) to share information of potential safety hazards on roadways | Share prediction of safety concerns to traveling public to reduce crashes |
| | Advanced Video Analytics | Detect Congestion | Reduce potential crashes caused by congestion |
| | | Detect stopped vehicles/objects on roadway | Reduce time to remove debris in roadway |
| | | Detect pedestrians on interstate and Detect Low Visibility | Reduce crashes from pedestrian activity in roadways |
| | | Detect stopped vehicles/objects on roadway | Reduce crashes from stalled vehicles in travel lanes |
| | | Detect wrong way drivers on roadway | Reduce crashes related to wrong way drivers |
| **Improve MoDOT Emergency Response (ER) response time** | Crash Risk Location Prediction & Incident Identification | Detect unusual congestion on roadway to send responders | Send emergency responders to location before congestion |
| | | Reduce response time based on identified incidents | Send emergency responders to location before crashes |

**Table 2: Summary of I-270 PLOI Goals, Objectives by Application, and Anticipated Outcomes (Contd.)**

| Goals | Technology | Objectives | Anticipated Outcomes |
|---|---|---|---|
| **Improve MoDOT Emergency Response (ER) response time** | Crash Risk Location Prediction & Incident Identification | Predict crashes in roadway to send responders | Send emergency responders to location before crashes |
| | Advanced Video Analytics | Detect stopped vehicles/objects on roadway | Improve incident response time for all incidents |
| | | Detect pedestrians on interstate and Detect Low Visibility | Improve response time when pedestrians on the interstate |
| | | Detect Congestion | Improve incident response time for only stalled and abandoned vehicles incidents |
| | | Detect wrong way drivers on roadway | Reduce response time to wrong-way drivers |
| **Reduce Congestion/ Improve Mobility** | IMRCP | Develop operations and maintenance plan to prepare for weather issues identified in the IMRCP | Improve mobility during weather events |
| | Crash Risk Location Prediction & Incident Identification | Detect unusual congestion on roadway | Improve mobility by detecting unusual detection early and responding according |
| | Advanced Video Analytics | Detect congestion on roadway | Improve average travel times |
| | | Detect stopped vehicles on roadway | |
| **Improve Effectiveness of Real-Time Integrated Transportation Information** | IMRCP | Implement mobile RWIS (road weather information system) on maintenance vehicles (IMRCP) | Provide accurate data to MoDOT operators that can be acted on |
| | Crash Risk Location Prediction & Incident Identification | Predict crashes on roadway | Share prediction of safety concerns to traveling public to reduce crashes |
| | Advanced Video Analytics | Give Operators automated information from video analytics | Improve incident response time based on more and better data |

**Table 2: Summary of I-270 PLOI Goals, Objectives by Application, and Anticipated Outcomes (Contd.)**

<table>
<tr><th>Goals</th><th>Technology</th><th>Objectives</th><th>Anticipated Outcomes</th></tr>
<tr><td rowspan="6">Improve Return on Investment and Realize Cost Savings</td><td rowspan="2">IMRCP</td><td rowspan="2">Compare winter weather operational scenarios in the IMRCP platform</td><td>Maximize material and labor</td></tr>
<tr><td>Improve efficiency of time and materials</td></tr>
<tr><td rowspan="2">Crash Risk Location Prediction & Incident Identification</td><td>Identify Return on Investment (ROI) due to crash prediction with varied levels of accuracy</td><td rowspan="2">Decreased costs related to serious and fatal crashes due to increased awareness of crash potential and faster responding from emergency providers</td></tr>
<tr><td>Identify ROI due to faster incident response</td></tr>
<tr><td>Advanced Video Analytics</td><td>Identify ROI from quicker incident identification and/or other traffic related anomaly detection</td><td>Improve efficiency of time and materials</td></tr>
</table>

### *3.4.4 Stakeholder*

The PLOI initiative included several different stakeholders to achieve the goals of the grant. A team of stakeholders was needed due to the technical complexity of each of the PLOI Application platforms, its requisite collaboration, the understanding of each project, and the needed validation documentation to perform the final evaluation.

The project involved multiple stakeholder teams for each stage of the project with the level of individual stakeholder involvement varying throughout the different stages of the project. These teams provided the necessary resources for the project to succeed from platform deployment, implementation, and management to platform functionality, validation, and outcome evaluation. The stakeholders' team included the MoDOT Leadership team, MoDOT Project team, as well as Crash Risk Location Prediction & incident identification, advanced video analytics, and IMRCP vendors. In addition, the MoDOT project team was supported by WSP USA Inc. WSP has been serving as the owner's representative on the I-270 North Project and supported this initiative through each project phase. Below are the brief descriptions of all stakeholders involved.

1. **The MoDOT Project team** involved MoDOT's Grant and Procurement Team, Implementation and Validation Team, and Project Evaluation Team.
2. **The Grant and Procurement Team** consisted of the following MoDOT Staff: I-270 North Project Director, I-270 North Project Engineer, Transportation Project Manager, District Traffic Engineer, and the Traffic Management and Operation Engineer. The primary

responsibility of the team was to help facilitate the procurement of each platform, as well as to identify funding to help with the procurement.

3. **The Implementation and Validation Team** involved MoDOT Transportation Project Manager, MoDOT Incident Management Coordinator, MoDOT operations and maintenance crews, MoDOT TMC and Emergency Response (ER) staff operators, District Maintenance Superintendents, District TMC Operations Manager, and District Incident Management Coordinator. The primary responsibilities of the team were ensuring and supervising the new platforms for PLOI Applications that were being integrated into the existing standard operation processes and maintenance decisions smoothly. With their help, the application was utilized and well-maintained to its fullest potential during the various stages of the project.
4. **The Project Evaluation Team** consisted of I-270 North Project Engineer, I-270 North Project Director, Transportation Project Manager, Incident Management Coordinator, and FHWA Transportation Specialist. This branch of the MoDOT Project team reported to the MoDOT Leadership about the project's validation and evaluation information every quarter. The team analyzed the efficiency of the platform, as well as tracking the material and labor changes over time to ensure that the progress report reflected the correct information of each platform and was being delivered to the MoDOT Leadership team on time as the project progressed.
5. **The MoDOT Leadership Team** consisted of the Deputy Director/Chief Engineer, St. Louis District Engineer, Chief Safety & Operations Officer, State Highway Traffic & Safety Engineer, Information Systems Director, Traffic Liaison Engineer, Assistant District Engineers, and other department leaders. The MoDOT Leadership provided a tremendous amount of support to the project and ensured the MoDOT Project team had enough resources and support at every crucial stage of the project from deployment, through implementation, and to final evaluation. At the end of the project, the Leadership team was responsible for evaluating specific elements of the project to determine future use of project technologies.

Table **3** outlines the primary stakeholders as currently known and describes their responsibilities for each PLOI application.

**Table 3: Stakeholder Responsibilities**

| PLOI Application | Stakeholder + Responsibilities |
|---|---|
| **Predictive Analytics** | ▪ MoDOT TMC and ER staff operators – Platform integration into standard processes<br>▪ Vendor – Platform deployment<br>▪ MoDOT Project team – Project management, Platform implementation & validation, Platform evaluation<br>▪ MoDOT leadership – analyze project outcomes reported by Project Evaluation Team. |

**Table 3: Stakeholder Responsibilities (Contd.)**

| PLOI Application | Stakeholder + Responsibilities |
|---|---|
| **Advanced Video Analytics** | ▪ TMC staff operators – Platform integration into standard processes<br>▪ Vendor– Platform deployment<br>▪ MoDOT Project team – Project management, Platform implementation & validation, Platform evaluation<br>▪ MoDOT leadership – analyze project outcomes reported by Project Evaluation Team. |
| **IMRCP** | ▪ MoDOT operations and maintenance crews – Platform integration into maintenance decisions<br>▪ Vendor – Platform Deployment<br>▪ MoDOT Project team – Project management, Platform implementation & validation, Platform evaluation<br>▪ MoDOT leadership – analyze efficiency & material, labor changes over time, and project outcomes reported by Project Evaluation Team. |

### *3.4.5 Purpose of Report*

This final report is intended to inform agencies and the public on how the grant was spent and clarify challenges and results of the use of technologies that can serve as an important enhancement to Missouri's transportation system. A preliminary report was created before the grant was spent, and this final report aims to identify which technologies were best suited for MoDOT's unique circumstances. The report outlines two methods for evaluating the performance of the chosen technologies: verification and evaluation. The verification process was intended to analyze the performance of the technology tools, specifically to determine whether they would provide high-quality data information for the operators. The evaluation process, on the other hand, focused on how the technology can be detrimental to immediate use and how well it can connect to other tools and the existing platform.

# 4 PROJECT TIMELINE

The project commenced with a kick-off meeting in April 2019, aiming to leverage Predictive Analytics for enhancing transportation safety in Missouri. After securing funding in June 2019, collaborations with vendors began to materialize. By December 2019, a vendor for incident identification technology was selected, marking the start of data gathering and project initiation. The scope was refined by March 2020, focusing on incident detection, congestion, crash prediction, and work zone management on I-270.

As the project advanced into 2020, the onset of COVID-19 introduced challenges, including disruptions to planned training sessions and coordination efforts. Despite these obstacles, discussions persisted on integrating the Incident Identification technology into the main ATMS platform and adapting to evolving needs and circumstances. By mid-2020, a test phase was initiated, with feedback highlighting the importance of reporting capabilities and the urgency to implement congestion and crash prediction algorithms.

Throughout 2021 and 2022, technology integration continued, with Incident Identification fully integrated by the end of 2021, followed by Crash Risk Predictions in early 2022. However, delays were encountered with the IMRCP tool integration, affecting operational functionality until the conclusion of the 2021-2022 winter season. Verification of technologies commenced in 2022, yet IMRCP's verification relied on snow conditions, resulting in insufficient data for validation. Overall, the project timeline was marked by continuous development, collaboration with vendors, and adaptation to challenges such as COVID-19 disruptions and integration delays.

**Table 4** highlights the procurement, development, deployment, testing, and evaluation periods for the PLOI initiative. A summary of the meeting notes is available in **Appendix A: Meeting Notes** and a detailed Project Timeline is available in **Appendix H: Project Timeline**

**Table 4: Summary Project Timeline**

| | 2019 (Q) | | | | 2020 (Q) | | | | 2021 (Q) | | | | 2022 (Q) | | | | 2023 (Q) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| **Crash Risk Location Prediction & Incident Identification** | | | | | | | | | | | | | | | | | | | | |
| Project Initiation | X | X | | | | | | | | | | | | | | | | | | |
| Technology/ Vendor Selection | | X | X | | | | | | | | | | | | | | | | | |
| Technology Integration | | | | | | | X | X | X | X | X | X | | | | | | | | |
| Deploy Platform | | | | | | | | | | X | X | | | | | | | | | |
| Test/Validate | | | | | | | | | | | X | X | X | X | X | X | X | X | | |
| Evaluation | | | | | | | | | | | | | | | X | X | X | X | X | X |
| **Advanced Video Analytics** | | | | | | | | | | | | | | | | | | | | |
| Project Initiation | X | X | | | | | | | | | | | | | | | | | | |
| Technology/ Vendor Selection | | | | X | X | X | X | X | X | X | | | | | | | | | | |
| Technology Integration | | | | | | | X | X | X | X | X | X | | | | | | | | |
| Deploy Platform | | | | | | | | | X | X | X | | | | | | | | | |
| Test/Validate | | | | | | | | | | | | X | X | X | X | X | X | X | | |
| Evaluation | | | | | | | | | | | | | | | | X | X | X | X | X |
| **Integrated Modeling for Road Condition Prediction (IMRCP)** | | | | | | | | | | | | | | | | | | | | |
| Project Initiation | X | X | X | | | | | | | | | | | | | | | | | |
| Technology/ Vendor Selection | | | X | X | | | | | | | | | | | | | | | | |
| Technology Integration | | | | | | | | X | X | X | X | X | | | | | | | | |
| Deploy Platform | | | | | | | | | | | X | X | | | | | | | | |
| Test/Validate | | | | | | | | | | | | | X | X | X | X | X | | | |
| Evaluation | | | | | | | | | | | | | | | | X | X | | | |

# 5 DESCRIPTION OF TECHNOLOGIES

## 5.1 Crash Risk Location Prediction & Incident Identification

The vendor offered a range of different technologies, but MoDOT specifically requested their predictive analytics tools combined with crash incident detection features. Both technologies underwent monthly verifications throughout the entire process.

The predictive analytics tool worked by taking a large amount of data, such as historical and current data for the selected region, to create Crash Risk Areas (CRA) in multiple locations. Each crash risk area had its own direction, start point, end point, and was usually made by a 3-hour range zone, except between September 2023 to December 2023 when the range was defined with a 1-hour window. The incident detection tool worked by combining multiple connected vehicle sources of input, such as Wejo, Waze, Video Cameras, CAD, HAAS Alert, iCone, and Otonomo applications with the validation of TMC Operators, to create and confirm the incident alert. With the use of Deep Learning, Machine Learning (ML), and Natural Language Processing—aka Artificial Intelligence (AI)—the company was able to develop a predictive analytics engine that can process and react to new data to quickly spot trends, allowing it to identify the circumstances that can lead to crashes before they occur. In addition, the vendor installed numerous cameras along I-270, enabling them to compare data from both the connected vehicle systems and the installed cameras, also referred to as Edge AI in **Section 7.1.3.** The algorithm utilized historical and projected data to predict CRAs 24 hours in advance for the majority of the project. However, from September 2023 to December 2023, it incorporated both historical and current data to enhance its predictions of CRAs.

## 5.2 Advanced Video Analytics

Advanced video analytics is a system capable of analyzing live CCTV camera feeds to identify events and conditions in real-time. On this project, Advanced Video Analytics was selected to help in providing safety by transforming MoDOT live cameras into advanced sensors. This technology provided incident alerts involving slow speeds, congestion, pedestrians, and stopped vehicles/objects on roadways, offering a solution to enhance overall traffic management and safety. Advanced Video Analytics also offered the “wrong way” incident alert classification; however, this was not achievable as MoDOT has no cameras that meet the position and angle required by the technology. In addition, Advanced Video Analytics platform offers further information such as volume and speed of the vehicles on each camera, allowing this information to be exported in a comma-separated values (.csv) file that specifies the different volumes and speeds throughout the day for every 15-minute count.

## 5.3 IMRCP

IMRCP is a research initiative by FHWA Road Weather Management Program (RWMP) to investigate and capture the potential of new approaches in road weather management. IMRCP has been chosen to deliver a system designed to enhance operational decision-making regarding dynamic traffic and road conditions. The primary focus was to provide timely insights to MoDOT, with a particular emphasis on the I-270 PLOI, regarding the impact of snow conditions on roads across the St. Louis region. This system aims to facilitate better resource management to effectively prepare for such weather events. The purpose of the IMRCP was to integrate historical traffic and road-weather event data with real-time data, to enable operational event forecasting that predicts changing traffic and road conditions. A potential application of the IMRCP is optimizing the use of salt and de-icing materials in cold weather conditions. The integrated model can suggest the right amount and timing for applying these materials to minimize environmental impact while maintaining road safety.

# 6 EVALUATION METHODOLOGY AND DATA MANAGEMENT

## 6.1 Evaluation Methodology

Evaluations are conducted to determine the extent to which the goals and objectives have been achieved. This section outlines the evaluation questions used for each application within PLOI, as detailed in the evaluation section at the end of the grant. **Table 5** illustrates how these evaluation questions are directly linked to the anticipated outcomes and performance metrics of each technology, as they relate to the project goals. It is important to note that for some measures, the evaluation relies on estimating potential impacts, such as the projected reduction in secondary crashes, rather than measuring realized impacts.

The 'Performance Metrics' column in **Table 5** corresponds to the original goals and performance metrics established at the beginning of the project before limitations and constraints were known. Performance metrics marked with an asterisk were not measured.

**Table 5: Evaluation Questions, Anticipated Outcomes, and Performance Metrics**

(blue-IMRCP; yellow-Crash Risk Location Prediction & Incident Identification; orange-Advanced Video Analytics)

| Goals | Technology | Evaluation Questions | Anticipated Outcomes | Performance Metrics |
|---|---|---|---|---|
| **Improve Safety** | IMRCP | Can this plan better prepare the responders for winter weather conditions? | Reduce serious injury and fatal crashes related to weather conditions | Crashes during weather events |
| | | | Reduce total crashes related to weather conditions | |
| | Crash Risk Location Prediction & Incident Identification | How can this platform prevent/reduce crashes? | Reduce total projected crashes (including secondary crashes) by getting responders to a safety concern area prior to crashes occurring | Number of alerts and actions |
| | | | Share prediction of safety concerns to traveling public to reduce crashes | Delta between previous ITS usage and moving forward* |
| | Advanced Video Analytics | How many and what type of incidents are detected from the video analytics? | Reduce potential crashes caused by congestion | Average Speed* |
| | | | Reduce time to remove debris in roadway | Number of debris logs* |
| | | | Reduce crashes from pedestrian activity in roadways | Number of pedestrian incidents on interstate |

**Table 5: Evaluation Questions, Anticipated Outcomes, and Performance Metrics (Contd.)**

| Goals | Technology | Evaluation Questions | Anticipated Outcomes | Performance Metrics |
|---|---|---|---|---|
| **Improve Safety** | Advanced Video Analytics | How many and what type of incidents are detected from the video analytics? | Reduce crashes from stalled vehicles in travel lanes | Number of stopped vehicles on roadway |
| | | | Reduce crashes related to wrong way drivers | Number of wrong way driving occurrences* |
| **Improve MoDOT Emergency Response (ER) response time** | Crash Risk Location Prediction & Incident Identification | How effective is the technology at predicting potential crashes for the MoDOT team to respond to? | Send emergency responders to location before congestion | Average speed + Travel Time* |
| | | | Send emergency responders to location before crashes | Delta between predicted crashes and recorded crashes |
| | Advanced Video Analytics | Do the TMC and ER operators get faster and more accurate information to keep the roads clear? | Improve incident response time for all incidents | Number of debris logs* |
| | | | Improve response time when pedestrians on the interstate | Time log of alert of pedestrian on interstate |
| | | | Improve incident response time for only stalled and abandoned vehicles incidents | Number of stopped vehicles on roadway |
| | | | Reduce response time to wrong-way drivers | Number of wrong way driving occurrences* |
| **Reduce Congestion/ Improve Mobility** | IMRCP | Did the plan help organize staff and materials? | Improve mobility during weather events | Operations and Maintenance supervisor interviews on decision making during weather events |
| | Crash Risk Location Prediction & Incident Identification | Does delay and congestion in the study area decrease? | Improve mobility by detecting unusual detection early and responding according | Number of crashes identified in platform |
| | Advanced Video Analytics | | Improve average travel times | Average Speed* |
| | | | | Number of stopped vehicles on roadway |
| | | | X | Operator input on alert efficiency |

**Table 5: Evaluation Questions, Anticipated Outcomes, and Performance Metrics (Contd.)**

| Goals | Technology | Evaluation Questions | Anticipated Outcomes | Performance Metrics |
|---|---|---|---|---|
| **Improve Effectiveness of Real-Time Integrated Transportation Information** | IMRCP | How good are the technologies combined to improve the information given to the traveling public? | Provide accurate data to MoDOT operators that can be acted on | Number of times mobile RWIS (Road Weather Information Systems) station sends back information* |
| | Crash Risk Location Prediction & Incident Identification | | Share prediction of safety concerns to traveling public to reduce crashes | Number of crashes identified in the platform* |
| | Advanced Video Analytics | | Improve incident response time based on more and better data | Number of alerts* |
| | | | X | Operator input on alert efficiency* |
| **Improve Return on Investment and Realize Cost Savings** | IMRCP | Did the plan save money on materials and staff time during weather events? | Maximize material and labor | Change in material usage from previous years* |
| | | | Improve efficiency of time and materials | Maintenance supervisor input on material and staffing decisions |
| | Crash Risk Location Prediction & Incident Identification | How much benefit do we realize based on predicted amount of crash reduction? | Decreased costs related to serious and fatal crashes due to increased awareness of crash potential and faster responding from emergency providers | Number of crashes |
| | Advanced Video Analytics | | Improve efficiency of time and materials | Operator input on alert efficiency |

**Performance Metrics that were not measured*

Regarding the measured performance metrics, a few examples include 'number of crashes during winter weather' for IMRCP and 'number of alerts and actions' for Crash Risk Location Prediction & Incident Identification. These metrics utilized both 'before' and 'after' evaluation data, with historical data supporting the data gathered throughout the evaluation process. Another example is the 'number of stopped vehicles/objects' for Advanced Video Analytics, which only had 'after' evaluation data, as no previous data was available for comparison. Qualitative measurements, such as interviews, had their baseline data comparing to how technologies were “before”, when existing or no technology was in place, and “after”, when each technology was implemented.

Additionally, some performance measurements initially deemed to be an important component for the evaluation process, however, did not produce any data during the project, as explained in **Section 8.** An example from the list, was the "Average speed + Travel Time" or the “Average Speed” measurements where data was originally intended to measure improvements related to travel time, however, were not able to be directly measured or data was produced but not able to draw any conclusions from it.

It is important to note that all performance metrics related to the goal of 'Improving Effectiveness of Real-Time Integrated Transportation Information' were not measured, since the real-time information was not disseminated to the public. More detailed information on why it was not possible to advertise this information is provided in **Section 8**.

All data generated and used in I-270 PLOI project are owned by MoDOT. Much of the same data that enables these projects to function can also be used to analyze the effectiveness of the deployments at the evaluation stage of the project. Many types of data and platforms were used for PLOI to function and be correctly evaluated if they achieved the benefits for which they were designed. **Table 6** summarizes limitations for each type of data that were used to evaluate against the project’s original goals, following the confounding factors faced when trying to achieve each goal. The data being collected and used in this project focuses on traffic crashes where someone was killed or seriously injured.

As mentioned in the previous section of the report, the PLOI received data from the following three applications:

1. Crash Risk Location Prediction and Incident Identification
2. Advanced Video Analytics
3. Integrated Modeling for Road Condition Prediction (IMRCP)

Initially, The Crash Risk Location Prediction platform had the intention of using Intelligent Transportation Systems (ITS) such as Dynamic Message Signs (DMS) to share safety information on roadways and send emergency responders to predicted safety concern areas on roadways, however due to many constraints, it was not able to be executed during the project timeline. The platform records spatial location, corridor type identification, and traffic volume information, which are then generated as comma-separated value (.csv) files. These files are used as outputs to be analyzed comparatively with comma-separated value (.csv) files provided by ATMS Crash Database.

The Advanced Video Analytics platform collected all the mediums of data from stakeholders and performs comparative analysis to evaluate the accuracy of the innovative technologies being used in the project. The platform also used the comma-separated value files to compare the data results between archived data and incident data reports. However, since the system is designed to identify safety hazards and prevent crashes and traffic congestions, the direct benefit to the general traffic may be difficult to quantify and measure if the crashes and traffic congestions were prevented in the first place.

The Road Weather Information Systems (RWIS) were installed to collect data and serve the purpose of monitoring by providing real-time information about weather conditions on roadways. The data provided by RWIS was meant to be used to compare the predictions from IMRCP platform. In further detail, the IMRCP program would use RWIS data collection and other tools to produce weather related predictions that would be available to MoDOT Operators. This would have helped the operators make operational decisions relative to weather conditions, which would help reduce crashes related to it. The RWIS would receive those weather-related predictions to create alerts providing information about the weather condition for the operators to act on. To elaborate, the mobile RWIS station would send back information to the operator on-maintenance vehicles, which would be recorded and used for evaluation. Staff interviews were planned to be conducted to evaluate the alert efficiency; however, they were not completed due to lack of use of the platform. In addition, some impacts are difficult to quantify due to different types of weather behavior and weather factors outside of this study that could greatly influence the operations.

The previous section discussed the limitations of the data. However, there are other factors that could cause discrepancies as the project progresses. One of these factors is technological failure, which could restrict each of the different platforms. To prove efficiency and practicality in the field, it is essential to validate the studied data and performance of each technology; testing and evaluation will provide an opportunity to work with the project members to change parameters and improve the performance of each technological platform. The limitations which may present themselves through evaluation include, but are not limited to, communication failures, lack of data related resources, lack of time for evaluation, weather-related environmental constraints, and irregular driving patterns from COVID-19. Human error is also a limitation that could present itself within the data. The evaluation of each of the analyzed technologies could be limited by incorrect variable definitions, data processing, calculations, and algorithms. Other than these, limited time contrariant is another challenge in integrating different data systems.

As mentioned earlier, each platform has its own developed standards for data and processing protocol since the data types and algorithms are not constant and subject to interpretation. Therefore, it is time consuming to create a new standard for the data to be shared, stored, and used for the project as the integration progresses.

PLOI was one of the pilot projects that was exploring system integration that merges functions of all platforms into one processing chain that automates real-time data exchange between the platforms. Since there is no guidance to follow, each of the integration has created newer challenges and a new learning curve to overcome since there are no previous example or documentation to follow.

**Table 6** shows a detailed list of the performance measures, data sources, and the limitations to the data used in the project.

**Table 6: Performance Metrics, Data Sources, and Limitations**

(blue-IMRCP; yellow-Crash Risk Location Prediction & Incident Identification; orange-Advanced Video Analytics)

<table>
<tr><th>Goals</th><th>Technology</th><th>Performance Metrics</th><th>Data Source</th><th>Limitations and Constraints</th></tr>
<tr><td rowspan="10">Improve Safety</td><td rowspan="2">IMRCP</td><td rowspan="2">Crashes during weather events</td><td rowspan="2">Vehicle Probe Data</td><td>Some impacts are difficult to quantify; Insufficient sample size of drivers who receive a warning</td></tr>
<tr><td>Some weather events may impair detection of general traffic. Many weather factors outside of this study influence operations</td></tr>
<tr><td rowspan="2">Crash Risk Location Prediction & Incident Identification</td><td>Number of alerts and actions</td><td rowspan="2">TMC log</td><td rowspan="2">Direct benefit to general traffic may be difficult to measure</td></tr>
<tr><td>Delta between previous ITS usage and moving forward*</td></tr>
<tr><td rowspan="6">Advanced Video Analytics</td><td>Average Speed*</td><td>Vehicle Probe Data</td><td>Some impacts are difficult to quantify</td></tr>
<tr><td>Number of debris logs*</td><td rowspan="5">TMC Log</td><td rowspan="5">Exploratory in nature, so expected results are unknown. Quality of monitoring may vary along corridor</td></tr>
<tr><td>Number of pedestrian incidents on interstate</td></tr>
<tr><td>Number of stopped vehicles on roadway</td></tr>
<tr><td>Number of wrong way driving occurrences*</td></tr>
<tr style="display:none"><td></td></tr>
<tr><td rowspan="2">Improve MoDOT Emergency Response (ER) response time</td><td rowspan="2">Crash Risk Location Prediction & Incident Identification</td><td>Average speed + Travel Time*</td><td>Vehicle Probe Data + Crash Risk Location Prediction & Incident Identification</td><td rowspan="2">Direct benefit to general traffic may be difficult to measure</td></tr>
<tr><td>Delta between predicted crashes and recorded crashes</td><td>Crash Risk Location Prediction & Incident Identification + TMC log</td></tr>
</table>

**Table 6: Performance Metrics, Data Sources, and Limitations (Contd.)**

| Goals | Technology | Performance Metrics | Data Source | Limitations and Constraints |
|---|---|---|---|---|
| **Improve MoDOT Emergency Response (ER) response time** | Advanced Video Analytics | Number of debris logs* | Vehicle Probe Data | Exploratory in nature, so expected results are unknown. Quality of monitoring may vary along corridor |
| | | Time log of alert of pedestrian on interstate | | |
| | | Number of stopped vehicles on roadway | | |
| | | Number of wrong way driving occurrences* | | |
| **Reduce Congestion/ Improve Mobility** | IMRCP | Operations and Maintenance supervisor interviews on decision making during weather events | Interviews | Findings may be site-specific and only represent this project's deployment Pre-existing system might cause a learning curve on the new deployed system |
| | Crash Risk Location Prediction & Incident Identification | Number of crashes identified in platform | Crash Risk Location Prediction & Incident Identification | Exploratory in nature, so expected results are unknown. Quality of monitoring may vary along the corridor |
| | Advanced Video Analytics | Average Speed* | Vehicle Probe Data | Some impacts are difficult to quantify |
| | | Number of stopped vehicles on roadway | TMC log | Exploratory in nature, so expected results are unknown |
| | | Operator input on alert efficiency | Interviews | Findings may be site-specific and only represent this project's deployment |
| **Improve Effectiveness of Real-Time Integrated Transportation Information** | IMRCP | Number of times mobile RWIS (Road Weather Information Systems) station sends back information* | RWIS | Varying capabilities of vehicles to provide requisite information |
| | Crash Risk Location Prediction & Incident Identification | Number of crashes identified in the platform* | Crash Risk Location Prediction & Incident Identification | Some impacts are difficult to quantify |

**Table 6: Performance Metrics, Data Sources, and Limitations (Contd.)**

| Goals | Technology | Performance Metrics | Data Source | Limitations and Constraints |
|---|---|---|---|---|
| **Improve Effectiveness of Real-Time Integrated Transportation Information** | Advanced Video Analytics | Number of alerts* | TMC log | Exploratory in nature, so expected results are unknown |
| | | Operator input on alert efficiency* | Interviews | Findings may be site-specific and only represent this project's deployment |
| **Improve Return on Investment and Realize Cost Savings** | IMRCP | Change in material usage from previous years* | Theoretical materials used | Findings may be site-specific and only represent this project's deployment |
| | | Maintenance supervisor input on material and staffing decisions | Interviews with maintenance supervisors | |
| | Crash Risk Location Prediction & Incident Identification | Number of crashes | Crash Risk Location Prediction & Incident Identification + TMC log | Direct benefit to general traffic may be difficult to measure |
| | Advanced Video Analytics | Operator input on alert efficiency | Interviews | Findings may be site-specific and only represent this project's deployment |

**Performance Metrics that were not measured*

Not all of the performance measures listed in **Table 5** and **Table 6** were measured. During the evaluations, it was noted that data for certain performance measures could not be collected. To provide clarity, **Table 7** includes a comprehensive list of the performance metrics that were successfully measured.

**Table 7: Measured Performance Metrics**

(blue-IMRCP; yellow-Crash Risk Location Prediction & Incident Identification; orange-Advanced Video Analytics)

| Goals | Technology | Measured Performance Metrics | Performance Metrics Data Availability |
|---|---|---|---|
| **Improve Safety** | IMRCP | Crashes during weather events | Before and After Data Available |
| | Crash Risk Location Prediction & Incident Identification | Number alerts and actions | Only After Evaluation |
| | Advanced Video Analytics | Number of pedestrian incidents on interstate | Only After Evaluation |
| | | Number of stopped vehicles on roadway | Only After Evaluation |
| **Improve MoDOT Emergency Response (ER) response time** | Crash Risk Location Prediction & Incident Identification | Number alerts and actions | Only After Evaluation |
| | Advanced Video Analytics | Number of pedestrian incidents on interstate | Only After Evaluation |
| | | Number of stopped vehicles on roadway | Only After Evaluation |
| **Reduce Congestion/ Improve Mobility** | IMRCP | Operations and Maintenance supervisor interviews on decision making during weather events | Only After Evaluation |
| | Crash Risk Location Prediction & Incident Identification | Number of crashes identified in platform | Only After Evaluation |
| | Advanced Video Analytics | Number of stopped vehicles on roadway | Only After Evaluation |
| | | Operator input on alert efficiency | Only After Evaluation |
| **Improve Effectiveness of Real-Time Integrated Transportation Information** | IMRCP | X | X |
| | Crash Risk Location Prediction & Incident Identification | X | X |
| | Advanced Video Analytics | X | X |
| **Improve Return on Investment and Realize Cost Savings** | IMRCP | X | X |
| | Crash Risk Location Prediction & Incident Identification | Number of crashes | Before and After Data Available |
| | Advanced Video Analytics | Operator input on alert efficiency | Only After Evaluation |

## 6.2 Data Management

There are many data elements that worked together in PLOI. **Table 8** lists all those elements and a brief description that are relevant to their evaluation process. Most data were aimed to be recorded through automated processes and collected, or accessed, at various frequencies.

**Table 9** lists the data used in the project and the frequency at which they were recorded and collected by the evaluation team.

**Table 8: Data Elements Used in Evaluation**

| Source | Data Element | Description |
|---|---|---|
| RWIS | Location | Describes the location by highway name |
| | Ambient temperature | Ambient temperature (degrees Fahrenheit) |
| | Wind direction | Wind Direction (N, NE, E etc.) |
| | Wind speed | Wind Speed (mph) |
| | Wind gust | Recently measured wind gusts (mph) |
| | Road temperature | Road temperature (degrees Fahrenheit) |
| | Road status | Road Status (ice covered, snow covered, wet, dry) |
| ATMS Data (CSV) | Event id | The unique ID for the incident |
| | Date created/ started/ cleared | The date which the incident was created, started, andended |
| | Event type | Accident, Multivehicle accident, and incident |
| | Agency | Police, Operator, Motorist Assistance |
| | Road type | Interstate, Ramp, Highway, etc.. |
| | Main street, cross street, &direction | The street the incident occurred on and nearest crossstreet as well as the direction |
| | Latitude & longitude | Latitude & longitude coordinates |
| | Estimated duration | The difference of the start and clearing of incident |
| | Total vehicle count | Number of vehicles involved in incident |
| | Weather | Rain or snow conditions |
| | Number of injuries & fatalities | Number of people injured or number of fatalities fromincident |
| Crash Risk Area Data (CSV) | Visibility | Whether the crash risk area (CRA) is visible to users |
| | Start & end date/time | Start and end dates and time for CRAs |
| | Start & end point latitude andlongitudes | Start and endpoint of the CRA segment |
| | Start & end corridor | The start and end corridor which the CRA segment is on |
| | Direction | The direction of crashes which the CRA is predicted for |
| | Start & end crossroad | The nearest crossroad to the CRA start and end |

**Table 8: Data Elements Used in Evaluation (Contd.)**

| Source | Data Element | Description |
|---|---|---|
| Advanced Video Analytics DataReport (CSV) | Camera name | The camera name (indicates the camera location) |
| | Date | The date of the archived data |
| | Time | The time of the archived data |
| | Volume | The volume of vehicles seen |
| | Speed | The speed of vehicles seen |
| | Camera movement | Yes or no in regard to has the camera been moved duringthe timeframe |
| | Timestamp | The time the incident was reported/classified |
| | Incident type | Category of reported incident (congestion, pedestrian, etc..) |
| | Cleared timestamp | When the incident cleared the system |

**Table 9: Data Collection Information**

| Source | Collection Frequency | Location | Data Collection Period |
|---|---|---|---|
| RWIS | 20 min | I-270 | 2022 Q1 - 2023 Q4 |
| ATMS Data (CSV) | Real-time | I-270 | |
| Crash Risk Area Data (CSV) | Real-time | I-270 | |
| Advanced Video Analytics Data Report (CSV) | Real-time | I-270 | |
| Survey responses | By Survey | N/A | |

**Table 9** portrays the data sources that were provided to assist in the verification of each technology. The results of the verification helped validate and quantify if the technologies/tools helped PLOI achieve the project main goals. An important note is that these technologies were not only used on I-270, where the segment of the construction happened, but also covering the entirety of St. Louis Interstate connections. Also, some of these technologies, such as ATMS, were not put in place just for this project.

The Crash Risk Area/Incident Identification vendor conducted an internal verification to assess the accuracy of Connected Vehicle (CV) data compared to Optical Sensor Data collected from their installed cameras along a 15-mile segment of I-270. CV data provided broad geospatial coverage and real-time traffic behavior insights, while Optical Sensor Data offered precise vehicle counts within camera view but required additional infrastructure. Both data sources were analyzed by matching geolocations and comparing metrics like vehicle count and speed. The findings were further discussed in **Section 7.1.3.**

Information plays a crucial role in the documentation, validation, and assessment of success of PLOI. The essential factor lies in gathering pertinent data that aligns with the objectives and potential expansions of the applications. The data, fundamental in the functioning of this project, also serves as a valuable resource for evaluating the overall effectiveness of the applications

# 7 VERIFICATION PROCESS AND RESULTS

This section explores the verification process employed in assessing the chosen technologies. Focused on determining their ability to deliver high-quality data for operators, this section goes through the verification process, challenges faced during the process, and verification outcomes/results that highlighted each technology's performance. This also sets the stage for a subsequent exploration into the evaluation process where the immediate utility for the project goals and seamless integration of these technologies can be analyzed within Missouri's transportation framework.

As highlighted earlier, the verification process focuses on the individual performance of each technology. In contrast, the evaluation process takes a broader perspective, translating numerical data into tangible benefits for MoDOT, and ultimately fulfilling the project goals set in the beginning of the development.

## 7.1 Crash Risk Location Prediction & Incident Identification

The technologies had two separate monthly verifications, one for the Crash Risk Prediction Areas and one for Incident Detection compared to the MoDOT crash database.

### *7.1.1 Crash Risk Prediction Area (CRA)*

**Verification Process:**

At the end of every month, the vendor would send all crash risk prediction data to the consultant and MoDOT would send the most updated crash data to the consultant. By combining these datasets, the consultant was able to verify if the CRA predicted any of the crashes that MoDOT reported. The CRA data would consist of a .csv excel spreadsheet format which contained the geolocation of the starting and end points of each of the crash risk predicted areas, where it would enable the consultant to use Google Earth to import the data and visualize geospatially.

The spreadsheet (as shown in **Figure 4**) would indicate whether the predicted crash risk area was visible on the platform for the operator. If not visible, it means these areas were generated in the algorithm backend and remained hidden from the operator. The purpose of having both visible and invisible crash risk prediction areas is for the algorithm to reach the maximum learning curve possible while only showing a selected array of them to the operators. Along with the spreadsheet, it was also mentioned the written location of those start and end points coupled with the direction of the prediction.

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | isVisible | startedat_ | endedat_ | startedat_ | endedat_ | startpoint | startpoint | endpointl | endpointl | startcorric | startdirect | startcross | endcorrid | enddirecti | endcrossr | distance | startaddre | endaddress |
| 2 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.61092 | -90.2051 | 38.58504 | -90.2182 | "I-55" | "SB" | "44" | "I-55" | "SB" | "Gasconac | 4284.822 | {"point":{" | {"point":{"coordinates" |
| 3 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.61092 | -90.2051 | 38.58504 | -90.2182 | "I-55" | "SB" | "44" | "I-55" | "SB" | "Gasconac | 4284.822 | {"point":{" | {"point":{"coordinates" |
| 4 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.57865 | -90.2285 | 38.61105 | -90.2042 | "I-55" | "NB" | "Broadwa | "I-55" | "NB" | "44" | 5208.373 | {"point":{" | {"point":{"coordinates" |
| 5 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.7207 | -90.3093 | 38.688 | -90.2502 | "I-70" | "EB" | "Hanley R | "I-70" | "EB" | "Bircher B | 6836.34 | {"point":{" | {"point":{"coordinates" |
| 6 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.63209 | -90.2885 | 38.62984 | -90.3409 | "I-64" | "WB" | "Hampton | "I-64" | "WB" | "170" | 5857.525 | {"point":{" | {"point":{"coordinates" |
| 7 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.61014 | -90.2064 | 38.64551 | -90.19 | "I-44" | "EB" | "55" | "I-44" | "EB" | "70" | 5781.391 | {"point":{" | {"point":{"coordinates" |
| 8 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.61092 | -90.2051 | 38.58504 | -90.2182 | "I-55" | "SB" | "44" | "I-55" | "SB" | "Gasconac | 4284.822 | {"point":{" | {"point":{"coordinates" |
| 9 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.57865 | -90.2285 | 38.61105 | -90.2042 | "I-55" | "NB" | "Broadwa | "I-55" | "NB" | "44" | 5208.373 | {"point":{" | {"point":{"coordinates" |
| 10 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.7207 | -90.3093 | 38.688 | -90.2502 | "I-70" | "EB" | "Hanley R | "I-70" | "EB" | "Bircher B | 6836.34 | {"point":{" | {"point":{"coordinates" |
| 11 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.63209 | -90.2885 | 38.62984 | -90.3409 | "I-64" | "WB" | "Hampton | "I-64" | "WB" | "170" | 5857.525 | {"point":{" | {"point":{"coordinates" |
| 12 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.62984 | -90.2729 | 38.61895 | -90.1865 | "I-64" | "EB" | "Hampton | "I-64" | "EB" | "55" | 8741.121 | {"point":{" | {"point":{"coordinates" |
| 13 | FALSE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.61092 | -90.2051 | 38.58504 | -90.2182 | "I-55" | "SB" | "44" | "I-55" | "SB" | "Gasconac | 4284.822 | {"point":{" | {"point":{"coordinates" |
| 14 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.57865 | -90.2285 | 38.61105 | -90.2042 | "I-55" | "NB" | "Broadwa | "I-55" | "NB" | "44" | 5208.373 | {"point":{" | {"point":{"coordinates" |
| 15 | TRUE | 00:00.0 | 00:00.0 | 2023-04-0 | 2023-04-0 | 38.7207 | -90.3093 | 38.688 | -90.2502 | "I-70" | "EB" | "Hanley R | "I-70" | "EB" | "Bircher B | 6836.34 | {"point":{" | {"point":{"coordinates" |

**Figure 4: Example of CRA data provided by Crash Risk Location Prediction Platform**

Both provided datasets had to be in a .csv format so Google Earth could read and interpret the numbers. After importing the data into Google Earth, the numbers could then be visually verified on a daily basis to check if each crash risk area predicted a crash. This process can be overwhelming visually if all entries are concurrently selected; therefore, it was ideal to separate each day, so the display is not crowded. Multiple verifications were done over a two-year period and some of the aspects of the crash risk areas changed over time, such as the range time.

**Challenges:**

The prediction of Crash Risk Locations is a difficult task and requires multiple data sources to be produced and managed. During the two-year verification period (2022–2023), Crash Risk Location Prediction technology consistently maintained algorithm accuracy. Significant advancements were noted after August 2023, with only one additional quarterly verification report remaining. Among the improvements observed was a reduction in the total number of CRA, directly enhancing the accuracy percentage of the algorithm. This compressed timeline posed a challenge for in-depth validation of the improvements made to the algorithm, thereby limiting the opportunity for MoDOT leadership to thoroughly assess and gain confidence in the improvements made. Throughout the project timeline, the introduction of a new ATMS platform posed an additional delay to the overall process. As is typical with new technologies, there is a required period for adjustment and alignment with organizational requirements. Staff members also needed time to acclimate and familiarize themselves with the intricacies of this new platform that will need feedback from it so it can improve. The new changes made data look different and caused issues connecting to previous data that was being provided.

Another interesting algorithm behavior was that most of the I-44 segment in St. Louis had an absence of CRA for a significant period, where the algorithm would create predictions to all the other interstates around St. Louis but under-predicted to I-44. This is explained by the technology's algorithm utilizing historical crash data to identify areas with a high concentration of incidents. By analyzing these clusters, the algorithm generates predictive crash risk areas. However, the historical crash data for I-44 in the St. Louis region revealed a scattered distribution with fewer concentrated crashes compared to other interstates. Near the completion of the project (2023), changes were made to the algorithm, and it started producing more CRA toward I-44; this was brought to the vendor's attention due to its importance to the St. Louis region being one of the largest and most traveled interstates.

**Verification Results:**

**Figure 5** and **Figure 6** show there was a learning curve during these two years of verification and reached improvements over some time. October of 2023, the last verification month completed, was the best month according to results. The graphs below exhibit the percentage of all visible crash risk locations that predicted a crash in the correct direction divided by all visible crash risk locations produced during each month, remembering that "visible" in this case means that is visually displaying on the platform to the operator.

These tables focus on the likelihood of predicting a crash and ultimately provide an opportunity to decrease the severity of a crash or even prevent it from happening. If MoDOT or any agency were to act upon these alerts and allocate resources to address all the predicted crash risk locations identified by Crash Risk Location Prediction technology during 2022-2023, there was a potential to avert accidents. Following this, we provide a visual representation of the equation utilized to derive the presented figures:

$$\%\ of\ Visible\ CRA\ that\ Predict\ a\ Crash\ (Correct\ direction)$$
$$= \frac{Correct\ Direction\ Predictions\ made\ by\ Visible\ CRA}{All\ Visible\ CRA}$$

To illustrate this calculation using a real-world scenario, suppose we have a total of 100 visible Crash Risk Areas produced by the platform for a specific month, and only 10 of them accurately predicted a crash in the correct direction. In this case, we would have a total of 10% of all Visible Crash Risk Areas accurately predicting a crash in the correct direction. And that is precisely what is being shown below for each month on the yearly comparison graphs.

**Figure 5** shows that predicted crashes in the correct direction in 2022 remained stagnant and represented reality where the algorithm had not presented any changes during this time. Significant changes to the algorithm were made in October 2023, such as the range of each CRA dropping down from 3 hours to 1 hour while increasing its accuracy compared to other months (**Figure 6**). A detailed summary of the Crash Risk Location Prediction tool's CRA quarterly verification is available in **Appendix C: Crash Risk Area (CRA) Monthly Verification Results**.

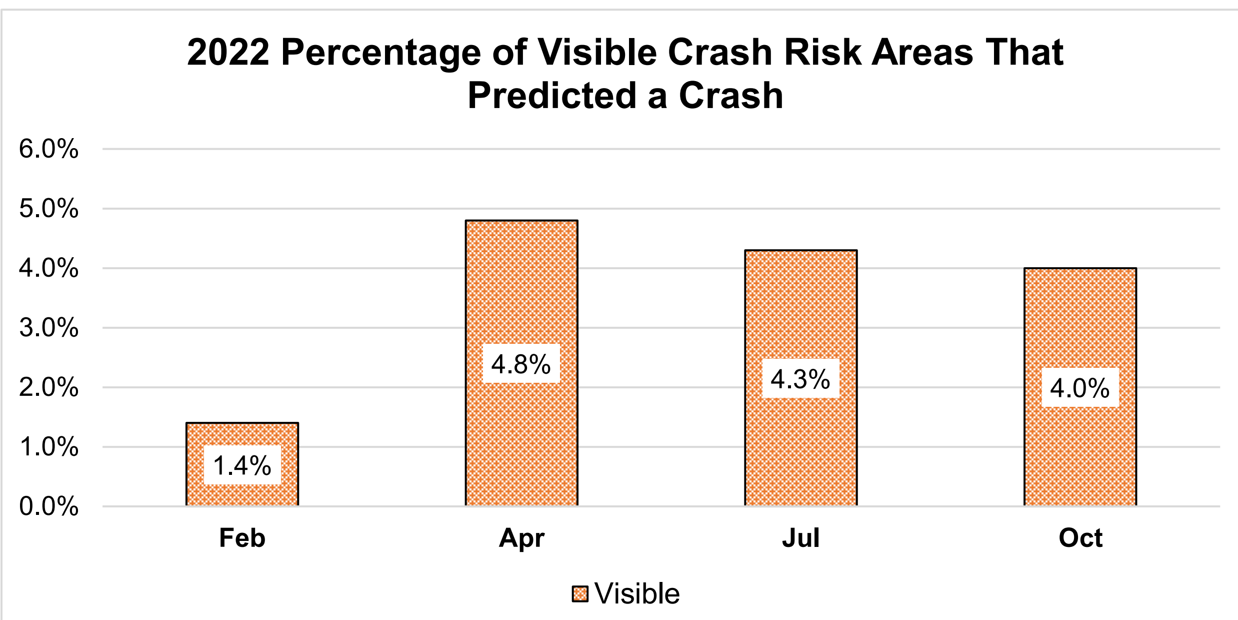


**Figure 5: 2022 Percentage of Visible CRA that Predicted a Crash**

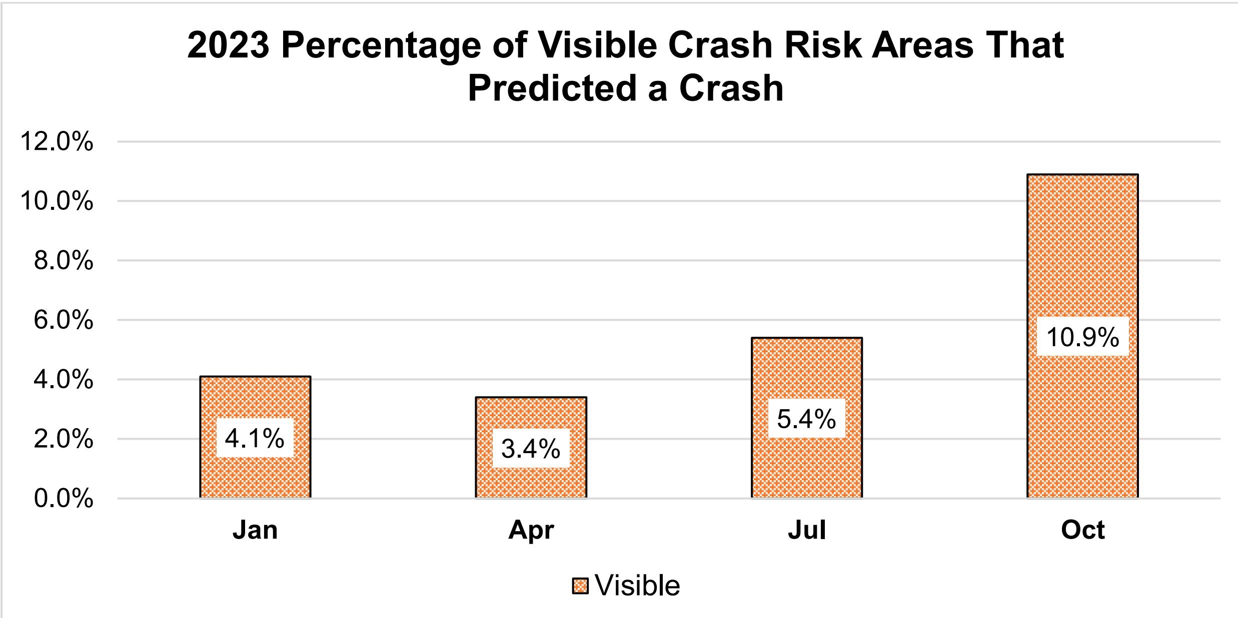


**Figure 6: 2023 Percentage of Visible CRA that Predicted a Crash**

### *7.1.2 Incident Identification*

**Verification Process:**

The technology not only provided a predictive tool for identifying high-risk crash areas but also offered a comprehensive incident identification tool that used diverse live data sources. The initial phase in validating incident identification involved extracting data from the Incident Identification platform, specifically filtering for crashes occurring in the designated month (**Figure 7**). The analysis aimed to compare the efficiency of the technology's platform in identifying crashes against other tools, such as radio, police, and cameras being monitored by TMC Operators employed by the Missouri Department of Transportation (MoDOT).

Both Incident Identification tool and ATMS crash data were exported in CSV format and subsequently imported into Google Earth, facilitating a visual comparison of alert locations and timestamps. The objective was to discern instances where the identified incidents aligned and establish which platform reported the crash first. This process enabled a systematic evaluation of the time efficiency of incident identification between the Incident Identification platform and alternative tools employed by MoDOT.

