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DEVELOPMENT OF A TRAFFIC INCIDENT MANAGEMENT TOOLBOX AND EVALUATION OF DATA SOURCES FOR EFFECTIVE EARLY WARNING AND DETECTION OF ABNORMAL TRAFFIC CONDITIONS

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16. Abstract

Traffic incident management (TIM) is important to maintain safe and reliable travel on Florida's limited access roadways. This research focused on evaluating existing and emerging data sources for early detection of abnormal traffic conditions and developing operational tools to improve TIM capabilities. A comprehensive literature review examined TIM technologies and data sources used in Florida and other states, including machine learning models and third-party platforms. Existing Florida Highway Patrol computer-aided dispatch (CAD), Waze, traffic sensor subsystem (TSS), Active 911, and PulsePoint data were collected and evaluated. Statewide Waze-CAD comparisons found that Waze reported events before CAD in 27.95% of matched cases with an average lead time of 8.42 minutes. In District 5, Active 911 was earlier than CAD for 43 of 113 matched events (average lead time of 7.07 minutes), while PulsePoint was earlier than CAD for 97 of 160 matched events (average lead time of 4.92 minutes). A TIM toolbox was developed which ranked the current Waze filters, relaxed Waze filters, Active 911, and PulsePoint by hour within each FDOT district based on their potential early warning benefits. Additionally, a machine learning classification framework was developed for TSS alerts which improved baseline precision by 75% and reduced false alerts by 39.5%. FDOT can use the TIM toolbox results and the developed TSS classification framework to improve and enhance their TIM programs. This research can be a foundation for future development of a comprehensive, real-time platform which utilizes these tools and results to enhance traffic operations and safety.

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Executive Summary

Effective traffic incident management (TIM) practices can help reduce the safety and operational impacts of traffic incidents on Florida Department of Transportation (FDOT) limited access roadways. Improving the ability of existing TIM systems to provide early warnings of traffic incidents or abnormal conditions will help FDOT be proactive in identifying and responding to incidents. This FDOT research project evaluated existing and emerging TIM data sources for early detection of abnormal traffic conditions, tested potential improvements to current systems utilized in Florida, and developed a TIM toolbox for operational use. Multiple TIM tools were evaluated and compared at a statewide and district level performance, including expansions and improvements of existing tools, to identify which tools would likely provide the most early warning benefits for different times and locations.

To establish a baseline understanding of TIM technologies and data sources, a comprehensive literature review was conducted covering early warning tools and practices used in Florida and other states. Available details on existing TIM data sources and tools currently used by transportation agencies throughout the United States (U.S.) were collected; these tools included intelligent transportation system cameras, traffic sensors, safety service patrols, traveler information platforms, crowdsourced applications (like Waze), and private-sector data services. Advanced and innovative TIM methods that have been applied or tested to improve early detection of incidents and abnormal traffic conditions were also studied. These included the use of crowdsourced and connected vehicle data, real-time traffic analysis techniques, machine learning models for incident prediction, and emerging third-party platforms offering predictive analytics and rapid incident reporting capabilities. Multiple tools with high potential for early warning benefits were identified, including Waze, Active 911, PulsePoint, Waycare, and Carbyne.

Five existing Florida TIM data sources were thoroughly analyzed and compared to understand where and when early warning benefits are currently present or are most needed. These data sources were Florida Highway Patrol (FHP) computer-aided dispatch (CAD) events, Waze alerts, threshold-based traffic sensor subsystem (TSS) alerts, Active 911, and PulsePoint. Waze and CAD data were compared at the statewide level. Buffers of 30 minutes and one mile were used to match Waze and CAD events based on buffer testing. For one year of data, there were 6,147 matched Waze-CAD events, with Waze reporting before CAD for 27.95% of these cases. The average lead time for events with Waze earlier was 8.42 minutes. Detailed analyses and the application of an extreme gradient boosting (XGBoost) model showed that Waze had the most potential early warning benefits for FDOT Districts 2, 4, and 6; roadways State Road (SR)-91 and SR-821; and late night and early warning hours.

Active 911 and PulsePoint are two systems utilized in FDOT District 5 (D5), which can supplement CAD data. These systems were evaluated to determine their potential in improving early detection compared to CAD. After matching these data with FHP CAD alerts, Active 911 was found to be earlier for 43 of 113 matched events (with an average lead time of 7.07 minutes), while PulsePoint was found to be earlier for 97 of 160 matched events (with an average lead time of 4.92 minutes). Projecting these D5 results to all Florida limited access facilities resulted in estimated annual congestion reduction benefits of about $3.30 million for Active 911 and $8.44 million for PulsePoint. These results indicate that Active 911 and PulsePoint could be effective early warning tools, especially during morning hours. It is therefore recommended to consider expanding these tools to other districts.

Review of the current statewide TSS data showed that most alerts are caused by recurring congestion patterns. To improve the usefulness of these data in detecting incidents (i.e., nonrecurring congestion), a machine learning framework was developed that only uses information from the timestamped and geolocated TSS threshold alerts with no other external data sources. Historical sensor patterns were used to engineer features that capture alert frequency, timing irregularity, and behavioral deviations. Alerts were labeled as either recurring or nonrecurring congestion by matching them to FHP CAD events. The statewide model achieved an accuracy of 0.643, a true positive rate of 0.682, a false positive rate of 0.363, and precision of 0.222. It improved on the baseline TSS precision by 75% and reduced false alerts by 39.5% for the statewide test set. Comparable performance was observed on a separate Florida's Turnpike Enterprise (FTE) test set. The model's true positive rate was highest between 9:00 AM and 10:00 PM on weekdays, and hourly performance heatmaps were created to guide targeted operational use in real time. By implementing this framework, FDOT could reduce the number of TSS alerts reported to traffic management centers (TMCs) while also ensuring that the reported alerts are more likely to be indicative of traffic incidents.

Based on the statewide Waze-CAD comparisons, it was decided to evaluate the potential of relaxing the existing Waze filters to include confidence level 3 alerts. Evaluations of these relaxed Waze filtering protocols for FTE and District 3 (D3) showed that relaxing filters for all hours would be highly cost-effective, with benefit-cost ratios of 6.10 for FTE and 7.91 for D3. These evaluations found that confidence level 3 alerts would provide an average of 4.95 minutes earlier detection than traditional methods and were estimated to generate substantial annual congestion reduction benefits of $3.6 million for FTE and $1.0 million for D3. However, implementing this approach would significantly increase the number of alerts requiring operator verification, necessitating careful consideration of operator workload capacity.

Two TIM systems used by other states were also assessed for potential Florida application. Waycare, which is used in Nevada, forecasts incidents using predictive analytics and historical patterns. Carbyne, which is used in Georgia, reduces dispatch times by transmitting caller location and media directly to TMCs. Early warning benefits were estimated for these tools using implementation data from Nevada and Georgia, with both tools showing potential, especially for areas with limited coverage by other TIM tools. However, it is recommended to pilot test these tools to obtain Florida-specific results before implementing them statewide.

The final output of this project was the development of a TIM toolbox for use by FDOT management and TMC operators. The toolbox includes rankings for Waze, Waze with relaxed filters, Active 911, and PulsePoint based on their estimated annual early warning benefits for each hour of the day within each FDOT district. The methodologies used to estimate these benefits can be easily updated or applied to other TIM tools in the future. Block charts were developed for each FDOT district to help FDOT management and TMC operators visualize which TIM sources are most effective for different times of day. These charts allow operators to prioritize alerts when multiple sources report the same event and support engineers in evaluating the potential benefits of implementing or expanding these tools.

Overall, this project demonstrated the value of integrating new and existing TIM data sources and analytical tools to improve early incident detection and response in Florida. It is recommended that FDOT continue to refine and deploy Waze filtering protocols to provide timely and accurate alerts to TMCs, with adjustments based on roadway type, location, and time of day to minimize unnecessary operator workload. Expansion of third-party sources such as Active 911 and PulsePoint could be considered in districts where analyses showed measurable lead-time advantages over CAD. Adaption of the developed TSS machine learning model to work in a real-time setting could allow it to act as a filter for TSS alerts before they are reported to TMCs. It could be especially useful in targeted locations and hours with high false alarm rates to reduce operator burden while maintaining detection performance. The findings and conclusions from this project can help FDOT make informed decisions on TIM data integration strategies that enhance traffic operations and improve safety on Florida's roadways. They can also provide a foundation for future research efforts to develop a real-time TIM platform which utilizes the TIM toolbox results to provide TMC operators with the most reliable and accurate data so they can efficiently identify traffic incidents.

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List of Abbreviations and Acronyms

AID	Automatic Incident Detection
AI-TOMS	Artificial Intelligence Transportation Operations Management System
API	Application Programming Interface
ATMS	Advanced Traffic Management System
AVID	Automated Video Incident Detection
B/C	Benefit-Cost
BlueTOAD	Bluetooth Travel-Time Origination and Destination
CAD	Computer-Aided Dispatch
Caltrans	California Department of Transportation
Car2X	Car to Everything
CAV	Connected and Automated Vehicle
CCTV	Closed-Circuit Television
CFX	Central Florida Expressway Authority
CLEAR	Crash Location and Engineering Analysis Repository
CV	Connected Vehicle
D1	District 1
D2	District 2
D3	District 3
D4	District 4
D5	District 5
D4	District 4
D5	District 5
D6	District 6
D7	District 7
DAV	Disabled and Abandoned Vehicle
DOT	Department of Transportation
EMS	Emergency Medical Services
FDOT	Florida Department of Transportation
FHP	Florida Highway Patrol
FHWA	Federal Highway Administration
FL511	Florida 511
FPR	False Positive Rate
FTE	Florida’s Turnpike Enterprise
GPS	Global Positioning System
HELP	Highway Emergency Link Platform
IDS	Incident Detection Subsystem
ITS	Intelligent Transportation System
KDOT	Kansas Department of Transportation
NOAA	National Oceanic and Atmospheric Administration
PennDOT	Pennsylvania Department of Transportation
ROC	Receiver Operating Characteristic
ROC-AUC	Area Under the Receiver Operating Characteristic Curve
RWIS	Road Weather Information Systems
SHAP	Shapley Additive Explanation
SR	State Road

SSP	Safety Service Patrol
TIM	Traffic Incident Management
TMC	Traffic Management Center
TOC	Traffic Operations Center
TPR	True Positive Rate
TRIP	Towing & Recovery Incentive Payment
TSM&O	Transportation Systems Management and Operations
TSS	Traffic Sensor Subsystem
UCF	University of Central Florida
V2I	Vehicle-to-Infrastructure
V2X	Vehicle-to-Everything
XGBoost	Extreme Gradient Boosting

Chapter 1: Introduction

Traffic incident management (TIM) is a critical component of transportation systems management and operations, serving a central role in mitigating congestion, enhancing roadway safety, and reducing the occurrence of secondary crashes. Effective TIM practices enable transportation agencies to detect incidents promptly, provide early warnings to motorists, and implement timely response measures that restore normal traffic operations while minimizing risk to both drivers and responders. As traffic volumes continue to grow and roadway networks operate closer to capacity, the ability to identify and address incidents with minimal delay has become increasingly essential for maintaining safe and efficient transportation systems.

The Federal Highway Administration (FHWA) focuses on fostering strong TIM programs for agencies across the United States by providing guidelines, resources, and TIM training. The Performance Measures subpage on FHWA's website establishes four key performance measures which agencies can use to judge whether improvements are needed in their respective TIM programs: roadway clearance time, incident clearance time, frequency and types of secondary crashes, and frequency and characteristics of incidents involving responders being struck by other vehicles (FHWA, 2024a). Figure 1-1 provides a visual representation of roadway and incident clearance time and how they relate to other incident-related measures. Additionally, FHWA collaborated with 30 state TIM programs through the program "The FHWA Every Day Counts Round Four" to improve data collection and performance measures of these 30 state TIM programs (FHWA, 2024a).

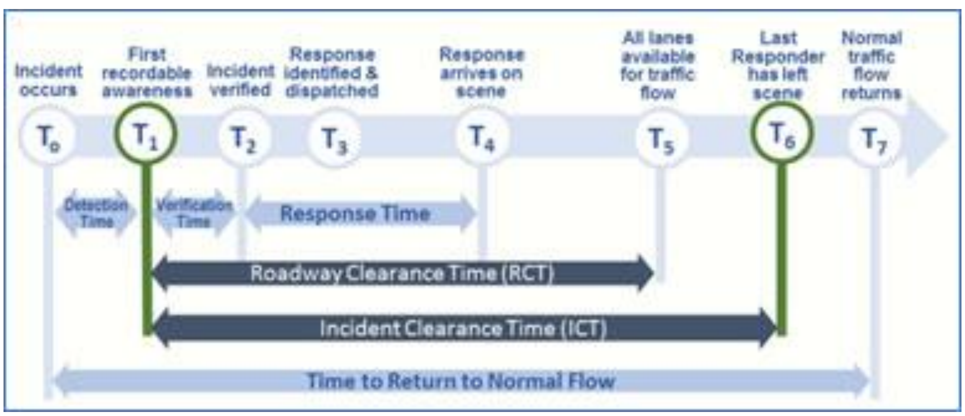

Figure 1-1: TIM Incident Duration Timeline and Performance Measures (FHWA, 2024a)

FHWA also encourages state and local agencies to adopt new methods for TIM. Such options include using back-of-queue warning, notification of responders in the area via a navigation app, and notification of incidents through the use of crowdsourced data (FHWA Center for Accelerating Innovation, 2023). These new approaches could potentially help agencies reduce incident detection time, identify incidents outside of their traditional TIM coverage area, and warn drivers of abnormal conditions to help proactively reduce crashes.

In line with FHWA's suggestions, the Florida Department of Transportation (FDOT) is interested in the potential of new TIM tools to improve early warning and detection of traffic incidents or abnormal traffic conditions. This project was undertaken to support FDOT in advancing its TIM capabilities through the identification, evaluation, and integration of various data sources and early warning technologies. The main goal of this project was to enhance FDOT's ability to detect incidents at the earliest possible stage, proactively notify drivers of abnormal traffic conditions, and reduce the likelihood of crashes and extended congestion. The end result would be a TIM toolbox which FDOT could use to select and deploy TIM tools across various operational scenarios to maximize early detection and response efficiency.

To achieve the goal of this FDOT project, Professor Haitham Al-Deek and his University of Central Florida (UCF) research team performed various tasks and met several objectives. First, a thorough literature review was conducted to understand the state of the practice in TIM tools and methods. This literature review focused specifically on TIM tools which could help provide early warning of abnormal traffic conditions to help proactively reduce crashes on limited access facilities. The results of this literature review can help FDOT and the UCF research team understand the strengths and weaknesses of various TIM tools and identify potential TIM tools for additional analysis and evaluation.

Next, the research team collected and analyzed data from six major TIM sources currently used in Florida: Florida Highway Patrol (FHP) computer-aided dispatch (CAD) events, Waze alerts, traffic sensor subsystem (TSS) alerts, road weather information system (RWIS) alerts, Active 911 alerts, and PulsePoint alerts. FHP CAD provides incident reports from law enforcement and 911 call centers. TSS alerts are generated when traffic speeds drop below a predefined threshold, signaling potential incidents. RWIS provides weather data such as precipitation and visibility. Waze alerts are real-time crowdsourced reports of crashes, hazards, and congestion. Active 911 and PulsePoint facilitate rapid communication of medical and traffic emergencies, often ahead of CAD reporting. These datasets were thoroughly compared and analyzed using filtering methodologies, statewide analyses, and advanced modeling to understand their relationships and effectiveness in early incident detection. The results of these analyses provide a baseline for comparison with new TIM tools and can show where and when certain tools provide the most early warning benefits.

The third task of this project focused on evaluating potential enhancements to existing TIM tools and assessing the usefulness of innovative systems used in other states. A classification model was developed to improve the early warning benefits of TSS alerts while also reducing the amount of false alerts received by traffic management center (TMC) operators. Potential early warning benefits of expanding Active 911 and PulsePoint from their current use in FDOT District 5 (D5) to the entire state were also estimated. Additionally, changes to Waze filtering protocols were examined to determine how relaxing the filters could improve early warning potential while balancing the added workload for TMC operators. These changes were evaluated for the Florida's Turnpike Enterprise (FTE) District and FDOT District 3 (D3). The potential benefits of Waycare (a predictive analytics platform used in Nevada) and Carbyne (a communication platform used in Georgia that enables TMC operators to quickly locate and respond to incidents) were also estimated for Florida. This task's findings can help FDOT identify TIM improvements and new tools which could provide the most early warning benefits for different scenarios.

The culmination of this research effort was the development of the TIM toolbox. This toolbox provides rankings of key TIM data sources across each FDOT district by hour of the day based on estimated annual early warning benefits. It provides FDOT engineers and TMC operators with a practical decision-support tool to understand the early warning benefits of various sources, prioritize sources when multiple alerts are received simultaneously, and apply the developed methodology to future data. The toolbox includes detailed hourly rankings of Active 911, PulsePoint, existing Waze filters, and relaxed Waze filters (referred to as Waze_3 throughout this report) for each FDOT district, along with block chart visualizations for easy operational use. By offering a detailed temporal and spatial understanding of early warning performance, the TIM toolbox equips FDOT and its partners with actionable insights to enhance incident detection, prioritize alerts, and reduce congestion and crashes on Florida's limited access roadways.

The remainder of this report details the tasks discussed in this chapter, including their methodologies and results. Chapter 2 discusses the literature review on current TIM practices and technologies with a focus on tools that provide early warning of abnormal traffic conditions. Chapter 3 discusses the collection and analysis of existing TIM data in Florida, including comparative analyses and modeling efforts to evaluate the relationships among the major data sources. Chapter 4 evaluates improvements to existing TIM data sources in Florida, expansions of select TIM tools, and potential benefits of advanced systems used in other states. Chapter 5 presents the development of the TIM toolbox, which integrates the findings from all phases of the project to provide FDOT with a practical framework for identifying, comparing, and deploying TIM tools to improve incident detection and response. Finally, Chapter 6 summarizes the key findings from all project phases and provides recommendations for future research and implementation to guide FDOT in optimizing TIM strategies statewide. Two appendices are included at the end of this report with Python programming codes developed using Python 3.13. Appendix A contains codes used to compare and evaluate the various Florida TIM data sources studied in this report and Appendix B contains code used to develop a classification model for TSS alerts.

Chapter 2: Literature Review

To understand the state of the practice in TIM tools and methods, a thorough literature review was conducted. Section 2.1 discusses the various TIM tools currently in use by agencies across the United States (U.S.) to detect incidents and provide early warnings of abnormal conditions, as well as emerging TIM technologies. Section 2.2 details various studies on crowdsourced data, real-time techniques to identify traffic incidents or abnormal conditions, and machine learning approaches to better understand the conditions that lead to traffic incidents. While TIM is a broad topic, this literature review focuses specifically on TIM tools which could help provide early warning of abnormal traffic conditions and proactively reduce crashes on limited access facilities. This means that tools to reduce response time once an incident is detected, reduce roadway clearance time once responders reach the incident, improve the safety of responders on the scene, or improve incident management on signalized roadways were not considered. These are all important aspects of TIM, but are outside the scope of this project, which is focused on early warning and detection of abnormal traffic conditions on limited access facilities.

2.1 TIM Data Sources and Tools Used by U.S. Agencies for Early Warning and Detection of Abnormal Traffic Conditions

Currently, the vast majority of state departments of transportation (DOTs) and other transportation agencies in the U.S. make use of TIM tools which are capable of detecting traffic conditions and incidents and providing warnings to TMC operators. Additionally, several technology companies offer tools for use by agencies to assist with TIM detection and warning. This section discusses the various TIM data sources and tools used by each DOT, sorted by region of the U.S., along with the emerging TIM technological tools currently being offered by different third-party vendors. It is important to note that the findings and results discussed in this section are based on the latest information found from the identified websites, articles, and other cited references when they were accessed. Information on some websites might not necessarily be up to date, but these were the latest results available when this literature review was conducted. Furthermore, these results have not always been verified or confirmed by independent parties and might not be the same if implemented in Florida.

2.1.1. Southeast Region

FDOT utilizes many intelligent transportation system (ITS) tools for their TIM program. The FDOT District Field Equipment and FTE Data Collection Equipment are important elements of the FDOT ITS architecture; these equipment include vehicle detectors and closed-circuit television (CCTV) cameras, which are useful tools for detection of traffic conditions and incidents (FDOT, 2023). Each FDOT district includes some type of TMC to monitor traffic conditions and manage incidents on FDOT roadways (including interstates and toll roads), with the SunGuide reporting platform used throughout all these TMCs. Some toll roads are operated by different agencies (such as the Central Florida Expressway Authority [CFX]), with these agencies having their own field equipment. The SunGuide platform can receive notifications from private sector information service providers, such as HERE and Waze, to provide additional information on roadway and traffic conditions to TMC operators (FDOT, 2023).

FDOT currently has an established partnership with Waze through which Waze receives information obtained by FDOT’s roadway sensors and FDOT receives access to reports filed on

Waze (WLRN, 2014). Due to the vast number of Waze alerts, FDOT currently filters these alerts so only traffic incident alerts with confidence scores of 4 or 5 are reported to the TMC. However, substantial benefits could be obtained by reporting other types of Waze alerts to TMC operators. Sandt, McCombs, Al-Deek, and Carrick (2023) investigated Waze data for disabled and abandoned vehicles (DAVs) on Florida limited access roadways. From July 2019 to December 2020, there were over 3.8 million DAV Waze alerts and 329 DAV crashes. Using spatiotemporal buffers of 0.31 mi (0.5 km) and 30 minutes showed that 41 out of 329 DAV crashes were associated with at least one matching Waze alert before the crash occurred. DAV crashes with preceding Waze alerts were most common in urban areas, on high-volume roadways, and during the morning peak hours. Using these Waze alerts, emergency and law enforcement responders could potentially have reached 12 DAVs before a crash happened, resulting in $23 million savings due to prevented fatalities, injuries, and property damage and $27,000 in congestion savings. An additional $2 million savings could have been obtained due to responders potentially preventing two other crashes and reducing congestion for 29 other crashes (Sandt, McCombs, Al-Deek, Carrick, 2023). This study shows the significant benefits that utilizing Waze data for DAVs could provide. It should be noted that FHP does not currently respond to non-lane-blocking DAVs on the shoulder while Road Rangers respond to DAVs they encounter while patrolling highways. These DAVs become a priority if they are lane-blocking.

More benefits due to the use of Waze in detecting DAV events were discussed by Sandt, McCombs, Cornelison, et al. (2023). Over two years of DAV Waze data from April 2019-December 2021 containing more than 10 million Waze alerts were compared with DAV events (crashes and non-crash data points) reported by the TMC. Approximately 66% of DAV crashes were associated with Waze alerts, with 37% having a Waze alert prior to the crash. Additionally, 70% of DAV non-crash events were associated with Waze alerts, with 47% having a Waze alert prior to the crash. On average, the first Waze alert happened 16 minutes before the DAV event was reported, with this time difference being the largest during daytime hours and in urban areas. A detailed investigation of I-4 in FDOT District 5 and State Road (SR) 91 in FDOT District 4 was then conducted to estimate the benefits and costs of utilizing these DAV alerts. The results showed that estimated congestion savings were $4.3 million and $2.6 million for I-4 and SR 91, respectively, with costs (time spent by TMC operators verifying all Waze alerts) of $71,000 and $96,000, respectively. This resulted in benefit-cost ratios of 61 for I-4 and 27 for SR 91. Additionally, $4.3 million savings in crash costs could have potentially been achieved due to responders reaching two DAVs before a crash and potentially preventing those crashes from occurring (Sandt, McCombs, Cornelison, et al., 2023).

Additional findings regarding the benefits of DAV Waze alerts for FDOT were discussed in Al-Deek et al. (2022). This report showed that Waze alerts had more benefits and higher benefit-cost ratios compared to Road Ranger expansions. An annual congestion savings over $3 million and a benefit-cost ratio of 18.39 were estimated for SR 91. The final outcome of the DAV Waze investigation showed that vast benefits could be achieved if DAV Waze alerts were reported to TMC operators, but further investigation is needed to ensure that TMC operators are not overwhelmed by false alerts (Al-Deek et al., 2022).

FDOT also utilizes the Florida 511 (FL511) system to provide travelers with information on traffic and roadway conditions. FL511 uses data from roadway sensors, cameras, SunGuide, Road Rangers, law enforcement, Waze, and the National Oceanic and Atmospheric Administration (NOAA). However, it only allows users to view information and does not let them report incidents or abnormal conditions (FDOT, n.d.).

In addition to these existing TIM tools, FDOT has two systems planned which could improve their ability to identify abnormal traffic conditions and incidents more quickly. The Data Integration and Video Aggregation System is a planned system that will allow for monitoring of real-time traffic information through live-streaming video and could help FDOT proactively identify conditions which could lead to traffic incidents (FDOT, 2023). The Connected and Automated Vehicle (CAV)-ITS Map Update System is another planned system that supports proactive incident detection by system operators using data from traveler information points and roadway data sets (FDOT, 2023).

Other states in the Southeast that utilize TIM tools for detection and/or early warning (such as patrol programs, ITS cameras, the Carbyne platform, and sensors) are Alabama, Arkansas, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. The Alabama Service and Assistant Patrol program helps detect incidents, with a study finding that a 1% increase in detection time was found to increase clearance time by 1%, due to the queuing that results from blockages increasing the time for responders to reach the incident scene (Islam, 2021). Areas covered by this program were associated with shorter clearance times, as the patrols can quickly detect incidents (Islam, 2021). This shows the importance of safety service patrol programs, such as the Road Ranger program used by FDOT, to detect incidents.

Arkansas DOT (2024) utilizes ITS technology in their TMC to detect traffic incidents through monitoring of ITS cameras. Similarly, the Kentucky Transportation Cabinet (2021) has implemented many ITS projects which involve cameras throughout Kentucky while Mississippi DOT (n.d.) also employs traffic monitoring video cameras. Cameras are known to be useful for operators to detect traffic incidents.

A document from Georgia DOT outlines the ITS equipment approved for use. Some of these equipment which are applicable for TIM include microwave vehicle detection systems, video detection systems, and CCTV cameras for detection of traffic incidents (Georgia DOT, 2024). Additionally, Georgia DOT has been using Carbyne to assist in TIM. Carbyne is a platform for users (typically drivers) which alerts TMCs of an incident and allows users to share their phone number for ease of locating traffic incidents (FHWA, 2024b). The TMC operator will then send the user a link requesting access to data from their smartphone, such as location (global positioning system [GPS] coordinates), camera images and video, speed, and nearest estimated building address. With this access, the operator can quickly and accurately determine the user's location and share this information with responders. The 3-month pilot program of the Carbyne system in Georgia resulted in a 20 minute reduction in dispatch times, along with improvements in clearance time and customer service (FHWA, 2024b). This system works with the existing call-handling platform to locate callers and could be beneficial for areas outside of the TIM coverage area.

The Louisiana Department of Transportation and Development has a webpage with general information on how ITS is integrated in the state of Louisiana (Louisiana Department of Transportation and Development, n.d.). Louisiana makes use of remote traffic microwave sensors and traffic cameras for detection. The remote traffic microwave sensors generate traffic congestion information which is received by system operators who can then ascertain if there is a traffic incident given any traffic abnormalities. According to the webpage, upgrades are being sought for the traffic cameras to improve the quality of video by changing the communication medium to optical fiber (Louisiana Department of Transportation and Development, n.d.).

North Carolina DOT utilizes the NCDrive Traveler Information System, comprising CCTV cameras and roadway weather information for TIM, enabling real-time monitoring and communication with motorists to minimize delays and enhance safety. The system does not have a feature that allows users to report traffic incidents (North Carolina DOT, 2019). South Carolina DOT has a similar 511 Traveler Information System, offering real-time traffic updates on highways. This free service aids motorists in navigating roadways by providing information about road work, closed lanes, incidents, and weather. Users can access updates via phone or website, with options to personalize alerts for specific routes or incidents. The information provided through this service is collected and updated by TMC operators based on data obtained from traffic cameras, law enforcement, and the State Highway Emergency Program (South Carolina DOT, 2010).

The Tennessee DOT SmartWay system provides real-time traffic updates, including incidents and road conditions, accessible via live cameras and electronic message boards. Data for this service are obtained from traffic speed sensors and TMC operators. In addition, Tennessee DOT introduced the 833-TDOTFIX hotline to allow drivers to report road safety hazards like potholes and maintenance issues (Tennessee DOT, 2022b). Furthermore, Tennessee DOT implements the HELP program which consists of trucks patrolling busy freeways daily, with extended hours during special events. They follow designated routes within city cores for a swift response to impactful incidents (Tennessee DOT, n.d.). Programs like this, such as the Road Rangers used in Florida or other safety service patrol programs in other states, can help notify TMC operators of abnormal conditions so the operators can proactively warn motorists of these conditions before a crash occurs. Tennessee DOT also monitors various performance measures to evaluate the effectiveness of its TIM procedures (Tennessee DOT, 2022a). These performance measures can be directly matched to or are very similar to the FHWA incident duration performance measures shown in Figure 1-1.

511Virginia, a tool utilized by Virginia DOT, integrates various transportation information systems to offer real-time traffic alerts, updates on weather and road conditions, notifications of traffic incidents, and access to CCTV cameras. This comprehensive platform empowers users to make informed travel decisions and navigate Virginia’s roadways safely and efficiently. Virginia DOT investigates TIM performance using various metrics such as incident clearance time, number of lanes impacted by incidents, arrival on scene time, patient destination, and patient outcome (Virginia DOT, 2024).

The WV 511 Drive Safe app, provided by West Virginia DOT, serves as the state’s official travel information service, delivering up-to-date traffic and weather updates, construction reports, live traffic camera feeds, traffic speeds, and weather alerts. The app operates in driving mode, automatically broadcasting West Virginia DOT advisories based on the user's location while driving. It allows for customization of location preferences and alerts without requiring interaction while driving, with alerts pausing and resuming if a call interrupts (West Virginia DOT, n.d.).

2.1.2. Northeast Region

States and jurisdictions in the Northeast that employ TIM tools for detection and/or early warning (such as traffic cameras, radar detectors, patrol programs, Waze, INRIX, and artificial intelligence) include Connecticut, Delaware, the District of Columbia, Maine, Maryland, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. Connecticut DOT outlines an incident management system installation project for which construction was scheduled to begin in 2019. This project involved installing highway traffic cameras along a few highway systems in Connecticut, enabling Connecticut DOT to detect traffic incidents (Connecticut DOT, 2024). No additional information on this installation project, such as when or if it was completed, was available. A report by Maine DOT discusses traffic cameras as a form of detection to tackle mobility issues within Maine (Maine DOT, 2018).

The Delaware DOT website mentions how they make use of integrated transportation management tools to respond to traffic incidents. Fixed video cameras enable TMC staff to monitor traffic conditions and detect traffic incidents. Radar detectors collect real-time traffic data, and changes to this data can be indicative of traffic incidents (Delaware DOT, n.d.b). Additionally, Delaware DOT is making strides in deploying artificial intelligence to assist with monitoring of incidents on roadways and decision-making. The goal with this innovative solution is to automate Delaware DOT's transportation management processes in a more efficient manner than a human operator could (Delaware DOT, n.d.a). This system is known as AI-TOMS, or Artificial Intelligence Transportation Operations Management System. AI-TOMS assists with managing live data, detecting incidents, and creating response plans (BlueHalo LLC, 2021).

The District of Columbia DOT's TMC makes use of CCTV cameras, traffic detectors, and environmental sensors on freeways (Metropolitan Washington Council of Governments, 2019). Maryland DOT employs an Advanced Traffic Management System (ATMS) package to deal with traffic incidents; this package encompasses CCTV cameras and traffic sensor systems (Maryland DOT, n.d.).

New Hampshire DOT has New England 511, which provides travel alerts for construction, restrictions, and incidents, along with weather conditions and road congestion updates. It features data from traffic CCTV cameras and RWIS (New Hampshire DOT, 2023). Rhode Island DOT employs a range of technologies and programs for TIM, including the RIDOTmaps app for real-time traffic information, a wrong-way driver warning system, Safety Service Patrol (SSP) for roadside assistance, and traffic cameras for monitoring road conditions. However, the application lacks a feature that allows users to report incidents (Rhode Island DOT, 2024). In Vermont, the TMC serves as a central hub for transportation-related activities (Vermont Agency of Transportation, 2024). TMC operators receive direct information from CCTV cameras and RWIS, along with indirect information from Google and Waze heat maps. The operators then disseminate information through incident alerts, a tri-state traveler information system, New England 511, Waze, and social media platforms like Facebook and Twitter (Vermont Agency of Transportation, 2024).

New Jersey DOT utilizes a statewide TIM program, which includes technologies such as CCTV and RWIS. Additionally, the department operates the 511NJ Traveler Information System to provide real-time updates on travel alerts, weather conditions, road congestion, and incident notifications to motorists, enhancing overall TIM efforts. Nevertheless, according to the New Jersey DOT website, the system lacks a feature that allows users to report incidents. Updated information on whether this feature has been added since 2020 was not available (New Jersey DOT, 2020). In addition, the New Jersey Turnpike Authority utilizes SafeTripNJ to alert TMCs of an incident and provide operators with the user's phone number. The TMC operator can then request access to data from the user's smartphone (GPS location, camera images and video, speed, and nearest address) to determine the user's location and share this information with responders (FHWA, 2024b). This system is similar to the Carbyne system used in Georgia. During a two-year period, approximately 13,000 requests were made through this system (7% of all aid calls through all notification systems), with about 80% of these providing detailed locations (FHWA, 2024b).

New York State DOT utilizes the 511NY system, providing real-time traffic updates, road conditions, and incident notifications to motorists (New York State DOT, n.d.b). Additionally, New York State DOT utilizes the Crash Location and Engineering Analysis Repository (CLEAR) for TIM. CLEAR serves as a safety management information system and it offers a suite of tools designed to query, visualize, and analyze crash data effectively. Among its key components is the CLEAR Crash Data Viewer, which enables users to query crash data and retrieve crash reports. The system also includes CLEAR Safety, which facilitates network screening and the generation of highway safety investigations. Furthermore, CLEAR features the Interactive Crash Editor, allowing users to edit crash locations and attributes seamlessly (New York State DOT, n.d.a).

Pennsylvania DOT (PennDOT) utilizes crowd-sourced incident data from Waze and INRIX, dynamically updating signage for queue protection. This system aggregates data from these platforms to create real-time travel information. TMCs utilize these data to gain insights into congestion length and road conditions, facilitating prompt dissemination of information for queue management and detours via the 511PA system. Recognizing the importance of addressing residual congestion post-incident clearance, PennDOT developed a corridor protection module within their ATMS. By piloting the first queue protection corridor in the nation using INRIX data, PennDOT can dynamically calculate the distance to slow or stopped traffic and deploy automated data-driven messages on changeable message signs (PennDOT Bureau of Innovations, 2023).

2.1.3. Midwest Region

States in the Midwest that make use of TIM tools for detection and/or early warning (such as CCTV cameras, Bosch cameras, and detectors) include Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. A presentation by Indiana DOT discusses the direction of ITS usage in Indiana through identification of Indiana DOT's past, present, and future usage of ITS. It outlines the different ITS devices currently employed in the field, which include CCTV cameras and vehicle detection (Wuertz & Sorenson, n.d.).

Michigan DOT outlines on their website the role ITS plays in different transportation operations centers throughout the state of Michigan. These centers make use of CCTV or traffic cameras and vehicle detection sensors to identify real-time traffic incidents (Michigan DOT, 2024). Similarly, Minnesota DOT employs cameras and vehicle detection technologies to detect real-time traffic incidents (Minnesota DOT, 2024). Missouri DOT's TIM program utilizes CCTV and traffic sensors to improve transportation network reliability and aid in quick incident detection and efficient agency coordination, leading to reduced disruptions and enhanced overall network performance (Missouri DOT, 2022).

The Illinois Statewide Intelligent Transportation Systems Strategic Plan report lays out Illinois DOT's vision for ITS technologies along Illinois roadways. It discusses infrastructure-based traffic surveillance, which includes traffic detectors, environmental sensors, and CCTV cameras to assist with detection of traffic incidents (Illinois DOT, 2019). The Illinois Tollway system makes use of the TIMS2GO mobile app; among the functions of this mobile app, it provides access to livestreaming video, thereby allowing traffic and incident managers to detect traffic incidents. Since the launch of TIMS2GO, the app has been utilized about 115 times per month on average for incident management on the Illinois Tollway system and resulted in the confirmation time for incidents being reduced by almost 12% (Roadway Safety Foundation, 2024).

Iowa DOT manages many ITS devices across the state, including CCTV cameras (Iowa DOT, n.d.b). Additionally, performance measures such as roadway clearance and secondary crashes in Iowa are tracked on ArcGIS with the help of Iowa State University (Iowa DOT, n.d.a). A review of roadway clearance times shows that these times have been consistent for the past few years, with the majority of crashes being cleared in less than 30 minutes (Iowa DOT, n.d.a).

The Kansas Statewide ITS Architecture Plan document lays out the ITS vision of Kansas DOT (KDOT), including all ITS elements currently in use or planned for usage. KDOT currently employs CCTV cameras which are vital for traffic incident management in monitoring and detecting traffic incidents (AECOM, 2016). The KDOT Cell Probe System is a planned tool which is intended for use in rural environments to increase the range of traffic monitoring and thus assist with incident detection (URS, 2008). Another tool is KDOT Video Feed via Satellite which involves equipping existing Communication on Wheels units with software and hardware to enable transmission of CCTV images through satellite communications. Such video feed can be relayed back to Kansas DOT to assist with incident detection (URS, 2008).

North Dakota DOT employs CCTV camera surveillance and traffic sensors for TIM. These technologies enable real-time monitoring of traffic conditions, incident verification, and provide motorists with current traffic information for safer and more efficient travel. The ND Roads mobile app offers users travel alerts, weather updates, and traffic conditions. However, it lacks a feature for users to report incidents (North Dakota DOT, 2024). South Dakota DOT employs SD511, providing real-time CCTV feeds, traffic updates, and weather conditions. This technology aids in TIM by enhancing situational awareness for both authorities and travelers, promoting safer and more efficient travel experiences (South Dakota DOT, 2024). Similarly, Nebraska DOT employs the Nebraska 511 mobile app, which provides hands-free audio notifications of traffic events, winter road conditions, and real-time roadside camera images. This technology enables timely dissemination of critical information to motorists, aiding in the management of traffic incidents. However, it lacks a feature where users can report incidents. (Nebraska DOT, n.d.).

Ohio DOT utilizes a statewide TMC along with various technologies such as travel time signs and traffic cameras to manage traffic incidents. These tools provide real-time traveler information through OHGO.com and its app, enabling motorists to stay informed about traffic conditions, incidents, work zones, and weather, while programs like Freeway Safety Patrol and Towing & Recovery Incentive Payment (TRIP) ensure quick incident clearance and assistance to stranded motorists. The mobile app also allows users to report traffic incidents by calling 677 (Ohio DOT, n.d.). Additionally, Ohio DOT has been implementing Bosch cameras for several projects across the state. These cameras enable operators to monitor real-time roadway conditions, collect roadway data, and generate incident alerts (Bosch Security Systems, LLC., 2024b). Two projects from Ohio DOT that incorporate Bosch technology include the I-670 SmartLane and the U.S. 33 Smart Mobility Corridor. The I-670 SmartLane, located in Columbus, Ohio, incorporates thirty Bosch cameras which contain intelligent video analytics that assist with detecting changes in traffic flow. These detected changes assist operators with discerning potential traffic incidents. The SmartLane is located on the eastbound shoulder of I-670, which can be opened by traffic monitors during congested traffic periods. The U.S. 33 Smart Mobility Corridor project employs Bosch cameras at interchanges and these cameras are often integrated with MH Corbin technology to allow for incident detection, as well as early warning of these incidents to motorists. There are plans for Ohio DOT to install more Bosch cameras along the corridor (Bosch Security Systems, LLC., 2024a).

The Emergency Traffic Control and Scene Management Guidelines document by Wisconsin DOT outlines the technologies utilized for traffic incident detection such as CCTV cameras and roadway detectors. These technologies provide real-time traffic monitoring and traveler information. Wisconsin DOT also controls traffic devices like ramp meters and notifies agencies and media about incidents. Media considerations involve establishing staging areas for efficient information dissemination (Traffic Incident Management Enhancement, 2014).

2.1.4. Southwest Region

States in the Southwest that make use of TIM tools for detection and/or early warning (such as traffic detectors and patrol programs) include Arizona, Oklahoma, and Texas. The Arizona Statewide ITS Architecture is discussed on a website which outlines the various ITS technologies utilized in Arizona's TIM program. It is mentioned that Arizona DOT employs a roadway incident detection system which involves the usage of traffic detectors (such as radar, thermal video, and loop detectors) and surveillance equipment (such as CCTV cameras) to detect traffic incidents (Arizona DOT, 2023).

Utilizing various technologies and programs, Oklahoma DOT enhances TIM to ensure road safety and efficiency. One such initiative involves GO-DOT safety patrol vehicles, which help stranded drivers by aiding and relocating vehicles to safe locations (Oklahoma DOT, 2020). Additionally, Oklahoma DOT offers real-time traffic information through webcams, traffic advisories, and interstate conditions, empowering motorists to make informed travel decisions and contributing to safer roadways, accessible through the OKtraffic website (Oklahoma DOT, 2021). One drawback of the website is its absence of a feature enabling drivers to report incidents.

Texas DOT utilizes ConnectSmart, a mobile app funded by a U.S. DOT grant, to provide intermodal travel options, transportation updates, predictive travel times, and transit ticketing (Texas DOT, 2024a). In addition, the DriveTexas website features live cameras and road condition reports for real-time traffic monitoring. Although the app allows users to report maintenance issues, it lacks a feature for reporting incidents (Texas DOT, 2024b).

2.1.5. West Region

States in the West that utilize TIM tools for detection and/or early warning (such as CCTV cameras, traffic detectors, patrol programs, Bluetooth Travel-Time Origination and Destination [BlueTOAD] detectors, and other technologies) include Alaska, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Utah, Washington, and Wyoming. The Alaska Iways Architecture Update document reports on the ITS architecture currently employed on Alaskan roadways. These ITS tools include CCTV cameras, automatic traffic data recorders, and traffic detectors (Alaska Department of Transportation & Public Facilities, 2022). Proposed updates to this ITS architecture include the use of connected vehicle (CV) roadside units and the implementation of Virtual Transportation Operations Center functions to consolidate data from multiple sources and send the processed data to appropriate outlets (such as the Alaska 511 system) (Alaska Department of Transportation & Public Facilities, 2022).

The California Department of Transportation (Caltrans) also utilizes CCTV cameras to monitor and detect incidents (Caltrans, 2024). Additionally, Caltrans makes use of ITS infrastructure-based traffic surveillance, which entails traffic detectors and other forms of surveillance equipment to detect incidents. This includes vehicle-based traffic surveillance which involves collecting traffic data (such as sudden vehicle turns or changes in speed) from vehicles; these traffic data can be indicative of a traffic incident. Another key resource utilized in California is roadway service patrols, which assist with monitoring roads and detecting incidents (Bay Area Mobility Network, n.d.).

The Fort Carson army post in Colorado Springs, Colorado makes use of a $1.17 million program known as the Artificial Intelligence for Traffic and Weather program in order to improve efficiency and safety of traffic. This program entails an application that utilizes weather data from the National Weather Service and an "Intellisense Micro Weather Station" that is installed at Fort Carson. The app also contains artificial intelligence that was taught historical weather, roadway, and crash data (US Ignite, 2024). With all this information, decision makers can anticipate areas where there is a greater chance of a crash and thereby allocate appropriate resources to improve TIM.

The Hawaii ITS Strategic Plan describes Hawaii DOT's plan for integrating ITS into their roadway systems. Spot speed detection allows Hawaii DOT to see real-time traffic conditions and can be used for incident detection by identifying when there are changes from free-flow speed. This system is already integrated on H-1, H-2, and H-201 highways and there are plans to expand spot speed detection throughout Hawaii (Hawaii DOT, 2015). Similarly, CCTV cameras exist on some highways but there are plans to expand coverage of these cameras to assist operators with detection of traffic incidents (Hawaii DOT, 2015).

A traffic manual from Idaho mentions the use of CCTV cameras by the Idaho Transportation Department for surveillance of traffic with the intention of monitoring for any traffic incidents (Idaho Transportation Department, 2020). The Idaho Transportation Department also makes use of BlueTOAD Bluetooth detectors to measure travel times on certain roadways (Idaho Transportation Department, 2020). More details about BlueTOAD detectors are discussed in section 2.1.6.

Montana DOT offers the MDT 511 Travel Info Mobile app, which provides travelers with alerts, weather updates, road conditions, and congestion information. Additionally, Montana DOT's Report a Problem Mobile app enables users to report issues like potholes and damaged signs. Users can also report crashes or incidents by calling an emergency line dedicated to reporting incidents (Montana DOT, n.d.).

Nevada DOT integrates various TIM tools and programs. The WayCare predictive analytics platform utilizes in-vehicle and traffic data to forecast incidents before they occur, enabling proactive resource allocation for emergency services. This platform has led to a 12-minute reduction in incident response time (National Operations Center of Excellence, 2019). Additionally, it has contributed to speeding being reduced by 43% and crashes by 18% in targeted corridors (Regional Transportation Commission of Southern Nevada, 2021; Huetter, 2021). These improvements have resulted in approximately $3 million in economic benefits and savings (Huetter, 2021). The Nexar vehicle-to-vehicle network provides real-time alerts to drivers, preventing collisions and enhancing incident prevention efforts. This system records videos from the surrounding area of a vehicle while measuring vehicle movements such as speed, braking, and turning. Alerts from nearby vehicles are then transmitted to drivers through a smartphone app (Nevada DOT, 2024).

New Mexico DOT utilizes the NMROADS traveler's information system, comprising cameras, road condition monitoring, weather updates, and construction alerts for TIM. Additionally, ITS technologies aid in retrieving seasonal data to reduce weather-related traffic incidents and minimize response and clearance times. However, NMROADS lacks a feature for users to report incidents (New Mexico DOT, 2021).

Utah DOT has a traveler information system called UDOTTraffic which employs live cameras, road condition monitoring, and fiber optic sensors to manage traffic incidents effectively. These technologies offer real-time visual information, aiding motorists and authorities in informed decision-making, enhancing traffic flow, and improving safety on Utah's highways (Utah DOT, n.d.). Utah also has an incident management team with 26 trucks which patrol Utah’s highways and provide emergency assistance to motorists (Utah DOT, 2024). Schultz et al. (2019) measured the performance of Utah DOT’s TIM program in terms of reducing clearance times. Crash response data from the Utah Highway Patrol, speeds, travel times, and volumes were used to determine performance measures of the Utah Highway Patrol units and incident management teams. A total of 83 crashes were analyzed to determine the traffic congestion and associated user cost resulting from each incident. The findings showed that for each minute of delay in response time, the roadway clearance time was increased by 0.8 minutes. Therefore, minimizing the response time is important to keep the roadway clearance time low. The study recommended that incident management teams be concentrated at the most congested times and areas to best reduce the impacts of incidents to travelers (Schultz et al., 2019).

Washington State DOT employs Active Traffic and Demand Management systems, utilizing overhead electronic signs to show variable speed limits, lane management symbols, and traffic condition messages, which help facilitate incident management and response (Washington State DOT, 2024a). Furthermore, the department has tested the use of avalanche drones for improved monitoring and management of avalanche-prone regions, but has not yet deployed these drones on a large scale (Washington State DOT, 2024b). It is possible that this drone technology could be adapted for other traffic monitoring purposes to make it useful for FDOT, such as during nighttime hours or in rural areas with limited ITS coverage, but testing would be needed before estimating potential benefits.

Wyoming DOT employs a range of technologies for TIM through the Wyoming Travel Information Service. This service integrates resources such as web cameras, weather updates, road conditions, dynamic message signs, and incident reports, providing real-time data to assist travelers and enhance roadway safety. Additionally, Wyoming DOT collaborates with entities like Esri, United States Geological Survey, TomTom, Garmin, NOAA, Bureau of Land Management, U.S. Environmental Protection Agency, and U.S. Fish and Wildlife Service to maintain and update these systems. These technologies facilitate efficient incident response, monitoring, and communication, contributing to the overall management and safety of Wyoming's roadways (Wyoming DOT, 2024).

2.1.6. Emerging TIM Technologies

This section covers the various technologies currently available which are promising technologies to assist agencies in early detection and warning of traffic conditions. Some of these technologies are used by various agencies, but results of deployments have either not been published or only been reported by the technology vendor and not state agencies. Several technological advancements have led to new strides in TIM. Sensys Networks, Inc. offers a variety of TIM tools that can be used by agencies to refine their TIM toolboxes. According to their website, Automatic Incident Detection (AID) allows for quicker response to incidents, with AID being about 5-10 times faster than other conventional methods such as observation of traffic cameras (Sensys Networks, Inc., 2023). Detection of incidents through this tool is subject to high levels of accuracy, with roughly one single false positive detected every 10 days (Sensys Networks, Inc., 2023). It is important to note that no studies by an independent third party verifying these claims were found. FlexMag3 is one of many sensor technologies that can serve highway applications; it allows for wireless detection, is very durable, and installation time and cost are reduced when compared to other sensor technologies such as inductive loops. FlexMag functions similarly to FlexMag3 and can support “over 300 million detections” while having a product life that is 30% longer than loops (Sensys Networks, Inc., 2023). RTMS Echo is another form of technology that is useful for monitoring traffic. The radar unit is mounted on a pole and can track up to 12 lanes of vehicles using a single device. The system that RTMS Echo is connected to can be accessed remotely and it is considered easy to deploy (Sensys Networks, Inc., 2023).

PulsePoint is a 911-based application that helps to streamline cooperation between dispatchers and citizens to respond to incidents regarding individuals experiencing cardiac arrest and supplying automated external defibrillators to individuals who need them (PulsePoint, 2024). PulsePoint utilizes standardized incident codes to provide context surrounding such emergency situations. Traffic Collision is one example of an incident code that crosses boundaries between the objective of PulsePoint and its applicability to traffic incident management. Since the app utilizes location services, incidents can be pinpointed anywhere in the vicinity of app users (PulsePoint, 2024). While FDOT D5 TMC operators currently receive traffic collision alerts from PulsePoint to assist in incident detection, additional benefits could be achieved by utilizing this application in other areas of Florida.

HERE Technologies recently introduced the Road Alerts service, which merges vehicle sensor data, such as headlights, fog lights, hazard lights, and emergency brakes, and incident data to enhance safety by delivering real-time warnings. This comprehensive service covers various hazards and utilizes diverse data sources, including vehicle sensors, GPS data, and governmental and journalistic sources to increase road safety. Low-latency delivery ensures timely alerts (Stone, 2023).