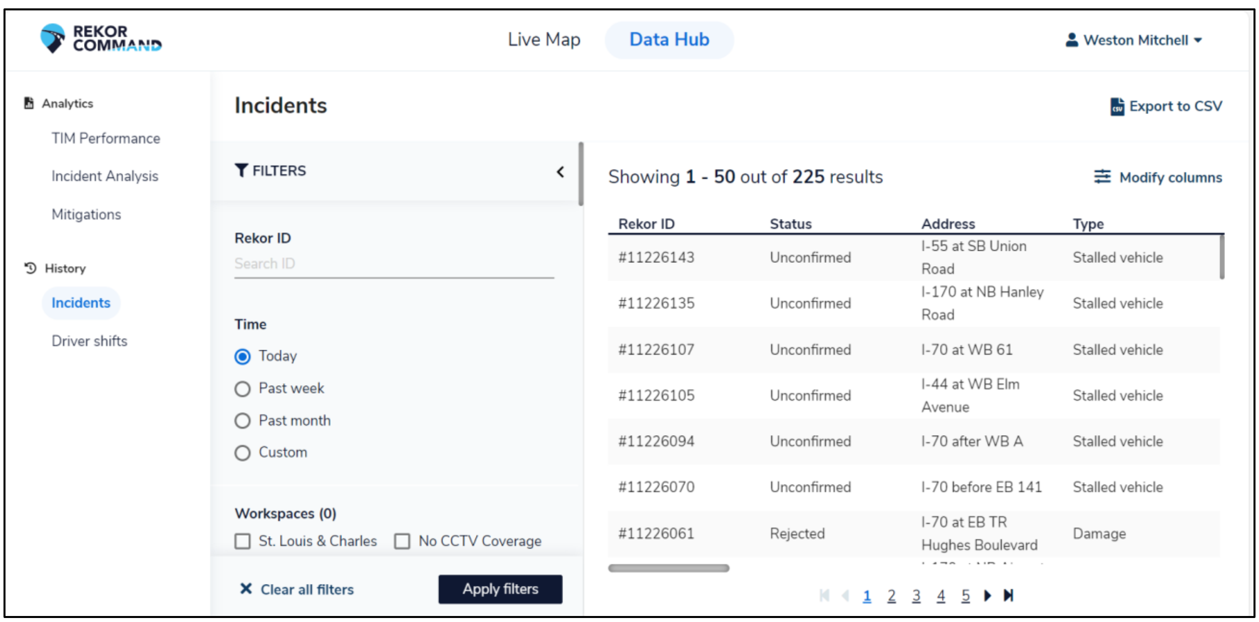


**Figure 7: Data Tab on the Incident Identification Platform**

**Challenges:**

This tool was creating a high number of duplicate events in the system, which was perceived negatively by the TMC Operators. They lost time verifying alerts that were just duplicates of incidents they recently verified. From a performance standpoint, Incident Identification tool has proven to be efficient, however it still has potential to improve its quality in generating alerts. Another integration-related complaint is that it is difficult to implement with ATMS and vehicle location Global Positioning System (GPS) due to accuracy issues.

**Verification Results:**

Incident Identification tool uses a wide variety of diverse sources to gather real time information. As of January 2022, Incident Identification tool was still slower than the standard MoDOT methods of incident detection. It was, however, faster than other tools 40.8% of the time as shown in **Figure 8.** The initial promising results remained consistent until October 2022, when the technology jumped up to a first to report rate of 54.1% and was faster than traditional methods for the first time. After October 2022, it kept its performance better than most of the tools available throughout the entirety of 2023 (**Figure 9**).

An interesting detail worth mentioning was the significant increase in 2023 by the same time incidents being reported in comparison to the current method. The cause for this behavior is explained by the new ATMS platform which connected Waze data into their platform, increasing the likelihood of having the same incident “start time” when comparing both, since they are the same alert. The previous ATMS platform did not have Waze information feeding into its datahub. A detailed summary of the Incident Identification tool quarterly verification is available in **Appendix D: Incident Identification Monthly Verification Results**.

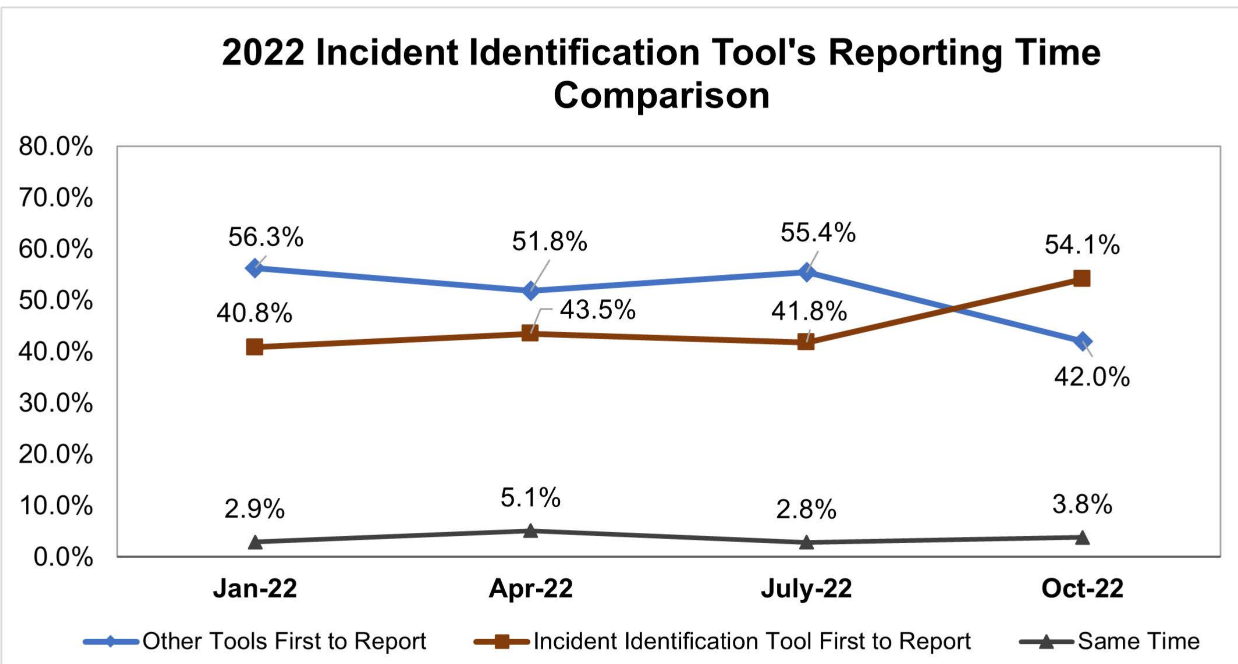


**Figure 8: 2022 Monthly Incident Comparison Verification**

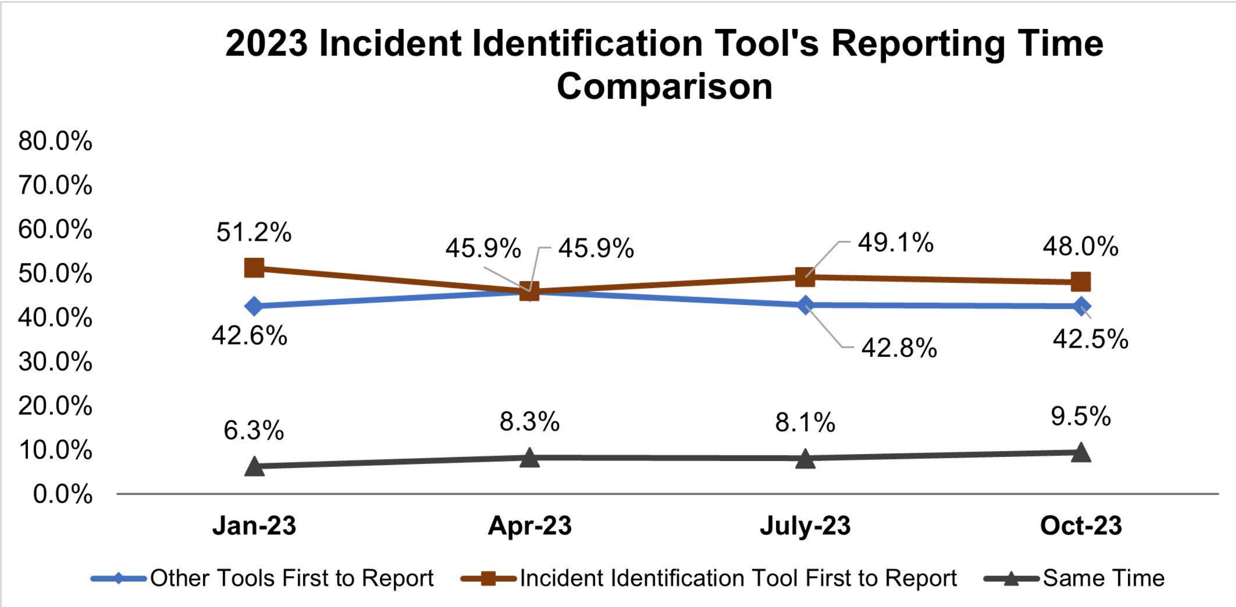


**Figure 9: 2023 Monthly Incident Comparison Verification**

### *7.1.3 Comparison of Connected Vehicle Data to Optical Sensor Data*

The Incident Identification tool's vendor performed internal verification comparing the accuracy of Connected Vehicle (CV) Data to Optical Sensor Data. Both served as a data source that were processed by the technology's algorithm which used AI/ML to produce the outcome or actionable insights and analytics as a final product.

The data used for this verification was from February to April 2023 (2 months) and covered only I-270 from W Florissant Ave Interchange (East Extreme) to Olive Blvd/MO-340 Interchange (West Extreme), roughly 15 miles of study area. Throughout this segment, 83 cameras participated in the data collection, while CV data covers the entire segment. Results from both sources were compiled together by hourly aggregates. The information in this section was provided directly by the Incident Identification tool vendor and included here by our team. This information is not available through any online or open-source platforms.

Data comparison was completed using QGIS (mapping software) by putting together both data sources from the same geolocations, comparing the vehicle count, speed data, correlating patterns.

*Connected Vehicle Data*: Broad geospatial coverage; Real-time location, speed and heading; Supplements existing infrastructure; Tell a broader story of traffic behavior.

*Optical Sensor Data*: Highly accurate and deterministic; Captures data by identifying vehicles passing between 2 systems; Limited to specific physical locations within the camera's field of view; Requires new infrastructure deployment and maintenance.

Speed Analysis

Edge AI System produced higher variation on speeds and a slightly lower middle value compared to CV Data. The reason might be attributed to the capture of all vehicles in between cameras while CV data only accounts for a subset of newer, privately owned vehicles as shown in Error! Reference source not found.**Figure 10.**

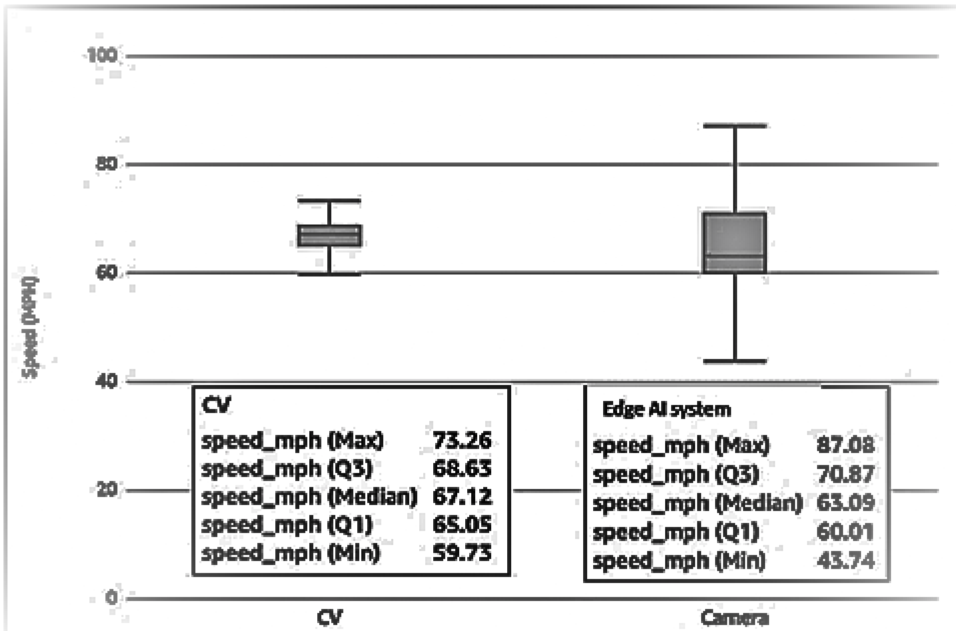


**Figure 10: Screenshot from the vendor's PowerPoint Verification Presentation indicating Speed Data comparison between CV and Edge AI system.**

Vehicle Count Analysis

**CV:** Captures 10-15% of vehicles on the road. Represents specific vehicle types.

**Edge AI system**: Captures nearly all vehicles passing between two specific points.

Conclusion

In conclusion to this internal verification, it was observed that the technology's Roadway Intelligence combines connected vehicle data with AI-driven roadside systems to transform raw data into actionable insights using artificial intelligence and machine learning.

The connected vehicle data offers a broad geospatial view, providing real-time information on location, speed, and direction, thereby enhancing existing infrastructure. Meanwhile, edge AI system data delivers high precision and certainty but is limited to the visual range provided by their cameras.

## 7.2 Advanced Video Analytics

**Verification Process:**

Advanced Video Analytics was selected as the technology to implement the Advanced Video Analytics segment of PLOI. Its platform was connected to the MoDOT cameras through a third-party video distribution platform that compresses the camera image and live feeds into the technology's online portal; **Figure 11** shows the Advanced Video Analytics online portal. **Figure 12** shows the "Data" tab of this platform, where the alerts were shown and updated real-time.

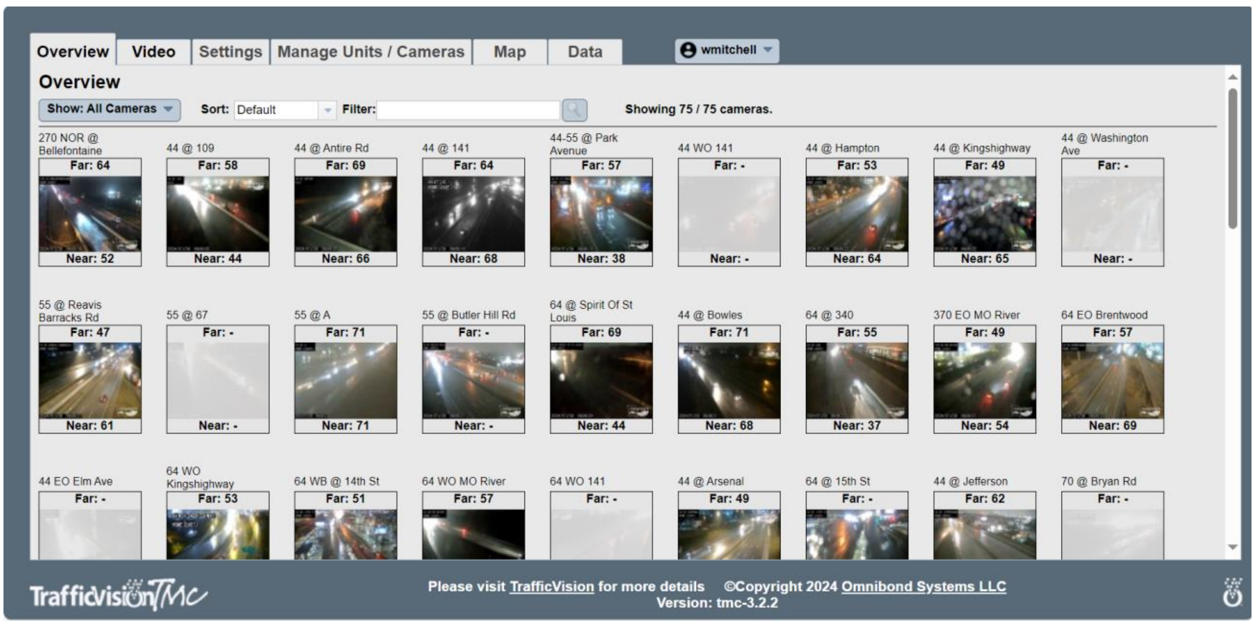


**Figure 11: Screenshot taken from the Overview tab on Advanced Video Analytics Platform**

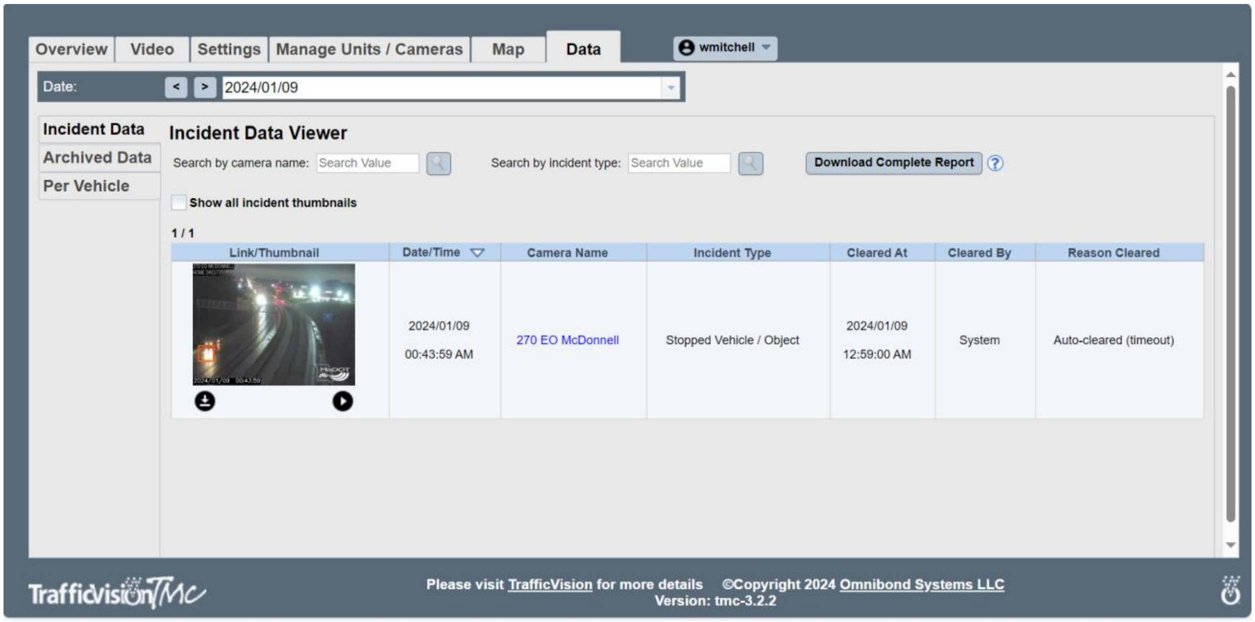


**Figure 12: Screenshot taken from the Data tab on Advanced Video Analytics Platform**

Each alert would consist of a few columns including "Date/Time", "Camera Name", "Incident Type", "Cleared At", "Cleared By", "Reason Cleared", and a small video fragment, which is also downloadable, of the location and time when the algorithm triggered the alert, so it can be verified. The incident type could be classified as "Stopped Vehicle/Object", "Pedestrian", "Congestion", "Slow Speeds", and "Low Visibility". Each alert was carefully verified on the same day by cross referencing the footage recorded by the platform to the incident type. In addition, every TMC Operator receives e-mail notifications from Advanced Video Analytics while they are working on multiple screens and facilitate their time management by only looking into it when notified. **Figure 13** shows an example e-mail notification, which notes the incident type and location of the camera stated in the title.

Another important detail when verifying each alert was to make sure the camera was observed in the preset position, especially when the alert was considered false. The most common false alert was directly tied to the camera not being at "home view", which is the preset view assigned and configured previously to the deployment of the technology. This could also be due to operators using PTZ or from camera drift.

Incident alert: Stopped vehicle/object @ NS-Z3 [55 @ A]

M To

Retention Policy Default 5 Year move to Recover Deleted Items (5 years, 6 months)


Snapshot: https://modot270.trafficvision.com/publinks/cb277f61-e06e-44ef-9476-09d156926d0c
Video: https://modot270.trafficvision.com/playclip?src=/publinks/88bac072-22ba-424c-9095-0389a9fba0b1

**Figure 13: Screenshot of Advanced Video Analytics' Incident Alert Notification**

**<u>Challenges:</u>**

The movement of the camera had a notable impact on the accuracy of both "Slow Speed" and "Congestion" alerts. The dynamic nature of the camera's positioning introduced challenges for the Advanced Video Analytics tool in accurately detecting and categorizing these traffic conditions.

Weather conditions, particularly rain and snow as well as camera drift, posed challenges to the algorithm's effectiveness. Notably, Advanced Video Analytics did not offer specific solutions to address issues happening from adverse weather conditions, such as raindrops sliding down the camera lens.

This limitation may have implications for the tool's reliability under varying weather scenarios. The absence of static cameras imposed limitations on the tool's maximum capabilities, particularly in scenarios where the identification of "Wrong Way" alerts would be highly beneficial. Also, the compression of video data from MoDOT cameras through third-party software negatively impacted the quality of the footage. This compression not only diminished the overall video quality but also complicated Advanced Video Analytics algorithmic classification, reducing the clarity of the tool's analysis. The processed streams also included a logo which covered part of the stream, reducing the available area for monitoring, and sometimes causing false alerts when positioned over the roadway detection zones. The issues with raindrops causing false alarms were also worsened by the pixelated images. The software could not as easily identify and ignore the obstruction.

**Verification Results:**

Advanced Video Analytics verification started February 2022 and went until October 2023. Since it started, 8 quarterly verifications were completed and had presented positive progression over the months as shown in **Figure 14** and **Figure 15**. The last 2 months had a drop in the verified performance. However, this was mostly due to the movement of the camera which increase the complexity for the Advanced Video Analytics algorithm to detect and make correct assumptions. While cameras were set to the preset home view position, the algorithm responded with high accuracy. A deeper dive into the explanation and numbers were made in **Appendix E: Advanced Video Analytics Monthly Verification Results.**

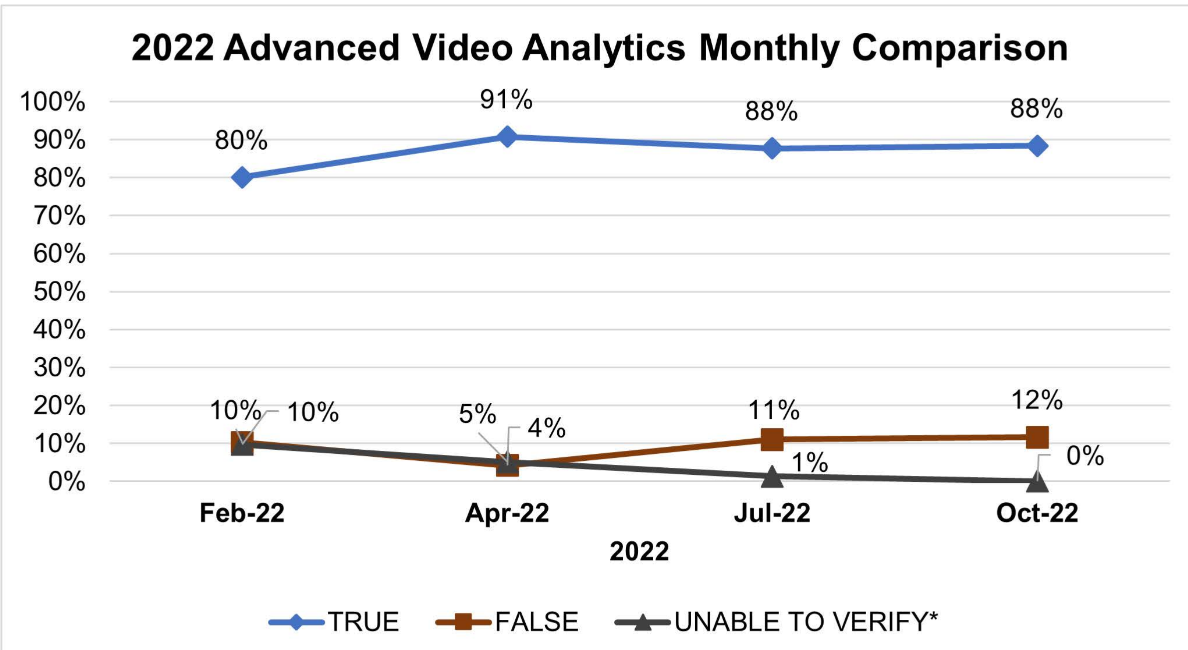


**Figure 14: 2022 Advanced Video Analytics Monthly Comparison**

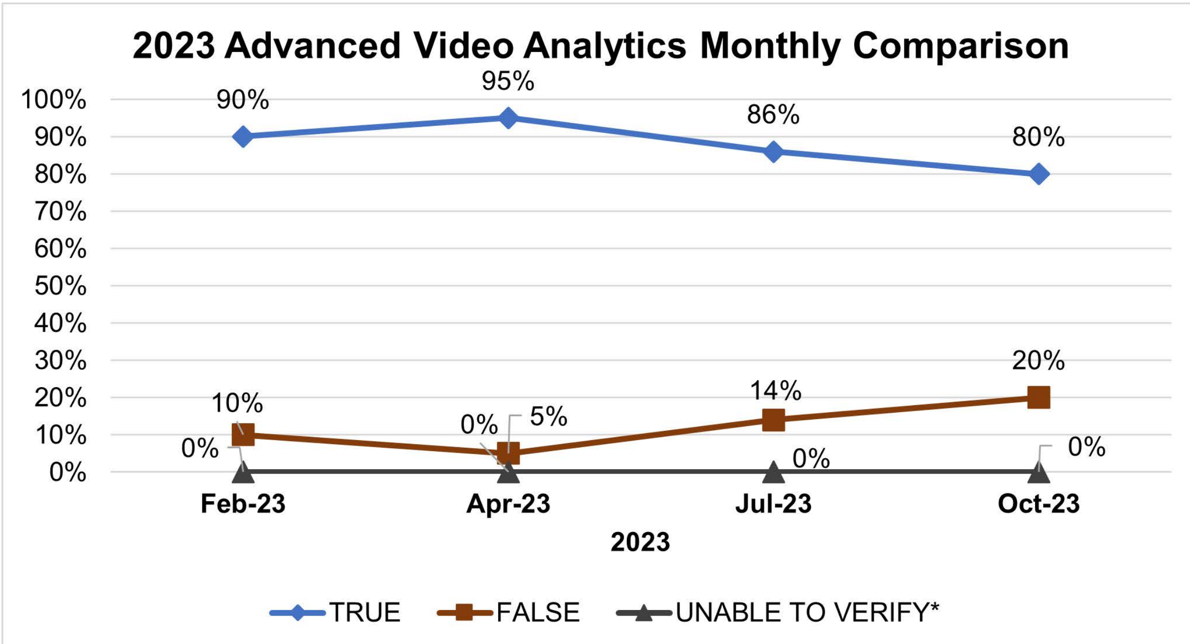


**Figure 15: 2023 Advanced Video Analytics Monthly Comparison**

## 7.3 IMRCP

As highlighted in the project timeline, IMRCP was fully operating by the 2021-2022 winter season, during which only one out of six days during the entire season marked above 2 inches of snow (**Figure 16**). During the following winter season (2022-2023), notable snowfall equivalent to 2 inches occurred only on January 25th, as illustrated in the figure below (**Figure 17**). Due to the limited snowfall events, there was insufficient data available to execute verification procedures with the providers regarding IMRCP.

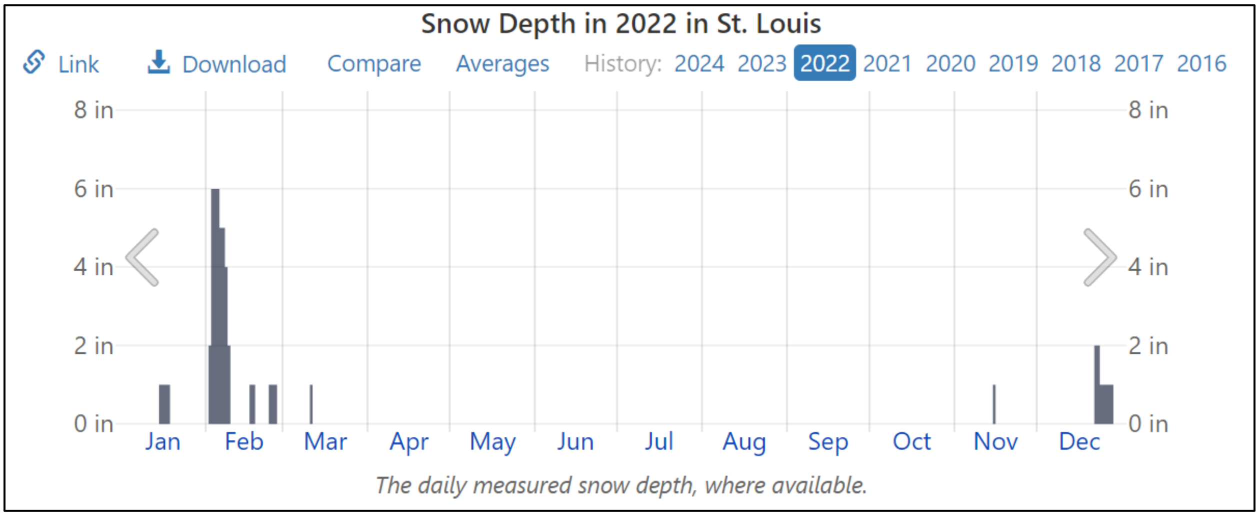


**Figure 16: Snow Depth in 2022 in St. Louis. *Source: weatherspark.com***

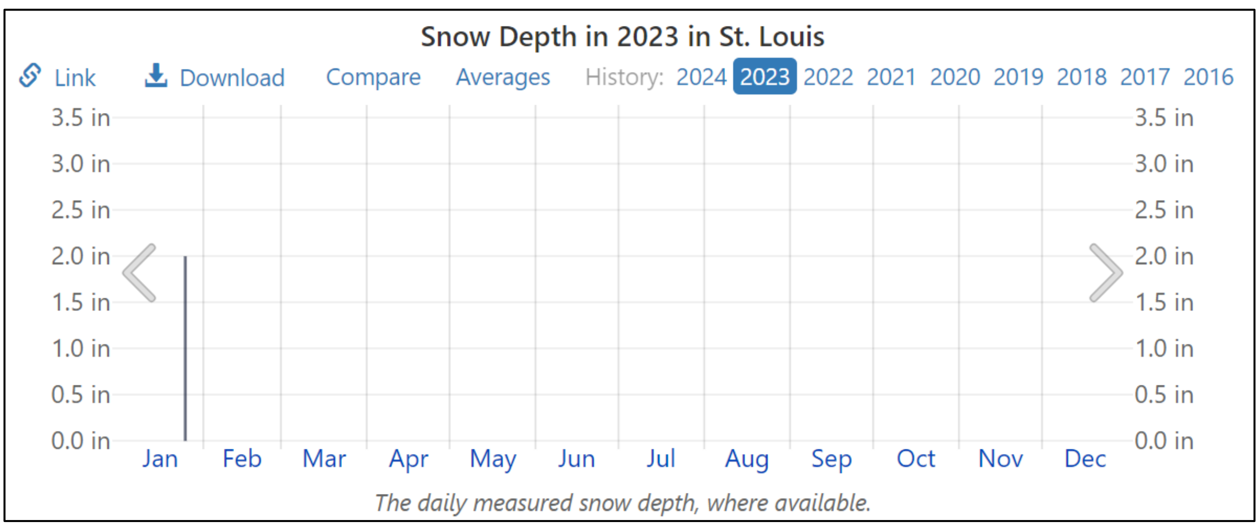


**Figure 17: Snow Depth in 2023 in St. Louis. *Source: weatherspark.com***

# 8 EVALUATION OF PROJECT GOALS

Evaluating technologies within the framework of PLOI was crucial to understanding their effectiveness, efficiency, and overall impact. This evaluation process was designed to assess whether the set goals and objectives of deploying specific technologies had been met. It involved a detailed examination of various applications implemented under PLOI.

The methodology for the evaluation of the project goals is a comprehensive approach that combined both qualitative and quantitative results. This dual approach ensures a total understanding of the technology's performance. Qualitative results offer insights into user satisfaction, usability, and the technology's impact on operational processes. They are typically gathered through interviews and observations, providing a narrative context to the numerical data. On the other hand, quantitative results provided hard data on performance metrics such as response times and other measurable outcomes, such as the quarterly verifications performed throughout the project.

By integrating both qualitative and quantitative data, the evaluation aimed to paint a complete picture of the technology's effectiveness. This approach not only assessed how well the technology meets its intended goals but also uncovered areas for improvement. This comprehensive evaluation process is vital for stakeholders to make informed decisions about future investments, enhancements, and the strategic direction of technology deployment.

## 8.1 Improve Safety

Each project goal was designated with specific objectives and associated questions, created in a mid-project preliminary report where we set expectations, designed to critically assess how these objectives might be achieved, including unsuccessful attempts. These questions were tailored to evaluate the contribution of each technology toward the primary goal, requiring a detailed response for each question.

### *8.1.1 IMRCP*

In the context of our goal to improve safety, IMRCP had the objective of developing an operations and maintenance plan to address weather issues identified in the IMRCP. By preparing for weather-related challenges, the project aimed to ensure that infrastructure and operations can seamlessly adapt to winter conditions, thereby minimizing risks to both the infrastructure and its users.

Notably, IMRCP is specifically intended for extreme weather conditions, providing enhanced tools for effective winter event management. By integrating road weather, traffic, and work zone incident data, IMRCP empowers various stakeholders, including Transportation Management Center (TMC) operators, maintenance providers, travelers, emergency responders, and work zone personnel, with real-time information.

**Figure 18** illustrates IMRCP's integration capabilities, while **Figure 19** highlights its ability to aggregate data from diverse sources such as Road Weather Information Systems (RWIS), Advanced Traffic Management Systems (ATMS), and social media. However, due to implementation challenges with the existing ATMS, we were unable to generate sufficient data for reliable verification results.

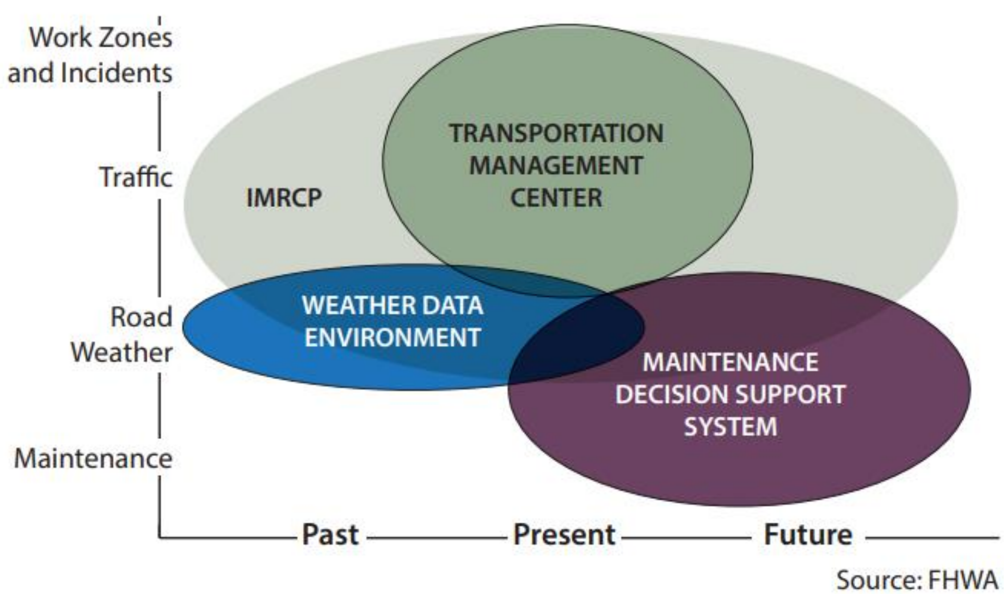


**Figure 18: IMRCP and Other Road Weather and Operation Applications**

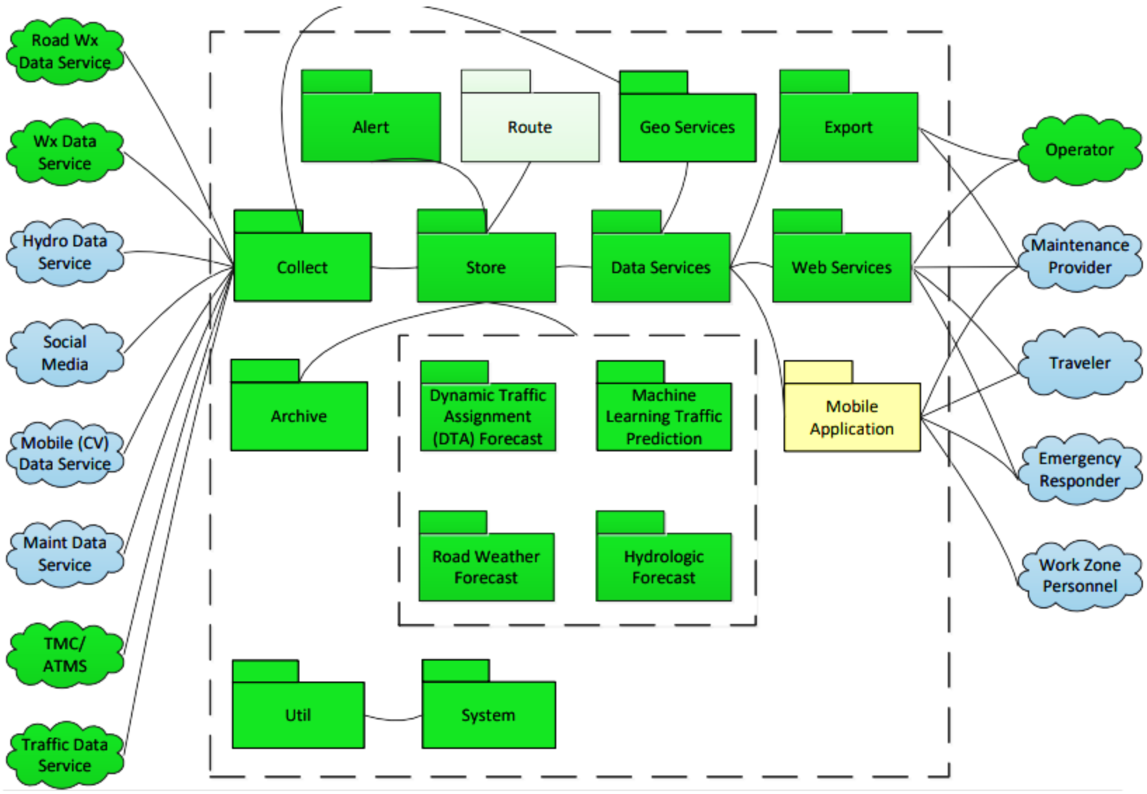


**Figure 19: IMRCP Functions (Source: MoDOT KC Scout)**

Our team also examined crash patterns during snow and ice events on interstates between 2018 and 2023. Approximately 4% of the overall crashes within the study area were weather-related. **Table 10** provides insights into the historical crash patterns associated with snow and ice events.

**Table 10: Crash Totals in St. Louis Region Interstates during Snow, Ice and Sleet (2018-2023)**

| Crash Totals in St. Louis Region Interstates during snow and Ice (2018-2023) | | | | | | |
|---|---|---|---|---|---|---|
| **Severity Type** | **No. of Weather-Related Crashes (Snow, Ice and Sleet)** | **Annualized Crashes (Weather related crashes/ Year)** | **% of Weather-Related Crashes in Work zones** | **% Weather-Related Crashes in Dark** | **Total Crashes throughout the study area** | **Weather-Related Crashes as a % of Total Crashes** |
| Fatal (K) | 7 | 1.2 | 14.30% | 28.60% | 256 | 2.70% |
| Serious Injury (A) | 42 | 7 | 0.00% | 51.50% | 1,260 | 6.80% |
| Minor Injury (B / C) | 492 | 82 | 1.80% | 15.00% | 13,787 | 3.60% |
| PDO (O) | 1,763 | 293.8 | 1.80% | 14.70% | 47,909 | 3.70% |

In our evaluation, we examined 6 years of historical data (2018-2023) to determine average snowfall days within the region (see **Table 11**). Notably, snowfall occurs between November and March, with an average of 4 snow days. While the occurrence of snow weather conditions on only 5 out of 365 days may initially seem insignificant, **Table 12** provides a crucial insight. Over the past six years, snow conditions have been linked to 4 fatal and 18 serious injuries. This analysis can be extrapolated to other adverse weather types, including sleet, ice, or rain, which similarly pose negative implications for road safety. These weather events not only present inherent risks but also trigger a domino effect, impacting emergency response times due to road closures and necessitating more cautious driving in hazardous conditions.

The introduction of IMRCP offers a promising opportunity to address and mitigate these risks. By potentially enhancing safety during harsh weather, IMRCP could play a pivotal role. While IMRCP's current findings have not yet provided conclusive evidence to validate its adoption, IMRCP still holds the promise not only to minimize existing risks but also to mitigate the potential for future crashes. The importance of persistently exploring and implementing advanced tools like IMRCP cannot be overstated. Doing so is not merely beneficial; it is essential for enhancing road safety and optimizing emergency response efficiency in adverse weather conditions. While the effectiveness of this tool remains unverified during the evaluation phase due to a combination of manpower constraints, it holds tremendous value provided proper training can be ensured. Furthermore, despite the lack of successful implementation thus far, there is reason to believe it could be particularly effective in northern counties within the state, as well as in northern states. A previous study conducted by Kansas City Scout (KC Scout) has yielded promising results from their evaluation (Dot.gov, 2020).

Currently, MoDOT's winter maintenance team relies on other tools, subscription-based services for the analysis of real-time weather information provided by Data Transmission Network and Dataline (DTN), which accurately predicts and notifies MoDOT staff of weather events and facilitates efficient winter crew deployment for maintenance. Considering the existing infrastructure, further deploying IMRCP may not be warranted at this time. Initially, the IMRCP was designed to provide detailed data for decision-making regarding resource deployment. However, during snowstorms, operations become chaotic, and IMRCP requires substantial data entry and staff time to run scenarios for each road segment. Existing tools in place, automatically determine the number of trucks (plow or plow & salt) needed in a more efficient manner by zone. Although IMRCP can offer more detailed guidance, such as specifying the amount of salt and the number of trucks required for each road segment based on current resource availability, it lacks user-friendliness and ease of information retrieval compared to the tools currently used by maintenance staff. The infrequent occurrence of snow events during the project timeline led staff to prefer technology that requires fewer inputs and provides quick answers, rather than a system that requires extensive data entry to generate detailed outputs.

**Table 11: Average Snowfall Days in St. Louis Region (2018-2023)**

| Snowfall days with accumulation ≥ 1" in St. Louis | | | | |
|---|---|---|---|---|
| **Days** | **Year** | **Inches** | **Centimeters** | **Annual Total Snow Accumulation (in inches)** |
| 1 | 2023 | 3 | 8 | 5.4 |
| 4 | 2022 | 15.1 | 38 | 15.0 |
| 2 | 2021 | 12.6 | 32 | 12.6 |
| 3 | 2020 | 8.1 | 21 | 8.0 |
| 8 | 2019 | 23.9 | 61 | 23.9 |
| 4 | 2018 | 10.6 | 27 | 10.5 |
| *3.7* | *Average* | *12.2* | *31.2* | *12.6* |

**Table 12: Crash Counts and Severity by Weather Type, and Road Surface Condition (2018-2023)**

| **Road Surface Condition** | **Weather Type** | | | | | |
|---|---|---|---|---|---|---|
| | Sleet | Freezing | Snow | Rain | **Total** | **Annualized** |
| Ice | 121.0 | 264.0 | 147.0 | 49.0 | **581.0** | **96.8** |
| Slush | 25.0 | 14.0 | 37.0 | 2.0 | **78.0** | **13.0** |
| Snowy | 15.0 | 83.0 | 952.0 | 13.0 | **1,063.0** | **177.2** |
| Dry | 3.0 | 177.0 | 14.0 | 88.0 | **282.0** | **47.0** |
| Gravel | 0.0 | 1.0 | 0.0 | 0.0 | **1.0** | **0.2** |
| Mud | 0.0 | 0.0 | 1.0 | 0.0 | **1.0** | **0.2** |
| Standing Water | 0.0 | 0.0 | 0.0 | 24.0 | **24.0** | **4.0** |
| Moving Water | 0.0 | 0.0 | 0.0 | 2.0 | **2.0** | **0.3** |
| Unknown | 0.0 | 2.0 | 0.0 | 1.0 | **3.0** | **0.5** |
| Wet | 57.0 | 88.0 | 303.0 | 6,267.0 | **6,715.0** | **1,119.2** |
| **Total** | **221.0** | **629.0** | **1,454.0** | **6,446.0** | | |
| **Annualized** | **36.8** | **104.8** | **242.3** | **1,074.3** | | |
| **Severity Type** | **Weather Type** | | | | | |
| | Sleet | Freezing | Snow | Rain | **Total** | **Annualized** |
| Fatal (K) | 0.0 | 3.0 | 4.0 | 13.0 | **20.0** | **3.3** |
| Serious Injury (A) | 3.0 | 21.0 | 18.0 | 98.0 | **140.0** | **23.3** |
| Minor Injury (B / C) | 52.0 | 146.0 | 294.0 | 1,562.0 | **2,054.0** | **342.3** |
| PDO (O) | 166.0 | 459.0 | 1,138.0 | 4,773.0 | **6,536.0** | **1,089.3** |
| **Total** | **221.0** | **629.0** | **1,454.0** | **6,446.0** | | |
| **Annualized** | **36.8** | **104.8** | **242.3** | **1,074.3** | | |

### 8.1.2 Crash Risk Location Prediction & Incident Identification

#### 8.1.2.1 Project Year Evaluation

At the basis of our project to enhance safety, we have established three objectives for the technology: send emergency responders to predict safety concern areas, send emergency responders to identified traffic incidents, and utilize other ITS devices (DMS) to share information of potential safety issues on roadways. These strategies are not only about proactive response but also about educating and alerting the public in real time to prevent incidents. This approach embodies our commitment to safety, setting the stage to explore how this integrated platform can significantly prevent or reduce crashes.

Before we dig deeper into the crash summary during the project years, it is important to note that the real-time integrated information shared to the public was not successfully achieved due to various reasons discussed later in **Section 8.4** of this document.

**Crash Risk Location Prediction tool:**

During the project years, the crash risk area tool was made available by the vendor, and it was fully integrated by the beginning of 2022. However, many constraints led MoDOT to not act on any of the CRA predictions, such as low staffing challenges and low accuracy levels from each CRA at the on-set of the project. Every quarter, from February 2022 until October 2023, monthly verifications were completed, and the most recent one presented a 10.9% accuracy on CRA predicting crashes in the correct direction. Since no action was taken during the project timeline, our team researched potential crash reduction numbers for a potential future implementation based on police deployment while taking in consideration varying accuracy levels on the technology's CRA prediction performance. Calculation and results of this research is explained in **Section 8.1.2.2.**

**Incident Identification Tool:**

As mentioned earlier, the incident identification tool was fully integrated by the end of 2021 and was fully active during the last years of the project (2022-2023). With that said, our team researched the crash history of the last five years and investigated if there was a relevant change in crash occurrences with the technology implemented. A slight increase of 36 crashes was observed from 2021 to 2022, however from 2022 to 2023 a significant drop was seen, registering 162 less crashes. Notably, the crash rate in the area during 2021-2022 was higher than the reported crash rate for the Saint Louis district. Various factors, including construction activities in the area during that period, may have contributed to these trends. **Figure 20** illustrates that and puts into context the total number of crashes that occurred each year taking only in consideration the project study area (I-270 between MO-67 and MO-367).

Multiple variables come into play when analyzing fluctuations in the total number of crashes along a busy interstate segment like I-270. While certain assumptions can be made, quantifying the precise impact of the incident identification tool on these crash figures remains elusive. It is widely acknowledged that during construction phases, crash rates tend to rise. On the other hand, the global pandemic had a substantial impact on societal behavior overall, which probably played a role in the crash statistics, especially during 2020 and 2021.

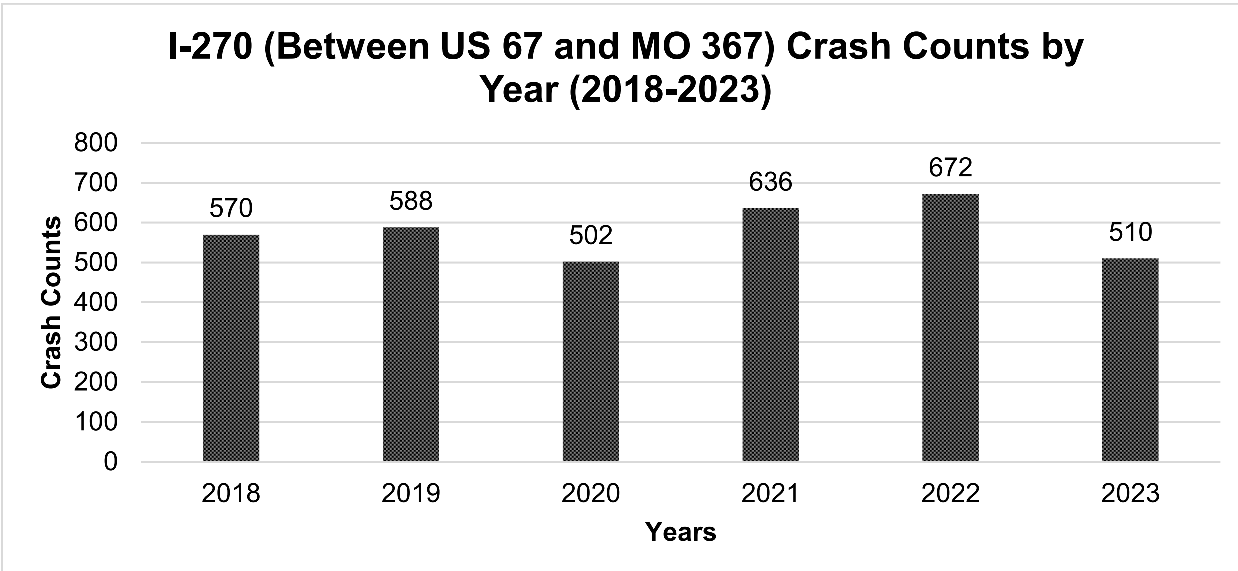


**Figure 20: I-270 (Project Segment Only) Total Crashes by Year**

**Figure 21** and **Figure 22** expand on the yearly crash numbers and delve deeper into the severity of each of those. It is observed that serious injury crashes increase from 2021 to 2022. In contrast, almost all severity types experienced a significant decrease in the total number from 2022 compared to 2023.

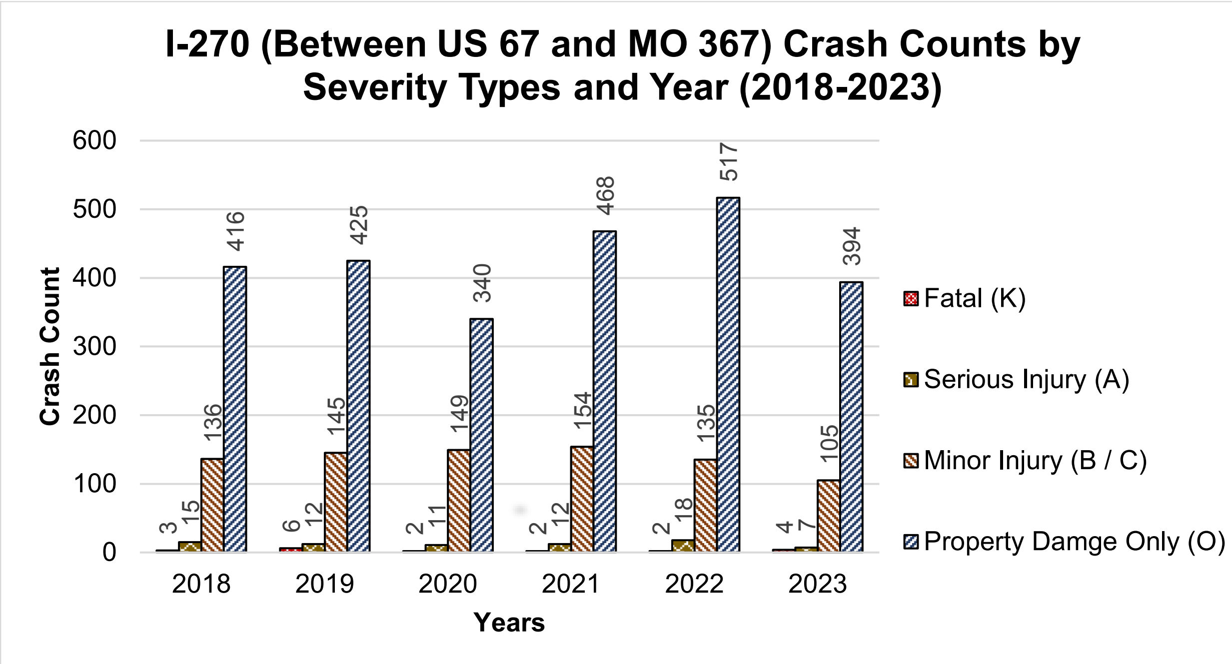


Figure 21: I-270 (Project Segment Only) Total Crashes by Severity Rating and Year

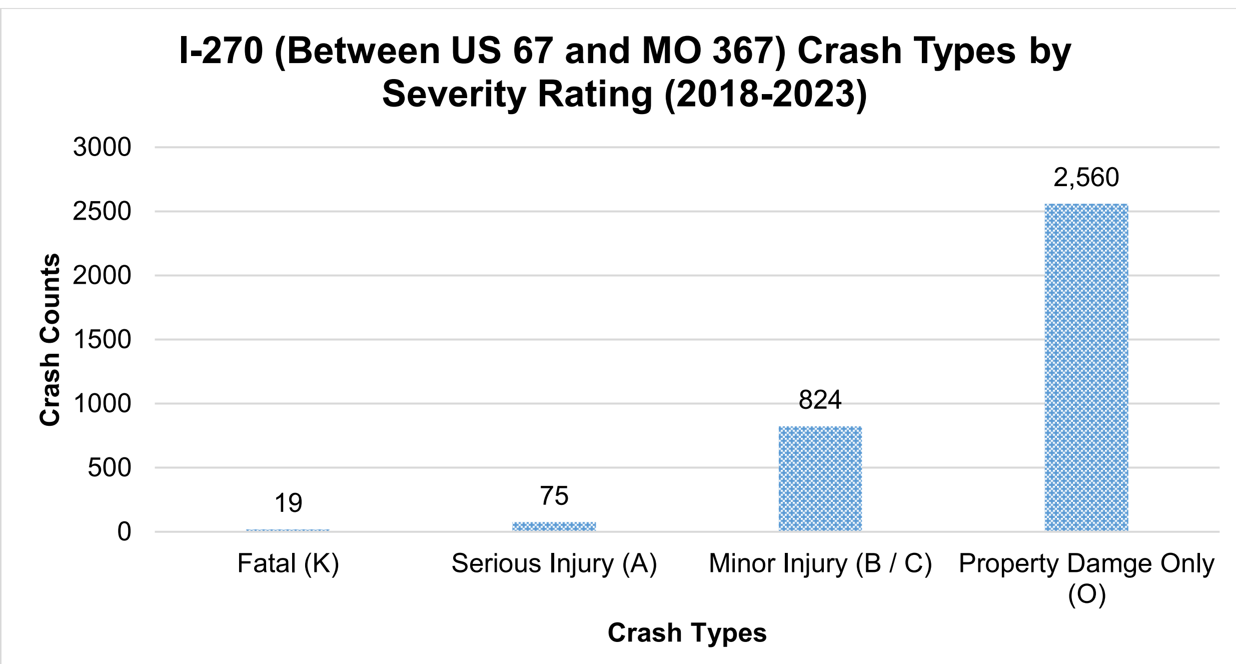


Figure 22: I-270 (Project Segment Only) Sum of Total Crashes by Severity Rating (2018-2023)

One crucial aspect of the project involved piloting the use of tablets to deliver real-time information to emergency response (ER) operators in the field. The goal was twofold: to improve decision-making and expedite response times. Additionally, these tablets aimed to streamline activity reporting by ER operators. However, the implementation faced challenges, notably with geolocation accuracy in the software. **Figure 23** demonstrates how the ER response is exhibited in the technology's Incident Identification platform, on the activity log tab inside of each incident. Our team conducted further research and identified a total of 62 accident-related incidents where the tablet implementation was in place. These incidents spanned across three years: 39 in 2020, 15 in 2021, and 8 in 2022. On average, ER mitigation took 12 minutes and 46 seconds during this period. **Table 13** provides a glimpse into a subset of incidents classified as "accidents." It highlights how the tablet directly informed users with precision, particularly regarding the ER team's time spent on each task.

It should be emphasized that the tablet deployment throughout the project served as a trial phase and did not constitute a comprehensive, full-scale rollout, as they were used for only a small fraction of the time relative to the total number of incidents. Despite various obstacles affecting consistent usage, operators identified potential enhancements. If these improvements are implemented, tablets could significantly enhance emergency response times which will lead to a projected reduction in secondary crashes and an overall boost in safety. As a lesson learned on this project, some agencies/municipalities were not willing/able to incorporate tablets due to low staff and budget constraints. Many municipalities cover principal arterials but not interstates, which also affected the overall performance and usage of the tablets.

On a qualitative note, feedback was gathered from the operators who evaluated Crash Risk Location Prediction & Incident Identification platform with the tablets on the field and highlighted need for improvements, such as the introduction of audible alerts to aid those driving in the field. Additional details on Operator's feedback are described in **Appendix B: Operator Interview Notes.**

4515948 | Crash | Primary

## I-270 170

SOURCE

| | |
|---|---|
| **Created by:** | smithrg |
| **Reported by:** | N/A |

TIME & LOCATION

| | |
|---|---|
| **Start time:** | Apr 27, 2022 03:31:26 PM |
| **End time:** | Apr 27, 2022 10:05:23 PM |
| **Duration:** | 06:33 |
| **Corridor:** | I-270 |
| **Direction:** | EB |
| **Orientation:** | at |
| **Crossroad:** | 170 |
| **Mile marker:** | 26 |
| **Road type:** | Freeway |
| **Affected lanes:** | Right shoulder; 3, Right lane; 2, Central lane; 1, Left lane; Left shoulder |
| **Latitude:** | 38.77648970567748 |
| **Longitude:** | -90.3453539889549 |

RESPONSE

| | |
|---|---|
| **First unit arrival time:** | Apr 27, 2022 04:02:38 PM |
| **Time between discovery to first unit arrival:** | 00:00 |
| **Time between first unit arrival to road clearance:** | 00:00 |
| **Time between road clearance to incident completion:** | 00:00 |
| **Associated units:** | 9758 ER - Accident |

IMPACT

| | |
|---|---|
| **Injuries:** | N/A |
| **Fatalities:** | N/A |
| **Involved vehicles:** | dark-grey Dodge , Private Licence no. Zpr9057, PA , white Dodge , Private Licence no. 3fbn32, MO |

MORE DETAILS

| | |
|---|---|
| **Additional info:** | Attached Ribbon, Tag Sticker |
| **Notes:** | 2 vehicle crash 2 injuries 2 tows No state damage Leaving vehicles for future tow |
| **End reason:** | Incident resolved |
| **End reason comment:** | N/A |

**Figure 23: Screenshot of Incident Identification Platform indicating ER response times into the Activity Log**

**Table 13: Sample ER Response Time from the Incident Identification platform during Tablet Implementation**

| Incident Identification ID | ER Response | ER Mitigation Time | Elapsed Time on Scene | Incident Type |
|---|---|---|---|---|
| 4515948 | 16:02 | 16:03 | 0:01 | Crash |
| 3911929 | 6:33 | 6:36 | 0:03 | Traffic Control for Tow Changing a Flat. |
| 3885821 | 6:53 | 6:55 | 0:02 | Abandoned vehicle |
| 3867643 | 9:35 | 9:39 | 0:04 | Stalled vehicle |
| 3858640 | 10:58 | 11:00 | 0:02 | Stalled vehicle |
| 3855906 | 6:49 | 6:53 | 0:04 | Stalled vehicle |
| 3845740 | 6:46 | 6:48 | 0:02 | Mechanical issue |
| 3845684 | 6:38 | 6:42 | 0:04 | Abandoned vehicle |
| 3789242 | 5:53 | 5:55 | 0:02 | Abandoned vehicle |
| 3913949 | 9:32 | 9:37 | 0:05 | Stalled vehicle |
| 3782800 | 9:53 | 10:17 | 0:24 | Stalled vehicle/ Flat Tire |
| 3780671 | 6:47 | 6:50 | 0:03 | Stalled vehicle/ Flat Tire |
| 3755514 | 6:32 | 6:50 | 0:18 | Crash |
| 3746762 | 7:30 | 7:34 | 0:04 | Stalled vehicle/ Flat Tire |
| 3746309 | 6:44 | 6:48 | 0:04 | Stalled vehicle/ Flat Tire |
| 3746230 | 6:39 | 6:40 | 0:01 | Abandoned vehicle |
| 3721452 | 9:45 | 9:47 | 0:02 | Abandoned vehicle |
| 3673461 | 8:35 | 8:50 | 0:15 | Stalled vehicle/ Out of fuel |
| 3782527 | 9:45 | 9:47 | 0:02 | Abandoned vehicle |
| 3914485 | 10:18 | 10:30 | 0:12 | Stalled vehicle/ Flat Tire |

#### *8.1.2.2 Future Implementation Projection*

Drawing from the insights gained through experience with these technologies over the project years, we will shape our future implementations. Our focus remains on safety and operational efficiency, and we are committed to applying lessons learned to enhance road safety.

The project team embarked on an in-depth analysis of historical crash data to discern patterns based on severity types within the project area. Specifically, this study focused on all interstates within the City of St. Louis, St. Louis County, and St. Charles County (approx. 237 centerline miles). The primary objective was to identify existing crash trends, which would inform future prediction efforts. To achieve this, the team leveraged the MoDOT crash statistics map online viewer, extracting data spanning the years 2018 to 2023. To mitigate any bias stemming from reduced crash incidents during the COVID-19 pandemic in 2020-2021, the team incorporated data from prior years (2018 and 2019) for comparison and to establish a baseline.

It is important to note that the analysis exclusively considered crashes occurring on interstates and excluded local crashes observed in other functional classes. Additionally, the study explored the impact of newer technologies by examining historical patterns on both weekdays and weekends. The findings are summarized in **Table 14**, which encompasses all crashes regardless of the time of the week. **Table 15** and **Table 16** provide insights into crash patterns specifically during weekdays and weekends, respectively. The crash severity type definitions are sourced from the Model Minimum Uniform Crash Criteria (MMUCC), a voluntary guideline established by the National Highway Traffic Safety Administration (NHTSA, 2017).

**Table 14: Crash Summary along all interstates (2018-2023)**

| All Interstates (St. Louis and St. Charles County, St. Louis City) | | | |
|---|---|---|---|
| **Crash Type** | **Total** | **Annualized** | **% of Total** |
| Fatal (K) | 256 | 42.7 | 0.40% |
| Serious Injury (A) | 1,260 | 210.0 | 1.99% |
| Minor Injury (B / C) | 13,787 | 2297.8 | 21.81% |
| Property Damage Only (O) | 47,909 | 7984.8 | 75.79% |
| **Total** | **63,212.00** | **10,535.33** | **100%** |

**Table 15: Crash Summary along all interstates (Weekdays Only, 2018-2023)**

| All Interstates (Weekdays) | | | |
|---|---|---|---|
| **Crash Type** | **Total** | **Annualized** | **% of Total** |
| Fatal (K) | 169 | 28.2 | 0.34% |
| Serious Injury (A) | 856 | 142.7 | 1.73% |
| Minor Injury (B / C) | 10,378 | 1729.7 | 20.93% |
| Property Damage Only (O) | 38,177 | 6362.8 | 77.00% |
| **Total** | **49,580.00** | **8,263.33** | **100%** |

**Table 16: Crash Summary along all interstates (Weekends Only, 2018-2023)**

| All Interstates (Weekends) | | | |
|---|---|---|---|
| **Crash Type** | **Total** | **Annualized** | **% of Total** |
| Fatal (K) | 87 | 14.5 | 0.64% |
| Serious Injury (A) | 404 | 67.3 | 2.96% |
| Minor Injury (B / C) | 3,409 | 568.2 | 25.01% |
| Property Damage Only (O) | 9,732 | 1622.0 | 71.39% |
| **Total** | **13,632.00** | **2,272.00** | **100%** |

**Crash Risk Location Prediction**

Drawing on the comprehensive data collected on interstate crashes across the City of St. Louis, St. Louis County, and St. Charles County, Crash Risk Location Prediction technology was strategically integrated to accelerate the incident identification process, detailed in **Section 8.2**, and predict crashes along the interstate corridors. By analyzing trends and identifying high crash risk areas, the platform aimed to alert agencies/users of the platform to ultimately achieve the reduction of crash incidents through targeted interventions and real-time information dissemination.

The objective was to quantify the benefits associated with reduced accidents. Our starting point was the crash prediction tool, which demonstrated stability and accuracy in its October 2023 version based on prior verification.

To establish CRA event frequency, we examined the average number of reported events across different days of the week (refer to **Figure 24**). Notably, most events occurred on weekdays, with fewer observed during weekends. Our verification results indicated that these predictions were accurate approximately 10.9% of the time. **Table 17** outlines the average event distribution for weekdays and weekends. The predicted number of events varied between 5 and 18 per day. For our analysis, we assumed that MoDOT could coordinate with nearby law enforcement authorities and deploy 5 patrol vehicles daily to patrol high-risk crash areas. We conservatively estimated that crash risk areas could be patrolled in up to 30% of the predicted cases.

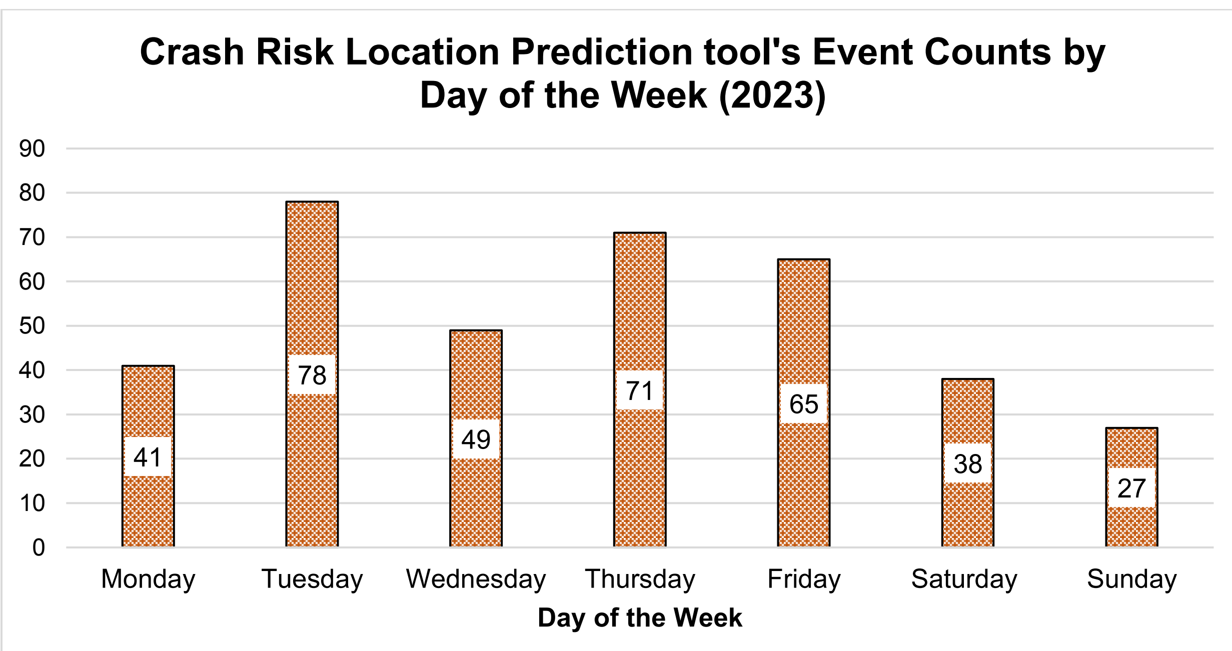


**Figure 24: Event Counts by Crash Risk Location Prediction Tool (October 2023)**

**Table 17: Determining Average Number of Events Reported Per Day by Crash Risk Location Prediction Technology**

| October 2023 Crash Risk Location Prediction/ CRA Event Summary* | | | | | |
|---|---|---|---|---|---|
| **Day of the Week** | **Oct 2023 Total CRA** | **Peak Hr CRA** | **Off-Peak Hr CRA** | **Avg CRA Events Per Day** | **Off-Peak Hr (Per Day)** |
| Saturday | 38 | 11 | 27 | 9.5 | 6.8 |
| Sunday | 27 | 7 | 20 | 5.4 | 4 |
| Monday | 41 | 17 | 24 | 8.2 | 4.8 |
| Tuesday | 78 | 45 | 33 | 15.6 | 6.6 |
| Wednesday | 49 | 22 | 27 | 12.3 | 6.8 |
| Thursday | 71 | 35 | 36 | 17.8 | 9 |
| Friday | 65 | 23 | 42 | 16.3 | 10.5 |

** 5 Sunday-Monday-Tuesday in October 2023*

*** Being conservative; more police deployment can be expected during off-peak*

In our comprehensive analysis, we not only examined the predicted frequency of crash events and projected scenarios for police deployment but also calculated the potential costs associated with their presence. Our approach involved considering various deployment scenarios, ranging from 0% to 30%. Notably, a study conducted in Nashville demonstrated a 20% reduction in crashes due to police patrols in areas with a history of high crash incidents. To quantify the benefits, we developed multipliers that itemize crash reductions as well as other benefits attributed to each software individually. By combining these, we arrived at a comprehensive assessment of the total crash reduction potential.

**Figure 25** and **Figure 26** illustrate the anticipated crash reduction annually based on these percentages during weekdays and weekends. Beyond verified cases, we explored scenarios where Crash Risk Location Prediction technology could be less or more productive. Our analysis analyzed CRA prediction accuracy from 5% to 20%.

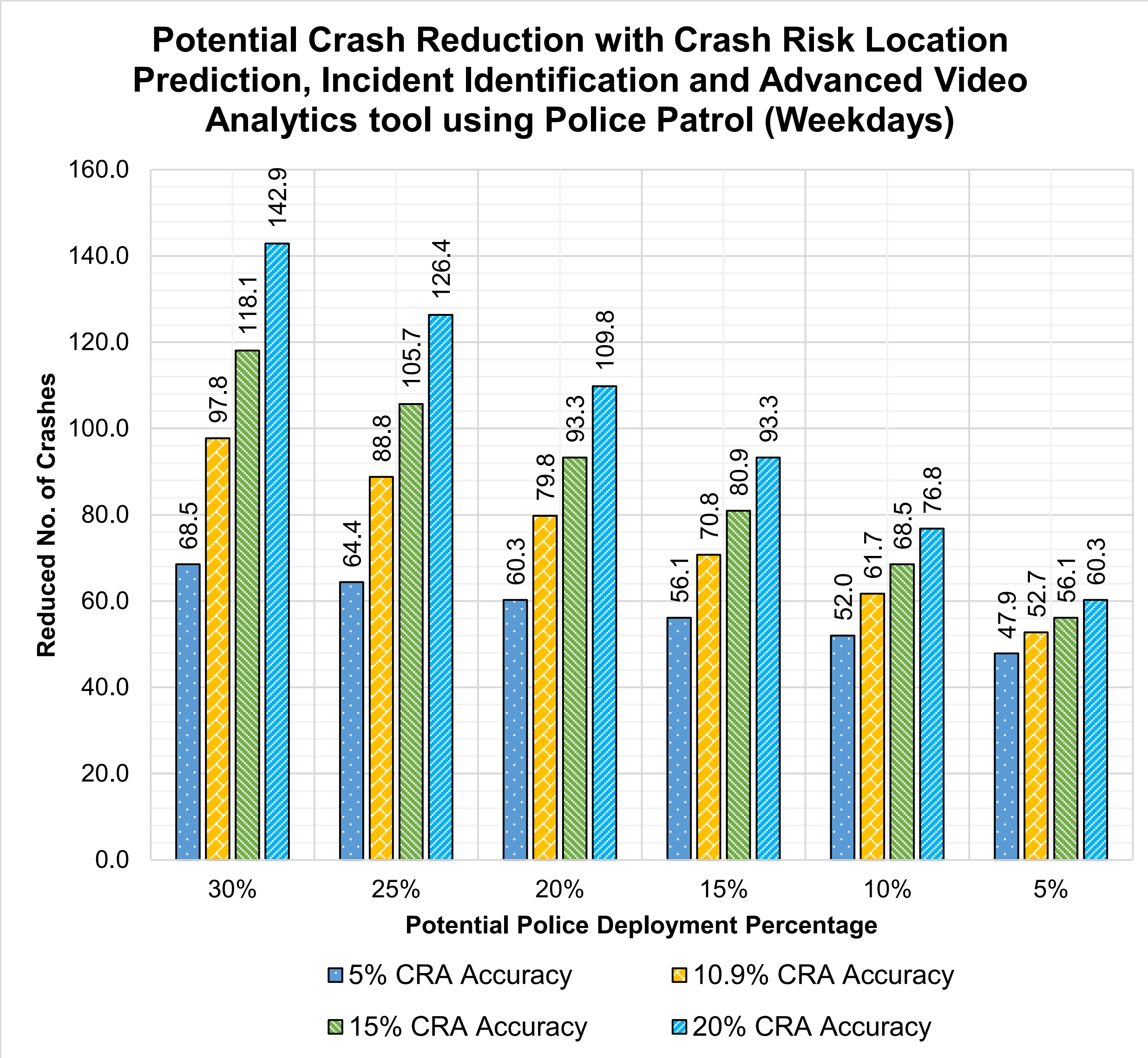


**Figure 25: Potential Crash Reduction with Crash Risk Location Prediction, Incident Identification and Advanced Video Analytics tool using Police Patrol (Weekdays)**

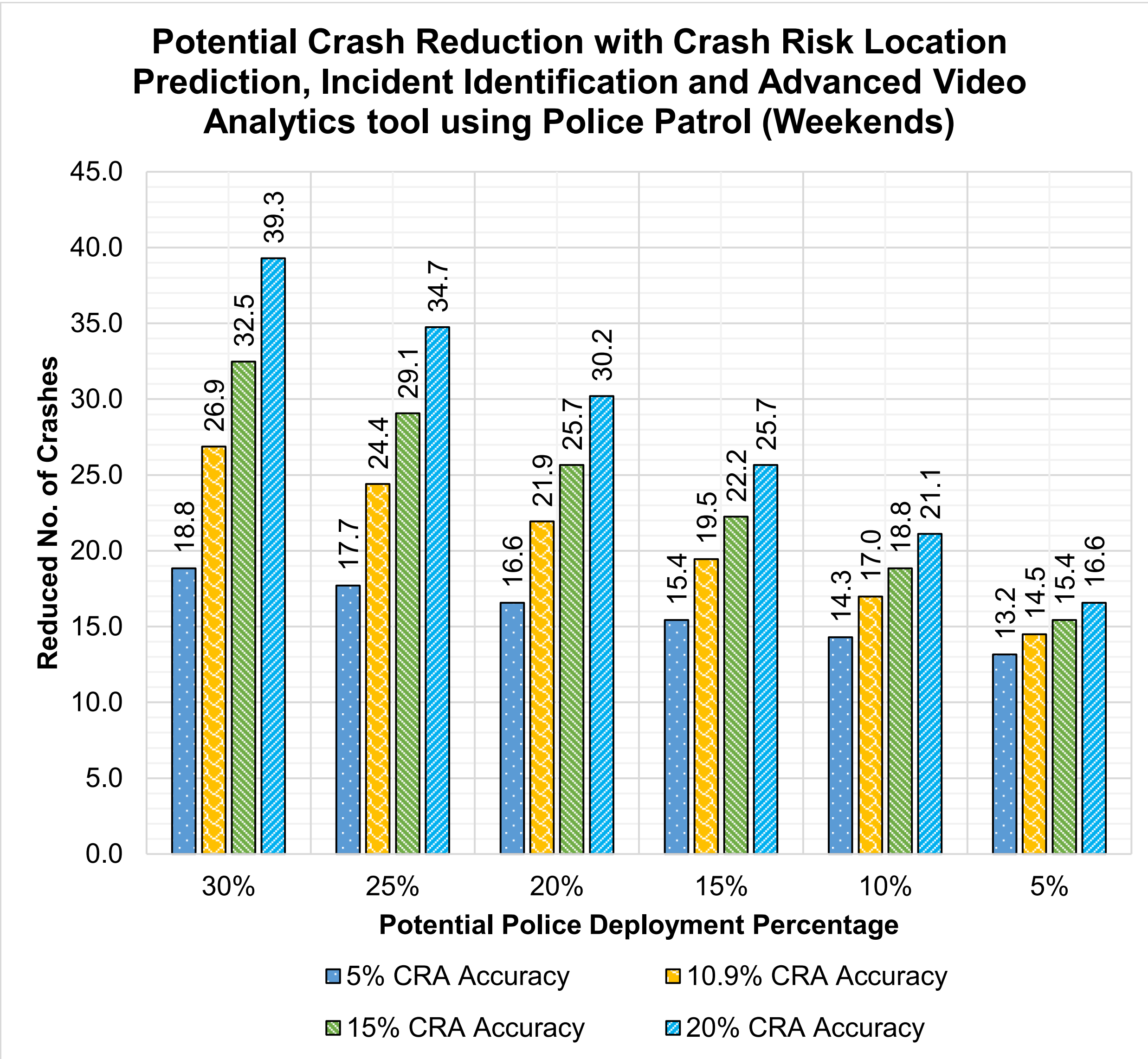


**Figure 26: Potential Crash Reduction with Crash Risk Location Prediction, Incident Identification and Advanced Video Analytics tool using Police Patrol (Weekends)**

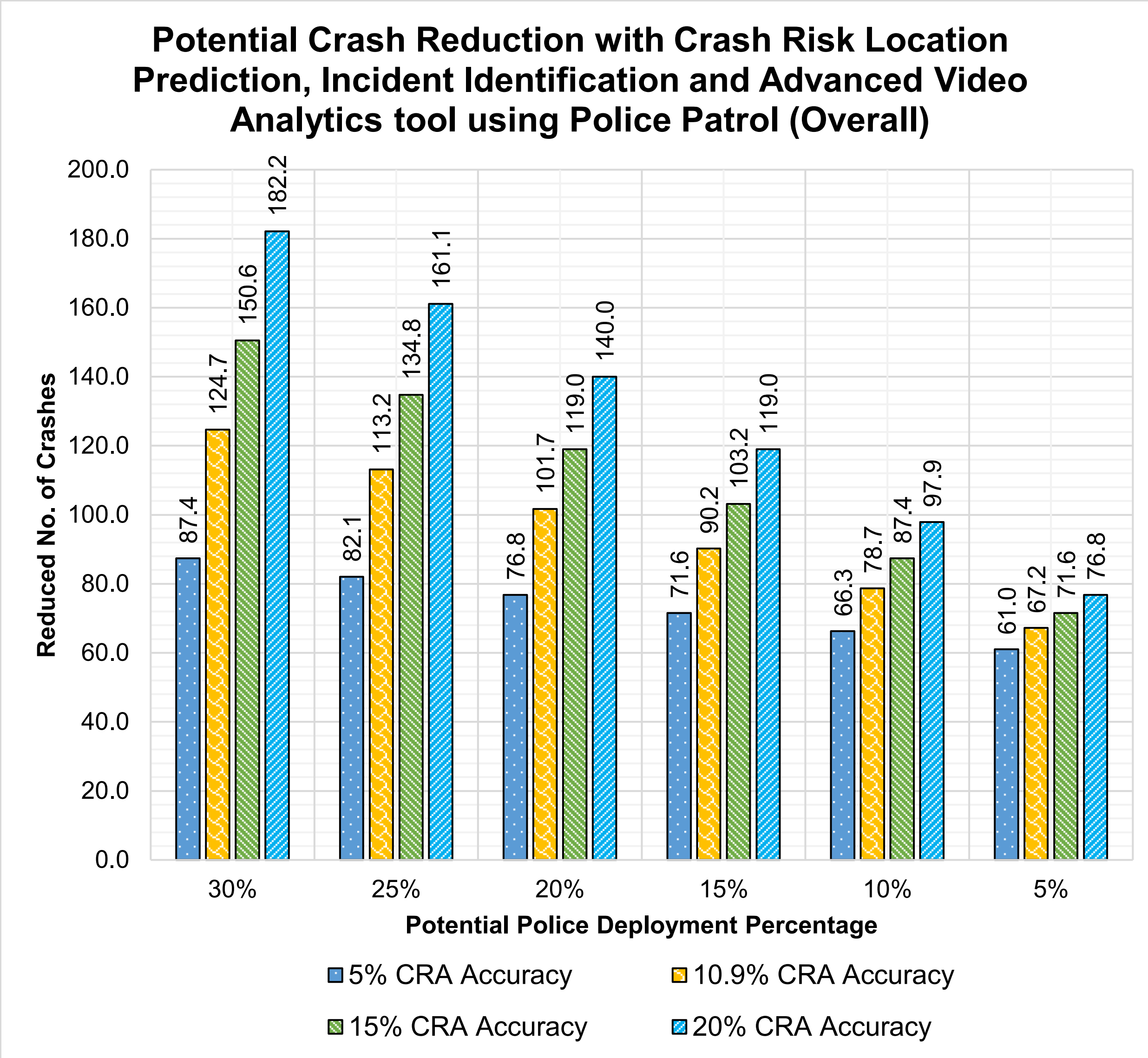


**Figure 27: Potential Crash Reduction with Crash Risk Location Prediction, Incident Identification and Advanced Video Analytics tool using Police Patrol (Overall)**

Additionally, we also identified the total number of potential crash reduction in cases when patrol will be available for all days of the week. **Figure 27** shows the crash reduction considering patrol presence throughout the entire week. For example, if there are 15 CRA events occurring daily, it is estimated that approximately 30% of these events can be effectively intercepted by law enforcement personnel. This would result in approximately 5 CRA's that would receive intervention by police. Then taking into account the 20% accuracy rate of the CRA prediction technology, it would result in 1 CRA where a crash would have actually occurred and could be prevented using the police intervention and mitigation efforts. Calculations based on these scenarios show the potential annual reduction in crashes would amount to 182.2 incidents.

However, if the technology's accuracy is limited to only 5%, the anticipated daily crash reduction would fall to around 87.4 incidents. This reduction of 182.2 crashes indicates a significant improvement, equivalent to 1.73% of the total annual crash reduction (10,535.3 crashes annually, as referenced in **Table 14**) within the study area. Notably, 25% of this reduction corresponds to crashes classified as 'Fatal and Injury' (FI).

To conclude, the analysis of crash reduction data aimed to inform potential police deployment strategies. However, throughout the project, actionable CRA insights presented on the Crash Risk Location Prediction platform were not acted upon at this time due to several factors, including the CRAs' low accuracy and limited staff availability to respond. The project team determined it would be more beneficial to perform this evaluation before engaging police coordination discussions. It is important to highlight that these scenarios are only based on Saint Louis area and would have different impact in another region.

### *8.1.3 Advanced Video Analytics*

Advanced Video Analytics data were thoroughly evaluated by our team every quarter. This platform can provide alerts in six categories: Slow Speeds, Congestion, Stopped Object/Vehicle, Pedestrian, Low Visibility, and Wrong-Way alerts. However, due to MoDOT's camera limitations, the Wrong-Way feature was inoperative, as it requires cameras to be static, leaving us with five functional alert categories.

The objectives set for Advanced Video Analytics were to detect multiple different scenarios, such as congestion on roadway, pedestrian movement on the interstates, stalled vehicles on the side of the road, and miscellaneous objects obstructing the road. **Figure 28** shows the monthly average number of alerts produced during the verification months (February, April, July, and October) by Advanced Video Analytics in 2022 separated by each of those five active categories. Due to the significant time investment required for monthly verification, we opted to conduct verification for one month out of each quarter rather than completing a full-year verification. **Figure 29** represents those same metrics performed in 2023 during the months of January, April, July, and October.

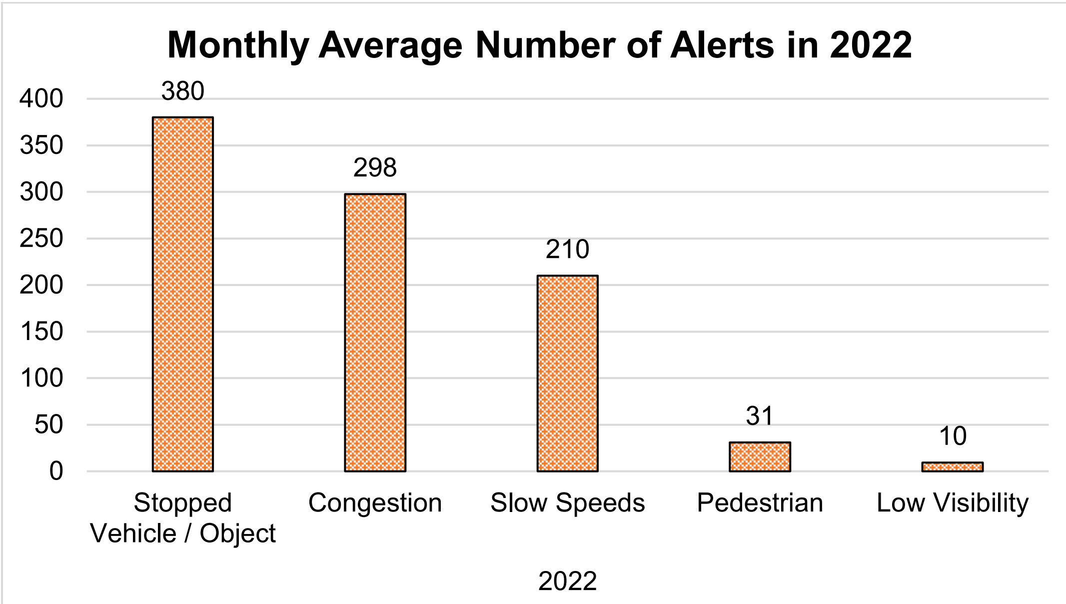


**Figure 28: Monthly Average Counts by Advanced Video Analytics (2022)**

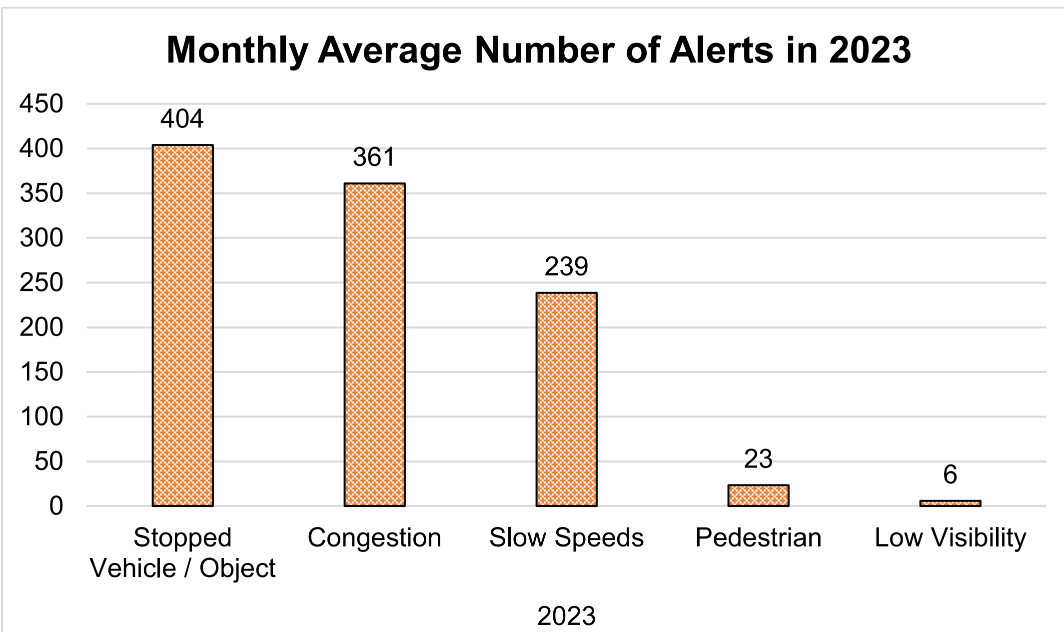


**Figure 29: Monthly Average Counts by Advanced Video Analytics (2023)**

Note that these numbers do not reflect on the entire year and only for the combinations of the months when verification were completed. The verification process has confirmed the high accuracy of incident detection. **Figure 30** and **Figure 31** illustrates the percentage of alerts that were considered accurate. These incidents, particularly in identifying pedestrians, play a crucial role in daily operations, demonstrating the technology's reliability and its contribution to improving safety conditions.

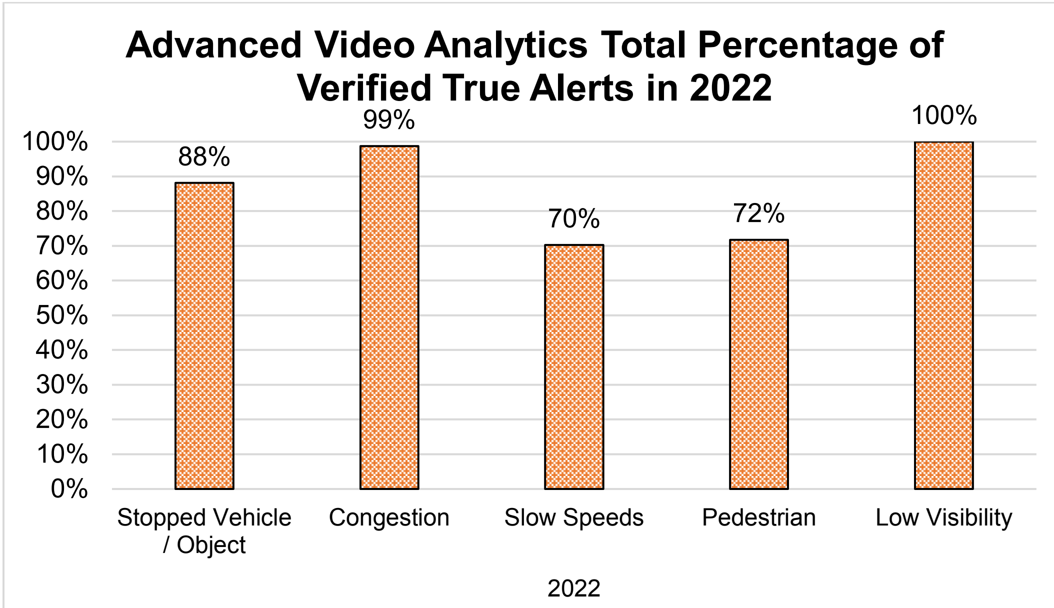


**Figure 30: Advanced Video Analytics Total Percentage of Verified True Alerts in 2022**

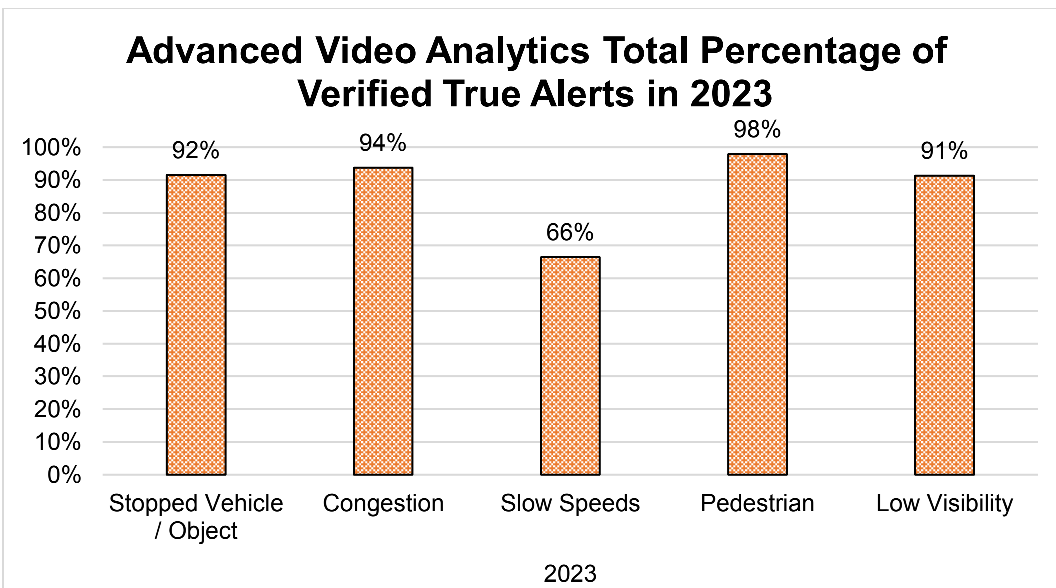


**Figure 31: Advanced Video Analytics Total Percentage of Verified True Alerts in 2023**

**Figure 30** and **Figure 31** exemplify numbers that do not reflect on the entire year and only for the combinations of the months when verification was completed.

For each of those alert types, TMC operators act differently. For congestion or slow speeds, TMC operators carefully analyze traffic against expected patterns. When traffic congestion deviates from the norm, operators investigate deeper, using additional tools to identify potential causes, such as crashes, which might be disrupting the flow. This meticulous approach helps in distinguishing between routine slowdowns and those requiring intervention.

When pedestrian incidents are alerted, operators promptly notify law enforcement for each incident. The outcomes of these alerts vary, and in some cases, the pedestrian may no longer be present when police arrive. This process ensures immediate attention to potential safety hazards, though the final resolution of each case often remains unknown. **Figure 32** illustrates an example of a pedestrian alert which had the potential to create other alerts such as congestion and/or stopped object/vehicle alert depending on the pedestrian activity, which cannot be predicted. Any instance a pedestrian gets closer to an interstate, any movement or interaction with the vehicles on the road can result in negative consequences for all users.


**Figure 32: Screenshot of a Pedestrian Alert from Advanced Video Analytics platform**

When alerts show stopped objects on the roadway, operators act promptly, especially if there's a possibility of a crash. Emergency response teams are dispatched to assess and manage the situation. This protocol has proven effective in quickly addressing incidents, demonstrated by cases where crashes led to stopped object alerts, prompting immediate on-site responses.

The total average monthly alert number for 2022 was 929, from those 55% were related to Congestion + Slow Speeds, 41% Stopped Object/Vehicle, and 3% as pedestrians. In 2023 was observed an average of 1,033 total alerts, 58% being Congestion + Slow Speeds, 39% Stopped Object/Vehicle, and 2% as pedestrians. Taking these numbers into consideration and their confidence levels portrayed in **Figure 30** and **Figure 31**, and their qualitative benefits to the operators, we can affirm with confidence that they play a role into the faster incident identification time proved in the multiple verifications done throughout the project.

Combined efforts of the Incident Identification tool and Advanced Video Analytics achieved earlier incident notifications in 45% of the incidents. This percentage was found by taking the average of the verification months completed in 2023 which gives us 46.8% to be exact, however our team decided to err on the side of caution and use 45% for all calculations to account for variability and minimize risks. Data from the beginning of 2022 was still adapting and was not optimally producing results during this adjustment period. Moreover, taking account only the incidents that were reported first by Incident Identification tool on those verification months and converting them into an average, our team reached a conclusion of a median time saving of 10 minutes per incident (Refer to **Table 18**).

FHWA statistics proved that there is a correlation between the emergency response reaching to the accident faster and the projected reduction of secondary crashes which are later explained in detail in **Section 8.2.1**. These crash reduction numbers are directly tied to the potential crash reduction illustrations in **Figure 25, Figure 26,** and **Figure 27.**

In summary, Advanced Video Analytics significantly enhances the capabilities of TMC operators. It aids in identifying potential scenarios that may lead to future accidents and assists in recognizing incidents that have not yet been addressed. While the exact impact of each alert type remains to be precisely quantified due to the concurrent use of Advanced Video Analytics alongside other tools, the accuracy and usefulness of these alerts are evident. Operators have seamlessly integrated them into their daily workflows, indicating an overall positive influence on safety across corridors.

## 8.2 Improve MoDOT Emergency Response (ER) Response Time

### *8.2.1 Crash Risk Location Prediction & Incident Identification*

With the aim of enhancing MoDOT's Emergency Response (ER) times, this project strategically leveraged Incident Identification technology. The project objectives included detecting abnormal congestion on roadways to promptly dispatch responders, reducing response times based on identified incidents, and predicting crashes to facilitate rapid response. These goals underscore MoDOT's unwavering commitment to harnessing advanced technology for enhanced safety and operational efficiency on the roads.

In this context, our team explored the efficacy of incident identification and CRA tool affecting the ER response time and were able to tie the results in time savings to projected secondary crash savings. Notably, Incident Identification tool has the capacity to reduce the first recorded crash awareness time, T1 (See **Figure 3**). Our verification results, as shown in **Table 18**, highlight the effectiveness of the technology's real-time notifications compared to ATMS (Advanced Traffic Management System). Based on the average of the verification results in 2023, Incident Identification notifications were observed to precede 45% of verified ATMS events. These timely alerts played a critical role in providing operators with significant time savings, allowing for swift notification of incident responders. As a result, it was anticipated that lane clearance was expedited, which was anticipated to lead to a projected reduction in secondary crashes and travel delays. Specifically, Incident Identification tool achieved earlier incident notifications in 45% of the cases, with a median time saved of 10-minutes (See **Table 18**).

**Table 18: Determination of Time Savings Relative to Incidents Reported First by Incident Identification Tool During Verification Months in 2022-2023**

| Verification Year | Month | % of time Incident Identification tool reported first | Average minutes reported first (mm:ss) |
|---|---|---|---|
| **2022** | February | 40.80% | 11:53 |
| | April | 43.50% | 7:10 |
| | July | 41.80% | 7:55 |
| | October | 54.10% | 8:08 |
| **2023** | January | 51.20% | 7:41 |
| | April | 45.90% | 13:26 |
| | July | 49.10% | 15:50 |
| | October | 48.00% | 9:03 |
| | | **Median Time Saved** | **10:00** |

** The "Average minutes reported first" column represents average difference in time between when the Incident Identification Tool first reported the incident versus the ATMS*

Our analysis draws upon crash data from the Missouri Department of Transportation (MoDOT), which revealed that approximately 4.2% of all crashes were projected to be secondary. Moreover, for every minute saved, overall crash rates can be reduced by 2.8%. Taking all of this into consideration, the future potential of crash reduction was compiled and combined with CRA crash reduction capabilities and Advanced Video Analytics tool, which were illustrated and summarized in **Figure 25**, **Figure 26**, and **Figure 27**. Lastly, regarding the objective of detecting unusual roadway congestion, the technology was equipped to alert us to uncommon traffic patterns, however our focus shifted primarily to utilizing Advanced Video Analytics for congestion detection. Incident Identification tool's capabilities in this area were not explored.

### *8.2.2 Advanced Video Analytics*

Improving ER response time is one of the benefits that Advanced Video Analytics provides alongside Incident Identification tool. These technologies significantly improved the speed and accuracy of information available to TMC and ER operators, enabling quicker and more effective road clearance actions.

A detailed evaluation of Advanced Video Analytics data provided real-time alerts across multiple scenarios, enhancing situational awareness. Despite challenges like camera limitations for the Wrong-Way alert, the overall impact was substantial in reducing response times while minimizing projected secondary crashes. The combination of technologies allowed for quicker notification and mobilization of incident responders, leading to faster lane clearance. This expedited response not only minimized projected secondary crashes but also lessened travel delays.

Similar to what was mentioned in **Section 8.1.2**, the efficacy of the Incident Identification tool combined with Advanced Video Analytics tool in delivering earlier incident notifications was observed in 45% of cases on average, with a median time saved of 10-minutes per incident (Refer to **Table 18**). According to MoDOT crash data, roughly 4.2% of all crashes were observed to be secondary throughout the interstate corridors in the Saint Louis District. Furthermore, it is estimated that for every minute of response time saved, the overall crash rate can be reduced by 2.8%. By integrating the crash reduction capabilities of the CRA prediction tool with Incident Identification tool, and Advanced Video Analytics tool, we demonstrated a clear path to significantly reduce crash rates.

While Incident Identification technology was initially considered for alerting to uncommon traffic patterns, the project's focus ultimately gravitated towards leveraging Advanced Video Analytics more extensively for congestion detection. The combined use of Incident Identification tool with Advanced Video Analytics has undeniably advanced MoDOT's ability to manage emergency responses more effectively and its future potential of crash reduction is portrayed in **Figure 25, Figure 26,** and **Figure 27**, tying to the first project goal, ultimately improving roadway safety and efficiency.

## 8.3 Reduce Congestion / Improve Mobility

### *8.3.1 IMRCP*

The project goal to reduce projected congestion and to improve mobility was aimed at enhancing road efficiency and traffic flow. Mainly, to reach this goal, the team set the objective to develop an operations and maintenance plan in response to weather issues, as identified by the IMRCP.

Addressing the question of whether the plan effectively organized staff and materials, IMRCP did provide a "Scenario Manager/Tools" which is intended to support the decision-making during the planning process. It is designed to facilitate the organization of staff and optimize the use of materials, although quantifying this effect proved challenging.

Qualitatively, the information provided by the IMRCP technology was valuable; however, the practical application of the scenario tool during winter weather events highlighted some operational challenges. Not only did the lack of winter events imposes difficulties to implement the technology, but also maintenance engineers found it difficult to quickly recall how to use the scenario tool and interpret the IMRCP's outputs effectively in a short time span. This highlights the need for further training and possibly tool refinement to ensure that the benefits of the IMRCP can be fully leveraged during adverse weather conditions.

### *8.3.2 Crash Risk Location Prediction & Incident Identification and Advanced Video Analytics*

The objectives designed for this project goal effectively ties into what was mentioned in **Section 8.2.** This initiative notably anticipates the potential reduction of delays and congestion in the study area. The application of Crash Risk Location Prediction & Incident Identification tool combined with Advanced Video Analytics advanced video analytics, anticipates an enhancement on emergency response times, leading to time savings that directly anticipates a projected decrease in secondary crashes.

Echoing the findings presented in **Section 8.1.2**, the integration of Advanced Video Analytics with the Incident Identification tool has been instrumental in improving mobility by achieving earlier incident notifications in 45% of cases on average, translating to a median time saving of 10-minutes per incident (Refer to **Table 18**). Leveraging MoDOT crash data, our team found that that 4.2% of all crashes throughout the interstate corridors in the Saint Louis District were secondary, and another study showed that every minute reduced in emergency response can lead to a 2.8% decrease in the overall crash rate, which reiterates the importance of every minute saved.