As previously mentioned, FDOT has a partnership with Waze to assist in incident detection and notification of motorists. Another benefit of Waze is that the Waze app can provide advance warnings to drivers, alerting them about hazards 30+ seconds earlier through the HAAS Alert's Safety Cloud service, which is accessible to various emergency and roadway fleets. When emergency responders activate their lights and sirens, nearby Waze app users receive instant alerts, allowing them more time to react and clear the road, thereby improving safety for both drivers and roadside workers (Waze, n.d.). This service is used by Road Rangers in Florida.

INRIX is a company that provides real-time safety data which agencies can use to detect incidents, speed differentials, and unexpected queues. By using these data, Pennsylvania DOT was able to improve response time for 35-50% of incidents (Burfeind, 2021). INRIX also established the Highway Emergency Link Platform (HELP), which is a specialized service designed for critical situations where travelers find themselves stranded on roads for prolonged periods, due to severe accidents, sudden road closures, or adverse weather conditions. HELP ensures direct communication with travelers during emergencies through its HELP Alerts system, which uses wireless emergency alerts (similar to Amber Alerts) to provide essential information and safety instructions to drivers. The service is administered by Information Logistics and is currently operational in Pennsylvania, Georgia, and New Jersey, with expansion plans for Texas and Maryland (Burfeind, 2021).

The BlueTOAD and VantageARGUS CV platform offered by Iteris provides a comprehensive suite of data collection, analytics, and management optimized for CV applications, including travel-time data aggregation and reporting. It serves as a foundation for various CV applications such as travel time and speed data collection, intelligent signal timing, transit/freight signal priority, emergency vehicle priority, and pedestrian/bicycle mobility and safety. With

VantageARGUS CV, users can visualize a wide range of vehicle-to-everything (V2X) message streams and gain insights into traffic behaviors and patterns. The BlueTOAD Spectra CV Roadside Unit combines Bluetooth, dedicated short-range communications, and CV-V2X technologies, enabling real-time monitoring and validation of CV data for safety and mobility applications. Additionally, it offers compatibility with any roadside unit, providing flexibility for transportation experts to monitor and decode CV data either on site or remotely (Iteris, Inc., 2024). BlueTOAD sensors can also be used to collect non-CV data, such as travel times and speeds (as demonstrated in Idaho) to help detect conditions which could lead to incidents.

Another key technology with TIM applications is analytical cameras. As of 2021, seven state DOTs have utilized or plan to utilize analytical cameras paired with video analysis software for TIM-related applications. The most implemented analytical software by DOTs is Traffic Vision, with other additional sources including Bosch (which is used by Ohio DOT) and Miovision (CTC & Associates, LLC, 2021). Analytical cameras paired with software can facilitate advancements in TIM, including reduced incident detection time and improvements in roadway monitoring. Traffic Vision is an analytical camera software that implements artificial intelligence to detect roadway incidents, anomalies, wrong-way driving, roadway attributes, weather, and other useful conditions for TIM in real time (Omnibond Systems, LLC, 2024). Another computer vision resource with TIM applications is the Miovision TrafficLink software. TrafficLink provides real-time data on traffic, vehicle patterns, pedestrians, and other roadway conditions to recommend improvements that increase transportation efficiency and reduce emissions (Miovision Technologies Incorporated, 2024a). In June 2016, in Waterloo, Canada, performance metrics such as increases in travel time and decreases in vehicle volumes collected by TrafficLink helped alert city engineers of a crash prior to citizen complaints, allowing for a quick response (Miovision Technologies Incorporated, 2024b). While TrafficLink's primary application is on arterial roadways, such as in the Waterloo case, this software includes real-time traffic analysis features that could potentially be applicable to limited access roadways.

Technologies that do not currently have TIM applications were also investigated for their potential use in future TIM applications. Although many state agencies utilize weather information in their respective TIM programs, there are other alternative weather information sources worthy of consideration. AEM is a company that provides emergency personnel with access to real-time weather information from over "17,500 automated weather stations and 1,800 lightning detection sensors" all over the world (AEM, 2024). Reliable weather data enables quicker response times and proper resource allocation concerning weather emergencies. This type of sophisticated platform could help agencies zero in on possible roadways where an incident is likely to occur based on the weather conditions.

Another weather tool that could be useful for TIM can be found on the Federal Aviation Administration website, which displays weather information on a map interface with pins denoting surface weather observation stations across the country (Federal Aviation Administration, 2024). The data from these weather stations could be analyzed to provide early warnings of potential abnormal weather conditions. Knowing locations where bad weather is likely to occur can help agencies notify travelers and prepare for potential incidents.

Flock crime cameras do not currently have TIM applications, but could potentially be used for TIM. These cameras, produced by the technology company Flock Safety, record license plate numbers for use by law enforcement to facilitate solving crimes (Murphy, 2023). Such technology has potential for data collection and incident detection applications. A major limitation in extending Flock crime cameras to TIM applications is that license plate data are stored for only 30 days before the data are deleted.

2.1.7. Summary of Existing TIM Data Sources and Tools

The understanding of TIM technologies and systems used across the U.S. can help FDOT develop a strategic approach aimed at improving the early detection of traffic incidents and abnormal conditions to proactively address these conditions, thereby reducing crashes and their associated fatalities, injuries, and congestion. This approach will need to incorporate a broad spectrum of systems and tools, anchored in ITS monitoring technologies and augmented by advanced data analytics platforms, CAV technologies, crowdsourced data, and novel solutions from third-party providers.

ITS monitoring technologies form the core of TIM efforts, characterized by the deployment of CCTV cameras and vehicle detection systems in many states. A majority of states, including Florida, employ CCTV cameras for real-time surveillance, facilitating quick identification and management of traffic incidents. Vehicle detection systems, involving utilization of inductive loops, radar, and infrared sensors, are implemented in some states to monitor traffic flow changes indicative of incidents, underscoring the widespread application of these technologies for traffic surveillance. Other innovative approaches to aid with and improve the detection of traffic incidents are seen in Delaware (with the AI-TOMS program), Colorado (with the Artificial Intelligence for Traffic and Weather program at the Fort Carson army post) and Ohio (with the Bosch cameras) (Bosch Security Systems, LLC., 2024b; Delaware Department of Transportation, n.d.a; US Ignite, 2024). Additionally, Georgia uses Carbyne, a platform which allows TMC operators to access location information on users' smartphones (with the user's permission) to accurately determine the incident location (FHWA, 2024b). This system has reduced dispatch times by 20 minutes, providing safety and travel time benefits. The New Jersey Turnpike Authority utilizes a similar system, called SafeTripNJ, through which about 13,000 requests were made in a two-year period (FHWA, 2024b).

Traveler information systems, such as 511 services or specialized websites, are used by multiple states to provide real-time traffic updates and safety information to travelers. These services offer valuable insights into traffic conditions, incidents, and weather-related advisories, aiding motorists in making informed decisions. While most states (including Florida) only use these services to report information from other sources (CCTV cameras, vehicle detectors, Waze, etc.) to motorists, some states, including Tennessee (Tennessee DOT, 2022b) and Ohio (Ohio DOT, n.d.), allow motorists to report maintenance issues, road hazards, or even incidents. Allowing users to report incidents or abnormal conditions through these systems can help TMC operators proactively identify and address these issues to reduce their impacts on safety and travel times. RWIS are integral to the ITS framework, focusing on the collection and analysis of weather-related data to inform operators of road conditions. Multiple states, including New Hampshire (New Hampshire DOT, 2023) and New Jersey (New Jersey DOT, 2020) utilize RWIS to gather atmospheric and pavement condition data, enabling predictive analyses of weather impacts on road safety and traffic flow. Understanding the relationship between environmental conditions and incidents or congestion can help operators proactively identify abnormal conditions and provide early warnings to motorists.

The advent of CAV technologies marks a significant evolution in TIM, promoting enhanced V2X communications. Florida's implementation of the CAV-ITS Map Update System (FDOT, 2023) exemplifies the integration of vehicle and infrastructure data to support AID and real-time traffic information dissemination, illustrating the potential of CAV technologies to transform traffic management practices. Currently, these systems can supplement traditional data sources, but they could become the primary source of data as CAV market penetration rates increase.

Collaborations between state DOTs and the private sector can help improve the ability for agencies to identify incidents and abnormal traffic conditions more effectively. The partnership between FDOT and Waze (WLRN, 2014) serves as a model for harnessing and leveraging real-time user-generated data, enhancing the accuracy and timeliness of traffic incident reporting and response efforts across the state. While the existing methods to collect and report Waze alerts to TMCs are effective, there is significant potential to improve these methods and allow for even quicker detection of incidents. Emerging technologies introduced by third-party providers, such as Sensys Networks' AID and sensor technologies (Sensys Networks, Inc., 2023), PulsePoint's mobile application for emergency medical response (PulsePoint, 2024), Iteris Inc.'s BlueTOAD and VantageARGUS CV platforms with real-time monitoring and data analytics (Iteris Inc., 2024), and INRIX's HELP system which delivers emergency alerts to stranded drivers (Burfeind, 2021) can all extend the capabilities of traditional TIM systems, making TIM more robust and effective. Similarly, Traffic Vision and Miovision are currently-implemented analytical camera technologies which help with detection of traffic incidents (Miovision Technologies Incorporated, 2024a; Omnibond Systems, LLC, 2024). There are also detailed weather information systems from AEM and the Federal Aviation Administration which could assist in TIM (AEM, 2024; Federal Aviation Administration, 2024).

Additional approaches that do not currently have any known TIM applications but could potentially be adapted for such purposes were also examined. Flock crime cameras record license plate numbers of cars for the purpose of solving crime, but this recording technology could potentially be extended for TIM purposes such as data collection and incident detection (Murphy, 2023). The use of fleet monitoring data for TIM purposes was investigated, but no studies of this nature have been conducted. Innovative practices used by municipal and local agencies were also researched, but no such practices were found.

To summarize the major findings from this section, Table 2-1 shows potential innovative tools which are recommended for further investigation by FDOT. Some of these tools are evaluated in later chapters of this report using Florida data and performance results from other states to estimate early warning benefits. It is believed that these tools could provide the most benefits to FDOT with respect to early detection of incidents and abnormal conditions. In addition to these tools, improvements to existing FDOT TIM tools, like allowing users to report incidents or abnormal conditions through FL511, could also help FDOT better identify these situations and provide early warnings to motorists.

Table 2-1: Potential Innovative TIM Tools for Further Investigation

TIM Tool	Description	Provider and Example Location of Deployment	Estimated Benefits
Predictive Analytics Platforms	Utilize traffic and vehicle data to forecast incidents and manage resources.	WayCare (Nevada)	12-minute reduction in incident response time (National Operations Center of Excellence, 2019); speeding reduced by 43% and crashes reduced by 18% in targeted corridors (Regional Transportation Commission of Southern Nevada, 2021; Huetter, 2021); $3 million in economic benefits and savings (Huetter, 2021)
Mobile Incident Detection and Reporting Platform	Alerts TMCs of incidents, allowing operators to request and access users' smartphone data (with permission) for rapid and accurate response coordination.	Carbyne (Georgia), SafeTripNJ (New Jersey)	20 minute reduction in dispatch time (FHWA, 2024b)
Crowdsourced Data Platforms	Aggregate real-time traffic data from platforms like Waze and INRIX for dynamic incident detection, traffic management, and queue identification.	Waze (Florida), INRIX (Pennsylvania)	**Waze:** Earlier detection by 16 minutes for DAV events with preceding Waze alerts; estimated 6-month congestion savings of $4.3 million and $2.6 million for DAV events on I-4 in FDOT District 5 and State Road 91 in FDOT District 4, respectively (Sandt, McCombs, Cornelison, et al., 2023) **INRIX:** Improved response time for 35-50% of incidents (Burfeind, 2021)

Table 2-1: Potential Innovative TIM Tools for Further Investigation (continued)

TIM Tool	Description	Provider and Example Location of Deployment	Estimated Benefits
Automated Incident Detection (AID) Systems	Sensor technologies for quick and accurate incident detection.	Sensys Networks	The company website claims these systems provide 5-10 times faster detection than conventional detection methods with roughly one false positive detected every 10 days (Sensys Networks, Inc., 2023). However, no independent studies verifying these claims were found.
PulsePoint Application	A mobile app that facilitates emergency response coordination for cardiac arrest incidents; includes a category for traffic collisions.	PulsePoint (FDOT District 5)	Estimated benefits not available
Vehicle-to-Vehicle Network	Provides real-time alerts to drivers to prevent collisions, using a network of CVs.	Nexar (Nevada)	Estimated benefits not available
BlueTOAD and VantageARGUS CV Platform	Travel time and speed data collection, allowing the visualization of V2X message streams, offering insights into traffic behaviors.	Iteris Inc. (Idaho)	Estimated benefits not available

2.2 Advanced and Innovative TIM Methods to Improve Detection of Incidents and Abnormal Traffic Conditions

The previous section discussed the various technologies used throughout the United States to collect data that TMCs can use to identify traffic incidents or abnormal conditions. However, just collecting these data is not enough, especially if TMCs want to be proactive in identifying potential high-risk situations. Various studies have applied advanced statistical methods, including machine learning techniques, to identify conditions that are more likely to result in incidents. Machine learning is a combination of artificial intelligence and computer science to produce results with high accuracy. These algorithms are strong enough to deal with any labeled or unlabeled data and produce reliable results (IBM, n.d.). Understanding how these advanced methods can be applied to real-time data, along with their strengths and weaknesses, will help identify potential methods that could be evaluated in future tasks of this project. Some recent studies have also examined the potential benefits of crowdsourced data, including Waze and Twitter data, in helping TMCs identify abnormal conditions. The use of Waze alerts to detect DAVs has been shown to have great potential in Florida (as discussed in the previous section), so investigating the benefits of crowdsourced data obtained by other agencies can help FDOT better evaluate the advantages and disadvantages of these data sources.

This section is split into four subsections. Section 2.2.1 discusses various studies that investigated the potential of crowdsourced data to improve TIM performance. Section 2.2.2 discusses studies that used ITS technologies and statistical techniques to better collect and understand real-time traffic data for TIM purposes, while section 2.2.3 discusses studies that used machine learning techniques to identify relationships between collected data and incident occurrence. Lastly, section 2.2.4 summarizes advanced and innovative TIM methods. Since many of these methods are data dependent, the results mentioned in these references could differ when applied to Florida data.

2.2.1. Use of Crowdsourced Data for TIM

The FHWA Center for Accelerating Innovation (2021) lists various crowdsourcing applications that agencies have used to improve transportation systems management and operations in different application areas. For incident management, Waze is the most common source of crowdsourced data, due to its high frequency and availability. Certain organizations have combined Waze data with CAD systems to enhance the response time, while other organizations have combined Waze data with data from other sources such as INRIX or HERE. One provided example is Iowa DOT, which used a combination of WAZE and INRIX data on rural roads. These data resulted in two positive outcomes: the expansion of coverage and an enhancement of incident detection by 9.8 minutes on average (FHWA Center for Accelerating Innovation, 2021). More details about the study of crowdsourced data in Iowa are provided in Amin-Naseri et al. (2018), as discussed later in this section. Another example is Nevada DOT and Nevada Highway Patrol, which used Waze data in combination with a machine learning algorithm to reduce incidents by 17% along a section of I-15 in Las Vegas (FHWA Center for Accelerating Innovation, 2021). This system and its results were already discussed in section 2.1.5 and Table 2-1. These are just two of the ten examples mentioned by FHWA (FHWA Center for Accelerating Innovation, 2021). Crowdsourced data also provide many other benefits not related to incident management, such as for traveler information and arterial management, but only the incident management benefits of crowdsourced data are discussed in this section since the focus of this project is TIM.

Souleyrette et al. (2018) analyzed and compared multiple data sources in Kentucky with respect to clearance times and the occurrence of secondary crashes. Data were collected from the Kentucky State Police Crash Database, traffic operations center (TOC) incident logs, and two sources of crowdsourced data (Waze and HERE). The assessment of these data sources indicated that the crash database and incident records from the TOC were the most reliable, but Waze and HERE were acknowledged to be excellent supplemental sources. Waze displayed a time lag between reported crash time and the Kentucky State Police collision/notification time, likely due to Waze alerts relying on users' interaction. However, Waze speeds seemed to better reflect the actual traffic conditions right after an incident and Waze jam alerts were typically created when low speeds were detected. Compared to Waze alerts, HERE data might not immediately reflect the impact of crashes, but HERE data was identified as providing a coverage advantage (Souleyrette et al., 2018).

Amin-Naseri et al. (2018) investigated the potential of Waze crowdsourced data in improving incident detection. Waze was compared with ATMS in Iowa for one year of data. The ATMS data contained incidents, hazards, and overcrowding cases obtained from sensors, cameras, or police reports. Waze reports represented 13.4% of the ATMS congestion and crash data. The results found that Waze provided an extra 34.1% of coverage compared to the ATMS data, or around 7,387 incidents yearly. Also, Waze alerts provided an earlier reporting time of 9.8 minutes compared to the probe-based alternative. Some identified issues with the Waze data included redundant information, errors, the need to have a reliable base for comparison, and that Waze reports were not as reliable in less congested hours from 12 AM - 6 AM. This study also found that, similar to findings from Souleyrette et al. (2018), Waze seemed to better reflect the actual traffic conditions in locations where there is a speed drop compared to locations with normal/uncongested traffic conditions (Amin-Naseri et al., 2018).

Goodall and Lee (2019) assessed the precision of Waze alerts by comparing them with traffic camera images on a stretch of Virginia urban highway. Out of the 40 crash reports in Waze, 26 (64%) corresponded to crashes that were confirmed by the cameras (these 26 reports were for 13 unique crashes) and only two (5%) were false reports. Two of the 13 unique crashes were first reported to Waze before being noticed by the TOC. For disabled vehicle reports, 149 of the 560 Waze reports (26%) were visually confirmed on camera, with 23% confirmed to be false reports. Only 4% of the disabled vehicle reports were reported by Waze before being reported by the TOC (Goodall & Lee, 2019). The results of this study indicate that Waze can help with incident detection, but false alerts could be an issue. These false alerts could become especially problematic for operators in large urban areas with high Waze usage. A similar comparison in Florida could be beneficial to fully understand how Waze data compares to existing detection methods. This was already done using historical crash and SunGuide data for Florida limited access facilities (Sandt, McCombs, Cornelison, et al., 2023) but not using real-time data. Applying a methodology like the one used by Goodall and Lee (2019) on a Florida limited access roadway segment with sufficient camera coverage could help FDOT improve their use of Waze data, especially for non-crash events.

Gu et al. (2016) proposed tweet text mining to collect incident data on highways and arterials to supplement existing data sources. Tweets are acquired from Twitter (currently known as X) using a Representational State Transfer Application Programming Interface in real time. A set of keywords which suggested traffic incidents were identified and used to categorize tweets based on whether or not they were related to a traffic incident. All traffic incident tweets were then geolocated and categorized based on incident type. This approach was applied in the Pittsburgh and Philadelphia metropolitan areas. The authors considered Twitter data posted by public agency or media accounts and individual users. The authors did not use Waze as a source of incident crowdsourcing data due to Waze requiring users to log in to access the app and log incidents in one of the preassigned categories (which can make the coverage and accuracy questionable). The study found that only 5% of collected tweets were useful and related to a traffic incident. There were 973 incidents reported through these tweets, with 206 of these incidents (about 20%) reported through Twitter only and not through government accounts or ITS systems. This shows the potential benefits of this methodology in processing and filtering tweets to efficiently and cost-effectively complement existing sources and highlights the versatility of Twitter in the incident detection and verification processes (Gu et al., 2016). Overall, this paper suggests that Twitter could be a better source of traffic incident data than Waze due to Twitter's ease of access and larger user base. However, more research is needed to see how Twitter usage compares to Waze usage in other regions, including Florida, to see if these findings are applicable elsewhere.

The studies discussed in this section show that crowdsourced data can be a great aid in detecting incidents swiftly and efficiently, either as a primary data source or as a supplement to existing TIM data sources. Multiple studies have shown that Waze data can help improve incident detection by minutes while also providing alerts about traffic slowdowns and incidents which would otherwise go unnoticed. However, since crowdsourced data are provided by users, they can be prone to errors and false alerts and also be affected by driver patterns (i.e., less frequent when there are less drivers on the road). Further investigation is needed to best understand when and where specific types of crowdsourced data (Waze, HERE, INRIX, Twitter, etc.) would be most beneficial without overwhelming TMC operators with excessive false alerts. Factors such as roadway characteristics, traffic volumes, driver familiarity, and driver ability to access social networks and other crowdsourced data applications need to be considered before deciding which data sources would be the most useful. Since FDOT already has a partnership with Waze, it is recommended to further investigate Waze data to identify potential improvements to FDOT's existing filtering protocols which could efficiently improve incident detection and early warning. It is also recommended to conduct a real-time comparison between Waze data and data collected from CCTV cameras or traffic detectors to better understand the potential benefits of Waze data.

2.2.2. Real-Time Data Techniques

Having appropriate and effective techniques to analyze real-time traffic data collected from ITS technologies is important to alert TMC operators of incidents or abnormal conditions which could result in incidents. This section discusses various methods used to identify abnormal situations and incidents from real-time data. Some researchers have used AID techniques and CV data to estimate when a traffic incident is happening or has occurred in a fast and efficient manner. Other studies have used more cost-effective techniques such as the implementation of

GPS equipment in vehicles combined with algorithms to predict the time and location of incidents, showing promising results with lower expenditures.

Rindt (2018) gives a thorough analysis of Automated Video Incident Detection (AVID) systems compared to other AID technologies and monitoring tools, including CAV technologies. Previous studies were summarized with respect to detection rate, false alarm rate, and time to detect. AID studies in Australia had promising results for detection rates and false alarm rates, suggesting further consideration of these methods. Practical application of those techniques in the U.S. demonstrated high false alarm rates, resulting in very few TMCs implementing these AID systems and these implementations requiring redundant systems to support everyday monitoring. Overall, this report provided a general overview of AVID and AID systems used for enhancing the TMC's awareness of abnormal traffic conditions and incidents, with it concluding that there is no one solution which can provide satisfactory results for all (Rindt, 2018).

Sheikh et al. (2020) utilized an ITS based method referred to as the hybrid observer method to detect incidents. This method utilizes an AID technique based on lane changing speed. It uses vehicle-to-infrastructure (V2I) communication to collect traffic data. Next, a piecewise switched linear model is used to determine if a traffic event is happening or has occurred. Finally, probabilistic data is applied to accurately detect traffic incidents. Compared to traditional AID methods, the hybrid observer method had 30% faster detection and 25% faster dissipation of traffic congestion for traffic incidents. Additionally, simulations showed that the hybrid observer method performed better than other advanced techniques, including some machine learning methods. Future work will include using 5G networks to obtain more accurate traffic information to better estimate traffic incidents (Sheikh et al., 2020). Since the hybrid observer method requires roadside units to collect data, this could require additional implementation costs. However, the promising results suggest that these costs could be justified, especially if 5G networks are utilized to provide better performance without increasing costs.

Another ITS approach was investigated by Farrag et al. (2021) in Oman to improve Car to Everything (Car2X) communications technologies. Car2X technologies can be used to improve roadway safety and the movement of commuters. The most crash-prone section of the Muscat Expressway was studied using traffic data, geometric data, and incident data. To conduct the simulation, Python and VISSIM were both used. Measures used to evaluate this solution included stop delays, all stops, vehicle delay, and time of travel. The study found that the simulation was promising, with a reduction of 6% in travel time with the use of Car2X technology. This technology was especially useful at reducing delay for incidents with more blocked lanes and longer incident durations. Additionally, if the incident's location was after a ramp merging segment, Car2X technology resulted in less stop delays and all stops (Farrag et al., 2021).

Grumert and Tapani (2018) evaluated the traffic state, speed, and density using CVs with stationary detectors. The goal of the study was to quickly and precisely estimate the traffic state to identify traffic condition changes. The location and speed of the CVs, frequency of CVs, and frequency of regular vehicles were required to implement the method. Simulation of the microscopic traffic during weekday afternoon peak hours with aggregated traffic counts and different positioning of detectors was used for evaluation. The resulting traffic densities from this method were compared to the densities from "one detector-based method, one combined method, and one connected-vehicle based method" (Grumert & Tapani, 2018). These comparisons showed that using CVs with stationary detectors was a promising approach for TMCs to rely on, especially at medium to high penetration percentages of CVs, for detecting changes in traffic conditions when incidents occurred. When penetration levels were low, the traffic conditions had to be homogenous within the segment to produce reliable results. Since this approach only uses CVs for data, the full picture of the traffic conditions cannot always be determined, especially for low penetration rates or segments with wide speed distributions (Grumert & Tapani, 2018).

Ali et al. (2021) explained how existing sensors used for networking have limitations and proposed a framework for real-time monitoring. This framework showed 97% accuracy by collecting and preprocessing social network data, employing ontology latent Dirichlet allocation for modeling, ontology for event recognition, sentiment analysis for polarity, and bidirectional long short-term memory for traffic event detection. Several important issues with the approach were discussed and addressed in this paper, including how to effectively collect "traffic information from social networks," the use of a pre-processing module to transform irregular and unstructured data into structured data, "polarity identification of traffic events based on a sentiment analysis method, and traffic event detection and condition analysis based on deep learning models" (Ali et al., 2021). The high accuracy of this approach in traffic event detection is promising, but further investigation is needed to understand how this method could be transferable to Florida and if FDOT could achieve similar results.

Other studies relied on the aid of GPS to provide more precise data, especially for speed measurements and locations. R. Wang et al. (2016) proposed a multiple model particle filter to aid in issues involving traffic conditions analysis and incident detection. It was expected that this filter would require less computational time than existing filters. The proposed system was tested with field data gathered from Interstate 880 in California focusing on highway geometry, inductive loop density data, and GPS speed measurements. The Caltrans Performance Measurement System internet-based tool was used to collect field data. Using these data, the effectiveness of algorithms with different filters was estimated, with the results showing that the proposed filter was capable of detecting incidents and providing accurate traffic state estimates while requiring less computational time compared to existing filters. For an example case with many models, a one hour simulation run took the existing filters 15 minutes to complete, compared to only 25 seconds for the new filter (R. Wang et al., 2016). Understanding the impacts different filters have on computational time is important for real-time algorithms to ensure that any detected abnormal conditions or incidents are reported to TMC operators in a timely manner.

Asakura et al. (2017) studied the properties and characteristics of traffic flow conditions during incidents and proposed a system that detects incidents using probe vehicles with GPS equipment. An algorithm then predicts incident times and locations. In Japan, the speeds and locations of 25,000 GPS-equipped vehicles were monitored. The study corridor contained two lanes with 3000-4000 vehicles per hour and multiple on- and off-ramps. Two algorithms were compared using traffic simulations. The first algorithm (which used probe vehicle counts and travel times) worked successfully with probe vehicle penetration rates greater than 1%. In these cases, incident detection rates exceeded 50% with minimal false alarms. The second algorithm (which used shockwave theory to detect incidents) had limited incident detection when the penetration rate was less than 1%, due to large headways between probe vehicles (Asakura et al., 2017). These results suggest that GPS probe vehicles are promising as a supplement to existing data sources (since they are not accurate enough to be a primary data source). However, this method requires the presence of a GPS device equipped in a certain percentage of vehicles, which could limit its usefulness in certain areas. The study area was also outside of the U.S., so other factors might need to be considered when transferring this approach.

Haule et al. (2018) studied the incident impact duration (time between when an incident is reported and when traffic goes back to normal) for traffic incidents in Florida. Two years (2015 and 2016) of SunGuide incident data were collected for a section of I-95 in Duval County. These data contained 8,248 incidents, including crashes, DAVs, and hazards. A method was developed to estimate the incident impact duration using speed data obtained from BlueTOAD devices. These devices contained receivers which were capable of reading the vehicle's active Bluetooth device's media access control address to measure its speed between pairs of devices. Three years (2014-2016) of speed data for 15-minute intervals were gathered along I-95. Collecting speed data is important since these speed data can be used by TMCs to detect abnormal conditions and/or incidents (Haule et al., 2018).

2.2.3. Machine Learning Techniques

Multiple studies have investigated the use of advanced machine learning techniques to improve incident detection using historical data or real-time data. Huang et al. (2020) compared shallow and deep learning models for crash prediction using a 13.78-mile corridor on the urban interstate 235 in Des Moines, Iowa. The studied data included TMC reports from Iowa DOT, which were filtered to include only the crash information for 2016 and 2017, including time and location. There were 856 crashes on the studied interstate corridor. Real-time traffic data were also collected through roadway sensors. Shallow learning models (including logistic regression, random forest, and support vector classification) and a deep learning convolution neural network were used to predict crashes. Sensitivity analysis was conducted using a time frame before the crash happened of 1 minute, 5 minutes, and 10 minutes. It was not possible to predict the traffic conditions 10 minutes before the crash. Overall, similar crash prediction performance was obtained by the deep learning and shallow learning models. However, the deep learning model with drop-out operation performed better in terms of crash detection compared to the shallow learning models. The accuracy for the deep learning model was slightly higher than the shallow learning models at different timeslots, with a tiny margin due to the high homogeneity of samples. Some major drawbacks for the deep learning model were that it was highly sensitive to the data as crash labels were required to implement the model, a special structure was needed because of the low number of observations, and the data points had to be close to achieve good prediction results (Huang et al., 2020).

An unsupervised learning approach for AID was tested to determine its performance with respect to incident detection rates (Hernandez-Potiomkin et al., 2018). A freeway network with real data (the M4 freeway in Sydney, Australia) and an urban network with simulated data were used as examples to confirm the performance of the model. Traffic flow and occupancy data with a 3-minute aggregation level were extracted from loop detectors, with these data being the only input for the model. It was found that the proposed method allowed for more accurate incident detection than the California algorithm series and their extensions. The AID model detected incidents early (within 1.5 minutes) and had a low false alarm rate (3.8%) for the simulated network, with an accuracy of 96.5% for the studied freeway and 81.8% for the simulated urban network (Hernandez-Potiomkin et al., 2018).

Ren et al. (2016) combined both AID and a support vector machine approach using a video-based detecting and placing method to analyze traffic states in roadway segments. Traffic flow, speed, and occupancy were collected for cells within each segment, with a fuzzy-identification methods used to judge traffic conditions in each cell. Incident locations were then identified using a support vector machine. The results of this study showed that the software could detect incident points with higher reliability than that of traditional AID models such as the direct detection method, which detects crashes and/or anomalies based on motion analysis, and locate incident points in a timely and accurate manner. This new approach had an average detection error of 0.811 compared to 1.703 for traditional methods. It was most effective when combining initial training data and online optimization in the training of the support vector machine and utilizing a modified background model improve accuracy. Although this approach was effective and accurate, it had two major limitations: limited coverage range and inaccuracies due to lighting and weather conditions (Ren et al., 2016).

Another study conducted a hybrid approach for AID combining both machine learning and time series analysis to examine a California freeway section (J. Wang et al., 2013). Time series analysis was used to identify normal traffic conditions based on historical conditions, while machine learning was used to identify traffic incidents by comparing the features and finding the differences for both the predicted and current normal traffic conditions. Traffic cameras, static sensors, and dynamic sensors were all used to collect the necessary data. The results showed that this hybrid approach resulted in both higher detection accuracy and shorter detection time compared to previous AID methods with the same false alarm rate. When the false alarm rate was larger than 2%, the hybrid approach had a detection rate of more than 80% compared to 50%-70% for AID methods. Additionally, the hybrid approach had an incident detection time of less than 10 minutes compared to 10-20 minutes for AID methods. When the false alarm rate was less 1%, the hybrid approach had a detection rate of 40%-60% compared to 10%-50% for AID methods, with the hybrid approach also having a lower incident detection time of 15-20 minutes compared to 20-40 minutes for AID methods (J. Wang et al., 2013). Therefore, combining AID models with other techniques can give promising results.

A recent study addressed the challenges regarding limited sample numbers and unbalanced data sets through a hybrid deep learning-based AID and management system (Yijing et al., 2023). This system utilized a stacked autoencoder to identify temporal and spatial associations between traffic conditions and incidents. A generative adversarial network was also employed to enhance the sample by balancing the datasets. This algorithm considered lane shifts and vehicle speed fluctuations due to traffic incidents. It achieved an incident detection accuracy of 94.1% and a classification rate of 93.3% with a false alarm rate of 3.9% (Yijing et al., 2023).

Ki et al. (2018) introduced the use of new sensors (in place of the long used loop detectors) for obtaining traffic information. This two-way probe car system is mainly a way to obtain specific roadway condition data and simultaneously broadcast various alerts back to vehicles. In this study, the authors suggested a new incident detection model based on this system and neural networks. A new artificial neural network model was introduced that detects incidents based on incidents being more likely to create upstream congestion and thus reducing downstream flow. After experimental testing, the developed algorithm had a detection rate of 72.5% (Ki et al., 2018).

Hatri and Boumhidi (2018) developed a fuzzy model which considered the spatial and temporal relationships between traffic flow and traffic incidents. The parameters were initiated through a stacked auto-encoder model and then adjusted through a back-propagation algorithm before a fuzzy deep learning approach was carried out to avoid the slow convergence rate. It was found that the fuzzy approach was a reliable approach to detect traffic incidents compared to various neural network approaches for a simulated network. The fuzzy approach increased the convergence speed as it only required seven iterations and 275 seconds, which was the lowest among all studied approaches. The fuzzy approach also had the highest detection rate of 98.23% compared to a high of 92.89% for the neural networks. It had a 0.24% false alarm rate, which was similar to the lowest false alarm rate of 0.23% for the neural networks (Hatri & Boumhidi, 2018).

Deep learning was used to detect traffic incidents using over 3 million tweets from northern Virginia and New York City (Z. Zhang et al., 2018). Paired tokens were used to capture the association between accident-related tweets, thus increasing incident detection accuracy. Deep belief network and long short-term memory machine learning techniques were implemented on these tokens. The deep belief network was the most accurate, with an overall accuracy of 85%. In order to validate the study, the authors compared accident-related tweets with traffic incident logs and loop detector data. Almost 66% of accident-related tweets were located using the incident logs and over 80% were associated to abnormal loop detector data. Additionally, the results suggested that some of the tweets captured accidents which were not documented by the police (Z. Zhang et al., 2018).

Dabiri and Heaslip (2019) applied supervised deep learning algorithms on tweets. They collected 51,100 tweets and categorized as either non-traffic, traffic incident, or traffic information. Next, the relationships between words in the tweets were measured by using tweets' word vectors. Convolution neural networks and recurrent neural networks were then applied to the tweets' word vectors to identify the traffic events; these are supervised deep learning approaches. The results showed these approaches outperformed other advanced methods. The convolution neural networks resulted in 0.986 accuracy for 2-class datasets and 0.974 for 3-class datasets, which are improvements of more than 2% compared to other methods. Some drawbacks of using tweets and supervised deep learning algorithms to predict incidents were also identified. These included the algorithms not being able to identify the cause of abnormal conditions and the algorithms predicting the results based on the first part of a tweet and not the whole tweet, both which could lead to wrong classifications (Dabiri & Heaslip, 2019). While deep learning approaches could be useful to study social media data, further investigation is needed on the potential viability of these data to detect abnormal conditions and traffic incidents in Florida before these more advanced approaches are considered.

Overall, the studies in this section show that combining AID with machine learning techniques typically provides higher accuracy and shorter detection time. Deep machine learning techniques (fuzzy approaches and neural networks) outperformed shallow learning models in terms of detecting traffic incidents. However, special data structures and sufficient sample sizes are required to accurately implement deep learning techniques. Therefore, further investigation on deep learning methods is recommended before utilizing them for proactive detection of abnormal traffic conditions in Florida.

2.2.4. Summary of Advanced and Innovative TIM Methods

The variety of studies in this chapter highlights the diverse nature of TIM and the wide range of tools and methodologies available for enhancing the detection of abnormal traffic conditions and traffic incidents. Approaches ranging from the use of crowdsourced data to real-time analysis techniques to machine learning techniques and advanced statistical methods are available, with each approach offering unique advantages and capabilities as well as its own challenges and considerations.

Crowdsourced data, mainly focusing on data from platforms like Waze and Twitter, show great potential in improving the detection of abnormal traffic conditions, as these sources provide real-time updates on traffic incidents and roadway conditions, facilitating swift detection and response. However, their use is usually controlled due to high false alerts and reliability issues, making the need for further filtering and validation necessary. Despite these issues and challenges, the potential benefits of crowdsourced data in enhancing TIM practices make these data worthy of further investigation. Even though FDOT already utilizes Waze data in a limited capacity, the existing filters could be opened slightly (with the best options varying by time and location) to provide more beneficial data to TMC operators without drastically increasing false alerts.

Effective real-time data techniques, including AID methods, are important to alert operators of abnormal conditions before traffic incidents occur. Methods that leverage V2I communications and Car2X technologies are promising approaches for accurate and efficient detection of abnormal conditions and incidents. The use of GPS-equipped vehicles can also give transportation agencies access to real-time data for incident detection and traffic conditions analysis. However, challenges such as equipment costs and coverage need to be addressed to realize the full potential of these techniques.

The integration of machine learning algorithms into AID systems can further improve the capabilities of these TIM systems. The use of neural networks and fuzzy algorithms can improve the accuracy of these systems compared to traditional modeling approaches. However, these deep learning methods require the data to be structured a certain way and need sufficient sample sizes. They are also more complicated than traditional methods and need to be tailored to Florida data. Therefore, careful consideration is needed before implementing these types of algorithms to ensure they are reliable and accurate.

Based on the studies discussed in section 2.2, Table 2-2 shows potential TIM data sources and advanced techniques which could be the most effective at improving early warning capabilities in Florida. This table shows the estimated benefits for these methods obtained from previous studies. In addition to these specific methods, the general findings from this section indicate that there is a need to refine data sources and validation techniques for crowdsourced data, especially platforms like Waze and Twitter, to optimize their incident detection capabilities and to minimize false alerts. Real-time comparisons between crowdsourced data and traditional sources like CCTV cameras are important to understand the reliability of crowdsourced data and how these two data sources can be implemented in combination to achieve optimal results. Real-time detection techniques, such as AID methods, can improve the detection of incidents and abnormal conditions compared to traditional TIM systems, with additional improvements by using machine learning approaches. However, each technique has its own limitations and issues, meaning that one method will not be appropriate for all situations. By developing a TIM program consisting of multiple systems and approaches, FDOT will be best able to detect abnormal traffic conditions and warn drivers before incidents occur.

Table 2-2: Potential TIM Data Sources and Advanced TIM Techniques for Further Investigation

TIM Technique	Description	Location	General Findings/Benefits
Hybrid Observer Method	Real-time modeling using AID and V2I communication.	Interstate 880, California	30% faster detection and 25% faster dissipation of traffic congestion relative to accident duration (Sheikh et al., 2020).
Car2X Technology	Communications technologies to improve roadway safety and commuter movement.	Muscat Expressway, Oman	Reduction of 6% in travel time during simulations with Car2X technology (Farrag et al., 2021).
Real Time Monitoring Framework	Framework that uses real-time monitoring of social network data processing and deep learning models.	30 authorized Twitter accounts from New York, Los Angeles, and Chicago	97% accuracy in traffic event detection (Ali et al., 2021).
GPS Probe Vehicle System	Incident detection using data from GPS probe vehicles.	Tokyo Metropolitan Expressway, Japan	Incident detection rate over 50% with minimal false alarms when more than 1% of vehicles are probes (Asakura et al., 2017).
Comparing Waze Data with Existing Incident Data	Comparing data extracted from Waze with ATMS data.	Iowa	Waze provided extra 34.1% coverage in comparison to ATMS and also reported 9.8 minutes earlier compared to probe-based alternative (Amin-Naseri et al., 2018).
Analyzing and Comparing Waze and HERE Data with Existing Incident Data	Comparing the effectiveness of HERE and Waze data with TOC and crash data with respect to roadway clearance time, incident clearance time, and secondary crashes.	Kentucky	Most reliable sources for assessing TIM performance measures were the crash database and TOC data. Waze and HERE provided valuable supplemental data. While Waze displayed a time lag in response time, it seemed to better reflect the post-incident speeds. HERE data might not directly reflect the impact of crashes but was deemed beneficial for the coverage advantage (Souleyrette et al., 2018).
Tweet Text Mining	Tweets were collected, categorized as traffic incident or not, geocoded, then finally classified into one of five incident categories.	Pittsburgh and Philadelphia, Pennsylvania	5% of acquired tweets contained most of the traffic incidents reported. These tweets highlighted 973 incidents, out of which 206 were exclusively reported on Twitter and not through official channels (Gu et al., 2016).

Table 2-2: Potential TIM Data Sources and Advanced TIM Techniques for Further Investigation (continued)

TIM Technique	Description	Location	General Findings/Benefits
Automatic Incident Detection (AID)	Testing performance of incident detection rates using AID.	M4 freeway, Sydney, Australia	An accuracy of 96.5% for the studied freeway and 81.8% for the simulated urban network (Hernandez-Potiomkin et al., 2018).
AID with a Support Vector Machine	Use of video-based detection to analyze the distribution characteristics of traffic states in individual cells of a road segment.	Roadways in China, with historic traffic video from Los Angeles, California, also used	An average detection error of 0.811 for the combined approach compared to 1.703 for the traditional method (Ren et al., 2016).
AID Hybrid Approach	Combined both time series analysis and machine learning techniques with AID.	California freeway section	The hybrid approach had higher detection rates and quicker incident detection compared to traditional AID methods for both low and high false alert rates, with the best performance of over 80% detection rate and less than 10 minutes detection time when false alert rate was greater than 2% (J. Wang et al., 2013).
Hybrid Deep Learning-Based AID and Management System	Utilized a stacked autoencoder to identify temporal and spatial relationships between traffic conditions and incidents.	Travis County, Texas	An incident detection accuracy of 94.1% and a classification rate of 93.3% with a false alarm rate of 3.9% (Yijing et al., 2023).
Fuzzy Model	Considered the traffic flow in terms of the spatial and temporal correlations for traffic incident detection.	Method was applied to a simulated network	The fuzzy approach increased the convergence speed compared to neural network approaches, only requiring seven iterations and 275 seconds. It also had a detection rate of 98.23%, which was higher than the neural network approaches, while having a similar false alarm rate to these approaches of 0.24% (Hatri & Boumhidi, 2018).

Chapter 3: Collection and Analysis of Existing TIM Data in Florida

Before evaluating new tools, it is important to understand the existing TIM data sources used by FDOT and how these data sources compare with each other. This chapter discusses the collection and analysis of existing TIM data in Florida. The detailed analyses and insights discussed in this chapter can help FDOT identify locations and times where improvements to their existing TIM data sources would likely provide the most early warning benefits and enhance TIM practices to reduce congestion, prevent crashes, and ultimately save lives. These analyses and comparisons provide a baseline of early warning benefits for the evaluations of improvements and new tools discussed in Chapter 4.

Data were collected from six major TIM data sources: FHP CAD data, Waze data, TSS data, RWIS data, Active 911 data, and PulsePoint data. The FHP CAD system contains incident reports from law enforcement officers and 911 emergency call centers, offering timely information on traffic incidents. TSS data, including speed, volume, and occupancy, are collected from various roadway sensors and enable real-time monitoring and detection of congestion or anomalies which could be indicative of incidents. Whenever these values get below certain thresholds, an alert is generated in SunGuide to indicate possible congestion. RWIS gather weather-related data which could affect road conditions and the likelihood of incidents, such as precipitation and visibility. Waze is a navigation app where users share real-time traffic and road information such as accidents, hazards, and traffic jams, providing timely incident reports that might not be immediately captured by official channels.

Active 911 is a commercial alerting platform used by fire and emergency medical services (EMS) agencies to receive real-time incident notifications on their mobile devices. The system connects to local CAD systems via email or paging protocols, forwarding incident information to Active 911 servers where it is parsed and delivered through a dedicated app. In D5, several public safety answering points dispatch fire and EMS agencies using this system, resulting in alert coverage that includes crashes and other roadway incidents, including those on limited access highways (Bejleri et al., 2020). Since Active 911 is separate from law enforcement dispatch systems such as FHP CAD, it offers a complementary stream of incident data that can be valuable for improving detection and response efficiency. The Active 911 system allows for quicker sharing of data between 911 emergency call centers and TMCs, which could allow for earlier reporting of traffic incidents and medical emergencies compared to the FHP CAD system. PulsePoint is a mobile application that provides real-time incident information for medical emergencies and other critical events to first responders. It offers an additional channel for real-time incident detection by pushing emergency alerts to responders' mobile devices shortly after events are dispatched (PulsePoint, 2025). Its value to TIM lies in the potential for earlier notification of incidents, particularly in cases where fire or EMS agencies arrive before law enforcement. In FDOT D5, PulsePoint alerts are often triggered rapidly after 911 dispatch, making the platform a useful candidate for potential early detection benefits. Improved integration of these data sources into SunGuide and FDOT's current TIM practices could allow FDOT to efficiently leverage crowdsourced and emergency call data to complement CAD data, improve the speed and accuracy of incident detection, and respond promptly to incidents, especially in scenarios where official data sources might have limitations or delays.

This chapter contains thorough discussions of the collected data, filtering methodologies, comparative analyses, and modeling efforts used to study and understand these data. Section 3.1 covers the specifics of the collected Florida TIM data. Section 3.2 discusses the comprehensive statewide data analyses comparing CAD and Waze data, including methods to filter and match these datasets. Section 3.3 details the advanced modeling techniques used to assess the factors which most impact the relationship between CAD and Waze events. Section 3.4 compares Active 911 and PulsePoint data with CAD data for FDOT D5, which is the only FDOT district currently integrating these data sources into SunGuide. Programming codes developed to conduct these comparisons are included in Appendix A.

3.1 Summary of Collected Florida TIM Data

Florida TIM data were collected from multiple data sources to identify the current usage of these data and potential areas for improvement. Four Florida statewide datasets were provided to the UCF research team by Enforcement Engineering, Inc.: FHP CAD, Waze, TSS, and RWIS data. All these datasets contained data from June 30, 2022, through June 30, 2023, for all FDOT districts. Details about these datasets are discussed in the bulleted list below.

- **FHP CAD:** This dataset contained 331,840 observations with information on time of detection and resolution, operator action, and location for all roadways where FHP operates.
- **Waze:** This dataset contained 170,256 observations with information on time of detection and resolution, operator action, and location. These Waze alerts were alerts reported through SunGuide after going through the existing FDOT filtering processes.
- **TSS:** This dataset contained 692,433 observations with information on time of detection and resolution, reason for the alert, operator action, detector details, and location. Review of this dataset indicated that less than 1% of the data were new events, with remaining data being either false alarms, cancelled by the system, or duplicates, all of which would not be helpful in determining the early warning benefits provided by TSS data. One reason for the low number of new events in the TSS data is that SunGuide did not allow operators to create new events from TSS alerts during the period when these data were collected. Changes were made to SunGuide after the period covered by the collected data which allowed new events to be created from TSS alerts. These changes have improved the usefulness of the TSS data over the last year, as evidenced by the FTE use of TSS data to identify congestion locations based on speed and occupancy thresholds. Due to these changes, the collected TSS dataset was not considered for further analysis in this chapter. However, a classification model was developed which improves the likelihood of TSS alerts reported to TMC operators being caused by nonrecurring congestion; this model is discussed in Chapter 4.
- **RWIS:** This dataset contained 8,214 observations with information on time of detection and resolution, reason for the alert, operator action, and location. Review of this dataset showed that only 28 observations (0.3%) were new events and 5,225 (63.6%) were either false alerts or automatically resolved by the system. Due to this low sample size of new events, the RWIS dataset was not considered for further analysis.

Based on the initial review of these four statewide datasets, the CAD and Waze datasets were selected for detailed investigation and further analysis. Comparing these two datasets will help identify situations (locations and times) for which Waze provides earlier detection and situations for which CAD provides earlier detection. The findings can help FDOT better utilize and improve these two data sources to provide earlier warnings of incidents and abnormal conditions to TMC operators. The comparisons of these two data sources and the development of a model to identify factors that increase the likelihood of either Waze or CAD being earlier are discussed in sections 3.2 and 3.3.

In addition to these statewide TIM datasets containing data from June 30, 2022, through June 30, 2023, additional datasets were collected for specific districts or more recent time periods. Table 3-1 summarizes these additional datasets, which were used for analyses discussed later in this chapter and evaluations discussed in Chapter 4. The first two datasets in this table contained Incident Detection Subsystem (IDS) data for the entire FTE system. These IDS data were from multiple sources (such as FHP CAD, Waze, and TSS data) so the number of observations shown in Table 3-1 includes all the IDS sources. The remaining datasets in this table only contained data from the one TIM source listed in the first column. The statewide Waze data from February 2025 through July 2025 were retrieved in real time by the UCF research team using the Waze Application Programming Interface (API). Waze alerts of all confidence levels for three different alert types (accident, hazard, and road_closed) were collected for this dataset as these are the major Waze alert types that currently pass through the FDOT filters. All other datasets in this table were provided to the UCF research team by FTE, D5, or D3.

Table 3-1: Additional TIM Data Sources

Data Type	Time Period	Geographical Coverage	Number of Observations
IDS	January 1, 2024 – December 31, 2024	FTE system	25,715
IDS	January 1, 2025 – March 31, 2025	FTE system	7,132
FHP CAD	December 31, 2023 – June 23, 2024	D5	8,312
Active 911	January 9, 2023 – August 8, 2024	D5	48,336
PulsePoint	February 1, 2024 – June 12, 2024	D5	38,616
FHP CAD	January 1, 2025 – April 30, 2025	D3	2,860
Waze	February 1, 2025 – July 31, 2025	Statewide	18,483,064

3.2 Comparisons of CAD and Waze Data

Waze data have great potential to provide early warnings. To identify the current early warning benefits of the Waze data utilized by FDOT, comparisons were made between the FHP CAD system data and crowdsourced Waze alerts at a statewide level. The goal of these comparisons was to assess how these data sources complement each other in real-time traffic management and incident response efforts and determine the effectiveness of each data source in providing timely alerts for different situations. These comparisons will serve as a basis for improving data integration practices and enhancing the use of both crowdsourced and CAD data in Florida's TIM operations.

To compare these two datasets, it was important to first understand the details of these data. Both the CAD and Waze datasets have the variables listed in Table 3-2, with the CAD data also containing information on the crossing street and mile marker for the location where the alert was reported. Using the Detected Timestamp and location-related variables, alerts could be matched between the two datasets.