The grouping efforts from Crash Risk Location Prediction tool as well as Incident Identification tool, and Advanced Video Analytics not only exemplifies a significant effort towards minimizing crash rates but also reinforces the project's commitment to mitigating congestion and improving mobility. The collaborative deployment of these technologies provide future potential of crash reduction is portrayed in **Figure 25, Figure 26,** and **Figure 27.**

## 8.4 Improve Effectiveness of Real-Time Integrated Transportation Information

### *8.4.1 IMRCP, Crash Risk Location Prediction & Incident Identification, and Advanced Video Analytics*

The improvement of the effectiveness of real-time integrated transportation information to the public is of extreme importance and some forms of communication are already in place using DMS boards, MoDOT's traveler map, and social media outlets. The intent is to keep improving on pushing accurate information to the road user and best inform the community, helping on better decision-making and by consequence enhancing safety and efficiency on the road. By implementing mobile RWIS on maintenance vehicles, predicting crashes in roadways, and providing operators with automated insights from video analytics, the initiative intended to create a cohesive and comprehensive real-time data ecosystem.

These efforts respond to the critical question of how the integration of advanced technologies can significantly improve the information conveyed to travelers, aiming to mitigate risks and optimize the transportation experience. Despite the ambitious goal of achieving real-time integration of all technologies from the project's inception, unforeseen challenges emerged. Time constraints, changes in the Advanced Traffic Management System (ATMS) vendor, and the unprecedented impact of the COVID-19 pandemic negatively impacted on the implementation of technologies into a unified platform. This initiative was considered as pilot years and served as testing phase to these technologies. Information was carefully verified during this period; however, the information was not pushed to the public as caution to not spread any data that could not be provided confidently.

This project proved the complexity associated with executing extensive technological integrations within transportation networks. Despite these complexities, the years dedicated to the project have demonstrated significant enhancements in precision, particularly evident with the Crash Risk Location Prediction tool. Looking ahead, this progress suggests a promising future where the reliability of the information generated by these tools is expected to be highly regarded, with increased confidence in disseminating this data to the public.

### *8.4.2 Operator Acceptance*

The operators are the conduit on providing real-time information, their verification on the information being delivered to the public is essential to help improve that stream of information. This was not one of the project goals but is considered as qualitative data to the project as a whole. Interviews were conducted with key staff to measure operator acceptance across the technologies. This process was separated into three different interviews, gathering feedback from three groups that are directly using or are affected by the implementation of these technologies. The interviews conducted on January 18, 2023, were:

- TMC Operators' Interview (9 Questions Total)
- Emergency Responders' Interview (9 Questions Total)
- Manager's Interview (11 Questions Total)

**TMC Operators' Interview**

The initial interview took place at MoDOT's Traffic Management Center (TMC) and involved Shift Supervisors, Operators, and a Training Coordinator. These key personnel shared their firsthand experiences with Crash Risk Location Prediction & Incident Identification and Advanced Video Analytics technologies.

The interview questions were meticulously crafted to delve into the TMC staff's familiarity with Crash Risk Location Prediction & Incident Identification and Advanced Video Analytics. The topics covered ranged from the specific roles of the respondents to their daily utilization of these tools. Additionally, the questions explored the frequency and purposes behind their use. The aim was to comprehensively understand the benefits and challenges associated with these technologies, including an assessment of their effectiveness and any desired enhancements.

Respondents were asked to rate both platforms on a scale of 1 to 5 (with 5 being the highest), and they provided insights into the unique value each technology brings. Preferences between the platforms were also explored, should a choice on which technologies to keep need to be made. Furthermore, the interview concluded by inquiring about interest in other types of platforms or data that could further enhance traffic management and emergency response efficiency.

The findings indicate that operators heavily rely on these tools for monitoring traffic incidents. Over 80% of respondents reported that they frequently log into both tools, utilizing the Advanced Video Analytics technology to detect, monitor, and verify crashes, and the Crash Risk Location Prediction & Incident Identification technology to monitor congestion and events. Some respondents noted that the CRA tool was often the first to report alerts for certain events compared to ATMS. Advanced Video Analytics received high praise for its comprehensive video analytics, achieving an average score of 4.25 out of 5 among TMC Operators. Meanwhile, the Crash Risk Location Prediction & Incident Identification tool was rated with an average score of 3.42 out of 5. Despite this lower rating, the CRA and Incident Identification tool was acclaimed for its alert system, with an acknowledgment of the need for further improvements. Challenges such as duplicate alerts and delayed reporting were acknowledged. Participants consistently rated Advanced Video Analytics more favorably for its accuracy and comprehensive overview. Suggestions for improving Crash Risk Location Prediction & Incident Identification tools included better integration with existing systems and minimizing duplicate information. Despite these challenges, there is a consensus among respondents regarding the value of both Crash Risk Location Prediction & Incident Identification and Advanced Video Analytics tools in enhancing traffic management and emergency response practices.

**Emergency Responders' Interview**

The second interview was conducted with Emergency Response (ER) personnel focusing on exploring their roles, technology usage patterns, and experiences with the Crash Risk Location Prediction & Incident Identification platform. The ER operators shared insights on when they sign into the platform, detailing its application in their day-to-day operations, particularly for the I-270 North project area and in detail about shoulder events.

The interview findings revealed that all participating ER operators consistently log into the CRA and Incident Identification tool at the beginning of their shifts. Two-thirds of the operators used the tool specifically for shoulder events related to the I-270 project. Some operators utilized the 'events list' feature to determine their next assignments. The use of these technologies was confined to the project area. It is important to note that Emergency Responders do not use any of the Advanced Video Analytics features, as these are intended exclusively for staff monitoring the cameras.

ER respondents rated the CRA and Incident Identification technology with an average score of 3.67 out of 5. Their feedback highlighted several benefits of the platform, such as reduced radio chatter and improved incident mapping, while also pointing out challenges like platform instability, accuracy issues, and the process of logging information. The effectiveness ratings varied, reflecting an appreciation for the advanced information provided by the tools, but also emphasizing the need for improvements, particularly in terms of GPS accuracy and user-friendliness.

Suggestions for better utilization of data included patrolling crash risk areas and enhancing the platform's alert system. The respondents also expressed mixed feelings about continuing to use Crash Risk Location Prediction & Incident Identification, citing its potential benefits against operational challenges. Finally, they indicated an interest in integrating additional platforms or data sources, such as Waze, to complement their tasks and improve overall emergency response efficiency.

**Manager's Interview**

The third interview in our study focused on engaging MoDOT and Kapsch (TMC floor contractor) management personnel. Their roles and experiences with the Crash Risk Location Prediction & Incident Identification and Advanced Video Analytics platforms were thoroughly examined throughout the project lifecycle. Starting with their specific positions and responsibilities, the interview delved into the evolution of their roles over time. It explored how these professionals effectively utilized Crash Risk Location Prediction & Incident Identification and Advanced Video Analytics in their daily operations. Topics included logging practices, alert applications, and overall platform utilization to support their tasks.

Findings from the manager's interview revealed that all respondents used the technologies infrequently and did not incorporate them into their daily tasks. Despite not using the technologies directly, they recognized their benefits through their observations of the operators and could correlate these benefits with their overall goals in managing the operators. Advanced Video Analytics received an average score of 3.25 out of 5 among managers, while the Crash Risk Location Prediction & Incident Identification tool was rated with an average score of 2.88 out of 5.

During the interview, managers candidly shared both benefits and challenges encountered. Notably, they discussed the integration of information within a single platform. Additionally, they highlighted stability and accuracy issues related to Crash Risk Location Prediction & Incident Identification's platform. The effectiveness of each platform was systematically assessed. Strengths in incident management were underscored, while areas for improvement—such as integration and accuracy—were identified. Future aspirations centered on leveraging data to enhance operational efficiency and incorporate crash risk information more effectively.

In conclusion, managers provided valuable suggestions for platform enhancements. These recommendations emphasized better integration with existing systems, improved usability, and the potential for expanding platform capabilities. The discussion also touched upon preferences between the two platforms. Notably, Advanced Video Analytics received positive feedback for its straightforward application and operational effectiveness. Lastly, the interviewees expressed keen interest in additional platforms and data types that could further support their tasks. This desire reflects a commitment to a holistic and comprehensive approach to traffic management and operations.

For complete details of these three interviews conducted with TMC Operators, ER Operators, and Managers, please refer to **Appendix B: Operator Interview Notes.**

## 8.5 Improve Return on Investment and Realize Cost Savings

A key objective of this project was to evaluate the cost-effectiveness of implementing the proposed technology in conjunction with the MoDOT TMC. This analysis is critical due to funding considerations and implementation complexities. By quantifying the financial implications, we can empower policymakers to make informed decisions on the technology's feasibility and incorporation within existing system infrastructure.

The cost-benefit analysis will inform transportation program planning, programming, and implementation, ensuring optimal return on investment within budgetary constraints. This analysis will guide selection of technology solutions that minimize long-term costs while maximizing safety benefits for all stakeholders involved. Additionally, it will allow policy makers to quantitatively compare alternative approaches, considering their impact on safety, mobility, the environment, and regional economies. This data-driven approach will provide robust documentation to justify and explain the decision-making process to both legislatures and the public.

In pursuit of our stated objectives, the research team examined various parameters to assess the advantages of incorporating cutting-edge technologies (such as Crash Risk Location Prediction & Incident Identification tool, Advanced Video Analytics, and IMRCP) into the existing Advanced Traffic Management System (ATMS) framework. This comprehensive analysis encompassed evaluating the benefits and costs related to incident management, travel time reduction, safety enhancements resulting from reduced crashes along the corridor, and the economic gains stemming from decreased fuel consumption and emissions.

### *8.5.1 Input Data*

One of the crucial steps to determine benefit-cost was to identify the unit cost associated with potential crash savings resulting from the adoption of the new crash prediction and incident identification software tools. MoDOT has meticulously developed an in-house comprehensive crash cost, which considers both economic costs associated to crashes and quality of life costs at a national level. This has been further adjusted to align with the unique characteristics of Missouri highways, using the Per-Capita Income (PCI) ratio. See **Appendix G: MISSOURI CRASH COST CALCULATION** for the calculation methodology.

For our study, we leveraged MoDOT's research findings on crash costs applicable to the study years spanning 2022 to 2026. These insights were then translated into estimated crash savings for the year 2023.

**Table 19** provides a summary of the comprehensive crash costs utilized throughout our analysis, serving as a critical reference point for assessing potential savings. **Table 19** presents a concise overview of the comprehensive crash costs employed in our analysis. This table serves as a pivotal reference for evaluating potential savings. Specifically, we utilized the "KABCO" injury scale, developed by the National Safety Council (NSC), which is commonly employed for determining crash costs by categorizing injuries. (Dot.gov, 2024):

- **K** – Fatal Injury
- **A** – Serious Injury
- **B / C** – Minor Injury
- **O** - No Injury

**Table 19: Comprehensive Crash Unit Cost for Missouri (2022-2026, Source: MoDOT)**

| Severity | Comprehensive Crash Unit Cost (2023 MO) |
|---|---|
| K | $11,653,800 |
| A | $675,800 |
| B / C | $175,800 |
| O | $12,300 |

In addition to safety benefits, our study also examined various other benefits associated with the project. These included travel time savings, enhanced reliability, reduced vehicle operating costs, and minimized emissions. By assessing these factors, we aimed to determine the overall benefits accruing to the project over the study period.

To facilitate our analysis, we employed an evaluation period spanning three years, coupled with a forward projection extending ten years into the future. The choice of a decade-long horizon was deliberate, considering the evolving landscape of technology. We anticipate that the impact of current technologies may diminish as newer innovations appear. Consequently, MoDOT may choose to upgrade their prediction and identification tools to align with these developments.

For our benefit-cost analysis, we relied on the NHTSA (National Highway Traffic Safety Administration) Travel Time Delay Factors from their publication titled "The Economic and Societal Impact of Motor Vehicle Crashes" (2010). Although more recent data was unavailable, we cautiously utilized the delay factors documented in that publication for our assessment. **Table 20** provides a concise summary of vehicle delay hours categorized by crash severity and roadway type, representing an average across all crashes.

**Table 20: NHTSA Vehicle Delay Hours by Crash Severity and Roadway Type, Average for All Crashes* (2010)**

| *Vehicle Hours (Types)* | *Urban Interstates/ Expressways* | *Urban Arterials* | *Urban Other* | *Rural Interstate/ Principal Arterials* | *Rural Other* |
|---|---|---|---|---|---|
| **Fatal Crashes** | | | | | |
| Total Vehicle Hours, All Crashes | 5147.70 | 1258.26 | 207.88 | 1780.31 | 104.82 |
| Total Vehicle Hours, Truck Crashes | 8590.02 | 2094.75 | 1400.59 | 3294.58 | 617.33 |
| Ratio, All/Truck | 0.60 | 0.60 | 0.15 | 0.54 | 0.17 |
| FMCSA Truck Vehicle Hours | 6729.00 | 483.00 | 291.00 | 464.00 | 99.00 |
| All Crashes Vehicle Hours | 4032.45 | 290.13 | 43.19 | 250.73 | 16.81 |

**Table 20: NHTSA Vehicle Delay Hours by Crash Severity and Roadway Type, Average for All Crashes* (2010) (Contd.)**

| ***Vehicle Hours (Types)*** | ***Urban Interstates/ Expressways*** | ***Urban Arterials*** | ***Urban Other*** | ***Rural Interstate/ Principal Arterials*** | ***Rural Other*** |
|---|---|---|---|---|---|
| **Injury Crashes** | | | | | |
| Total Vehicle Hours, All Crashes | 345.29 | 68.56 | 15.40 | 207.68 | 13.86 |
| Total Vehicle Hours, Truck Crashes | 1022.25 | 145.66 | 87.83 | 711.47 | 108.99 |
| Ratio, All/Truck | 0.34 | 0.47 | 0.18 | 0.29 | 0.13 |
| FMCSA Truck Vehicle Hours | 2522.00 | 137.00 | 108.00 | 159.00 | 34.00 |
| All Crashes Vehicle Hours | 851.85 | 64.48 | 18.94 | 46.41 | 4.32 |
| **PDO Crashes** | | | | | |
| Total Vehicle Hours, All Crashes | 215.00 | 49.94 | 10.32 | 146.25 | 10.33 |
| Total Vehicle Hours, Truck Crashes | 636.06 | 139.40 | 82.49 | 415.83 | 81.13 |
| Ratio, All/Truck | 0.34 | 0.36 | 0.13 | 0.35 | 0.13 |
| FMCSA Truck Vehicle Hours | 2144.00 | 109.00 | 91.00 | 134.00 | 28.00 |
| All Crashes Vehicle Hours | 724.71 | 39.05 | 11.38 | 47.13 | 3.57 |

**Source: National Highway Traffic Safety Administration, The Economic and Societal Impact of Motor Vehicle Crashes, 2010, Accessed at: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812013. Table 3-21. Vehicle Delay Hours by Crash Severity and Roadway Type, Average for All Crashes*

Coupled with the vehicle delay hours, the analysis used average value of travel per hour to develop the actual benefit numbers. **Table 21** shows average value of travel per hour by road type obtained from “Benefit-Cost guidance for Discretionary Grant Programs” published by USDOT in 2023 (Benefit-Cost Analysis Guidance for Discretionary Grant Programs, 2023). This document outlines recommended hourly values for travel time savings, both for general passenger travel and commercial operators, along with corresponding occupancy rates for different vehicle types.

Specifically, the analysis utilized an hourly value of $19.60 for all general passenger travel and $33.50 for truck drivers. The occupancy rates applied were 1.67 for general passenger vehicles and 1.00 for trucks. Notably, these figures were originally published in 2022 dollars. To account for inflation, a Consumer Price Index (CPI) adjustment factor of 1.0411645 was employed to convert the values to 2023 dollars.

**Table 21: Average Value of Travel (VOT) per Hour by Road Type (2023 Dollars)**

| Road Type | Average VOT (Per Hour) | VOT for Passenger Vehicles | VOT all Trucks |
|---|---|---|---|
| Urban Interstate/ Expressway | $34.18 | $ 34.08 | $ 34.88 |

**Source: Benefit-Cost Analysis Guidance for Discretionary Grant Programs. (2023). Available at: https://www.transportation.gov/sites/dot.gov/files/2023-12/Benefit%20Cost%20Analysis%20Guidance%202024%20Update.pdf [Accessed 28 May 2024].*

Similar to the travel time factors, more recent data involving net increase in cost of fuel consumption was unavailable for fatal, injury, and PDO crashes. For that, fuel costs savings related to vehicle operations were calculated using the data reported on the same NHTSA document (2010). It was assumed that the fuel consumption related to different crash types remains the same during analysis years. **Table** 22 shows the net increase in and cost of fuel consumption for different crash severity and roadway facility types.

**Table 22: NHTSA Net increase in and cost of fuel consumption for different crash types* (2010)**

| Net Increase in and Cost of Fuel Consumption, Fatal Crashes | |
|---|---|
| **Facility Type** | **Gallons/fuel** |
| Urban Interstate/Expressway | 1951.00 |
| Urban Arterial | 504.00 |
| Urban Other | 39.00 |
| Rural Interstate/ Principal Arterials | 294.00 |
| Rural Other | 36.00 |
| Average All Roadway Types | 376.00 |
| **Net Increase in and Cost of Fuel Consumption, Injury Crashes** | |
| **Facility Type** | **Gallons/fuel** |
| Urban Interstate/ Expressway | 412.00 |
| Urban Arterial | 112.00 |
| Urban Other | 17.00 |
| Rural Interstate/Principal Arterials | 54.00 |
| Rural Other | 9.00 |
| Average All Roadway Types | 81.00 |

**Table 22: NHTSA Net increase in and cost of fuel consumption for different crash types* (2010) (Contd.)**

| Net Increase in and Cost of Fuel Consumption, PDO Crashes | |
|---|---|
| **Facility Type** | **Gallons/fuel** |
| Urban Interstate/Expressway | 351.00 |
| Urban Arterial | 68.00 |
| Urban Other | 10.00 |
| Rural Interstate/ Principal Arterials | 55.00 |
| Rural Other | 8.00 |
| Average All Roadway Types | 64.00 |

**Source: National Highway Traffic Safety Administration, The Economic and Societal Impact of Motor Vehicle Crashes, 2010, Accessed at: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812013*

To quantify actual fuel savings, our study team examined fuel costs reported by the Federal Reserve Economic Data for the St. Louis Region during the period from 2021 to 2023. To establish a meaningful benchmark, we compared these regional fuel costs against the nationwide average for large metropolitan areas. It is to be noted that the fuel prices were heavily impacted during the beginning of the study period for COVID-19 due to a worldwide supply chain disruption.

Remarkably, the fuel costs within our study area were notably lower than those observed in other regions**.** Drawing insights from **Figure 33**, we determined an average fuel cost of $2.82 per gallon. This figure served as a critical input for our analysis in assessing vehicle operation cost savings.

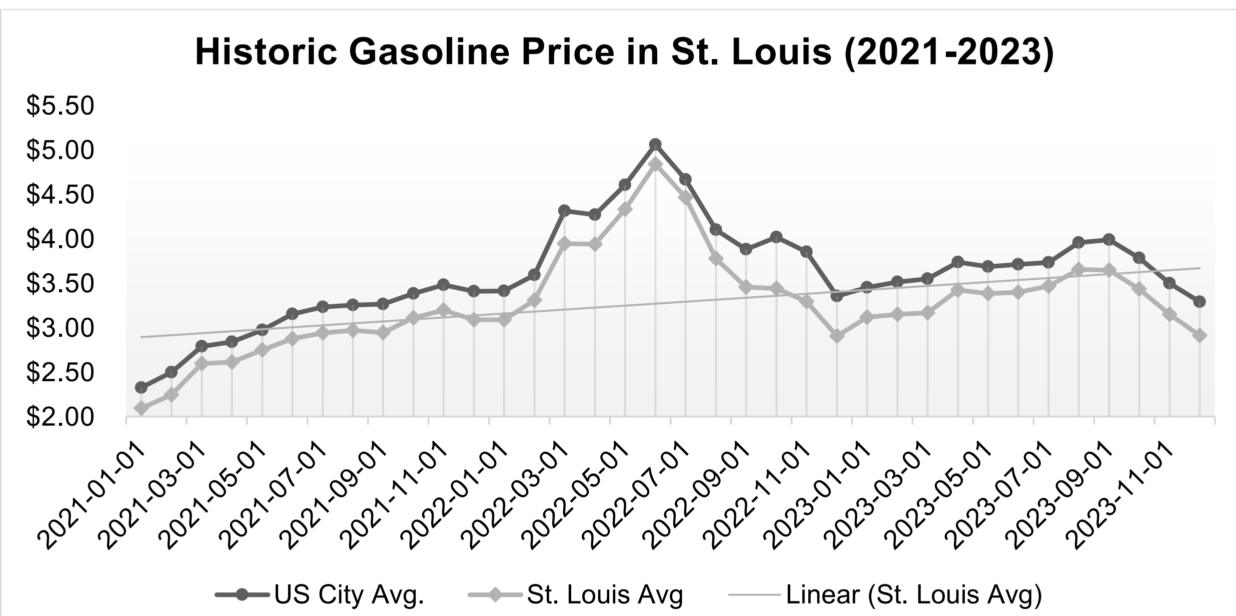


**Figure 33: Historic Gasoline Prices in St. Louis Area (2021-2023, Source: FRED)**

In addition, to determine the emission benefits associated with crash savings, the team utilized NHTSA estimated value of net emissions per crash and facility types. The amount reported in "The Economic and Societal Impact of Motor Vehicle Crashes" (2010) were updated based on CPI inflation adjustments to come up with 2023-dollar numbers. **Table 23** shows the updated estimated value of net emissions/crash by facility types which were used to determine the emission costs. It is to be noted that, NHTSA's method does not directly report actual emission quantities and for that the values estimated, particularly for $CO_2$, may be lower than the current USDOT guidance.

**Table 23: NHTSA Estimated Value of Net Emissions/Crash by Facility Type* (2023 Dollars)**

| Estimated Value of Net Emissions/Crash by Facility Type, All Fatal Crashes ($ 2023 Dollars, converted from $2017) | | | | | |
|---|---|---|---|---|---|
| **Facility Type** | **$CO_2$** | **$NO_x$** | **$PM_{2.5}$** | **$SO_2$** | **VOC** |
| Urban Interstate/ Expressway | $1,029.14 | $245.62 | $1,113.20 | $87.99 | $29.35 |
| Urban Arterial | $265.59 | $62.48 | $166.35 | $22.49 | $4.97 |
| Urban Other | $20.35 | $4.91 | $11.09 | $1.76 | $0.33 |
| Rural Interstate/ Principal Arterials | $154.89 | $74.24 | $222.07 | $12.91 | $3.03 |
| Rural Other | $19.23 | $7.80 | $21.80 | $1.59 | $0.35 |
| Average for All Road Types | $198.24 | $55.14 | $197.87 | $16.82 | $4.74 |
| **Estimated Value of Net Emissions/Crash by Facility Type, All Injury Crashes ($ 2023 Dollars, converted from $2017)** | | | | | |
| **Facility Type** | **$CO_2$** | **$NO_x$** | **$PM_{2.5}$** | **$SO_2$** | **VOC** |
| Urban Interstate /Expressway | $217.43 | $51.89 | $235.13 | $18.62 | $6.20 |
| Urban Arterial | $58.90 | $13.85 | $36.24 | $4.99 | $1.09 |
| Urban Other | $8.92 | $2.14 | $4.68 | $0.77 | $0.15 |
| Rural Interstate/ Principal Arterials | $28.56 | $13.69 | $41.08 | $2.41 | $0.55 |
| Rural Other | $4.88 | $1.98 | $5.45 | $0.40 | $0.08 |
| Average for All Road Types | $42.62 | $11.69 | $41.58 | $3.62 | $1.01 |
| **Estimated Value of Net Emissions/Crash by Facility Type, All PDO Crashes ($ 2023 Dollars, converted from $2017)** | | | | | |
| **Facility Type** | **$CO_2$** | **$NO_x$** | **$PM_{2.5}$** | **$SO_2$** | **VOC** |
| Urban Interstate/ Expressway | $184.92 | $44.14 | $199.65 | $15.76 | $5.27 |
| Urban Arterial | $35.69 | $8.40 | $22.80 | $3.00 | $0.66 |
| Urban Other | $5.38 | $1.30 | $2.79 | $0.44 | $0.10 |
| Rural Interstate/ Principal Arterials | $29.06 | $13.93 | $41.50 | $2.38 | $0.57 |
| Rural Other | $4.08 | $1.66 | $4.47 | $0.35 | $0.07 |
| Average for All Road Types | $33.77 | $9.57 | $34.62 | $2.85 | $0.82 |

** Source: National Highway Traffic Safety Administration, The Economic and Societal Impact of Motor Vehicle Crashes, 2010, Accessed at: https://crashstats.nhtsa.gov/Api/Public/ViewPublication/812013*

### 8.5.2 Calculation of Benefit-Cost

After gathering cost data related to safety, travel time, fuel consumption, vehicle delays, and emissions, our team delved into developing crash predictions for future years. Basing on the number of CRA detailed in **Section 8.1**, where we included the use of law enforcement to create potential scenarios of crash reductions, our team assessed the total anticipated costs incurred by those agencies. To arrive at accurate cost estimates, we utilized the following factors:

- ***Median Wage of Patrol Officers:*** We based our calculations on the median wage for patrol officers in the St. Louis Metropolitan area (Bls.gov, 2018).
- ***Overhead Costs:*** These include administrative expenses, equipment, and infrastructure.
- ***Annual Benefits:*** Factoring in benefits such as health insurance, retirement plans, and other perks.
- ***Vehicle Costs:*** Considering the acquisition, maintenance, and fuel expenses for police vehicles.
- ***Insurance:*** Covering liability and other insurance costs.

By combining these elements, we arrived at an hourly rate of $120 for police deployment. **Table 24** shows the breakdown of cost and Error! Reference source not found. outlines the anticipated costs for varying levels of police presence during weekdays, weekends, and throughout the entire week.

**Table 24: Hourly Cost of a Patrol Car in St. Louis**

| **Hourly Cost of a Patrol Car** | |
|---|---|
| Annual Officer Salary in St. Louis | $61,110 |
| Annual Benefits (50% of Salary) | $30,555 |
| Overhead (200% of salary) | $122,221 |
| Patrol Car Cost/Year | $16,667 |
| Fuel | $9,400 |
| Annual Maintenance | $5,000 |
| Insurance | $1,500 |
| **Total** | **$246,453** |
| **Hourly Cost (Approx.)** | **$120** |

**Table 25: Cost of Police Deployment in Different Scenarios**

| Police Deployment | No. of Events | Hours Per Event | Cost of Patrol/Day | Cost Per Year | | |
|---|---|---|---|---|---|---|
| | | | | Weekdays | Weekends | 7-Days |
| 30% | 5.0 | 1 | $600 | $156,000 | $62,400 | $218,400 |
| 25% | 4.2 | 1 | $500 | $130,000 | $52,000 | $182,000 |
| 20% | 3.3 | 1 | $400 | $104,000 | $41,600 | $145,600 |
| 15% | 2.5 | 1 | $300 | $78,000 | $31,200 | $109,200 |
| 10% | 1.7 | 1 | $200 | $52,000 | $20,800 | $72,800 |
| 5% | 0.8 | 1 | $100 | $26,000 | $10,400 | $36,400 |
| 0% | 0.0 | 1 | $0 | $0 | $0 | $0 |

For analysis, we not only considered the costs associated with police deployments based on crash risk area predictions but also factored in additional expenses. The evaluation period spanning 2021 to 2023 encompassed the total cost of technology deployments, including Crash Risk Area, Incident Identification, Advanced Video Analytics, and IMRCP. Additionally, we accounted for costs related to MoDOT Traffic Management Center (TMC) operators during the same period. For future-year projections, recurring costs were a critical consideration. These included annual maintenance expenses for the software packages, costs associated with MoDOT operators, supervisors, project managers, interagency communication, and police patrol. **Table 26** shows the cost basis used for calculation of benefit-cost for evaluation period as well as future projections. Costs associated with interagency communication and police deployment as shown in Error! Reference source not found. is only utilized for future year projections.

**Table 26: Cost basis used for benefit-cost calculation**

| Cost Areas | Annualized Costs (in Dollars) |
|---|---|
| Crash Risk Location Prediction & Incident Identification | $ 573,000.00 |
| Advanced Video Analytics | $ 63,750.00 |
| IMRCP | $ 24,600.00 |
| MODOT TMC Cost (Assumed 15% of yearly total contract which includes operators' salary as well as other associated expenses) | $ 150,000.00 |
| Interagency Communication Cost for future years | $ 50,000.00 |

Having identified these major cost areas, we turned our attention to potential savings resulting from enhanced police presence within crash risk areas. Furthermore, we explored projected secondary crash savings facilitated by Incident Identification tool. Notably, Incident Identification tool has the capacity to reduce the first recorded crash awareness time, T1 (See **Figure 3**).

This study leveraged the combined potential of Crash Risk Area (CRA) for high-risk crash predictions and Incident Identification tool in conjunction with Advanced Video Analytics for incident identification and response. The strategy involved assessing the impact of varying patrol presence levels - specifically, during weekdays, weekends, and continuous deployment throughout the week.

Key components of our approach:

- **Crash Risk Location Prediction:** By incorporating CRA prediction, we aimed to predict and mitigate crashes within high-risk areas. Our verified accuracy rate of 10.9% served as a foundation for further exploration.
- **Incident Identification and Advanced Video Analytics:** These tools were synergistically employed by Traffic Management Center (TMC) operators to enhance incident identification and response times.
- **Crash Reduction Potential:** We quantified the crash reduction potential across different police deployment scenarios, ranging from 0% (no patrol available) to 30% (maximum predicted cases with patrol deployment).

Our team rigorously evaluated the benefit-cost ratios associated with deploying advanced technologies aimed at enhancing safety, reliability, and efficiency. These benefits encompass a range of critical factors: safety benefits, reliability and travel time savings, vehicle operating cost savings, and emission reduction. Our analysis extends beyond crash scenarios, meticulously calculating benefit/cost ratios for various deployment scenarios—weekdays, weekends, and continuous coverage throughout the week. Recognizing the varying availability of Traffic Management Center (TMC) operators and emergency responders, we tailored our assessment to provide a scenario-specific return on investment. For analysis, we employed a discounting rate of 3%. In economic analysis, a discount rate serves as a percentage factor that transforms future monetary values into equivalent present values. Historically, this rate has typically ranged between 0% and 5% (FHWA, 2024). Given the 10-year time horizon for analyzing this project, we have selected a discount rate of 3%.

#### *8.5.2.1 Crash Risk Location Prediction*

In our analysis of potential benefit costs, we explored three sequential approaches. Initially, we focused on the return on investment (ROI) specifically related to Crash Risk Location Prediction (CRA prediction). To achieve this, we varied the prediction accuracy of crash risk areas using the technology (scenario showing varying accuracy). Subsequently, we assessed the potential benefits across different levels of police patrol deployment (between 5% to 30%). **Figure 34** and **Figure 35** illustrate the potential benefit-cost ratios for scenarios showing weekdays and weekends only (depending on the availability of law enforcement personnel). Additionally, **Figure 36** provides a concise summary of the benefit-cost ratio associated with deploying CRA prediction technology within the MoDOT TMC infrastructure, accounting for varying police patrol levels throughout the week.

It is important to acknowledge that the cost associated with either CRA prediction or Incident Identification was considered as the combined total cost of both. This assumption is based on the fact that the individual components required for prediction or identification remain consistent across both software solutions. However, it is crucial to recognize that the system’s capability and usability can vary for end-users, as vendors offer the flexibility to toggle features on or off.

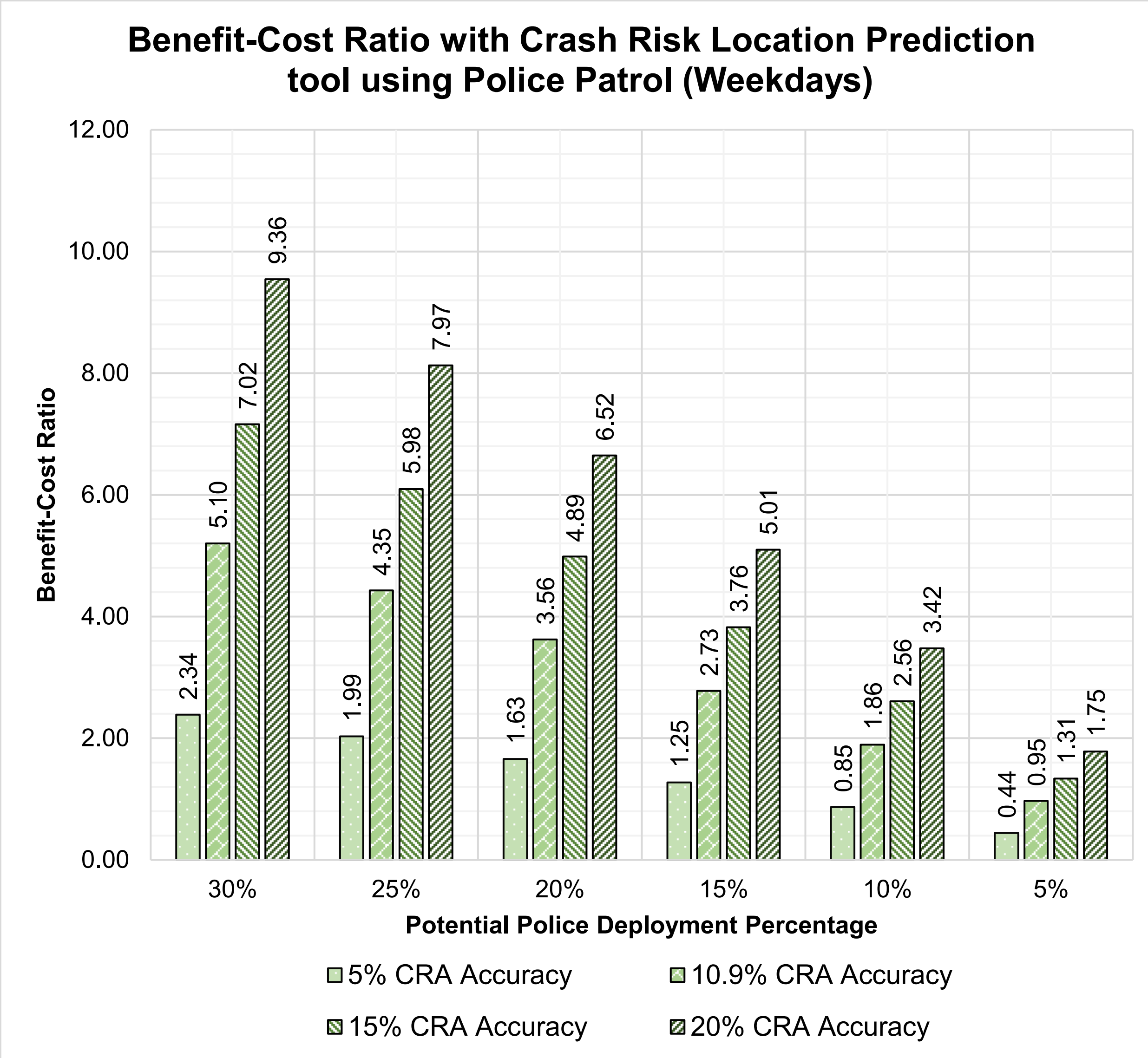


**Figure 34: Benefit-Cost Ratio with Crash Risk Location Prediction tool using Police Patrol (Weekdays)**

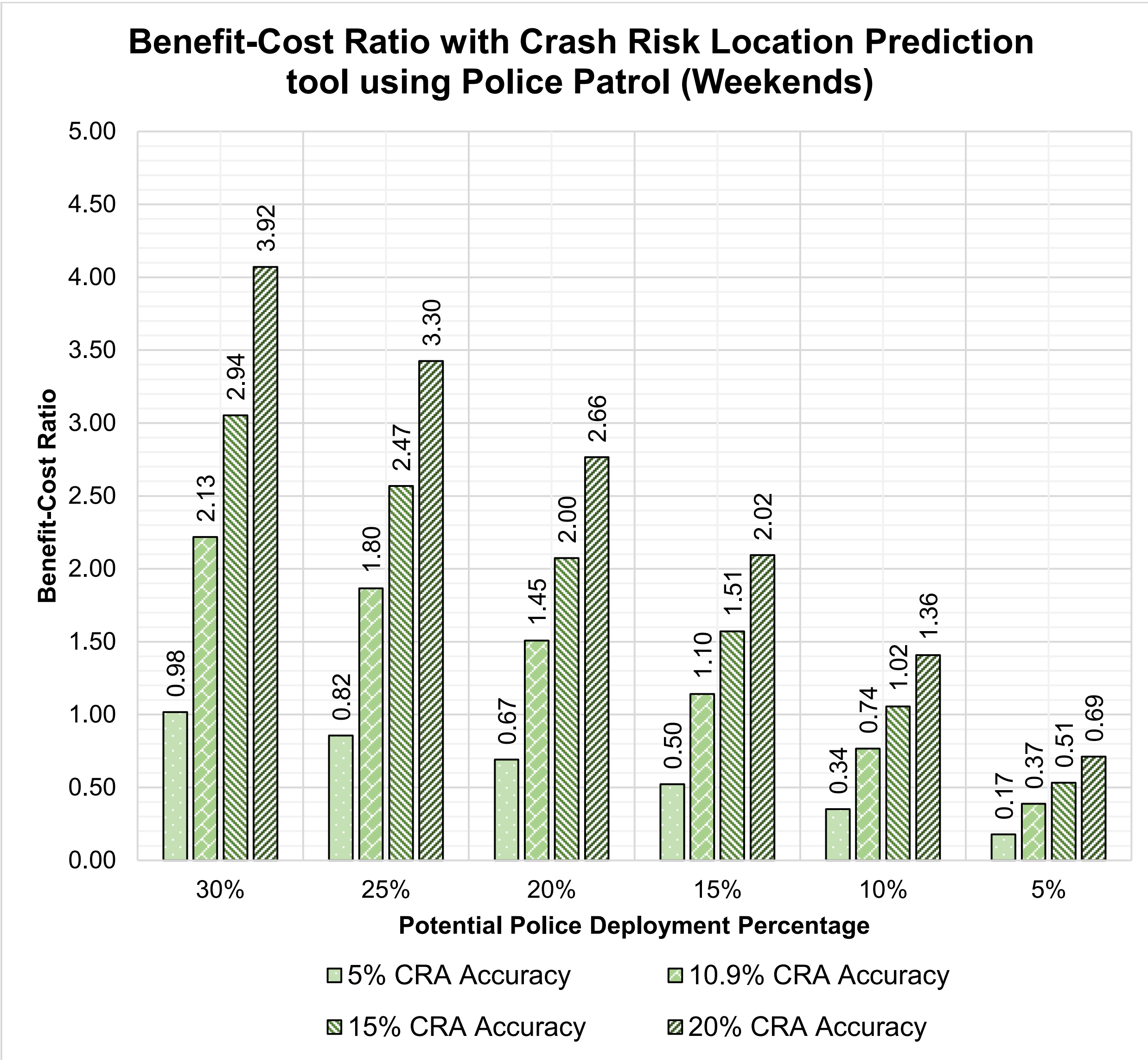


**Figure 35: Benefit-Cost Ratio with Crash Risk Location Prediction tool using Police Patrol (Weekends)**

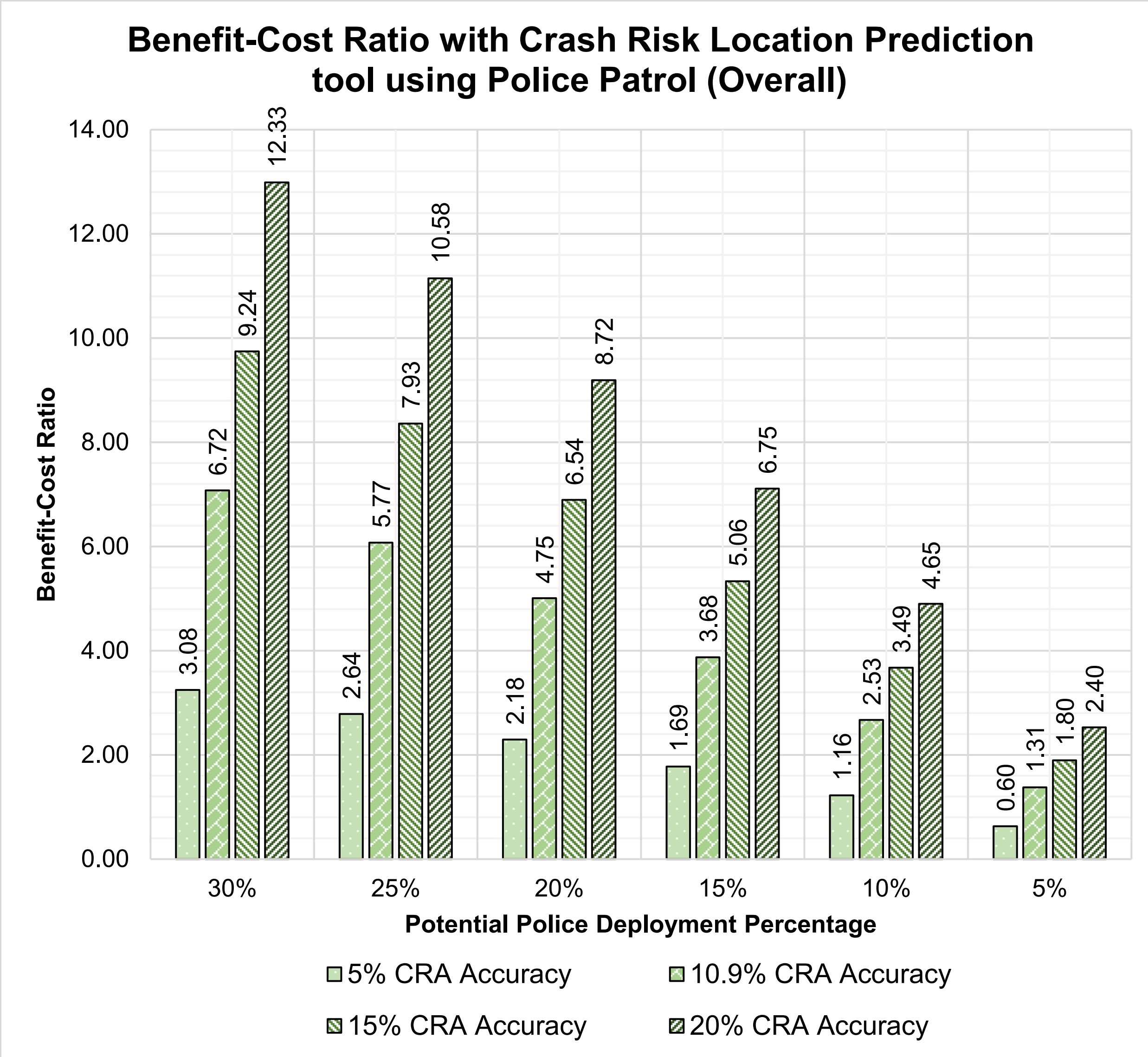


**Figure 36: Benefit-Cost Ratio with Crash Risk Location Prediction tool using Police Patrol (Overall)**

Based on **Figure 36**, if CRA prediction tool is exclusively utilized for crash predictions and its accuracy stands at only 5%, the potential benefit resulting from technology deployment yields a benefit-cost ratio of 3.08 - assuming police deployment occurs 30% of the time. However, if police presence is limited to just 5%, the effectiveness diminishes significantly, resulting in a B/C ratio of only 0.60. Therefore, it is crucial to ensure that when integrating CRA prediction as a future technology into the Traffic Management Center (TMC), police deployment is guaranteed to be at least 10% of the time.

*8.5.2.2 Incident Identification and Advanced Video Analytics*

In addition to CRA, our team assessed the benefit-cost relationship associated with both the Incident Identification software and Advanced Video Analytics. During the evaluation phase, Advanced Video Analytics was integrated into the Incident Identification infrastructure, providing targeted accident notifications to TMC operators. While Advanced Video Analytics can function independently, for the purposes of this project, quantifying its individual benefits proved challenging. On the other hand, Incident Identification tool operates autonomously, even without support from Advanced Video Analytics. Consequently, we conducted separate benefit-cost calculations for Incident Identification tool as a standalone entity and then analyzed the combined impact of Incident Identification and Advanced Video Analytics. Refer to **Figure 37** for a visual representation of the benefit-cost dynamics related to these two components.

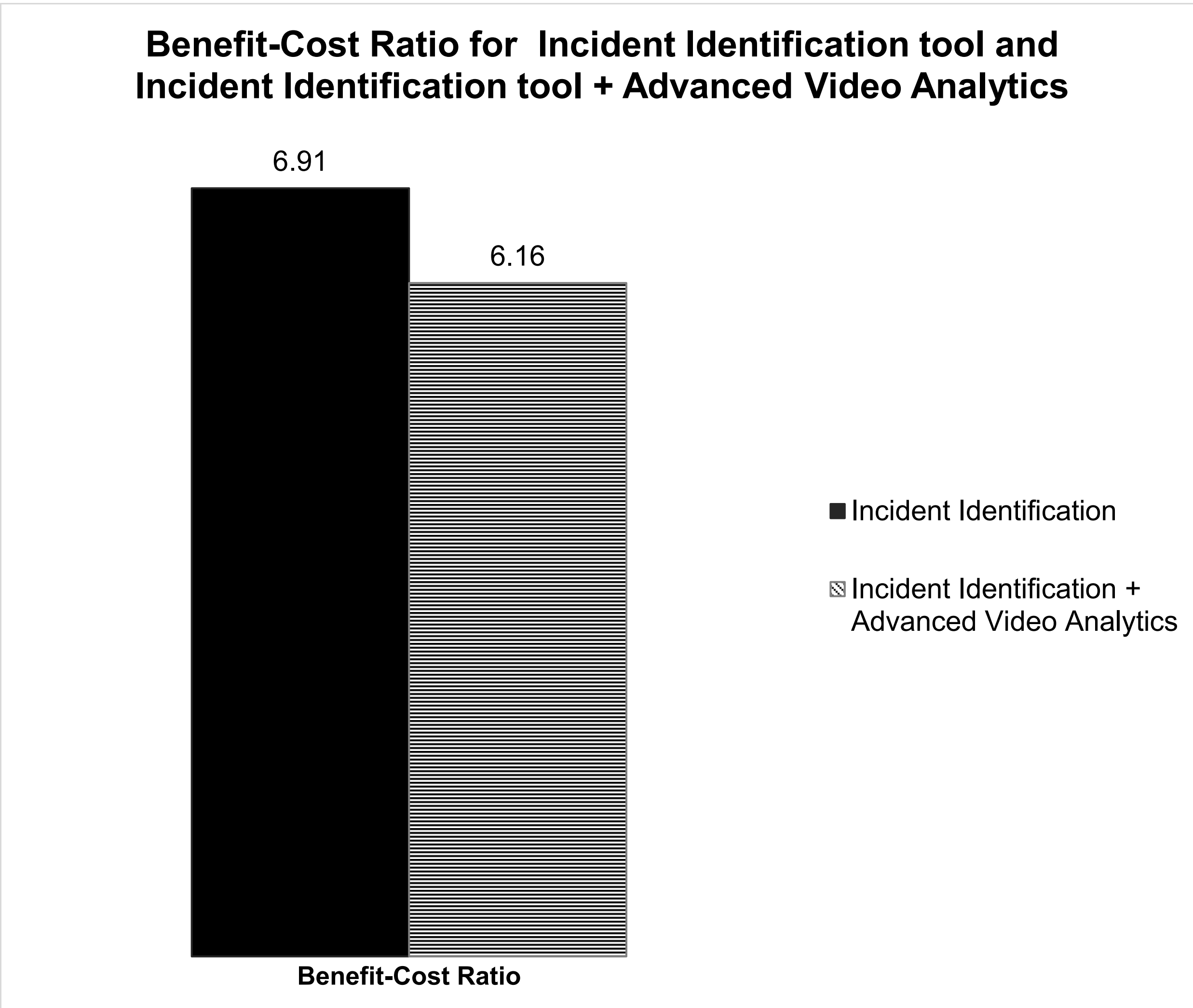


**Figure 37: Benefit-Cost Ratio for Incident Identification tool and Incident Identification tool + Advanced Video Analytics**

Based on the figure above, the benefit-cost associated with the Incident Identification tool is 6.91. Meanwhile, the benefit-cost ratio resulting from the combined effect of the Incident Identification tool and Advanced Video Analytics stands at 6.16. However, calculating the return on investment for the Advanced Video Analytics tool as a standalone entity proved challenging. During application, this tool was integrated with the Incident Identification tool to provide real-time incident notifications. While we could estimate the crash mitigation effect for the Incident Identification tool either separately or in combination with the Advanced Video Analytics tool, the latter posed a unique challenge. The Advanced Video Analytics Tool did not report geotagged crash locations; only the camera locations were available. As a result, our analysis treated the overall benefit of the Incident Identification tool (when used independently) and the combined benefit of Incident Identification with Advanced Video Analytics as equivalent. This assumption was based on the expected reduction in crashes being the same. Despite the similar benefits, the different implementation costs led to varying return on investments.

While the figure indicates that Incident Identification offers greater value than when combined with Advanced Video Analytics, it’s crucial to recognize that Advanced Video Analytics itself boasts several unique benefits. These include real-time incident and anomaly detection (such as identifying slowed traffic, stopped vehicles, roadway debris, low visibility, pedestrians, and wrong-way drivers), as well as comprehensive data collection (including speeds per lane and direction, vehicle counts, lane occupancy, density, congestion index, and level of service). Additionally, Advanced Video Analytics seamlessly integrates with existing or newly added cameras from various vendors without the need for extra hardware or sensors. Notably, TMC operators have highly praised its performance in user surveys. Therefore, these distinctive advantages should be carefully considered when making final decisions.

#### *8.5.2.3 Crash Risk Location Prediction, Incident Identification, and Advanced Video Analytics*

Additionally, the team calculated the combined effect of all three technologies (Crash Risk Location Prediction, Incident Identification, and Advanced Video Analytics) considering they all remain during the future years. **Figure 38** and **Figure 39** presents comparative benefit-cost analyses for police deployment during weekdays and weekends, while **Figure 40** highlights the benefit-cost ratio when patrols are available throughout the entire week.