Table 3-2: Statewide FHP CAD and Waze Dataset Variables

Variable	**Description**	**Type**
Alarm ID	Identification number of the alert	Index
Detected Timestamp	Date and time the alert was detected	Datetime
Resolved Timestamp	Date and time the alert was resolved	Datetime
Action Taken	The action taken by the operator once the alert was received	Categorical
District	The district where the alert was reported	Categorical
County	The county where the alert was reported	Categorical
Roadway	The roadway where the alert was reported	Categorical
Direction	The direction on the roadway where the alert was reported (e.g., East, North)	Categorical
Latitude and Longitude	The coordinates where the alert was reported	Numerical

3.2.1. Data Filtering

Before matching Waze and CAD alerts, some filtering was needed. First, any alerts not associated with an actual incident were removed. While the provided data did not explicitly specify the type of incident for each alert, the Action Taken variable contained sufficient information to determine which alerts were relevant and which ones could be excluded. This variable included eight distinct categories which provided insight into the operator's response to each alert:

- **Acknowledged**: The operator cleared the alert without further action.
- **Already Created:** The alert's incident already had an existing SunGuide event, indicating that the incident was already detected by another data source.
- **Associated**: Similar to "Already Created", the operator linked the alert to an existing SunGuide event, indicating that the incident was already detected by another data source.
- **False Alarm**: The operator reviewed the alert and found no associated incident.
- **New Event**: The operator created a new event in SunGuide based on the alert, indicating that this alert was the first detection of a specific incident.
- **Responder Arrival**: This is a duplicate of a previous alert (same alert ID) which marks the time of a responder's arrival at the incident scene.
- **Responder Departure**: This is a duplicate of a previous alert (same alert ID) which marks the time of a responder's departure from the incident scene.

- **System Resolved**: The alert was automatically cleared by SunGuide because the event was closed on the FHP side before any action was taken by the TMC, which occasionally happens during high alert periods or with arterial events.

Figures 3-1 and 3-2 show the distribution of alerts by action taken for the CAD and Waze datasets, respectively. Most of the CAD alerts were categorized as either Associated, Acknowledged, or New Event, while most of the Waze alerts were categorized as Acknowledged. Based on the category definitions discussed above, alerts categorized as Acknowledged, False Alarm, and System Resolved would not contribute meaningfully to the analysis since they were not associated with actual incidents. Additionally, the Responder Arrival and Responder Departure categories were duplicates of other alerts and represented only a small fraction of the dataset. Therefore, all alerts in these five categories (plus the 1 CAD alert with a missing value for the action taken) were excluded from both the CAD and Waze datasets, leaving only the Already Created, Associated, and New Event alerts for further analysis in each of these datasets.

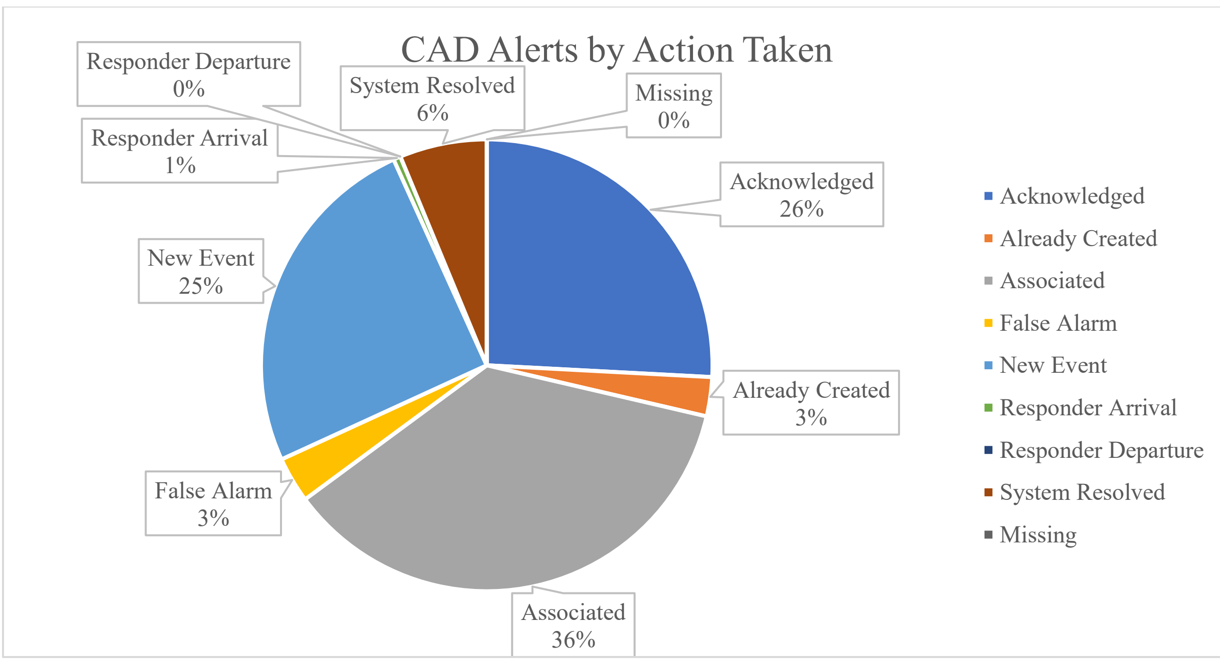

Figure 3-1: Distribution of FHP CAD Alerts by Action Taken

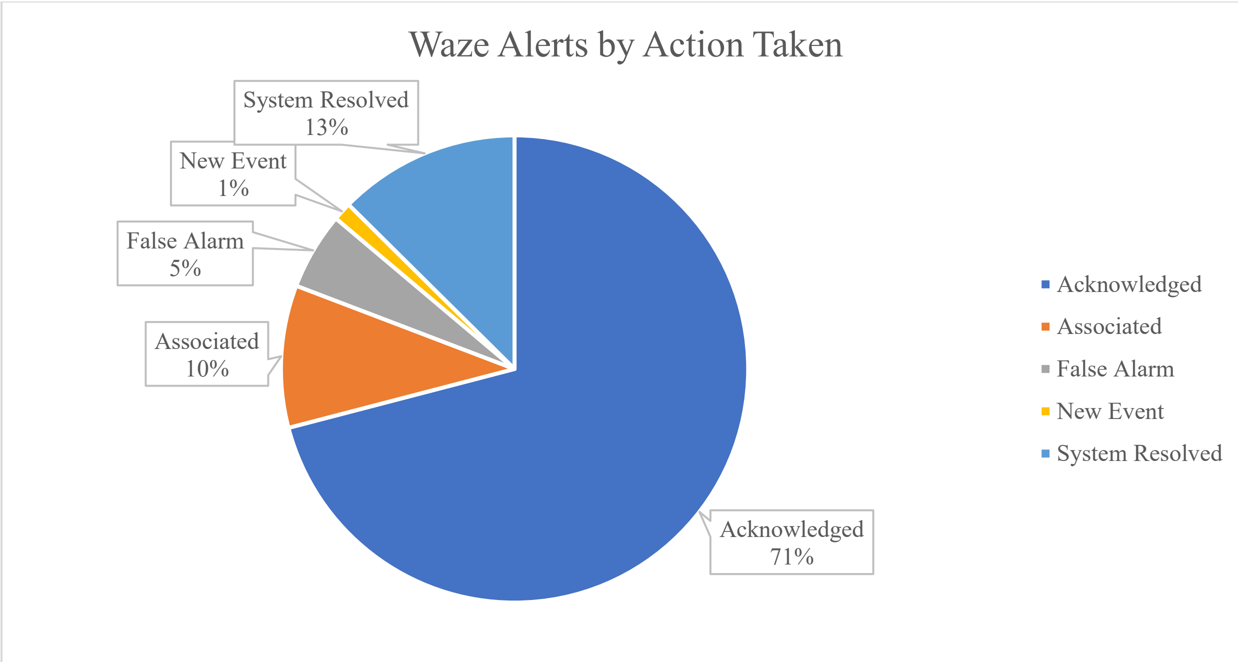

Figure 3-2: Distribution of Waze Alerts by Action Taken

Next, the remaining data were filtered to exclude alerts which did not occur on Florida's limited access roadways. Using FDOT's geodatabase, both the CAD and Waze datasets were filtered to include only alerts within 215 feet (65 meters) of limited access roadways. This buffer distance was chosen after testing various distances to ensure that all relevant alerts on limited access roadways were captured, particularly for roadways with large separations between directions, while excluding alerts not related to these roadways. Records with missing values were also removed during this process, with the resulting datasets used to determine the appropriate spatial and temporal buffers for matching alerts.

3.2.2. Identification of Appropriate Spatiotemporal Buffers

Having appropriate spatial and temporal buffers is important to ensure that the CAD and Waze data are properly matched to each other. These buffers are needed since the times and locations are not exactly the same between datasets for the same event due to differences in reporting time and location accuracy. Waze alerts often have less accurate locations than CAD alerts due to Waze users often reporting incidents after passing them. Using buffers that are too small could result in alerts for the same event not being matched together, while using buffers that are too large could result in alerts associated with different events being matched together.

In the initial buffer testing, four temporal buffers (15 minutes, 30 minutes, 45 minutes, and 60 minutes) and five spatial buffers (0.25 mile, 0.5 mile, 1 mile, 1.5 miles, and 2 miles) were used to identify potential matches between the CAD and Waze datasets. Figure 3-3 shows the number of matched events for all 20 buffer combinations. These results suggested that a 1-mile spatial buffer was optimal, as increasing the buffer beyond one mile yielded a marginal increase in matched events, whereas reducing it led to a substantial decline in matched events. For the temporal buffers, increasing from 15 minutes to 30 minutes provided a large increase in the number of matched events while the increases from 30 minutes to 45 minutes and 45 minutes to 60 minutes were much smaller. These findings suggested that a 30-minute buffer was optimal.

To verify these findings, further testing of temporal buffers ranging from 5 minutes to 30 minutes in 5-minute intervals were conducted. As shown in Figure 3-4, the increases in the number of matched events when changing the temporal buffer from 15 minutes to 20 minutes, 20 minutes to 25 minutes, and 25 minutes to 30 minutes were fairly similar. A 35-minute buffer was also tested, but the results were nearly identical to the 30-minute buffer and are therefore not shown in Figure 3-4 since they would almost directly overlap with the 30-minute buffer line.

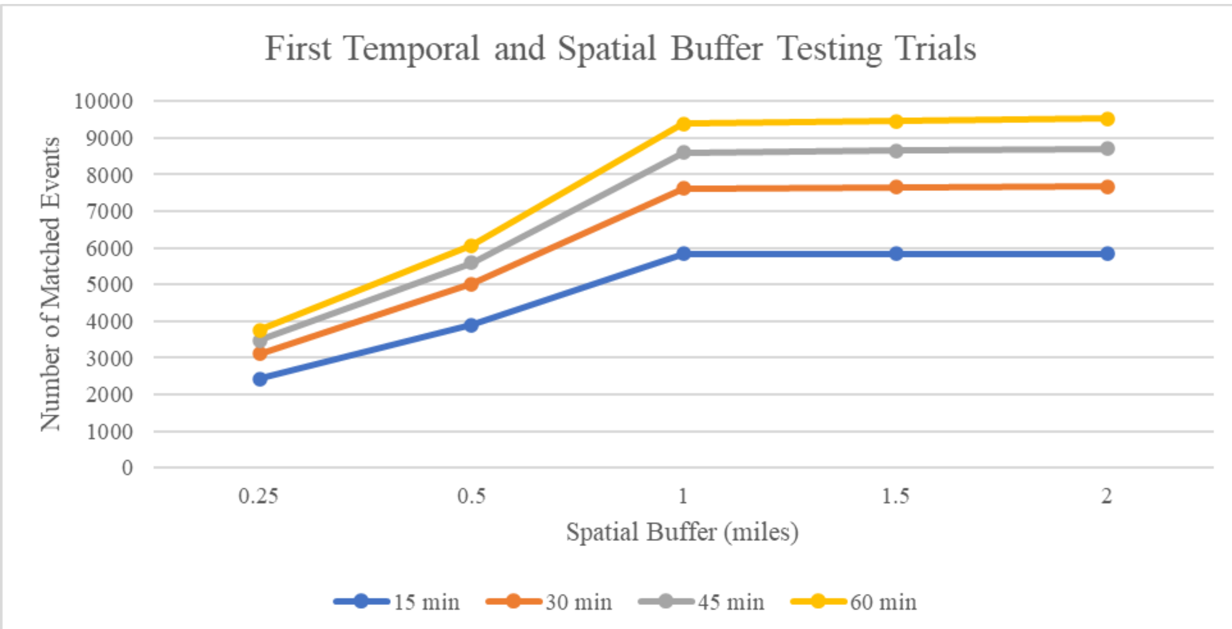

Figure 3-3: Initial Spatiotemporal Buffer Testing

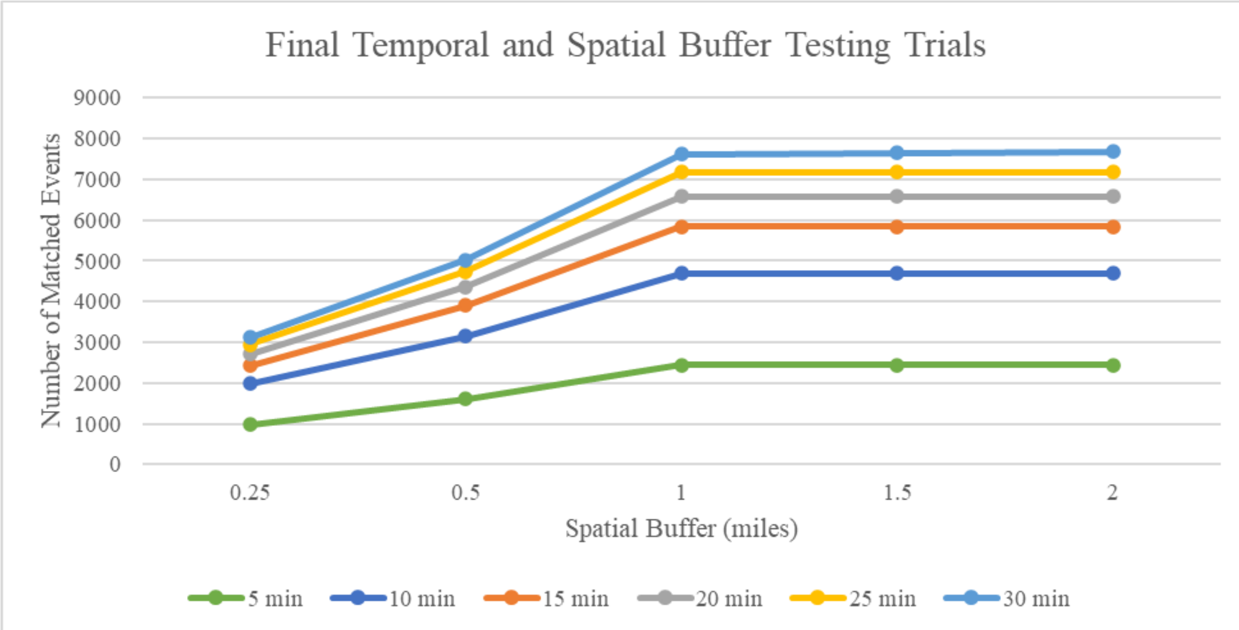

Figure 3-4: Final Spatiotemporal Buffer Testing

Based on these tests, a 1-mile spatial buffer and a 30-minute temporal buffer were chosen as the most suitable buffers for matching CAD and Waze alerts. These buffer values align with those used in prior research by Sandt, McCombs, Cornelison, et al. (2023) for matching DAV SunGuide and Waze events, reinforcing their suitability. After applying these buffers, the matched events were manually reviewed to remove any alerts not located on limited access roadways (such as those near overpasses) and eliminate duplicate entries so each matched event was independent and only contained the CAD and Waze alerts with the earliest detection time. This filtering process resulted in a final dataset of 6,147 matched events.

3.2.3. Analysis of Matched CAD and Waze Events

Three new variables were created for the 6,147 matched events to analyze the relationship between CAD and Waze alerts. A binary variable named Waze_earlier was created to identify situations where Waze provides earlier detection than CAD. This variable was assigned a value of 1 if the matched Waze alert occurred before the matched CAD alert and 0 if the matched CAD alert occurred before the matched Waze alert. A continuous variable named time_difference was created to capture the absolute time difference (in minutes) between the matched Waze and CAD alerts and another continuous variable named distance was created to capture the distance (in miles) between the matched Waze and CAD alerts. The Waze_earlier and time_difference variables were analyzed for different FDOT districts, limited access roadways, and times of day to assess the effectiveness of each data source in different situations.

To assist in these analyses, binary variables were created for each FDOT district, limited access roadway, and hour of the day, where a value of 1 indicated that the event was first reported in the specified FDOT district, on the specified roadway, or in the specified hour. Eight binary district variables were created for the seven FDOT geographical districts (District 1 [D1], District 2 [D2], D3, District 4 [D4], D5, District 6 [D6], and District 7 [D7]) and the FTE district. Since some roadways had multiple names across different events, the roadway names were manually reviewed and grouped into 13 roadway categories, with a binary variable created for each category: I-10, I-110, I-275, I-295, I-4, I-75, I-95, SR-112, SR-821, SR-836, SR-874, SR-91, and Other. The Other category included all roadways which individually represented less than 0.1% of the data. Hourly binary variables were created for each hour of the day, with hour 0 being 12:00 AM – 12:59 AM, hour 1 being 1:00 AM – 1:59 AM, and so on through hour 23 (11:00 PM – 11:59 PM). This labeling of hours is used throughout the remainder of this report.

Using these newly created variables, the number and percentage of matched events where the Waze alert was earlier (Waze_earlier = 1), where the CAD alert was earlier (Waze_earlier = 0) and totals were obtained for each district, roadway, and hour (Table 3-3). These percentages are the percentage of the total Waze_earlier = 1 events, Waze_earlier = 0 events, or all 6,147 events with the specified feature (e.g., 23.5% of the events with Waze_earlier = 1 occurred in D7). Note that the percentages shown in Table 3-3 for each type of feature (district, roadway, or hour) might not add up to exactly 100% due to rounding. The FTE district had the most events (466) with Waze earlier = 1 among all districts, representing 27.1% of the total Waze earlier = 1 events. Features with a higher percentage of Waze earlier events compared to CAD earlier events, such as the FTE district, SR-91, and hour 21, highlight locations and times where Waze alerts could potentially offer greater benefits for operators and law enforcement. Note that D4 did not have any matched events on non-FTE limited access roadways, so it is not listed in Table 3-3.

Overall, 1,718 of the 6,147 matched events (27.95%) had the Waze alert earlier than the CAD alert (Waze_earlier = 1). On average, Waze earlier events had a mean time difference of 8.42 minutes and a mean distance of 0.43 miles, whereas CAD earlier events had a mean time difference of 10.65 minutes and a mean distance of 0.38 miles. The smaller time differences when Waze alerts are earlier could be due to FDOT's current filtering protocols, which require multiple reliable Waze alerts before they are forwarded to the TMC, creating a delay between when the event is first reported in Waze and when it is reported in SunGuide. The larger distances for Waze earlier events could be due to users reporting incidents after passing them, particularly on high-speed limited access roads. In contrast, CAD earlier events could be more likely to coincide with traffic congestion, reducing the distance between the first CAD and Waze alerts. Districts and roadways with more matched events, such as D7, the FTE district, D3, I-75, I-10, and I-275, could have higher Waze usage than other districts or roadways. It is important to note that D3 opens up their Waze filters at certain times of the day, which contributes to them having higher matched event counts than many other FDOT districts. Matched events were more common during evening hours (6:00 PM through 10:59 PM) and less common during morning hours (1:00 AM through 10:59 AM), suggesting that Waze users are more active in the evening than in the morning.

Table 3-3: District, Roadway, and Hour-of-Day Counts and Percentages for Waze Earlier and CAD Earlier Events

Feature	Waze_earlier = 1 (Waze Alert Earlier)		Waze_earlier = 0 (CAD Alert Earlier)		Total Matched Events	
	Count	Percentage	Count	Percentage	Count	Percentage
D7	404	23.5%	1,322	29.8%	1,726	28.1%
FTE District	466	27.1%	549	12.4%	1,015	16.5%
D3	139	8.1%	867	19.6%	1,006	16.4%
D2	346	20.1%	619	14.0%	965	15.7%
D1	163	9.5%	569	12.8%	732	11.9%
D6	190	11.1%	454	10.3%	644	10.5%
D5	10	0.6%	49	1.1%	59	1.0%
I-75	293	17.1%	1,099	24.8%	1,392	22.6%
I-10	184	10.7%	900	20.3%	1,084	17.6%
I-275	267	15.5%	732	16.5%	999	16.3%
SR-91	321	18.7%	412	9.3%	733	11.9%
I-95	265	15.4%	462	10.4%	727	11.8%
SR-821	144	8.4%	137	3.1%	281	4.6%
I-4	51	3.0%	224	5.1%	275	4.5%
I-295	107	6.2%	163	3.7%	270	4.4%
SR-836	59	3.4%	152	3.4%	211	3.4%
SR-112	17	1.0%	65	1.5%	82	1.3%
I-110	5	0.3%	53	1.2%	58	0.9%
SR-874	3	0.2%	24	0.5%	27	0.4%
Other Roadway	2	0.1%	6	0.1%	8	0.1%
Hour 21 (9:00 PM–9:59 PM)	167	9.7%	362	8.2%	529	8.6%
Hour 20 (8:00 PM–8:59 PM)	158	9.2%	354	8.0%	512	8.3%
Hour 19 (7:00 PM–7:59 PM)	137	8.0%	350	7.9%	487	7.9%
Hour 22 (10:00 PM–10:59 PM)	122	7.1%	283	6.4%	405	6.6%
Hour 18 (6:00 PM–6:59 PM)	113	6.6%	253	5.7%	366	6.0%
Hour 11 (11:00 AM–11:59 AM)	103	6.0%	241	5.4%	344	5.6%
Hour 17 (5:00 PM–5:59 PM)	81	4.7%	251	5.7%	332	5.4%
Hour 12 (12:00 PM–12:59 PM)	111	6.5%	217	4.9%	328	5.3%
Hour 23 (11:00 PM–11:59 PM)	105	6.1%	192	4.3%	297	4.8%
Hour 15 (3:00 PM–3:59 PM)	87	5.1%	182	4.1%	269	4.4%
Hour 0 (12:00 AM–12:59 AM)	64	3.7%	193	4.4%	257	4.2%
Hour 13 (1:00 PM–1:59 PM)	64	3.7%	191	4.3%	255	4.1%
Hour 16 (4:00 PM–4:59 PM)	57	3.3%	193	4.4%	250	4.1%
Hour 14 (2:00 PM–2:59 PM)	60	3.5%	169	3.8%	229	3.7%
Hour 10 (10:00 AM–10:59 AM)	61	3.6%	146	3.3%	207	3.4%
Hour 2 (2:00 AM–2:59 AM)	54	3.1%	149	3.4%	203	3.3%
Hour 1 (1:00 AM–1:59 AM)	37	2.2%	139	3.1%	176	2.9%
Hour 3 (3:00 AM–3:59 AM)	40	2.3%	107	2.4%	147	2.4%
Hour 4 (4:00 AM–4:59 AM)	23	1.3%	96	2.2%	119	1.9%
Hour 9 (9:00 AM–9:59 AM)	27	1.6%	77	1.7%	104	1.7%

Table 3-3: District, Roadway, and Hour-of-Day Counts and Percentages for Waze Earlier and CAD Earlier Events (continued)

Feature	Waze_earlier = 1 (Waze Alert Earlier)		Waze_earlier = 0 (CAD Alert Earlier)		Total Matched Events	
	Count	Percentage	Count	Percentage	Count	Percentage
Hour 5 (5:00 AM–5:59 AM)	16	0.9%	76	1.7%	92	1.5%
Hour 8 (8:00 AM–8:59 AM)	10	0.6%	77	1.7%	87	1.4%
Hour 7 (7:00 AM–7:59 AM)	9	0.5%	70	1.6%	79	1.3%
Hour 6 (6:00 AM–6:59 AM)	12	0.7%	61	1.4%	73	1.2%

Figure 3-5 shows the percentage of Waze earlier and CAD earlier events by FDOT district. For all districts, the CAD earlier percentages were higher than Waze earlier percentages. The FTE district, D6, and D2 had the highest percentages of Waze earlier events, indicating that Waze alerts in these districts are more likely to provide early warnings of events. Improving the early warning benefits of Waze by modifying the current FDOT filtering protocols would likely be most beneficial in these districts. Districts with more rural areas, such as D1 and D3, had lower Waze earlier percentages (likely due to reduced Waze usage in those districts) and would therefore likely not benefit as much from opening up the existing FDOT filters.

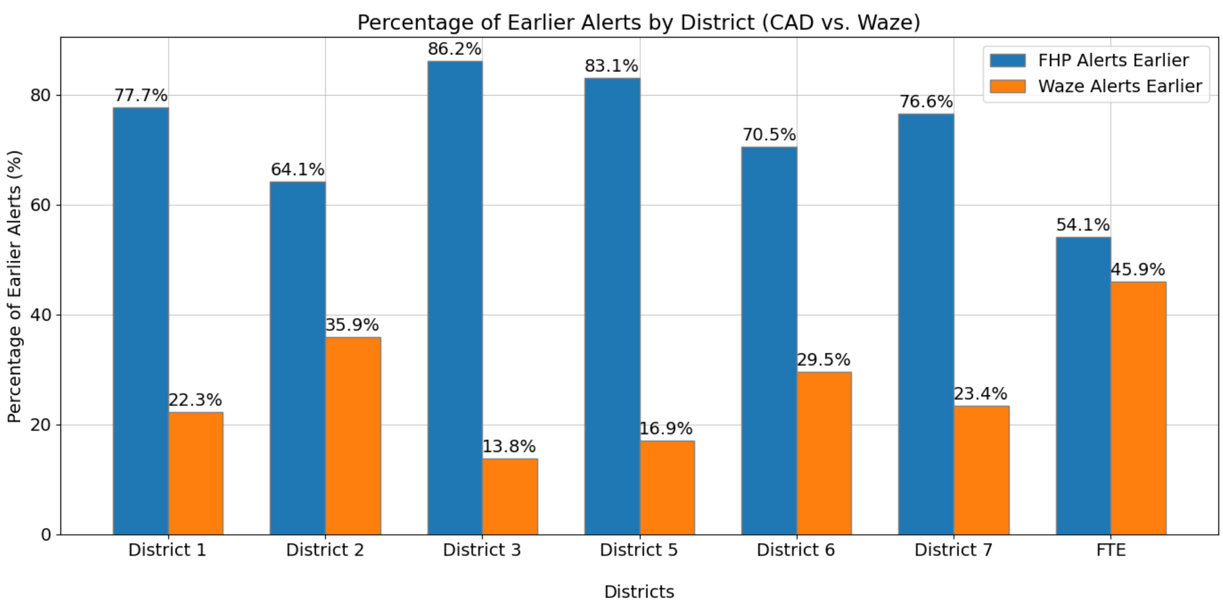

Figure 3-5: Waze Earlier and CAD Earlier Percentages by FDOT District

Figure 3-6 shows the average time difference (in minutes) for Waze earlier and CAD earlier events across the FDOT districts. Districts with high time differences for Waze earlier alerts (like D5, D3, and D6) are districts where Waze provides the most early warning benefits. D3 was the only district with a larger time difference for Waze earlier events than for CAD earlier events, suggesting that Waze alerts tend to be timely in D3. This supports D3's decision to relax the existing Waze filters during select hours of the day. While the low frequency of Waze earlier events in D3 compared to other districts limits the current potential early warning benefits from Waze for D3, increased Waze usage by D3 drivers in the future could make Waze extremely valuable for D3. The FTE district had the highest time difference for CAD earlier events, indicating that CAD events are very timely compared to Waze events on FTE roadways. Based on Table 3-3 and the findings from Figures 3-5 and 3-6, Waze alerts appear to best complement CAD data in urban regions compared to rural regions, as Waze usage seems to be lower in rural areas. Opening the Waze filters for FTE roadways (where Waze earlier events are common), D6 (where the average time difference for Waze earlier events is high), and D7 (which has the most matched events) could potentially provide the most early warning benefits.

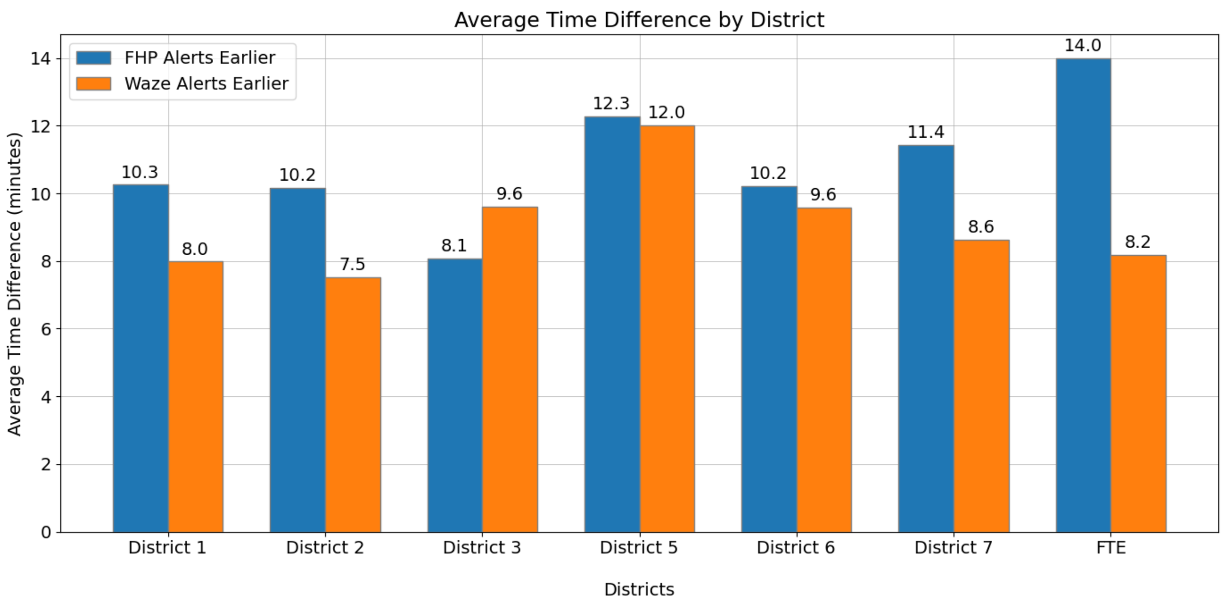

Figure 3-6: Average Time Difference for Waze Earlier and CAD Earlier Events by FDOT District

Figure 3-7 shows the percentage of Waze earlier and CAD earlier events by roadway. SR-821 was the only roadway where the percentage of Waze earlier events exceeded the percentage of CAD earlier events. SR-91, I-295, and I-95 also had relatively high percentages of Waze earlier events. These are primarily urban roadways, indicating that Waze usage tends to be higher in urban areas. In contrast, roadways with lower Waze earlier percentages tended to be either short, such as I-110 and SR-874, or contain long rural stretches, like I-10 and I-75.

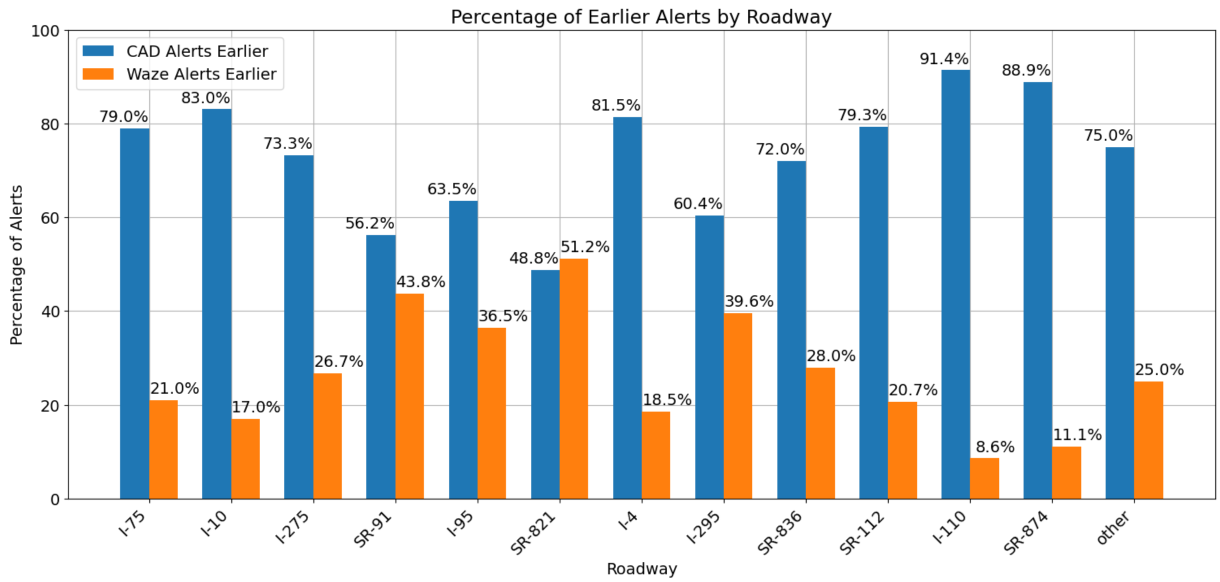

Figure 3-7: Waze Earlier and CAD Earlier Percentages by Roadway

Figure 3-8 shows the average time difference (in minutes) for Waze earlier and CAD earlier events by roadway. I-10 and I-110 were the only roadways where the time difference for Waze earlier events exceeded the time difference for CAD earlier events. As these roads are more rural, this reinforces the idea that Waze can offer the most time-saving benefits in rural areas. However, the low frequency of Waze alerts in rural areas diminishes these potential benefits. On primarily urban roadways like I-95 and SR-836, the time differences between Waze earlier and CAD earlier events were similar, suggesting that Waze data could effectively complement CAD data in these urban settings. Based on Table 3-3 and the findings from Figures 3-7 and 3-8, I-95, SR-821, and SR-91 are the roadways where Waze data would likely provide the most early warning benefits and best complement CAD data. However, more urban portions of I-75 and I-10 could also potentially receive improved early warning benefits by opening the Waze filters.

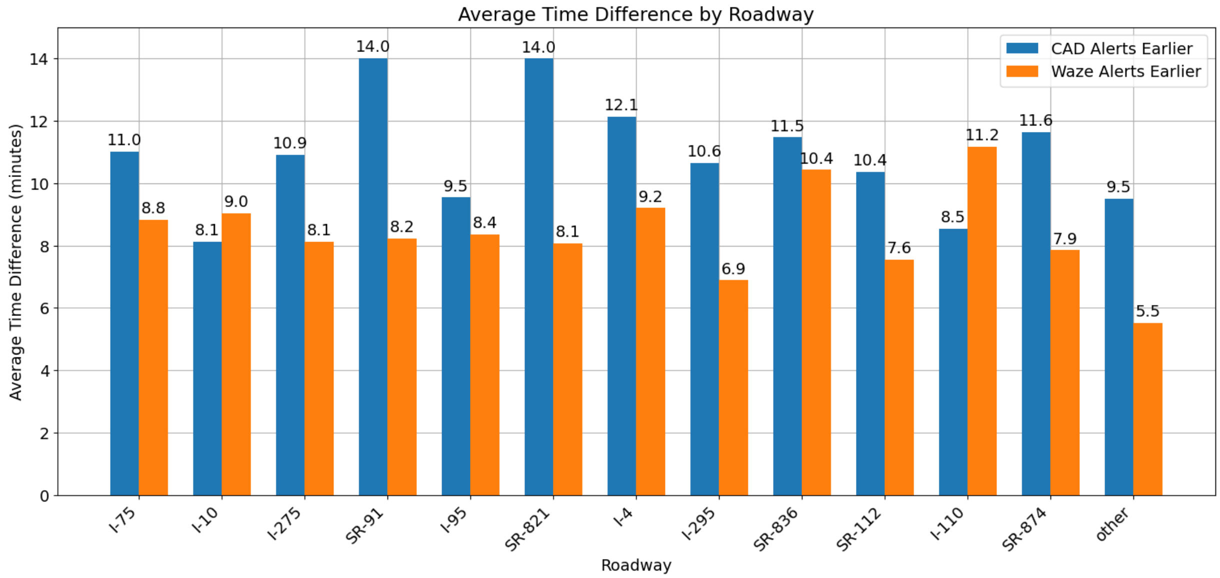

Figure 3-8: Average Time Difference for Waze Earlier and CAD Earlier Events by Roadway

Figure 3-9 shows the percentage of Waze earlier and CAD earlier events by hour of the day. While CAD earlier events were more frequent than Waze earlier events for all hours, Waze earlier events were most frequent during midday and nighttime hours, with the highest percentage (35.4%) occurring in hour 23. In contrast, the lowest percentages of Waze earlier events were observed between hours 4 and 8, with the lowest at 11.4% during hour 7. These findings, along with the counts in Table 3-3, indicate that Waze alerts are less frequent and not as timely during morning hours.

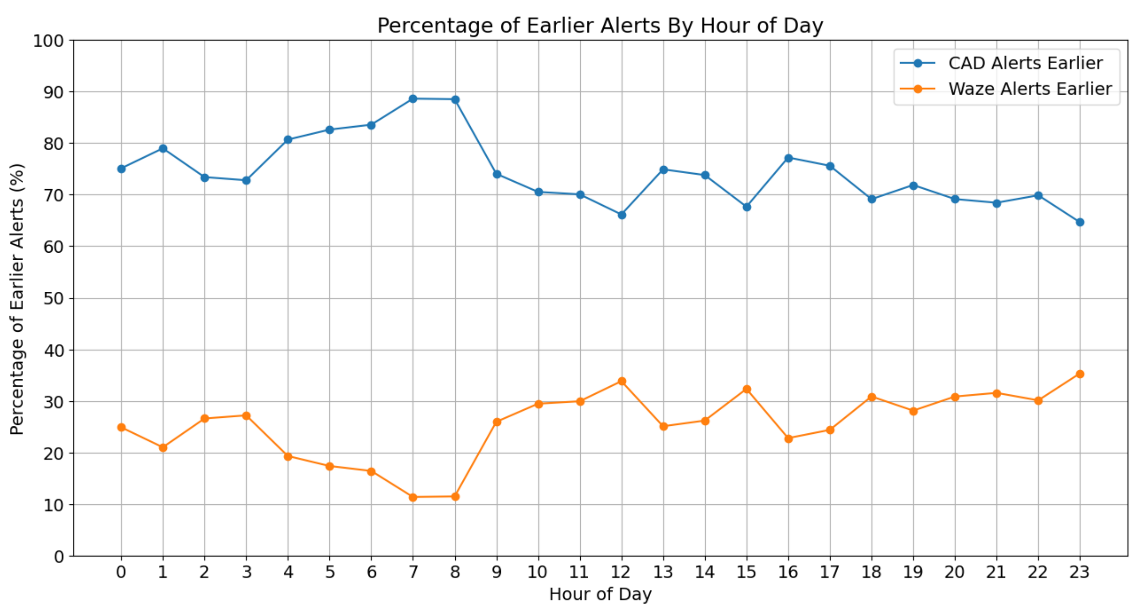

Figure 3-9: Waze Earlier and CAD Earlier Percentages by Hour

Figure 3-10 shows the average time difference (in minutes) for Waze earlier and CAD earlier events across different hours of the day. The time differences ranged from 6.4 to 11.6 minutes for Waze earlier events and 8.8 to 11.8 minutes for CAD earlier events. Waze earlier events had greater time differences than CAD earlier events during hours 2, 7, 8, and 16. Overall, the highest Waze earlier and CAD earlier time differences occurred during the late night and early morning hours, with CAD earlier events also showing elevated time differences between hours 9 and 13. These findings suggest that Waze data offers the most early warning benefits during nighttime and morning peak hours. Taken together with the findings from Figure 3-9, opening up the Waze filters would likely provide the most early warning benefits during late night and early morning hours, especially 10:00 PM – 3:59 AM. Increasing the Waze alerts reported to the TMC operators during these hours would also be better compared to increasing the alerts during daytime hours when operators are busier due to higher traffic volumes and associated congestion and incidents.

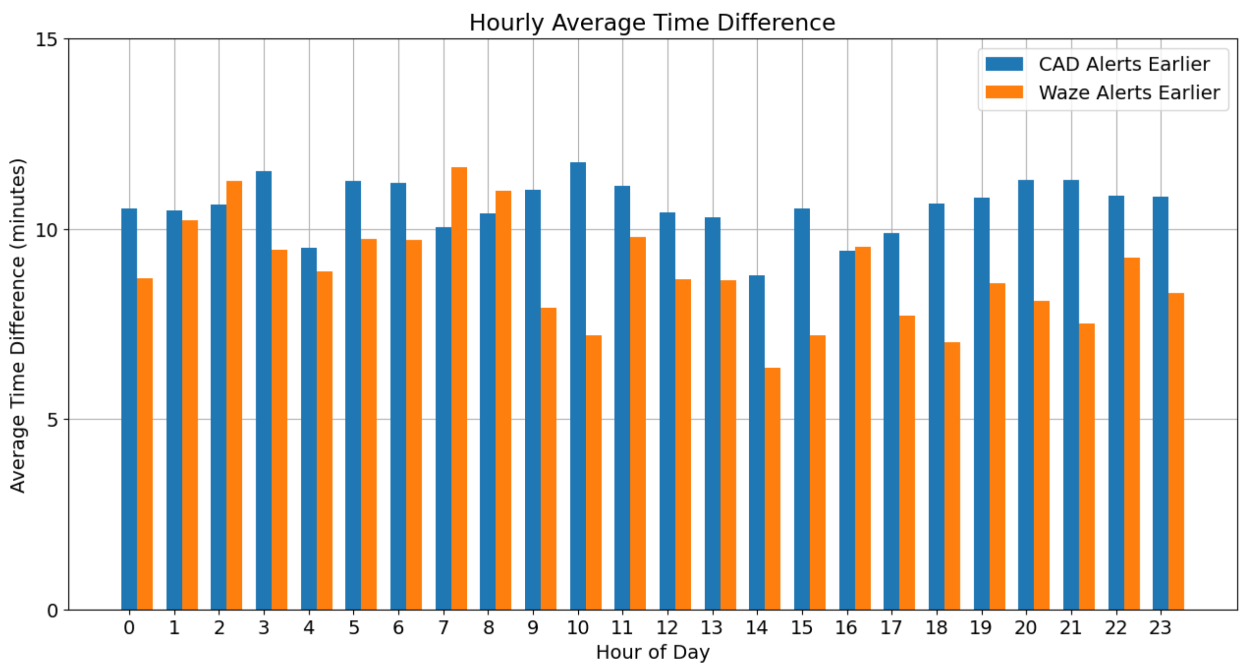

Figure 3-10: Average Time Difference for Waze Earlier and CAD Earlier Events by Hour

To better understand the potential early warning benefits of Waze alerts for FTE roadways, the 1,015 matched events in the FTE district were analyzed by hour of the day. All but one of these FTE events occurred on either SR-91 or SR-821 (with the one other event occurring on SR-570), so individual roadway analyses for these FTE events would not provide any additional insights to those obtained from Figures 3-7 and 3-8. Table 3-4 shows the counts and percentages of Waze earlier, CAD earlier, and total FTE district matched events by hour. Like Table 3-3, each percentage is the percentage of the total Waze earlier events, CAD earlier events, or all 1,015 events that occurred in the specified hour and the percentages shown in Table 3-4 might not add up to exactly 100% due to rounding. FTE matched events were most common between 6:00 PM and 12:59 AM. The Waze earlier percentages were higher than the CAD earlier percentages for two nighttime hours (22 and 23), two morning hours (7 and 9), and six daytime or evening hours (11, 12, 14, 15, 16, and 18), suggesting that Waze alerts could potentially provide the most early warning benefits on FTE roadways during these times.

Table 3-4: Hour-of-Day Counts and Percentages for FTE District Waze Earlier and CAD Earlier Events

Hour	**Waze_earlier = 1 (Waze Alert Earlier)**		**Waze_earlier = 0 (CAD Alert Earlier)**		**Total Matched Events**	
	Count	Percentage	Count	Percentage	Count	Percentage
Hour 21 (9:00 PM–9:59 PM)	47	10.1%	58	10.6%	105	10.3%
Hour 20 (8:00 PM–8:59 PM)	45	9.7%	60	10.9%	105	10.3%
Hour 22 (10:00 PM–10:59 PM)	41	8.8%	43	7.8%	84	8.3%
Hour 19 (7:00 PM–7:59 PM)	31	6.7%	42	7.7%	73	7.2%
Hour 0 (12:00 AM–12:59 AM)	28	6.0%	41	7.5%	69	6.8%
Hour 23 (11:00 PM–11:59 PM)	32	6.9%	36	6.6%	68	6.7%
Hour 18 (6:00 PM–6:59 PM)	42	9.0%	23	4.2%	65	6.4%
Hour 2 (2:00 AM–2:59 AM)	20	4.3%	34	6.2%	54	5.3%
Hour 11 (11:00 AM–11:59 AM)	25	5.4%	25	4.6%	50	4.9%
Hour 17 (5:00 PM–5:59 PM)	21	4.5%	26	4.7%	47	4.6%
Hour 1 (1:00 AM–1:59 AM)	12	2.6%	28	5.1%	40	3.9%
Hour 3 (3:00 AM–3:59 AM)	14	3.0%	25	4.6%	39	3.8%
Hour 12 (12:00 PM–12:59 PM)	25	5.4%	13	2.4%	38	3.7%
Hour 16 (4:00 PM–4:59 PM)	16	3.4%	18	3.3%	34	3.3%
Hour 13 (1:00 PM–1:59 PM)	14	3.0%	19	3.5%	33	3.3%
Hour 15 (3:00 PM–3:59 PM)	17	3.6%	11	2.0%	28	2.8%
Hour 14 (2:00 PM–2:59 PM)	11	2.4%	7	1.3%	18	1.8%
Hour 10 (10:00 AM–10:59 AM)	6	1.3%	8	1.5%	14	1.4%
Hour 9 (9:00 AM–9:59 AM)	5	1.1%	5	0.9%	10	1.0%
Hour 8 (8:00 AM–8:59 AM)	1	0.2%	9	1.6%	10	1.0%
Hour 5 (5:00 AM–5:59 AM)	3	0.6%	6	1.1%	9	0.9%
Hour 7 (7:00 AM–7:59 AM)	5	1.1%	3	0.5%	8	0.8%
Hour 4 (4:00 AM–4:59 AM)	3	0.6%	5	0.9%	8	0.8%
Hour 6 (6:00 AM–6:59 AM)	2	0.4%	4	0.7%	6	0.6%

Figure 3-11 shows the percentage of Waze earlier and CAD earlier events by hour of the day on FTE roadways. Waze earlier events were most frequent during midday and evening hours, with the highest percentage (65.8%) occurring at hour 12. In contrast, the lowest percentages of Waze earlier events were observed between hours 1 and 6, as well as hour 8, which had the lowest percentage (10%). These findings suggest that Waze alerts do not provide early warnings compared to CAD as often during early morning hours for FTE roadways.

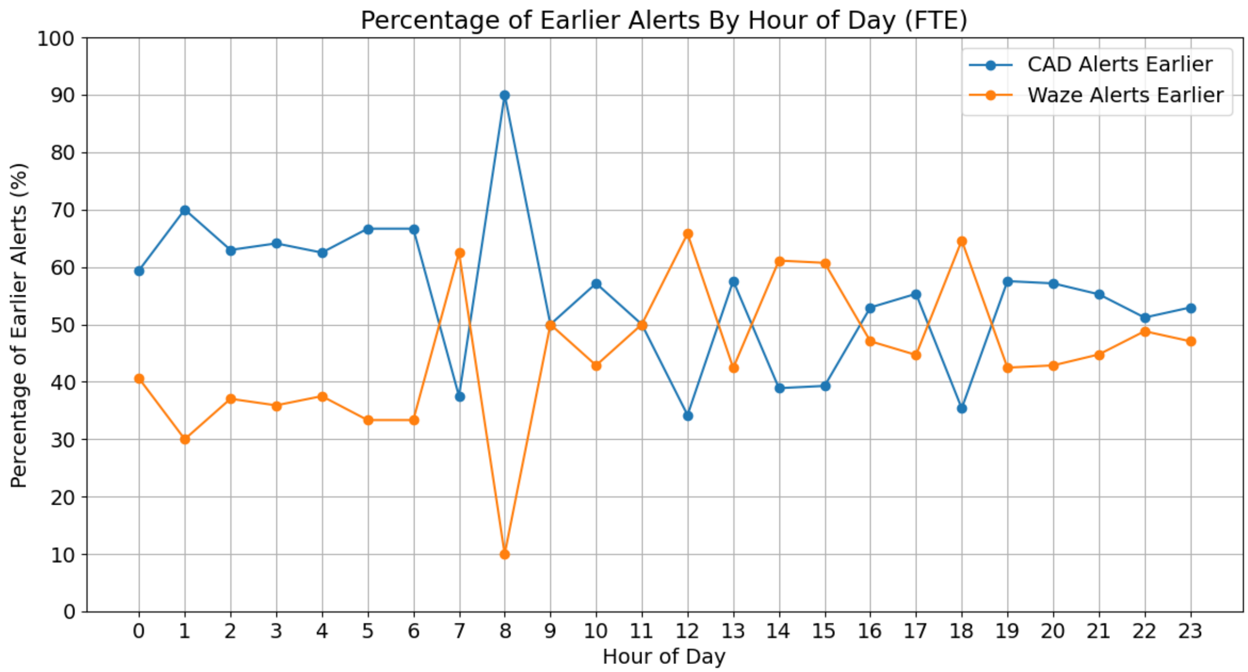

Figure 3-11: Waze Earlier and CAD Earlier Percentages by Hour for FTE District Events

Figure 3-12 shows the average time difference (in minutes) for Waze earlier and CAD earlier events by hour of the day for FTE roadways. These time differences ranged from 2 to 16.5 minutes for Waze earlier events and 7.2 to 20.8 minutes for CAD earlier events. Waze earlier events had greater time differences than CAD earlier events during hours 1 and 7. In general, the highest time differences for Waze earlier events occurred during early morning and morning peak hours, while the highest time differences for CAD earlier events occurred during midday and early morning hours. These findings suggest that Waze data can best complement CAD data and offer the most potential early warning benefits during peak morning hours. Taken together with the findings from Figure 3-11, opening Waze filters for FTE roadways during late night or early morning hours would likely provide the most early warning benefits while also reducing their potential burdens on TMC operators.