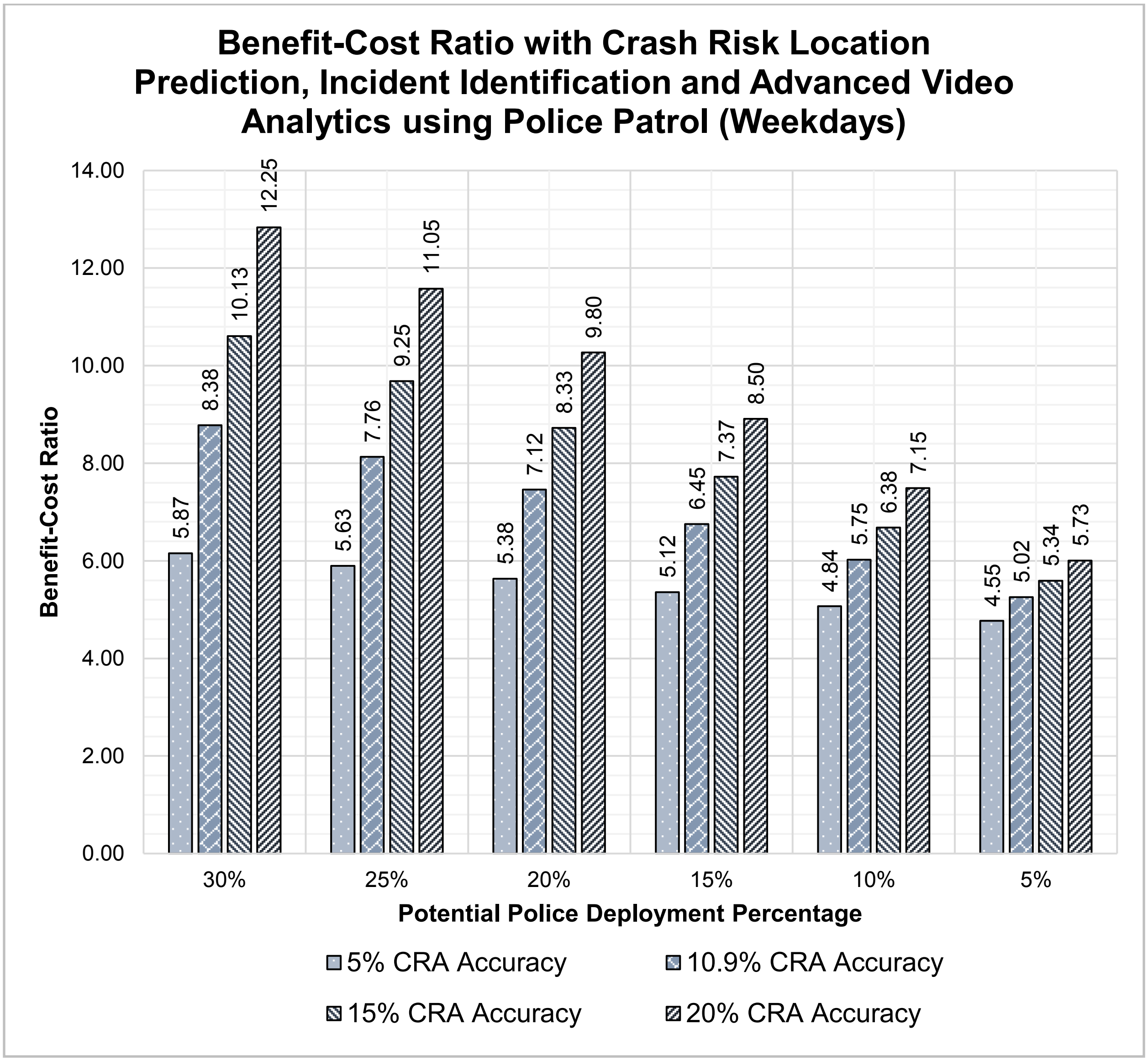


**Figure 38: Benefit-Cost Ratio with Crash Risk Location Prediction, Incident Identification and Advanced Video Analytics using Police Patrol (Weekdays)**

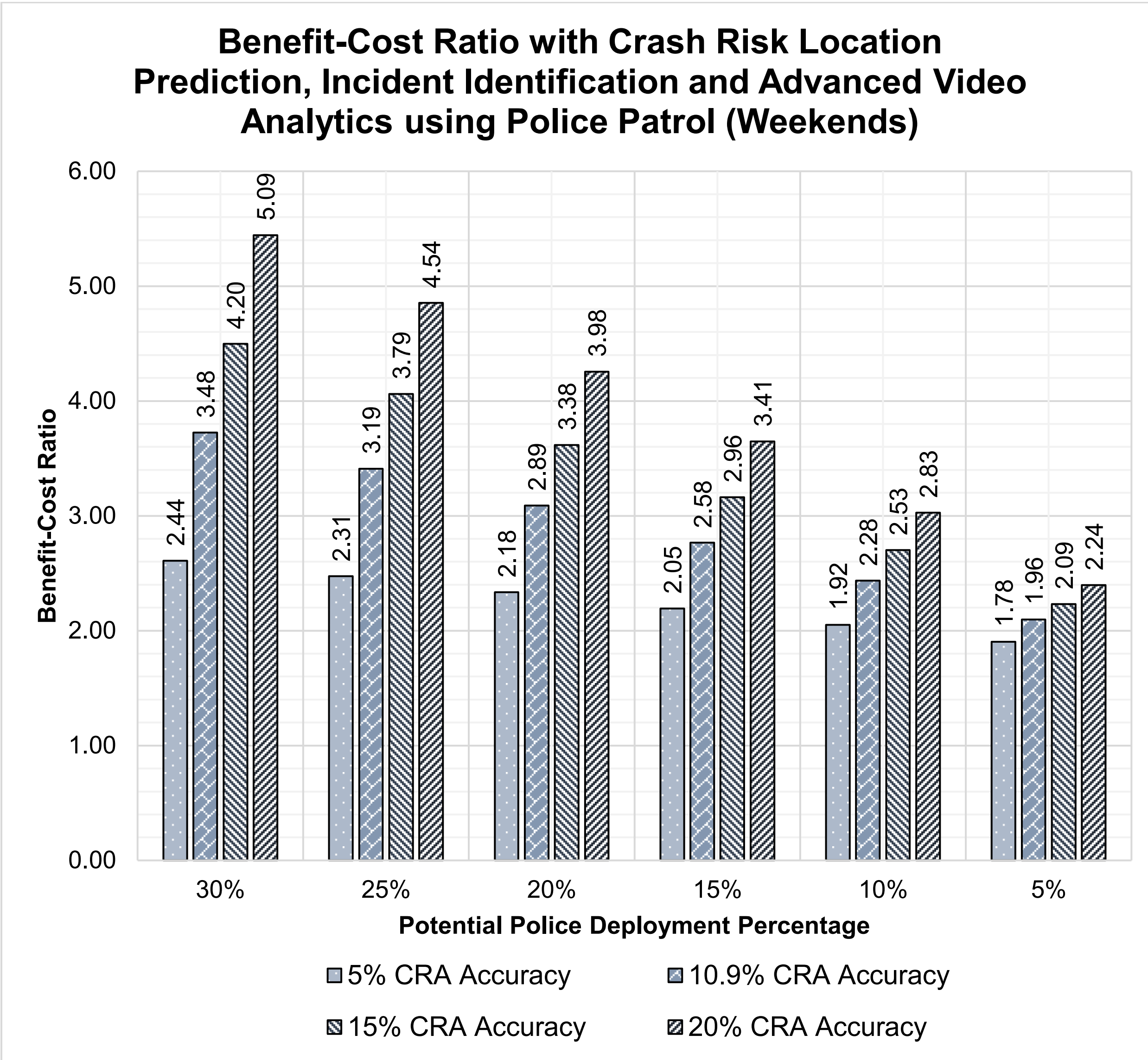


**Figure 39: Benefit-Cost Ratio with Crash Risk Location Prediction, Incident Identification and Advanced Video Analytics using Police Patrol (Weekends)**

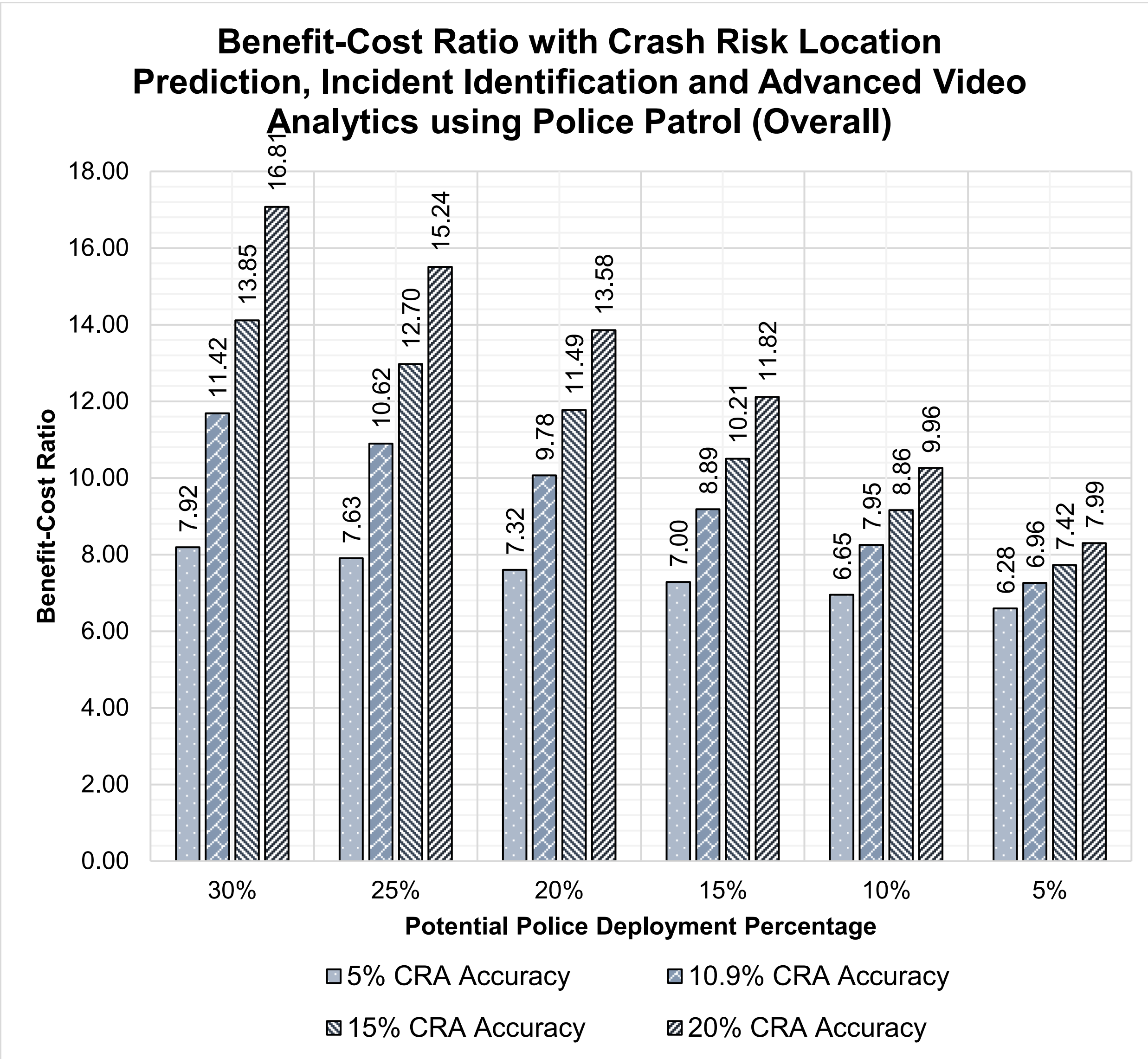


**Figure 40: Benefit-Cost Ratio with Crash Risk Location Prediction, Incident Identification and Advanced Video Analytics using Police Patrol (Overall)**

From the figure above, for instance, if Crash Risk Location Prediction tool (CRA) predicts crash risk areas correctly 5% of the time, then combined with the benefits from Incident Identification and Advanced Video Analytics, the entire deployment has the potential to bring in a 6.28X Return on Investment (ROI) considering patrol is only available 5% of the cases during the entire week, where it has the potential to bring in an ROI of 7.92X if we can increase the patrol response to 30%. With time, the prediction algorithm is only expected to output improved results which will increase the ROI substantially. If the technology can predict crash risk areas correctly for 20% of the time, that will render a ROI between 7.99X and 16.81X considering police presence varies anywhere from 5% to 30%. For a comprehensive benefit-cost ratio calculation, please refer to **Appendix F: BENEFIT-COST CALCULATION.**

#### *8.5.2.4 IMRCP*

In our comprehensive analysis, we have considered the benefit-cost ratios associated with deploying advanced technologies, focusing on the impact of the Integrated Management of Road Conditions Program (IMRCP).

As discussed in the safety section, the potential to significantly reduce winter weather-related crashes underscores the value of this tool. However, due to delays related to implementation challenges and lack of verified data we were unable to produce a reliable benefit estimation on savings related to materials and staff time during weather events. These limitations hindered any possibility of comparison between winter weather operational scenarios in the IMRCP platform.

# 9 LESSONS LEARNED AND RECOMMENDATIONS

## 9.1 Lessons Learned

The key takeaways from this project are that modern technology and tools are here to help overcome challenges such as staff shortage and reduce costs for any DOT. Just as any technology, there are always a learning curve where the technology molds to the current need and optimize its use to the necessity of the region.

### *9.1.1 Communication*

Over the course of the four-year project, we gained valuable insights. Notably, delays—ranging from contract execution to technology deployment—resulted in a two-year setback, impacting our ability to fully operationalize all three technologies simultaneously. This experience underscored the critical role of clear and consistent communication across all project levels. Importantly, the challenges posed by miscommunication were exacerbated by the COVID-19 pandemic, introducing additional uncertainty for organizations.

Another significant lesson emerged from the process, which were confusions regarding technology capabilities and limitations that led to unrealistic expectations. To address this, effective communication of objectives and expectations between all parties involved in the project demonstrated to be vital. Continuous dialogue was essential to align understanding and project goals. Moving forward, transparency and clarity in communication will remain central to our approach in future projects.

### *9.1.2 Technology*

Integrating multiple technologies into a unified platform presents a complex set of challenges, a task made even more daunting during the COVID-19 pandemic. The experience of MoDOT with technologies such as those provided by Crash Risk Location Prediction & Incident Identification as well as ATMS vendors illustrates these difficulties, particularly in an environment constrained by pandemic-related restrictions and staffing limitations.

One of the primary hurdles was ensuring compatibility between diverse systems. Each technology, including the technology's vehicle recognition systems and different ATMS vendors, comes with its unique specifications, data formats, and communication protocols. Achieving seamless integration requires extensive customization and sometimes even redevelopment of certain components to ensure they can communicate effectively.

### *9.1.3 People*

The integration of advanced technologies at MoDOT has been critical in addressing staffing challenges and enhancing productivity. Through technologies such as advanced video analytics and incident identification, routine tasks from TMC operators were able to be automated and enabled proactive management of road safety, allowing the workforce to focus on more strategic tasks. This shift not only optimizes human resources but also increases job satisfaction by reducing manual workload. Operator's feedback has been positive on this regard.

These technologies have the ability to expand MoDOT's real-time monitoring of cameras without the need for proportional increases in staff, demonstrating a significant impact in operational capabilities. By leveraging predictive analytics, resources are used more effectively, ensuring critical needs are being addressed.

Facing short staffing has been a significant hurdle, emphasizing the necessity for strategic resource allocation and the importance of technological adaptation to maintain operational standards. This challenge necessitated a creative approach to workflow management and the technologies introduced in this project were demonstrated to play a critical role in compensating for workforce limitations. The combination of short staff, COVID-19 pandemic, and considerable amount of delay encouraged a reevaluation of priorities and tasks, ensuring that essential services remained operational while adapting an environment that supports technology development.

Adding to this, a notable lesson learned was the difficulties on adapting staff routines to accommodate new technologies. Initially, challenges were observed when trying to find the best way to incorporate them into daily operator workflows. This experience highlighted the need for flexibility and continuous attention to the operator's routine tasks while adopting technological advancements. Ensuring that staff understands how the new technologies work and understand their part in the process was imperative to enhance their operational efficiency and effectiveness.

### *9.1.4 Budgeting*

The pandemic led to budgetary constraints and resource allocation issues. Prioritizing public health and safety meant that some projects, including technology integration efforts, faced cutbacks or were deprioritized in favor of immediate COVID-19 response measures.

Additionally, the pandemic also emphasized the necessity of agile staff allocation strategies due to low staff, where team members could be reassigned as needed to support critical functions, balancing between the demands of the project and the constraints imposed by limited budgets for new technology acquisitions. These lessons have been instrumental in refining our approach to project management and budgeting, ensuring better preparations for similar challenges in the future.

### *9.1.5 COVID-19 Restrictions*

The pandemic introduced unprecedented obstacles to staff training and deployment. With social distancing protocols in place and a significant portion of the workforce either working remotely or unable to be present due to health concerns, the usual hands-on, collaborative approach to training and system implementation was not fully viable. This situation pushed to remote training sessions, which, while useful, could not entirely replicate the effectiveness of in-person learning experiences.

## 9.2 Recommendations

This section offers recommendations for moving forward with the technologies piloted during the I-270 PLOI. It highlights the importance of ongoing monitoring and coverage throughout the Saint Louis area, evaluation, and flexibility to ensure that the initiative can adapt and mold to MoDOT's needs while achieving its intended goals. Also, this recommendation section offers updates reflecting what was mentioned previously in the Annual Report submitted to FHWA in December of 2022.

As seen in the Cost Benefit Analysis section, there are multiple benefits observed in the potential to coordinate with police and it is recommended that MoDOT maximizes its efforts to warrant the procurement and management of staff to achieve the best results possible resulting from the technologies.

Another important recommendation is to ensure comprehensive understanding of all stakeholders within MoDOT's executive team regarding the upcoming technology deployment. Additionally, providing a clear overview of the technology's strengths and weaknesses, and establishing aligned expectations to raise awareness across the team is highly recommended. Having positive feedback from operators that are daily verifying and using these platforms/tools is considered key for them to build a sense of ownership from the technologies being used.

It is also recommended to assess the relevance and utility of existing organizational data for the proposed project. If additional data sources are required, such as connected vehicle data, then an analysis of the associated costs should be considered in order to determine their strategic value before considering the investment. Also, secure adequate technical support for the project, including expertise from professionals such as data scientists.

Lastly, is important to highlight that some technologies require a longer implementation and evaluation period before generating consistent results. It is recommended to recognize that those time constraints impose a significant challenge when deploying new technology within fixed timelines, especially during a worldwide health pandemic.

### *9.2.1 Advanced Video Analytics*

As seen on the verification segment of this document, the technology chosen for Advanced Video Analytics had a high level of effectiveness and efficiency throughout each quarter. During the evaluation period, advanced analytics enabled quicker identification of incidents in nearly half the observed incidents and is also able to be implemented statewide. TMC operators highly praised the technology and are positively inclined towards its continuation. This technology maximizes ITS infrastructure that MoDOT already utilizes on a daily basis and makes more efficient use of operators' time and focus.

### *9.2.2 Crash Risk Area Prediction*

This tool in specific requires more data and relies on more variables compared to the other tools, being considered relatively multifaceted to be highly successful due to the complexity of the end goal. The correct use and integration of this tool can derive additional benefits for in-house research projects on AI/ML that needs to build more knowledge upon predictive analytics endeavors while also contributing to MoDOT's crash reduction efforts. While this tool may need the most development before it can contribute to TMC operations it has the most potential for providing a significant decrease in crashes and reduction of crash associated costs.

### *9.2.3 Real-Time Incident Identification*

Allowing integration of multiple data sources and technologies into a single platform, this tool has shown to be effective and efficient while also reducing detection and verification time, improving the overall response time. While this technology will continue to be developed and refined it is able to provide meaningful benefits in its current state. In addition, this technology allows MoDOT to share its data access to any partner that find it valuable.

### *9.2.4 Integrated Modeling for Road Condition Prediction*

IMRCP offers several benefits, including support and funding from FHWA, in addition to the active promotion by them. In addition to that, the scenario feature offers predictive insights into pavement conditions based on applied treatments. Challenges regarding usability were noted with the scenario feature, and insufficient data from winter storms proved difficult to complete a comprehensive evaluation of the results. The St. Louis District may not experience an adequate amount of severe and winter weather events to warrant continued use, but northern MoDOT districts may be better suited for this technology.

# 10 CONCLUSION

The I-270 Predictive Layered Operations Initiative (PLOI), funded by the Advance Transportation Congestion Management Technologies Deployment (ATCMTD) grant, aimed to enhance traffic safety and mobility in the St. Louis region. The project implemented and evaluated three key technologies: Crash Risk Location Prediction & Incident Identification, a machine learning platform predicting crash risk areas and identifying incidents in real time; Advanced Video Analytics, an advanced video analytics system detecting congestion and traffic events using existing CCTV cameras; and IMRCP, an integrated modeling platform forecasting road conditions based on weather data and mobile Road Weather Information Systems (RWIS).

The project team conducted a thorough evaluation of the implemented technologies, focusing on their performance and alignment with project goals. Overall, this initiative has been highly successful. Below are the key findings:

- **Improve Safety:** The initiative aimed to predict crash risk areas (CRA) and potentially decrease crash severity or prevent crashes. The technology's algorithm initially required more data and refinement to achieve higher accuracy and reliability. However, it used historical crash data to identify high-risk areas over a two-year period, which improved over time, especially after August 2023. This contributed to better identification of projected CRAs. It is to be noted that the technology faced some challenges in integrating with MoDOT's ATMS during the evaluation period. Advanced Video Analytics on the other hand, demonstrated high efficiency and accuracy in detecting traffic events and alerting operators. These potentially reduced the emergency response time and translated to improved safety.
- **Improve ER Response Time:** The Crash Risk Location Prediction & Incident Identification algorithm combined with Advanced Video Analytics enabled quicker identification of potential crash sites for nearly 45% of all occurrences. This initiative likely enabled MoDOT and other agencies to respond more quickly to incidents, thereby improving emergency response times.
- **Reduce Congestion/ Improve Mobility:** The prediction of CRAs was expected to help manage traffic flow better by anticipating and mitigating potential crash sites, thus reducing potential congestion, and improving mobility. Though the use of CRA was limited during the evaluation period, continuation of this in future will potentially result in substantial amount of crash reduction and congestion mitigation. Like CRA, Advanced Video Analytics also provided alerts on different road conditions e.g. debris on the road, or pedestrians etc. which enabled quicker identification in nearly half the measured cases – and thus was anticipated to improve emergency response times.
- **Real-Time Information Effectiveness:** The new ATMS platform introduced during the project was designed to enhance the effectiveness of real-time transportation information, although it required a period of adjustment. Combined with crash prediction, incident identification, and weather-related tools, these have the potential to improve real-time traveler information in the form of MoDOT's "Traveler Information Map', "DMS", or social media.

- **Cost Savings:** The initiative sought to improve the return on investment and realize cost savings. The project team identified substantial savings in future years in the form of safety, travel time, vehicle operating costs, reliability, and emissions benefits from advanced crash prediction, quicker incident identification, and rapid emergency response deployment. IMRCP for road condition prediction was not fully implemented and evaluated due to insufficient data and time. The technology had potential benefits for optimizing winter maintenance operations and reducing crashes related to weather events, but also had usability issues and required more training and support.

Based on the verification and evaluation results, the project team made the following recommendations for future deployment and enhancement of the technologies:

- Crash Risk Location Prediction & Incident Identification – Continuous data collection and analysis is required to improve the crash risk prediction and incident identification algorithms. MoDOT needs to explore new ways to integrate the technology into its ATMS platform and other ITS devices to disseminate information to emergency responders and the public. Based on the evaluation, integrating the CRA prediction platform into MoDOT's emergency responders' vehicle communication system using tablets or laptops is expected to have proven effective in crash response. With that and the coordination with police and other stakeholders will potentially maximize the benefits of the technology for crash prevention and mitigation.
- Advanced Video Analytics – MoDOT should expand the coverage and functionality of the technology to include more cameras and traffic events. From operators' response, this technology can prove to be more effective in supporting their day-to-day responsibilities if the user interface is enhanced and more customization options are introduced to suit their needs and preferences. The technology's data and analytics capabilities can also be leveraged to support performance measures and reporting.
- IMRCP - The feasibility and value of the technology should be assessed in depth for the St. Louis region, considering the frequency and severity of weather events. Also, the usability and compatibility issues of the platform needs to be addressed and adequate technical support and training should be provided. Further, the technology's impact on winter maintenance operations and crash reduction using historical and real-time data should be evaluated.

Over the course of four years, our team has gained invaluable insights that will shape the future projects and guide decision-making process. One pivotal lesson we learned was the profound impact of effective communication. This realization came to light as we encountered significant delays throughout the project timeline, from contract execution to technology deployment. These delays, spanning two years, underscored the critical role of clear and consistent communication at all levels of the project. The challenges posed by the COVID-19 pandemic further emphasized the need for proactive communication strategies. Uncertainty became an additional hurdle for organizations, making transparent dialogue even more crucial. Moving forward, we recognize that managing expectations is key. Misunderstandings about technology capabilities and limitations can lead to unrealistic projections. Therefore, we will continue to prioritize open and continuous communication between all parties to ensure alignment of understanding and expectations.

In conclusion, the I-270 PLOI project was a successful initiative that showcased the potential of emerging technologies for improving traffic safety and mobility in the St. Louis region. The project also provided valuable insights and lessons learned for future technology deployment and evaluation. The project team hopes that this report will serve as a useful reference and guide for MoDOT, and other transportation agencies interested in adopting and advancing these technologies. Moving forward, MoDOT's focus on continuous staff training and adopting a culture of innovation will sustain the benefits of technology integration. This approach is essential for enhancing the quality of services provided and ensure the safety and satisfaction of the communities involved.

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# APPENDIX A: MEETING NOTES

| Date / Year | Coordination Summary |
|---|---|
| **2019** | - Advanced Video Analytics and Crash Risk Location Prediction & Incident Identification vendor got selected for this project in December 2019. |
| **02/26/2020** | - First discussion regarding how Crash Risk Location Prediction & Incident Identification supplier could collaborate with MoDOT, and which other agencies could be interested in Predictive Analytics tools that the vendor exhibited during the meeting. |
| **03/03/2020** | - MoDOT met with Crash Risk Location Prediction & Incident Identification vendor, deciding who should be the test users and checking if their devices would be applicable to their software. |
| **03/10/2020** | - Internal meeting with MoDOT and St. Louis County, discussing primarily on how St. Louis County can share their crash data to feed into Crash Risk Location Prediction & Incident Identification tools. St. Louis county had difficulties/obstacles to share this data.<br>- Meeting with MoDOT, WSP, and Crash Risk Location Prediction & Incident Identification tool supplier to establish how data should be shared and finalize agreements based on the data being shared. |
| **03/11/2020** | - Meeting with Crash Risk Location Prediction & Incident Identification tool supplier, MoDOT and St. Louis County discussing the overview of the Predictive Analytics project, St. Charles County expressed difficulty in incident identification from their TMC operators. I-270 project included to scope a smart work zone adding vehicle data. MoDOT agreed on sharing Crash Risk Location Prediction & Incident Identification tool information with St. Charles County by “view only”. |
| **03/19/2020** | - Crash Risk Location Prediction & Incident Identification tool supplier vendor and MoDOT got together and defined scope of the project:<br><br>1. For I-270: standard algorithm (incident detection, irregular congestion, and crash prediction) and additional technology in-vehicle data to help identify potential issues within dynamic and complex work zone.<br>2. - For St. Louis Metro Area (St. Louis County, St. Louis City, St. Charles County): only standard algorithm (incident detection, irregular congestion, and crash prediction). |
| **03/24/2020** | - Meeting with Crash Risk Location Prediction & Incident Identification vendor, MoDOT and WSP, questioning how MoDOT should push information to public (website, twitter, or traveler map). Making sure the vendor sets up an FTP site for ATMS provider to share live feeds (road incident, road sensor, DMS, construction, etc.). MoDOT leadership discussed with St. Charles County Police & MSHW to both share their data. Also, the vendor wants to be involved at a larger stage. |

| Date / Year | Coordination Summary |
|---|---|
| **03/26/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification Vendor, and ATMS vendor mainly to discuss ATMS integration. How to receive the data and how to make it easier for TMC users after receiving notification of an incident. Questioning also if Crash Risk Location Prediction & Incident Identification tool should be the main program and push the information to ATMS or ATMS be the main program, or even a third option where TMC operators can receive the notification from Crash Risk Location Prediction & Incident Identification tool and enter information into ATMS. Waiting on ATMS vendor to improve their system to be compatible with Crash Risk Location Prediction & Incident Identification tool's data feeds.<br>- 2nd meeting on March 26th, MoDOT, WSP, and Crash Risk Location Prediction & Incident Identification vendor went through Change Management Process Presentation.<br>- 3rd meeting on March 26th, internal meeting at MoDOT to discuss what is the best option for TMC and ER Operators to receive the incident notification and which platform to insert additional information without causing further challenges/constraints to the operators. |
| **04/02/2020** | - Meeting with MoDOT and Crash Risk Location Prediction & Incident Identification tool vendor decided on making their tool the main program for incident detection and predicting crashes. All the information and incident notification will happen through them and then their API will push this information into ATMS Event Receiver. |
| **04/07/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification vendor, and WSP still discussing on how to push information to the public. Also, MoDOT wants to share information to Waze about I-270 work zone information. |
| **04/21/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification vendor, and WSP discussing on how to push information to the public. One change at this meeting, MoDOT shared excel of planned construction & Crash Risk Location Prediction & Incident Identification tool supplier reviewed if this can be used in the platform. |
| **04/23/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification vendor, and ATMS supplier mainly discussing the integration of ATMS and Crash Risk Location Prediction & Incident Identification tool and receiving updates from both parties. The later received and reviewing the event field descriptions from ATMS. On this meeting, there was a question whether Crash Risk Location Prediction & Incident Identification data should go into the event receiver or the ATMS. Also, MoDOT working on to give Crash Risk Location Prediction & Incident Identification tool supplier a GIS file for lane mapping feature additionally with excel construction schedules. |
| **05/04/2020** | - Internal meeting with MoDOT members to discuss CAD integration data and discussing challenges from different Districts. Highlighting that CAD data in the urban area (KC) did not help much (video analytics are faster for incident identification) but would be extremely helpful in rural areas and MSHP would be a great fit for CAD. If SL district use Tellus then no cost needed to share data with KC district. |

| Date / Year | Coordination Summary |
|---|---|
| **05/05/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification tool supplier, and WSP still discussing on how to push information to the public.<br>- 2nd meeting of the day, with MoDOT and MSHP and discussed about the receival of CAD data from Troop A and some of Troop C for SL and KC district (approved). MSHP agreed to push CAD data to MoDOT without going through third vendor like Tellus (completed by end of May 2020). MoDOT's CAD data will be automatically pushed to a central area, which will filter all the data and send it based on county, date, time, location, latitude/longitude, county, troop name, and location description. The exact method of pushing the data is currently unknown. |
| **05/11/2020** | - Meeting with MoDOT and Crash Risk Location Prediction & Incident Identification tool supplier discussing about the ATMS Event Manager Field, specifically deciding which fields to keep and set the ones never used. |
| **05/13/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification tool supplier, and WSP discussing on how to push information to the public.<br>- 2nd meeting of the day, with MoDOT and MSHP and discussed about the receival of CAD data from Troop A and some of Troop C for SL and KC district (approved). MSHP agreed to push CAD data to MoDOT without going through third vendor like Tellus (completed by end of May 2020). CAD data will be automatically push to MoDOT but unsure how exactly. Most probable being pushed to central area, which will filter all the data, and finally send the data based on county (date, time, location, Lat/Long, county, Troop name, location description). |
| **05/19/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification tool supplier, and WSP discussing on Test User Launch Date (June 29/30), this was during COVID-19 so had to go through COVID-19 visitation restrictions protocols. |
| **05/21/2020** | - Meeting with MoDOT and Crash Risk Location Prediction & Incident Identification tool supplier, just briefly explaining to Crash Risk Location Prediction & Incident Identification tool supplier on how TMC Operators enter event into ATMS event manager. |
| **05/27/2020** | - Meeting with MoDOT and Crash Risk Location Prediction & Incident Identification tool supplier, discussing how MoDOT update and manage construction information, what they update specifically and explaining why they set up the process in this manner. |
| **06/02/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification tool supplier, and WSP discussing on Test User Launch Date (June 29) and details regarding data and process adjustment. |
| **06/03/2020** | - Meeting with MoDOT, MSHP, and ATMS supplier, having MSHP approving for all counties SL and KC to get Troop A and Troop C CAD data. Discussion between MSHP and ATMS vendor on how to push data to MoDOT. Also, MSHP agreed to create an FTP site and share data with MoDOT and ATMS vendor. |
| **06/10/2020** | - Meeting with MoDOT, Crash Risk Location Prediction & Incident Identification tool supplier, and ATMS vendor, discussed about the ATMS Event Manager function while looking into API key from HERE (no changes in the existing systems). |
| **06/11/2020** | - Meeting with MoDOT and Crash Risk Location Prediction & Incident Identification tool supplier, discussing challenges to create a training plan for Crash Risk Location Prediction & Incident Identification tool supplier such as COVID-19 guidelines, share work program, and iPads. Overall training time about 2-3 weeks. |

| Date / Year | Coordination Summary |
|---|---|
| **06/12/2020** | - Internal meeting with MoDOT Leadership, discussing regarding Crash Risk Location Prediction & Incident Identification vendor's contract (2020-2023) and clarifying that contract will not be extended if not wanted.<br><br>1. Quick history recap<br>a. Predictive Analytics funding was approved in June 2019<br>b. Selected Crash Risk Location Prediction & Incident Identification tool supplier in December 2019<br>c. Signed contract with Crash Risk Location Prediction & Incident Identification tool supplier in January 2020<br>d. Start gathering data process in January 2020<br>2. Current Implementation Schedule<br>a. Training – Starting the week of June 29th.<br>b. Soft Launch – July 5th<br>c. Final Version Rollout – November 2020 |
| **06/15/2020** | - Meeting with MoDOT and Crash Risk Location Prediction & Incident Identification tool supplier, discussing challenges to create a training plan for TMC and ER Operators. |
| **09/11/2020** | - Internal meeting with MoDOT Leadership, Predictive Analytics Quarterly Leadership Call (Kickoff), test phase was launched on July 1st with selected users from TMC and ER Operators. Experience feedback from the training executed in July included:<br><br>1. Training Challenges<br>a. COVID-19 guideline<br>2. Devices Challenges<br>b. One iPad pass over shift to shift, person to person<br>c. No chargers<br>3. Test Phased ended July 29th<br>4. Positive and Negative feedback from the users<br>d. Functions that are easy and simple to use<br>e. New function that we don't currently have<br>f. Need to work more on communication process and protocol.<br>- At this meeting, it was planned to launch for Semi End Users around mid-October 2020, while TMC and ER operators were still in training. The need for reporting capabilities from Crash Risk Location Prediction & Incident Identification tool supplier was highlighted, in addition to implementing a congestion algorithm for irregular traffic patterns. The crash prediction feature was scheduled to be launched by December 2020. Video Analytics options were still being discussed with WSP. MoDOT is working with the provider on the IMRCP project in the St. Louis District. |

| Date / Year | Coordination Summary |
| --- | --- |
| **12/11/2020** | - Internal meeting with MoDOT Leadership with updates discussed since the kickoff meeting. Irregular Congestion Algorithm and Crash Prediction Algorithm was released by Crash Risk Location Prediction & Incident Identification tool supplier with the addendum that it would take 1 month to 1 year to refine the algorithm. Predictive Analytics performance measurement was aimed to be released in Spring 2021 (number of crashes, average response time, average delay time). TMC operators provided some feedback using the system, such as: incidents seen on Waze, not appearing on Crash Risk Location Prediction & Incident Identification tool. Also, asking for a better communication between ER and TMC. On the other hand, ER operators, had some positive feedback saying that is quicker to monitor incidents using Crash Risk Location Prediction & Incident Identification tool, however the location at times was inaccurate and responsiveness of the system could be better. Next steps were considered, IMRCP and Video Analytics (similar to KC Scout) to be implemented in SL district Spring 2021. |

# APPENDIX B: OPERATOR INTERVIEW NOTES

## TMC Interview Questions – Conducted on January 18, 2023

4 Interviews were conducted.

1. **What is your position?**
    a. Stephen (S) – TMC Shift Supervisor for Kapsch (TMC Contractor), formerly an ER operator.
    b. Antonia (A) – TMC Operator for Kapsch (TMC Contractor) started less than a year ago.
    c. Dawn (D) – TMC Supervisor for Kapsch (TMC Contractor).
    d. John (J) – Level 3 Operator for Kapsch (TMC Contractor).
    e. Lynnsy (L) – TMC Supervisor, Training Coordinator (TMC Contractor).
    f. Kimberly (K) – TMC Operator Level 2 (TMC Contractor).

2. **When do you sign into Crash Risk Location Prediction & Incident Identification tool and Traffic Vision? Do you use Crash Risk Location Prediction & Incident Identification tool and Traffic Vision all the time or only when stationed on Tunnel Monitoring?**
    a. S – Advanced Video Analytics every day and keep open all the time, Crash Risk Location Prediction & Incident Identification tool only if short-staffed or when on Tunnel monitoring.
    b. A – Nearly every shift for both (75% of the time)
    c. D – Every shift for both
    d. J – Every shift for both
    e. L –
    f. K – Start of shift for all positions

3. **How often do you use Crash Risk Location Prediction & Incident Identification tool and Traffic Vision and how do you use them to support your typical tasks? How do you get and use alerts from the platforms?**
    a. S – Proactively follow alerts for Advanced Video Analytics, usually monitor Crash Risk Location Prediction & Incident Identification tool every 15 minutes.
        i. Most of time split between traffic vision and pulse point to monitor fire station calls – web based and app (pulse point).
        ii. Crash Risk Location Prediction & Incident Identification tool isn't as proactive as identifying information.
            1. Sometimes Crash Risk Location Prediction & Incident Identification tool has identified a crash before other sources.
            2. Usually, day to day it is on par or a little behind on identifying crashes.
    b. A – Constantly monitor Advanced Video Analytics email alerts, use systems to find incidents and monitor congestion. Get alerts from Advanced Video Analytics

thru email. Crash Risk Location Prediction & Incident Identification tool keep window open and then verify on cameras.

c. D – It mostly helps with identifying crashes and stalled vehicles.
d. J – Use to find and verify crashes.
e. L – Use to find incidents. Good at finding moving roadwork that was not called in.
f. K – Use Crash Risk Location Prediction & Incident Identification tool to find events. Use TV alerts from email.

4. **What has been the biggest benefit you have seen with Crash Risk Location Prediction & Incident Identification tool and Traffic Vision? What is the biggest difficulty you have experienced?**
    a. S – Benefit is that it brings all of the information together and identifies that may be missed otherwise. Advanced Video Analytics video recording in alert is valuable. Difficulty is the staffing to monitor. Crash Risk Location Prediction & Incident Identification tool benefit is being able to see other responders in the field. However, it has many duplicate incident alerts.
    b. A – Benefits – Finding debris thru Crash Risk Location Prediction & Incident Identification tool in locations where it's hard to see on cameras, Advanced Video Analytics is good at finding incidents especially crashes and stalled vehicles. Issues – Delay in Reporting major incidents on Crash Risk Location Prediction & Incident Identification tool and duplicates. A lot of time we already know about incidents by the time its reported in Crash Risk Location Prediction & Incident Identification tool.
    c. D – Prompts operator to use cameras near incident. Helps with measuring queues. Issue is duplicates in Crash Risk Location Prediction & Incident Identification tool. Advanced Video Analytics seems to have a delay for emails.
    d. J – Helps pinpoint location of incident, helps during peak hours when it is busy. Issue is duplicates in Crash Risk Location Prediction & Incident Identification tool. Good for finding cameras that are offline. Blocking incidents come through quicker and more accurately.
    e. L – Crash Risk Location Prediction & Incident Identification tool benefit – finding stall vehicles. TV benefit – snapshot is very beneficial along with video. Crash Risk Location Prediction & Incident Identification tool difficulty – duplicate events, can't very incidents like potholes easily. TV difficulty – congestion alert in the beginning will come as false alert.
    f. K – Crash Risk Location Prediction & Incident Identification tool Benefit – find more incident easier than other tools. TV benefit – find more incidents. Difficulty – duplicate events.

5. **How effective is each platform? 1 – 5 scale with 5 is very effective**
    a. Explain more after rating.
        i. S – Crash Risk Location Prediction & Incident Identification tool 3.5, lower score because it has a lot of info that an operator should already know. Seems like a lot of duplicate information. Usually useful and beneficial

when non-normal rush hour traffic. Probably more valuable for newer staff.

1. Advanced Video Analytics 4 – sometimes get false alarms, impressive when picking up pedestrians. All the pedestrian notifications have been accurate.

ii. A – Crash Risk Location Prediction & Incident Identification tool 2, repetitive information, delay in reporting and inaccurate info. Advanced Video Analytics 3, maintenance vehicles show as stopped vehicles. Might be more effective if operators could see platform.
iii. D – Crash Risk Location Prediction & Incident Identification tool 4 lower score because of duplicates, Advanced Video Analytics 5 – gives view of everything.
iv. J – Crash Risk Location Prediction & Incident Identification tool 4 helps identify maintenance operations when they forget to call in but too many duplicates, also good during special events, Advanced Video Analytics 5 – email alerts are beneficial, do not have access to the platform.
v. L – Crash Risk Location Prediction & Incident Identification tool 4 (lower because of duplicates), TV 4.5. Crash Risk Location Prediction & Incident Identification tool finds more incidents more accurately.
vi. K – Crash Risk Location Prediction & Incident Identification tool 3 (lower because of duplicates), TV 4.

b. How often does it provide unique valuable information.
   i. S -
   ii. A -
   iii. D -
   iv. J –

**6. What do you want to use this data for that we are not currently doing?**

a. What action do you want to take when you know crash risk location information?
   i. S – Monitor series of cameras and put on wall. Have ER start heading toward that area.
   ii. A – Constantly monitor and watch
   iii. D – Doesn't help or give information beyond normal congestion
   iv. J –
   v. L – CRA not helpful and not accurate so stopped using. If it was more accurate would put on wall.
   vi. K – Put high crash risk area on Wall to monitor.

b. What other actions could be added using data from either platform?
   i. S – Coordination with highway patrol and police agencies for pedestrian alerts.
   ii. A – If see something, make notification and contact ER
   iii. D – If heavy congestion, put up on DMS boards
   iv. J –
   v. L –

vi. K –

7. **Are there any improvements you would like to see implemented in either platform?**
    a. Alerts
    b. Not enough data, too much data
    c. Ease of use of the platforms
    d. Integration with other platforms
    e. Other
        i. S – Integration with other platforms including ATMS and integration with highway patrol. Would like Advanced Video Analytics on all cameras. Would prefer to error on side of accuracy of information vs. more information. Some less tech savvy operators have more troubles.
            1. It would be nice to be able to adjust presets on CCTV.
        ii. A – Integration with ATMS, Remove duplicates in Crash Risk Location Prediction & Incident Identification tool. More specific alerts in Advanced Video Analytics for lane or shoulder.
        iii. D – Integration with ATMS, Advanced Video Analytics – differentiate between police/maintenance from other incidents.
        iv. J – Integration with ATMS. Get rid of duplicates. Advanced Video Analytics available to all operators.
        v. L – Happy with current platform.
        vi. K – Would prefer separate platforms in order to verify incidents first.

8. **If you could only keep one platform which one would you choose? Or do you want both? Why?**
    a. S – Advanced Video Analytics but both is preferred.
        i. Crash Risk Location Prediction & Incident Identification tool brings data together in one spot – though there are ways to find data if the system goes away.
    b. A – Advanced Video Analytics – less time consuming. Keep Crash Risk Location Prediction & Incident Identification tool if integrated with ATMS.
    c. D – Advanced Video Analytics, gives good view of everything, would miss both systems if didn't have them.
    d. J – Crash Risk Location Prediction & Incident Identification tool, don't have full access to Advanced Video Analytics so less experience with it.
    e. L – Crash Risk Location Prediction & Incident Identification tool – user friendly, accurate. Keep both if an option.
    f. K – Crash Risk Location Prediction & Incident Identification tool – ease of use, accurate. Keep both if an option.

9. **Are there other types of platforms or data that you would like to have to help with your tasks?**
    a. S – Pulse point – would like to be able to see more first responder agencies at once
        i. in the app you can monitor 25 agencies and in the web base you can only pick 15 agencies
    b. A - None
    c. D – Get connected into GPS
    d. J –
    e. L – More DMS and more cameras.  CAD information from first responders.
    f. K – More DMS and more cameras.  CAD information from first responders.

## ER Interview Questions

1. **What is your position?**
    a. Curtis (C) – ER Shift Supervisor
    b. Donald Duclos (D) – ER Operator
    c. Jason Preis (J) – ER Operator

2. **When do you sign into Crash Risk Location Prediction & Incident Identification tool?**
    a. Curtis (C) – Sign in as ER operator, do not sign in as a supervisor.
    b. Donald Duclos (D) – Every shift, sign in before getting on the road at start of shift.
    c. Jason Preis (J) – When in North Area, at beginning of shift.

3. **How often do you use Crash Risk Location Prediction & Incident Identification tool and how do you use it to support your typical tasks? How do you get and use alerts from the platform?**
    a. Curtis (C) – Sign in every day and use it for 270 North project area. Shoulder events only.
    b. Donald Duclos (D) – Whenever response on scene. Only use it when get on scene, do not use the need action tab.
    c. Jason Preis (J) – Use it in the 270 North project area for shoulder events. Use to gather data and to enter data instead of radio chat. Use events lists to determine where need to go next (use as a guide but don't enter into tablet if it is outside of 270 project).

4. **What has been the biggest benefit you have seen with Crash Risk Location Prediction & Incident Identification tool? What is the biggest difficulty you have experienced?**
    a. Curtis (C) – Benefit – shows incidents on map, less radio chatter when TMC is busy. Difficulty – Platform not stable and not accurate.
    b. Donald Duclos (D) – Benefit – helps cover with license plate. Easy access to information and cameras. Verifies location of ER for safety situation. Difficulty – I don't like technology and logging in can be difficult. Still need to use radio.
    c. Jason Preis (J) – Benefit – Cuts down on radio traffic, incident identification to guide where to go next. Difficulty – GPS location isn't accurate. Takes longer to enter information. It is harder to determine where the exact incident location is.

5. **How effective is the platform? 1 – 5 scale with 5 is very effective**
    a. Explain more after rating.
    b. How often does it provide unique valuable information:
        i. Curtis (C) – 4 for what it could do, 2 because of time consuming to enter, 3 for prediction that needs better accuracy.
        ii. Donald Duclos (D) – 4, it is effective with information. Provide on the road, advance information to manage time for you to get to the location.

Helps with measurement of traffic queue. Provides more information and more accuracy than other tools like Waze, scanner, etc.

iii. Jason Preis (J) – 3.0 – it is too new and needs a lot of improvement. Incident identification provides accurate information daily.

6. **What do you want to use this data for that we are not currently doing?**
   a. What action do you want to take when you know crash risk location information?
   b. What other actions could be added using data from the platform?
      i. Curtis (C) – Patrol CRA area to prevent crashes. Accuracy is more important than more locations.
      ii. Donald Duclos (D) – CRA will be beneficial but wasn't aware of this feature before now.
      iii. Jason Preis (J) – Nothing right now, need to narrow down CRA and be more accurate. If accurate would use CRA to patrol the area in case of crash. Would be good to use MSHP or partner police agency to use Crash Risk Location Prediction & Incident Identification tool.

7. **Are there any improvements you would like to see implemented in the platform?**
   a. Alerts
   b. Not enough data, too much data
   c. Ease of use of the platform
   d. Other
      i. Curtis (C) – Good with current information.
      ii. Donald Duclos (D) – Keep screen on. Match ER daily report into platform. Need keypad to enter truck number instead of predetermined dropdown list.
      iii. Jason Preis (J) – Improve GPS location. Tablet – camera in Crash Risk Location Prediction & Incident Identification tool freezes due to internet issues.

8. **Do you want to keep Crash Risk Location Prediction & Incident Identification tool and use it for your tasks? Why?**
   a. Curtis (C) – No, don't feel comfortable using it with time consuming to enter information. Crash Risk Location Prediction & Incident Identification tool works better with police than MoDOT ER.
   b. Donald Duclos (D) – Yes, because it is easy and convenient.
   c. Jason Preis (J) – Yes, if they can fix the problems above. Crash Risk Location Prediction & Incident Identification tool isn't setup for the big area, big highway system.

9. **Are there other types of platforms or data that you would like to have to help with your tasks?**
   a. Curtis (C) – Waze, pulse point and scanner
   b. Donald Duclos (D) – Convert emergency response daily report sheet into database. Or adjust sheet to be better like adding injury and fatality information.

c. Jason Preis (J) – Potholes Truck (New York DOT). Truck camera detection with alert sound to warn ER to get out of the way.

**<u>Manager Interview Questions – Conducted on January 18, 2023</u>**

4 Interviews were conducted.

1. **What is your position?**
    a. Jamie Rana (J) – MoDOT Project Manager TMC contract
    b. Kevin Vogel (K) – Deputy Operations Manager for Kapsch (TMC Contractor)
    c. Alex Wassman (AW) – MoDOT Traffic Management and Operations Engineer
    d. Alan Heathman (AH) – MoDOT Incident Manager Coordinator

2. **Explain your role/responsibility during the deployment of the project. How has it changed through the different phases of the project?**
    a. From procurement to current time
        i. J – From procurement through implementation as traffic operations engineer and oversaw management of the TMC floor staff
            1. Assisted in training of floor staff.
        ii. K – Involved during the initial implementation and currently train new employees on systems.
        iii. AW – Wrote the ATCMTD grant, enabled coordination and connections between internal departments, providing on-going support and oversight. More involved in the beginning, less involved as project progresses.
        iv. AH – Implementation of Crash Risk Location Prediction & Incident Identification tool through evaluation, coordinating collaboration. Provided suggestions and advice and defined process for ER protocol to use tablet. Have not been involved in or seen Advanced Video Analytics.

3. **Do you log into the system yourself?**
    a. If yes, how often do you use Crash Risk Location Prediction & Incident Identification tool and Traffic Vision and how do you use them to support your typical tasks? How do you get and use alerts from the platform?
        i. J – Didn't ever log into Advanced Video Analytics. Don't log into Crash Risk Location Prediction & Incident Identification tool now but did in the beginning.
        ii. K – Crash Risk Location Prediction & Incident Identification tool - Yes during training of employees. Advanced Video Analytics – Not typically, usually just review email alerts.
        iii. AW – Infrequently, usually just to see the data, looking for data to use in other projects and initiatives.
        iv. AH – Used Crash Risk Location Prediction & Incident Identification tool in the beginning but not recently. Quit using because of too many issues in the platform.
    b. If no, please explain.
        i. J –
        ii. K –
        iii. AW –

4. **What has been the biggest benefit you have seen with Crash Risk Location Prediction & Incident Identification tool and Traffic Vision? What is the biggest difficulty you have experienced?**
    a. Personal feedback
        i. J – One platform
            1. Nice to have everything in web-based platform.
            2. modern approach and consolidated information.
            3. more direct camera feed would bring more benefit.
            4. it was not the level of experience we wanted.
            5. it was a good experience for staff to monitor incidents vs normal process.
            6. Difficulty
                a. A lot of shortcuts had to be created to make work.
                b. it didn't work as smoothly as
                c. we had to sell to our operators to use even when we knew it was not working.
                d. lost trust with operators
            7. not many complaints about traffic vision
        ii. K – Crash Risk Location Prediction & Incident Identification tool - Coordination thru tablet and thru Waze is beneficial, issue is some incidents are hard or time consuming to verify. Advanced Video Analytics – like the video recording with alerts, issues are limitations on camera views and congestion alerts for experienced personnel can be a distraction.
        iii. AW – Providing MoDOT with an evaluation and initial use of the available technology, getting organizational experience. Difficulty has been getting multiple vendors to work together on specialized integration. Also, MoDOT does not have the full staff buy-in due to this being a temporary project. For Advanced Video Analytics the camera feeds are lower quality due to MoDOT limitations that affect accuracy.
        iv. AH – Crash Risk Location Prediction & Incident Identification tool has potential to provide information but right now it isn't advanced enough to be helpful. Difficulty – Crash Risk Location Prediction & Incident Identification tool was delayed in providing information compared to other tools like Waze. Tablet screen turns off while driving and there are no audible alerts, operators have to login every time. Many issues with ATMS integration and location accuracy. Predictions are not accurate. Duplicate work to enter information when radio has to be used.
    b. Employee feedback
        i. J – Not accurate enough
        ii. K –
        iii. AW –

5. **How effective is each platform? 1 – 5 scale with 5 is very effective**
    a. Explain more after rating.
        i. J – Advanced Video Analytics 3.5, Crash Risk Location Prediction & Incident Identification tool 2.5 it's good to help operators think differently but it was not the system that was marketed
        ii. K – Advanced Video Analytics 4.5 its simple and fast to use, Crash Risk Location Prediction & Incident Identification tool 2.5 too many duplicate alerts, hard to verify and too many false incidents
        iii. AW – Advanced Video Analytics 4 could use it for more locations. Crash Risk Location Prediction & Incident Identification tool 2.5, incident identification is strong but crash risk is different than what was marketed. MoDOT could have developed a system from scratch and avoided some of the issues and delays experienced.
        iv. AH – Crash Risk Location Prediction & Incident Identification tool 1 for predictability and 4 for incident management (could be 5 with full integration)
    b. How often does it provide unique valuable information.
        i. J –
        ii. K –
        iii. AW –
        iv. AH – not very often

6. **What do you want to use this data for that we are not currently doing?**
    a. What action do you want to take when you know crash risk location information?
        i. J – Change our operation based on predictions. Customize shifts to high crash times. It would be nice to see police and patrol have access so they can respond and integrated into data.
        ii. K – Would prefer crash risk for unusual locations and times
        iii. AW – would like only the unusual events, would prefer the Las Vegas example response of sharing with public.
        iv. AH – It is not accurate enough to act on. Experienced staff already knows where to preposition. Would need to be 100% accurate to act on predictions.
    b. What other actions could be added using data from either platform?
        i. J – Make operations staff more efficient – more ability to customize what we do when crashes happen.
        ii. K – Use historical information to make roadway improvements that other data wouldn't have indicated a safety issue.
        iii. AW – Use data for larger trends. Analyze effectiveness of workzone tools. Look for insights to use around the state on large workzones. i.e. near misses, data to support increased enforcement or to make improvement decisions not just daily traffic management.

7. **Are there any improvements you would like to see implemented in either platform?**
    a. Alerts
    b. Not enough data, too much data
    c. Ease of use of the platforms
    d. Integration with other platforms
    e. Other
        i. J – Integration with ATMS. It would be ideal to bring all the systems to speak to each other.
            1. Accuracy has to be most important and more accurate than the radio to get the benefit.
            2. It creates more work than its worth if not accurate.
            3. In order to maintain efficiency of staffing and team – with turnover and troubleshooting if issues with accuracy – need to make sure process is streamlined.
            4. Expanding out doesn't make sense if not accurate.
        ii. K – Integration with ATMS
        iii. AW – Ease of integration, operating within the intent of working with other systems, standardize data feeds.
        iv. AH – Audible alerts while driving. Right now, the tablet screen has to go dark for safety while driving. Dashboards of information are good. Push notifications of high crash zone to public. All data in one platform to share with other agencies and platforms like Waze.

8. **How can we incorporate data from Crash Risk Location Prediction & Incident Identification tool and Traffic Vision into daily operation in the future?**
    a. J – Collaboration with other agencies
    b. K – Sharing info about hotspots. Arrange ER operators near crash risk areas.
    c. AW – Use of tablet by field staff, get into ATMS without extra steps. Advanced Video Analytics – expand to additional locations, filter for alerts.
    d. AH – The Crash Risk Location Prediction & Incident Identification tool platform isn't ready.

9. **If you could only keep one platform which one would you choose? Or do you want both? Why?**
    a. J – Advanced Video Analytics, more straightforward and it's working well.
        i. Crash Risk Location Prediction & Incident Identification tool needs big improvement - if could integrate ATMS and give probability of accuracy, then consider.
    b. K – Advanced Video Analytics – helps verify incidents, effective to respond to an incident, keep both if possible.
    c. AW – Advanced Video Analytics – easily scalable, could expand in St. Louis and be used in other districts. Crash Risk Location Prediction & Incident Identification

tool has potential but it is not what was marketed and wasn't ready. Could use something else like it in the future.

d. AH – Yes, if you could merge everything into one system and have it ready for use. Would not keep for CRA but would keep for incident identification with full integration to ATMS.

**10. If no to question 9 on both platforms, what can be improved in the future to continue with both platforms?**

a. J –
b. K – Integration with ATMS. Debris and damage (i.e. potholes) incident alerts need to be improved or maybe not reported. They can be very hard to verify and are very time consuming. Too unreliable or uncertain of exact location in order to submit a work request.
c. AW – Crash Risk Location Prediction & Incident Identification tool - Shortening crash risk windows, make it easy to use.
d. AH – Full integration with ATMS.

**11. Are there other types of platforms or data that you would like to have?**

a. J – RIDSI and Titan. Need to understand the systems we have fully first before looking for new platforms.
b. K – Something to share info back out to end users or first responders.
c. AW – ATSPM without equipment in the field. MoDOT needs data analyst.
d. AH – One single platform with ability to share information with other agencies like police.

In February 2023, I-270 PLOI project team interviewed six Transportation Management Center (TMC) operators, three Emergency Response (ER) operators, and four managers on the performance of the Crash Risk Location Prediction & Incident Identification tool and Advanced Video Analytics. **Table 27** shows the results from the interviews separated by group.

**Table 27: Operator Interview Notes**

| Interviewed Party | Benefits | Difficulties |
|---|---|---|
| TMC Operators | - Crash Risk Location Prediction & Incident Identification tool and Advanced Video Analytics identify unknown incidents accurately and quickly.<br>- Crash Risk Location Prediction & Incident Identification tool and Traffic Vision help pinpoint location of incidents. | - Multiple data sources feeding into the platforms creates duplicate incident listings which create additional work. |
| ER Operators | - Crash Risk Location Prediction & Incident Identification tool gives operators map of incidents.<br>- Crash Risk Location Prediction & Incident Identification tool reduces radio traffic. | - GPS location issues.<br>- MoDOT safety protocols prevent full use. |
| MoDOT Supervisors and Managers | - Crash Risk Location Prediction & Incident Identification tool and Advanced Video Analytics consolidated information.<br>- Both platforms create historical data.<br>- Both platforms provide organizational experience. | - Crash Risk Location Prediction & Incident Identification tool was not user ready when it first deployed.<br>- Crash Risk Prediction Area accuracy. |

# APPENDIX C: CRASH RISK AREA (CRA) MONTHLY VERIFICATION RESULTS

Crash Risk Location Prediction tool defined Crash Risk Areas (CRA) for the prediction of crashes; **Table 28** shows the percentage of predicted crashes of visible CRA only. At the start of the program, the number of CRA were 205 and stayed in the 200s during the first year. In October 2022, MoDOT leadership wanted to increase the number visible CRAs; The vendor increased the number of visible CRAs without keeping a proportionate number of invisible CRAs, which led to a decrease in accuracy of predicted crashes for January and April of 2023.

In response to the dip in accuracy, the company announced improvements to its program and focused on producing visible CRAs, which ultimately reduced the total number of CRA. These changes resulted in improved accuracy, doubling the percentage of predicted crashes from July 2023 to October 2023.

**Table 28: Percentage of Predicted Crashes in Visible CRA**

| Month / Year | # of Visible CRA | % of Predicted Crashes |
|---|---|---|
| February 2022 | 205 | 4.4% |
| April 2022 | 272 | 5.9% |
| July 2022 | 260 | 5.0% |
| October 2022 | 357 | 6.4% |
| January 2023 | 752 | 4.1% |
| April 2023 | 766 | 3.4% |
| July 2023 | 904 | 5.4% |
| October 2023 | 367 | 10.9% |

# APPENDIX D: INCIDENT IDENTIFICATION MONTHLY VERIFICATION RESULTS

## November 2021

This was the first verification completed on the Incident Identification tool. **Table 29** shows that by the end of 2021, the tool was being outperformed by other tools used by MoDOT, displaying 42.5% of the time being the fastest compared to 55.8% from other tools. It is important to note that in November 2021, was not observed any incident reported at the same time by both tools.

**Table 29: November 2021 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:20 | 0:09 | -- |
| **Average Report Time (<1 hour)** | 0:14 | -- | -- |
| **Average Report Time (>1 hour)** | 4:00 | -- | -- |
| **Total Incident Count** | 124 | 91 | -- |
| **Total Incident Count (<1 hour)** | 120 | -- | -- |
| **Total Incident Count (>1 hour)** | 4 | -- | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 55.8% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 42.3% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | -- | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 1.9% | -- | -- |

## February 2022

Beginning of 2022 did not display improvements by Incident Identification tool. **Table 30** shows that, in fact, displayed a decrease in the performance metrics compared to other tools, reporting incidents first were at 42.5% of the time and in February 2022 dropped to 40.8%.

**Table 30: February 2022 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:23 | 0:11 | -- |
| **Average Report Time (<1 hour)** | 0:16 | 0:10 | -- |
| **Average Report Time (>1 hour)** | 1:51 | 1:54 | -- |
| **Total Incident Count** | 138 | 100 | 7 |
| **Total Incident Count (<1 hour)** | 128 | 99 | -- |
| **Total Incident Count (>1 hour)** | 10 | 1 | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 56.3% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 40.8% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | 2.9% | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 4.1% | 0.4% | -- |

## April 2022

After observing a decrease in the performance in February 2022, Incident Identification tool demonstrated to experience slight improvements and improved its report time compared to other tools. **Table 31** shows Incident Identification tool reporting incidents 43.4% of the time, which meant a 2.6% increase.

**Table 31: April 2022 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:16 | 0:07 | -- |
| **Average Report Time (<1 hour)** | 0:13 | 0:06 | -- |
| **Average Report Time (>1 hour)** | 1:27 | 1:02 | -- |
| **Total Incident Count** | 132 | 111 | 13 |
| **Total Incident Count (<1 hour)** | 127 | 110 | -- |
| **Total Incident Count (>1 hour)** | 5 | 1 | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 51.6% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 43.4% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | 5.1% | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 2.0% | 0.4% | -- |

## July 2022

During July 2022, Incident Identification tool suffered setbacks and reported incidents first only 41.8% of the time. In addition to this, **Table 32** shows the decrease in the percentage in incidents reported at the same time of both tools.

**Table 32: July 2022 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:15 | 0:07 | -- |
| **Average Report Time (<1 hour)** | 0:12 | 0:07 | -- |
| **Average Report Time (>1 hour)** | 2:09 | -- | -- |
| **Total Incident Count** | 138 | 104 | 7 |
| **Total Incident Count (<1 hour)** | 135 | 104 | -- |
| **Total Incident Count (>1 hour)** | 3 | 0 | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 55.4% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 41.8% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | 2.8% | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 1.2% | 0.0% | -- |

## October 2022

After suffering a setback in July 2022, Incident Identification tool made improvements to the platform and made October 2022 to be the best month since the beginning of the verification process. **Table 33** shows that for the first time Incident Identification tool surpassed other tools and had a majority of the incidents being reported first by them. An increase of 12.3% from the previous quarter.

**Table 33: October 2022 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:20 | 0:08 | -- |
| **Average Report Time (<1 hour)** | 0:12 | 0:07 | -- |
| **Average Report Time (>1 hour)** | 2:13 | 1:05 | -- |
| **Total Incident Count** | 132 | 170 | 12 |
| **Total Incident Count (<1 hour)** | 123 | 169 | -- |
| **Total Incident Count (>1 hour)** | 9 | 1 | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 42.0% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 54.1% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | 3.8% | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 2.9% | 0.3% | -- |

## January 2023

January 2023 presented that Incident Identification tool maintained the majority of the incidents being reported first, however the increase of incidents being reported at the same time by both tools doubled from October 2022. **Table 34** depicts the performance metrics of this month.

**Table 34: January 2023 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:20 | 0:08 | -- |
| **Average Report Time (<1 hour)** | 0:14 | 0:07 | -- |
| **Average Report Time (>1 hour)** | 3:11 | 1:47 | -- |
| **Total Incident Count** | 163 | 196 | 24 |
| **Total Incident Count (<1 hour)** | 157 | 194 | -- |
| **Total Incident Count (>1 hour)** | 6 | 2 | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 42.6% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 51.2% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | 6.3% | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 1.6% | 0.5% | -- |

## April 2023

The increase on the number of incidents being reported at the same time, reflected on Incident Identification tool's performance compared to other tools. In this month, ATMS completed the integration of Waze data into their platform, which impacted in both tools having more identical incident report times. **Table 35** shows 45.9% for both tools first reporting incidents.

**Table 35: April 2023 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:16 | 0:13 | -- |
| **Average Report Time (<1 hour)** | 0:15 | 0:12 | -- |
| **Average Report Time (>1 hour)** | 1:08 | 1:09 | -- |
| **Total Incident Count** | 150 | 150 | 27 |
| **Total Incident Count (<1 hour)** | 147 | 147 | -- |
| **Total Incident Count (>1 hour)** | 3 | 3 | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 45.9% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 45.9% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | 8.3% | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 0.9% | 0.9% | -- |

## July 2023

July 2023 represented the quarter where Incident Identification tool returned to have majority of incidents being reported first compared to other tools. The significant percentage of incidents being reported at the same time by both tools remained at a similar rate compared to April 2023 as shown in **Table 36**.

**Table 36: July 2023 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:27 | 0:15 | -- |
| **Average Report Time (<1 hour)** | 0:13 | 0:07 | -- |
| **Average Report Time (>1 hour)** | 4:55 | 3:09 | -- |
| **Total Incident Count** | 137 | 157 | 26 |
| **Total Incident Count (<1 hour)** | 130 | 150 | -- |
| **Total Incident Count (>1 hour)** | 7 | 7 | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 42.8% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 49.1% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | 8.1% | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 2.2% | 2.2% | -- |

## October 2023

October 2023 marked as the last verification month for all technologies in this project and solidified by presenting another month with the majority of the incidents being reported first by Incident Identification tool.

The last monthly verification has a different importance because it represents the most updated status of the technology. **Table 37** shows that in the last verification month, Incident Identification tool reported incidents first 48% of the time compared to other tools, which achieved 42.5%. Incidents reported at the same time by both tools continued to present an increase reaching to 9.5% of the time in October 2023.

**Table 37: October 2023 Incident Report Comparison Between Tools**

| | Other Tools First to Report | Incident Identification tool First to Report | Both Tools Report at Same Time |
|---|---|---|---|
| **Average Report Time** | 0:13 | 0:09 | -- |
| **Average Report Time (<1 hour)** | 0:11 | 0:07 | -- |
| **Average Report Time (>1 hour)** | 1:52 | 1:32 | -- |
| **Total Incident Count** | 193 | 218 | 43 |
| **Total Incident Count (<1 hour)** | 188 | 214 | -- |
| **Total Incident Count (>1 hour)** | 5 | 4 | -- |
| **Percentage Comparison** | | | |
| **Incidents First Reported by Other Tools** | 42.5% | -- | -- |
| **Incidents First Reported by Incident Identification tool** | 48.0% | -- | -- |
| **Incidents Reported by Both Tools at Same Time** | 9.5% | -- | -- |
| **Incidents Reported by Incident Identification tool (>1 hour)** | 1.1% | 0.9% | -- |

# APPENDIX E: ADVANCED VIDEO ANALYTICS MONTHLY VERIFICATION RESULTS

The incidents detected by Advanced Video Analytics in Crash Risk Areas (CRA) were verified manually to check the accuracy of detection and other key performance measures. Verifications were done quarterly for 2022 (February, April, July, and October) and 2023 (January, April, July, and October). February 2022 and April 2022 were key months for establishing a standard verification process. These two months were verified for the last three weeks of each month; as this verification process evolved, the verification went from three weeks to four weeks.

## February 2022

Feburary 2022 was the first verification month of the project and took place for the last three weeks. Winter conditions in St. Louis can continue through early March and can cause weather-related incidents. To account for this, two assessments of Advanced Video Analytics took place: one total assessment of the month and one assessment that excluded weather-related incidents that Advanced Video Analytics created false alerts.

**Figure 41** shows the verifcation results for February 2022, with highlights including:

**Overall:**

True Alerts: 80%
False Alerts: 10%
Unable to Verify Alerts: 10%

**Overall (Without Weather Related Alerts):**

True Alerts: 86%
False Alerts: 3%
Unable to Verify Alerts: 11%

## Traffic Vision February Verification
## Dates Observed: February 6 - February 26, 2022
## Time Period Observed: All Day

| Total | |
|---|---|
| (T) True | 631 |
| (F) False | 83 |
| (NV) Unable to Verify* | 78 |
| (T) Side of Interstate | 16 |
| (T) Weather Related | 12 |
| (T) Stopped Object | 0 |
| (T) Gridlocked Traffic | 327 |
| (T) Vehicle Pulled to Shoulder | 276 |
| (F) Weather Related | 60 |
| (F) Incorrect Classification | 23 |
| (F) Snow Malfunction | 0 |
| (F) No Visible Vehicles | 0 |
| (NV) Unable to Verify* | 78 |

| Congestion | |
|---|---|
| (T) True | 188 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Gridlocked Traffic | 188 |
| (T) Crash | 0 |

| Low Visibility | |
|---|---|
| (T) True | 7 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Weather Related | 0 |

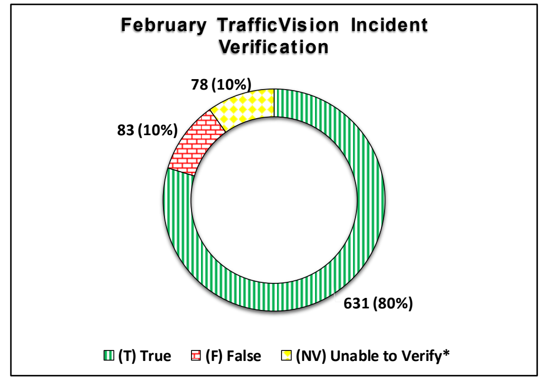
| Pedestrian | |
|---|---|
| (T) True | 16 |
| (F) False | 11 |
| (NV) Unable to Verify* | 1 |
| (T) Crash | 0 |
| (T) Side of Interstate | 16 |
| (F) Incorrect Classification | 2 |
| (F) Weather Related | 9 |
| (NV) Unable to Verify* | 1 |

| | | |
|---|---|---|
| (T) | = | Description of True Alert |
| (F) | = | Description of False Alert |
| (NV) | = | Alerts were unable to be verified* |

| Slow Speeds | |
|---|---|
| (T) True | 123 |
| (F) False | 7 |
| (NV) Unable to Verify* | 68 |
| (T) Crash | 0 |
| (T) Weather Related | 5 |
| (T) Gridlocked Traffic | 118 |
| (F) Incorrect Classification | 7 |
| (F) No Visible Vehicles | 0 |
| (NV) Unable to Verify* | 68 |

| Stopped Vehicle / Object | |
|---|---|
| (T) True | 297 |
| (F) False | 65 |
| (NV) Unable to Verify* | 9 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 21 |
| (T) Vehicle Pulled to Shoulder | 276 |
| (F) Incorrect Classification | 14 |
| (F) No Visible Vehicles | 0 |
| (F) Weather Related | 51 |
| (F) Snow Malfunction | 0 |
| (NV) Unable to Verify* | 9 |

| Wrong Way Driver | |
|---|---|
| (T) True | 0 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |



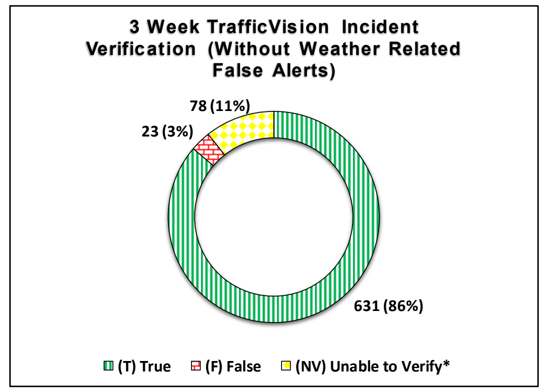




**Figure 41: February 2022 Advanced Video Analytics Verification Result**

**Figure 42** shows the break-down of false incidents by the contributing circumstance. More than half (61.4%) of the false alerts were caused by stopped vehicles or objects in the road; 51 of these alerts were weather related.

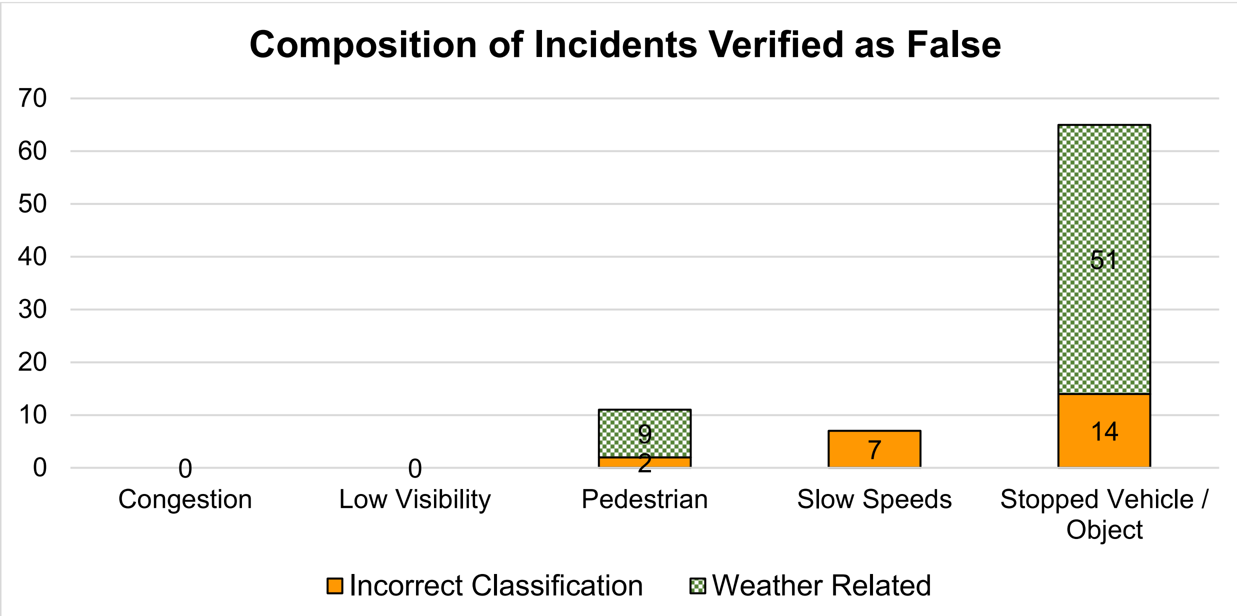



**Figure 42: February 2022 Advanced Video Analytics False Alert Incident Composition**

## April 2022

Verification of results in April 2022 took place for the last three weeks. Spring in St. Louis typically begins in March, therefore it was expected that weather-related events would decrease; however, an analysis of weather-related alerts were kept in the assessment process to see the impacts that rain had on incident detection.

**Figure 43** shows the verifcation results for February 2022, with highlights including:

**<u>Overall:</u>**

True Alerts: 91%
False Alerts: 4%
Unable to Verify Alerts: 5%

**<u>Overall (Without Weather Related Alerts):</u>**

True Alerts: 92%
False Alerts: 3%
Unable to Verify Alerts: 5%

Based on these results, weather-related alerts were not as present as they were in February.

## Traffic Vision April Verification
## Dates Observed: April 10 - April 30, 2022
## Time Period Observed: All Day

| Total | |
|---|---|
| (T) True | 876 |
| (F) False | 40 |
| (NV) Unable to Verify* | 49 |
| (T) Side of Interstate | 44 |
| (T) Weather Related | 2 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 579 |
| (T) Vehicle Pulled to Shoulder | 240 |
| (T) Crossing Lanes | 0 |
| (T) Construction Equipment | 11 |
| (F) Snow Malfunction | 0 |
| (F) Weather Related | 12 |
| (F) Incorrect Classification** | 27 |
| (F) No Visible Vehicles | 0 |
| Total Incidents | 965 |

| Congestion | |
|---|---|
| (T) True | 461 |
| (F) False | 3 |
| (NV) Unable to Verify* | 3 |
| (T) Gridlocked Traffic | 461 |
| (T) Crash | 0 |
| (F) Incorrect Classification | 2 |
| (F) Weather Related | 1 |

| Low Visibility | |
|---|---|
| (T) True | 2 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Weather Related | 2 |

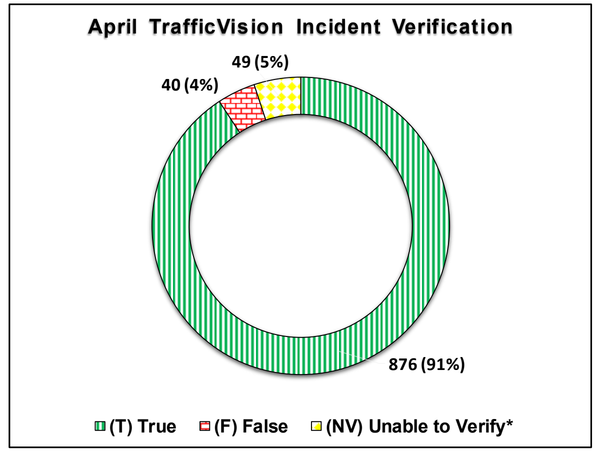
| Pedestrian | |
|---|---|
| (T) True | 44 |
| (F) False | 13 |
| (NV) Unable to Verify* | 0 |
| (T) Crossing Lanes | 0 |
| (T) Side of Interstate | 44 |
| (T) Crash | 0 |
| (F) Moved Camera | 0 |
| (F) Incorrect Classification | 12 |
| (F) Weather Related | 1 |

| | | |
|---|---|---|
| (T) | = | Description of True Alert |
| (F) | = | Description of False Alert |
| (NV) | = | Alerts were unable to be verified* |

| Slow Speeds | |
|---|---|
| (T) True | 105 |
| (F) False | 1 |
| (NV) Unable to Verify* | 46 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 105 |
| (F) Incorrect Classification | 0 |
| (F) Weather Related | 0 |

| Stopped Vehicle / Object | |
|---|---|
| (T) True | 264 |
| (F) False | 23 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 13 |
| (T) Vehicle Pulled to Shoulder | 240 |
| (T) Stopped Object | 11 |
| (F) Incorrect Classification | 13 |
| (F) Weather Related | 10 |

| Wrong Way Driver | |
|---|---|
| (T) True | 0 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |



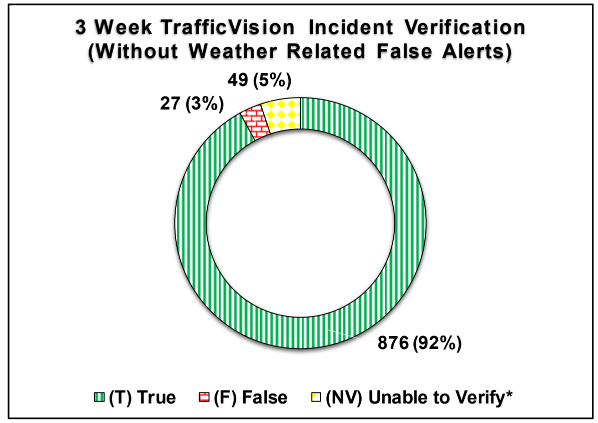




Figure 43: April 2022 Advanced Video Analytics Verification Results

**Figure 44** shows the break-down of false incidents by the contributing circumstance. Like February, stopped vehicle and objects in the road were the largest false incident type (57.5%). However, weather was no longer a major contributor for false identification, as only 25% of false indicents were weather-related; **Figure 45** shows that the majority of false incident identification (85%) was improper positioning of cameras (e.g., cameras not preset to the home view).

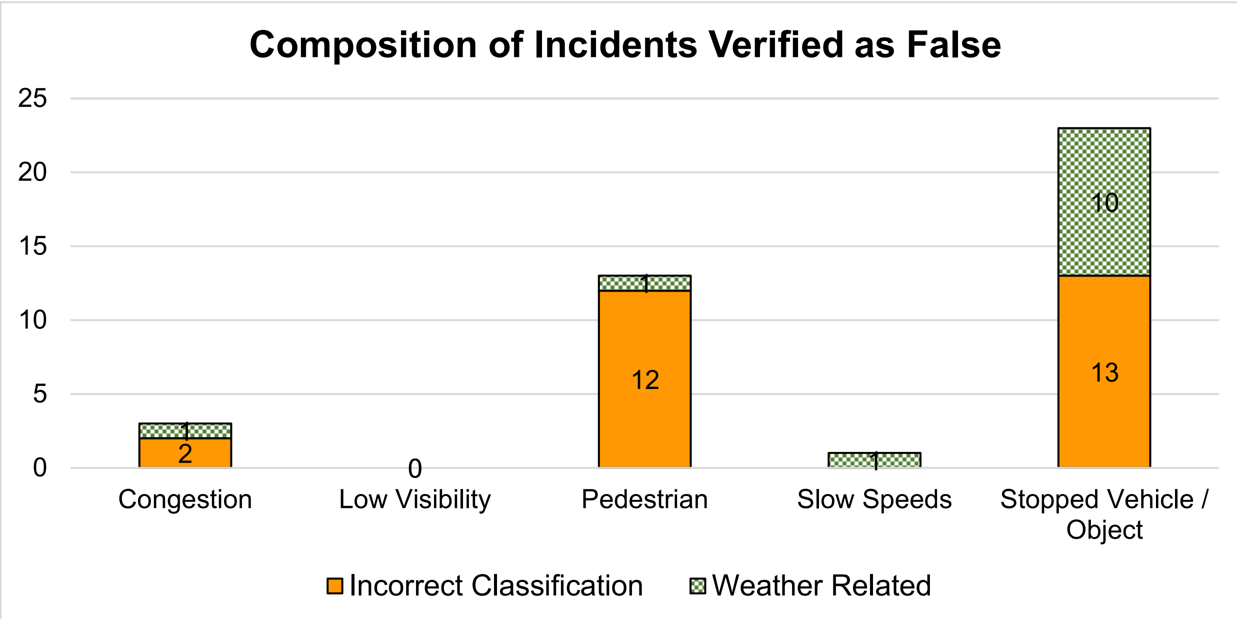



**Figure 44: April 2022 Advanced Video Analytics False Alert Incident Composition**

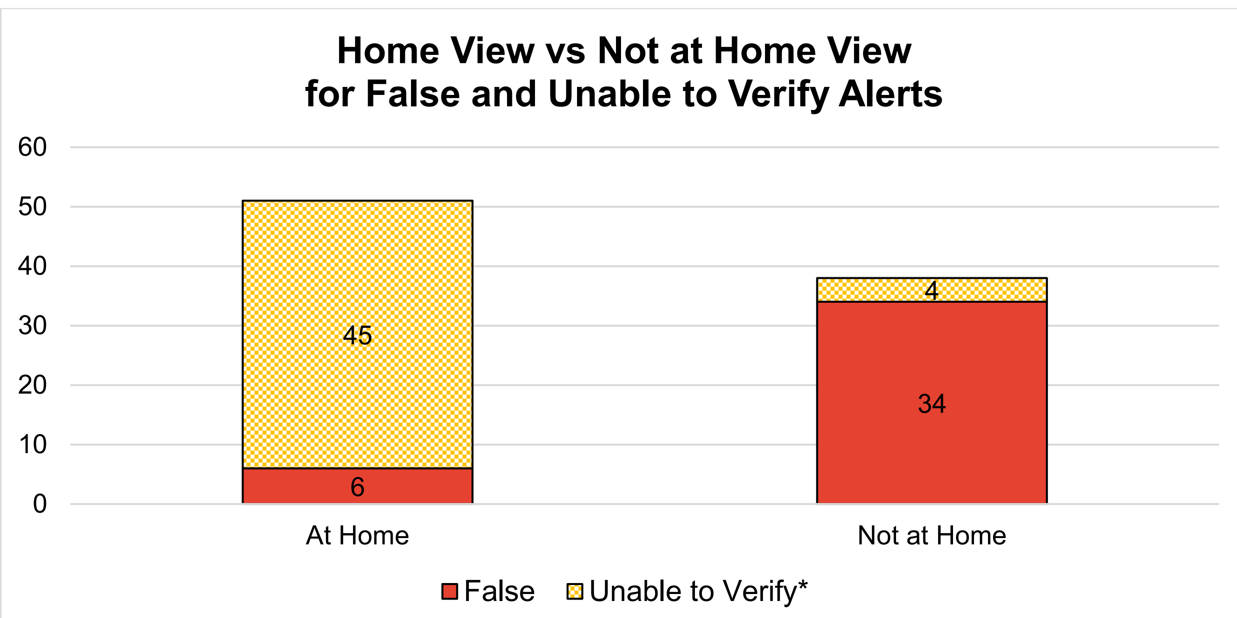



**Figure 45: April 2022 Advanced Video Analytics Home View vs Not at Home View of False and Unable to Verify Alerts**

## July 2022

July 2022 marked the beginng of 4-week (entire month) verification analysis process. Summer in St. Louis typically starts in July; as weather conditions are typically mild during this season, they were expected to not be a large contributor to false alerts.. During the verification process, false alerts pertaining to slow speeds significantly increased; therefore, the two major assessments were made with and without slow speeds false alerts.

**Figure 46** shows the verifcation results for July 2022, with highlights including:

**Overall:**

True Alerts: 88%
False Alerts: 11%
Unable to Verify Alerts: 1%

**Overall (Without Slow Speed False Alerts):**

True Alerts: 94%
False Alerts: 5%
Unable to Verify Alerts: 1%

**Traffic Vision July Verification**

**Dates Observed: July 1 - July 31, 2022**

**Time Period Observed: All Day**

| Total | |
|---|---|
| (T) True | 855 |
| (F) False | 107 |
| (NV) Unable to Verify* | 10 |
| (T) Side of Interstate | 16 |
| (T) Weather Related | 28 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 374 |
| (T) Vehicle Pulled to Shoulder | 407 |
| (T) Crossing Lanes | 0 |
| (T) Stopped Object | 30 |
| (F) Snow Malfunction | 0 |
| (F) Weather Related | 15 |
| (F) Incorrect Classification** | 92 |
| (F) No Visible Vehicles | 0 |
| Rain Malfunction | 0 |
| Gridlocked Traffic | 1 |
| (NV) Unable to Verify* | 9 |
| Total Incidents | 972 |

| Congestion | |
|---|---|
| (T) True | 192 |
| (F) False | 0 |
| (NV) Unable to Verify* | 2 |
| (T) Gridlocked Traffic | 192 |
| (T) Crash | 0 |
| (F) Incorrect Classification** | 0 |
| (F) Weather Related | 0 |

| Low Visibility | |
|---|---|
| (T) True | 28 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Weather Related | 28 |

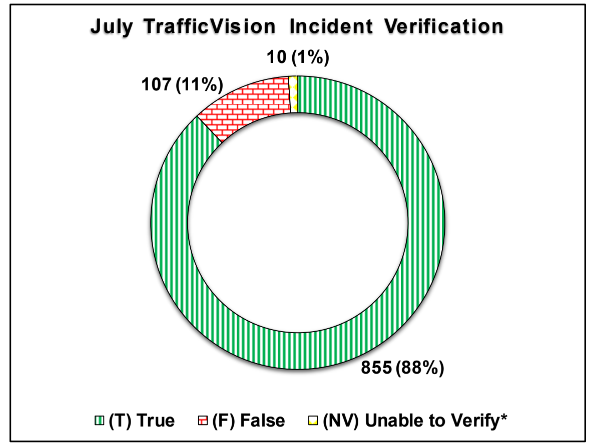
| Pedestrian | |
|---|---|
| (T) True | 16 |
| (F) False | 10 |
| (NV) Unable to Verify* | 0 |
| (T) Crossing Lanes | 0 |
| (T) Side of Interstate | 16 |
| (T) Crash | 0 |
| (F) Moved Camera | 0 |
| (F) Incorrect Classification** | 10 |
| (F) Weather Related | 0 |

| | | |
|---|---|---|
| (T) | = | Description of True Alert |
| (F) | = | Description of False Alert |
| (NV) | = | Alerts were unable to be verified* |

| Slow Speeds | |
|---|---|
| (T) True | 182 |
| (F) False | 57 |
| (NV) Unable to Verify* | 8 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 182 |
| (F) Incorrect Classification** | 57 |
| (F) Weather Related | 0 |

| Stopped Vehicle / Object | |
|---|---|
| (T) True | 437 |
| (F) False | 40 |
| (NV) Unable to Verify* | 3 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 0 |
| (T) Vehicle Pulled to Shoulder | 407 |
| (T) Stopped Object | 30 |
| (F) Incorrect Classification** | 25 |
| (F) Weather Related | 15 |

| Wrong Way Driver | |
|---|---|
| (T) True | 0 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |



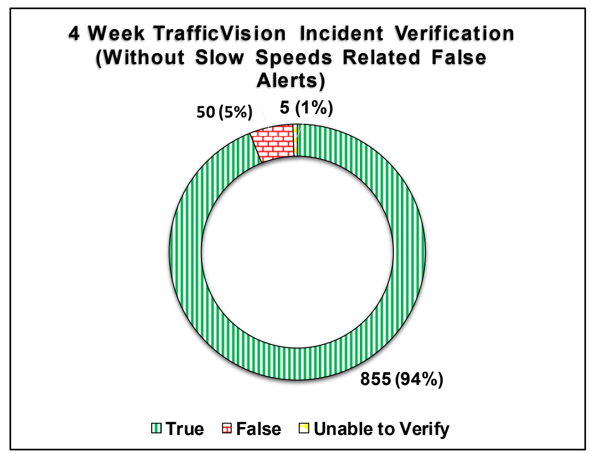




Figure 46: July 2022 Advanced Video Analytics Verification Results

**Figure 47** shows the break-down of false incidents by the contributing circumstance; slow speeds were the largest type of false incident detected (53.2%).

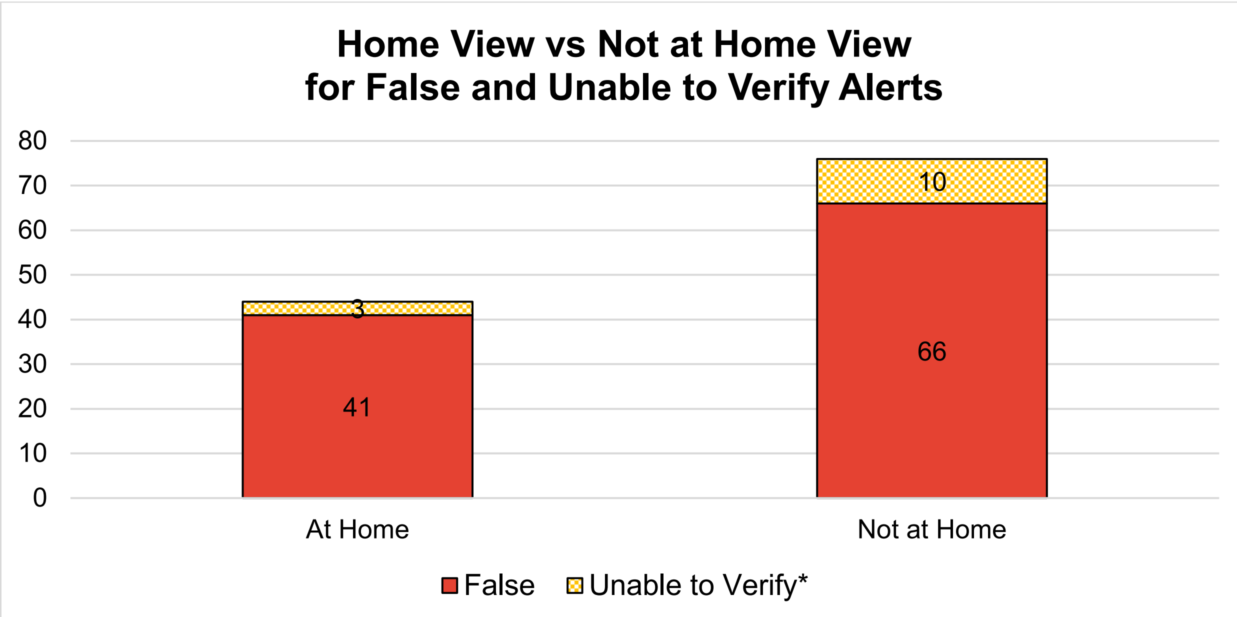



**Figure 47: July 2022 Advanced Video Analytics Home View vs Not at Home View of False and Unable to Verify Alerts**

**Figure 48** shows that more than half of false incident identification (61.6%) was improper positioning of cameras (e.g., cameras not preset to the home view).

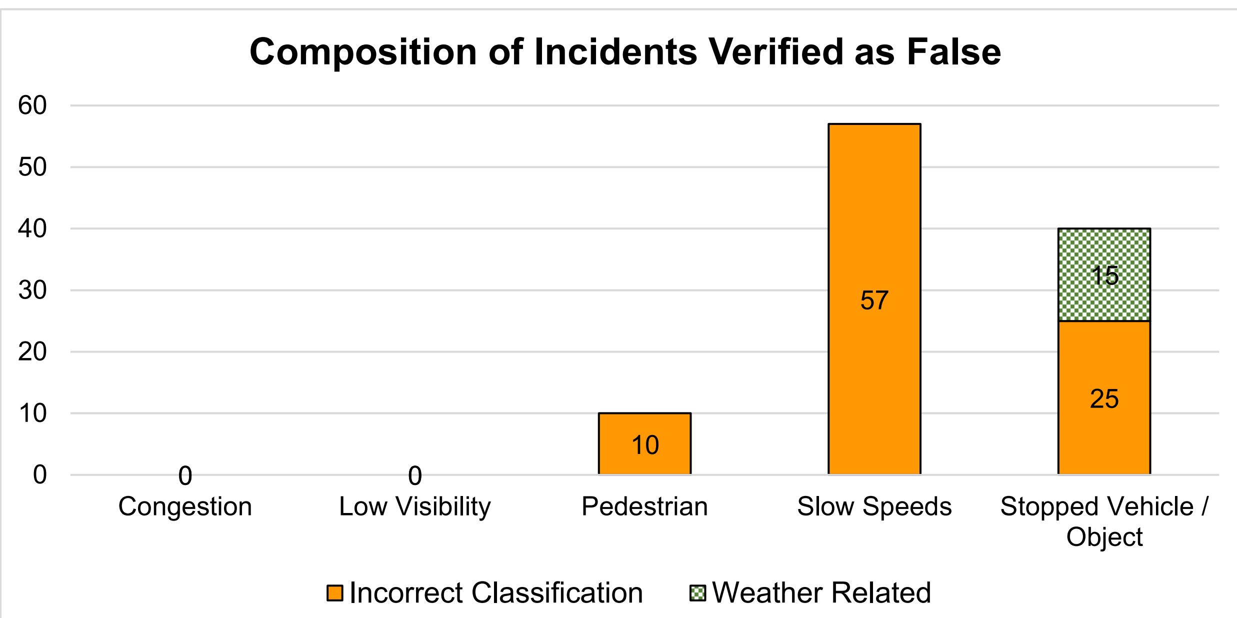



**Figure 48: July 2022 Advanced Video Analytics False Alert Incident Composition**

## October 2022

Verifcation results in October 2022 presented similarly July 2022, with the largest category of false alerts being slow speeds. Fall in St. Louis typically starts in late-September; as weather conditions are typically mild during this season, they were expected to not be a large contributor to false alerts. October 2022 marked the first month where no alerts were consider unverifiable, as the previous iterations of verification made the verification team aware of all scenarios possible and the definition of true or false incidents was made clear. Two total assesments were made, comparing with and without slow speeds false alerts.

**Figure 49** shows the verifcation results for October 2022, with highlights including:

**Overall:**

True Alerts: 88%
False Alerts: 12%
Unable to Verify Alerts: 0%

**Overall (Without Slow Speed False Alerts):**

True Alerts: 95%
False Alerts: 5%
Unable to Verify Alerts: 0%

## Traffic Vision October Verification
## Dates Observed: October 1 - October 31, 2022
## Time Period Observed: All Day

**Total**

| | |
|---|---|
| (T) True | 867 |
| (F) False | 114 |
| (NV) Unable to Verify | 0 |
| (T) Side of Interstate | 12 |
| (T) Weather Related | 1 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 513 |
| (T) Vehicle Pulled to Shoulder | 339 |
| (T) Crossing Lanes | 0 |
| (T) Stopped Object | 2 |
| (F) Snow Malfunction | 0 |
| (F) Rain Malfunction | 0 |
| (F) Incorrect Classification** | 114 |
| (F) No Visible Vehicles | 0 |
| (NV) Rain Malfunction | 0 |
| (NV) Gridlocked Traffic | 0 |
| (NV) Unable to Verify* | 0 |
| Total Incidents | 981 |

**Congestion**

| | |
|---|---|
| (T) True | 335 |
| (F) False | 7 |
| (NV) Unable to Verify* | 0 |
| (T) Gridlocked Traffic | 334 |
| (T) Crash | 0 |
| (F) Incorrect Classification** | 7 |
| (F) Weather Related | 0 |

**Low Visibility**

| | |
|---|---|
| (T) True | 1 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Weather Related | 1 |

**Pedestrian**

| | |
|---|---|
| (T) True | 12 |
| (F) False | 1 |
| (NV) Unable to Verify* | 0 |
| (T) Crossing Lanes | 0 |
| (T) Side of Interstate | 12 |
| (T) Crash | 0 |
| (F) Moved Camera | 0 |
| (F) Incorrect Classification** | 1 |
| (F) Weather Related | 0 |

| | | |
|---|---|---|
| (T) | = | Description of True Alert |
| (F) | = | Description of False Alert |
| (NV) | = | Alerts were unable to be verified* |

**Slow Speeds**

| | |
|---|---|
| (T) True | 179 |
| (F) False | 64 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 179 |
| (F) Incorrect Classification** | 64 |
| (F) Weather Related | 0 |

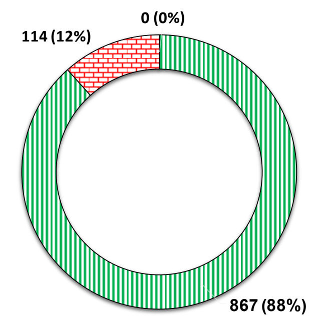
**Stopped Vehicle / Object**

| | |
|---|---|
| (T) True | 340 |
| (F) False | 42 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 0 |
| (T) Vehicle Pulled to Shoulder | 338 |
| (T) Stopped Object | 2 |
| (F) Incorrect Classification** | 42 |
| (F) Weather Related | 0 |

**Wrong Way Driver**

| | |
|---|---|
| (T) True | 0 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |

**October TrafficVision Incident Verification**




**4 Week TrafficVision Incident Verification (Without Slow Speeds Related False Alerts)**

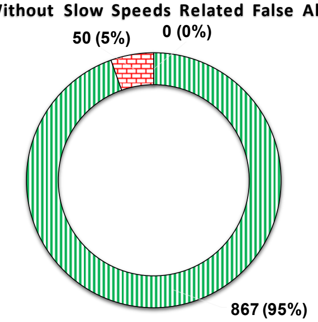



Figure 49: October 2022 Advanced Video Analytics Verification Results

**Figure 50** shows the break-down of false incidents by the contributing circumstance; slow speeds were the largest type of false incident detected (56.1%). **Figure 51** shows that more than half of false incident identification (69.2%) was improper positioning of cameras (e.g., cameras not preset to the home view).

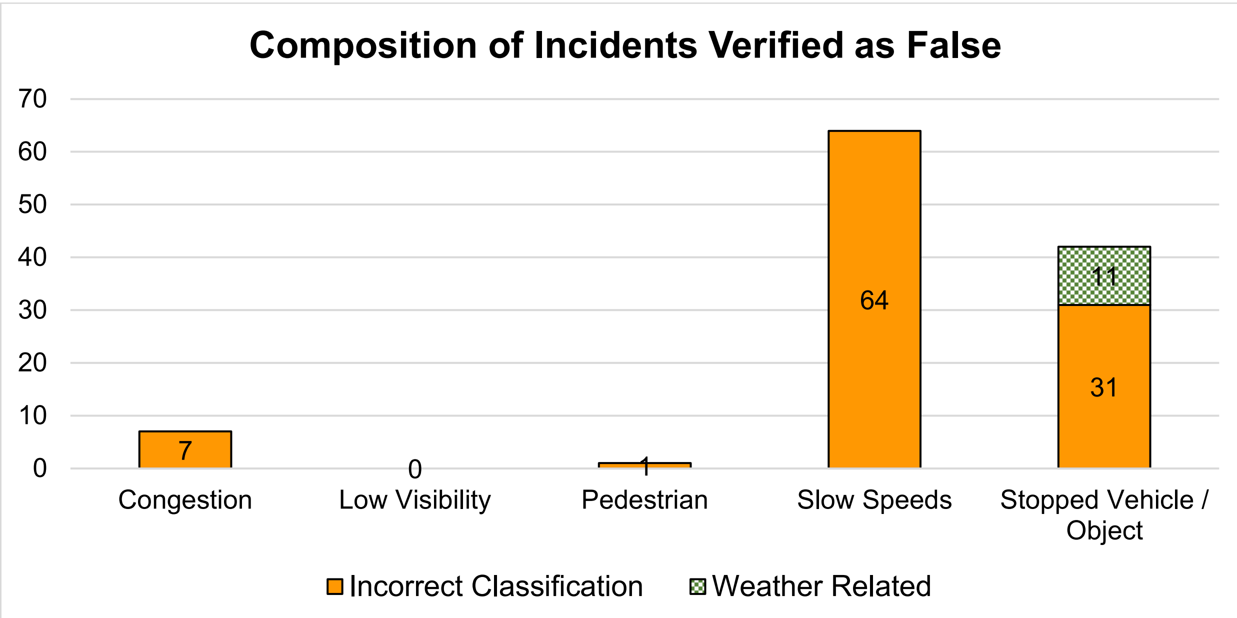



**Figure 50: October 2022 Advanced Video Analytics False Alert Incident Composition**

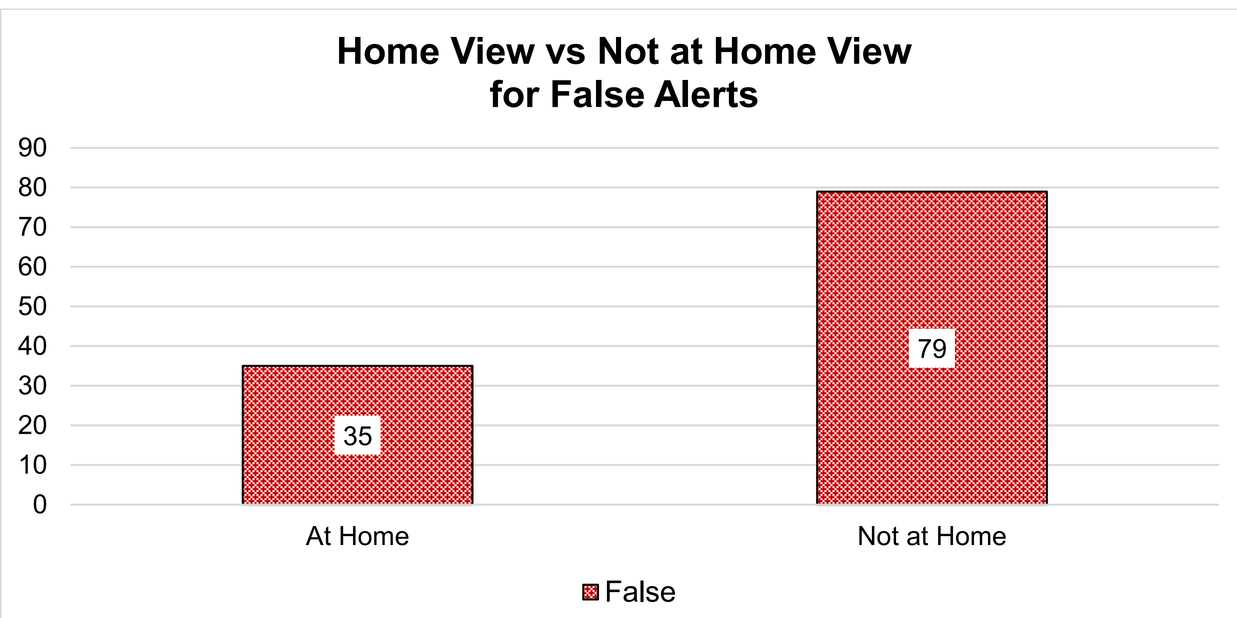



**Figure 51: October 2022 Advanced Video Analytics Home View vs Not at Home View for False Alerts**

## January 2023

January 2023 was expected to have more than average weather-related alerts due to being winter weather conditions, like February 2022. Although weather-related alerts did increase from the previous verification months, the assessment focused on slow speeds false alerts as it contributed slightly more than weather-related alerts. Two total assesments were made, comparing with and without slow speeds false alerts.