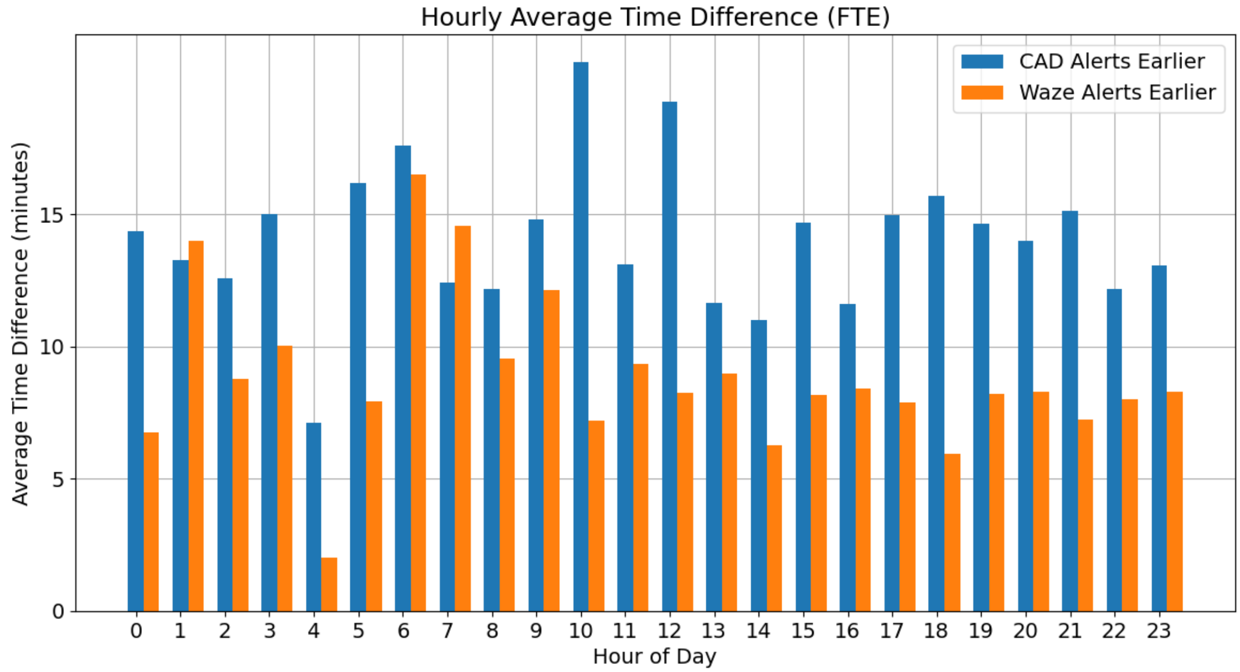

Figure 3-12: Average Time Difference for Waze Earlier and CAD Earlier Events by Hour for FTE District Events

3.2.4. Modeling of Statewide Matched Waze and CAD Events

While the data analyses conducted in section 3.2.3 provide valuable insights into where and when Waze alerts could best complement CAD data and provide early warning alerts, modeling is necessary to identify the most influential factors and the order of importance for these factors. Identifying the most important factors can be challenging, particularly given the variation in the number of events by hour, district, and roadway. Statistical modeling can help identify these important factors to help FDOT understand better the situations for which Waze typically provides earlier warning of incidents than CAD.

The primary goal of the modeling was to predict whether a Waze alert or a CAD alert was more likely to occur first, using the Waze_earlier variable as the response variable. Potential predictors included the time_difference, distance, and binary variables for each hour, roadway, and district. For this model, the purpose of the district variables was to identify differences in Waze usage for different geographic areas of Florida. Since the FTE district covers multiple geographic areas, it was decided to only consider D1 through D7 in the modeling. All FTE district events were therefore reallocated to their appropriate geographical district based on their location. This model will help pinpoint specific conditions under which Waze alerts are more likely to precede CAD alerts and provide earlier warning of incidents. FDOT can use these results to better optimize the use of Waze and CAD data.

1. Data Preprocessing

Before beginning the modeling process, the data were reviewed for skewness, imbalance, and outliers. The continuous predictor variables time_difference and distance were first assessed for skewness, which refers to the asymmetry in their distributions. As shown in Figure 3-13, both variables displayed skewness and non-normal distributions. To correct this, a Yeo-Johnson transformation was applied to both variables, which helps stabilize variance and make the data more normally distributed (Yeo & Johnson, 2000). The resulting distributions after this transformation are shown in Figure 3-14.

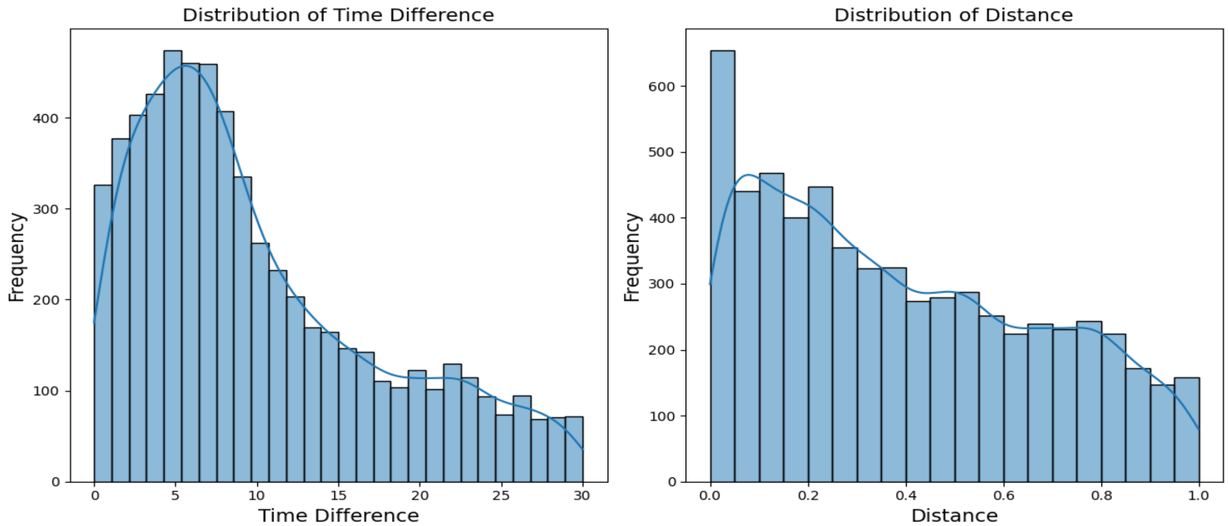

Figure 3-13: Original Distributions of Time Difference and Distance Variables

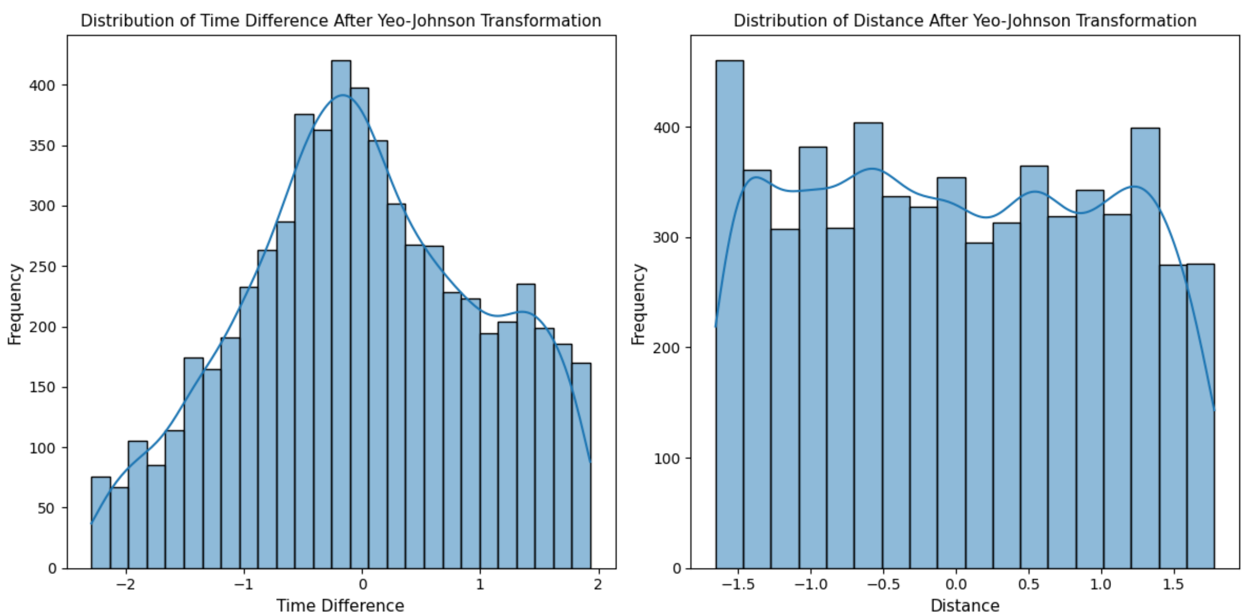

Figure 3-14: Distributions of Time Difference and Distance Variables after Yeo-Johnson Transformation

Next, the response variable was examined for data imbalance, which occurs when one class of a binary or categorical variable is significantly underrepresented compared to others. Of the 6,147 matched events, 1,718 (27.95%) had Waze_earlier = 1, making it the minority class and Waze_earlier = 0 the majority class. To mitigate this imbalance, a class weight adjustment was applied. This technique assigns weights inversely proportional to class frequencies, ensuring a more balanced class representation and enhancing model performance in imbalanced datasets.

For example, if the class weight is determined to be 2, observations from the minority class would be assigned twice the importance of those from the majority class during model training. The appropriate class weight was determined after the final modeling approach was selected and is discussed later in this section.

The final data preprocessing step was assessing the continuous variables for outliers using boxplots (Figure 3-15). This assessment identified 28 outliers, which were kept in the dataset due to their low count (less than 0.5% of the dataset) and expected minimal impact on model performance.

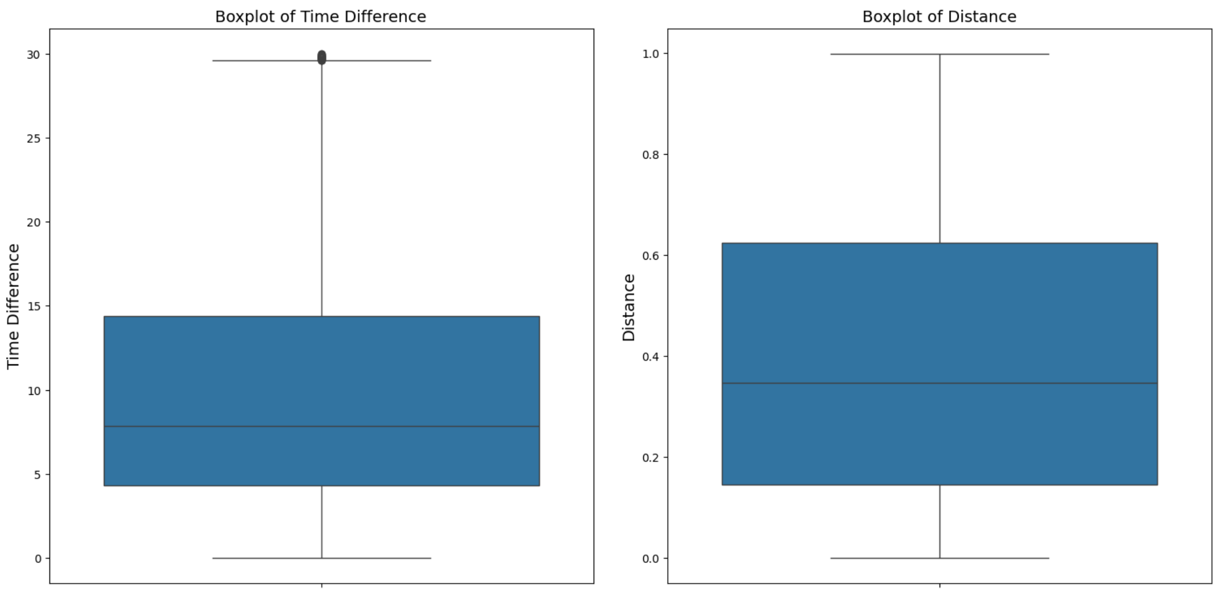

Figure 3-15: Outlier Identification Using Boxplots

2. Model Selection

Several regression and machine learning models were tested, including logistic regression, random forest, support vector machine, and extreme gradient boosting (XGBoost), with XGBoost selected as the preferred approach. XGBoost is a powerful ensemble learning algorithm that improves predictive accuracy by sequentially adding decision trees, each designed to correct the errors of the previous ones. This method uses gradient boosting, where a gradient descent algorithm minimizes a loss function representing the difference between predicted and actual outcomes. XGBoost also includes regularization to prevent overfitting by penalizing overly complex models, thus improving generalizability (Chen & Guestrin, 2016). It effectively handles class imbalance and provides insights into variable importance through Shapley Additive Explanation (SHAP) values and is also robust to outliers and noise. However, XGBoost is sensitive to hyperparameters, making hyperparameter tuning essential for optimal performance.

3. Hyperparameter Tuning

Hyperparameters, such as the learning rate and number of trees, are preset values that control the model's training process and structure. Hyperparameter tuning is crucial to optimize model performance. Proper hyperparameter tuning prevents the model from overfitting, ensuring it generalizes well to new, unseen data. A grid search was utilized to systematically evaluate different combinations of hyperparameters and find the best set (Anggoro & Mukti, 2021). This method was chosen for its thoroughness since it explores all potential combinations of hyperparameters. Table 3-5 shows the various hyperparameters, their grid search values, and brief definitions. These hyperparameters were selected for XGBoost based on computational complexity and prior research. For each hyperparameter, the values chosen represent a balance between exploring a range of possibilities and ensuring computational feasibility. The detailed explanation of each hyperparameter and the rationale for the selected values are as follows:

- **Number of estimators (n_estimator) – Values of [100, 200, 300]**: The number of estimators represents the total number of decision trees in the model. Increasing the number of trees generally improves model accuracy, as each tree corrects mistakes made by the previous ones. However, after a certain point, adding more trees leads to only minor improvements while significantly increasing computational costs. To find a balance, a range of 100 to 300 trees was tested. This range is enough to avoid underfitting, but not too large as to be overly expensive to compute. Large steps of 100 between the different values were chosen instead of small increments (like 101, 102, 103) to observe noticeable changes more efficiently. This approach helps evaluate the effect of adding more trees while optimizing computational resources and model performance.
- **Maximum depth (max_depth) – Values of [3, 5, 7]**: The maximum depth of a decision tree refers to how many levels the tree can have, which determines how detailed the model can get when learning from data. A shallow tree (e.g., max_depth = 3) means the model will only consider a few layers of decisions, making it faster and less likely to overfit to the training data, which is especially useful for simpler datasets. On the other hand, deeper trees (e.g., max_depth = 5 or 7) allow the model to understand more complex patterns, which is essential when dealing with more intricate data. Setting the depth above 7 risks overfitting, particularly with smaller datasets, while values below 3 may not capture the complexity of real-world problems effectively.
- **Learning rate (learning_rate) – Values of [0.01, 0.1, 0.2]**: The learning rate controls the size of each step the model takes when optimizing the loss function, effectively determining how much to adjust the model in response to each error during training. Smaller values (e.g., 0.01) lead to more gradual, careful updates, which results in slower but more precise convergence and lowers the risk of overfitting. Medium values (e.g., 0.1) provide a good balance between learning speed and stability, while larger values (e.g., 0.2) speed up convergence but may cause the model to overshoot the optimal solution and reduce accuracy. The range of learning rates used (0.01, 0.1, and 0.2) represents a mix of conservative, standard, and aggressive approaches, which are commonly used in XGBoost.
- **Subsample ratio (subsample) – Values of [0.6, 0.8, 1.0]**: The subsample ratio controls what fraction of the training data is used to grow each tree, introducing randomness that helps reduce overfitting. Overfitting happens when the model learns patterns that are too specific to the training data, which makes it less effective on new, unseen data. For a low subsample ratio of 0.6, each tree only uses 60% of the training data, which makes the trees more diverse and helps the model become more general and less sensitive to specific details of the training data. However, this means

that a smaller sample is used to build each tree, which can result in larger errors. A high subsample ratio of 1.0 means that 100% of the dataset is used for every tree, which reduces randomness and can increase the risk of overfitting. The chosen values (0.6, 0.8, and 1.0) were selected to understand the impact of different levels of randomness on the model's generalization.

- **colsample_bytree – Values of [0.6, 0.8, 1.0]**: The colsample_bytree parameter controls the fraction of features used by each tree during model training. Similar to data subsampling, this feature sampling introduces randomness that helps reduce overfitting, especially in datasets with many features (high dimensionality). For a low value of 0.6, each tree only considers 60% of the available features, which encourages diversity among the trees and helps prevent the model from becoming overly dependent on specific features. A high value of 1.0 means that every tree considers all features, reducing randomness and potentially increasing the risk of overfitting. The chosen values (0.6, 0.8, and 1.0) were selected to explore the impact of different levels of feature sampling on model performance, providing a balanced view of how much variability contributes to effective generalization.

After the grid search tuning, the best parameters were identified as n_estimator = 200, max_depth = 7, learning_rate = 0.01, subsample = 0.8, and colsample_bytree = 0.8. Once these hyperparameters were determined, the class weight was adjusted to 1.77 to address class imbalance, as discussed previously.

Table 3-5: XGBoost Hyperparameters Grid Search Values and Definitions

Hyperparameter	**Grid Search Values**	**Definition**
n_estimator	[100, 200, 300]	Number of trees in the model
max_depth	[3, 5, 7]	Maximum depth of each tree
learning_rate	[0.01, 0.1, 0.2]	Step size during the gradient descent
subsample	[0.6, 0.8, 1.0]	Fraction of the training data to be used for each tree
colsample_bytree	[0.6, 0.8, 1.0]	Fraction of features to be used by each tree

4. *Model Performance Evaluation*

The performance of the XGBoost model was evaluated using various metrics to provide a comprehensive overview of its classification capabilities for the binary response variable Waze_earlier. A training set containing 80% of the data (4,917 observations) was used to develop the model. The following metrics were then calculated on a testing set containing the remaining 20% of the data (1,230 observations):

- Accuracy: The ratio of correctly predicted observations to the total observations (Equation 3-1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3-1}$$

Where:
TP = number of true positives (actual and predicted value of 1);
TN = number of true negatives (actual and predicted value of 0);

FP = number of false positives (actual value of 0, predicted value of 1); and
FN = number of false negatives (actual value of 1, predicted value of 0).

- Precision: The ratio of correctly predicted positive observations to the total predicted positive observations (Equation 3-2).

$$Precision = \frac{TP}{TP + FP} \tag{3-2}$$

- Recall: The ratio of correctly predicted positive observations to the total actual positive observations (Equation 3-3). This is equivalent to the true positive rate (TPR).

$$Recall = TPR = \frac{TP}{TP + FN} \tag{3-3}$$

- F1 Score: The harmonic mean of precision and recall (Equation 3-4).

$$F1\ Score = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3-4}$$

- Area Under the Receiver Operating Characteristic Curve (ROC-AUC): The Receiver Operating Characteristic (ROC) curve measures the ability of the model to distinguish between classes. The ROC curve plots the TPR (Equation 3-3) against the false positive rate (FPR) (Equation 3-5), with the ROC-AUC used as a performance measure. The ROC-AUC can range from 0.5 to 1, where 0.5 is equivalent to random guessing, and 1 indicates a model with perfect prediction accuracy. The ROC curve visually represents the trade-off between the TPR and the FPR at various threshold settings. A model's performance is better when its ROC curve significantly deviates from the diagonal line (indicating random guessing) shown in Figure 3-16 as a grey dashed line. The ROC-AUC quantifies this deviation. The closer the curve is to the top left corner (approaching an ROC-AUC of 1), the more capable the model is at accurately classifying the two groups with minimal error. This illustrates the model's effectiveness in distinguishing classes and highlights its reliability in prediction accuracy. Higher ROC-AUC values indicate fewer misclassifications of negative classifications as positive classifications.

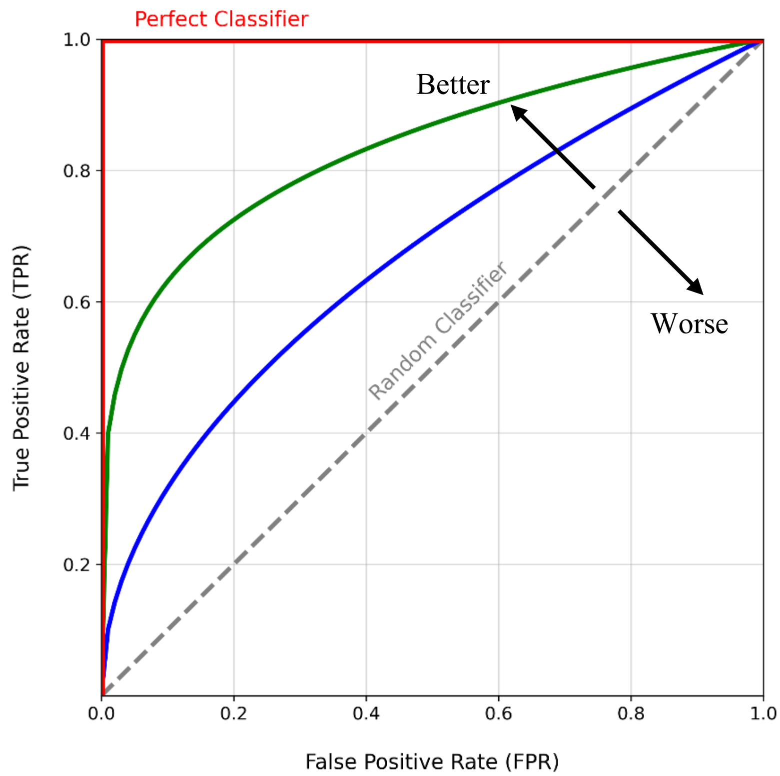

Figure 3-16: ROC Curve Demonstration

$$FPR = \frac{FP}{FP + TN}$$

(3-5)

Due to the nature of the dataset and modeling goals, balancing recall and precision was considered more important than achieving high accuracy. This balance provides a more accurate assessment of the model's performance, particularly in the context of imbalanced datasets, where high accuracy can often be misleading (Bown, 2024). For the developed XGBoost model, the accuracy represents the overall correctness but does not reflect the effectiveness of the model in capturing all relevant early Waze alerts (recall) while minimizing the instances where an alert is incorrectly flagged as having Waze earlier (precision). This distinction is vital because high accuracy could result from the model correctly identifying cases where CAD was earlier, since that is the majority class. For example, a model that always predicted CAD earlier would have an accuracy of 72% since CAD was earlier for 72% of cases. However, this model would have precision and recall values of zero since it would not have predicted any cases with Waze earlier correctly. Therefore, balancing precision and recall is better for this dataset, especially since it is imbalanced and failing to correctly identify an early Waze alert could significantly impact the results.

To evaluate the model, stratified k-fold cross-validation with k = 10 was employed. This method works by dividing the dataset into k equal parts, or "folds," while ensuring that each fold reflects the same class distribution as the original dataset. For example, if 70% of the data belongs to one class and 30% to another, each fold will maintain this 70-30 split. The model is trained on k-1 folds and tested on the remaining fold, with this process repeated k times so that every fold serves as the test set once. This approach ensures that the evaluation is fair and accounts for imbalanced data, preventing any single fold from disproportionately influencing the results while also providing a more comprehensive assessment of how well the model generalizes. (Fontanari et al., 2022).

5. Shapley Additive Explanations

SHAP values are a way to interpret the predictions of machine learning models by assigning an importance value to each feature (predictor variable) for a specific prediction. The core idea is based on SHAP values from cooperative game theory, which ensures a fair distribution of a reward among players (Lundberg & Lee, 2017). The SHAP value for a feature i (ϕ_i) is computed using Equation 3-6, where each feature is a specific predictor variable (time_difference, distance, hour binary variable, roadway binary variable, or district binary variable) and the prediction is either 1 (if Waze is earlier) or 0 (if CAD is earlier). These SHAP values indicate how important each feature is in contributing to the prediction, with larger positive SHAP values indicating that the feature is more important in predicting that Waze is earlier and larger negative values indicating that the feature is more important in predicting that CAD is earlier.

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{3-6}$$

Where:
N = set of all features,
S = subset of features not containing i,
$f(S)$ = prediction based on the features in S, and
$f(S \cup \{i\})$ = prediction based on the features in S plus feature i.

6. XGBoost Modeling Results and SHAP values

Using the appropriate hyperparameters discussed previously, an XGBoost model was developed using the training set. When this model was applied to the testing set, it achieved an accuracy of 0.74, a precision of 0.52, a recall of 0.44, and an F1 score of 0.48. Based on the literature, typical acceptable ranges for these measures are 0.5–0.75 for accuracy, 0.4–0.6 for precision, 0.5–0.8 for recall, and 0.4–0.75 for the F1 score (Chang & Chien, 2013; Liu et al., 2018; Sakaki et al., 2010; Senarath et al., 2021; J, Zhang et al., 2018). The developed model's values fall within all these ranges except for recall (which is slightly below the range), suggesting that the model performs well. Figure 3-17 presents the ROC curve, where the diagonal dashed line represents the baseline performance of a random classifier (ROC-AUC = 0.5). The blue line in the figure demonstrates the model's ability to distinguish between the two classes, with an ROC-AUC of 0.73, meaning the model correctly differentiates between Waze earlier and CAD earlier events 73% of the time.

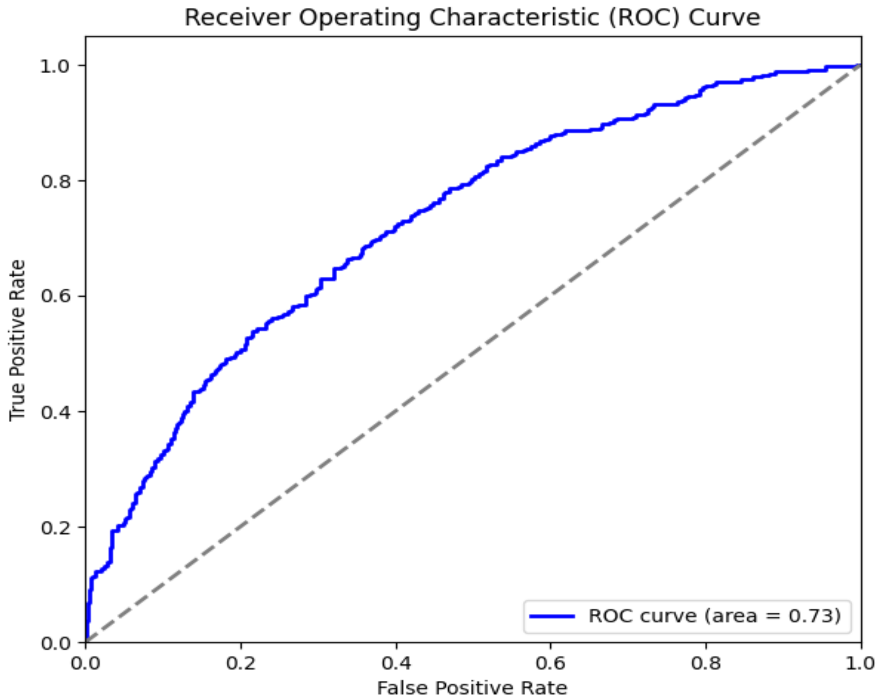

Figure 3-17: ROC Curve

The model was further evaluated using stratified 10-fold cross-validation, yielding the following average performance metrics: mean accuracy = 0.723 (standard deviation = 0.0192), mean precision = 0.513 (standard deviation = 0.041), mean recall = 0.433 (standard deviation = 0.0156), mean F1 score = 0.469 (standard deviation = 0.024), and mean ROC-AUC = 0.635 (standard deviation = 0.0168). The low standard deviation values compared to the mean values indicate that the model's performance is consistent across different subsets of the data, demonstrating its robustness and reliability in predicting Waze earlier or CAD earlier events (Basso et al., 2018; Haley, 2017).

The SHAP summary plot (Figure 3-18) visualizes the impact of each feature on the prediction across all observations. Each dot represents an individual observation, with features arranged in order of importance (most influential feature at the top). The color of the dots reflects the feature value; red indicates high values for continuous variables or a value of 1 for binary variables, while blue represents low values for continuous variables or a value of 0 for binary variables. The horizontal position of each dot shows its effect on the prediction. Observations with positive SHAP values (right side of the figure) are more likely to predict Waze earlier, whereas observations with negative SHAP values (left side of the figure) have a higher likelihood of predicting CAD earlier.

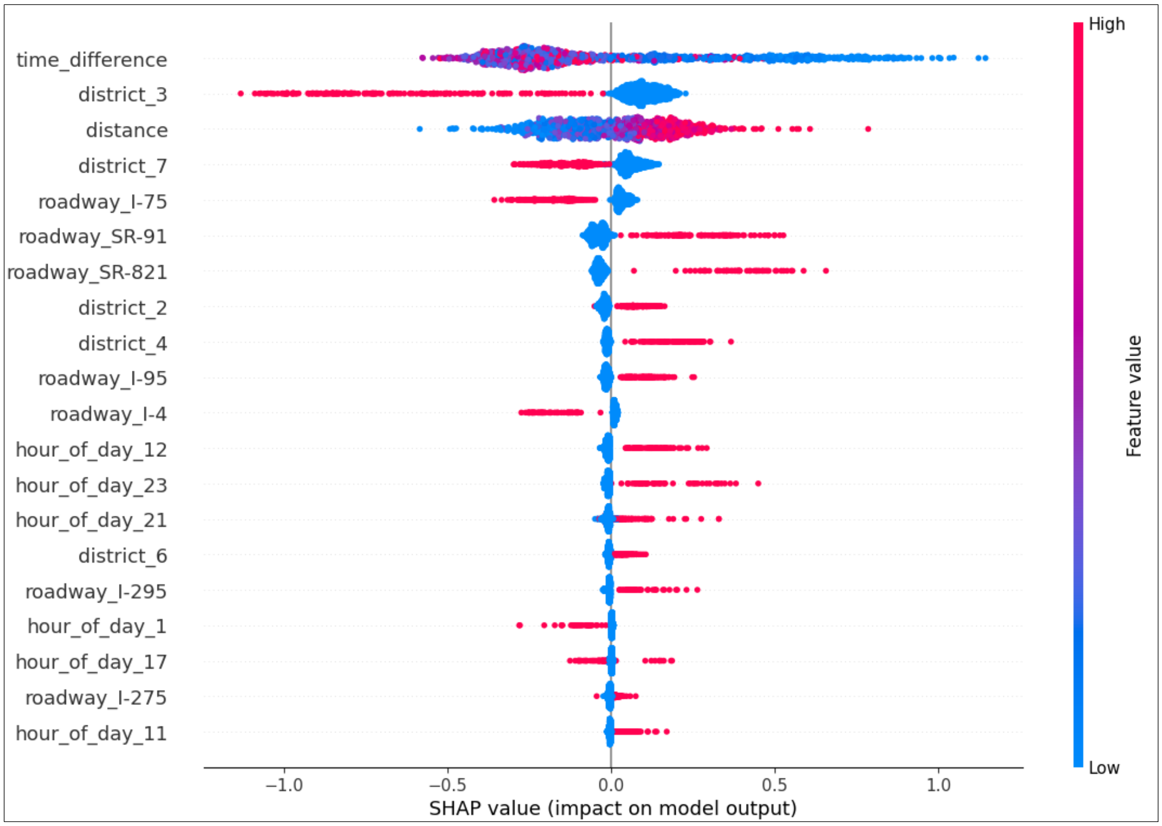

Figure 3-18: SHAP Summary Plot

The SHAP summary plot provides insights into which features most strongly influence the model's predictions and how they do so. For example, the variable "district_3" is a binary variable with a value of 1 if the event occurred in D3 and 0 if it occurred in another FDOT district. Since it is a binary variable, red dots represent values of 1 and blue dots represent values of 0. The red dots for district_3 are mainly on the left side of the plot, indicating that events in D3 are more likely to have CAD earlier, consistent with the findings in Figure 3-5, where D3 had the lowest percentage of Waze earlier events. As "district_3" is the most important district variable, an event occurring in D3 influences the prediction more than events occurring in any other district.

The variable "time_difference", which was identified as the most important variable, is a continuous variable that can take any positive value up to 30 minutes, based on the temporal buffer used to match Waze and CAD alerts. The observations range in color from blue (low values) to purple (medium values) to red (high values). High "time_difference" values are concentrated on the left side of the plot, meaning CAD was more likely to be earlier when the time difference was large. This could be due to low Waze usage in certain areas and FDOT's current filtering protocols for Waze alerts causing a delay between when an incident is first reported in Waze and when it is reported in SunGuide. Conversely, observations with low time differences are generally associated with positive SHAP values, meaning Waze was more likely to be earlier.

The important district variables shown in this SHAP summary plot are D3, D7, D2, D4, and D6. Similar to D3, D7 was more likely to have CAD earlier, whereas D2, D4, and D6 were more likely to have Waze earlier. These results suggest that D2, D4, and D6 have the most potential for Waze to complement CAD data, especially if FDOT adjusts some filters to reduce the time lag between a Waze report and TMC notification. Note that all D4 events were on FTE roadways, suggesting that the FTE district is a good candidate for adjustments to the existing Waze filtering protocols. For roadways, I-75 and I-4 had a higher likelihood of CAD earlier, while SR-91 and SR-821 were the most significant roadways where Waze was more likely to be earlier. These findings align with Figure 3-7 and could be attributed to differences in law enforcement presence and Waze usage. I-75 contains long rural segments where Waze usage may be lower, while I-4 connects major tourist destinations, likely increasing law enforcement presence and containing drivers who are less familiar with Waze. Meanwhile, SR-91 and SR-821 are toll roads used by commuters who might be more inclined to use Waze. Reducing the reporting time lag for Waze alerts on these FTE roads could help close the gap in time differences between Waze and CAD, but it is important to ensure that any changes to the Waze filtering processes do not overwhelm TMC operators with additional Waze alerts.

The hour of day features were generally less important than location features, with hours 12, 23, and 21 being the most significant for predicting Waze earlier. Since TMC operators are typically busier during daytime hours, it is not recommended to loosen Waze filters around 12:00 PM. However, providing TMCs with more Waze alerts during the less busy nighttime hours between 9:00 PM and 11:59 PM could be beneficial, especially for districts or roadways where Waze alerts would likely provide the most early warning benefits, such as D2, D6, or FTE roadways.

3.3 Analysis of District 5 CAD, Active 911, and PulsePoint TIM Data

While Waze data are utilized throughout Florida, Active 911 and PulsePoint data are only used in select Florida areas. D5 uses both these data sources to help identify and respond to traffic incidents more quickly. Understanding the situations where these data could best provide early warning benefits can help other FDOT districts decide how best to utilize these data sources in the future.

The FHP CAD, Active 911, and PulsePoint alert data from D5 shown in Table 3-1 were used to compare these data sources. Table 3-6 shows the variables in the D5 CAD dataset, Table 3-7 shows the variables in the Active 911 dataset, and Table 3-8 shows the variables in the PulsePoint dataset. These tables show that the information and formats of the D5 CAD, Active 911, and PulsePoint datasets vary. Therefore, data preprocessing was a critical step to ensure consistency and compatibility between the datasets for analysis. Each dataset required specific preprocessing techniques to standardize formats and align variable types before matching alerts between datasets. The FHP CAD dataset required minimum preprocessing since the included variables were properly formatted with no missing values, while the Active 911 and PulsePoint datasets each required their own preprocessing and filtering steps.

Table 3-6: FHP CAD Dataset Variables (D5)

Variable	**Description**	**Type**
Incident Alarm ID	Identification number of the alert	Index
Start Time	Date and time the alert was first reported	Datetime
End Time	Date and time the alert was resolved	Datetime
Event Type	Information regarding the type of event (e.g., accident, obstruction, unknown).	Categorical
Description	Brief description of the event (e.g., injury accident, disabled vehicle)	Categorical
District	The district where the alert was reported	Categorical
County	The county where the alert was reported	Categorical
Roadway	The roadway where the alert was reported	Categorical
Direction	The direction on the roadway where the alert was reported (e.g., East, North)	Categorical
Cross Street	The nearest crossing street where the alert was reported	Categorical
Mile Marker	The nearest mile marker where the alert was reported	Categorical
Latitude and Longitude	The coordinates where the alert was reported	Numerical

Table 3-7: Active 911 Dataset Variables (D5)

Variable	**Description**	**Type**
Timestamp	Date and time the incident was reported	Datetime
Description	Type of incident (e.g., crash, vehicle fire)	Categorical
Agency	The 911 agency (county or city) that received the call	Categorical
Location	The approximate location (street and crossing street) where the incident was reported	Text

Table 3-8: PulsePoint Dataset Variables (D5)

Variable	**Description**	**Type**
ID	Alert identification number	Index
Type	The incident's category, represented by a 2- or 3-letter code	Categorical
Longitude and Latitude	The coordinates where the alert was reported	Numerical
Address	The address where the alert was reported	Text
Timestamp	Date and time the alert was reported	Datetime

3.3.1. Data Preprocessing and Filtering

The Active 911 dataset was limited in the information provided, with only a description of the type of call and general location information. Notably, it lacked geographic coordinates for each alert, making it impossible to accurately map these data. The initial preprocessing step involved filtering the dataset to retain only the Active 911 calls related to traffic incidents. The dataset contained 140 unique descriptions, of which 48 were identified as traffic-related. These 48 categories were consolidated into the following five distinct categories: Vehicle Fire, Motor

Vehicle Collision, Abandoned Vehicle, Reported Traffic Violation, and Street Obstruction. Filtering the data to just calls in these five categories resulted in 38,525 observations.

Next, the alert timestamps were compared to the CAD timestamps to identify the Active 911 alerts which could potentially overlap with the CAD data using a 30-minute temporal buffer. However, the Active 911 dataset timestamps lacked any time zone specification. To ensure accuracy and facilitate cross-dataset comparisons, all timestamps in the Active 911 dataset were converted to Coordinated Universal Time and then adjusted as needed for daylight savings time. After these modifications to the timestamp variable, the 38,525 Active 911 calls were temporally aligned with the FHP CAD dataset to exclude any calls that did not occur within 30 minutes of an FHP CAD alert. This temporal filtering ensured that only Active 911 calls with the potential to match an FHP CAD alert, irrespective of location, were retained. After this temporal filtering, the dataset was reduced to 10,520 Active 911 calls.

The next filtering step was to exclude events not on limited access facilities. Due to the lack of coordinates in the Active 911 dataset, all 10,520 remaining observations were manually reviewed to identify ones which occurred on limited access facilities based on the provided location information. This manual review resulted in 943 Active 911 calls. A new variable was then introduced to denote the specific limited access highway where each alert occurred. Matching was then done between the Active 911 and CAD datasets based on location and time using two criteria: incidents from both datasets had to occur on the same limited access highway and within a 30-minute window of each other. All identified matched events were then manually inspected to verify that the matched alerts were spatially near each other based on the provided location information. Once completed, 113 matched events were identified. Figure 3-19 summarizes the Active 911 filtering and matching procedures and the number of observations for each step.

Figure 3-19: Active 911 Data Filtering and Matching Procedures and Number of Observations

As shown in Table 3-8, the PulsePoint dataset included a “type” variable which indicated the nature of the reported incident. A total of 45 distinct incident categories were identified, with the nature of each category determined from PulsePoint (2024). Out of these 45 categories, 16 were determined to be related to traffic incidents and contain at least one alert on a limited access facility. After filtering the dataset to only include these 16 categories and removing all alerts with no provided latitude or longitude coordinates, 23,372 alerts remained. These alerts were then filtered to only include alerts on limited access facilities, resulting in 633 PulsePoint alerts on limited access facilities. Lastly, spatiotemporal matching was conducted between the PulsePoint and CAD data, using a 1-mile buffer and a 30-minute time window, resulting in 160 matched events. Figure 3-20 summarizes the PulsePoint data filtering and matching procedures and number of observations for each step.

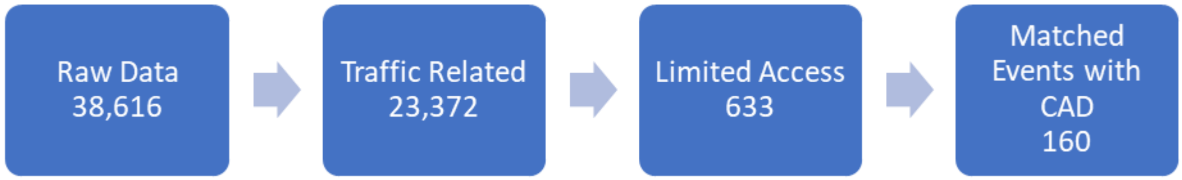

Figure 3-20: PulsePoint Data Filtering and Matching Procedures and Number of Observations

3.3.2. Data Comparisons and Analyses

1. Active 911 and FHP CAD Comparisons

The 113 Active 911 and FHP CAD matched events were analyzed with respect to roadway and hour of the day. Similar to the statewide CAD and Waze comparisons discussed in section 3.2.3, a binary variable named "Active_911_earlier" was created with a value of 1 for events where the Active 911 alert occurred first and a value of 0 for events where the CAD alert occurred first. A "time_difference" variable was also created to represent the difference between the Active 911 alert and the CAD alert, in minutes. An "hour" variable was created to indicate what hour the event was reported in (ranging from hour 0 to hour 23 like the statewide Waze and CAD comparisons). The roadway variable created during the data filtering procedures was also used. I-75, I-4, and I-95 were the three limited access roadways in D5 with matched Active 911 and CAD events. Due to the lack of coordinates for the Active 911 data, the variable "distance" was not included in the analysis. Overall, 38.05% of the matched events had the Active 911 alert occur before the CAD alert. The average time difference of Active 911 earlier events was 7.07 minutes whereas the average time difference of CAD earlier events was 6.21 minutes. Table 3-9 shows the counts and percentages of the matched CAD and Active 911 events by roadway and hour of the day. These percentages are the percentage of Active 911 earlier events, CAD earlier events, and total events for each individual roadway and hour of the day, with the percentages not necessarily adding up to exactly 100% due to rounding. These results show that the matched events were most common on I-75 and during daytime hours. I-4, I-95, and hours 8 and 12 had much higher active 911 earlier percentages than CAD earlier percentages, suggesting that Active 911 could potentially provide the most early warning benefits on these roadways and during these time periods.

Table 3-9: Roadway and Hour-of-Day Counts and Percentages for D5 Active 911 Earlier and CAD Earlier Events

Feature	Active 911 Earlier		CAD Earlier		Total Matched Events	
	Count	Percentage	Count	Percentage	Count	Percentage
I-75	31	72.1%	68	97.1%	99	87.6%
I-4	9	20.9%	1	1.4%	10	8.8%
I-95	3	7.0%	1	1.4%	4	3.5%
Hour 13 (1:00 PM–1:59 PM)	3	7.0%	6	8.6%	9	8.0%
Hour 15 (3:00 PM–3:59 PM)	3	7.0%	6	8.6%	9	8.0%
Hour 8 (8:00 AM–8:59 AM)	5	11.6%	2	2.9%	7	6.2%
Hour 12 (12:00 PM–12:59 PM)	4	9.3%	3	4.3%	7	6.2%
Hour 16 (4:00 PM–4:59 PM)	3	7.0%	4	5.7%	7	6.2%
Hour 6 (6:00 AM–6:59 AM)	3	7.0%	3	4.3%	6	5.3%
Hour 3 (3:00 AM–3:59 AM)	2	4.7%	4	5.7%	6	5.3%
Hour 18 (6:00 PM–6:59 PM)	2	4.7%	4	5.7%	6	5.3%
Hour 17 (5:00 PM–5:59 PM)	0	0.0%	6	8.6%	6	5.3%
Hour 5 (5:00 AM–5:59 AM)	2	4.7%	3	4.3%	5	4.4%
Hour 9 (9:00 AM–9:59 AM)	2	4.7%	3	4.3%	5	4.4%
Hour 14 (2:00 PM–2:59 PM)	2	4.7%	3	4.3%	5	4.4%
Hour 11 (11:00 AM–11:59 AM)	1	2.3%	4	5.7%	5	4.4%
Hour 7 (7:00 AM–7:59 AM)	2	4.7%	2	2.9%	4	3.5%
Hour 21 (9:00 PM–9:59 PM)	1	2.3%	3	4.3%	4	3.5%
Hour 23 (11:00 PM–11:59 PM)	1	2.3%	3	4.3%	4	3.5%
Hour 19 (7:00 PM–7:59 PM)	2	4.7%	1	1.4%	3	2.7%
Hour 20 (8:00 PM–8:59 PM)	2	4.7%	1	1.4%	3	2.7%
Hour 22 (10:00 PM–10:59 PM)	1	2.3%	2	2.9%	3	2.7%
Hour 4 (4:00 AM–4:59 AM)	0	0.0%	3	4.3%	3	2.7%
Hour 10 (10:00 AM–10:59 AM)	0	0.0%	3	4.3%	3	2.7%
Hour 1 (1:00 AM–1:59 AM)	2	4.7%	0	0.0%	2	1.8%
Hour 2 (2:00 AM–2:59 AM)	0	0.0%	1	1.4%	1	0.9%
Hour 0 (12:00 AM–12:59 AM)	0	0.0%	0	0.0%	0	0.0%

Figure 3-21 shows the percentage of Active 911 earlier and CAD earlier alerts across the three D5 limited access roadways. Both I-4 and I-95 had higher percentages of Active 911 earlier events (90% and 75%, respectively) compared to CAD earlier events, while I-75 had a higher percentage of CAD earlier events (68.7%). However, both I-4 and I-95 had low matched event counts of 10 and four, respectively, so it unclear how representative these results are. One reason for the low matched event counts is that FHP does not manage events within city limits (such as I-4 in Orlando), as these are managed by local police departments. Therefore, Active 911 could be useful within these city limits to provide FDOT with earlier warning of traffic incidents before being notified by local law enforcement agencies. Even with the low sample size, the results still suggest that Active 911 can be useful to provide early warning alerts on all D5 limited access roadways.

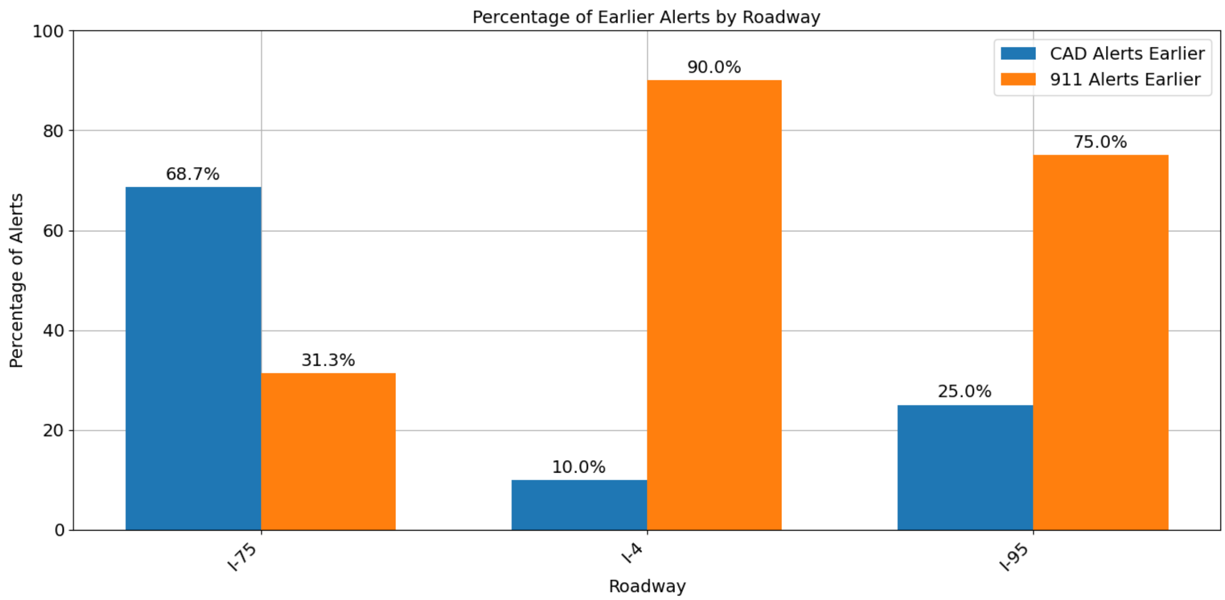

Figure 3-21: Active 911 Earlier and CAD Earlier Percentages by Roadway

Figure 3-22 presents the average time difference (in minutes) for Active 911 earlier and CAD earlier events across the three D5 limited access roadways. On I-4 and I-95, Active 911 earlier events had much higher average time differences compared to CAD earlier events, mainly due to each of these roadways only having one CAD earlier event each. For I-75, CAD earlier events had a slightly higher time difference compared to Active 911 earlier events. The high Active 911 earlier time differences for I-4 and I-95 compared to I-75 suggest that even though these two roadways have a low frequency of Active 911 alerts, these alerts can provide substantial early warning benefits compared to CAD alerts when they occur. These findings could be used by other districts to determine the best roadways where Active 911 could be utilized based on their similarities to these D5 roadways.

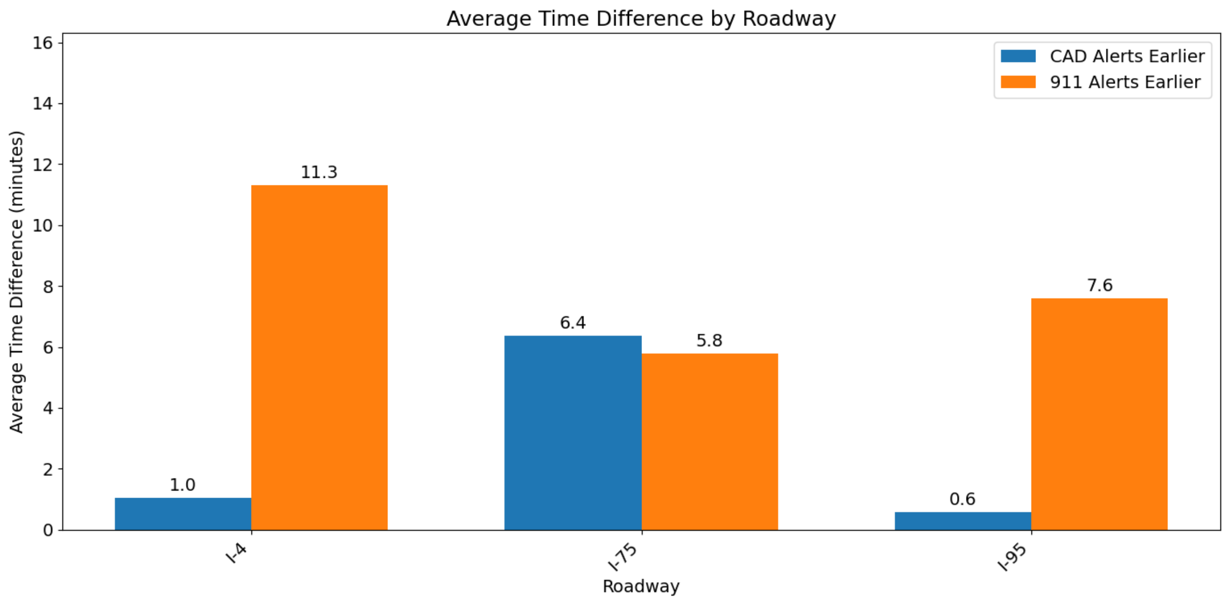

Figure 3-22: Average Time Difference for Active 911 Earlier and CAD Earlier Events by Roadway

Figure 3-23 shows the percentage of Active 911 earlier and CAD earlier events across different hours of the day. CAD earlier events were more frequent during early morning and midday/afternoon hours, while Active 911 earlier events were more frequent during the morning hours of 6:00 AM through 8:59 AM, as well as 12:00 PM to 12:59 PM, 7:00 PM to 8:59 PM, and 1:00 AM to 1:59 AM. The absence of Active 911 data in certain hours (due to the limited number of matched events after filtering) makes it difficult to understand the full potential of Active 911.