**Figure 52** shows the verifcation results for January 2023, with highlights including:

**<u>Overall:</u>**

True Alerts: 90%
False Alerts: 10%
Unable to Verify Alerts: 0%

**<u>Overall (Without Slow Speed False Alerts):</u>**

True Alerts: 93%
False Alerts: 7%
Unable to Verify Alerts: 0%

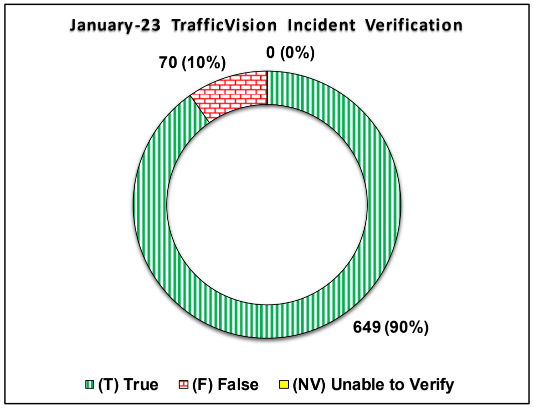
## Traffic Vision January Verification
## Dates Observed: Jnauary 1 - January 31, 2023
## Time Period Observed: All Day

| Total | |
|---|---|
| (T) True | 649 |
| (F) False | 70 |
| (NV) Unable to Verify | 0 |
| (T) Side of Interstate | 14 |
| (T) Weather Related | 16 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 307 |
| (T) Vehicle Pulled to Shoulder | 312 |
| (T) Crossing Lanes | 0 |
| (T) Stopped Object | 0 |
| (F) Snow Malfunction | 0 |
| (F) Rain Malfunction | 0 |
| (F) Incorrect Classification** | 47 |
| (F) No Visible Vehicles | 0 |
| (NV) Rain Malfunction | 0 |
| (NV) Gridlocked Traffic | 0 |
| (NV) Unable to Verify* | 0 |
| Total Incidents | 719 |

| Congestion | |
|---|---|
| (T) True | 196 |
| (F) False | 2 |
| (NV) Unable to Verify* | 0 |
| (T) Gridlocked Traffic | 195 |
| (T) Crash | 0 |
| (F) Incorrect Classification** | 2 |
| (F) Weather Related | 0 |

| Low Visibility | |
|---|---|
| (T) True | 16 |
| (F) False | 1 |
| (NV) Unable to Verify* | 0 |
| (T) Weather Related | 16 |
| (F) Weather Related | 1 |

| Pedestrian | |
|---|---|
| (T) True | 14 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Crossing Lanes | 0 |
| (T) Side of Interstate | 14 |
| (T) Crash | 0 |
| (F) Moved Camera | 0 |
| (F) Incorrect Classification** | 0 |
| (F) Weather Related | 0 |




| | | |
|---|---|---|
| (T) | = | Description of True Alert |
| (F) | = | Description of False Alert |
| (NV) | = | Alerts were unable to be verified* |

| Slow Speeds | |
|---|---|
| (T) True | 112 |
| (F) False | 33 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 112 |
| (F) Incorrect Classification** | 33 |
| (F) Weather Related | 0 |

| Stopped Vehicle / Object | |
|---|---|
| (T) True | 311 |
| (F) False | 34 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 0 |
| (T) Vehicle Pulled to Shoulder | 311 |
| (T) Stopped Object | 0 |
| (F) Incorrect Classification** | 11 |
| (F) Weather Related | 23 |

| Wrong Way Driver | |
|---|---|
| (T) True | 0 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |

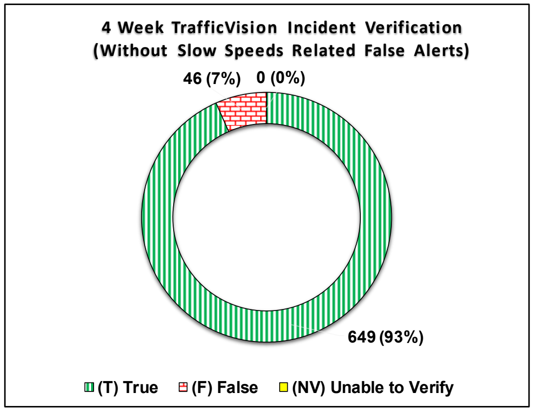



**Figure 52: January 2023 Advanced Video Analytics Verification Result**

**Figure 53** shows the break-down of false incidents by the contributing circumstance; stopped vehicles and objects in the roadway were the largest type of false incident detected (48.6%), followed closely by slow speeds (47.1%). Weather incidents did increase from the previous months, accounting for 32.9% of false incidents detected**. Figure 54** shows that false incident detection was equally distributed amongst cameras in home view and cameras out of home view.

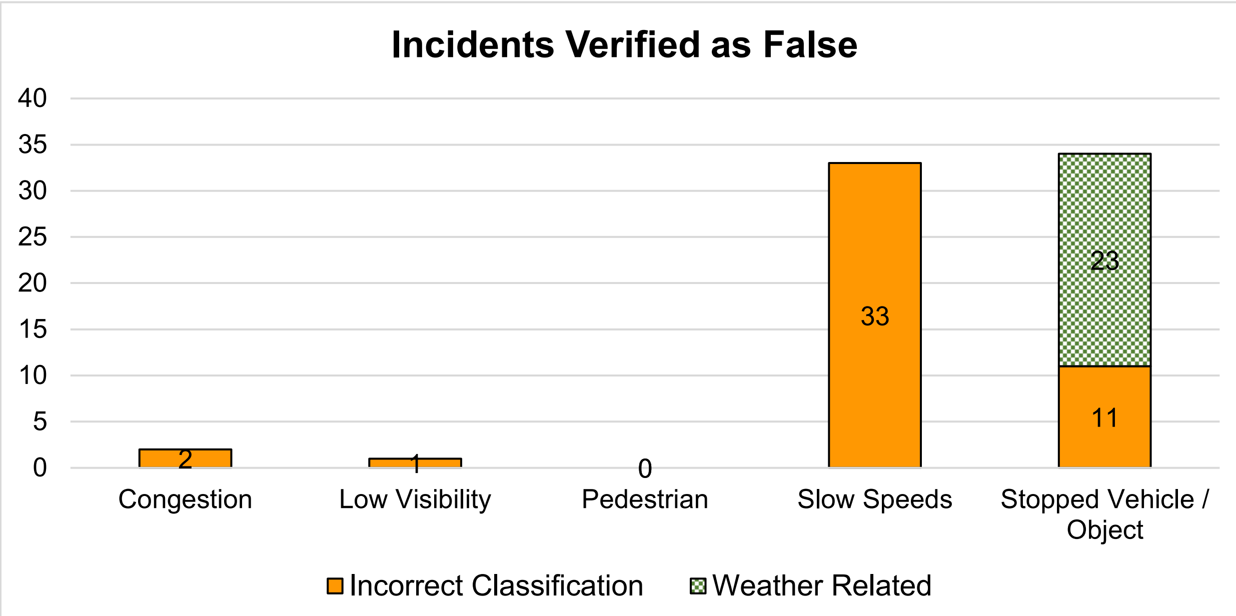



**Figure 53: January 2023 Advanced Video Analytics False Alert Incident Composition**

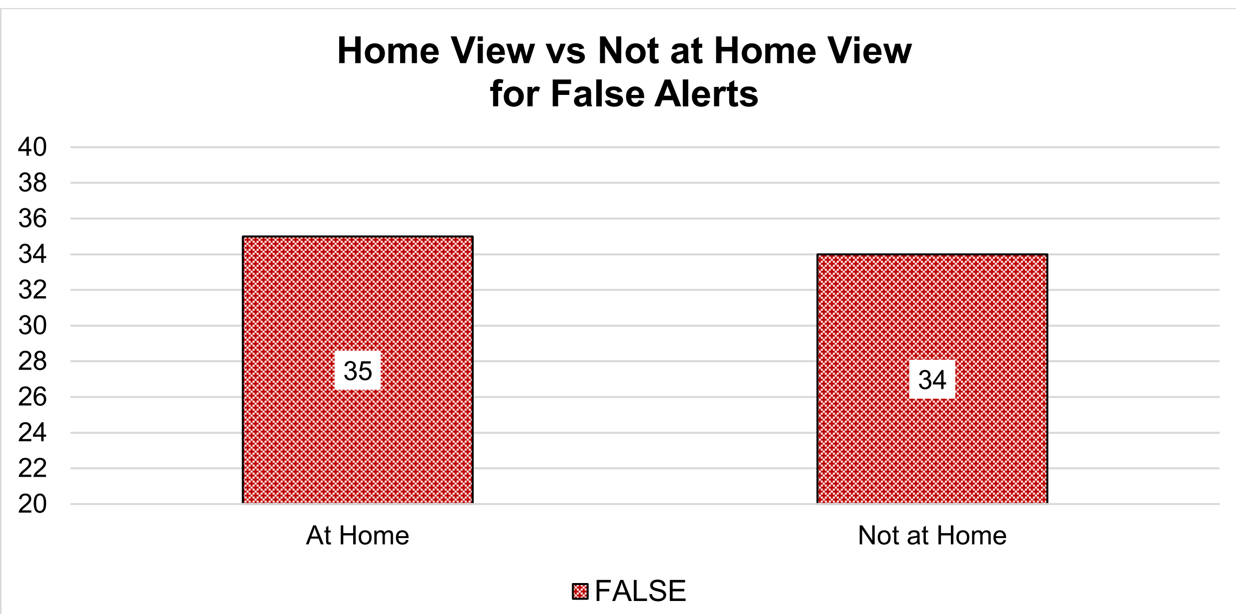



**Figure 54: January 2023 Advanced Video Analytics Home View vs Not at Home View for False Alerts**

## April 2023

April 2023 was one of the best perfomancing months, as only 5% of all alerts were false alerts. Assessments focused on slow speeds false alerts, as the spring weather resulted in a decrease of weather-related false alerts. Two total assesments were made, comparing with and without slow speeds false alerts.

**Figure 55** shows the verifcation results for April 2023, with highlights including:

**Overall:**

True Alerts: 95%
False Alerts: 5%
Unable to Verify Alerts: 0%

**Overall (Without Slow Speed False Alerts):**

True Alerts: 93%
False Alerts: 7%
Unable to Verify Alerts: 0%

## Traffic Vision April Verification
## Dates Observed: April 1 - April 30, 2023
## Time Period Observed: All Day

| Total | |
|---|---|
| (T) True | 986 |
| (F) False | 55 |
| (NV) Unable to Verify | 0 |
| (T) Side of Interstate | 30 |
| (T) Weather Related | 1 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 578 |
| (T) Vehicle Pulled to Shoulder | 375 |
| (T) Crossing Lanes | 0 |
| (T) Stopped Object | 2 |
| (F) Snow Malfunction | 0 |
| (F) Rain Malfunction | 7 |
| (F) Incorrect Classification** | 48 |
| (F) No Visible Vehicles | 0 |
| (NV) Rain Malfunction | 0 |
| (NV) Gridlocked Traffic | 0 |
| (NV) Unable to Verify* | 0 |
| Total Incidents | 1041 |

| Congestion | |
|---|---|
| (T) True | 394 |
| (F) False | 12 |
| (NV) Unable to Verify* | 0 |
| (T) Gridlocked Traffic | 394 |
| (T) Crash | 0 |
| (F) Incorrect Classification** | 12 |
| (F) Weather Related | 0 |

| Low Visibility | |
|---|---|
| (T) True | 1 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Weather Related | 1 |
| (F) Weather Related | 0 |

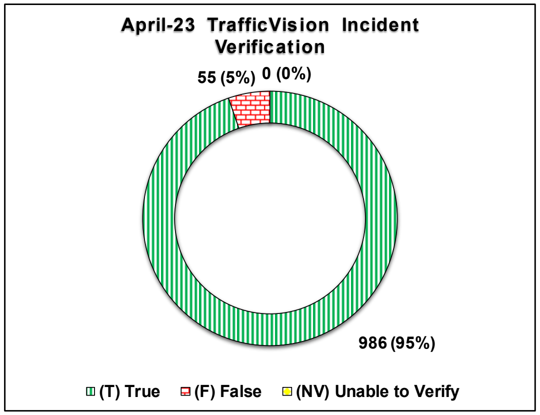
| Pedestrian | |
|---|---|
| (T) True | 30 |
| (F) False | 1 |
| (NV) Unable to Verify* | 0 |
| (T) Crossing Lanes | 0 |
| (T) Side of Interstate | 18 |
| (T) Construction Related | 12 |
| (F) Moved Camera | 0 |
| (F) Incorrect Classification** | 1 |
| (F) Weather Related | 0 |

| | | |
|---|---|---|
| (T) | = | Description of True Alert |
| (F) | = | Description of False Alert |
| (NV) | = | Alerts were unable to be verified* |

| Slow Speeds | |
|---|---|
| (T) True | 182 |
| (F) False | 20 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 181 |
| (F) Incorrect Classification** | 20 |
| (F) Weather Related | 0 |

| Stopped Vehicle / Object | |
|---|---|
| (T) True | 379 |
| (F) False | 22 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 3 |
| (T) Vehicle Pulled to Shoulder | 374 |
| (T) Stopped Object | 2 |
| (F) Incorrect Classification** | 15 |
| (F) Weather Related | 7 |

| Wrong Way Driver | |
|---|---|
| (T) True | 0 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |



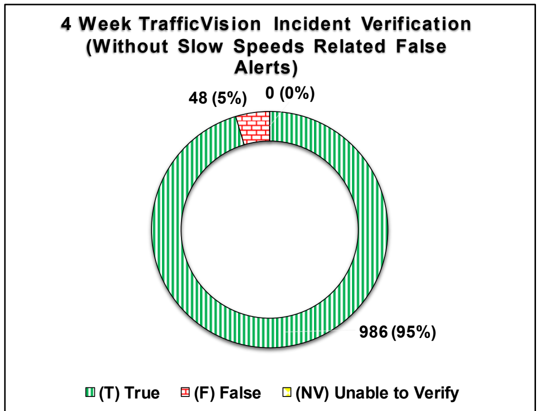




Figure 55: April 2023 Advanced Video Analytics Verification Results

**Figure 56** shows the break-down of false incidents by the contributing circumstance; stopped vehicles and objects in the roadway were the largest type of false incident detected (40.0%), followed closely by slow speeds (36.4%). The false alerts involving stopped vehicles and objects in the roadway were caused by a variety of scenarios, such as rain, light, and shadows interfering with the algorithm. **Figure 57** shows that more than half of false incident identification (54.5%) was improper positioning of cameras (e.g., cameras not preset to the home view).

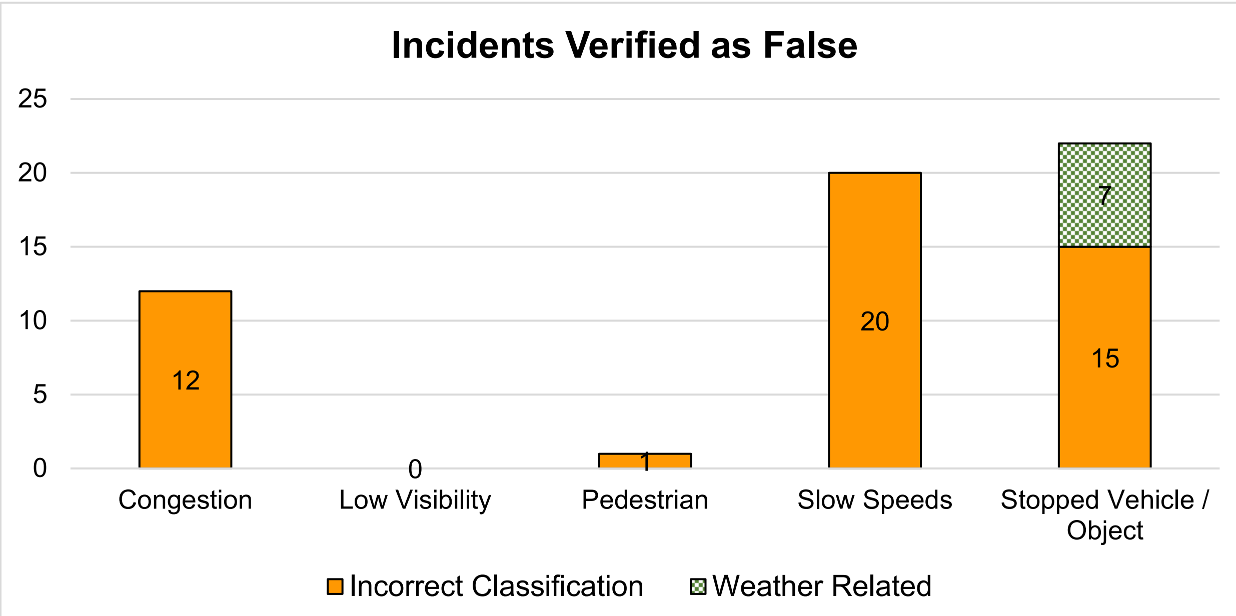



**Figure 56: April 2023 Advanced Video Analytics False Alert Incident Composition**

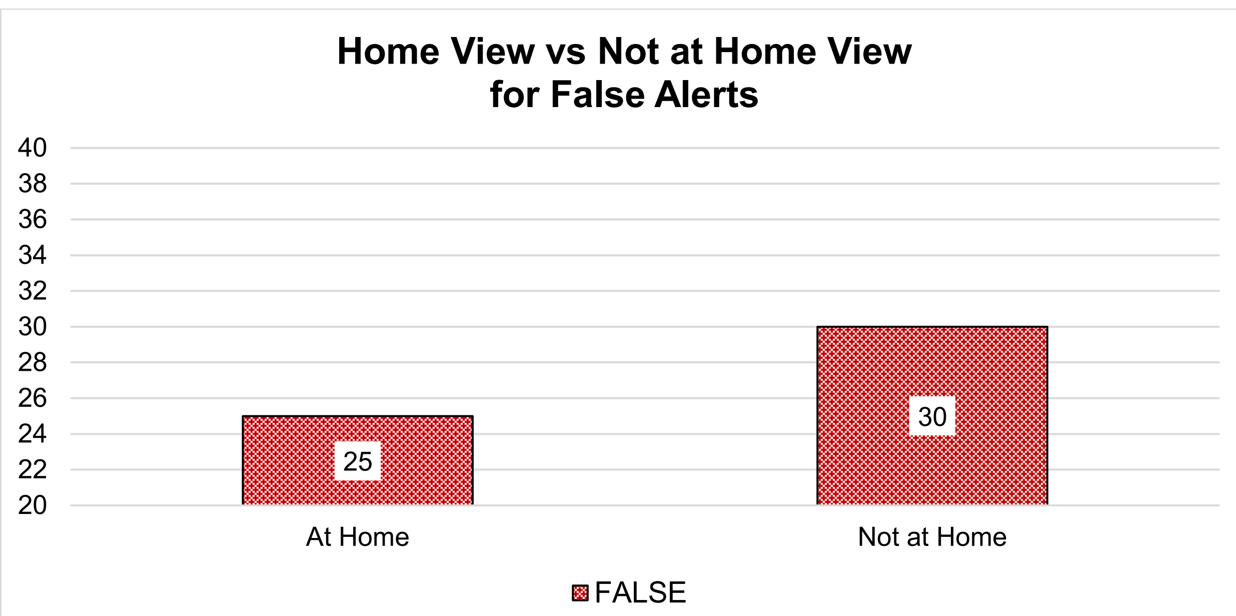



**Figure 57: April 2023 Advanced Video Analytics Home View vs Not at Home View for False Alerts**

## July 2023

July 2023 was one of the worst months regarding false alerts; many issues arose concerning the preset home view position of the cameras. Advanced Video Analytics did see an increase in the difficulty of detecting speed outside the zones created for the home view preset. Two total assesments were made, comparing with and without slow speeds false alerts.

**Figure 58** shows the verifcation results for July 2023, with highlights including:

**<u>Overall:</u>**

True Alerts: 86%
False Alerts: 14%
Unable to Verify Alerts: 0%

**<u>Overall (Without Slow Speed False Alerts):</u>**

True Alerts: 93%
False Alerts: 7%
Unable to Verify Alerts: 0%

**Traffic Vision July Verification**
**Dates Observed: July 1 - July 31, 2023**
**Time Period Observed: All Day**

| Total | |
|---|---|
| (T) True | 790 |
| (F) False | 132 |
| (NV) Unable to Verify* | 0 |
| (T) Side of Interstate | 27 |
| (T) Weather Related | 3 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 421 |
| (T) Vehicle Pulled to Shoulder | 320 |
| (T) Crossing Lanes | 0 |
| (T) Stopped Object | 19 |
| (F) Rain | 0 |
| (F) Weather Related | 9 |
| (F) Incorrect Classification** | 116 |
| (F) No Visible Vehicles | 0 |
| (NV) Rain Malfunction | 0 |
| (NV) Gridlocked Traffic | 0 |
| (NV) Unable to Verify* | 0 |
| Total Incidents | 922 |

| Congestion | |
|---|---|
| (T) True | 286 |
| (F) False | 25 |
| (NV) Unable to Verify* | 0 |
| (T) Gridlocked Traffic | 286 |
| (T) Crash | 0 |
| (F) Incorrect Classification** | 25 |
| (F) Weather Related | 0 |

| Low Visibility | |
|---|---|
| (T) True | 3 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Weather Related | 3 |
| (F) Weather Related | 0 |

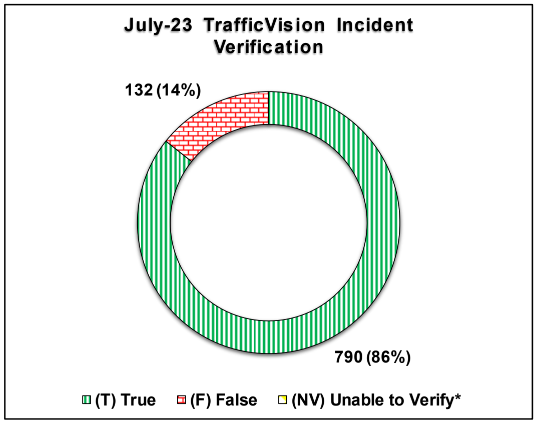
| Pedestrian | |
|---|---|
| (T) True | 27 |
| (F) False | 1 |
| (NV) Unable to Verify* | 0 |
| (T) Crossing Lanes | 0 |
| (T) Side of Interstate | 24 |
| (T) Construction Related | 3 |
| (F) Moved Camera | 0 |
| (F) Incorrect Classification** | 1 |
| (F) Weather Related | 0 |

| | | |
|---|---|---|
| (T) | = | Description of True Alert |
| (F) | = | Description of False Alert |
| (NV) | = | Alerts were unable to be verified* |

| Slow Speeds | |
|---|---|
| (T) True | 136 |
| (F) False | 77 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 135 |
| (F) Incorrect Classification** | 76 |
| (F) Weather Related | 1 |

| Stopped Vehicle / Object | |
|---|---|
| (T) True | 338 |
| (F) False | 29 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 0 |
| (T) Vehicle Pulled to Shoulder | 319 |
| (T) Stopped Object | 19 |
| (F) Incorrect Classification** | 14 |
| (F) Weather Related | 15 |

| Wrong Way Driver | |
|---|---|
| (T) True | 0 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |



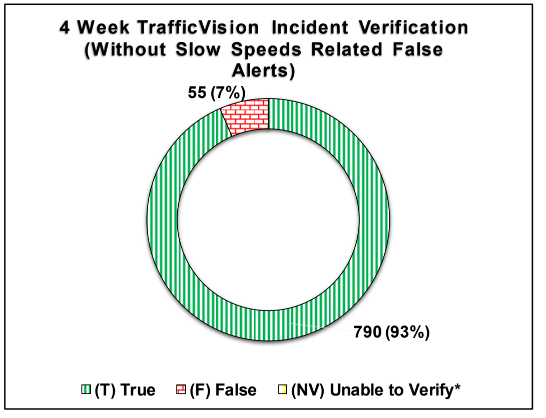




**Figure 58: July 2023 Advanced Video Analytics Verification Results**

**Figure 59** shows the break-down of false incidents by the contributing circumstance; slow speeds were the largest type of false incident detected (58.3%), followed by stopped vehicles and objects in the roadway (22.0%) and congestion (18.9%). **Figure 60** shows that the majority of false incident identification (80.3%) was improper positioning of cameras (e.g., cameras not preset to the home view) or from detections made at night.

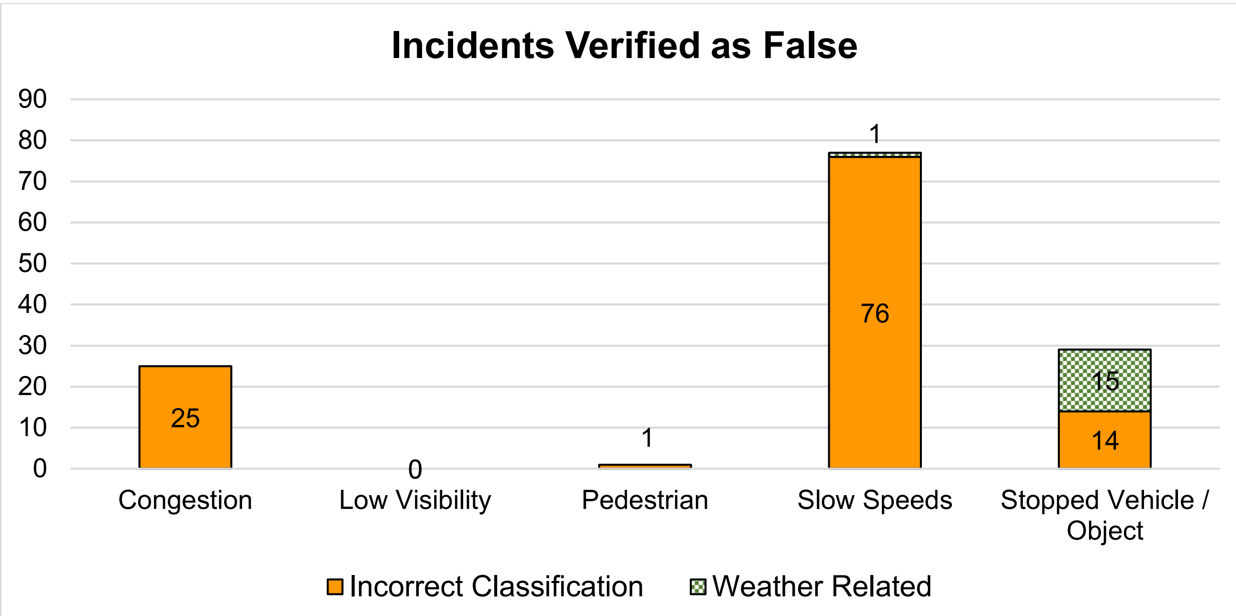



**Figure 59: July 2023 Advanced Video Analytics False Alert Incident Composition**

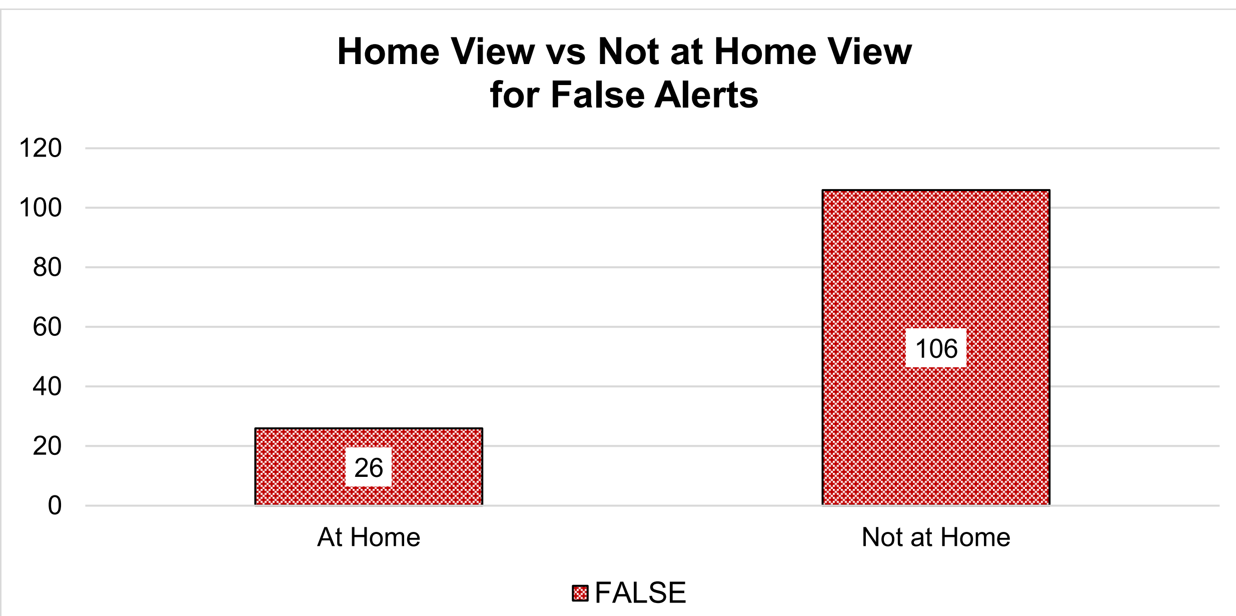



**Figure 60: July 2023 Advanced Video Analytics Home View vs Not at Home View for False Alerts**

## October 2023

Similar to July 2023, October 2023 saw issues regarding the preset home view of the cameras, causing most of the “congestion” and “slow speeds” alerts to be erroneous. October 2023 saw the highest number of false alerts identified (281, which is twice as many false alerts identified in July 2023). However, this issue is not considered detrimental to the overall technology performance since the algorithm has to go above and beyond to be able to identify what the camera is focusing on. It is important to note that the quality of the MoDOT cameras are highly affected by the third party connector that sends the video image to the Advanced Video Analytics algorithm, which is compressed and resolution is lost in the process. This makes it very dificult for the algorithm to read any scenarios outside the home view..

**Figure 61** shows the verifcation results for October 2023, with highlights including:

**Overall:**

True Alerts: 80%
False Alerts: 20%
Unable to Verify Alerts: 0%

**Overall (Without Slow Speed False Alerts):**

True Alerts: 93%
False Alerts: 7%
Unable to Verify Alerts: 0%

## Traffic Vision October Verification

**Dates Observed: October 1 - October 31, 2023**

**Time Period Observed: All Day**

| Total | |
|---|---|
| (T) True | 1152 |
| (F) False | 281 |
| (NV) Unable to Verify* | 0 |
| (T) Side of Interstate | 20 |
| (T) Weather Related | 1 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 682 |
| (T) Vehicle Pulled to Shoulder | 449 |
| (T) Crossing Lanes | 0 |
| (T) Stopped Object | 0 |
| (F) Rain | 0 |
| (F) Weather Related | 13 |
| (F) Incorrect Classification | 268 |
| (F) No Visible Vehicles | 0 |
| (NV) Rain Malfunction | 0 |
| (NV) Gridlocked Traffic | 0 |
| (NV) Unable to Verify* | 0 |
| Total Incidents | 1433 |

| Congestion | |
|---|---|
| (T) True | 478 |
| (F) False | 51 |
| (NV) Unable to Verify* | 0 |
| (T) Gridlocked Traffic | 478 |
| (T) Crash | 0 |
| (F) Incorrect Classification | 51 |
| "NOT At Home View" | 51 |
| "At Home View" | 0 |
| (F) Weather Related | 0 |
| "NOT At Home View" | 0 |
| "At Home View" | 0 |

| Low Visibility | |
|---|---|
| (T) True | 1 |
| (F) False | 1 |
| (NV) Unable to Verify* | 0 |
| (T) Weather Related | 1 |
| (F) Incorrect Classification | 1 |
| "NOT At Home View" | 1 |
| "At Home View" | 0 |

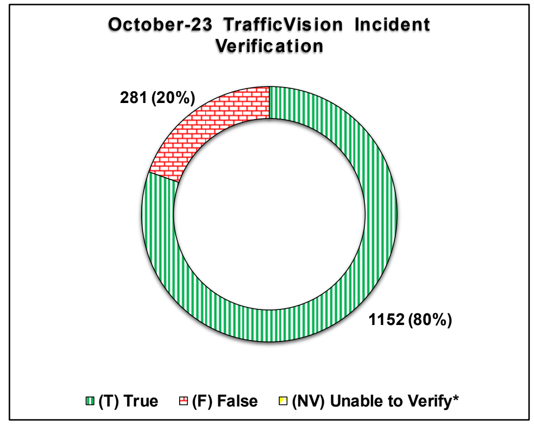
| Pedestrian | |
|---|---|
| (T) True | 20 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |
| (T) Crossing Lanes | 0 |
| (T) Side of Interstate | 15 |
| (T) Construction Related | 5 |
| (F) Moved Camera | 0 |
| (F) Incorrect Classification | 0 |
| "NOT At Home View" | 0 |
| "At Home View" | 0 |
| (F) Weather Related | 0 |
| "NOT At Home View" | 0 |
| "At Home View" | 0 |

| | | |
|---|---|---|
| (T) | = | Description of True Alert |
| (F) | = | Description of False Alert |
| (NV) | = | Alerts were unable to be verified* |

| Slow Speeds | |
|---|---|
| (T) True | 204 |
| (F) False | 190 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 204 |
| (F) Incorrect Classification | 189 |
| "NOT At Home View" | 171 |
| "At Home View" | 18 |
| (F) Weather Related | 1 |
| "NOT At Home View" | 0 |
| "At Home View" | 1 |

| Stopped Vehicle / Object | |
|---|---|
| (T) True | 449 |
| (F) False | 39 |
| (NV) Unable to Verify* | 0 |
| (T) Crash | 0 |
| (T) Gridlocked Traffic | 0 |
| (T) Vehicle Pulled to Shoulder | 449 |
| (T) Stopped Object | 0 |
| (F) Incorrect Classification | 27 |
| "NOT At Home View" | 13 |
| "At Home View" | 14 |
| (F) Weather Related | 12 |
| "NOT At Home View" | 2 |
| "At Home View" | 10 |

| Wrong Way Driver | |
|---|---|
| (T) True | 0 |
| (F) False | 0 |
| (NV) Unable to Verify* | 0 |



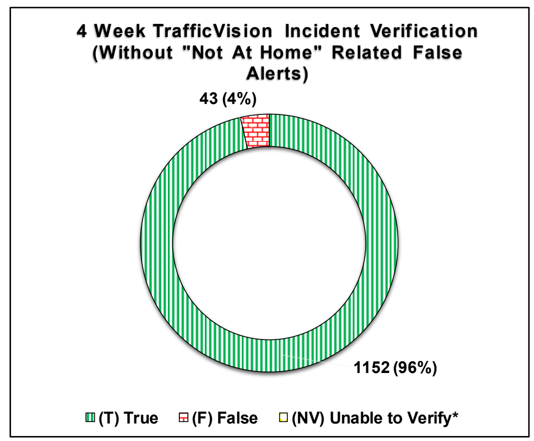




**Figure 61: October 2023 Advanced Video Analytics Verification Result**

**Figure 62** shows the break-down of false incidents by the contributing circumstance; slow speeds were the largest type of false incident detected (67.6%), followed by congestion (18.1%) and stopped vehicles and objects in the roadway (13.9%). **Figure 63** shows that the majority of false incident identification (84.7%) was improper positioning of cameras (e.g., cameras not preset to the home view) or from detections made at night.

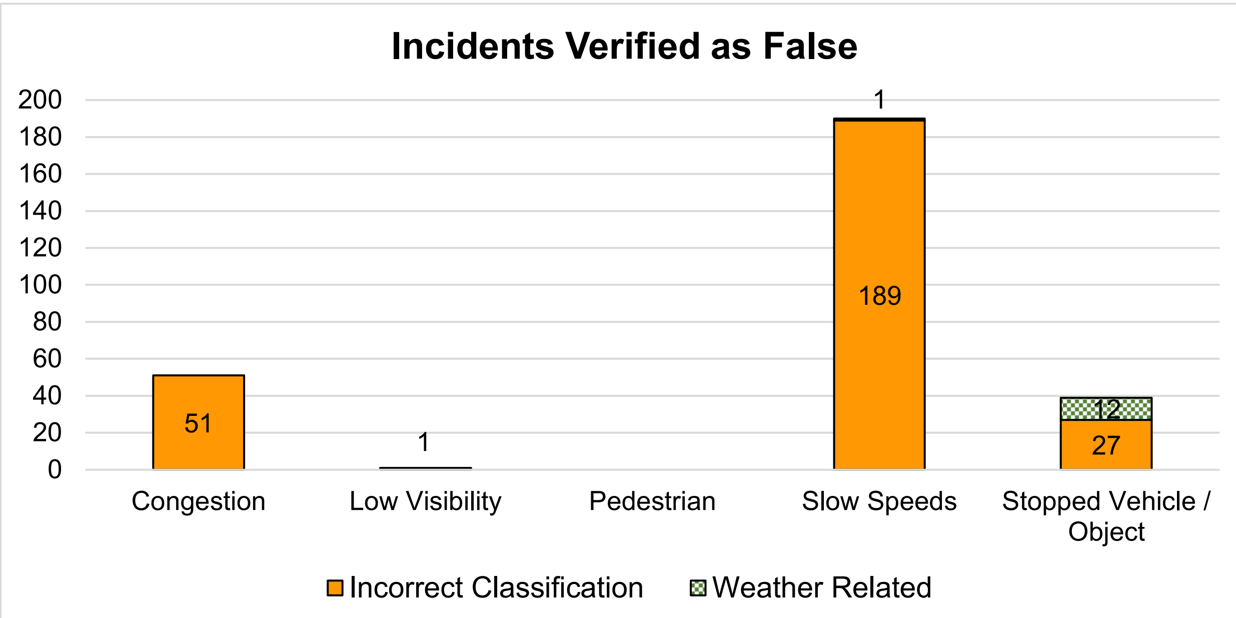



**Figure 62: October 2023 Advanced Video Analytics False Alert Incident Composition**

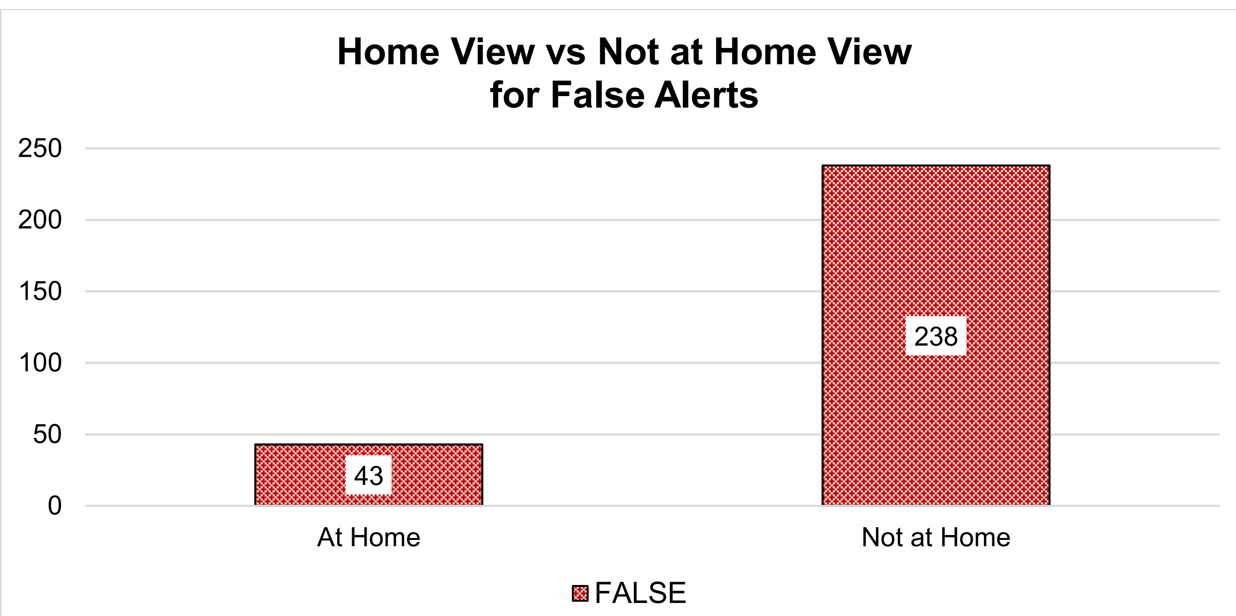



**Figure 63: October 2023 Advanced Video Analytics Home View vs Not at Home View for False Alerts**

# APPENDIX F: BENEFIT-COST CALCULATION

This study calculates Benefit-Cost using the FHWA Benefit-Cost Analysis tool (Highway Safety Benefit-Cost Analysis Tool | FHWA. [online] Available at: https://highways.dot.gov/safety/data-analysis-tools/rsdp/rsdp-tools/highway-safety-benefit-cost-analysis-tool [Accessed 28 May 2024]). As described earlier in **Section 8.5**, project-specific input data (such as facility type, analysis period, discount rate, fuel cost, value of time for passenger and freight vehicles, segment length, number of lanes, free flow speed, peak period traffic volume, direct and subsequent project costs, and estimated annual crashes by severity types) were utilized. These inputs helped determine the present value of user benefits and total project costs. The user benefits include crash benefits, travel time benefits, reliability benefits, vehicle operations benefits, and emissions benefits. The following table shows the key parameters and values used for analysis:

| Key Parameters | Value |
|---|---|
| **Roadway Facility Type** | Urban Interstate/ Expressway |
| **Analysis Period (Years)** | 10 |
| **Length of Construction Period (Years)** | 3 |
| **Total Period** | 13 |
| **Annual Discount Rate (Percent)** | 3% |
| **Percent of Trucks in the Flow (Percent)** | 12% |
| **Fuel Cost (Dollars/Gallon)** | $2.82 |
| **Value of Time ($/Hr.) Personal** | $34.08 |
| **Value of Time ($/Hr.) Freight** | $34.88 |
| **Calculated Combined Value of Time ($/Hr.)** | $34.18 |
| **Segment Length (Miles)** | 237 |
| **Number of Lanes** | 3 |
| **Free Flow Speed (MPH)** | 60 |
| **Traffic Volume (during peak period)** | 9,186 |
| **Link Capacity** | 13,200 |
| **Hours of Peak Traffic per Day** | 2 |
| **Days of Analysis per Year** | 260 |
| **Reliability Ratio Personal** | 1 |
| **Reliability Ratio Freight** | 1.2 |

The following sections provides a summary of how these benefits have been calculated:

1. **Crash Benefits Calculation:** For the calculation of crash benefits, this study used average annual historic crash numbers, categorized by severity types, for the overall study

area. As a treatment option, crash modification factors (CMFs) were developed to determine the reduction in the number of crashes for three different scenarios, as discussed in the aforementioned section. Additionally, the CMF for the Crash Risk Location Prediction tool incorporated factors such as the potential crash prediction percentage by crash risk location prediction, potential crash interception percentage by police patrol, and police patrol deployment percentage. Similarly, the CMF developed for the Incident Identification and Advanced Video Analytics tool considered the potential reduction in secondary crashes, the percentage of occurrence when incident interception time was reduced (from verification), and the amount of time saved per event. Multiplying the annual numbers of reduced crashes by Missouri specific comprehensive crash unit cost renders the annual crash reduction benefits.

2. **Travel Time Benefits Calculation:** Using the number of reduced crashes from the previous step, the team used the NHTSA's delay reduction factors to determine the delay reduction benefits (in hours). Multiplying that to the Unit Value of Time (in dollars) rendered the total annual benefit of reduction in delay (in dollars).
3. **Reliability Benefits Calculation:** The tool utilizes facility-specific input data, including the period of analysis (in years), segment type, segment length (in miles), number of lanes, free flow speed (in MPH), traffic volume (during peak periods), vehicle hours of travel at free flow speed (during peak periods), freeway link capacity (across all lanes during peak periods), hours of peak traffic per day, days of analysis per year, personal value of time ($/hr), personal reliability ratio, and freight reliability ratio. Using these inputs, the tool calculates the value of recurring delay using the Highway Capacity Manual (HCM) methods.
4. **Vehicle Operations Benefit Calculation:** Annual fuel use reduction depends on two main factors: Estimated Annual Crash Reduction and the NHTSA Fuel Use Factor. The NHTSA maintains a fuel consumption table that correlates crash types with changes in fuel consumption. By multiplying the net reduction in fuel consumption (attributed to reduced crash incidents) by the unit value of fuel, the annual vehicle operating cost was calculated.
5. **Emission Benefits Calculation:** The study utilized NHTSA's emission factors, which estimate the net emissions per crash based on facility type. By multiplying the annual crash reduction figures with these emission factors, the study determined the annual emissions benefits for $CO_2$, CO, $NO_x$, $PM_{10}$, $PM_{2.5}$, $SO_2$, and VOC.