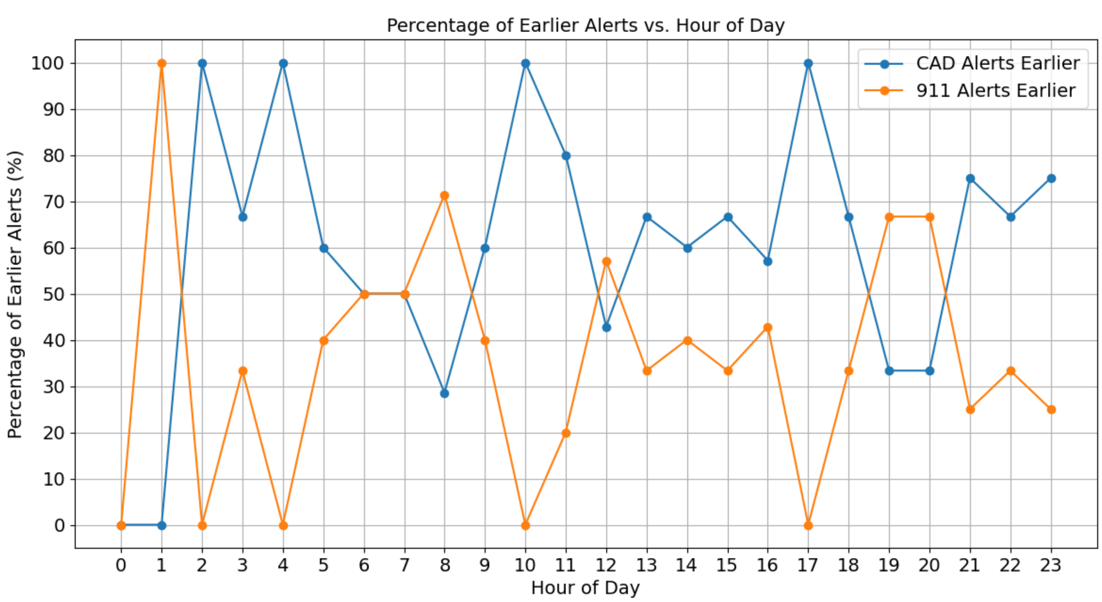

Figure 3-23: Active 911 Earlier and CAD Earlier Percentages by Hour

Figure 3-24 shows the average time difference (in minutes) between Active 911 earlier and CAD earlier events across different hours of the day. These time differences range from 0.7 to 25.2 minutes when Active 911 is earlier and from 0.4 to 11.6 minutes when CAD is earlier. Active 911 earlier events had notably large time differences during the hours of 1:00 AM to 1:59 AM, 7:00 AM to 7:59 AM, 1:00 PM to 1:59 PM, 3:00 PM to 3:59 PM, and 11:00 PM to 11:59 PM. CAD earlier events tended to have larger time differences during early morning and afternoon hours. While the overall pattern does not indicate a consistent trend for either dataset (as Active 911 earlier or CAD earlier events do not have consistently larger time differences than the other), the results suggest that Active 911 alerts could provide timely early warnings compared to CAD alerts during late night and morning peak hours. Based on Table 3-9 and Figures 3-23 and 3-24, Active 911 alerts seem like they would best complement CAD data and provide the most early warning benefits during the early morning hours of 5:00 AM through 8:59 AM. However, the limited data sample makes it hard to fully understand the most beneficial time periods for use of Active 911.

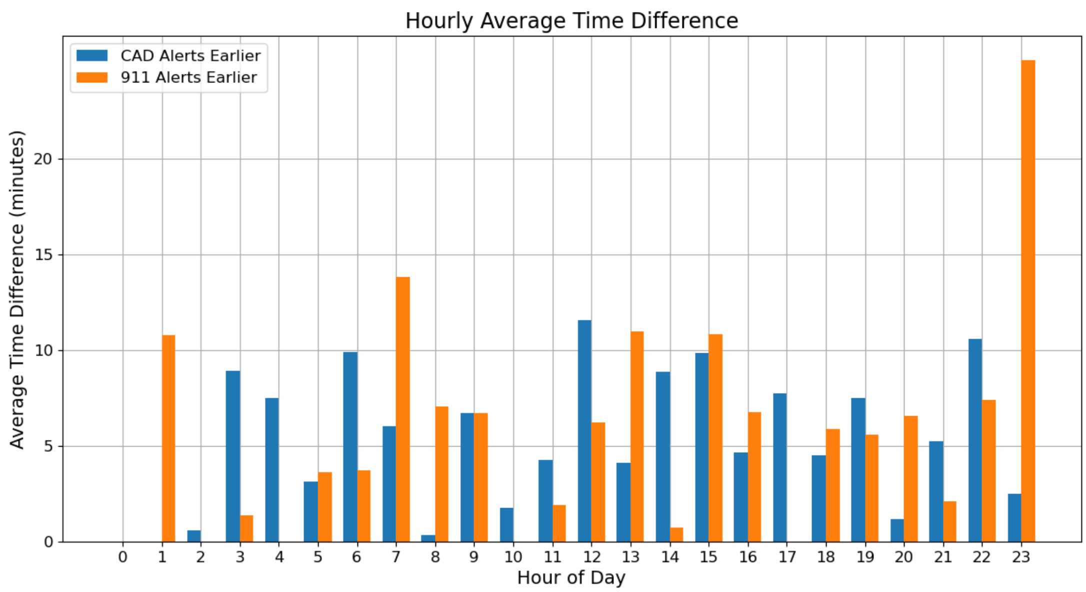

Figure 3-24: Average Time Difference for Active 911 Earlier and CAD Earlier Events by Hour

2. PulsePoint and FHP CAD Comparisons

The 160 matched PulsePoint and CAD events (all of which occurred on I-75) were analyzed with respect to hour of the day. A binary variable named "PulsePoint_earlier" was created with a value of 1 if the PulsePoint alert was earlier and 0 if the CAD alert was earlier. A "time_difference" variable was also created, along with an "hour" variable (similar to the ones created for the Active 911 and CAD comparisons). Since the PulsePoint data contained geographic coordinates, a "distance" variable was also created (like the "distance" variable created for the statewide Waze and CAD comparisons).

Table 3-10 shows the counts and percentages of PulsePoint earlier events and CAD earlier events per hour. Due to rounding, these percentages might not add up to exactly 100%. Overall, 60.63% of the matched events had the PulsePoint alert before the CAD alert. The average time difference for PulsePoint earlier events was 4.92 minutes whereas the average time difference for CAD earlier events was 7.17 minutes. Additionally, the average distance for PulsePoint earlier events was 0.53 miles, and the average distance for CAD earlier events was 0.46 miles. The results in Table 3-10 show that daytime hours tended to have the most matched events, with hours 11 and 12 having substantially higher PulsePoint earlier percentages than CAD earlier percentages.

Table 3-10: Hour-of-Day Counts and Percentages for D5 PulsePoint Earlier and CAD Earlier Events

Feature	**PulsePoint Earlier**		**CAD Earlier**		**Total Matched Events**	
	Count	Percentage	Count	Percentage	Count	Percentage
Hour 13 (1:00 PM–1:59 PM)	8	8.2%	7	11.1%	15	9.4%
Hour 14 (2:00 PM–2:59 PM)	7	7.2%	7	11.1%	14	8.8%
Hour 17 (5:00 PM–5:59 PM)	7	7.2%	4	6.3%	11	6.9%
Hour 10 (10:00 AM–10:59 AM)	4	4.1%	7	11.1%	11	6.9%
Hour 12 (12:00 PM–12:59 PM)	9	9.3%	1	1.6%	10	6.3%
Hour 15 (3:00 PM–3:59 PM)	4	4.1%	6	9.5%	10	6.3%
Hour 16 (4:00 PM–4:59 PM)	4	4.1%	6	9.5%	10	6.3%
Hour 11 (11:00 AM–11:59 AM)	8	8.2%	1	1.6%	9	5.6%
Hour 7 (7:00 AM–7:59 AM)	5	5.2%	4	6.3%	9	5.6%
Hour 22 (10:00 PM–10:59 PM)	6	6.2%	2	3.2%	8	5.0%
Hour 21 (9:00 PM–9:59 PM)	1	1.0%	7	11.1%	8	5.0%
Hour 18 (6:00 PM–6:59 PM)	5	5.2%	1	1.6%	6	3.8%
Hour 8 (8:00 AM–8:59 AM)	4	4.1%	2	3.2%	6	3.8%
Hour 19 (7:00 PM–7:59 PM)	4	4.1%	2	3.2%	6	3.8%
Hour 3 (3:00 AM–3:59 AM)	3	3.1%	2	3.2%	5	3.1%
Hour 5 (5:00 AM–5:59 AM)	3	3.1%	1	1.6%	4	2.5%
Hour 20 (8:00 PM–8:59 PM)	3	3.1%	1	1.6%	4	2.5%
Hour 0 (12:00 AM–12:59 AM)	3	3.1%	0	0.0%	3	1.9%
Hour 6 (6:00 AM–6:59 AM)	3	3.1%	0	0.0%	3	1.9%
Hour 23 (11:00 PM–11:59 PM)	2	2.1%	1	1.6%	3	1.9%
Hour 1 (1:00 AM–1:59 AM)	2	2.1%	0	0.0%	2	1.3%
Hour 9 (9:00 AM–9:59 AM)	1	1.0%	1	1.6%	2	1.3%
Hour 2 (2:00 AM–2:59 AM)	1	1.0%	0	0.0%	1	0.6%
Hour 4 (4:00 AM–4:59 AM)	0	0.0%	0	0.0%	0	0.0%

Figure 3-25 shows the percentage of PulsePoint earlier and CAD earlier alerts for each hour of the day. PulsePoint exhibits 100% earlier alerts during the late night hours from 12:00 AM through 2:59 AM and from 6:00 AM through 6:59 AM, indicating that PulsePoint is most beneficial during nighttime and early morning hours. Overall, PulsePoint has higher percentages of earlier alerts during most hours, with CAD earlier alerts only being just as common or more common than PulsePoint earlier alerts for a few hours, primarily during the afternoon (1:00 PM to 4:59 PM). These results show that PulsePoint could provide early warnings for events throughout the day.

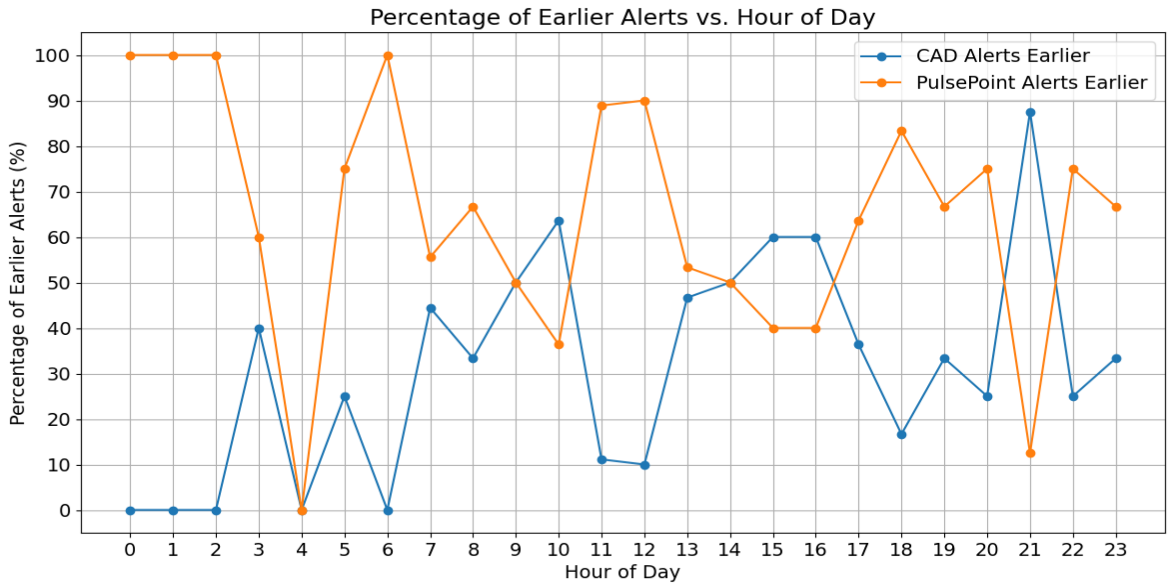

Figure 3-25: PulsePoint Earlier and CAD Earlier Percentages by Hour

Figure 3-26 shows the average time difference (in minutes) for PulsePoint earlier and CAD earlier events across different hours of the day. The time differences range from 1.8 to 10.7 minutes when PulsePoint is earlier and from 4 to 20.6 minutes when CAD is earlier. PulsePoint earlier events had higher time differences than CAD earlier events from 12:00 AM through 3:59 AM, 9:00 AM to 9:59 AM, 11:00 AM to 11:59 AM, and 1:00 PM to 1:59 PM. CAD earlier events had larger time differences than PulsePoint earlier events during most daytime hours. Based on Table 3-10 and Figures 3-25 and 3-26, PulsePoint would likely best complement CAD data and provide the most early warning benefits from morning peak through evening peak hours. However, the limited data sample makes it hard to obtain a representative picture of how PulsePoint data complement and improve on CAD data for different hours.

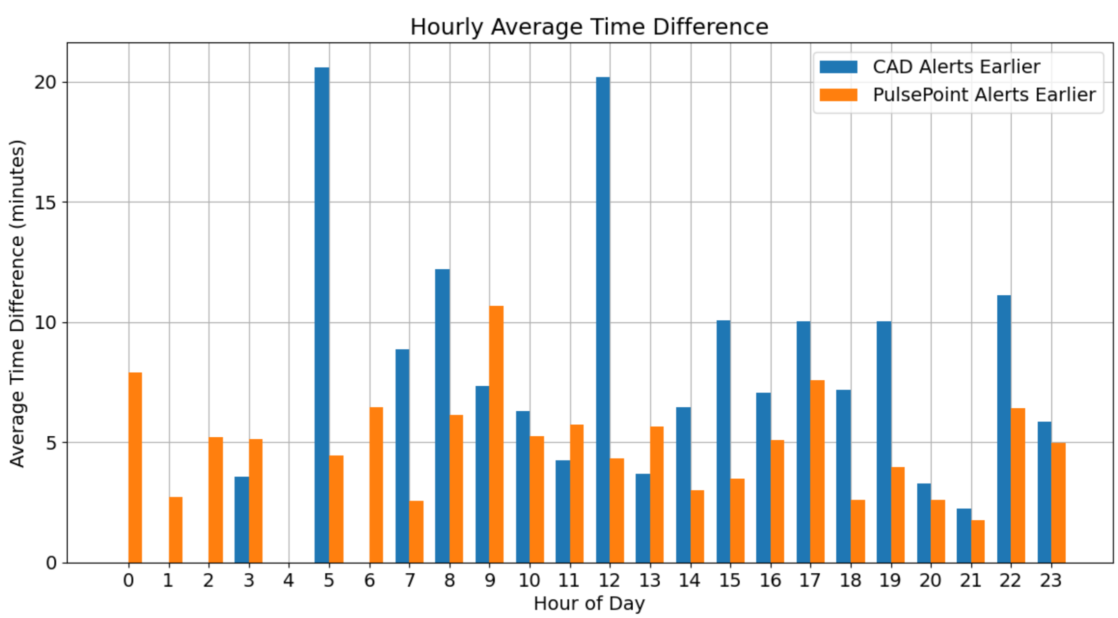

Figure 3-26: Average Time Difference for PulsePoint Earlier and CAD Earlier Events by Hour

Chapter 4: Evaluation of New TIM Data Sources and Early Warning Systems

Evaluating the effectiveness of TIM tools is critical to help transportation agencies detect incidents early and initiate timely and appropriate responses. This chapter presents the findings related to the assessment of changes or expansions to TIM tools currently used in Florida, as well as the hypothetical evaluation of TIM tools implemented in other states but not in Florida. Four TIM tools currently utilized in Florida and two TIM tools utilized in other states were evaluated. The insights obtained in this chapter support improvements to FDOT's TIM network and serve as a foundation for the TIM toolbox presented in Chapter 5.

Section 4.1 discusses the development and application of a classification model to improve the usefulness of TSS alerts in reporting nonrecurring congestion to TMC operators. TSS alerts were compared to FHP CAD incidents to differentiate between recurring and nonrecurring congestion alerts. Various features related to specific sensors and alert history were developed from the TSS data and used to classify alerts as either recurring or nonrecurring congestion. This model was applied to statewide TSS data and FTE TSS data to showcase its flexibility. Considerations for real-time deployment of this framework are also discussed. The programming code for this model is included in Appendix B.

In section 4.2, the potential early warning benefits of expanding Active 911 and PulsePoint to the entire state are estimated. These systems have only been used in D5. Data from these deployments were compared with statewide CAD data to project potential statewide benefits for other FDOT districts. Data details, methodological steps, and results are all discussed.

Section 4.3 discusses how changes to the existing Waze filtering protocols were tested to determine potential early warning benefits. The findings from Chapter 3 showed that Waze data provide substantial early warning benefits compared to relying solely on CAD. By relaxing the filtering protocols to allow lower confidence alerts through, these benefits could increase. However, this change would result in more alerts (both actual and false alerts) reaching the TMC, which could overburden the TMC operators. Evaluating the potential effects of this change can help FDOT decide on the best way to adjust their existing filtering protocols. To conduct these evaluations, an evaluation tool was developed which utilizes raw Waze data and FHP CAD data to determine the potential benefits of relaxing the filtering protocols. These benefits were estimated for the FTE system and D3, illustrating differences in potential early warning benefits and operational costs for TMC operators in these districts. The future potential of this evaluation tool as a real-time application to quickly and accurately identify Waze alerts associated with incidents is also discussed. The programming code used to evaluate the relaxed Waze filtering protocols can be found in Appendix A.

The final evaluations, discussed in section 4.4, focused on two advanced TIM systems implemented in other states. Waycare, which is used in Nevada, leverages traffic and in-vehicle data to predict incidents before they occur and notify emergency services. Carbyne, which is used in Georgia, enables TMC operators to communicate directly with drivers and quickly locate incidents. Potential benefits for Florida were estimated by combining performance metrics from prior deployments with Florida-specific traffic and incident data.

4.1 Development of a Classification Model to Improve TSS Data

The statewide TSS dataset provided to the UCF research team mainly contained duplicate or false alerts, as discussed in section 3.1. However, TSS alerts can be used to quickly identify unexpected slowdowns if properly utilized. This section presents a lightweight, data-efficient classification model developed to improve the operational value of TSS alerts by classifying them as either recurring or nonrecurring congestion. The model acts as a second-layer filter, using only the spatial and temporal attributes of each alert. All features are engineered from historical alert patterns without relying on external data sources, enabling potential real-time deployment. The objective is to improve the operational utility of TSS alerts by reducing false positives and prioritizing alerts that are more likely to represent nonrecurring events.

4.1.1. Data Collection, Filtering, and Matching

As stated in section 3.1.1, TSS alert data and FHP CAD incident data were obtained from FDOT for June 30, 2022 through June 30, 2023. TSS alerts are generated when the speed measured by a sensor falls below a location-specific threshold established by FDOT. These alerts can be triggered by recurring or nonrecurring congestion. The FHP CAD data contain the nonrecurring traffic congestion incidents which occurred on Florida roadways. The TSS dataset contained 692,420 alerts from 1,873 sensors and the FHP CAD dataset contained 116,770 alerts after filtering to only include events on limited access roadways. Figures 4-1 and 4-2 present the geographic distribution of these TSS and CAD alerts, respectively, throughout Florida. The TSS alerts were highly concentrated around Jacksonville, Orlando, and Sarasota (west coast below Tampa) while the CAD alerts had a high concentration around Miami.

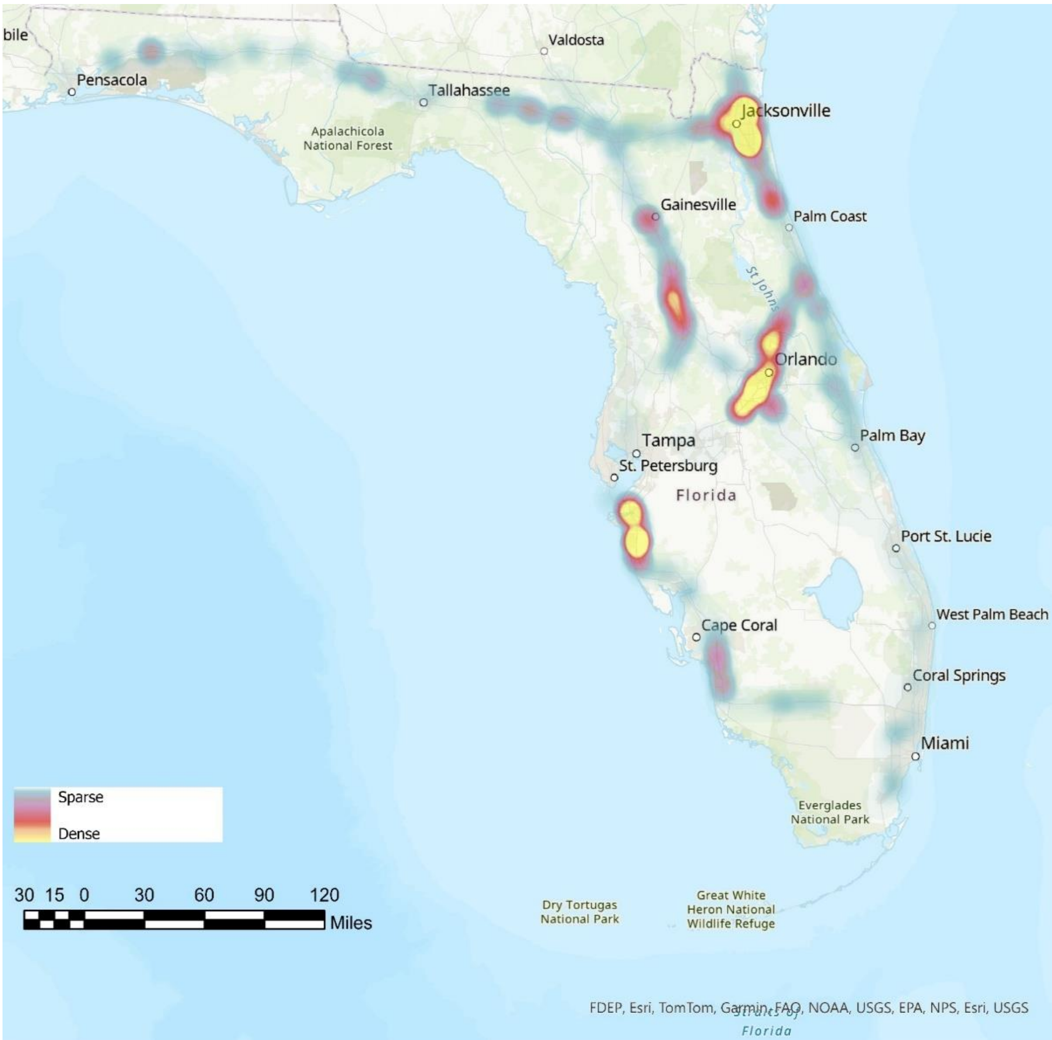

Figure 4-1: TSS Data Coverage

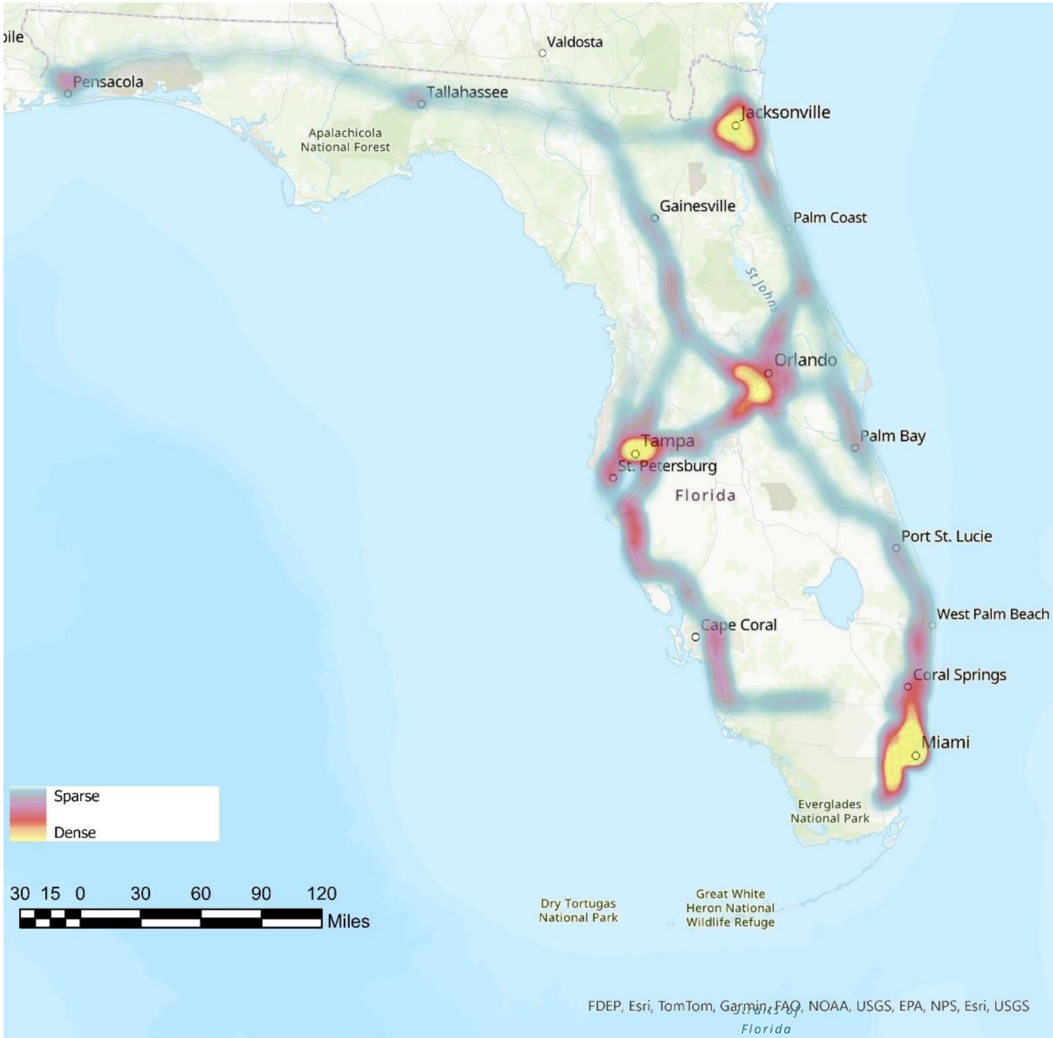

Figure 4-2: FHP CAD Data Coverage

Distinguishing between TSS alerts triggered by nonrecurring incidents and those resulting from recurring congestion is difficult when relying solely on TSS data. To address this challenge, the CAD data were utilized to label the historical TSS alerts as either recurring or nonrecurring congestion. Figure 4-3 presents the average density of TSS alerts within one mile of CAD-reported incidents which occurred between 120 minutes before the CAD incident and 120 minutes after the CAD incident. The density curve shows that TSS alert activity peaks near the time of the CAD event, followed by a gradual decline in alert density as the temporal distance increases. This indicates that multiple TSS alerts are often triggered by a single CAD-reported incident. Therefore, a one-to-many matching approach was implemented, where each CAD event was linked to several temporally adjacent TSS alerts.

The density distribution shown in Figure 4-3 indicates that, on average, only 22.6% of TSS alerts occurred within 15 minutes of a CAD event and 40.7% occurred within a 30-minute window. Although a 30-minute temporal buffer was considered adequate for the previous comparisons in this report, using a 30-minute buffer to match TSS and CAD events would exclude nearly 60% of TSS alerts which could have been triggered due to nonrecurring congestion. Extending the buffer to 60 minutes captures 67.3% of alerts, offering broader coverage of the temporal impact of nonrecurring congestion. Additionally, the low average alert density, peaking at 0.0075 TSS alerts per CAD event, reflects the sparsity of surrounding TSS activity near CAD-reported incidents. This low density is caused by many CAD events having no associated TSS alerts, likely due to there being no sensor near the CAD incident or the incident not resulting in congestion. Therefore, alerts occurring within one mile and ±60 minutes of a CAD event were labeled as nonrecurring congestion (target class of 1) to reflect the real-world duration and spread of incident-induced congestion. TSS alerts outside this window were labeled as recurring congestion (target class of 0), helping to establish a cleaner separation between typical and abnormal congestion patterns. A similar 60-minute matching window was adopted by Hossain et al. (2025) to match Waze alerts with crash reports. With this labeling approach, 78,089 of the 692,420 TSS alerts (11.3%) were labeled as nonrecurring congestion.

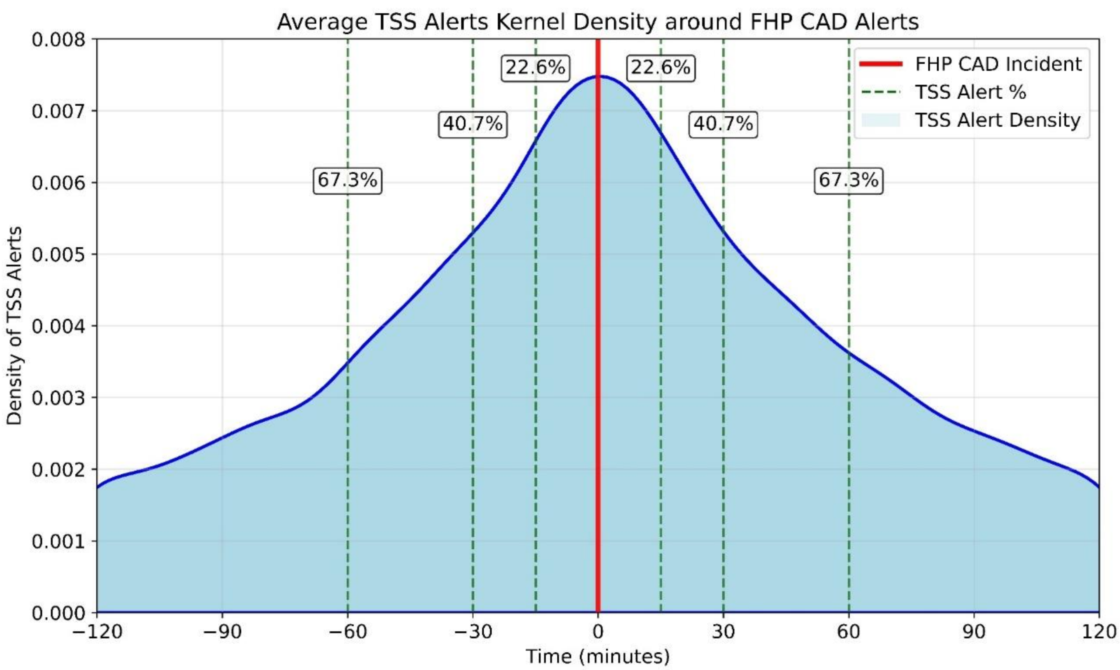

Figure 4-3: Average TSS Alert Kernal Density Surrounding FHP CAD Alerts

4.1.2. Feature Engineering

Feature engineering involves the transformation or creation of new variables from raw data to improve the model's ability to differentiate between classes. For example, given a timestamp, one can derive a binary feature indicating whether an alert occurred on a weekday or a weekend. To ensure data integrity, feature engineering must be performed after the dataset is split into training and testing subsets. This sequencing is critical to avoid data leakage, which would otherwise lead to overly optimistic model performance. For datasets with temporal dependencies (such as the TSS data being studied), a random split is inappropriate. Instead, a temporally ordered split should be employed where the model is trained on earlier data and evaluated on later observations. This approach simulates a real-time operational environment and provides a more realistic estimate of model performance in deployment. In this study, the training set consisted of 484,693 TSS alerts between July 1, 2022, and March 8, 2023 (70% of the data), while the test set comprised 207,727 TSS alerts from March 9, 2023, to June 30, 2023 (30% of the data).

For each TSS alert, the timestamp of the alert and geographic coordinates of the sensor were used to derive a set of engineered features as potential predictor variables. These features capture various spatial, temporal, and behavioral patterns to differentiate between recurring and nonrecurring congestion. The methodologies used to compute each of these features and how each feature contributes to the classification task are discussed below. All values and figures discussed for these features are for the training data only.

1. Alerts per Day

This feature (Equation 4-1) calculates the average daily alert frequency for a sensor by dividing the total number of alerts at the sensor by the operational period in days. For the training data, the operational period is defined as the number of days between the first and last recorded alert for each sensor. This metric establishes the normal operational baseline for each sensor location. When a typically low-activity sensor experiences elevated alert frequency, it is likely that the identified congestion is due to an incident rather than routine congestion patterns.

$$Alerts\ per\ day = \frac{Total\ alerts}{Operational\ period} \tag{4-1}$$

The cumulative distribution of average daily alerts shown in Figure 4-4 reveals that 80% of sensors produced fewer than 12.9 alerts per day, with values ranging from 0.01 to 200.1. This indicates a substantial concentration of low-activity sensors within the network. Such sparsity introduces heterogeneity in temporal alert density, which can hinder the model’s ability to reliably differentiate between recurring and nonrecurring congestion patterns. This pronounced variability in alert frequency across sensors underscores the value of incorporating the “alerts per day” feature into the model. It provides essential context for typical sensor activity, allowing the model to account for location-based differences. However, given that many sensors report very few alerts per day, this feature alone is insufficient. Additional features are required to compensate for the limited temporal information available from low-activity sensors.

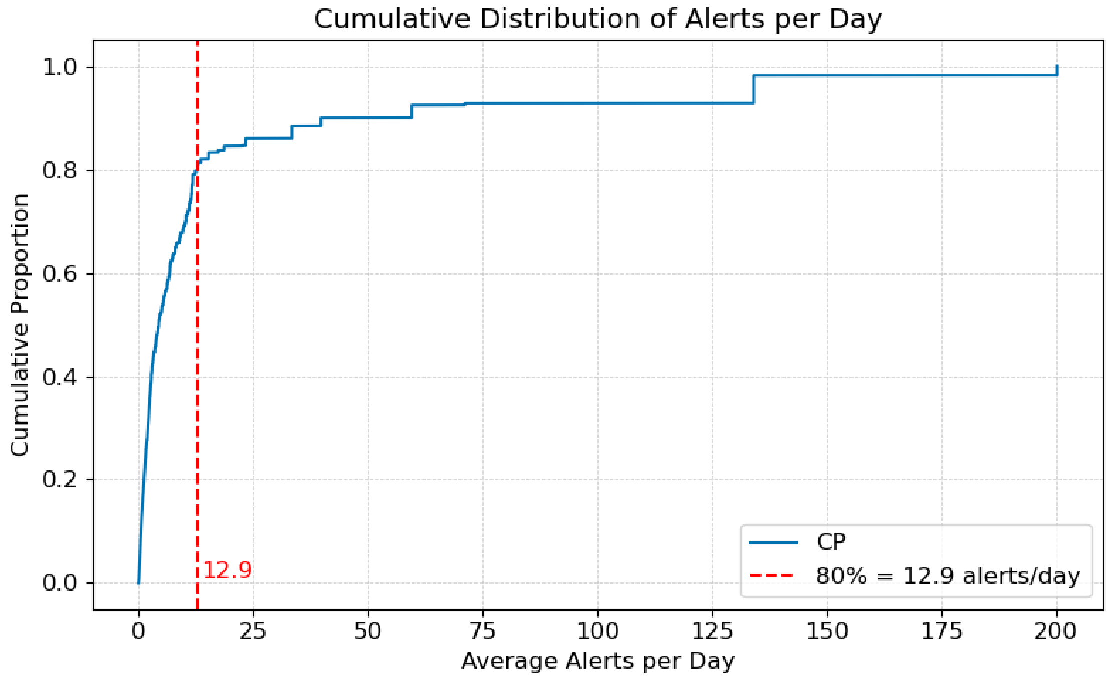

Figure 4-4: Cumulative Distribution of Average Daily Alerts per Sensor

2. Sensor Predictability

This metric (Equation 4-2) calculates the inverse of the sensor's alert frequency variance, quantifying behavioral consistency. Highly predictable sensors maintain consistent daily alert counts with minimal variation, while unpredictable sensors exhibit significant variability in daily alert frequency. When highly predictable sensors deviate from their established patterns, such deviations strongly indicate incident occurrence. Conversely, naturally variable sensors provide less discriminative information due to their inherent operational inconsistency.

$$Sensor\ predictability = 1 \Big/ \left[1 + \frac{std(alerts_{24h})}{(Alerts\ per\ day) + 1}\right] \tag{4-2}$$

Where:

std($alerts_{24h}$) = standard deviation of the number of alerts within the past 24 hours. Note that the constant 1 in the denominator is added to prevent division by zero.

Figure 4-5 shows that recurring congestion alerts (class 0) are generally associated with sensors exhibiting higher predictability, while nonrecurring alerts (class 1) tend to originate from sensors with more variable behavior. The mean sensor predictability is 0.47 for recurring alerts and 0.38 for nonrecurring alerts, indicating a measurable separation between the two target classes. Given the theoretical range of 0 to 1, the mean predictability values indicate higher predictability for recurring alerts and lower predictability for nonrecurring alerts.

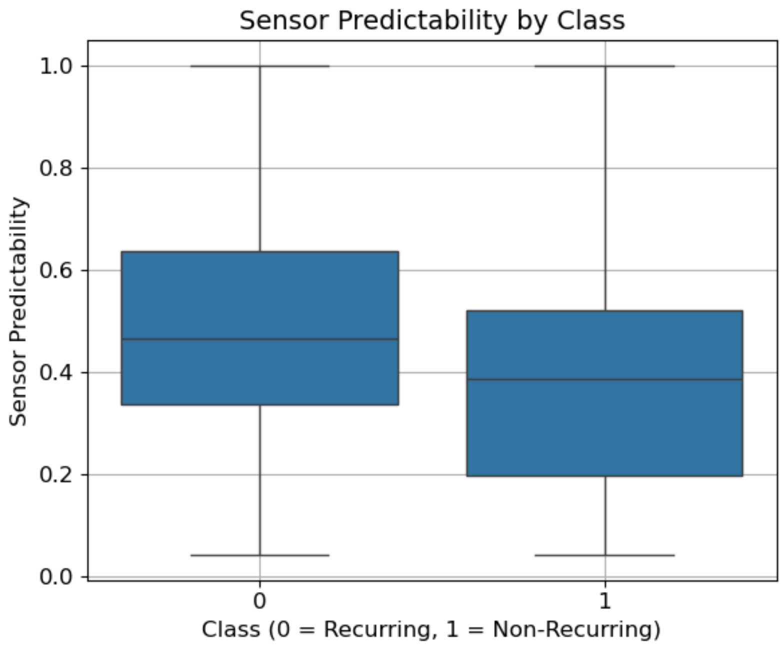

Figure 4-5: Boxplot of Sensor Predictability for Recurring and Nonrecurring Congestion TSS Alerts

3. *Minutes since Last Alert*

This feature captures the temporal gap between the current alert and the previous alert from the same sensor, helping to distinguish between alerts that occur after a long period of no activity and those that are part of an ongoing pattern. Figure 4-6 shows the proportion of alerts that occurred within various intervals of the previous alert relative to the total number of alerts in the target class (recurring or nonrecurring). Nonrecurring alerts are more concentrated in the 0–5 minute bin and the nonrecurring alert proportion remains higher than the recurring alert proportion in the 5–10 minute range. Around 10–20 minutes, the distribution becomes more balanced between the two classes. Beyond that point, the pattern reverses where recurring alerts begin to dominate, especially in the larger-gap bins such as 1–2 hours and >4 hours. This trend reflects the tendency of nonrecurring events to cluster briefly after long quiet periods while recurring alerts follow more regular temporal patterns.

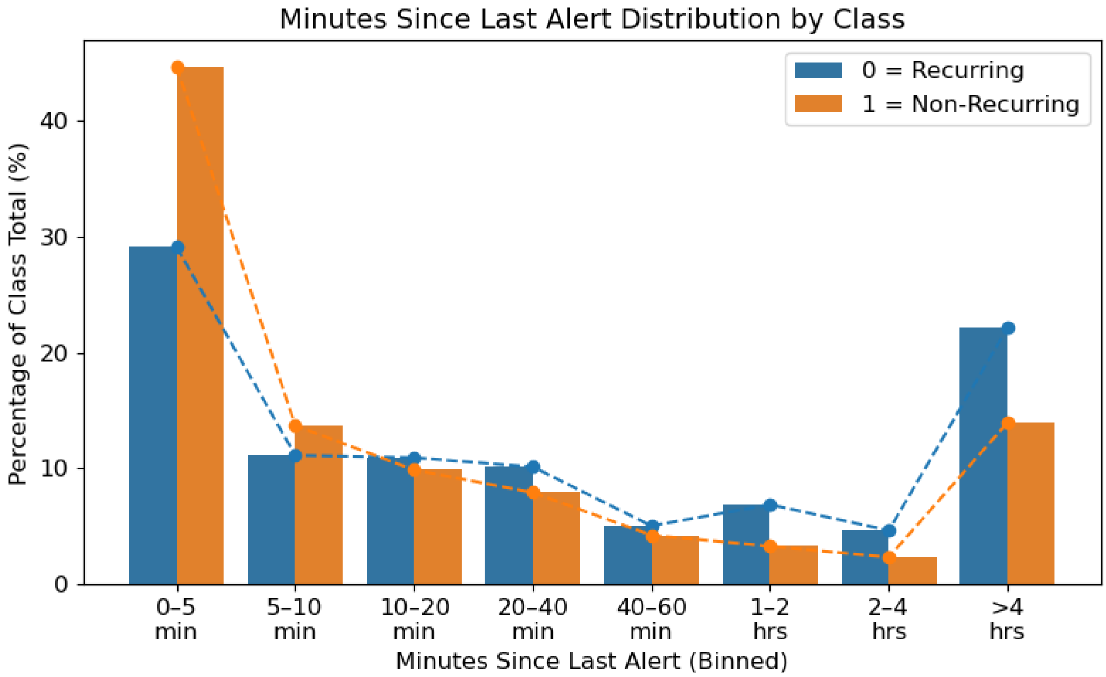

Figure 4-6: Distribution of Minutes since Last Alert for Recurring and Nonrecurring Congestion TSS Alerts.

4. Weighted Alert Density

This feature quantifies how strongly recent alert activity is concentrated near the time of the current alert at the same sensor. It assigns higher weights to alerts occurring closer in time, such as those within the past one hour, and progressively lower weights to alerts further in the past, up to 24 hours. A higher score indicates that most of the alert activity occurred recently, which is often characteristic of lingering or sustained traffic disruptions. In contrast, a lower score reflects a more evenly distributed pattern over time, which is typical of routine and recurring congestion.

Let A_h denote the number of alerts detected in the past h hours, for $h \in \{1,2,6,24\}$. Then the alert density gradient is defined as:

$$\textit{Weighted alert density} = \left(A_1 + \frac{A_2}{2} + \frac{A_6}{6} + \frac{A_{24}}{24}\right) \Big/ A_{24} \tag{4-3}$$

Figure 4-7 shows the distribution of the weighted alert density feature across recurring (class 0) and nonrecurring (class 1) alerts. Nonrecurring alerts tend to have higher weighted alert density values, indicating a recent burst of alert activity relative to the past 24 hours. In contrast, recurring alerts generally exhibit lower values, reflecting more gradual or evenly distributed patterns. This trend supports the feature's relevance in distinguishing between sudden, irregular events and expected, pattern-based congestion.

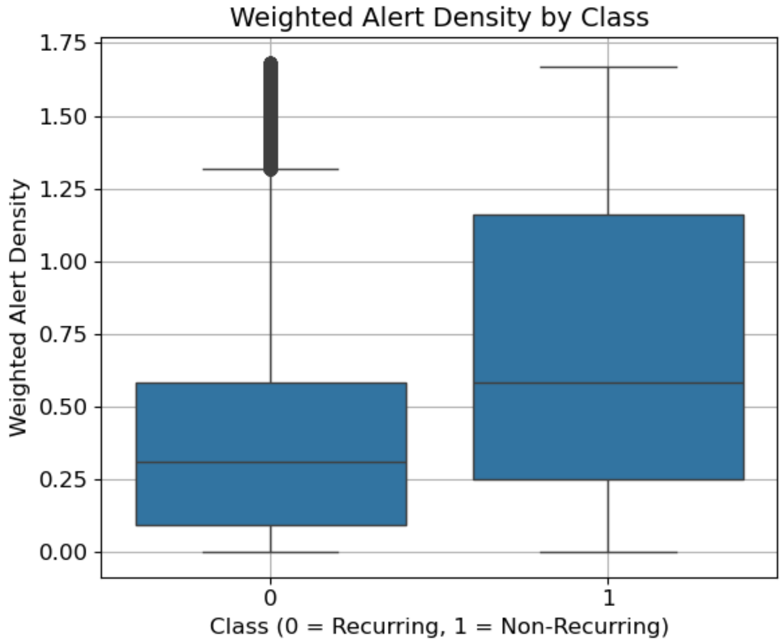

Figure 4-7: Boxplot of Weighted Alert Density for Recurring and Nonrecurring Congestion TSS Alerts

Table 4-1 summarizes the engineered features, showing their definitions, theoretical range of values, and actual range of values from the training set.

Table 4-1: Summary of Engineered Features.

Feature	Definition	Theoretical Range	Actual Range
Alerts per day	Average daily count of alerts recorded at a sensor location.	Unbounded positive value	0.01 – 200.13
Sensor predictability	Inverse variation in 24-hour alerts counts across sensor alerts.	Between 0 and 1, inclusive	0.04 – 1.00
Minutes since last alert	Time elapsed in minutes since the previous alert from the same sensor relevant to current alert.	Unbounded positive value	0 – 349,903
Weighted alert density	Time-weighted measure of prior alert activity over the past 24 hours.	Between 0 and 1.708, inclusive	0.42 – 1.69

4.1.3. Model Selection and Evaluation

To identify appropriate modeling methods, it was important to understand the characteristics of the dataset. Each observation in this dataset corresponded to a TSS alert which was labeled as either recurring congestion (class 0) or nonrecurring congestion (class 1). The dataset contained a mix of temporal and spatial features, with a substantial number of samples and a significantly imbalanced class distribution since most alerts corresponded to recurring congestion. The relationships among the potential predictor variables were expected to be non-linear, which limits the applicability of simpler models.

Logit-based models, such as logistic regression, are valued for their ability to reveal how specific variables influence outcomes, making them well-suited for contexts where interpretability is a primary objective (Iranitalab & Khattak, 2017). However, the model's assumption of a linear relationship between features and log-odds limits its ability to capture the complex, non-linear patterns present in traffic alerts data related to congestion. For the TSS data, the objective is not explanatory insight but operational effectiveness in reducing false TSS alerts. Therefore, interpretability was not prioritized in model selection.

Support vector machines can handle non-linear decision boundaries; however, modeling non-linear relationships typically requires kernel methods, which are computationally intensive and sensitive to kernel choice, making them less suitable for large datasets or real-time deployment (Nalepa & Kawulok, 2018). Neural networks, while powerful, are typically better suited for high-dimensional data such as images or time series and may not offer substantial performance benefits for structured, tabular data like the TSS data (Borisov et al., 2024).

Given these considerations, XGBoost was selected as the preferred model. It is well-suited for large-scale, tabular data, efficiently handles class imbalance, and captures complex non-linear interactions between features (Imani et al., 2025; Mushava & Murray, 2024). Its ability to deliver high predictive performance without extensive preprocessing, combined with its maturity and stability in operational settings, makes it an effective choice for developing a classifier aimed at reducing false alarms in traffic management applications.