## F-1: Benefit-Cost Calculation Combining Crash Risk Location Prediction, Incident Identification, and Advanced Video Analytics

## SCENARIO-1

Weekdays (Police Depoyment for 30% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Itemized Benefits - Crash Risk Location Prediction | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 30% | 0.0030 | 0.0053 | 0.9917 | ***5.87*** | $ 10,260,409 | $ 17,527,973.05 | $ 1,728,486.59 | $ 2,327,907.26 | $ 201,712.63 | $ 21,188.22 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 60,274,867.31 |
| **10.90%** | 20% | 30% | 0.0065 | 0.0053 | 0.9882 | ***8.38*** | $ 10,260,409 | $ 38,210,981.24 | $ 3,768,100.77 | $ 5,074,034.81 | $ 439,733.52 | $ 46,190.33 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 86,006,640.24 |
| 15% | 20% | 30% | 0.0090 | 0.0053 | 0.9857 | ***10.13*** | $ 10,260,409 | $ 52,583,919.14 | $ 5,185,459.78 | $ 6,981,849.14 | $ 605,137.88 | $ 63,564.67 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 103,887,530.17 |
| 20% | 20% | 30% | 0.0120 | 0.0053 | 0.9827 | ***12.25*** | $ 10,260,409 | $ 70,111,892.19 | $ 6,913,946.37 | $ 9,307,884.62 | $ 806,850.50 | $ 84,752.89 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 125,692,926.14 |

Weekends (Police Depoyment for 30% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 30% | 0.0030 | 0.0053 | 0.9917 | ***2.44*** | $ 9,529,736 | $ 7,138,158.40 | $ 514,470.07 | $ 692,948.07 | $ 56,658.05 | $ 6,960.25 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 23,242,977.27 |
| **10.90%** | 20% | 30% | 0.0065 | 0.0053 | 0.9882 | ***3.48*** | $ 9,529,736 | $ 15,561,185.32 | $ 1,121,544.75 | $ 1,510,555.62 | $ 123,514.55 | $ 15,173.35 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 33,165,756.01 |
| 15% | 20% | 30% | 0.0090 | 0.0053 | 0.9857 | ***4.20*** | $ 9,529,736 | $ 21,414,475.21 | $ 1,543,410.20 | $ 2,078,678.21 | $ 169,974.16 | $ 20,880.76 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 40,061,200.96 |
| 20% | 20% | 30% | 0.0120 | 0.0053 | 0.9827 | ***5.09*** | $ 9,529,736 | $ 28,552,633.62 | $ 2,057,880.27 | $ 2,771,460.30 | $ 226,632.21 | $ 27,841.01 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 48,470,229.82 |

| Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| ***7.92*** | $ 10,747,525 | $ 26,737,544.83 | $ 2,053,562.46 | $ 2,765,605.55 | $ 258,370.68 | $ 28,147.25 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 85,146,097.93 |
| ***11.42*** | $ 10,747,525 | $ 58,287,847.72 | $ 4,476,766.15 | $ 6,027,782.36 | $ 563,248.08 | $ 61,361.01 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 122,719,872.50 |
| ***13.85*** | $ 10,747,525 | $ 80,212,634.48 | $ 6,160,687.37 | $ 8,293,930.40 | $ 775,112.03 | $ 84,441.75 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 148,829,673.21 |
| ***16.81*** | $ 10,747,525 | $ 106,950,179.31 | $ 8,214,249.82 | $ 11,056,651.43 | $ 1,033,482.71 | $ 112,589.00 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 180,670,019.45 |

## SCENARIO-2

Weekdays (Police Depoyment for 25% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 25% | 0.0025 | 0.0053 | 0.9922 | ***5.63*** | $ 10,057,444 | $ 14,606,644.21 | $ 1,440,405.49 | $ 1,939,966.09 | $ 168,093.85 | $ 17,656.85 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 56,640,366.06 |
| **10.90%** | 20% | 25% | 0.0055 | 0.0053 | 0.9893 | ***7.76*** | $ 10,057,444 | $ 31,842,484.37 | $ 3,140,083.98 | $ 4,228,568.35 | $ 366,444.60 | $ 38,491.94 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 78,083,672.80 |
| 15% | 20% | 25% | 0.0075 | 0.0053 | 0.9872 | ***9.25*** | $ 10,057,444 | $ 43,819,932.62 | $ 4,321,216.48 | $ 5,818,597.61 | $ 504,281.56 | $ 52,970.56 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 92,984,598.40 |
| 20% | 20% | 25% | 0.0100 | 0.0053 | 0.9847 | ***11.05*** | $ 10,057,444 | $ 58,426,576.82 | $ 5,761,621.98 | $ 7,757,263.55 | $ 672,375.42 | $ 70,627.41 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 111,156,064.75 |

Weekends (Police Depoyment for 25% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 25% | 0.0025 | 0.0053 | 0.9922 | ***2.31*** | $ 9,448,550 | $ 5,948,465.34 | $ 428,725.06 | $ 577,460.57 | $ 47,215.04 | $ 5,800.21 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 21,841,448.64 |
| **10.90%** | 20% | 25% | 0.0055 | 0.0053 | 0.9893 | ***3.19*** | $ 9,448,550 | $ 12,967,654.43 | $ 934,620.62 | $ 1,258,814.61 | $ 102,928.79 | $ 12,644.46 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 30,110,445.34 |
| 15% | 20% | 25% | 0.0075 | 0.0053 | 0.9872 | ***3.79*** | $ 9,448,550 | $ 17,845,396.01 | $ 1,286,175.17 | $ 1,732,266.42 | $ 141,645.13 | $ 17,400.63 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 35,856,665.78 |
| 20% | 20% | 25% | 0.0100 | 0.0053 | 0.9847 | ***4.54*** | $ 9,448,550 | $ 23,793,861.35 | $ 1,714,900.22 | $ 2,309,611.72 | $ 188,860.17 | $ 23,200.84 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 42,864,216.72 |

| Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| ***7.63*** | $ 10,463,374 | $ 22,281,287.36 | $ 1,711,302.05 | $ 2,304,738.14 | $ 215,308.90 | $ 23,456.04 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 79,838,959.66 |
| ***10.62*** | $ 10,463,374 | $ 48,573,206.44 | $ 3,730,638.46 | $ 5,023,469.48 | $ 469,373.40 | $ 51,134.17 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 111,150,689.12 |
| ***12.70*** | $ 10,463,374 | $ 66,843,862.07 | $ 5,133,906.14 | $ 6,912,209.70 | $ 645,926.69 | $ 70,368.13 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 132,909,139.90 |
| ***15.24*** | $ 10,463,374 | $ 89,125,149.42 | $ 6,845,208.19 | $ 9,214,944.10 | $ 861,235.59 | $ 93,824.17 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 159,443,228.65 |

## SCENARIO-3

Weekdays (Police Depoyment for 20% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 20% | 0.0020 | 0.0053 | 0.9927 | ***5.38*** | $ 9,854,480 | $ 11,685,315.36 | $ 1,152,324.40 | $ 1,552,007.57 | $ 134,475.08 | $ 14,125.48 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 53,005,847.46 |
| **10.90%** | 20% | 20% | 0.0044 | 0.0053 | 0.9903 | ***7.12*** | $ 9,854,480 | $ 25,473,987.50 | $ 2,512,067.18 | $ 3,383,019.51 | $ 293,155.68 | $ 30,793.55 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 70,160,622.99 |
| 15% | 20% | 20% | 0.0060 | 0.0053 | 0.9887 | ***8.33*** | $ 9,854,480 | $ 35,055,946.09 | $ 3,456,973.19 | $ 4,655,190.16 | $ 403,425.25 | $ 42,376.45 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 82,081,510.70 |
| 20% | 20% | 20% | 0.0080 | 0.0053 | 0.9867 | ***9.80*** | $ 9,854,480 | $ 46,741,261.46 | $ 4,609,297.58 | $ 6,206,365.45 | $ 537,900.34 | $ 56,501.93 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 96,618,926.31 |

Weekends (Police Depoyment for 20% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 20% | 0.0020 | 0.0053 | 0.9927 | ***2.18*** | $ 9,367,364 | $ 4,758,772.27 | $ 342,980.04 | $ 461,971.53 | $ 37,772.03 | $ 4,640.17 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 20,439,918.47 |
| **10.90%** | 20% | 20% | 0.0044 | 0.0053 | 0.9903 | ***2.89*** | $ 9,367,364 | $ 10,374,123.55 | $ 747,696.50 | $ 1,007,066.30 | $ 82,343.04 | $ 10,115.57 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 27,055,127.37 |
| 15% | 20% | 20% | 0.0060 | 0.0053 | 0.9887 | ***3.38*** | $ 9,367,364 | $ 14,276,316.81 | $ 1,028,940.13 | $ 1,385,840.80 | $ 113,316.10 | $ 13,920.50 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 31,652,116.78 |
| 20% | 20% | 20% | 0.0080 | 0.0053 | 0.9867 | ***3.98*** | $ 9,367,364 | $ 19,035,089.08 | $ 1,371,920.18 | $ 1,847,738.55 | $ 151,088.14 | $ 18,560.67 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 37,258,179.04 |

| Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| ***7.32*** | $ 10,179,223 | $ 17,825,029.88 | $ 1,369,041.64 | $ 1,843,844.00 | $ 172,247.12 | $ 18,764.83 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 74,531,794.65 |
| ***9.78*** | $ 10,179,223 | $ 38,858,565.15 | $ 2,984,510.77 | $ 4,019,029.65 | $ 375,498.72 | $ 40,907.34 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 99,581,378.80 |
| ***11.49*** | $ 10,179,223 | $ 53,475,089.65 | $ 4,107,124.91 | $ 5,530,248.73 | $ 516,741.36 | $ 56,294.50 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 116,988,366.32 |
| ***13.58*** | $ 10,179,223 | $ 71,300,119.54 | $ 5,476,166.55 | $ 7,372,809.96 | $ 688,988.47 | $ 75,059.33 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 138,216,011.03 |

## SCENARIO-4

Weekdays (Police Depoyment for 15% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 15% | 0.0015 | 0.0053 | 0.9932 | ***5.12*** | $ 9,651,515 | $ 8,763,986.52 | $ 864,243.30 | $ 1,164,031.70 | $ 100,856.31 | $ 10,594.11 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 49,371,311.51 |
| **10.90%** | 20% | 15% | 0.0033 | 0.0053 | 0.9914 | ***6.45*** | $ 9,651,515 | $ 19,105,490.62 | $ 1,884,050.39 | $ 2,537,388.28 | $ 219,866.76 | $ 23,095.16 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 62,237,490.78 |
| 15% | 20% | 15% | 0.0045 | 0.0053 | 0.9902 | ***7.37*** | $ 9,651,515 | $ 26,291,959.57 | $ 2,592,729.89 | $ 3,491,626.73 | $ 302,568.94 | $ 31,782.33 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 71,178,267.02 |
| 20% | 20% | 15% | 0.0060 | 0.0053 | 0.9887 | ***8.50*** | $ 9,651,515 | $ 35,055,946.09 | $ 3,456,973.19 | $ 4,655,190.16 | $ 403,425.25 | $ 42,376.45 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 82,081,510.70 |

Weekends (Police Depoyment for 15% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 15% | 0.0015 | 0.0053 | 0.9932 | ***2.05*** | $ 9,286,178 | $ 3,569,079.20 | $ 257,235.03 | $ 346,480.95 | $ 28,329.03 | $ 3,480.13 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 19,038,386.76 |
| **10.90%** | 20% | 15% | 0.0033 | 0.0053 | 0.9914 | ***2.58*** | $ 9,286,178 | $ 7,780,592.66 | $ 560,772.37 | $ 755,310.68 | $ 61,757.28 | $ 7,586.67 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 23,999,802.09 |
| 15% | 20% | 15% | 0.0045 | 0.0053 | 0.9902 | ***2.96*** | $ 9,286,178 | $ 10,707,237.61 | $ 771,705.10 | $ 1,039,401.35 | $ 84,987.08 | $ 10,440.38 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 27,447,553.94 |
| 20% | 20% | 15% | 0.0060 | 0.0053 | 0.9887 | ***3.41*** | $ 9,286,178 | $ 14,276,316.81 | $ 1,028,940.13 | $ 1,385,840.80 | $ 113,316.10 | $ 13,920.50 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 31,652,116.78 |

| Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| ***7.00*** | $ 9,895,073 | $ 13,368,772.41 | $ 1,026,781.23 | $ 1,382,923.12 | $ 129,185.34 | $ 14,073.63 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 69,224,602.91 |
| ***8.89*** | $ 9,895,073 | $ 29,143,923.86 | $ 2,238,383.08 | $ 3,014,462.83 | $ 281,624.04 | $ 30,680.50 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 88,011,941.49 |
| ***10.21*** | $ 9,895,073 | $ 40,106,317.24 | $ 3,080,343.68 | $ 4,148,047.38 | $ 387,556.02 | $ 42,220.88 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 101,067,352.37 |
| ***11.82*** | $ 9,895,073 | $ 53,475,089.65 | $ 4,107,124.91 | $ 5,530,248.73 | $ 516,741.36 | $ 56,294.50 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 116,988,366.32 |

## SCENARIO-5

Weekdays (Police Depoyment for 10% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | B/C | Present Value Costs | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| 5% | 20% | 10% | 0.0010 | 0.0053 | 0.9937 | ***4.84*** | $ 9,448,550 | $ 5,842,657.68 | $ 576,162.20 | $ 776,038.49 | $ 67,237.54 | $ 7,062.74 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 45,736,758.21 |
| **10.90%** | 20% | 10% | 0.0022 | 0.0053 | 0.9925 | ***5.75*** | $ 9,448,550 | $ 12,736,993.75 | $ 1,256,033.59 | $ 1,691,674.63 | $ 146,577.84 | $ 15,396.78 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 54,314,276.15 |
| 15% | 20% | 10% | 0.0030 | 0.0053 | 0.9917 | ***6.38*** | $ 9,448,550 | $ 17,527,973.05 | $ 1,728,486.59 | $ 2,327,907.26 | $ 201,712.63 | $ 21,188.22 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 60,274,867.31 |
| 20% | 20% | 10% | 0.0040 | 0.0053 | 0.9907 | ***7.15*** | $ 9,448,550 | $ 23,370,630.73 | $ 2,304,648.79 | $ 3,103,737.58 | $ 268,950.17 | $ 28,250.96 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 67,543,817.79 |

Weekends (Police Depoyment for 10% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | B/C | Present Value Costs | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| 5% | 20% | 10% | 0.0010 | 0.0053 | 0.9937 | ***1.92*** | $ 9,204,992 | $ 2,379,386.13 | $ 171,490.02 | $ 230,988.84 | $ 18,886.02 | $ 2,320.08 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 17,636,853.52 |
| **10.90%** | 20% | 10% | 0.0022 | 0.0053 | 0.9925 | ***2.28*** | $ 9,204,992 | $ 5,187,061.77 | $ 373,848.25 | $ 503,547.76 | $ 41,171.52 | $ 5,057.78 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 20,944,469.51 |
| 15% | 20% | 10% | 0.0030 | 0.0053 | 0.9917 | ***2.53*** | $ 9,204,992 | $ 7,138,158.40 | $ 514,470.07 | $ 692,948.07 | $ 56,658.05 | $ 6,960.25 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 23,242,977.27 |
| 20% | 20% | 10% | 0.0040 | 0.0053 | 0.9907 | ***2.83*** | $ 9,204,992 | $ 9,517,544.54 | $ 685,960.09 | $ 923,918.46 | $ 75,544.07 | $ 9,280.34 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 26,046,029.92 |

| Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| B/C | Present Value Costs | Itemized Benefits - Crash Risk Location Prediction | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| ***6.65*** | $ 9,610,922 | $ 8,912,514.94 | $ 684,520.82 | $ 921,975.50 | $ 86,123.56 | $ 9,382.42 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 63,917,384.41 |
| ***7.95*** | $ 9,610,922 | $ 19,429,282.57 | $ 1,492,255.38 | $ 2,009,768.97 | $ 187,749.36 | $ 20,453.67 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 76,442,377.14 |
| ***8.86*** | $ 9,610,922 | $ 26,737,544.83 | $ 2,053,562.46 | $ 2,765,605.55 | $ 258,370.68 | $ 28,147.25 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 85,146,097.93 |
| ***9.96*** | $ 9,610,922 | $ 35,650,059.77 | $ 2,738,083.27 | $ 3,687,260.16 | $ 344,494.24 | $ 37,529.67 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 95,760,294.29 |

## SCENARIO-6

Weekdays (Police Depoyment for 5% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | B/C | Present Value Costs | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| 5% | 20% | 5% | 0.0005 | 0.0053 | 0.9942 | ***4.55*** | $ 9,245,585 | $ 2,921,328.84 | $ 288,081.10 | $ 388,027.92 | $ 33,618.77 | $ 3,531.37 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 42,102,187.56 |
| **10.90%** | 20% | 5% | 0.0011 | 0.0053 | 0.9936 | ***5.02*** | $ 9,245,585 | $ 6,368,496.87 | $ 628,016.80 | $ 845,878.54 | $ 73,288.92 | $ 7,698.39 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 46,390,979.09 |
| 15% | 20% | 5% | 0.0015 | 0.0053 | 0.9932 | ***5.34*** | $ 9,245,585 | $ 8,763,986.52 | $ 864,243.30 | $ 1,164,031.70 | $ 100,856.31 | $ 10,594.11 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 49,371,311.51 |
| 20% | 20% | 5% | 0.0020 | 0.0053 | 0.9927 | ***5.73*** | $ 9,245,585 | $ 11,685,315.36 | $ 1,152,324.40 | $ 1,552,007.57 | $ 134,475.08 | $ 14,125.48 | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 53,005,847.46 |

Weekends (Police Depoyment for 5% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | B/C | Present Value Costs | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| 5% | 20% | 5% | 0.0005 | 0.0053 | 0.9942 | ***1.78*** | $ 9,123,806 | $ 1,189,693.07 | $ 85,745.01 | $ 115,495.19 | $ 9,443.01 | $ 1,160.04 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 16,235,318.74 |
| **10.90%** | 20% | 5% | 0.0011 | 0.0053 | 0.9936 | ***1.96*** | $ 9,123,806 | $ 2,593,530.89 | $ 186,924.12 | $ 251,777.53 | $ 20,585.76 | $ 2,528.89 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 17,889,129.62 |
| 15% | 20% | 5% | 0.0015 | 0.0053 | 0.9932 | ***2.09*** | $ 9,123,806 | $ 3,569,079.20 | $ 257,235.03 | $ 346,480.95 | $ 28,329.03 | $ 3,480.13 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 19,038,386.76 |
| 20% | 20% | 5% | 0.0020 | 0.0053 | 0.9927 | ***2.24*** | $ 9,123,806 | $ 4,758,772.27 | $ 342,980.04 | $ 461,971.53 | $ 37,772.03 | $ 4,640.17 | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 20,439,918.47 |

| Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| B/C | Present Value Costs | Itemized Benefits - Crash Risk Location Prediction | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| ***6.28*** | $ 9,326,771 | $ 4,456,257.47 | $ 342,260.41 | $ 461,001.12 | $ 43,061.78 | $ 4,691.21 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 58,610,139.17 |
| ***6.96*** | $ 9,326,771 | $ 9,714,641.29 | $ 746,127.69 | $ 1,004,948.04 | $ 93,874.68 | $ 10,226.83 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 64,872,685.72 |
| ***7.42*** | $ 9,326,771 | $ 13,368,772.41 | $ 1,026,781.23 | $ 1,382,923.12 | $ 129,185.34 | $ 14,073.63 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 69,224,602.91 |
| ***7.99*** | $ 9,326,771 | $ 17,825,029.88 | $ 1,369,041.64 | $ 1,843,844.00 | $ 172,247.12 | $ 18,764.83 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 74,531,794.65 |

## SCENARIO-7

Weekdays (Police Depoyment for 5% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | B/C | Present Value Costs | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| 5% | 20% | 0% | 0.0000 | 0.0053 | 0.9947 | ***4.25*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 38,467,599.56 |
| **10.90%** | 20% | 0% | 0.0000 | 0.0053 | 0.9947 | ***4.25*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 38,467,599.56 |
| 15% | 20% | 0% | 0.0000 | 0.0053 | 0.9947 | ***4.25*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 38,467,599.56 |
| 20% | 20% | 0% | 0.0000 | 0.0053 | 0.9947 | ***4.25*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 30,919,344.46 | $ 3,049,050.35 | $ 4,106,007.66 | $ 355,821.07 | $ 37,376.03 | $ 38,467,599.56 |

Weekends (Police Depoyment for 5% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | Incident Identification + Advanced Video Analytics | CMF | Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | B/C | Present Value Costs | Itemized Benefits | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | Potential Crash Reduction Multiplier | | | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| 5% | 20% | 0% | 0.0000 | 0.0053 | 0.9947 | ***1.64*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 14,833,782.42 |
| **10.90%** | 20% | 0% | 0.0000 | 0.0053 | 0.9947 | ***1.64*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 14,833,782.42 |
| 15% | 20% | 0% | 0.0000 | 0.0053 | 0.9947 | ***1.64*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 14,833,782.42 |
| 20% | 20% | 0% | 0.0000 | 0.0053 | 0.9947 | ***1.64*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 12,591,711.43 | $ 907,525.20 | $ 1,222,323.11 | $ 99,944.80 | $ 12,277.88 | $ 14,833,782.42 |

| Benefit-Cost Calculation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| B/C | Present Value Costs | Itemized Benefits - Crash Risk Location Prediction | | | | | Itemized Benefits - Incident Identifications + Advanced Video Analytics | | | | | Total Benefits |
| | | Safety | Travel Time | Reliability | VOC | Emissions | Safety | Travel Time | Reliability | VOC | Emissions | |
| ***5.89*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 53,302,867.18 |
| ***5.89*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 53,302,867.18 |
| ***5.89*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 53,302,867.18 |
| ***5.89*** | $ 9,042,620 | $ - | $ - | $ - | $ - | $ - | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 53,302,867.18 |

## F-2: Benefit-Cost Calculation for Crash Risk Location Prediction Tool Only

SCENARIO-1

Weekdays (Police Depoyment for 30% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits - Crash Risk Location Prediction | | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits | |
| 5% | 20% | 30% | 0.0030 | 0.9970 | 2.34 | $ 9,318,238 | $ 17,527,973.05 | $ 1,728,486.59 | $ 2,327,907.26 | $ 201,712.63 | $ 21,188.22 | $ 21,807,267.75 | |
| 10.90% | 20% | 30% | 0.0065 | 0.9935 | 5.10 | $ 9,318,238 | $ 38,210,981.24 | $ 3,768,100.77 | $ 5,074,034.81 | $ 439,733.52 | $ 46,190.33 | $ 47,539,040.68 | |
| 15% | 20% | 30% | 0.0090 | 0.9910 | 7.02 | $ 9,318,238 | $ 52,583,919.14 | $ 5,185,459.78 | $ 6,981,849.14 | $ 605,137.88 | $ 63,564.67 | $ 65,419,930.60 | |
| 20% | 20% | 30% | 0.0120 | 0.9880 | 9.36 | $ 9,318,238 | $ 70,111,892.19 | $ 6,913,946.37 | $ 9,307,884.62 | $ 806,850.50 | $ 84,752.89 | $ 87,225,326.57 | |

Weekends (Police Depoyment for 30% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 30% | 0.0030 | 0.9970 | 0.98 | $ 8,587,564 | $ 7,138,158.40 | $ 514,470.07 | $ 692,948.07 | $ 56,658.05 | $ 6,960.25 | $ 8,409,194.85 |
| 10.90% | 20% | 30% | 0.0065 | 0.9935 | 2.13 | $ 8,587,564 | $ 15,561,185.32 | $ 1,121,544.75 | $ 1,510,555.62 | $ 123,514.55 | $ 15,173.35 | $ 18,331,973.59 |
| 15% | 20% | 30% | 0.0090 | 0.9910 | 2.94 | $ 8,587,564 | $ 21,414,475.21 | $ 1,543,410.20 | $ 2,078,678.21 | $ 169,974.16 | $ 20,880.76 | $ 25,227,418.54 |
| 20% | 20% | 30% | 0.0120 | 0.9880 | 3.92 | $ 8,587,564 | $ 28,552,633.62 | $ 2,057,880.27 | $ 2,771,460.30 | $ 226,632.21 | $ 27,841.01 | $ 33,636,447.40 |

| Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 3.08 | $ 9,805,354 | $ 24,667,302.40 | $ 2,242,956.66 | $ 3,020,669.45 | $ 258,370.68 | $ 28,147.25 | $ 30,217,446.44 |
| 6.72 | $ 9,805,354 | $ 53,774,719.24 | $ 4,889,645.52 | $ 6,583,707.52 | $ 563,248.08 | $ 61,361.01 | $ 65,872,681.36 |
| 9.24 | $ 9,805,354 | $ 74,001,907.21 | $ 6,728,869.98 | $ 9,058,855.93 | $ 775,112.03 | $ 84,441.75 | $ 90,649,186.90 |
| 12.33 | $ 9,805,354 | $ 98,669,209.61 | $ 8,971,826.64 | $ 12,076,374.83 | $ 1,033,482.71 | $ 112,589.00 | $ 120,863,482.79 |

SCENARIO-2

Weekdays (Police Depoyment for 25% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 25% | 0.0025 | 0.9975 | 1.99 | $ 9,115,273 | $ 14,606,644.21 | $ 1,440,405.49 | $ 1,939,966.09 | $ 168,093.85 | $ 17,656.85 | $ 18,172,766.49 |
| 10.90% | 20% | 25% | 0.0055 | 0.9946 | 4.35 | $ 9,115,273 | $ 31,842,484.37 | $ 3,140,083.98 | $ 4,228,568.35 | $ 366,444.60 | $ 38,491.94 | $ 39,616,073.24 |
| 15% | 20% | 25% | 0.0075 | 0.9925 | 5.98 | $ 9,115,273 | $ 43,819,932.62 | $ 4,321,216.48 | $ 5,818,597.61 | $ 504,281.56 | $ 52,970.56 | $ 54,516,998.84 |
| 20% | 20% | 25% | 0.0100 | 0.9900 | 7.97 | $ 9,115,273 | $ 58,426,576.82 | $ 5,761,621.98 | $ 7,757,263.55 | $ 672,375.42 | $ 70,627.41 | $ 72,688,465.18 |

Weekends (Police Depoyment for 25% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 25% | 0.0025 | 0.9975 | 0.82 | $ 8,506,378 | $ 5,948,465.34 | $ 428,725.06 | $ 577,460.57 | $ 47,215.04 | $ 5,800.21 | $ 7,007,666.22 |
| 10.90% | 20% | 25% | 0.0055 | 0.9946 | 1.80 | $ 8,506,378 | $ 12,967,654.43 | $ 934,620.62 | $ 1,258,814.61 | $ 102,928.79 | $ 12,644.46 | $ 15,276,662.92 |
| 15% | 20% | 25% | 0.0075 | 0.9925 | 2.47 | $ 8,506,378 | $ 17,845,396.01 | $ 1,286,175.17 | $ 1,732,266.42 | $ 141,645.13 | $ 17,400.63 | $ 21,022,883.36 |
| 20% | 20% | 25% | 0.0100 | 0.9900 | 3.30 | $ 8,506,378 | $ 23,793,861.35 | $ 1,714,900.22 | $ 2,309,611.72 | $ 188,860.17 | $ 23,200.84 | $ 28,030,434.30 |

| Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 2.64 | $ 9,521,203 | $ 20,556,085.34 | $ 1,869,130.55 | $ 2,517,297.56 | $ 215,308.90 | $ 23,456.04 | $ 25,181,278.39 |
| 5.77 | $ 9,521,203 | $ 44,812,266.03 | $ 4,074,704.60 | $ 5,486,769.73 | $ 469,373.40 | $ 51,134.17 | $ 54,894,247.93 |
| 7.93 | $ 9,521,203 | $ 61,668,256.01 | $ 5,607,391.65 | $ 7,549,703.07 | $ 645,926.69 | $ 70,368.13 | $ 75,541,645.55 |
| 10.58 | $ 9,521,203 | $ 82,224,341.34 | $ 7,476,522.20 | $ 10,064,812.10 | $ 861,235.59 | $ 93,824.17 | $ 100,720,735.40 |

SCENARIO-3

Weekdays (Police Depoyment for 20% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 20% | 0.0020 | 0.9980 | 1.63 | $ 8,912,308 | $ 11,685,315.36 | $ 1,152,324.40 | $ 1,552,007.57 | $ 134,475.08 | $ 14,125.48 | $ 14,538,247.89 |
| 10.90% | 20% | 20% | 0.0044 | 0.9956 | 3.56 | $ 8,912,308 | $ 25,473,987.50 | $ 2,512,067.18 | $ 3,383,019.51 | $ 293,155.68 | $ 30,793.55 | $ 31,693,023.42 |
| 15% | 20% | 20% | 0.0060 | 0.9940 | 4.89 | $ 8,912,308 | $ 35,055,946.09 | $ 3,456,973.19 | $ 4,655,190.16 | $ 403,425.25 | $ 42,376.45 | $ 43,613,911.14 |
| 20% | 20% | 20% | 0.0080 | 0.9920 | 6.52 | $ 8,912,308 | $ 46,741,261.46 | $ 4,609,297.58 | $ 6,206,365.45 | $ 537,900.34 | $ 56,501.93 | $ 58,151,326.75 |

Weekends (Police Depoyment for 20% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 20% | 0.0020 | 0.9980 | 0.67 | $ 8,425,192 | $ 4,758,772.27 | $ 342,980.04 | $ 461,971.53 | $ 37,772.03 | $ 4,640.17 | $ 5,606,136.05 |
| 10.90% | 20% | 20% | 0.0044 | 0.9956 | 1.45 | $ 8,425,192 | $ 10,374,123.55 | $ 747,696.50 | $ 1,007,066.30 | $ 82,343.04 | $ 10,115.57 | $ 12,221,344.95 |
| 15% | 20% | 20% | 0.0060 | 0.9940 | 2.00 | $ 8,425,192 | $ 14,276,316.81 | $ 1,028,940.13 | $ 1,385,840.80 | $ 113,316.10 | $ 13,920.50 | $ 16,818,334.36 |
| 20% | 20% | 20% | 0.0080 | 0.9920 | 2.66 | $ 8,425,192 | $ 19,035,089.08 | $ 1,371,920.18 | $ 1,847,738.55 | $ 151,088.14 | $ 18,560.67 | $ 22,424,396.62 |

| Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 2.18 | $ 9,237,052 | $ 16,444,868.27 | $ 1,495,304.44 | $ 2,013,896.47 | $ 172,247.12 | $ 18,764.83 | $ 20,145,081.13 |
| 4.75 | $ 9,237,052 | $ 35,849,812.83 | $ 3,259,763.68 | $ 4,389,693.28 | $ 375,498.72 | $ 40,907.34 | $ 43,915,675.84 |
| 6.54 | $ 9,237,052 | $ 49,334,604.81 | $ 4,485,913.32 | $ 6,040,287.78 | $ 516,741.36 | $ 56,294.50 | $ 60,433,841.76 |
| 8.72 | $ 9,237,052 | $ 65,779,473.08 | $ 5,981,217.76 | $ 8,052,783.17 | $ 688,988.47 | $ 75,059.33 | $ 80,577,521.82 |

SCENARIO-4

Weekdays (Police Depoyment for 15% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 15% | 0.0015 | 0.9985 | 1.25 | $ 8,709,343 | $ 8,763,986.52 | $ 864,243.30 | $ 1,164,031.70 | $ 100,856.31 | $ 10,594.11 | $ 10,903,711.95 |
| 10.90% | 20% | 15% | 0.0033 | 0.9967 | 2.73 | $ 8,709,343 | $ 19,105,490.62 | $ 1,884,050.39 | $ 2,537,388.28 | $ 219,866.76 | $ 23,095.16 | $ 23,769,891.21 |
| 15% | 20% | 15% | 0.0045 | 0.9955 | 3.76 | $ 8,709,343 | $ 26,291,959.57 | $ 2,592,729.89 | $ 3,491,626.73 | $ 302,568.94 | $ 31,782.33 | $ 32,710,667.46 |
| 20% | 20% | 15% | 0.0060 | 0.9940 | 5.01 | $ 8,709,343 | $ 35,055,946.09 | $ 3,456,973.19 | $ 4,655,190.16 | $ 403,425.25 | $ 42,376.45 | $ 43,613,911.14 |

Weekends (Police Depoyment for 15% Events a day)

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 15% | 0.0015 | 0.9985 | 0.50 | $ 8,344,006 | $ 3,569,079.20 | $ 257,235.03 | $ 346,480.95 | $ 28,329.03 | $ 3,480.13 | $ 4,204,604.34 |
| 10.90% | 20% | 15% | 0.0033 | 0.9967 | 1.10 | $ 8,344,006 | $ 7,780,592.66 | $ 560,772.37 | $ 755,310.68 | $ 61,757.28 | $ 7,586.67 | $ 9,166,019.67 |
| 15% | 20% | 15% | 0.0045 | 0.9955 | 1.51 | $ 8,344,006 | $ 10,707,237.61 | $ 771,705.10 | $ 1,039,401.35 | $ 84,987.08 | $ 10,440.38 | $ 12,613,771.52 |
| 20% | 20% | 15% | 0.0060 | 0.9940 | 2.02 | $ 8,344,006 | $ 14,276,316.81 | $ 1,028,940.13 | $ 1,385,840.80 | $ 113,316.10 | $ 13,920.50 | $ 16,818,334.36 |

| Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 1.69 | $ 8,952,901 | $ 12,333,651.20 | $ 1,121,478.33 | $ 1,510,466.17 | $ 129,185.34 | $ 14,073.63 | $ 15,108,854.67 |
| 3.68 | $ 8,952,901 | $ 26,887,359.62 | $ 2,444,822.76 | $ 3,292,478.13 | $ 281,624.04 | $ 30,680.50 | $ 32,936,965.05 |
| 5.06 | $ 8,952,901 | $ 37,000,953.61 | $ 3,364,434.99 | $ 4,530,609.95 | $ 387,556.02 | $ 42,220.88 | $ 45,325,775.43 |
| 6.75 | $ 8,952,901 | $ 49,334,604.81 | $ 4,485,913.32 | $ 6,040,287.78 | $ 516,741.36 | $ 56,294.50 | $ 60,433,841.76 |

## SCENARIO-5

**Weekdays (Police Depoyment for 10% Events a day)**

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 10% | 0.0010 | 0.9990 | ***0.85*** | $ 8,506,378 | $ 5,842,657.68 | $ 576,162.20 | $ 776,038.49 | $ 67,237.54 | $ 7,062.74 | $ 7,269,158.65 |
| **10.90%** | 20% | 10% | 0.0022 | 0.9978 | ***1.86*** | $ 8,506,378 | $ 12,736,993.75 | $ 1,256,033.59 | $ 1,691,674.63 | $ 146,577.84 | $ 15,396.78 | $ 15,846,676.59 |
| 15% | 20% | 10% | 0.0030 | 0.9970 | ***2.56*** | $ 8,506,378 | $ 17,527,973.05 | $ 1,728,486.59 | $ 2,327,907.26 | $ 201,712.63 | $ 21,188.22 | $ 21,807,267.75 |
| 20% | 20% | 10% | 0.0040 | 0.9960 | ***3.42*** | $ 8,506,378 | $ 23,370,630.73 | $ 2,304,648.79 | $ 3,103,737.58 | $ 268,950.17 | $ 28,250.96 | $ 29,076,218.23 |

**Weekends (Police Depoyment for 10% Events a day)**

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 10% | 0.0010 | 0.9990 | ***0.34*** | $ 8,262,820 | $ 2,379,386.13 | $ 171,490.02 | $ 230,988.84 | $ 18,886.02 | $ 2,320.08 | $ 2,803,071.10 |
| **10.90%** | 20% | 10% | 0.0022 | 0.9978 | ***0.74*** | $ 8,262,820 | $ 5,187,061.77 | $ 373,848.25 | $ 503,547.76 | $ 41,171.52 | $ 5,057.78 | $ 6,110,687.09 |
| 15% | 20% | 10% | 0.0030 | 0.9970 | ***1.02*** | $ 8,262,820 | $ 7,138,158.40 | $ 514,470.07 | $ 692,948.07 | $ 56,658.05 | $ 6,960.25 | $ 8,409,194.85 |
| 20% | 20% | 10% | 0.0040 | 0.9960 | ***1.36*** | $ 8,262,820 | $ 9,517,544.54 | $ 685,960.09 | $ 923,918.46 | $ 75,544.07 | $ 9,280.34 | $ 11,212,247.50 |

| Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| ***1.16*** | $ 8,668,750 | $ 8,222,434.13 | $ 747,652.22 | $ 1,007,006.67 | $ 86,123.56 | $ 9,382.42 | $ 10,072,599.00 |
| ***2.53*** | $ 8,668,750 | $ 17,924,906.41 | $ 1,629,881.84 | $ 2,195,124.23 | $ 187,749.36 | $ 20,453.67 | $ 21,958,115.51 |
| ***3.49*** | $ 8,668,750 | $ 24,667,302.40 | $ 2,242,956.66 | $ 3,020,669.45 | $ 258,370.68 | $ 28,147.25 | $ 30,217,446.44 |
| ***4.65*** | $ 8,668,750 | $ 32,889,736.54 | $ 2,990,608.88 | $ 4,027,325.64 | $ 344,494.24 | $ 37,529.67 | $ 40,289,694.96 |

## SCENARIO-6

**Weekdays (Police Depoyment for 5% Events a day)**

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 5% | 0.0005 | 0.9995 | ***0.44*** | $ 8,303,413 | $ 2,921,328.84 | $ 288,081.10 | $ 388,027.92 | $ 33,618.77 | $ 3,531.37 | $ 3,634,588.00 |
| **10.90%** | 20% | 5% | 0.0011 | 0.9989 | ***0.95*** | $ 8,303,413 | $ 6,368,496.87 | $ 628,016.80 | $ 845,878.54 | $ 73,288.92 | $ 7,698.39 | $ 7,923,379.52 |
| 15% | 20% | 5% | 0.0015 | 0.9985 | ***1.31*** | $ 8,303,413 | $ 8,763,986.52 | $ 864,243.30 | $ 1,164,031.70 | $ 100,856.31 | $ 10,594.11 | $ 10,903,711.95 |
| 20% | 20% | 5% | 0.0020 | 0.9980 | ***1.75*** | $ 8,303,413 | $ 11,685,315.36 | $ 1,152,324.40 | $ 1,552,007.57 | $ 134,475.08 | $ 14,125.48 | $ 14,538,247.89 |

**Weekends (Police Depoyment for 5% Events a day)**

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 5% | 0.0005 | 0.9995 | ***0.17*** | $ 8,181,634 | $ 1,189,693.07 | $ 85,745.01 | $ 115,495.19 | $ 9,443.01 | $ 1,160.04 | $ 1,401,536.32 |
| **10.90%** | 20% | 5% | 0.0011 | 0.9989 | ***0.37*** | $ 8,181,634 | $ 2,593,530.89 | $ 186,924.12 | $ 251,777.53 | $ 20,585.76 | $ 2,528.89 | $ 3,055,347.20 |
| 15% | 20% | 5% | 0.0015 | 0.9985 | ***0.51*** | $ 8,181,634 | $ 3,569,079.20 | $ 257,235.03 | $ 346,480.95 | $ 28,329.03 | $ 3,480.13 | $ 4,204,604.34 |
| 20% | 20% | 5% | 0.0020 | 0.9980 | ***0.69*** | $ 8,181,634 | $ 4,758,772.27 | $ 342,980.04 | $ 461,971.53 | $ 37,772.03 | $ 4,640.17 | $ 5,606,136.05 |

| Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| ***0.60*** | $ 8,384,599 | $ 4,111,217.07 | $ 373,826.11 | $ 503,517.94 | $ 43,061.78 | $ 4,691.21 | $ 5,036,314.11 |
| ***1.31*** | $ 8,384,599 | $ 8,962,453.21 | $ 814,940.92 | $ 1,097,631.53 | $ 93,874.68 | $ 10,226.83 | $ 10,979,127.17 |
| ***1.80*** | $ 8,384,599 | $ 12,333,651.20 | $ 1,121,478.33 | $ 1,510,466.17 | $ 129,185.34 | $ 14,073.63 | $ 15,108,854.67 |
| ***2.40*** | $ 8,384,599 | $ 16,444,868.27 | $ 1,495,304.44 | $ 2,013,896.47 | $ 172,247.12 | $ 18,764.83 | $ 20,145,081.13 |

## SCENARIO-7

**Weekdays (Police Depoyment for 5% Events a day)**

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 0% | 0.0000 | 1.0000 | ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| **10.90%** | 20% | 0% | 0.0000 | 1.0000 | ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| 15% | 20% | 0% | 0.0000 | 1.0000 | ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| 20% | 20% | 0% | 0.0000 | 1.0000 | ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |

**Weekends (Police Depoyment for 5% Events a day)**

| Crash Risk Location Prediction Crash Prediction & Police Deployment | | | | | Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Itemized Benefits | | | | | |
| Potential Crash Prediction by Crash Risk Location Prediction | Potential Crash Interception with Patrol* | Percent of Time Police Patrol is Deployed | Crash Reduction Multiplier | CMF | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| 5% | 20% | 0% | 0.0000 | 1.0000 | ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| **10.90%** | 20% | 0% | 0.0000 | 1.0000 | ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| 15% | 20% | 0% | 0.0000 | 1.0000 | ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| 20% | 20% | 0% | 0.0000 | 1.0000 | ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |

| Benefit-Cost Calculation | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Itemized Benefits - Crash Risk Location Prediction | | | | | |
| B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
| ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |
| ***0.00*** | $ 8,352,929 | $ - | $ - | $ - | $ - | $ - | $ - |

## F-3: Benefit-Cost Calculation for Incident Identification Tool, and Incident Identification Tool + Advanced Video Analytics

| Technologies | B/C | Present Value Costs | Safety | Travel Time | Reliability | VOC | Emissions | Total Benefits |
|---|---|---|---|---|---|---|---|---|
| ***Incident Identification*** | ***6.91*** | $ 7,710,131 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 53,302,867.18 |
| ***Incident Identification + Advanced Video Analytics*** | ***6.16*** | $ 8,652,303 | $ 43,513,121.44 | $ 3,956,575.55 | $ 5,327,752.57 | $ 455,765.88 | $ 49,651.75 | $ 53,302,867.18 |

# APPENDIX G: MISSOURI CRASH COST CALCULATION

**Crash Costs for Highway Safety Analysis, by FHWA Safety Program, FHWA-SA-17-071, January 2018.**

http://sharepoint/systemdelivery/TR/safety/Projects/bcCosts/DivShared/fhwasa17071.pdf

**Table from Summary:**

| Severity | Comprehensive Crash Unit Cost 2016 | Comprehensive Crash Unit Cost 2022 | Report's translation of KABCO to Missouri's Severity System: | | Crash Incidence | Minor Injury wtd average: |
|---|---|---|---|---|---|---|
| K | $ 11,295,400 | $ 13,404,240.79 | Fatal | | 4502 | |
| A | $ 655,000 | $ 777,287.90 | Serious Injury (Call an ambulance!) | | 33247 | |
| B | $ 198,500 | $ 235,559.77 | Minor Injury | (First aid needed.) | 62474 | $ 202,200 |
| C | $ 125,600 | $ 149,049.40 | | (Nothing visible.) | 39222 | |
| O | $ 11,900 | $ 14,121.72 | Property Damage Only | | 115451 | |

Levels of non-fatal injuries in KABCO:

- A Obvious, significant, non-fatal injuries. (Medical treatment needed.)
- B Visible injuries, but less significant. (First aid treatable.)
- C No visible injuries, but reported by the person. (Nothing for first aid treatments.)
- O Neither apparent nor reported injuries, PDO.

* MoDOT's Equivalent Pattern is:

| | | |
|---|---|---|
| 9 | Fatal | As in, each fatal crash is equal to 9 PDO crashes. |
| 6 | Serious Injury | http://sharepoint/systemdelivery/TR/safety/Shared%20Documents/Crash%20Costs/2015%20Crash%20Costs.x |
| 3 | Minor Injury | |
| 1 | PDO | |

**Chapter 6, Steps 1, 2, and 3** convert costs-per-person to costs-per-crash, where a fatal crash is presumed to include injuries and property damage. This is consistent with how we typically identify a crash as one type, instead of identifying number of persons and extent of injuries per persons. However, one aspect of tailoring it to Missouri could be examining the national average. For instance, are the average number of injured persons in a Missouri fatal crash consistent with the national average? Presuming we don't need to do this, we can proceed to step 4:

**Step 4: Update costs to current year.**

Costs listed above were adjusted from 2016 crash data to 2022, and then rounded to the nearest $100. Their "procedure should provide adequate cost estimates for roughly 5 years or until the next major DOT update of unit crash cost data and methods."

https://data.bls.gov/cgi-bin/cpicalc.pl

**Step 5: Adjust National to State.**

The report's method to "adjust" the national data is to use their same data collection and processing on the state's specific crash data for five years of crash data. Then following the same procedure as the report to convert past crash data into economic projected data, with state specific Consumer Price Indicies. Including processing the crash data to determine the state's averge number of persons injured per fatal crash, and such. The report does not provide a way to directly scale national to state values.

**Proposed Cost per Crash, per crash classified as Fatal, SI, MI, or PDO, with "adjustment" for Missouri:**

**Table 54*. State Crash Cost PCI Ratio Adjustment Factors.**

| | |
|---|---|
| US Average | $ 63,444 |
| Missouri | $ 55,159 |

*Table 54 is based on 2016 PCI from the Bureau of Economic Analysis table SAINC1 - Personal Income Summary: Personal Income, Population, Per Capita Personal Income
https://apps.bea.gov/iTable/iTable.cfm?reqid=70&step=1#reqid=70&step=1

Thus...

Missouri is 87% of the National Average.

This applied to National Crash Costs, to the nearest $100:

| | Proposed | MoDOT 2015 | Increase | % Increase | Not rounded: |
|---|---|---|---|---|---|
| **F** | **$ 11,653,800** | $ 5,026,924 | $ 6,626,889 | 131.8% | $ 11,653,813.09 |
| **SI** | **$ 675,800** | $ 314,183 | $ 361,601 | 115.1% | $ 675,783.73 |
| **MI*** | **$ 175,800** | $ 81,687 | $ 94,108 | 115.2% | $ 175,795.19 |
| **PDO** | **$ 12,300** | $ 4,569 | $ 7,708 | 168.7% | $ 12,277.60 |

* With Minor Inury based on weighted average of B & C crash instances in KABCO scale.
Crash Data obtained from Table 30 in the Crash Costs for Highway Safety Analsyis report.

# APPENDIX H: Project Timeline

## Project Initiation (2019)

The project kick-off meeting between St. Louis leadership occurred on April 22nd, 2019, to discuss how could Predictive Analytics be useful to save lives and improve transportation safety in Missouri. After three additional meetings with the MoDOT leadership team and the American Association of State Highway and Transportation Officials (AASHTO), the idea was presented to the Executive team on May 30th, 2019. On June 5th, 2019, the Executive team approved $1M funding to match the $1M ATCMTD grant, so $2M total was available for this project. The first meeting with International Business Machines Corporation (IBM) took place on June 11th, 2019, followed by the first meeting with Crash Risk Location Prediction & Incident Identification technology vendor on June 19th, 2019. At this point in time, MoDOT was looking for the best incident identification technology possible, considering the selected vendor as well as another provider as potential MoDOT partners. After that, multiple meetings were held between MoDOT and the two suppliers on separate occasions. After thorough review from MoDOT procurement team, by December 2019, one vendor was selected, and the contract was signed by January 2020. Approval was granted to begin gathering data for the process. **Table 38** briefly demonstrates the project initiation timeline.

**Table 38: Project Initiation Timeline**

| Application | Task | 2019 (Q) | | | | 2020 (Q) | | | | 2021 (Q) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| Crash Risk Location Prediction & Incident Identification | Project Initiation | X | X | | | | | | | | | | |
| | Technology Vendor Selection | | X | X | | | | | | | | | |
| | Technology Integration | | | | | | | X | X | X | X | X | X |
| Advanced Video Analytics | Project Initiation | X | X | | | | | | | | | | |
| | Technology Vendor Selection | | | | X | X | X | X | X | X | X | | |
| | Technology Integration | | | | | | | X | X | X | X | X | X |
| Integrated Modeling for Road Condition Prediction (IMRCP) | Project Initiation | X | X | X | | | | | | | | | |
| | Technology Vendor Selection | | | X | X | | | | | | | | |
| | Technology Integration | | | | | | | | X | X | X | X | X |

## Technology Vendor Selection (2020)

### History and Initial Planning (2019-2020)

In June 2019, funding for the Predictive Analytics project was approved, leading to the selection of Crash Risk Location Prediction & Incident Identification vendor in December 2019. The collaboration formally began in January 2020, with discussions advancing in the following months, starting with data input applicability on test users. The scope of the project was defined on March 19, 2020, covering the technology's standard algorithms for incident detection, irregular congestion, and crash prediction on I-270, with additional technology for dynamic work zones. Meetings continued to iron out details on data sharing, integration with the Advanced Traffic Management System (ATMS) and determining the selected technology as an additional technology for incident identification.

### Implementation and Challenges (2020)

As the project progressed into April and May 2020, COVID-19 became prevalent in the United States and uncertainty spread throughout all industries. Projects continued; however, following strict safety guidelines disrupted the planned in-person training process for these new technologies to be implemented. Leadership discussions targeted pushing information to the public, integrating Computer-Aided Dispatch (CAD) data, and refining the process for incident notifications. The decision was made on June 2nd, 2020, to make Crash Risk Location Prediction & Incident Identification an additional tool to the main ATMS platform for incident detection and prediction, pushing information into the ATMS Event Receiver. At that time, the technology was only focused on incident identification. Challenges included coordination amongst multiple agencies, managing CAD data reception from Missouri State Highway Patrol (MSHP), and adapting to COVID-19-related restrictions. A test user launch was scheduled for June 29th and 30th, leading to a soft launch on July 5th, with the final version planned to launch in November 2020.

### Test Phase and Future Plans (2020-2021)

The test phase commenced on July 1st, 2020, with selected users providing feedback on training challenges, device issues, and system functionality. The need for reporting capabilities from Crash Risk Location Prediction & Incident Identification, implementing a congestion algorithm, and launching the crash prediction feature by December 2020 were highlighted. Video Analytics options were still under discussion, and collaborations with WSP and IMRCP vendor on projects in the St. Louis District were mentioned. An internal meeting on December 11th, 2020, provided updates on the release of irregular congestion and crash prediction algorithms, with plans to refine these over the following months. Performance measurements for Incident Identification were expected to be released in Spring 2021, focusing on metrics such as the number of crashes, average response time, and average delay time. Challenges, feedback, and next steps were discussed to enhance the system's effectiveness. During the discussion, the implementation of data sources—such as St. Louis County and Missouri State Highway Patrol CAD crash data—feeding into the system was also addressed. By September 2021, the ATCMTD Grant was finalized and executed.

The entire management process timeline is summarized in **Table 39**.

**Table 39: Management Process Timeline (2020)**

| Sender/Organizer | Event | 2020 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | April | May | June | July | August | Septembe | October | November | December |
| Crash Risk Location Prediction & Incident Identification Vendor/MoDOT | Awareness Session | X | | | | | | | | |
| MoDOT | Senior Management Communication | | X | | | | | | | |
| MoDOT | Identifying Users | | X | | | | | | | |
| MoDOT | Test User Intro | | X | | | | | | | |
| Crash Risk Location Prediction & Incident Identification Vendor/MoDOT | Impact Assessment (Test Phase) | | X | X | | | | | | |
| MoDOT | Test User Training Schedule | | | X | | | | | | |
| Crash Risk Location Prediction & Incident Identification Vendor/MoDOT | Test User Training | | | X | | | | | | |
| Crash Risk Location Prediction & Incident Identification Vendor/MoDOT | Test User Survey | | | | X | | | | | |
| Crash Risk Location Prediction & Incident Identification Vendor/MoDOT | Impact Assessment (End User Go Live Phase) | | | | | | | X | | |
| MoDOT | End User Training Schedule Communication | | | | | | | X | | |
| Crash Risk Location Prediction & Incident Identification Vendor/MoDOT | End User Training | | | | | | | | X | |
| Crash Risk Location Prediction & Incident Identification Vendor/MoDOT | End User Survey | | | | | | | | X | |
| Crash Risk Location Prediction & Incident Identification Vendor/MoDOT | Feedback Session | | | | | | | | | X |

## Technology Integration (2021/22)

By the end of 2021, Crash Risk Location Prediction & Incident Identification technology started integration and was fully integrated with its Incident Identification tool while Crash Risk Predictions tool came some months later in the first quarter in 2022. Additional installation of cameras was provided by the technology's supplier with no extra charge, fitting the purpose of having better data and more precise results to the Crash Risk Prediction tool.

Advanced Video Analytics had a similar timeline as the Incident Identification tool, where it started the integration with MoDOT around the third quarter of 2021 and fully deployed by the first quarter of 2022. However, the provider of the IMRCP tool, encountered integration delays, resulting in full operational functionality being achieved only by the conclusion of the 2021-2022 winter season. This affected data collection efforts for said season, relying on snowfall events occurring during the following winter season of 2022-2023, which notably featured minimal snowfall occurrences. **Table 40** presents visual timelines detailing the integration progress from 2021 to 2022.

**Table 40: 2021/2022 Technology Integration Schedule**

| Application | Task | 2021 (Q) | | | | 2022 (Q) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| Crash Risk Location Prediction & Incident Identification | Performance measurement of the software | | | X | X | X | | | |
| | Cameras Installation | | | | | | | X | |
| | Camera's performance measurement | | | | | | | X | X |
| Advanced Video Analytics | Server set up and configuration | | | X | | | | | |
| | Data feed into the system | | | X | | | | | |
| | Troubleshooting | | | X | X | X | | | |
| | Training for all users | | | | | X | | | |
| | Performance measurement of the software | | | | | X | X | X | X |
| Integrated Modeling for Road Condition Prediction (IMRCP) | Server set up and configuration | | | X | | | | | |
| | Data feed into the system | | | X | X | | | | |
| | Troubleshooting | | | X | X | X | | | |
| | Training for all users | | | X | | | | | |
| | Performance measurement of the software | | | | | X | | | |
| Combined Technologies | Full operation | | | | | | X | X | X |

## Technology Verification (2022/23)

All technologies were deployed and ready to be verified in a quarterly manner since the beginning of 2022, however IMRCP technology relies on snow conditions to be able to be verified and 2022-2023 winter season had insufficient snow data to be verified. Hence, the "Performance measurement of the software" is white throughout the schedule in **Table 41.**

**Table 41: 2022/2023 Technology Verification Schedule**

| Application | Task | 2022 (Q) | | | | 2023 (Q) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| **Crash Risk Location Prediction & Incident Identification** | Performance measurement of the software | X | X | X | X | X | X | X | X |
| | Cameras Installation | | | X | X | | | | |
| | Camera performance measurement | | | | | X | X | X | X |
| **Advanced Video Analytics** | Performance measurement of the software | X | X | X | X | X | X | X | X |
| **Integrated Modeling for Road Condition Prediction (IMRCP)** | Winter Season Preparation | | | X | X | | | | |
| | Performance measurement of the software | | | | | | | | |

**Table 42** highlights the procurement, development, deployment, testing, and evaluation periods for the PLOI initiative. A summary of the meeting notes is available in **Appendix A: Meeting Notes.**

**Table 42: Summary Project Timeline**

| Application | Task | 2021 (Q) | | | | 2022 (Q) | | | | 2023 (Q) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| Crash Risk Location Prediction & Incident Identification | Procure Platform | X | X | | | | | | | | | | |
| | Deploy Platform | | X | X | | | | | | | | | |
| | Test/Validate | | | X | X | X | X | X | X | X | | | |
| | Evaluation | | | | | | | X | X | X | X | X | X |
| Advanced Video Analytics | Procure Platform | X | X | | | | | | | | | | |
| | Deploy Platform | X | X | X | | | | | | | | | |
| | Test/Validate | | | | X | X | X | X | X | X | X | | |
| | Evaluation | | | | | | | X | X | X | X | X | X |
| Integrated Modeling for Road Condition Prediction (IMRCP) | Procure Platform | X | X | X | | | | | | | | | |
| | Deploy Platform | | | X | X | | | | | | | | |
| | Test/Validate | | | | | X | X | X | X | X | X | | |
| | Evaluation | | | | | | | | X | X | X | X | X |