While many metrics exist to evaluate classification models, only a subset of these measures is typically reported, depending on the goals of the application. In this study, three metrics were selected to evaluate the model based on operational priorities: accuracy, TPR, and FPR. Accuracy (Equation 4-4) measures the model's overall prediction capability across both classes. This is similar to the equation for accuracy shown in Equation 3-1. High values are preferred as they indicate that the model is better in correctly classifying alerts. Reported accuracy values for similar classification tasks in prior studies typically ranged between 0.81 and 0.97 (Dogru & Subasi, 2018; Hossain et al., 2025; Lu et al., 2012; Xie et al., 2022). The TPR (Equation 4-5) is the proportion of actual nonrecurring incidents correctly detected, similar to the TPR calculated in Equation 3-3. High values are preferred as they indicate that the model is good at correctly identifying nonrecurring congestion alerts. Reported TPR values for similar classification tasks in prior studies typically ranged between 0.58 and 0.82 (Abdel-Aty et al., 2024; Hossain et al., 2025; Imani et al., 2025). The FPR (Equation 4-6) is the proportion of recurring alerts incorrectly classified as nonrecurring, similar to the FPR calculated in Equation 3-5. Low values are preferred as they indicate that less false alarms would be sent to TMCs operators. Reported FPR values for similar classification tasks in prior studies typically ranged between 0.11 and 0.32 (Abdel-Aty et al., 2024; Anbaroglu et al., 2014; Hossain et al., 2025). This set of metrics provides a balanced view of model performance in terms of both detection effectiveness and operational impact.

$$Accuracy = \frac{Correctly\ classified\ alerts}{Total\ alerts}$$

(4-4)

$$TPR = \frac{Correctly\ classified\ non - recurring\ alerts}{Total\ non - recurring\ alerts}$$

(4-5)

$$FPR = \frac{Incorrectly\ classified\ recurring\ alerts}{Total\ recurring\ alerts}$$

(4-6)

Two additional performance measures were used to compare the model's results to the existing TSS data handled by TMC operators. The precision (Equation 4-7) of the model represents how many of the alerts received by the operators are actually related to nonrecurring congestion. For the existing TSS data, the denominator is the total number of TSS alerts which require operator attention. For the classification model, the denominator is the total number of alerts predicted to be nonrecurring. Having higher precision for the model compared to existing conditions indicates that more of the alerts being reported to the TMC are actually nonrecurring alerts. The percent change in false alerts received (Equation 4-8) is the difference between the quantity of recurring congestion alerts received by the TMC operators for the base TSS data ($Recurring_{base}$) and the quantity of recurring congestion alerts received by the TMC operators after the model is applied ($Recurring_{model}$). Positive values are preferred since they indicate that the model results in less recurring congestion TSS alerts being sent to the operators, thereby reducing the time operators have to spend handling these alerts.

$$Precision = \frac{Non - recurring\ alerts\ received\ by\ operators}{Total\ alerts\ received\ by\ operators}$$

(4-7)

$$Percent\ change\ in\ false\ alerts = \frac{Recurring_{base} - Recurring_{model}}{Recurring_{base}} \times 100\%$$

(4-8)

4.1.4. Modeling Results

Before modeling, the TSS data were analyzed to determine the variation in hourly frequencies and current baseline performance. Figure 4-8 presents the average hourly distribution of TSS alerts for weekdays (Monday through Friday) and weekends (Saturday and Sunday). While a steady increase in alerts is observed during weekday mornings, the expected bimodal peak typically associated with commuter traffic is not prominent. Instead, both recurring and nonrecurring alerts are concentrated around the early afternoon. This pattern remains consistent across both weekdays and weekends, though weekends exhibit lower early-morning activity (06:00 AM to 08:00 AM) and a midday concentration between 11:00 AM and 2:00 PM. The absence of pronounced morning and evening peaks could be attributed to the threshold-based nature of TSS alerting. It could also reflect the aggregation of data across urban and rural highway segments, where rural areas are less likely to follow conventional commuter traffic patterns.

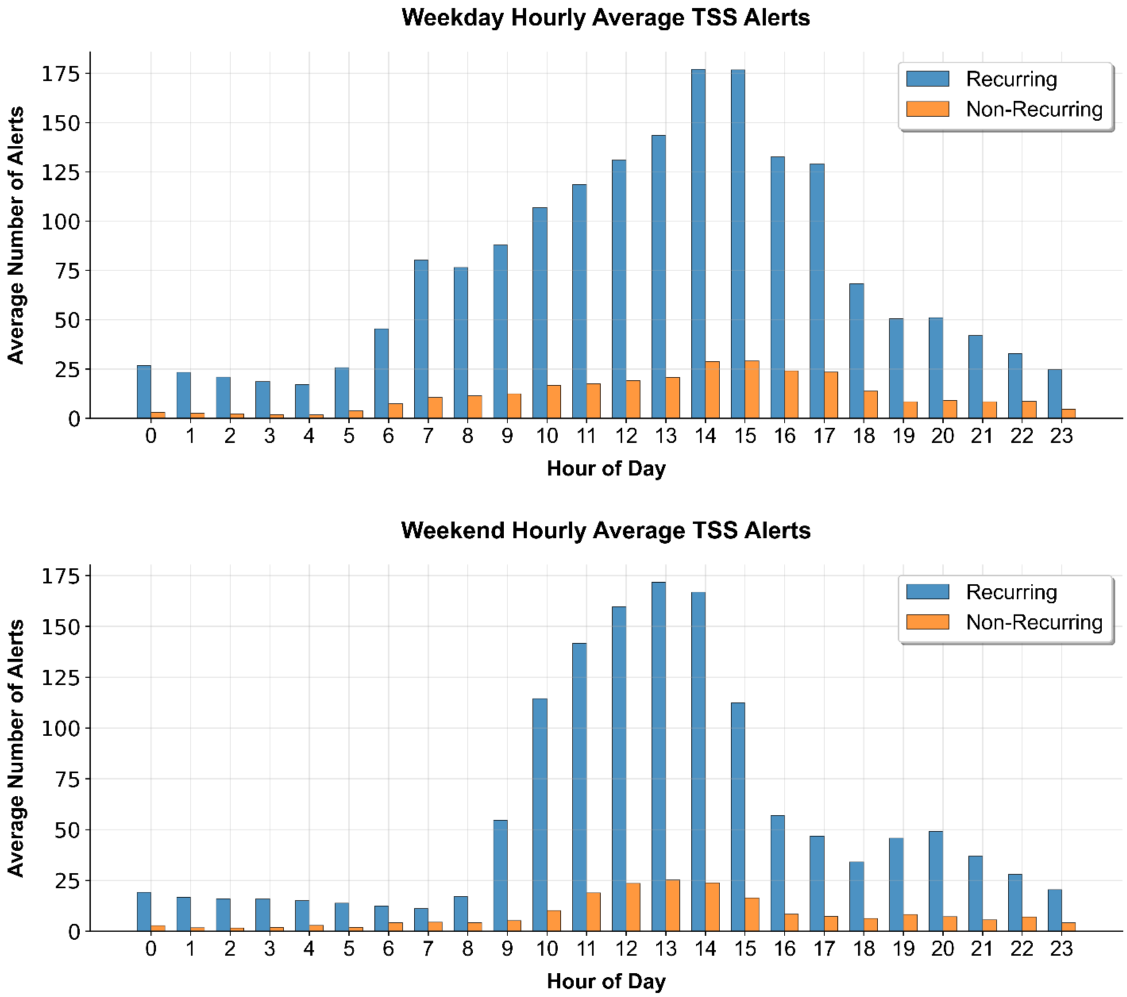

Figure 4-8: Average Hourly TSS Alert Distribution for Weekdays and Weekends

Each TSS alert in the dataset was labeled with an action taken that reflected how it was handled by either the SunGuide system or TMC operators. For analysis purposes, these actions were grouped into two categories: system resolved and operator resolved. System resolved alerts are ones which were automatically cleared without operator intervention, typically because the situation was closed at the dispatch level. In contrast, operator resolved alerts are ones which required review by a TMC operator. Table 4-2 summarizes the distribution of alerts by operator and system resolved categories. The operator resolved alerts in the test dataset will be compared with the results from the model to determine if the model would improve precision and reduce the number of false alerts received by the TMC operators compared to the existing procedures.

Table 4-2: Summary of Statewide TSS Alert Data

Category	Training Dataset				Test Dataset			
	Recurring (0)		Nonrecurring (1)		Recurring (0)		Nonrecurring (1)	
	Count	Percent	Count	Percent	Count	Percent	Count	Percent
Operator Resolved	236,500	89.3%	28,454	10.7%	108,317	87.3%	15,729	12.7%
System Resolved	197,473	89.9%	22,266	10.1%	72,041	86.1%	11,640	13.9%
Total	**433,973**	**89.5%**	**50,720**	**10.5%**	**180,358**	**86.8%**	**27,369**	**13.2%**

Using the engineered features, a classification model was developed using XGBoost modeling to determine whether a TSS alert corresponds to a recurring or nonrecurring incident based on the labels derived from CAD incidents. To ensure the model performed well on unseen data, five-fold cross validation was used and hyperparameters were tuned appropriately. Refer to section 3.2.4 for information on cross-validation and hyperparameter tuning.

Figure 4-9 presents the confusion matrix after applying the developed model to the test set. This matrix summarizes the number of correct and incorrect predictions made by the model for each class. The developed model resulted in 18,664 true positives, 8,705 false negatives, 65,554 false positives, and 114,804 true negatives for the test set. Using these values in Equations 4-4 through 4-7 resulted in an accuracy of (18,664 + 114,804) / 207,727 = 0.643, a TPR of 18,664 / (18,664 + 8,705) = 0.682, an FPR of 65,554 / (65,554 + 114,804) = 0.363, and precision of 18,664 / (18,664 + 65,554) = 0.222. Based on the counts in Table 4-2, the current TSS system yields a precision of 15,729 / (108,317 + 15,729) = 0.127, indicating that the model improved precision by 75%. The percent change in false alerts due to applying the model was (108,317 – 65,554) / 108,317 = 39.5%. These results show that applying the model to the test dataset would cause the alerts sent to TMC operators to contain fewer false alerts and be more likely to indicate nonrecurring congestion than without the model.

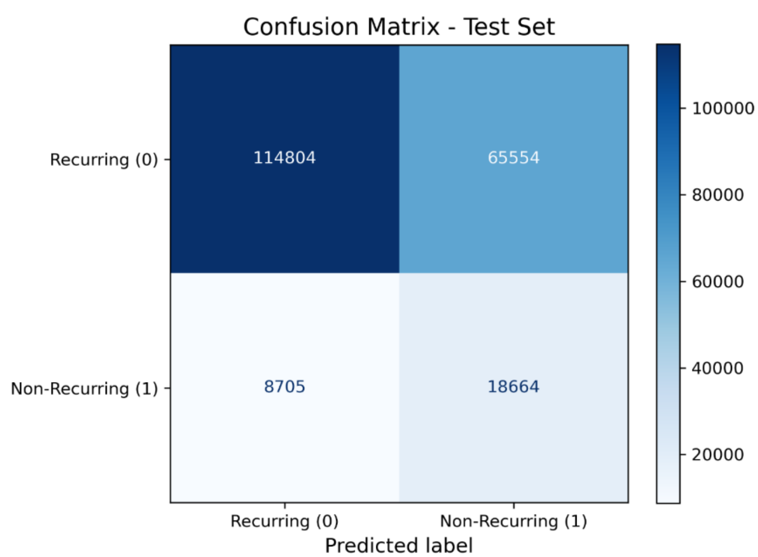

Figure 4-9: Statewide Test Set Confusion Matrix

The model results were also analyzed with respect to hour and day of the week to reveal patterns which can inform operational deployment of the model. As shown in Figure 4-10, the highest TPRs occur between hours 8 and 18 (8:00 AM through 6:59 PM) on Tuesday through Friday, indicating this is the most reliable period for automated alert classification. The average TPR for this period is 0.731. Conversely, TPRs drop significantly during overnight hours (12:00 AM to 5:00 AM) when alert volume is low. During these times, manual verification can be preferable due to the reduced model confidence and an increased risk of misclassification. Additionally, the low volume of alerts during overnight hours limits the operational benefits of the model since it is unlikely to significantly ease the workload of TMC operators.

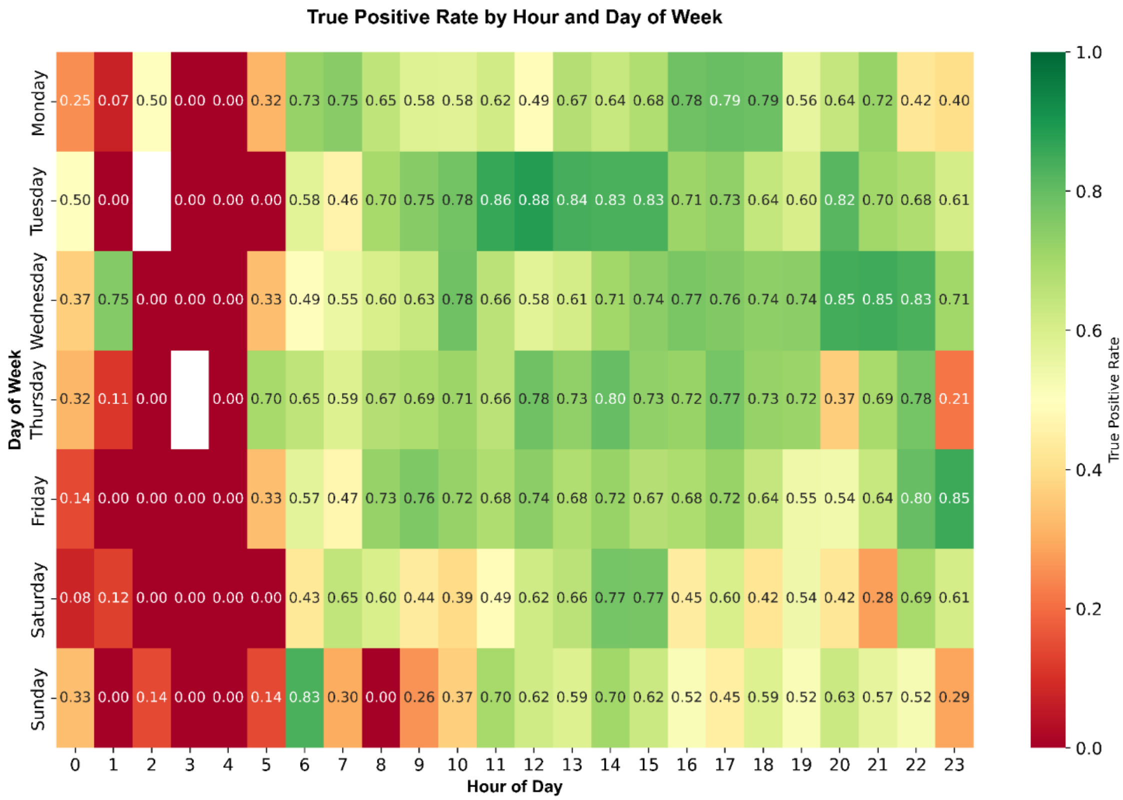

Figure 4-10: Heatmap of True Positive Rate by Hour of Day

Figure 4-11 shows that the highest FPRs occur on Monday through Friday from 2:00 PM to 6:59 PM. This might reflect background traffic fluctuations during peak travel periods, which reduce the model's ability to differentiate between recurring and nonrecurring events. In contrast, late evening hours tend to exhibit lower FPRs, suggesting that automated classification could be beneficial during those periods. The early morning hours have very low FPRs due to the low number of TSS alerts, so manual verification should be used during those times. Based on these temporal patterns, the model would likely be most beneficial to operators between 9:00 AM and 6:59 PM on Tuesday through Friday. The existing TSS alert reporting system can be used during nighttime hours and on Mondays and weekends. Depending on TMC activity, the existing system might also be preferred during late afternoon and early evening weekday hours to avoid excessive false alerts.

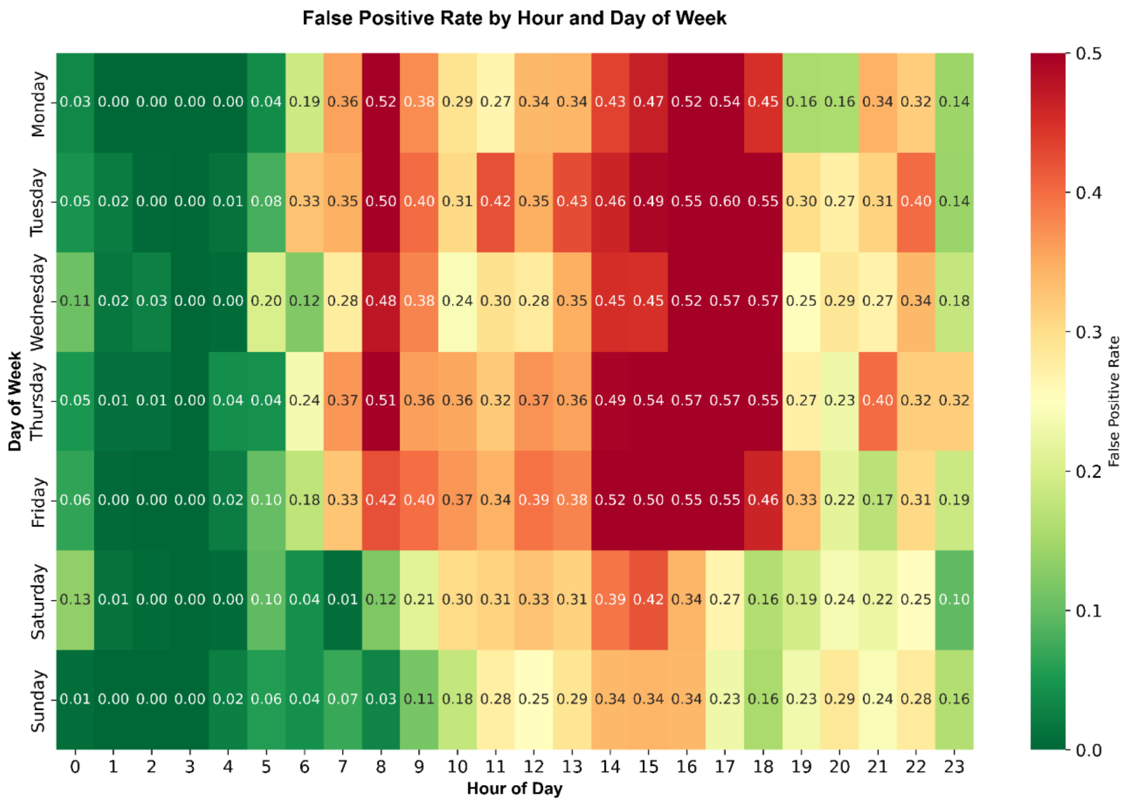

Figure 4-11: Heatmap of False Positive Rate by Hour and Day

To evaluate the generalizability of the proposed modeling methodology, the same modeling approach was applied to a different dataset consisting only of TSS alerts from FTE roadways. These FTE TSS alerts were obtained from the IDS datasets provided to the UCF research team by FTE. The FTE TSS alerts from January 1, 2024, to March 26, 2025, were split into a training set covering January 1, 2024, to December 8, 2024, and a test set covering December 9, 2024, to March 26, 2025. Table 4-3 shows the composition of the training, test, and overall datasets. Unlike the statewide TSS data, the FTE dataset included only operator resolved alerts with no system resolved alerts. This key difference makes the FTE dataset a useful contrast case for evaluating model generalizability.

Table 4-3: Summary of FTE TSS Alert Data

Label	**Training**	**Test**	**Total**
Recurring (0)	7,011 (88.1%)	3,082 (90.3%)	10,093 (88.7%)
Nonrecurring (1)	951 (11.9%)	331 (9.7%)	1,282 (11.3%)
Total	**7,962**	**3,413**	**11,375**

Figure 4-12 shows the confusion matrix for the FTE test set. The developed FTE model had an accuracy of (2,057 + 216) / 3,413 = 0.666, a TPR of 216 / (216 + 115) = 0.653, an FPR of 1,025 / (1,025 + 2,057) = 0.333, and precision of 216 / (216 + 1,025) = 0.174. Based on the counts in Table 4-3, the current TSS system for FTE roadways yields a precision of 331 / (3,082 + 331) = 0.097, indicating the model improved precision by 79%. The percent change in false alerts due to applying the model was (3,082 –1,025) /3,082 = 66.7%. These results are consistent with those obtained from the statewide dataset, demonstrating the robustness of the methodology and its applicability to different sized roadway networks.

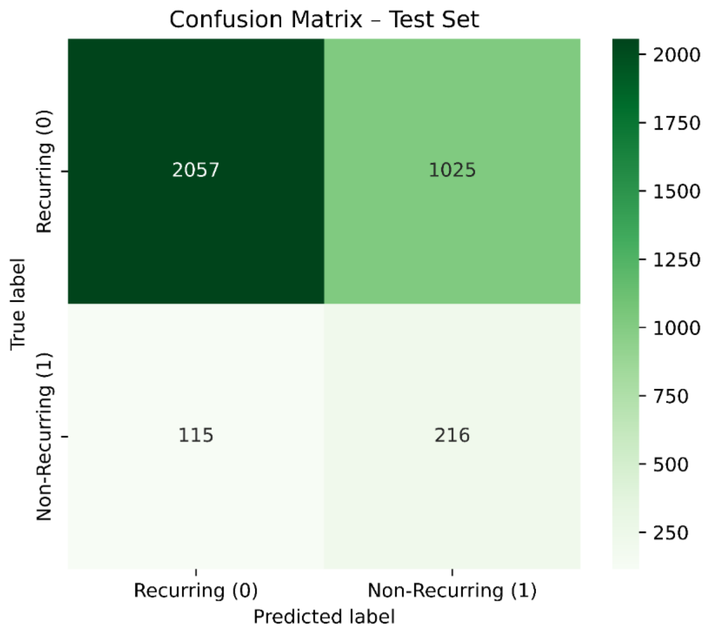

Figure 4-12: FTE Test Set Confusion Matrix

The proposed methodology is feasible for real-time deployment and can be integrated into operational traffic management systems. All engineered features are derived exclusively from recent alert history and rely solely on sensor-level and timestamp-based inputs without requiring external data sources. By maintaining a rolling window of historical alerts for each sensor (with the appropriate length of this window dependent on sensor activity), the system can efficiently update relevant statistics and compute the required features for each incoming alert in real time. This setup will enable the model to generate timely predictions with minimal processing overhead and support scalable integration into TMC workflows. While this TSS classification framework shows strong generalizability and is designed for real-time deployment, limitations related to the labeling process, static temporal buffers, and lack of live-system testing remain. Future research should address these aspects to support full operational integration and further improve classification accuracy.

4.2 Evaluation of Active 911 and PulsePoint to Improve Early Detection in Florida

Chapter 3 in this report estimated the potential early warning benefits provided by existing TIM tools used in Florida (specifically FHP CAD, Waze, Active 911, and PulsePoint). These analyses were important to provide a performance baseline which can be used to evaluate potential changes or expansions. This section builds on these previous efforts by evaluating the potential benefits of expanding Active 911 and PulsePoint usage throughout Florida. D5 is the only FDOT district which has utilized both these data sources. Comparisons of these sources with FHP CAD in Chapter 3 showed that both systems provided early warning benefits in D5. Using the results of these comparisons, the potential benefits of expanding these systems statewide were estimated.

This section details the evaluations of expanding Active 911 and PulsePoint statewide. The goal of these evaluations is to help FDOT understand each system's potential so they can identify possible locations for future implementation of these systems. Relevant findings from Chapter 3 (such as the number of Active 911 and PulsePoint alerts with matched FHP CAD alerts and lead-time advantages over FHP CAD alerts) were used to estimate annual early detection benefits on Florida limited access facilities. Associated congestion reduction benefits due to earlier detection were also estimated based on delay cost assumptions from prior research by Sandt, McCombs, Cornelison, et al. (2023).

Section 4.2.1 discusses the evaluation of Active 911 expansion and section 4.2.2 discusses the evaluation of PulsePoint expansion. Each evaluation required various steps and assumptions to obtain alert projections for D5 and all Florida limited access facilities. Figure 4-13 illustrates the methodology used to evaluate the potential early detection and congestion reduction benefits for the statewide implementation of these systems. Three main data sets were used for these evaluations: statewide FHP CAD data from July 2022 through June 2023 (as discussed in section 3.1), matched Active 911-CAD pairs for D5 limited access facilities, and matched PulsePoint-CAD pairs for D5 limited access facilities. Details on how the two matched pair datasets were obtained can be found in section 3.3. The first step in the methodology was to filter the statewide CAD data to only include alerts on D5 limited access facilities. Then, the matched pair datasets were used to project the ratio of matched pairs to CAD alerts for an entire year. These ratios were then used to estimate the annual number of matched pairs for all statewide limited access facilities based on the full statewide CAD dataset. Next, early detection benefits were estimated based on the percentage of D5 matched pairs with Active 911 or PulsePoint earlier and the average Active 911 or PulsePoint lead times for these pairs. Finally, the projected early detection benefits were used to estimate congestion reduction benefits. The early detection and congestion reduction benefits were estimated individually for limited access roadway segments within each district. For example, I-75 passes through D1, D2, D4, D5, D6, and D7, so separate benefits were calculated for each of these six I-75 portions.

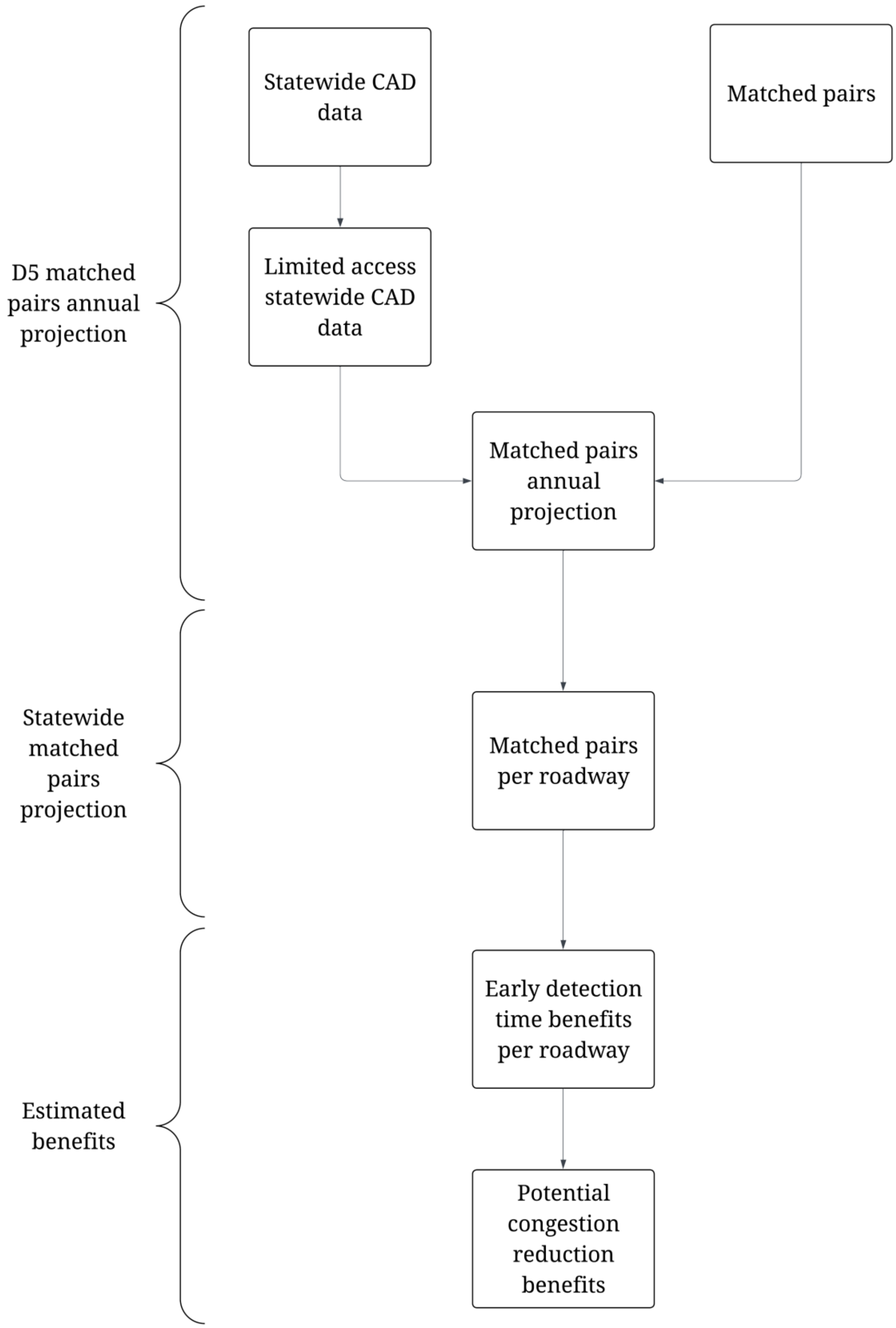

Figure 4-13: Methodology to Evaluate the Potential Early Detection and Congestion Reduction Benefits for Statewide Active 911 and PulsePoint Expansions

4.2.1. Evaluation of Statewide Active 911 Expansion

In Chapter 3, a one-mile spatial buffer and a 30-minute temporal buffer were used to identify matched Active 911–CAD pairs. These buffers account for the same incident being reported at slightly different times and locations in each dataset. Using these buffers, 113 matched Active 911-CAD pairs were identified, with 43 pairs (38.05%) having an Active 911 alert before the first CAD alert. For these 43 matched pairs, Active 911 had an average lead time of 7.07 minutes compared to CAD. These findings are important to estimate the benefits of expanding Active 911 statewide.

1. D5 Annual Projection

Since D5 is the only FDOT district to use Active 911, the number of matched Active 911-CAD pairs per year was determined for D5. First, the statewide FHP CAD dataset was filtered to only include Associated alerts (alerts linked to an existing SunGuide event) and New Event alerts (alerts for which a new SunGuide event was created) on D5 limited access facilities. This is consistent with the filtering process used to match Active 911 and CAD alerts in Chapter 3. Alerts on the CFX toll road network were not included since CFX was listed separately from the FDOT districts in the statewide CAD dataset. Table 4-4 shows the number of D5 limited access CAD alerts for each month in the statewide FHP CAD dataset. Overall, there were 21,614 CAD alerts on D5 limited access facilities from July 2022 through June 2023.

Table 4-4: D5 Limited CAD Alerts by Month

Month	D5 Limited Access CAD Alerts
January 2023	1,637
February 2023	1,526
March 2023	2,042
April 2023	1,843
May 2023	1,868
June 2023	1,955
July 2022	1,829
August 2022	1,928
September 2022	1,779
October 2022	1,671
November 2022	1,840
December 2022	1,696
Annual Total	**21,614**

Next, the 113 matched Active 911-CAD pairs were used to estimate the annual number of matched Active 911-CAD pairs on D5 limited access roadways per year. Table 4-5 summarizes the number of matched Active 911-CAD pairs per month.

Table 4-5: Matched Active 911-CAD Pairs by Month

Month	Matched Pairs
January 2023	25
February 2023	13
March 2023	16
April 2023	4
January 2024	11
February 2024	11
March 2024	17
April 2024	12
June 2024	4
Total	**113**

Since the identified matched Active 911-CAD pairs did not span a full calendar year, the number of matched Active 911-CAD pairs had to be projected for the remaining months. Table 4-6 shows the number of D5 limited access CAD alerts (same values as in Table 4-4), ratio of matched pairs to CAD alerts, and number of matched pairs per month. For January, February, March, and April, the matched pair counts shown in Table 4-5 were used to determine the ratio of matched pairs to CAD alerts. The 2023 matched pair counts were used rather than the 2024 counts since the CAD counts were for 2023. These four months contained 7,048 CAD alerts and 58 matched pairs, resulting in a ratio of 58/7048 = 0.00823. This ratio of 0.00823 was multiplied with the number of CAD alerts for each month from May through December to project the number of matched pairs in these months (rounded to the nearest whole number). Based on these projections, the annual number of matched pairs for D5 limited access facilities was 178. Dividing this value by the total number of CAD alerts (21,614) resulted in an annual matched pairs to CAD ratio of 0.00824. This ratio of 0.00824 was used to estimate the number of matched pairs for each limited access roadway.

Table 4-6: Matched Active 911-CAD Pairs Annual Projection for D5

Month	D5 Limited Access CAD Alerts	Ratio of Matched Pairs to D5 Limited Access CAD Alerts	Matched Pairs
January	1,637	0.01527	25
February	1,526	0.00852	13
March	2,042	0.00784	16
April	1,843	0.00217	4
May	1,868	0.00823	16
June	1,955	0.00823	17
July	1,829	0.00823	15
August	1,928	0.00823	16
September	1,779	0.00823	15
October	1,671	0.00823	14
November	1,840	0.00823	16
December	1,696	0.00823	14
Total	**21,614**	**0.00824**	**178**

2. *Statewide Projection and Estimated Benefits*

Each Florida limited access roadway was split by FDOT district, resulting in 49 roadway segments. The annual number of FHP CAD alerts with alert types of New Event or Associated was determined for each segment using the statewide CAD dataset from July 2022 through June 2023. These values were multiplied by 0.00824 (annual matched pairs to CAD ratio determined in Table 4-6 for D5) to obtain the estimated number of matched Active 911-CAD pairs for each segment. Then, the number of pairs with Active 911 earlier was determined for each segment by multiplying the number of pairs by 38.05% since that was the percentage of the 113 matched pairs in D5 which had the Active 911 alert occurring before the CAD alert. Finally, the early detection benefits for each segment were calculated by multiplying the number of pairs with Active 911 earlier by the average Active 911 lead time of 7.07 minutes.

Table 4-7 shows the annual CAD alerts, estimated annual matched Active 911-CAD pairs, estimated annual number of pairs with Active 911 earlier, and estimated annual early detection benefits (minutes) for each Florida limited access roadway segment. Note that only the eight FDOT districts (D1 through D7 and FTE) are considered in this table. This means that limited access roadway portions operated by other agencies (such as the portion of SR-417 operated by CFX) are included in the appropriate FDOT district based on their geographical location. It is also important to note that the statewide CAD dataset contained few alerts for D4, causing many of the D4 roadway segments to have no CAD alerts or associated early detection benefits. Overall, it was projected that expanding Active 911 to all Florida limited access facilities would result in 320 matched pairs per year with Active 911 earlier than CAD and early detection benefits of 2262.4 minutes (37.7 hours) per year.

Table 4-7: Estimated Annual Early Detection Benefits per Roadway Segment for Active 911

Roadway	**FDOT District**	**Annual CAD Alerts**	**Annual Matched Active 911-CAD Pairs**	**Annual Matched Pairs with Active 911 Earlier**	**Annual Early Detection Benefits (minutes)**
I-10	2	4,282	35	13	91.91
I-10	3	6,518	54	21	148.47
I-110	3	411	3	1	7.07
I-195	6	96	1	0	0
I-275	1	6	0	0	0
I-275	7	5,271	43	16	113.12
I-295	2	8,082	67	25	176.75
I-375	7	1	0	0	0
I-395	6	79	1	0	0
I-4	5	9,148	75	29	205.03
I-4	7	4,019	33	13	91.91
I-595	4	49	0	0	0
I-75	1	13,385	110	42	296.94
I-75	2	2,907	24	9	63.63
I-75	4	0	0	0	0
I-75	5	4,434	37	14	98.98
I-75	6	4	0	0	0

Table 4-7: Estimated Annual Early Detection Benefits per Roadway Segment for Active 911 (continued)

Roadway	FDOT District	Annual CAD Alerts	Annual Matched Active 911-CAD Pairs	Annual Matched Pairs with Active 911 Earlier	Annual Early Detection Benefits (minutes)
I-75	7	3,802	31	12	84.84
I-95	2	7,639	63	24	169.68
I-95	4	0	0	0	0
I-95	5	6,502	54	21	148.47
I-95	6	923	8	3	21.21
SR-112	6	5	0	0	0
SR-23	FTE	91	1	0	0
SR-407	FTE	23	0	0	0
SR-408	5	1,392	11	4	28.28
SR-414	5	123	1	0	0
SR-417	5	2,286	19	7	49.49
SR-417	FTE	608	5	2	14.14
SR-429	5	1,703	14	5	35.35
SR-429	FTE	349	3	1	7.07
SR-451	5	3	0	0	0
SR-453	5	11	0	0	0
SR-528	5	1,173	10	4	28.28
SR-528	FTE	611	5	2	14.14
SR-55	1	0	0	0	0
SR-55	7	4	0	0	0
SR-570	FTE	324	3	1	7.07
SR-589	FTE	1,259	10	4	28.28
SR-618	7	5	0	0	0
SR-821	FTE	5,370	44	17	120.19
SR-836	6	3,073	25	10	70.7
SR-869	FTE	1,276	11	4	28.28
SR-874	6	456	4	2	14.14
SR-878	6	87	1	0	0
SR-884	1	1	0	0	0
SR-91	FTE	4,243	35	13	91.91
SR-924	6	289	2	1	7.07
SR-93	1	12	0	0	0
Total	**-**	**102,335**	**843**	**320**	**2,262.40**

To estimate the congestion reduction benefits due to the early detection benefits shown in Table 4-7, the methodology and assumptions from Sandt, McCombs, Cornelison, et al. (2023) were used as a foundation. This previous study examined the congestion reduction benefits of Waze for DAV events on I-4 in FDOT D5 and SR-91 in FDOT District 4. The results from I-4 in D5 were used for this project since the Active 911 data were collected for D5 and D4 had limited CAD data in the statewide dataset. Due to data limitations, it was not possible to know lane blockage durations, flow rates, and capacity reductions for the statewide CAD alerts or D5 Active 911 alerts. Therefore, the methodology used to calculate congestion reductions in the previous study was utilized for this section due to similarities in roadway context, incident conditions, and traffic management practices.

The same assumptions used in Sandt, McCombs, Cornelison, et al. (2023) were made for this evaluation of Active 911. These assumptions included that flow rates and roadway capacities were constant during each incident, the incident resulted in congestion, any reported lane or shoulder blockage lasted for the full duration of the incident, TMC operators would act on the alert as soon as it was received, and the incident duration (length of time from detection to clearance) would remain unchanged (i.e., Active 911 would only reduce the time to detect the incident and not impact response time). For the D5 I-4 evaluation in Sandt, McCombs, Cornelison, et al. (2023), the total estimated congestion reduction benefits were approximately $4.34 million for 186 incidents, resulting in average benefits of $23,357 per incident. Dividing this value by the reported 16-minute average Waze lead time results in congestion reduction benefits of $1,460 per minute of early detection for I-4 in D5 (Sandt, McCombs, Cornelison, et al., 2023). To estimate the congestion reduction benefits for Active 911, this value was applied to all statewide limited access facilities by multiplying it with the average Active 911 lead time of 7.07 minutes. This resulted in estimated congestion reduction benefits of $10,321 per matched pair with Active 911 earlier on any Florida limited access facility.

Table 4-8 shows the estimated annual congestion reduction benefits for statewide expansion of Active 911 using the average benefits of $10,321 per matched pair with Active 911 earlier. These benefits are only shown for the 29 Florida limited access roadway segments projected to have at least one matched pair with Active 911 earlier per year in Table 4-7, as all other segments would have no annual congestion reduction benefits due to Active 911. The total estimated congestion reduction benefits for expanding Active 911 to all Florida limited access facilities were $3,302,652 per year. I-75 was the roadway with the highest estimated congestion reduction benefits ($794,701 per year across all four segments), with I-75 in D1 having the highest individual segment congestion reduction benefits of $433,473 per year. These findings suggest that I-75 would be a good candidate for testing Active 911 to better understand its potential in providing early warnings outside of D5.

Table 4-8: Estimated Annual Congestion Reduction Benefits per Roadway Segment for Active 911

Roadway	FDOT District	Annual Matched Active 911-CAD Pairs	Annual Matched Pairs with Active 911 Earlier	Annual Early Detection Benefits (minutes)	Estimated Annual Congestion Reduction Benefits/Year
I-10	2	35	13	91.91	$134,170
I-10	3	54	21	148.47	$216,737
I-110	3	3	1	7.07	$10,321
I-275	7	43	16	113.12	$165,133
I-295	2	67	25	176.75	$258,020
I-4	5	75	29	205.03	$299,303
I-4	7	33	13	91.91	$134,170
I-75	1	110	42	296.94	$433,473
I-75	2	24	9	63.63	$92,887
I-75	5	37	14	98.98	$144,491
I-75	7	31	12	84.84	$123,849
I-95	2	63	24	169.68	$247,699
I-95	5	54	21	148.47	$216,737
I-95	6	8	3	21.21	$30,962
SR-408	5	11	4	28.28	$41,283
SR-417	5	19	7	49.49	$72,246
SR-417	FTE	5	2	14.14	$20,642
SR-429	5	14	5	35.35	$51,604
SR-429	FTE	3	1	7.07	$10,321
SR-528	5	10	4	28.28	$41,283
SR-528	FTE	5	2	14.14	$20,642
SR-570	FTE	3	1	7.07	$10,321
SR-589	FTE	10	4	28.28	$41,283
SR-821	FTE	44	17	120.19	$175,453
SR-836	6	25	10	70.7	$103,208
SR-869	FTE	11	4	28.28	$41,283
SR-874	6	4	2	14.14	$20,642
SR-91	FTE	35	13	91.91	$134,170
SR-924	6	2	1	7.07	$10,321
Total	**-**	**838**	**320**	**2,262.40**	**$3,302,652**

Table 4-9 summarizes the estimated annual congestion reduction benefits by FDOT district for the projected expansion of Active 911. D5 had the highest estimated annual congestion reduction benefits ($866,946 per year), which shows that D5 made a good decision to incorporate Active 911 into their TIM program. D2 and the FTE district were the two districts outside of D5 with the highest projected congestion reduction benefits ($732,776 per year and $454,115 per year, respectively). D4 was the only district with no projected benefits due to a lack of CAD data for this district. These district-level estimates can help FDOT decide on potential areas for future Active 911 implementation.

Table 4-9: Estimated Annual Congestion Reduction Benefits per FDOT District for Active 911

District	Estimated Annual Congestion Reduction Benefits
1	$433,473
2	$732,776
3	$227,057
4	$0
5	$866,946
6	$165,133
7	$423,152
FTE	$454,115
Total	**$3,302,652**

4.2.2. Evaluation of Statewide PulsePoint Expansion

In Chapter 3, a one-mile spatial buffer and a 30-minute temporal buffer were used to identify matched PulsePoint–CAD alert pairs (same as for the Active 911-CAD pairs). Using these buffers, 160 matched PulsePoint-CAD pairs were identified, with 97 pairs (60.63%) having a PulsePoint alert before the first CAD alert. For these 97 matched pairs, PulsePoint had an average lead time of 4.92 minutes compared to CAD. These findings are important to estimate the benefits of expanding PulsePoint statewide. Data differences between the Active 911 and PulsePoint datasets caused some details to change when applying the methodology shown in Figure 4-13 to the PulsePoint data compared to the Active 911 application.

1. *D5 Annual Projection*

The same D5 limited access CAD alerts shown in Table 4-4 were used for the PulsePoint evaluation. Additionally, the 160 matched PulsePoint-CAD pairs were used to estimate the annual number of matched PulsePoint-CAD pairs on D5 limited access roadways per year. Table 4-10 summarizes the number of matched PulsePoint-CAD pairs per month. Since the PulsePoint data only contained data for the first 12 days of June 2024, the number of matched pairs (10) was converted to an estimated monthly count by multiplying it by 30/12 (since June has 30 days and there were only 12 days in the dataset), resulting in a monthly estimate of 25 matched pairs for June 2024.

Table 4-10: PulsePoint-CAD Matched Pairs by Month

Month	Matched Pairs
February 2024	38
March 2024	35
April 2024	40
May 2024	37
June 2024	10 (1^{st}-12^{th}); 25 (estimate for entire month)
Total	**160 (175 with entire month of June)**

The matched PulsePoint-CAD pairs did not span a full calendar year, so the number of matched PulsePoint-CAD pairs had to be projected for the remaining months. Table 4-11 shows the number of D5 limited access CAD alerts each month (same values as in Table 4-4), ratio of matched pairs to CAD alerts, and number of matched pairs per month. Even though the PulsePoint data was for 2024, the statewide CAD values for 2022 and 2023 were used to estimate the number of matched pairs per month. D5 CAD data were available for 2024, but they did not contain the same information about action taken as the statewide CAD data. Therefore, the 2024 D5 CAD data could not be filtered the same way as the 2022-2023 statewide CAD data, so the 2022-2023 statewide CAD data values in Table 4-4 were used to estimate the number of matched pairs in D5.

For February, March, April, May and June, the number of matched pairs shown in Table 4-10 was used to determine the ratio of matched pairs to CAD alerts. These five months contained 9,234 CAD alerts and 175 matched pairs, resulting in a ratio of 175/9234 = 0.0190. This ratio of 0.0190 was multiplied with the number of CAD alerts for each month for January and July through December to project the number of matched pairs in these months (rounded to the nearest whole number). Based on these projections, the annual number of matched pairs for D5 limited access facilities was 411. This is much higher than the annual predicted number of matched pairs for Active 911 (178 matched pairs), suggesting that PulsePoint could provide earlier detection for more incidents than Active 911. Dividing this value by the total number of CAD alerts (21,614) resulted in an annual matched pairs to CAD ratio of 0.0190. This ratio of 0.0190 was used to estimate the number of matched pairs for each Florida limited access roadway.

Table 4-11: Matched PulsePoint-CAD Pairs Annual Projection for D5

Month	**D5 Limited Access CAD Alerts**	**Ratio of Matched Pairs to D5 Limited Access CAD Alerts**	**Matched Pairs**
January	1,637	0.0190	31
February	1,526	0.0249	38
March	2,042	0.0171	35
April	1,843	0.0217	40
May	1,868	0.0198	37
June	1,955	0.0128	25
July	1,829	0.0190	35
August	1,928	0.0190	37
September	1,779	0.0190	34
October	1,671	0.0190	32
November	1,840	0.0190	35
December	1,696	0.0190	32
Total	**21,614**	**0.0190**	**411**

2. *Statewide Projection and Estimated Benefits*

For each of the 49 Florida limited access roadway segments, the annual number of FHP CAD alerts with alert types of New Event or Associated was determined using the statewide CAD dataset (same number of CAD alerts as in Table 4-7). These values were multiplied by 0.0190 (annual matched pairs to CAD ratio for D5) to obtain the estimated number of matched PulsePoint-CAD pairs for each segment. Then, the number of pairs with PulsePoint earlier was determined for each segment by multiplying the number of pairs by 60.63% since that was the percentage of the 160 matched pairs in D5 which had the PulsePoint alert occur before the CAD alert. Finally, the early detection benefits for each segment were calculated by multiplying the number of pairs with PulsePoint earlier by the average PulsePoint lead time of 4.92 minutes.

Table 4-12 shows the annual CAD alerts, estimated annual matched PulsePoint-CAD pairs, estimated annual number of pairs with PulsePoint earlier, and estimated annual early detection benefits (minutes) for each Florida limited access roadway segment. These are the same segments shown in Table 4-7. Overall, it was projected that expanding PulsePoint to all Florida limited access facilities would result in 1,175 matched pairs per year having PulsePoint before CAD and early detection benefits of 5,781 minutes (96.4 hours) per year. These early detection benefits are more than 2.5 times higher than the early detection benefits for Active 911 due to the higher number of matched PulsePoint-CAD pairs compared to Active 911-CAD pairs and higher percentage of pairs with PulsePoint earlier compared to Active 911 earlier.

Table 4-12: Estimated Annual Early Detection Benefits per Roadway Segment for PulsePoint

Roadway	FDOT District	Annual CAD Alerts	Annual Matched PulsePoint-CAD Pairs	Annual Matched Pairs with PulsePoint Earlier	Annual Early Detection Benefits (minutes)
I-10	2	4,282	81	49	241.08
I-10	3	6,518	124	75	369
I-110	3	411	8	5	24.6
I-195	6	96	2	1	4.92
I-275	1	6	0	0	0
I-275	7	5,271	100	61	300.12
I-295	2	8,082	153	93	457.56
I-375	7	1	0	0	0
I-395	6	79	1	1	4.92
I-4	5	9,148	173	105	516.6
I-4	7	4,019	76	46	226.32
I-595	4	49	1	1	4.92
I-75	1	13,385	254	154	757.68
I-75	2	2,907	55	33	162.36
I-75	4	0	0	0	0
I-75	5	4,434	84	51	250.92
I-75	6	4	0	0	0
I-75	7	3,802	72	44	216.48
I-95	2	7,639	145	88	432.96
I-95	4	0	0	0	0
I-95	5	6,502	123	75	369
I-95	6	923	17	10	49.2
SR-112	6	5	0	0	0
SR-23	FTE	91	2	1	4.92
SR-407	FTE	23	0	0	0

Table 4-12: Estimated Annual Early Detection Benefits per Roadway Segment for PulsePoint (continued)

Roadway	FDOT District	Annual CAD Alerts	Annual Matched PulsePoint-CAD Pairs	Annual Matched Pairs with PulsePoint Earlier	Annual Early Detection Benefits (minutes)
SR-408	5	1,392	26	16	78.72
SR-414	5	123	2	1	4.92
SR-417	5	2,286	43	26	127.92
SR-417	FTE	608	12	7	34.44
SR-429	5	1,703	32	19	93.48
SR-429	FTE	349	7	4	19.68
SR-451	5	3	0	0	0
SR-453	5	11	0	0	0
SR-528	5	1,173	22	13	63.96
SR-528	FTE	611	12	7	34.44
SR-55	1	0	0	0	0
SR-55	7	4	0	0	0
SR-570	FTE	324	6	4	19.68
SR-589	FTE	1,259	24	15	73.8
SR-618	7	5	0	0	0
SR-821	FTE	5,370	102	62	305.04
SR-836	6	3,073	58	35	172.2
SR-869	FTE	1,276	24	15	73.8
SR-874	6	456	9	5	24.6
SR-878	6	87	2	1	4.92
SR-884	1	1	0	0	0
SR-91	FTE	4,243	80	49	241.08
SR-924	6	289	5	3	14.76
SR-93	1	12	0	0	0
Total	**-**	**102,335**	**1,937**	**1,175**	**5,781.00**

The same approach used to estimate the congestion reduction benefits due to earlier detection for the statewide expansion of Active 911 was used for the statewide PulsePoint expansion. This approach utilized the methodology, assumptions, and results from Sandt, McCombs, Cornelison, et al. (2023). Multiplying the congestion reduction benefits of $1,460 per minute of early detection from this previous study by the average PulsePoint lead time of 4.92 minutes yields estimated congestion reduction benefits of $7,182 per matched pair with PulsePoint earlier.

Table 4-13 shows the estimated annual congestion reduction benefits for statewide expansion of PulsePoint using the average benefits of $7,182 per matched pair with PulsePoint earlier. These benefits are only shown for the 35 Florida limited access roadway segments projected to have at least one matched pair with PulsePoint earlier per year in Table 4-12, as all other segments would have no estimated congestion reduction benefits due to PulsePoint. The total annual estimated congestion reduction benefits for expanding PulsePoint to all Florida limited access facilities were $8,439,104 per year. I-75 was the roadway with the highest estimated congestion reduction benefits ($2,025,385 per year across all four segments), with I-75 in D1 having the highest individual segment congestion reduction benefits of $1,106,061 per year. Since the estimated congestion reduction benefits for statewide expansion of PulsePoint are much higher than for statewide expansion of Active 911, it is recommended to test the use of PulsePoint on limited access facilities beyond D5. I-75 in D1, I-295 in D2, and I-95 in D2 are estimated to have the most potential congestion reduction benefits, so it is recommended to try testing PulsePoint and/or Active 911 on these roadway segments. These tests will help provide a better understanding of these technologies' potential to improve early warning and allow for more accurate estimation of early warning benefits for other roadways.

Table 4-14 shows the estimated annual congestion reduction benefits by FDOT district for the projected expansion of PulsePoint. D5 had the highest estimated annual congestion reduction benefits ($2,197,758 per year), followed by D2 ($1,888,923 per year) and FTE ($1,177,883 per year). Therefore, it is recommended to consider expansion of PulsePoint to D2 and the FTE district.

Table 4-13: Estimated Annual Congestion Reduction Benefits per Roadway Segment for PulsePoint

Roadway	**FDOT District**	**Annual Matched PulsePoint-CAD Pairs**	**Annual Matched Pairs with PulsePoint Earlier**	**Annual Early Detection Benefits (minutes)**	**Annual Estimated Congestion Reduction Benefits**
I-10	2	81	49	241.08	$351,929
I-10	3	124	75	369	$538,666
I-110	3	8	5	24.6	$35,911
I-195	6	2	1	4.92	$7,182
I-275	7	100	61	300.12	$438,115
I-295	2	153	93	457.56	$667,946
I-395	6	1	1	4.92	$7,182
I-4	5	173	105	516.6	$754,133
I-4	7	76	46	226.32	$330,382
I-595	4	1	1	4.92	$7,182
I-75	1	254	154	757.68	$1,106,061
I-75	2	55	33	162.36	$237,013
I-75	5	84	51	250.92	$366,293
I-75	7	72	44	216.48	$316,018
I-95	2	145	88	432.96	$632,035
I-95	5	123	75	369	$538,666
I-95	6	17	10	49.2	$71,822
SR-23	FTE	2	1	4.92	$7,182
SR-408	5	26	16	78.72	$114,915
SR-414	5	2	1	4.92	$7,182
SR-417	5	43	26	127.92	$186,738
SR-417	FTE	12	7	34.44	$50,276
SR-429	5	32	19	93.48	$136,462
SR-429	FTE	7	4	19.68	$28,729
SR-528	5	22	13	63.96	$93,369
SR-528	FTE	12	7	34.44	$50,276
SR-570	FTE	6	4	19.68	$28,729
SR-589	FTE	24	15	73.8	$107,733
SR-821	FTE	102	62	305.04	$445,297
SR-836	6	58	35	172.2	$251,378
SR-869	FTE	24	15	73.8	$107,733
SR-874	6	9	5	24.6	$35,911
SR-878	6	2	1	4.92	$7,182
SR-91	FTE	80	49	241.08	$351,929
SR-924	6	5	3	14.76	$21,547
Total	**-**	**1,937**	**1,175**	**5,781.00**	**$8,439,104**

Table 4-14: Estimated Annual Congestion Reduction Benefits per FDOT District for PulsePoint

District	Estimated Annual Congestion Reduction Benefits
1	$1,106,061
2	$1,888,923
3	$574,577
4	$7,182
5	$2,197,758
6	$402,204
7	$1,084,515
FTE	$1,177,883
Total	**$8,439,104**

4.3 Evaluation of Adjusted Waze Filtering Protocols

In Chapter 3 of this report, Florida statewide Waze and CAD alerts were compared to identify specific times and locations where relaxing filtering protocols could potentially improve Waze early detection rates. Based on this analysis, it was recommended to ease the current Waze filters in D2, D4, D6, and on SR-91 and SR-821, particularly during nighttime hours from 9:00 PM to 11:59 PM. This section discusses the development and application of a tool to determine the potential early detection benefits of relaxing the Waze filters using recent Waze data. The potential for this Waze evaluation tool to be utilized as a real-time TIM tool in the future is also discussed.

To quantify the potential early detection benefits from relaxing the existing Waze filtering protocols, it was first necessary to determine what changes to make to these existing protocols. FDOT currently filters the incoming Waze data so only traffic incident alerts with a confidence level of 4 or 5 are reported to the TMC. Each Waze alert has a confidence level calculated by Waze ranging from 0 to 5. This level is based on user feedback (such as “Thumbs up” and “Not there” reactions), with a higher confidence level reflecting more positive confirmations from Waze users. Alerts with confidence levels of 4 or 5 can be considered reliable and thus are sent to TMC operators for verification and appropriate response. This confidence level filter helps ensure that the TMC operators only receive Waze alerts likely to be actual incidents without overwhelming them with false alerts. However, receiving alerts at lower confidence levels could improve early detection and warning of incidents because it takes time for an incident to reach confidence level 4 or 5. Therefore, it was decided to develop a Waze evaluation tool which could estimate the potential early detection benefits (and associated congestion reduction benefits and costs) if alerts with a confidence level of 3 were allowed through the existing filters alongside the currently accepted level 4 and 5 alerts. Waze also generates a reliability score ranging from 0 to 10, which incorporates both the confidence level and the reporting user’s experience. FDOT does not currently use this reliability score to filter Waze alerts, but this could potentially be examined in the future to see if the reliability score or the confidence level is a better filtering criterion.

Several studies have used Waze confidence levels and reliability scores when studying Waze alerts, but no studies have evaluated confidence levels or reliability scores directly. Senarath et al. (2020) incorporated the Waze reliability score as a weighting factor in Bayesian information fusion for incident detection but did not evaluate the reliability score independently. Li et al. (2020) used the reliability score solely to filter alerts prior to analysis, while Goodall and Lee (2019) compared reliability scores to ground truth video footage and found no correlation with actual incident accuracy. Another study by Hossain et al. (2025) included Waze confidence levels as predictor variables in a binary logit model to estimate the likelihood that an alert matched an actual crash report. None of the confidence levels were found to be statistically significant, indicating that confidence scores were not reliable predictors of real-world incident validity in their model. These findings suggest that Waze's internal scoring metrics are often used in data filtering or modeling, but their validity remains largely unexamined. Due to the unknown relationship between confidence level and incident accuracy, FDOT utilizes Waze as a secondary source rather than a primary source for traffic incidents. This means that Waze alerts reported to the TMC must be verified by an operator through a primary source (traffic cameras, law enforcement, etc.) before further action is taken. Future research on the relationship between confidence, reliability, and accuracy could improve FDOT's trust in these data.

The Waze evaluation tool discussed in this section was developed and tested using two months of FTE IDS data filtered to only include FHP CAD alerts (February 2025 and March 2025), three months of D3 FHP CAD data (February 2025 – April 2025), and six months of raw Waze data (February 2025 – July 2025) retrieved in real time using the Waze API. These data sources are shown in Table 3-1. Filtering the FTE and D3 data to only include unique events on limited access roadways for the months specified resulted in 2,335 alerts for FTE and 1,078 alerts for D3. With these data, the evaluation tool was developed and used to estimate the number of Waze alerts that would reach the TMC operators under the new relaxed protocols and how much earlier Waze alerts would arrive using these new protocols compared to the current filtering protocols. The remainder of this section details the development of the tool, its findings, and its future potential as a real-time tool to assist in earlier detection of traffic incidents or abnormal conditions.

4.3.1. Evaluation Tool for Waze Confidence Level 3 Alerts (FTE)

Using the collected Waze and FHP CAD data, a Python based tool was developed to determine the potential early detection benefits for Waze confidence level 3 alerts. The first step was to import and standardize the historical Waze and FHP CAD data. These datasets were aligned in terms of structure and formatting to enable efficient processing and matching. This step involved ensuring consistent timestamp formats and aligning spatial reference systems so the datasets could be accurately matched by time and location.

The next step involved spatiotemporal matching of Waze and CAD alerts. The same spatiotemporal buffers selected in Chapter 3 (a one-mile spatial buffer and a 30-minute temporal buffer) were used by this tool to match Waze and CAD alerts. Only Waze alerts with confidence levels of 3, 4, or 5 were considered for this matching process. The raw Waze data contained 141,543 confidence level 3 alerts and 697,497 confidence level 4 or 5 alerts for February and March 2025. Applying the spatiotemporal buffers resulted in 183 matched Waze-CAD pairs on the FTE system for the months of February and March 2025. The first Waze alert was earlier than the first CAD alert for 54.64% of these pairs (100 pairs), the first CAD alert was earlier than the first Waze alert for 42.62% of these pairs (78 pairs), and the first Waze and CAD alert occurred at the same time for the remaining 2.73% of pairs (five pairs). Additionally, 44.81% of the 183 matched pairs (82 pairs) included a confidence level 3 Waze alert which occurred earlier than the first CAD alert, but would have been filtered out under the existing protocol. These 82 pairs are important as they are ones where the relaxed Waze filters would provide early detection benefits compared to the existing FDOT Waze filters.

To determine the early detection benefits for these 82 pairs, it was first necessary to quantify how long it typically takes for a Waze alert to transition between confidence levels. This quantification will provide a better understanding of how alerts evolve over time and can help evaluate whether lower confidence alerts can serve as early indicators of actual incidents. When collecting the Waze data for this evaluation, the data were retrieved using two different time intervals. Waze data through March 20th, 2025, were retrieved using five-minute intervals (i.e., the real-time Waze data were obtained through the Waze API every five minutes), while Waze data after March 20th, 2025, were retrieved using one-minute intervals. Only the Waze alerts retrieved using one-minute intervals (2,920,563 alerts) were used to determine the transition times between confidence levels. A five-minute gap between alerts was regarded as too large in this context since alert progression can occur rapidly within minutes. This means that shifts from one confidence level to the next could be missed entirely if five-minute intervals were used, making it impossible to determine the actual transition timing. By only using the data retrieved using one-minute intervals, each alert's progression could be more clearly observed with sufficient temporal resolution, allowing for precise computation of transition times between consecutive confidence levels.

Using the one-minute interval data, the transition from confidence level 3 to 4 was analyzed. The dataset was first filtered to include only alerts with confidence levels 3 or 4, retaining 138,101 out of the 2,920,563 alerts. For each unique alert ID, the timestamp of its first occurrence with confidence level 3 was recorded, followed by the timestamp of its first occurrence with confidence level 4. The time difference between these two occurrences was calculated to determine the transition time. Only transitions that occurred within 30 minutes from the first appearance of a confidence level 3 alert were retained, resulting in a total of 8,458 alerts. This 30-minute threshold was chosen to estimate the distribution of these transition times over a short time window which would be useful for TMC operators. Figure 4-14 shows the distribution of transition times from level 3 to level 4 using this 30-minute threshold. This distribution is heavily right-skewed with the majority of transitions occurring a few minutes after the initial level 3 alert. Approximately 5,413 alerts transitioned within the first three minutes and 6,597 transitioned within the first five minutes. Beyond 10 minutes, the frequency of transitions dropped off significantly.

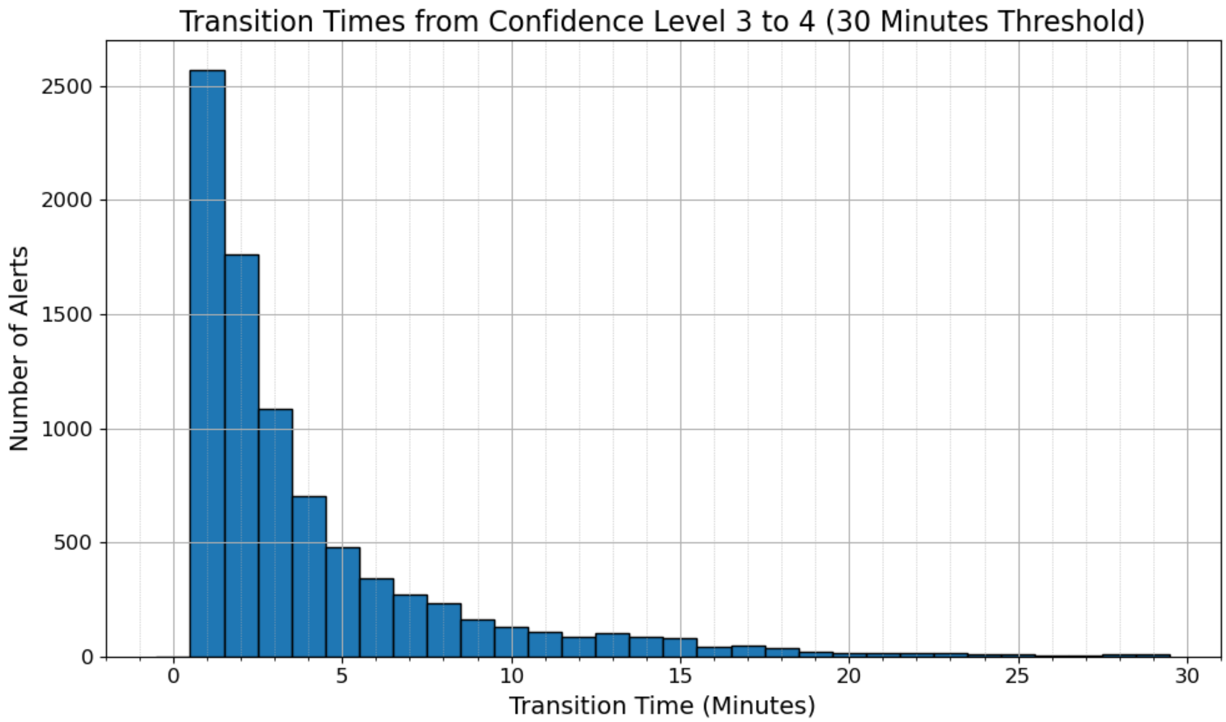

Figure 4-14: Histogram of Transition Times from Waze Confidence Level 3 to Confidence Level 4 within a 30-minute Threshold

The histogram in Figure 4-14 was used to develop a cumulative distribution of the transition times from confidence level 3 to confidence level 4 for a 30-minute threshold. This cumulative distribution is shown in Figure 4-15. The steep rise in the first few minutes indicates that a large portion of alerts transitioned early, with over 64% transitioning within three minutes and more than 78% transitioning within five minutes. The curve begins to flatten after the 15-minute mark, suggesting that transitions occurring after 15 minutes are uncommon.

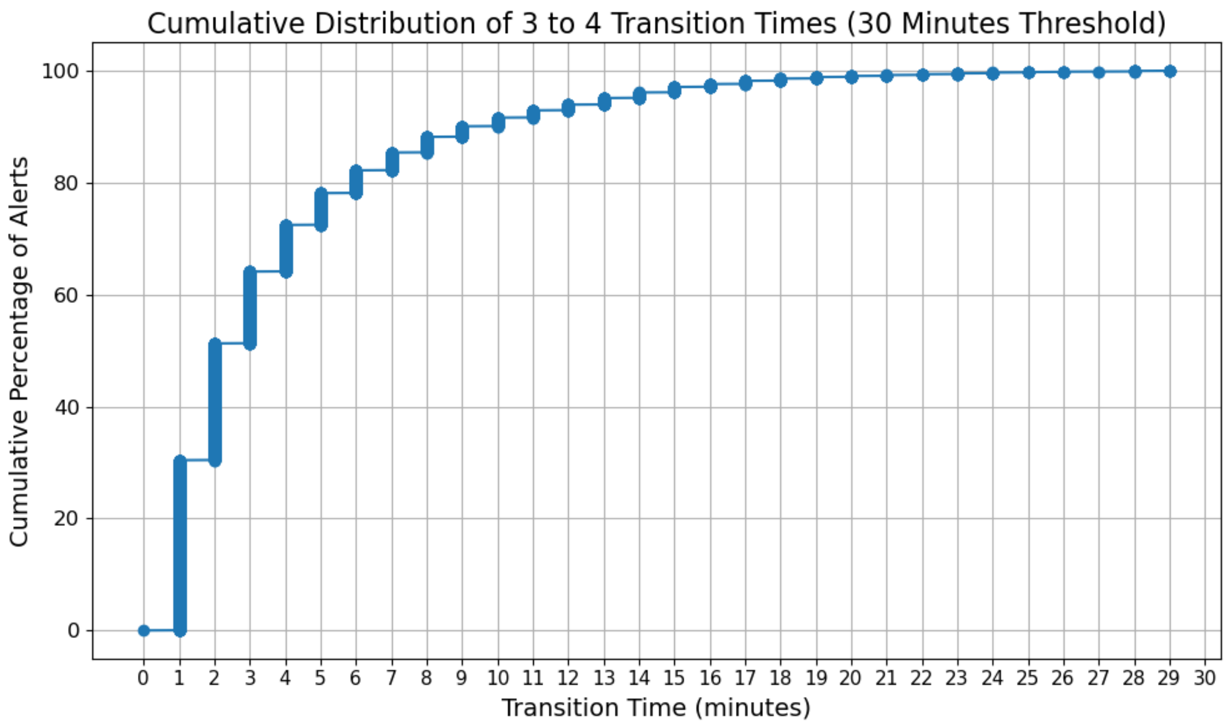

Figure 4-15: Cumulative Distribution of Transition Times from Waze Confidence Level 3 to Confidence Level 4 within a 30-minute Threshold.

These two figures show that a majority of Waze alerts transition from confidence level 3 to 4 within the first few minutes. However, it is important not to limit the analysis to only short-duration transitions. Certain types of incidents, such as roadway hazards, might not immediately transition to a higher confidence level, particularly if they are initially detected by a small number of users or receive limited confirmation. Since relaxing the filter would allow all confidence level 3 Waze alerts through, incidents that take longer to transition from confidence level 3 to 4 need to be accounted for when determining average transition times. Excluding these incidents would underestimate the potential early detection benefits of Waze and overlook valid and operationally meaningful transitions which could occur over longer periods.

To capture the broader behavior of alert progression, the transition time analysis was extended to examine transitions across all confidence levels (0 to 5) and longer thresholds. For each unique incident (which typically contained multiple Waze alerts), the timestamps for the first Waze alert of each confidence level (0, 1, 2, 3, 4, or 5) were identified. The time difference between consecutive confidence levels was then computed. While most alerts took only a few minutes to reach the next confidence level, some remained at a low confidence level for several hours or never progressed at all. Including excessively slow transitions would distort the average transition time and reduce the operational relevance of the results. For example, if the first confidence level 2 alert for an incident appeared at 8:00 AM and the first confidence level 3 alert for the same incident appeared at 8:10 AM, the transition time would be 10 minutes. This transition time fits within a typical TIM timeline. However, if the first confidence level 3 alert occurred at 2:00 PM instead, the transition time would be six hours. This transition time is unlikely to be operationally useful since many incidents are cleared in less than six hours. To address this issue, a maximum threshold constraint was introduced. With this constraint, only transitions occurring within a certain number of hours after an incident's first alert were considered. Maximum thresholds ranging from one to 12 hours were tested to determine representative average transition times between different confidence levels. Understanding how these average transition times change as the threshold increases will help to identify a cutoff threshold which will provide a representative average transition time that is not biased by excessively long transition times.

Figure 4-16 shows the average time required for a Waze alert to transition between confidence levels. The x-axis shows the considered maximum threshold constraints from one to 12 hours. For each maximum threshold, only alerts that lasted less than or equal to the specified duration were included in the calculation. The y-axis shows the average transition time between confidence levels for these different maximum threshold constraints. Each colored line corresponds to a transition between different confidence levels (blue for level 0 to level 1, orange for level 1 to level 2, green for level 2 to level 3, red for level 3 to level 4, and purple for level 4 to level 5). As expected, the average transition time increases with longer maximum thresholds for all levels (since there are more alerts with longer transition times to raise the average). A maximum threshold of four hours was chosen as a cutoff threshold to limit the alert durations considered in the analysis since the transition lines generally flatten out after a four-hour maximum threshold. This means that the average transition times using a four-hour cutoff are generally representative for all alerts.

An interesting finding from this graph is that the transition times between confidence levels did not consistently increase or decrease as the confidence level increased. For instance, the average transition time between levels 1 and 2 was higher than the average transition times for all other levels. Table 4-15 shows the average transition times between each confidence level using a four-hour maximum threshold. The average transition time between confidence level 3 and 4 was 4.95 minutes, suggesting that relaxing the Waze filters to include confidence level 3 alerts could provide almost 5 minutes of earlier detection compared to the existing Waze filters for every incident with a confidence level 3 alert. Additionally, this table suggests that opening the filter to include confidence levels below level 3 would not be a good idea based on the collected data. The average transition time between confidence level 2 and 3 is only 1.5 minutes, so including confidence level 2 alerts would not provide much more earlier warning. Moreover, confidence level 2 alerts are much more likely to contain false alarms than higher confidence level alerts, so TMC operators would have to spend much more time reviewing useless alerts. Therefore, it is not recommended to expand the FDOT filters to include confidence levels below 3 on the FTE system. Further research is needed to see how the transition times differ for various Florida regions and roadways to see if the filters could potentially be relaxed more in some areas without negatively impacting TMC operators. D3 already relaxes the FDOT Waze filters on some roadways at nighttime, so this approach could potentially be utilized in similar regions throughout the state.

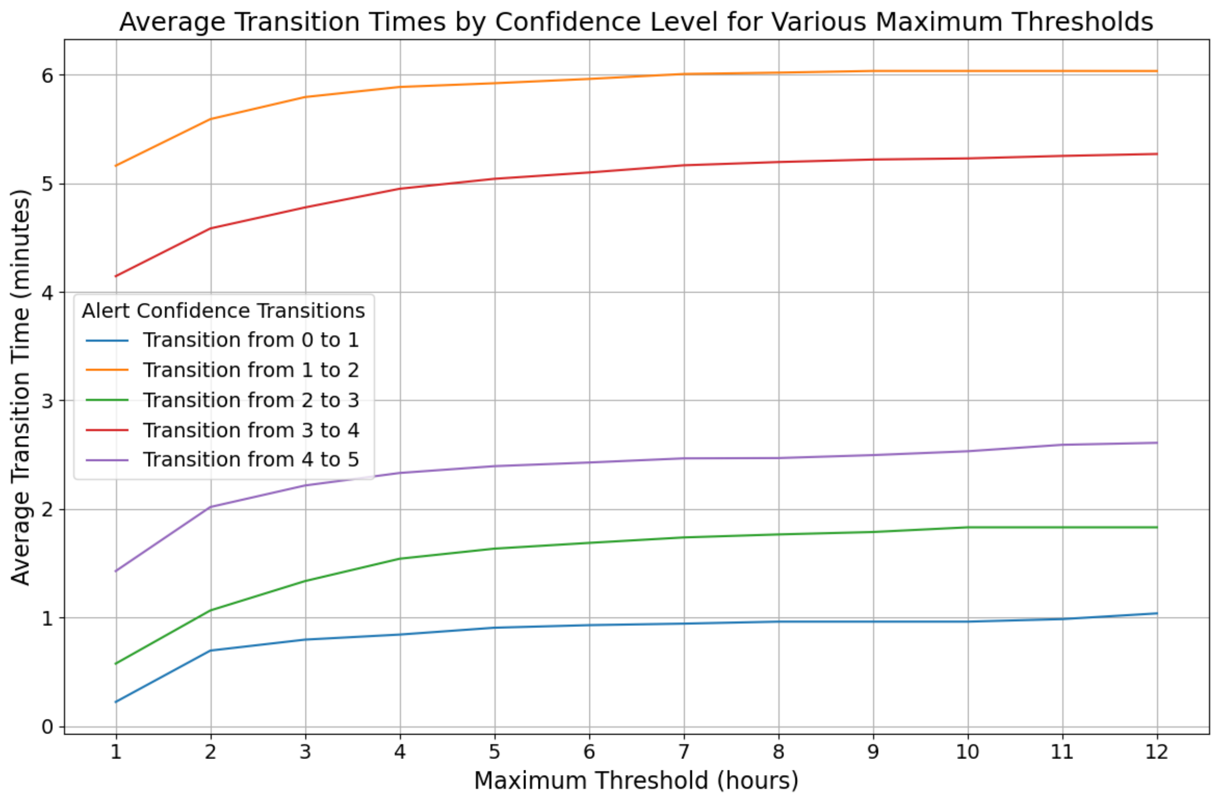

Figure 4-16: Waze Alerts Average Transition Times between Confidence Levels for Various Maximum Time Thresholds

Table 4-15: Average Transition Times between Waze Confidence Levels Using a Four-Hour Maximum Threshold

Confidence Level Transition	Average Transition Time (minutes)
0 to 1	0.84
1 to 2	5.89
2 to 3	1.54
3 to 4	4.95
4 to 5	2.33

The developed evaluation tool was used to estimate the annual early detection benefits, congestion reduction benefits, and operator costs due to relaxing the Waze filters for the FTE system compared to the existing Waze filtering protocols. Two examples were considered. The first example assumes that the FDOT filtering protocols would be relaxed to include confidence level 3 Waze alerts only during the hours of 9:00 PM and 11:59 PM. These hours were identified as having high potential for Waze early warning benefits in Chapter 3. The second example assumes the filtering would be relaxed to include confidence level 3 Waze alerts for the entire day to provide a broader understanding of these potential early warning benefits.

Multiple parameters and assumptions were needed to estimate the benefits and costs for these examples. Early warning benefits were calculated for the 82 matched Waze-CAD pairs with a confidence level 3 Waze alert before the first CAD alert identified by the evaluation tool in the previous section, with 5 of these 82 matched pairs occurring between 9:00 PM and 11:59 PM. Since these counts were for a two-month period, they were multiplied by six to obtain annual projections. On average, a confidence level 3 Waze alert is expected to provide 4.95 minutes of earlier detection than a confidence level 4 Waze alert (Table 4-15). This value can be multiplied by the annual number of pairs with a confidence level 3 Waze earlier than the CAD alert to obtain estimated annual early detection benefits. A value of $1,460 per minute was used to calculate the congestion reduction benefits. This was adopted from Sandt, McCombs, Cornelison, et al. (2023) and is the same value used for the Active 911 and PulsePoint evaluations earlier in this chapter.

To estimate the costs of relaxing the Waze filter, the number of annual confidence level 3 alerts for the FTE system was projected based on the collected raw Waze data. It was assumed that it would take TMC operators two minutes to verify each of these alerts, which is consistent with the target verification time of two minutes outlined in the District Six Transportation Systems Management and Operations (TSM&O) Annual Report for the 2023–2024 fiscal year (FDOT District Six, 2024). The average operator's hourly wage was set at $20.60, which is the value used by Sandt, McCombs, Cornelison, et al. (2023).

Table 4-16 presents the results of the annual benefit-cost (B/C) analysis for relaxing the Waze alert filtering protocols between 9:00 PM and 11:59 PM on FTE roadways. The total estimated annual congestion reduction benefits were $216,780, while the annual operator costs associated with verifying additional alerts were estimated at $91,909, resulting in a B/C ratio of 2.36. Therefore, it would be cost-effective to relax the Waze filters during this time period on FTE roadways. Chapter 5 compares the early warning benefits of relaxing the Waze filters to the early warning benefits from other TIM data sources for each hour and FDOT district to provide a more comprehensive picture of the most effective TIM tools.

Table 4-16: Example B/C Analysis for Relaxing Waze Filtering from 9:00 PM–11:59 PM (FTE)

Parameter	**Value**
Matched Pairs with Confidence Level 3 Waze Alert Earlier (February and March 2025)	5
Projected Annual Matched Pairs with Confidence Level 3 Waze Alert Earlier	30
Minutes Saved per Matched Pair	4.95
Total Annual Minutes Saved	148.5
Congestion Reduction Benefits per Minute Saved	$1,460
Total Annual Congestion Reduction Benefits	**$216,780**
Total Annual Waze Level 3 Alerts (9:00 PM - 11:59 PM)	133,848
Verification Time per Alert (minutes)	2
Operator Time Spent Verifying Alerts (hours)	4,461.6
Operator Cost Per Hour	$20.60
Total Annual Operator Cost	**$91,909**
B/C Ratio	**2.36**

Table 4-17 presents the results of the annual B/C analysis for relaxing the Waze alert filtering protocols during all hours of the day on FTE roadways. The total estimated annual congestion reduction benefits were $3,555,197, while the annual operator costs associated with verifying additional alerts were estimated at $583,157, resulting in a B/C ratio of 6.10. Therefore, it would be cost-effective to relax the Waze filters for all time periods on FTE roadways. This B/C ratio is almost three times higher than the B/C ratio shown in Table 4-16, suggesting that relaxing the Waze filters from 9:00 PM – 11:59 PM might not be the most beneficial. The high benefits for this example compared to the statewide expansion of Active 911 and PulsePoint suggest that relaxing the Waze filters might be the most cost-efficient approach to improve early warning of traffic incidents. However, care is needed to ensure that the additional alerts do not overwhelm TMC operators.

Table 4-17: Example B/C Analysis for Relaxing Waze Filtering during All Hours (FTE)

Parameter	Value
Matched Pairs with Confidence Level 3 Waze Alert Earlier (February and March 2025)	82
Projected Annual Matched Pairs with Confidence Level 3 Waze Alert Earlier	492
Minutes Saved per Matched Pair	4.95
Total Annual Minutes Saved	2,435.4
Congestion Reduction Benefits per Minute Saved	$1,459.80
Total Annual Congestion Reduction Benefits	**$3,555,197**
Total Annual Waze Level 3 Alerts (all hours)	849,258
Verification Time per Alert (minutes)	2
Operator Time Spent Verifying Alerts (hours)	28,308.6
Operator Cost Per Hour	$20.60
Total Annual Operator Cost	**$583,157**
B/C Ratio	**6.10**

There are several important limitations to consider when interpreting the results of these B/C analyses. The annual projections were based on only two months of data, which might not fully capture seasonal variations or broader trends in Waze alert timing and confidence level progression. The assumption that all confidence level 3 alerts would provide meaningful earlier detection might not hold in all cases, potentially overestimating the benefits. However, there could be additional incidents previously detected by CAD first which could be detected earlier by confidence level 3 Waze alerts. Earlier detection of these incidents would increase the estimated benefits. Additionally, the congestion reduction benefits per incident were based on a previous study and applied uniformly across all alerts, which might not reflect variations in delay impacts by time of day or location. Finally, the analysis only considered operator time as an implementation cost and excluded other potential expenses such as system integration, software modifications, and facility upgrades, all of which could affect the B/C ratio.

4.3.2. Evaluation Tool for Waze Confidence Level 3 Alerts (D3)

The same evaluation tool and methodology described in section 4.3.1 were used to assess the potential benefits and costs of relaxing Waze filtering protocols in FDOT D3. The matching process and B/C analysis were conducted using the same spatial and temporal buffers, parameters, and cost assumptions used for the FTE system, with the only change being the use of D3 data. Applying the matching procedure resulted in 57 matched Waze-CAD pairs on the D3 system for the studied three-month period. Of these, 27 pairs (47.37%) had the first Waze alert earlier than the first CAD alert and 30 pairs (52.63%) had the first CAD alert earlier. Additionally, 36 of the matched pairs (63.16%) included a confidence level 3 Waze alert that occurred before the first CAD alert and would have been filtered out under the current FDOT Waze filtering protocols. These pairs represent the potential early detection benefits from relaxing the Waze filters in D3. The early detection benefits per matched pair were assumed to be 4.95 minutes, as derived in Table 4-15.

Like the FTE evaluation, two scenarios were considered for D3: relaxing the Waze filter to include confidence level 3 alerts during the hours of 9:00 PM to 11:59 PM and relaxing the filter to include confidence level 3 alerts during all hours of the day. Annual projections were obtained by multiplying the observed matched pair counts by four (since the D3 dataset spanned three months). The same congestion reduction benefits of $1,460 per minute and operator costs of two minutes per alert at a rate of $20.60 per hour from Sandt, McCombs, Cornelison, et al. (2023) used for the FTE evaluation were used for D3.

Table 4-18 shows the annual B/C results for relaxing the Waze filter in D3 between 9:00 PM and 11:59 PM, while Table 4-19 shows the annual B/C results relaxing the Waze filter in D3 for all hours of the day. The B/C ratio for 9:00 PM – 11:59 PM was only slightly higher than 1.00, indicating that the congestion reduction benefits barely outweigh the costs. This B/C ratio is lower than for FTE roads during the same time period, possibly due to low Waze usage in D3 during nighttime hours. For all hours, the B/C ratio for D3 (7.91) was higher than for FTE (6.10). This suggests that relaxing Waze filters in D3 could be most beneficial during daytime hours.

Table 4-18: Example B/C Analysis for Relaxing Waze Filtering from 9:00 PM–11:59 PM (D3)

Parameter	Value
Matched Pairs with Confidence Level 3 Waze Alert Earlier (February - April 2025)	1
Projected Annual Matched Pairs with Confidence Level 3 Waze Alert Earlier	4
Minutes Saved per Matched Pair	4.95
Total Annual Minutes Saved	19.8
Congestion Reduction Benefits per Minute Saved	$1,460
Total Annual Congestion Reduction Benefits	**$28,904**
Total Annual Waze Level 3 Alerts (9:00 PM - 11:59 PM)	30,111
Verification Time per Alert (minutes)	2
Operator Time Spent Verifying Alerts (hours)	1,003.7
Operator Cost Per Hour	$20.60
Total Annual Operator Cost	**$20,676**
B/C Ratio	**1.40**

Table 4-19: Example B/C Analysis for Relaxing Waze Filtering during All Hours (D3)

Parameter	Value
Matched Pairs with Confidence Level 3 Waze Alert Earlier (February - April 2025)	36
Projected Annual Matched Pairs with Confidence Level 3 Waze Alert Earlier	144
Minutes Saved per Matched Pair	4.95
Total Annual Minutes Saved	712.8
Congestion Reduction Benefits per Minute Saved	$1,460
Total Annual Congestion Reduction Benefits	**$1,040,545**
Total Annual Waze Level 3 Alerts (all hours)	191,499
Verification Time per Alert (minutes)	2
Operator Time Spent Verifying Alerts (hours)	6,383.3
Operator Cost Per Hour	$20.60
Total Annual Operator Cost	**$131,496**
B/C Ratio	**7.91**

Like the FTE evaluation, the projected benefits for D3 are limited by the duration of the dataset and assumptions about alert progression and TMC verification. Although Waze usage in D3 is lower than in more urbanized districts, there are indications that its usage could grow over time. The district has already adjusted its Waze filtering protocols during select hours to increase the number of usable alerts available to operators. If Waze usage in the region continues to gradually expand, its role in supporting CAD could become more comparable to what has been observed in other districts. Nonetheless, this D3 application provides a parallel assessment to the FTE analysis and helps illustrate how relaxed Waze filtering protocols could be utilized across Florida.

4.3.3. Potential Real-Time Implementation

The methods and results presented in sections 4.3.1 and 4.3.2 showcase how the developed evaluation tool can be used on historical data to identify potential area of improvement. However, to provide the most early warning benefits, it is recommended to develop a real-time tool that leverages Waze confidence level 3 alerts to support incident detection and verification at Florida's TMCs. Although confidence level 3 alerts are filtered out in current operational workflows, the findings suggest that these alerts can hold value if appropriately classified using historical data. Future research is needed to properly develop and test such a tool, but some general ideas on how this tool would function are discussed below.

This tool would operate as a real-time decision-support layer, applying a classification model trained on historically matched Waze and CAD incidents. As new confidence level 3 alerts appear in the Waze stream, the model would assess the likelihood that each alert corresponds to a true incident. Alerts exceeding a predefined probability threshold would be flagged for review by TMC operators, allowing them to take timely and informed action. The model would incorporate several key features to improve classification accuracy:

1. Spatial features, including the alert's location and whether it occurs on a limited access roadway.
2. Temporal features, such as the time of day, day of the week, and month.
3. Alert type and subtype as reported by Waze.

4. Crowdsourced validation reflected by the number of user confirmations (e.g., "thumbs up") or Waze reliability score.
5. Historical frequency, capturing how often true incident alerts have occurred in the same area.

Future research efforts to develop and train this classification model and test it for various situations would provide a basis for eventual statewide implementation. By integrating this tool into existing Waze alert workflows, FDOT could gain earlier insight into potentially valid incidents that would otherwise be excluded. The system would be designed to run in parallel with current operations, enhancing existing data pipelines and TMC protocols. This approach supports a proactive and data-informed response strategy using the power of crowdsourced traffic data to provide earlier detection and warning of traffic incidents and abnormal conditions.

4.4 Hypothetical Evaluation of New TIM Tools in Florida

The previous sections in this chapter focused on the modification or expansion of TIM tools currently utilized in Florida. However, there are other TIM tools which have been successfully implemented in other states. This section assesses the potential value of two emerging TIM technologies, Waycare and Carbyne. These tools have been utilized in Nevada and Georgia, respectively, to reduce incident detection times, but have not been thoroughly evaluated. In this section, hypothetical implementations of both these tools in Florida are evaluated. These evaluations aim to estimate the operational early detection benefits and congestion reduction benefits these tools could generate if deployed under similar conditions to their current deployments outside of Florida. Performance metrics from these previous deployments were combined with Florida-specific data and assumptions to develop projected benefits, serving as illustrative examples of their potential impact on a high-volume limited access facility. Section 4.4.1 discusses the evaluation of the Waycare system and section 4.4.2 discusses the evaluation of the Carbyne system.

4.4.1. Waycare

Waycare enhances traffic management by bringing together data from sources that traditional systems do not typically capture, such as crowdsourced applications, in-vehicle telematics, and social media reports (ITS Joint Program Office, 2020; Suzan, 2018). Instead of relying solely on fixed sensors and manual reporting, it aggregates early warning signs of incidents and traffic hazards from a wide range of real-time inputs. Waycare also offers a shared, cloud-based dashboard accessible to law enforcement, service patrols, and traffic operators directly in their vehicles, providing them with verified incident details, precise GPS locations, responder positions, and even live video clips from nearby cameras. Automated traveler alerts are generated and distributed through platforms like Waze, text messaging, and social media with minimal operator input, ensuring faster public notification (National Operations Center of Excellence, 2019).

To estimate the potential early detection benefits of implementing Waycare on all Florida limited access facilities, performance data from the deployment of Waycare in Nevada were utilized. These performance data showed a 12-minute average reduction in incident response time (National Operations Center of Excellence, 2019). It was decided to compare the Waycare system to Active 911, since they are both real-time external alert streams that can quickly provide alerts to TMC operators.

Table 4-20 shows the results of the hypothetical implementation of Waycare on all Florida limited access facilities. From Table 4-7, 320 annual matched Active 911-CAD pairs were predicted for all Florida limited access facilities. For each of these 320 pairs, an average earlier detection time of 7.07 minutes would be provided by the Active 911 alerts. Based on the Nevada data, it is reasonable to assume that the Waycare system could improve this earlier detection time from 7.07 minutes to 12 minutes (improvement of 4.93 minutes). Applying this improvement to all 320 annual matched pairs with Active 911 earlier and multiplying by the average congestion reduction benefits of $1,460 per minute saved (Sandt, McCombs, Cornelison, et al., 2023) results in annual congestion reduction benefits of $2,302,980 for this hypothetical implementation. These congestion reduction benefits are in addition to the ones calculated for Active 911 expansion.

Table 4-20: Waycare Hypothetical Annual Congestion Reduction Benefits for All Florida Limited Access Facilities

Parameter	Value
Projected Annual Matched Active 911-CAD Pairs with Active 911 Earlier	320
Average Reduction in Response Time Compared to Active 911 (minutes)	4.93
Annual Minutes Saved Compared to Active 911 (minutes)	1,577.6
Congestion Reduction Benefits per Minute Saved	$1,460
Projected Annual Congestion Reduction Benefits	**$2,302,980**

While these benefits are substantial, implementing a system similar to Waycare in Florida would likely involve several major cost components. These costs would include a platform subscription or licensing fees, the purchase and installation of Automatic Vehicle Locator devices and tablets in service patrol and law enforcement vehicles, and associated cellular data plans. Additional costs would arise from integrating the system with existing backend platforms such as SunGuide, camera networks, and CAD systems. Expenses for training and onboarding multi-agency personnel, customizing the system to Florida's operational needs, and providing ongoing maintenance, technical support, and data storage would also need to be considered. Additionally, it is unknown how this system would perform in Florida. Active 911, PulsePoint, and Waze have all been implemented in Florida, so the performance evaluations for these systems were able to use Florida data. It is difficult to accurately estimate the benefits and costs of Waycare without Florida data. Therefore, it is recommended to consider the other tools discussed in this chapter (relaxing Waze filters, expanding PulsePoint, or expanding Active 911) over the implementation of a Waycare system. However, Waycare seems to be an effective solution which could have potential in Florida as a complement to other TIM tools.

4.4.2. Carbyne

Carbyne is an advanced communication platform that enhances 911 call centers' operations by enabling real-time location and multimedia sharing between motorists and dispatchers without requiring an app download (Carbyne, 2025). When a motorist places a 911 call, the dispatcher receives the caller's phone number through the existing call handling system. With the caller's consent, the dispatcher sends a secure link via text message. Once the caller clicks on the link and accepts the request, Carbyne enables the dispatcher to access the phone's real-time location, camera images, and live video directly. These data are shared voluntarily by the caller, solely to help responders reach and assist them more effectively. By allowing operators to quickly pinpoint incidents, Carbyne significantly reduces response times, improves resource dispatching, and minimizes reliance on costly roadside devices. Its quick deployment and reliance on traveler-owned smartphones make it especially applicable to Florida, where extensive rural areas and gaps in camera and sensor coverage exist, offering a cost-effective solution to enhance incident detection and management across the state's diverse roadway network.

To accurately estimate the potential benefits of implementing Carbyne in Florida, data from the Georgia Department of Transportation pilot test of Carbyne were utilized. According to FHWA (2024b), Carbyne implementation in Georgia was associated with a 17-minute reduction in response times. Furthermore, user engagement during the pilot was estimated at approximately 13 uses per week. These users were voluntary 911 callers who agreed to share their location or media when contacted by dispatchers during an actual emergency. Like the Waycare evaluation, it was decided to compare the Carbyne system to Active 911.

Table 4-21 shows the results of the hypothetical implementation of Carbyne on all Florida limited access roadways. A weekly usage of 13 uses per week would result in an annual usage of (13 uses per week x 52 weeks per year) = 676 events per year. Each of these 676 events would have an average earlier detection time of 7.07 minutes due to Active 911. Based on the Georgia data, it is reasonable to assume that the Carbyne system could improve this earlier detection time from 7.07 minutes to 17 minutes (improvement of 9.93 minutes). Applying this improvement to all 676 annual events and multiplying by the average congestion reduction benefits of $1,460 per minute saved (Sandt, McCombs, Cornelison, et al., 2023) results in annual congestion reduction benefits of $9,799,170 for this hypothetical implementation. These congestion reduction benefits are in addition to the ones calculated for Active 911 expansion.

Table 4-21: Carbyne Hypothetical Annual Congestion Reduction Benefits for All Florida Limited Access Facilities

Parameter	Value
Uses per Week (Events)	13
Projected Annual Events	676
Average Reduction in Response Time Compared to Active 911 (minutes)	9.93
Annual Minutes Saved Compared to Active 911 (minutes)	6,712.7
Congestion Reduction Benefits per Minute Saved	$1,460
Projected Annual Congestion Reduction Benefits	**$9,799,170**

The estimated congestion reduction benefits for the Carbyne system are much higher than the estimated congestion reduction benefits for the Waycare system. Like the Waycare evaluations, these benefits were not based on Florida data, so actual performance would likely differ. Because the Carbyne system is mainly helpful in locations where existing systems have gaps in coverage, this system could be useful in certain locations in Florida. Additionally, this evaluation did not consider deployment or maintenance costs, which could influence the overall outcome. Several factors must be considered, including market penetration and user engagement levels, public acceptance, deployment costs, operational expenses, and personnel training to determine accurate performance estimates. It is not recommended to consider the use of Carbyne over existing TIM systems in Florida, but it could be a potential option to complement existing systems in areas with limited TIM coverage.

Chapter 5: Development of TIM Toolbox

Evaluating and comparing the performance of TIM tools is a key priority for transportation agencies seeking to reduce incident response times and improve roadway safety. In this chapter, a TIM toolbox is developed which calculates annual early warning benefits by hour of day for key TIM data sources across all FDOT districts and ranks these sources by their early warning potential. This TIM toolbox has been prepared for both FDOT engineers and TMC operators to help them understand the early warning benefits of these sources, prioritize sources when multiple alerts are received simultaneously, and apply the developed methodology to additional data in the future.

Previous chapters in this report laid the foundation for evaluating early warning performance across TIM data sources and developing the TIM toolbox. Chapter 3 quantified early warning potential by comparing alternative TIM sources against FHP CAD data and measuring average lead times. Chapter 4 expanded on this by estimating the monetary benefits of early warnings on Florida's limited access roadways. This chapter advances this approach by developing the TIM toolbox and introducing a more granular time-of-day analysis for multiple FDOT districts to show how early warning benefits vary for each source by hour and district. By combining the results of these evaluations with earlier findings, the toolbox offers a practical framework to identify, compare, and deploy TIM tools across a range of operational scenarios to reduce incident detection times. The TIM toolbox offers a detailed temporal breakdown which enables more targeted and operationally relevant comparisons between data sources. This can help TMC operators prioritize various TIM sources and assist FDOT management in identifying times and locations where implementing certain TIM data sources would likely provide the most early warning benefits.

Section 5.1 presents the methodology used to estimate annual early warning benefits at the hourly level for four TIM data sources: Active 911, PulsePoint, the existing Waze filters used by FDOT (where only alerts with confidence levels of 4 or 5 are reported to the TMC), and relaxed Waze filters where alerts with confidence levels of 3, 4, or 5 are reported to the TMC (referred to as Waze_3 in this chapter). These calculations were performed across all FDOT districts with available CAD data using historical data and projections as needed. This section's results can be used by FDOT engineers and management to identify potential changes to operating procedures or filtering protocols. FDOT can also utilize the methodology from this section to estimate early warning benefits for additional TIM systems or for additional data in the future.

Section 5.2 builds on the results from section 5.1 to generate hourly TIM data source rankings for each studied FDOT district. For every hour of the day, the four studied TIM sources were ranked from first to fourth based on their total estimated annual early warning benefits. These hourly rankings are visualized using block charts, allowing TMC operators to quickly identify which sources provide the most early warning value during specific time periods. The programming code used to develop these charts can be found in Appendix A. These diagrams highlight patterns across districts and provide practical insights into source prioritization strategies that TMCs can adopt based on time of day. The strength of this methodology lies in its ability to operate effectively across a wide range of data availability scenarios, reflecting the real-world variability in TIM data sources across districts and times of day. The ability to produce consistent and actionable results despite this variability highlights the robustness of the approach and supports its potential for real-time operational use.

Overall, this TIM toolbox offers a comprehensive view of how early warning performance varies not only by data source, but also by hour of day and district. By translating early warning benefits into hourly rankings, this TIM toolbox equips FDOT and TMCs with practical insights that can support more informed decision-making regarding the integration and prioritization of available TIM data sources during daily operations. The TIM toolbox can also be used by FDOT management to compare other TIM data sources in the future and help decide where and when these data sources should be implemented to obtain the most early warning benefits.

5.1 Estimation of Annual Early Warning Benefits for Use by FDOT Engineers and Management

To quantify the operational value of early warning tools across Florida, this section estimates the annual early warning benefits for four major TIM data sources compared to CAD data: Active 911, PulsePoint, Waze, and Waze_3. Estimated benefits were obtained for each FDOT district and disaggregated by hour of day. This approach offers a detailed perspective on when each source provides the greatest advantage over CAD and can help support informed decisions regarding the integration and prioritization of various TIM detection systems within TMCs. FDOT engineers and management can use the results from this section to assist in implementation and procedural decisions regarding these TIM tools. FDOT can also utilize this section's methods to collect and evaluate additional data for specific districts or estimate early warning benefits for additional TIM tools in the future.

Section 5.1.1 provides an overview of the datasets utilized to estimate the annual early warning benefits of the mentioned TIM data sources. FHP CAD data served as the baseline against which all other data sources were compared. Due to limitations in spatial or temporal coverage, all datasets were not available for an entire year within all FDOT districts. Therefore, annual projections were developed based on the relationships between the applicable TIM data source and CAD data. These projections were then applied to other districts, allowing for consistent statewide estimations and comparisons. This means that the actual early warning benefits could differ due to variations in TIM data activity across districts. Section 5.1.2 discusses the methods used to estimate the annual early warning benefits for each data source, along with the estimated results by hour of day and district. These results are used to develop hourly rankings by district in section 5.2.

5.1.1. Overview of Data Sources

Table 5-1 summarizes the four types of TIM data (Active 911, PulsePoint, Waze, and Waze_3) for which annual early warning benefits were calculated in this section, along with the three CAD datasets used for comparison. These datasets are also shown in Table 3-1. Statewide Waze and CAD data were available for an entire year, but the remaining data sources had limited spatial and temporal coverage. Active 911 and PulsePoint were only available from FDOT D5 for select months in 2023 and 2024. Waze_3 data were collected by the UCF research team for the entire state, but only data from D3 and the FTE were used since CAD data were available for both these districts during the same time period as the collected Waze_3 data. The D3 data were used to project Waze_3 benefits to other FDOT districts due to the D3 data containing an additional month of data and being more representative of a typical FDOT district than the FTE data (due to the fact that FTE roadways are spread statewide and are not limited by geographical boundaries like the other districts). The FTE data were used to calculate the Waze_3 early benefits for the FTE district. Additionally, the statewide CAD dataset only included a few CAD alerts from D4, so it was decided to exclude D4 from all evaluations since these limited CAD data likely did not represent actual CAD activity in D4.

Table 5-1: TIM and CAD Data Sources Utilized to Develop the TIM Toolbox

Source	**Spatial Coverage**	**Temporal Coverage**
Active 911	D5	January 2023 – April 2023, January 2024 – April 2024, June 2024
PulsePoint	D5	February 2024 – June 2024
Waze	Statewide	June 2022 – June 2023
Waze_3	D3	February 2025 – April 2025
	FTE	February 2025 – March 2025
FHP CAD	Statewide (except D4)	June 2022 – June 2023
	D3	February 2025 – April 2025
	FTE	February 2025 – March 2025

5.1.2. Estimated Early Warning Benefits

Each TIM source was matched with CAD data based on temporal and spatial proximity. Chapters 3 and 4 discuss the details of these matching procedures, including how the buffers were determined. A 30-minute temporal buffer and 1-mile spatial buffer were used to match PulsePoint, Waze, and Waze_3 alerts with CAD alerts. For Active 911, a 30-minute temporal buffer was used to identify potential matches, then all potential matches on limited access facilities were reviewed manually to identify matches based on location. This was done since the Active 911 data did not contain geographical coordinates. The matched pair counts were then converted to annual counts as needed depending on the temporal coverage of the TIM dataset. Annual projections were not needed for the Waze data since one year of data was available.

After identifying the matched pairs for each TIM data source, these matched pairs were analyzed to determine whether the TIM alert was recorded prior to the corresponding CAD alert. Pairs which met this condition were considered to be early warnings for the TIM data source. The total annual early warning benefits were then calculated by multiplying the number of early detection pairs by the average lead time (in minutes) provided by the TIM data source. These benefits were estimated for each hour of the day across all FDOT districts except D4 due to the limited CAD data in D4 as mentioned previously. Since Active 911 and PulsePoint alerts were only available for D5, the results from D5 were used to estimate the annual number of matched pairs and early warning benefits for all other districts. Likewise, the Waze_3 results for D3 were used to estimate the annual number of matched pairs and early warning benefits for all other districts (except the FTE district where the actual Waze_3 and CAD data for the FTE district were used). D3 was selected instead of FTE for projections to other districts because using FTE data would have likely overestimated the early detection benefits due to higher ratios of matched pairs to CAD alerts in the FTE district compared to D3. These hourly breakdowns are essential to identify the specific times when each source offers the greatest early warning value and support the rankings of the TIM data sources.

1. Active 911 Early Warning Benefits

Since Active 911 was only implemented in D5, the annual early warning benefits of Active 911 were estimated for D5, then projected to the other FDOT districts. Table 5-2 summarizes the early warning benefit results for Active 911 in D5. First, the number of matched Active 911-CAD pairs in each hour, percentage of the total matched pairs for each hour, and percentage of the matched pairs within each hour with Active 911 earlier were obtained. These values are shown in the second, third, and fourth columns of Table 5-2, respectively, and were based on the values shown in Table 3-9. In Table 4-6, it was shown that projecting the D5 matched pair count to an annual value resulted in 178 matched pairs. Using this result and the values shown in the third column of Table 5-2, the number of projected annual pairs was calculated for each hour (fifth column). Note that these counts are shown as integer values in Table 5-2, but the actual values (including decimal places) were used for the remaining calculations in this table. Next, the percentage of matched pairs with Active 911 earlier (fourth column) was multiplied by the projected annual pair count (fifth column) to estimate the number of pairs with Active 911 earlier per hour (sixth column). The seventh column shows the average number of minutes that Active 911 alerts were earlier than CAD alerts based on the Active 911-CAD pairs in that hour. Multiplying these values by the number of projected annual pairs with Active 911 earlier results in the estimated annual early warning benefits per hour (eighth column). The last two columns show the number of annual D5 limited access CAD alerts per hour based on the statewide CAD dataset and the ratio of the projected annual pairs (fifth column) and the annual CAD alerts. These ratios were used to estimate the Active 911 early warning benefits for all other FDOT districts.

Table 5-3 summarizes the projected total annual early warning benefits (in minutes) by hour of the day for all FDOT districts except D4, which was excluded due to the absence of CAD data as discussed previously. The D5 values are the same as the ones in the eighth column of Table 5-2. For all other districts, these benefits were projected by multiplying the ratios in the last column of Table 5-2 by the number of annual CAD alerts in the district for each hour to obtain the projected annual pairs. These counts were then multiplied by the percentage of Active 911 alerts earlier values (fourth column of Table 5-2) to obtain the number of pairs with Active 911 earlier. Finally, these counts were multiplied by the average time earlier values (seventh column of Table 5-2) to obtain the estimated annual early warning benefits. As a result of this approach, it was assumed that the detection patterns observed in D5 would be representative of detection patterns in other districts. For example, since hours 0, 2, 4, 10, and 17 had no matched pairs with Active 911 earlier in D5, these same hours had zero estimated early warning benefits for all other districts. If FDOT decides to implement Active 911 in other districts, it is recommended to collect actual data from these implementations and use these data to assist in operational decisions. However, the results shown in Table 5-3 can provide FDOT with general estimates to identify potential times and locations for Active 911 deployment based on the implementation of this system in D5.

Table 5-2: Estimated Annual Early Warning Benefits per Hour of Day for Active 911 in D5

Hour	**Active 911-CAD Pairs**	**% of Total Pairs**	**% Pairs with Active 911 earlier**	**Projected Annual Pairs**	**Projected Annual Pairs with Active 911 earlier**	**Average Time Earlier (min)**	**Annual Early Warning Benefits (min)**	**Annual CAD Alerts**	**Annual Pairs over CAD Ratio**
0	0	0.00%	0.00%	0	0	0.00	0.00	1,114	0.0000
1	2	1.77%	100.00%	3	3	10.79	34.00	995	0.0032
2	1	0.88%	0.00%	2	0	0.00	0.00	943	0.0017
3	6	5.31%	33.33%	9	3	1.38	4.36	836	0.0113
4	3	2.65%	0.00%	5	0	0.00	0.00	747	0.0063
5	5	4.42%	40.00%	8	3	3.63	11.45	799	0.0099
6	6	5.31%	50.00%	9	5	3.72	17.59	2,124	0.0044
7	4	3.54%	50.00%	6	3	13.83	43.58	2,444	0.0026
8	7	6.19%	71.43%	11	8	7.06	55.58	2,995	0.0037
9	5	4.42%	40.00%	8	3	6.73	21.19	2,572	0.0031
10	3	2.65%	0.00%	5	0	0.00	0.00	2,345	0.0020
11	5	4.42%	20.00%	8	2	1.90	2.99	2,425	0.0032
12	7	6.19%	57.14%	11	6	6.22	39.17	2,631	0.0042
13	9	7.96%	33.33%	14	5	10.99	51.96	2,596	0.0055
14	5	4.42%	40.00%	8	3	0.73	2.31	3,456	0.0023
15	9	7.96%	33.33%	14	5	10.83	51.19	3,612	0.0039
16	7	6.19%	42.86%	11	5	6.77	32.00	4,113	0.0027
17	6	5.31%	0.00%	9	0	0.00	0.00	4,205	0.0022
18	6	5.31%	33.33%	9	3	5.89	18.56	3,904	0.0024
19	3	2.65%	66.67%	5	3	5.61	17.67	3,058	0.0015
20	3	2.65%	66.67%	5	3	6.58	20.71	2,275	0.0021
21	4	3.54%	25.00%	6	2	2.12	3.33	1,790	0.0035
22	3	2.65%	33.33%	5	2	7.40	11.66	1,819	0.0026
23	4	3.54%	25.00%	6	2	25.17	11.14	1,293	0.0049
Total	**113**	**100.00%**	**38.05%**	**178**	**68**	**7.07**	**450.44**	**55,091**	**0.0032**

Table 5-3: Estimated Annual Early Warning Benefits per Hour of Day for Active 911 by FDOT District (minutes)

Hour	D1	D2	D3	D5	D6	D7	FTE
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	12.30	20.64	5.67	34.00	17.39	11.69	24.50
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	1.92	2.89	0.72	4.36	1.68	2.07	3.23
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	6.52	9.01	2.38	11.45	5.64	6.25	12.23
6	8.86	11.01	1.87	17.59	6.04	7.93	15.86
7	30.10	32.03	6.69	43.58	20.10	20.15	42.05
8	31.88	35.91	10.82	55.58	25.07	21.58	54.73
9	12.72	15.14	4.74	21.19	11.26	7.60	21.87
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	1.65	2.31	0.64	2.99	1.28	1.19	2.94
12	22.78	29.85	8.05	39.17	18.31	17.33	37.55
13	33.70	43.05	11.89	51.96	23.24	23.88	53.28
14	1.19	1.55	0.46	2.31	0.99	0.99	2.25
15	26.90	41.02	9.94	51.19	21.27	24.82	46.91
16	16.32	24.50	5.59	32.00	12.82	14.25	29.64
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	9.72	13.77	3.40	18.56	8.23	8.40	16.15
19	8.97	12.31	2.93	17.67	7.90	7.33	14.00
20	10.35	13.14	4.23	20.71	8.70	9.07	17.44
21	1.90	2.80	0.66	3.33	2.69	1.45	2.97
22	5.20	11.07	2.17	11.66	8.19	4.75	11.26
23	19.53	33.05	8.28	11.14	30.17	18.30	38.94
Total	**262.52**	**355.04**	**91.14**	**450.44**	**230.99**	**209.02**	**447.78**

2. PulsePoint Early Warning Benefits

The same approach used to estimate the Active 911 early warning benefits was implemented for the PulsePoint data. Table 5-4 shows the estimated D5 annual early warning benefits by hour. This table includes the same columns as Table 5-2 and used the same calculation methods, but with PulsePoint data instead of Active 911 data. The values in the second, third, and fourth columns of Table 5-4 were based on the values shown in Table 3-10, while the total annual projection of 411 matched PulsePoint-CAD pairs was calculated in Table 4-11. Using the ratios in the last column of Table 5-4, the annual early warning benefits (in minutes) were estimated for each hour of the day and each FDOT district, as shown in Table 5-5. These values were calculated using the same methods as for Table 5-3. Overall, the early warning benefits for PulsePoint alerts were higher than for Active 911, primarily due to a higher number of matched pairs and a higher percentage of PulsePoint alerts occurring before matched CAD alerts (60.63%) compared to Active 911 (38.05%). Like Table 5-3, the results in Table 5-5 assume that all districts would have similar PulsePoint alert patterns to D5, so actual deployments of PulsePoint could result in different early warning benefits.

Table 5-4: Estimated Annual Early Warning Benefits per Hour of Day for PulsePoint in District 5

Hour	**PulsePoint-CAD Pairs**	**% of total Pairs**	**% Pairs with PulsePoint Earlier**	**Projected Annual Pairs**	**Projected Annual Pairs with PulsePoint Earlier**	**Average Time Earlier (min)**	**Annual early Warning Benefits (min)**	**Annual CAD Alerts**	**Annual Pairs over CAD Ratio**
0	3	1.88%	100.00%	8	8	7.91	60.97	1,114	0.0069
1	2	1.25%	100.00%	5	5	2.73	14.00	995	0.0052
2	1	0.63%	100.00%	3	3	5.20	13.36	943	0.0027
3	5	3.13%	60.00%	13	8	5.14	39.64	836	0.0154
4	0	0.00%	0.00%	0	0	0.00	0.00	747	0.0000
5	4	2.50%	75.00%	10	8	4.47	34.46	799	0.0129
6	3	1.88%	100.00%	8	8	6.48	49.92	2,124	0.0036
7	9	5.63%	55.56%	23	13	2.58	33.14	2,444	0.0095
8	6	3.75%	66.67%	15	10	6.15	63.23	2,995	0.0051
9	2	1.25%	50.00%	5	3	10.67	27.40	2,572	0.0020
10	11	6.88%	36.36%	28	10	5.25	53.94	2,345	0.0120
11	9	5.63%	88.89%	23	21	5.74	117.86	2,425	0.0095
12	10	6.25%	90.00%	26	23	4.33	100.01	2,631	0.0098
13	15	9.38%	53.33%	39	21	5.65	116.19	2,596	0.0148
14	14	8.75%	50.00%	36	18	2.99	53.77	3,456	0.0104
15	10	6.25%	40.00%	26	10	3.49	35.88	3,612	0.0071
16	10	6.25%	40.00%	26	10	5.09	52.32	4,113	0.0062
17	11	6.88%	63.64%	28	18	7.57	136.06	4,205	0.0067
18	6	3.75%	83.33%	15	13	2.60	33.39	3,904	0.0039
19	6	3.75%	66.67%	15	10	3.97	40.80	3,058	0.0050
20	4	2.50%	75.00%	10	8	2.60	20.04	2,275	0.0045
21	8	5.00%	12.50%	21	3	1.75	4.50	1,790	0.0115
22	8	5.00%	75.00%	21	15	6.41	98.81	1,819	0.0113
23	3	1.88%	66.67%	8	5	4.99	36.32	1,293	0.0060
Total	**160**	**100%**	**60.63%**	**411**	**249**	**4.92**	**1,236.01**	**55,091**	**0.0075**

Table 5-5: Estimated Annual Early Warning Benefits per Hour of Day for PulsePoint by FDOT District (minutes)

Hour	D1	D2	D3	D5	D6	D7	FTE
0	27.14	39.29	10.73	60.97	38.25	26.21	55.49
1	5.07	8.50	2.34	14.00	7.16	4.81	10.09
2	5.52	7.75	1.87	13.36	4.97	4.55	10.17
3	17.50	26.27	6.59	39.64	15.32	18.87	29.40
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	19.63	27.13	7.16	34.46	16.99	18.81	36.84
6	25.15	31.23	5.31	49.92	17.13	22.49	45.01
7	22.89	24.35	5.08	33.14	15.28	15.32	31.97
8	36.27	40.85	12.31	63.23	28.52	24.55	62.26
9	16.45	19.58	6.14	27.40	14.56	9.83	28.28
10	31.10	40.95	10.33	53.94	28.46	22.57	50.82
11	65.08	90.89	25.08	117.86	50.60	46.95	115.77
12	58.16	76.21	20.56	100.01	46.75	44.25	95.87
13	75.37	96.28	26.59	116.19	51.96	53.40	119.15
14	27.68	36.13	10.67	53.77	22.98	23.06	52.31
15	18.85	28.75	6.96	35.88	14.91	17.39	32.88
16	26.67	40.05	9.15	52.32	20.96	23.29	48.45
17	59.92	98.07	25.92	136.06	56.53	58.76	121.27
18	17.48	24.77	6.12	33.39	14.81	15.11	29.06
19	20.72	28.42	6.76	40.80	18.25	16.92	32.33
20	10.01	12.71	4.10	20.04	8.42	8.77	16.87
21	2.57	3.78	0.89	4.50	3.62	1.96	4.00
22	44.05	93.81	18.36	98.81	69.42	40.31	95.44
23	12.63	21.38	5.36	36.32	19.52	11.84	25.19
Total	**645.93**	**917.16**	**234.37**	**1,236.01**	**585.39**	**530.02**	**1,148.91**

3. Waze Early Warning Benefits

Both Waze and CAD data were available statewide for an entire year, so no projections were needed. Waze-CAD pairs were previously matched and analyzed with respect to hour of day and district, as shown in Table 3-3. These values were used to estimate the early warning benefits (in minutes) provided by the existing Waze filters for each hour of the day and FDOT district, with these results shown in Table 5-6. These benefits were obtained by multiplying the number of matched Waze-CAD pairs with Waze earlier in each hour and district by the number of minutes that Waze was earlier. Note that D5 has low estimated annual early warning benefits from Waze, likely due to D5 limiting its use of Waze as a detection source because of high false alert volumes.

Table 5-6: Estimated Annual Early Warning Benefits per Hour of Day for Waze by FDOT District (minutes)

Hour	D1	D2	D3	D5	D6	D7	FTE
0	15.94	6.30	25.85	0.00	45.25	96.59	2.96
1	0.53	10.00	0.00	0.00	41.35	37.61	23.81
2	26.68	0.00	0.00	5.41	19.53	22.23	105.89
3	71.93	0.00	0.00	0.00	17.73	28.41	0.00
4	0.00	0.00	7.83	0.00	0.00	34.81	29.27
5	12.04	18.26	0.00	0.00	0.00	91.48	66.02
6	126.09	98.30	0.00	0.00	119.66	308.78	47.97
7	121.26	111.11	64.53	0.00	85.07	163.28	170.37
8	189.11	113.06	290.23	20.15	27.45	80.81	179.54
9	70.90	49.17	20.65	9.70	37.74	63.48	97.01
10	124.92	226.88	81.52	0.00	26.27	53.75	70.85
11	25.44	102.01	96.36	0.00	86.34	43.24	141.33
12	42.38	186.60	43.40	0.00	88.66	21.37	138.96
13	47.23	113.27	131.44	0.00	104.16	111.60	193.72
14	52.58	130.74	41.06	0.00	92.70	281.61	253.62
15	84.84	351.18	24.54	64.22	190.01	345.78	260.23
16	63.75	324.96	114.15	0.00	87.64	271.86	331.07
17	54.44	331.67	69.66	0.17	84.39	307.92	370.22
18	64.23	50.87	97.20	0.00	213.48	453.71	394.71
19	58.92	94.83	104.47	3.86	90.73	309.28	299.20
20	28.95	41.50	50.92	7.30	96.03	179.10	170.98
21	12.62	44.94	28.55	0.00	107.56	43.64	155.50
22	6.35	63.22	27.04	0.00	133.38	78.77	257.18
23	0.00	134.66	16.19	7.07	24.92	55.13	49.08
Total	**1,301.13**	**2,603.52**	**1,335.58**	**117.87**	**1,820.06**	**3,484.26**	**3,809.50**

4. Waze_3 Early Warning Benefits

The relaxation of FDOT's existing Waze filters to report confidence level 3 alerts to TMCs (in addition to confidence level 4 and 5 alerts which are currently reported to TMCs) was discussed in detail in Chapter 4. In that chapter, benefits were estimated for the FTE district using two months of data and D3 using three months of data. This section uses those results to estimate the potential early warning benefits provided by relaxing the Waze filter in D3, with these findings then projected to other FDOT districts. For the FTE district, the two months of FTE data analyzed in Chapter 4 were used to estimate the early warning savings per hour instead of using projections based on the D3 data.

Table 5-7 summarizes the early warning benefits for Waze_3 in D3. First, the number of CAD alerts, number of matched Waze_3-CAD pairs, and number of matched pairs with Waze_3 earlier were calculated for each hour. These values were then multiplied by four to obtain annual counts (since the D3 data were for a three-month period). The second and third columns of Table 5-7 show the projected annual matched pairs and matched pairs with Waze_3 earlier, respectively, the fourth column shows the percentage of matched pairs with Waze_3 earlier, and the seventh column shows the projected annual CAD alert counts. Next, the average time earlier values were calculated for all pairs with Waze_3 earlier (fifth column), with these values then multiplied by the number of pairs with Waze_3 earlier (third column) to estimate the annual early warning benefits (sixth column). Lastly, the ratio of the annual matched pair count (second column) and the annual CAD count (seventh column) was determined for each hour, with these values shown in the eighth column of Table 5-7. These ratios were used to estimate the Waze_3 early warning benefits for other FDOT districts.

Table 5-7: Estimated Annual Early Warning Benefits per Hour of Day for Waze_3 in District 3

Hour	Annual Waze_3-CAD Pairs	Annual Pairs with Waze_3 Earlier	% Pairs with Waze_3 Earlier	Average Time Earlier (min)	Annual Early Warning Benefits (min)	Annual CAD Alerts	Annual Pairs over CAD Ratio
0	0	0	0.00%	0.00	0.00	60	0.000
1	0	0	0.00%	0.00	0.00	108	0.000
2	0	0	0.00%	0.00	0.00	60	0.000
3	0	0	0.00%	0.00	0.00	52	0.000
4	0	0	0.00%	0.00	0.00	52	0.000
5	0	0	0.00%	0.00	0.00	108	0.000
6	0	0	0.00%	0.00	0.00	96	0.000
7	4	0	0.00%	0.00	0.00	108	0.037
8	12	4	33.33%	28.08	112.32	264	0.045
9	24	4	16.67%	1.43	5.72	284	0.085
10	8	8	100.00%	7.19	57.52	264	0.030
11	4	0	0.00%	0.00	0.00	264	0.015
12	12	4	33.33%	0.55	2.20	268	0.045
13	4	4	100.00%	29.60	118.40	236	0.017
14	44	12	27.27%	13.41	160.92	276	0.159
15	8	0	0.00%	0.00	0.00	224	0.036
16	28	12	42.86%	6.95	83.40	308	0.091
17	28	4	14.29%	19.58	78.32	328	0.085
18	12	0	0.00%	0.00	0.00	320	0.038
19	0	0	0.00%	0.00	0.00	152	0.000
20	8	4	50.00%	4.93	19.72	184	0.043
21	0	0	0.00%	0.00	0.00	120	0.000
22	0	0	0.00%	0.00	0.00	104	0.000
23	0	0	0.00%	0.00	0.00	72	0.000
Total	**196**	**56**	**28.57%**	**11.40**	**638.52**	**4,312**	**0.045**

The same methods used to project the Active 911 and PulsePoint early warning benefits from D5 to other districts were used to project the Waze_3 early warning benefits from D3 to other districts. The only exception was the FTE district since two months of Waze_3 and CAD data were available. These two months of data were used to estimate early warning benefits for FTE in the same manner as was done for D3. Table 5-8 summarizes the estimated annual early warning benefits (in minutes) for all FDOT districts except D4 (excluded due to lack of CAD data). Since there were no matched pairs with Waze_3 earlier in D3 for hours 0 to 7, 11, and 15, these hours had zero estimated early warning benefits for all districts with projected benefits based on the D3 data. These estimates assume that the detection patterns observed in D3 would be representative of detection patterns in other districts. If FDOT decides to relax the Waze filter in other districts, it is recommended to collect actual data from these implementations and use these data to assist in operational decisions. However, the results shown in Table 5-8 can provide FDOT with general estimates to identify potential times and locations for relaxing the Waze filters. It is also important to note that additional false alerts reported to the TMCs due to relaxing the Waze filters were not considered, so care is needed to ensure that any changes to the filtering procedures do not result in excessive false alerts being sent to TMCs.

Table 5-8: Estimated Annual Early Warning Benefits per Hour of Day for Waze_3 (minutes)

Hour	**D1**	**D2**	**D3**	**D5**	**D6**	**D7**	**FTE**
0	0.00	0.00	0.00	0.00	0.00	0.00	6.60
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	59.87
6	0.00	0.00	0.00	0.00	0.00	0.00	169.07
7	0.00	0.00	0.00	0.00	0.00	0.00	153.80
8	730.93	823.25	112.32	1,274.24	574.79	494.80	20.13
9	31.10	37.02	5.72	51.80	27.53	18.59	392.87
10	294.57	387.82	57.52	510.93	269.52	213.74	124.73
11	0.00	0.00	0.00	0.00	0.00	0.00	181.47
12	12.56	16.46	2.20	21.60	10.10	9.56	258.27
13	844.85	1,079.15	118.40	1,302.40	582.47	598.52	315.20
14	1,037.23	1,353.83	160.92	2,015.00	861.16	864.07	303.33
15	0.00	0.00	0.00	0.00	0.00	0.00	98.47
16	567.82	852.68	83.40	1,113.71	446.24	495.80	130.53
17	442.22	723.74	78.32	1,004.07	417.15	433.63	453.07
18	0.00	0.00	0.00	0.00	0.00	0.00	336.27
19	0.00	0.00	0.00	0.00	0.00	0.00	112.40
20	121.86	154.65	19.72	243.82	102.46	106.75	147.13
21	0.00	0.00	0.00	0.00	0.00	0.00	175.20
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.07
Total	**4,083.15**	**5,428.61**	**638.52**	**7,537.57**	**3,291.41**	**3,235.45**	**3,438.47**

5.2 Ranking of Studied TIM Tools for TMC Operators

The results discussed in section 5.1 can help FDOT understand where and when each of the studied TIM data sources are expected to provide the most early warning benefits. TMC operators can also use these results to prioritize alert validation and detect incidents in a timely manner. For this purpose, the studied TIM tools (Active 911, PulsePoint, Waze, and Waze_3) were ranked based on their estimated early warning benefits for each hour within each FDOT district. This section discusses these rankings for each district and how TMC operators can use them to improve incident detection.

These rankings are based on the early warning benefits calculated in section 5.1. Tables 5-3, 5-5, 5-6, and 5-8 show the estimated annual early warning benefits for each hour by FDOT district for Active 911, PulsePoint, Waze, and Waze_3, respectively. Note that rankings were not developed for D4 since it had limited CAD data to allow for representative early warning estimates. Using these results, the studied TIM data sources were ranked from first to fourth place within each hour for each district, with the first place source having the highest estimated annual early warning benefits. If multiple data sources had the same estimated benefits for a specific hour, the number of estimated annual alerts was used to determine the ranking order, with the source with more expected alerts ranked closer to first. For cases where the estimated benefits and number of alerts were the same for multiple sources, these sources were ranked in the same order as they were in the previous hour. This ranking structure provides a clear indication of which data source is likely to be the best at detecting incidents earlier than CAD data for any given time. TMC operators can refer to the ranking chart for their specific district to determine how to best prioritize these TIM data sources for optimal early warnings of incidents and abnormal traffic conditions. They can be especially useful when alerts from different TIM data sources are received simultaneously to ensure that the alerts most likely to provide early warnings are reviewed first. While the rankings listed in this section are based on historical data, it would be possible to use a similar methodology to obtain rankings that dynamically change based on real-time data. This would require algorithms that could compare real-time CAD and TIM data and update average lead times and matched pair counts for different TIM data sources.

Figure 5-1 presents the ranked TIM sources by hour of day for D1. In this figure and all subsequent figures in this section, consecutive hours with identical rankings for all four TIM data sources have been aggregated into a single block. Only the Waze early warning benefits were calculated using actual data from D1, with the Active 911 and PulsePoint benefits projected using D5 data and the Waze_3 benefits projected using D3 data. Waze was ranked first for 10 hours (mainly morning and evening), Waze_3 was ranked first for seven hours (mainly daytime), PulsePoint was ranked first for five hours (nighttime and midday), and Active 911 was ranked first for two nighttime hours. These results indicate that PulsePoint and Active 911 could be useful during nighttime hours when Waze alerts are less common. While Waze_3 alerts could provide the most early warning benefits during daytime hours, care is needed to ensure that relaxing the Waze filters during these hours does not overwhelm TMC operators with excessive false alerts.

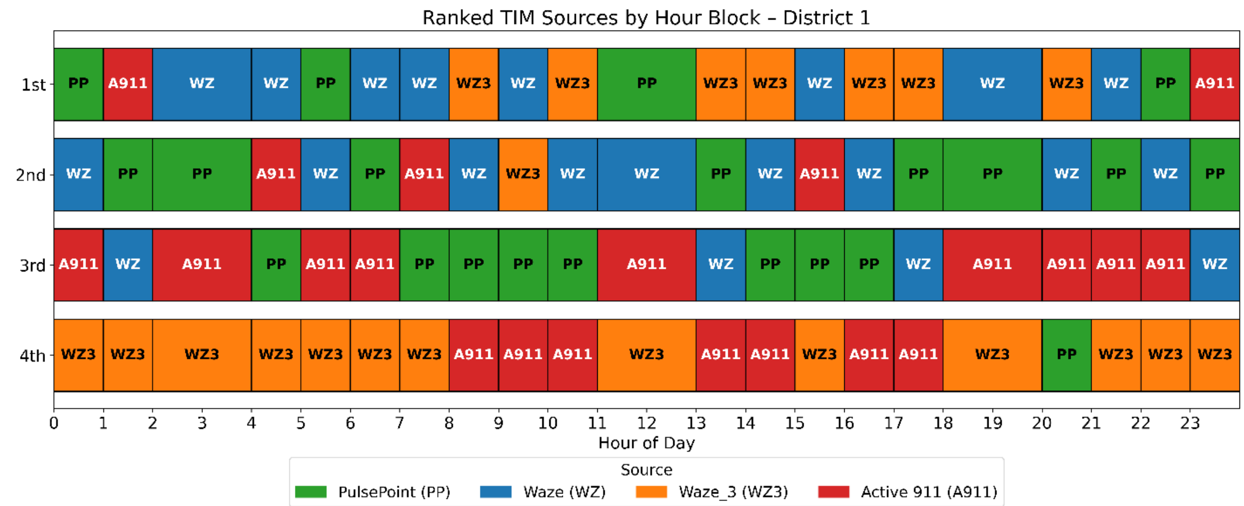

Figure 5-1: Ranked TIM Early Warning Sources by Hour of Day for District 1

Figure 5-2 presents the ranked TIM sources by hour of day for D2. Similar to D1, only the Waze early warning benefits were calculated using actual data from D2, with the rest projected from D5 or D3 data. These rankings are similar to D1, with Waze and Waze_3 most commonly ranked first. Waze was ranked first for 11 hours (mainly early morning and daytime), Waze_3 was ranked first for seven hours (mainly daytime), PulsePoint was ranked first for five hours (nighttime and early morning), and Active 911 was only ranked first for hour 1. Like D1, these results suggest that PulsePoint and Active 911 could help provide early warnings during nighttime hours.

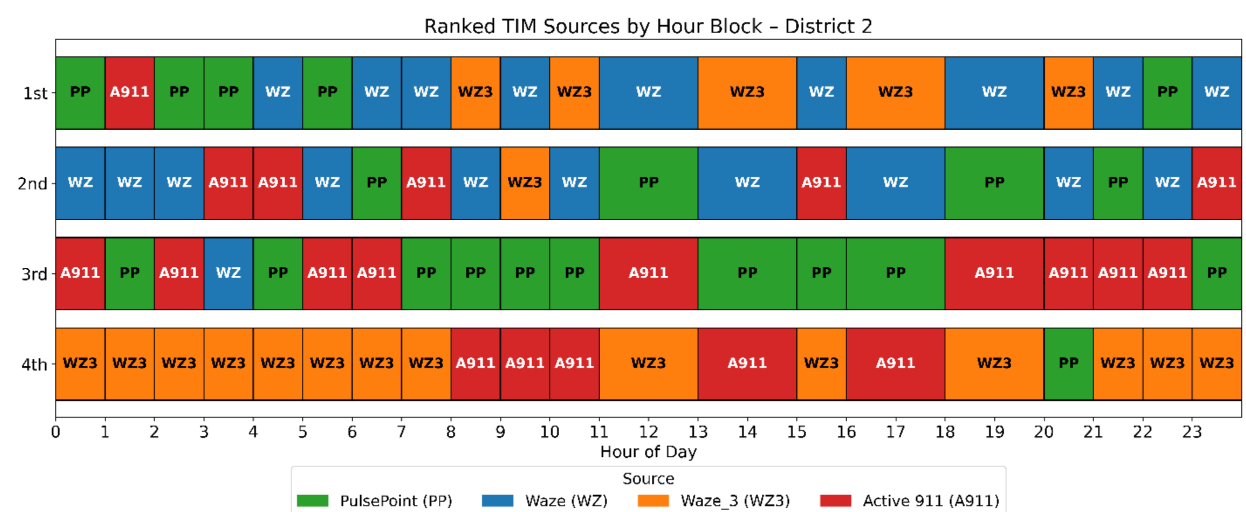

Figure 5-2: Ranked TIM Early Warning Sources by Hour of Day for District 2

Figure 5-3 presents the ranked TIM sources by hour of day for D3. Both the Waze and Waze_3 benefits were estimated using actual data from D3, with the Active 911 and PulsePoint data projected from D5 data. Waze was ranked first for 17 hours, PulsePoint was ranked first for four early morning hours, Waze_3 was ranked first for two daytime hours, and Active 911 was ranked first for hour 1. D3 currently relaxes the existing Waze filters during nighttime hours, which is likely why Waze is ranked first during most hours and Waze_3 is only ranked first during daytime hours. These results suggest that D3's current Waze procedures are successful but that PulsePoint and Active 911 could potentially improve early warning benefits even more during early morning hours.

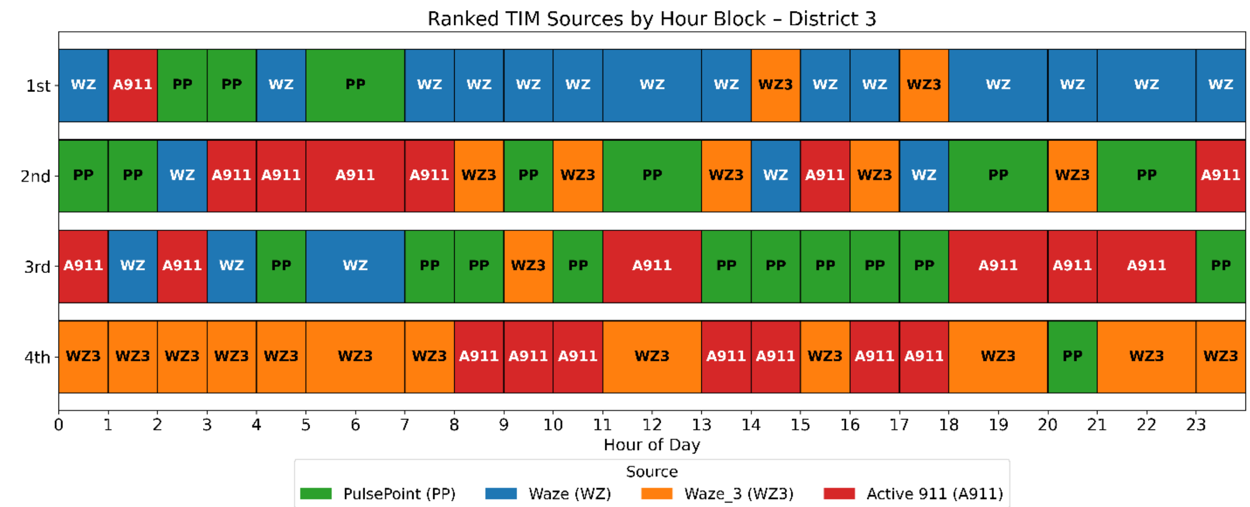

Figure 5-3: Ranked TIM Early Warning Sources by Hour of Day for District 3

Figure 5-4 presents the ranked TIM sources by hour of day for D5. The early warning benefits for Active 911, PulsePoint, and Waze were estimated using actual data from D5, with only the Waze_3 benefits projected from D3 data. Therefore, these results provide a clearer picture of how Active 911 and PulsePoint compare to Waze than the results from other districts. PulsePoint was ranked first for 12 hours (mainly early morning, evening, and nighttime), Waze_3 was ranked first for eight hours (morning, daytime, and evening), Active 911 was ranked first for three early morning hours, and Waze was only ranked first for hour 15. These results suggest that PulsePoint and Active 911 are important early warning sources for D5 and that they have potential to provide more early warning benefits than estimated for other districts. Relaxing the existing Waze filters could also provide substantial early warning benefits, but care is needed to avoid overburdening TMC operators during busy daytime hours.

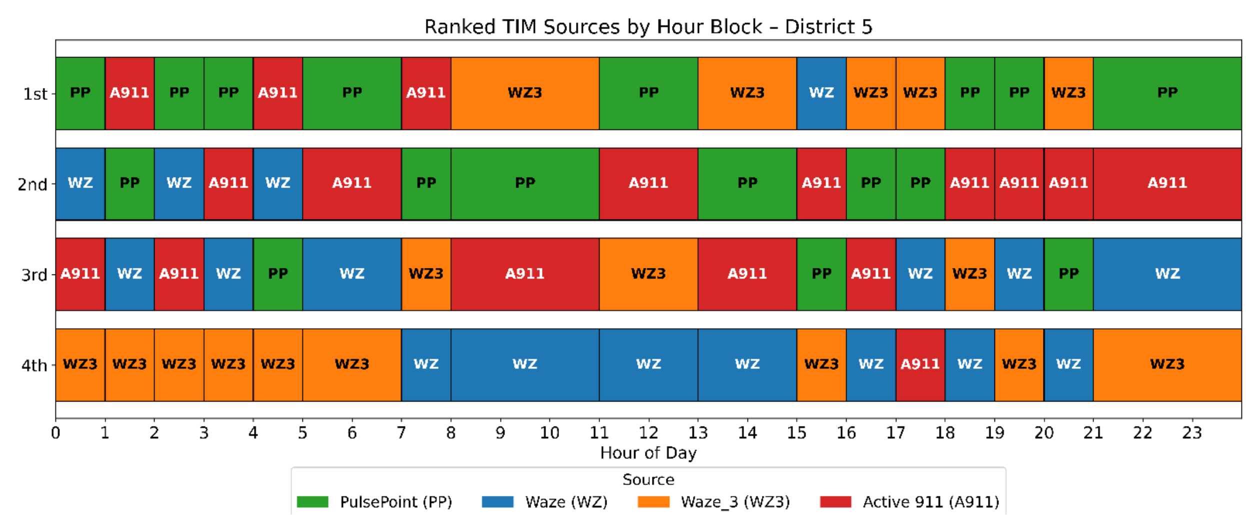

Figure 5-4: Ranked TIM Early Warning Sources by Hour of Day for District 5

Figure 5-5 presents the ranked TIM sources by hour of day for D6. Only the Waze early warning benefits were calculated using actual data from D6, with the rest projected from D5 or D3 data. Waze was ranked first for 15 hours (mainly early morning and daytime), Waze_3 was ranked first for seven hours (mainly daytime), and Active 911 and PulsePoint were each ranked first for one hour (hours 23 and 5, respectively). These results suggest that D6 would likely benefit less from PulsePoint or Active 911 than other districts.

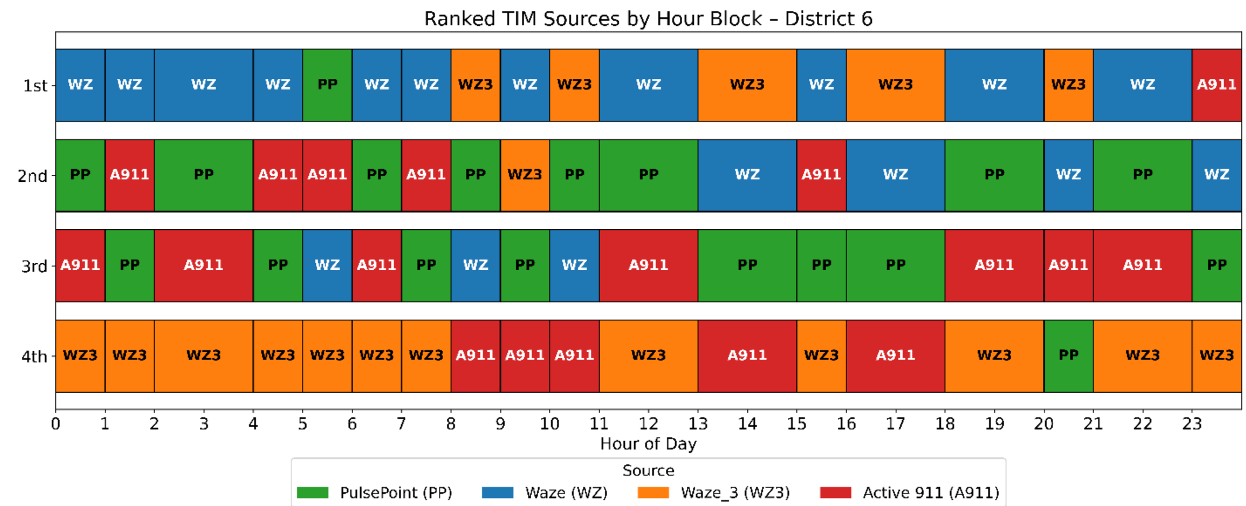

Figure 5-5: Ranked TIM Early Warning Sources by Hour of Day for District 6

Figure 5-6 presents the ranked TIM sources by hour of day for D7. Only the Waze early warning benefits were calculated using actual data from D7, with the rest projected from D5 or D3 data. Waze was ranked first for 16 hours (mainly morning, evening, and nighttime), Waze_3 was ranked first for six daytime hours, and PulsePoint was ranked first for two midday hours. Like D6, these results suggest that D7 would benefit less from Active 911 and PulsePoint than other districts.

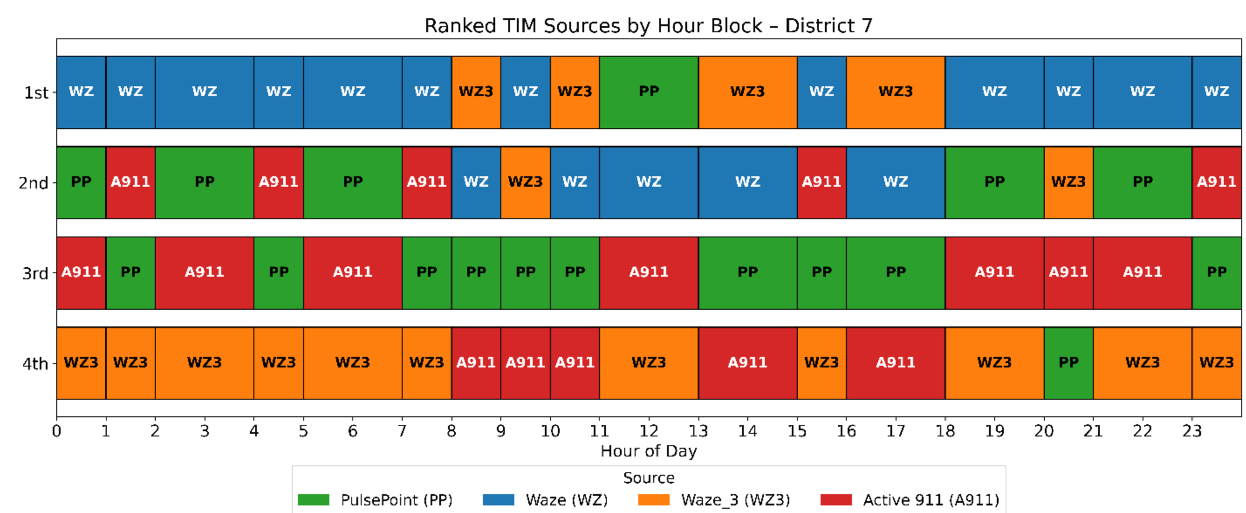

Figure 5-6: Ranked TIM Early Warning Sources by Hour of Day for District 7

Figure 5-7 presents the ranked TIM sources by hour of day for the FTE district. The early warning benefits of Waze and Waze_3 were estimated using actual data from the FTE district, with Active 911 and PulsePoint projected from D5 data. Waze was ranked first for 12 hours (mainly morning, evening, and nighttime), Waze_3 was ranked first for six consecutive daytime hours (hours 9-14) and three additional early morning and late evening hours, PulsePoint was ranked first for two nighttime hours, and Active 911 was ranked first only during hour 1. These results suggest that Waze could be a better early warning source at nighttime in the FTE district compared to most other districts, possibly due to high Waze usage on FTE roadways.

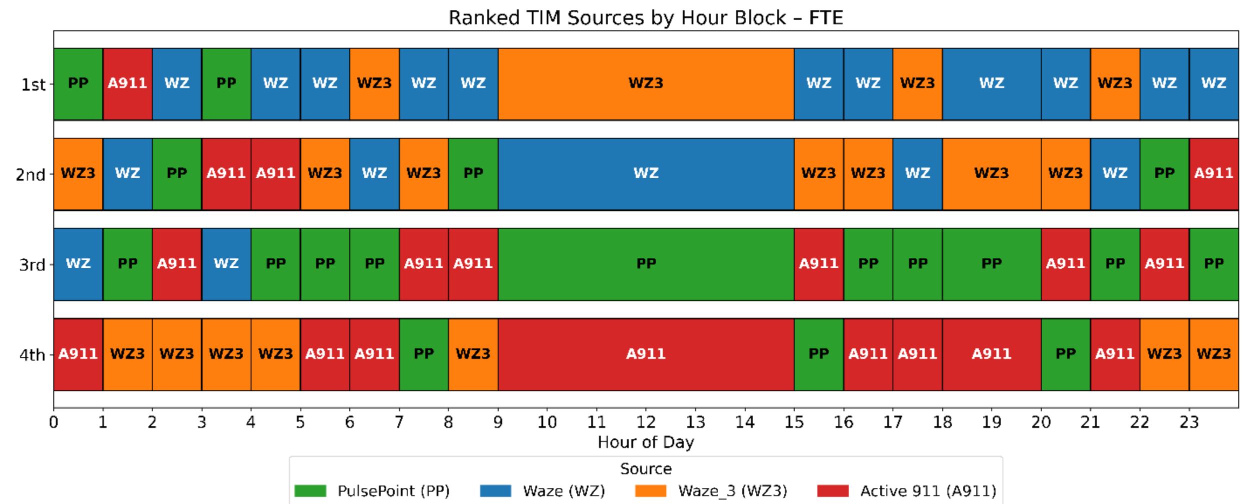

Figure 5-7: Ranked TIM Early Warning Sources by Hour of Day for FTE District

Chapter 6: Conclusions and Recommendations

This comprehensive TIM research project represents a multifaceted investigation into the current TIM tools used by FDOT, improvements to these tools, and additional tools used by other states to enhance incident detection and early warning capabilities on Florida's limited access highways. The study encompassed a thorough examination of existing TIM practices across the U.S., detailed analysis of millions of traffic alerts from Florida's current data systems, systematic evaluations of emerging technologies and data sources, and the development of a practical decision-support toolbox for future TIM deployments. The overarching goal was to identify opportunities for improving FDOT's ability to proactively detect abnormal traffic conditions and warn drivers of potential incidents, ultimately contributing to reduced congestion, improved safety outcomes, and advancement toward the state's Target Zero initiative.

The literature review established the foundation for understanding current TIM practices and emerging technological opportunities across the transportation industry. This comprehensive examination revealed that while traditional monitoring systems including CCTV cameras, vehicle detection sensors, and 511 services remain the backbone of most state TIM programs, significant opportunities exist for innovation through integration of crowdsourced data, CAV technologies, and advanced analytics approaches. The review identified successful innovative implementations across various states, demonstrating the value of adapting technologies to local conditions and operational needs. Emerging third-party technologies and enhanced integration of crowdsourced platforms like Waze were identified as potentially useful TIM improvements for Florida's operational environment. The literature review emphasized that effective TIM programs increasingly rely on multimodal data fusion, combining traditional infrastructure-based detection with real-time information from diverse sources, while carefully balancing detection sensitivity with false alert management to maintain operational efficiency.

Building upon these insights, the data collection and analysis phase examined the performance characteristics of FDOT's current TIM data sources through detailed comparison of FHP CAD, Waze, Active 911 and PulsePoint data. A statewide comparison of FHP CAD and Waze was undertaken to understand the relationship between these data sources and the potential early warning benefits that the current Waze filtering protocols provide. Detailed filtering and matching procedures were developed and applied to the more than 1.2 million alerts, resulting in 6,147 matched Waze-CAD events for comprehensive comparison. Waze alerts preceded CAD alerts in 28% of matched events and provided an average lead time of 8.42 minutes. Geographic analyses demonstrated that urban toll facilities like SR-821 and SR-91 showed the highest potential for early warning benefits, while temporal analyses revealed that Waze was most effective during midday and nighttime hours, particularly during late night and early morning periods from 10:00 PM through 3:59 AM. An XGBoost model was also developed to identify which spatial and temporal features most influenced an event having Waze earlier or CAD earlier. This model showed that events with large time differences between the first Waze and CAD alert, in D3 or D7, on I-75 or I-4, or in hours 1 (1:00 AM – 1:59 AM) and 17 (5:00 PM – 5:59 PM) were more likely to have CAD earlier. Conversely, events with larger distances between the Waze and CAD alerts, in D2 or D4, on SR-91 or SR-821, or in hours 12 (12:00 PM – 12:59 PM) and 23 (11:00 PM – 11:59 PM) were more likely to have Waze earlier.

Comparisons were also conducted between Active 911 and PulsePoint data from D5 and FHP CAD data. These comparisons provided encouraging preliminary results for these tools, suggesting that they should be considered for implementation in other FDOT districts. Active 911 demonstrated early warning capability in 38% of matched events (average lead time of 7.1 minutes) with PulsePoint showing even greater promise as 61% of matched events had PulsePoint earlier (average lead time of 4.9 minutes). The findings from these various analyses of Waze, Active 911, and PulsePoint established the empirical foundation for understanding how different TIM data sources complement each other and identified specific times and locations where improved integration could provide the greatest operational benefits.

Next, potential improvements to and expansions of FDOT's existing TIM tools were evaluated. The existing TSS data were found to be difficult for operators to utilize due to a high quantity of alerts caused by recurring congestion. To address this, an XGBoost classification model was developed to identify nonrecurring congestion alerts based on TSS data features. Applying this model to a statewide test set improved precision by 75% and reduced false alerts by 40% compared to the raw data. This means that the model would not only reduce the number of TSS alerts reported to TMC operators, but also increase the likelihood of those alerts actually being caused by nonrecurring congestion. Similar results were obtained for FTE TSS data, indicating the transferability of this modeling approach. The model could be adapted for real-time integration as a second-layer filter of TSS alerts.

Since Active 911 and PulsePoint were found to provide early warning benefits compared to FHP CAD in D5, potential expansions of these tools to other FDOT districts were evaluated. Projecting the Active 911 performance results from D5 to all Florida limited access roadways resulted in estimated annual statewide early detection benefits of 2,262.4 minutes (almost 38 hours), or approximately $3.3 million in congestion reduction benefits. PulsePoint demonstrated even better performance with estimated annual statewide early detection benefits of 5,781 minutes (over 96 hours) and $8.4 million in congestion reduction benefits. These findings illustrate the early warning potential of these systems throughout Florida. Therefore, it is recommended to consider deployment of one or both of these systems in other FDOT districts, not just D5.

The potential early warning benefits of relaxing the existing Waze filters to report confidence level 3 alerts to TMCs (in addition to the currently reported confidence level 4 and 5 alerts) were also evaluated. Allowing confidence level 3 Waze alerts to reach TMCs was estimated to provide early warning for 45% of matched Waze-CAD events. The detailed transition time analysis showed that 64% of confidence level transitions occurred within three minutes and that events took an average of 4.95 minutes to transition from confidence level 3 to confidence level 4. B/C evaluations were conducted for FTE and D3. Relaxing the filter for all times of day in D3 had the highest B/C ratio (7.91), while only relaxing the filter from 9:00 PM – 11:59 PM in D3 had the lowest B/C ratio (1.40). Therefore, it is recommended to consider relaxing the Waze filter during daytime hours in D3. However, care is needed to prevent TMC operators from being overwhelmed with false alerts.

Evaluations were also conducted on the Waycare and Carbyne systems which have previously been implemented in Nevada and Georgia, respectively. These evaluations, which used performance data from these other states, indicated potential annual congestion reduction benefits of $2.3 million and $9.8 million, respectively. However, the lack of Florida-specific data for these systems makes the results of these evaluations much more uncertain than the evaluations of Waze, Active 911, and PulsePoint. If FDOT is interested in pursuing these situations, it is recommended to test and evaluate them in a small area (preferably areas with limited TIM coverage from other systems) before deploying them statewide.

The culmination of this research was the development of a comprehensive TIM toolbox which synthesized all findings into a practical decision-support framework for FDOT engineers, management personnel, and TMC operators. This toolbox provides hourly rankings of TIM data source effectiveness across Florida's districts, enabling data-driven decisions about optimal deployment times and locations for different technologies. The methodology used to develop this toolbox is a replicable framework for evaluating TIM tool performance that can accommodate future data sources and changing operational conditions. Hourly rankings revealed that Waze and relaxed Waze filters ranked first for most hours across all districts, reflecting the broad coverage and real-time nature of crowdsourced data. Active 911 and PulsePoint provided superior performance during specific time periods, particularly nighttime and early morning hours when traditional reporting mechanisms may be less responsive and Waze usage is low. District-specific patterns also emerged, with D5 showing the strongest performance for Active 911 and PulsePoint due to actual deployment experience, suggesting that the projected benefits for these tools in other districts might be conservative and actual deployment could yield even greater improvements than estimated. The developed toolbox is intended to act as a simple guide for operators in determining which data source to rely on during specific hours of the day. While the charts provide hourly details, operators can instead follow broader trends rather than switching sources from one hour to the next. For example, if Waze dominates most hours of a shift except for one or two hours where another source performs slightly better, it is more practical for operators to rely on Waze throughout the full shift. This approach simplifies decision-making while still retaining most of the benefits. The toolbox framework extends beyond simple rankings to provide a foundation for continuous improvement and adaptation, with a methodology that can easily incorporate new data sources, updated performance metrics, and changing operational priorities.

This research project makes several significant contributions to the broader TIM field beyond its immediate benefits to FDOT operations. The comprehensive methodology for comparing disparate data sources provides a template that other transportation agencies can adapt to their specific conditions and available technologies, while the empirical validation of crowdsourced data benefits adds to the growing body of evidence supporting integration of citizen-generated information in transportation management. The detailed documentation of temporal and geographic performance variations provides insights with national implications, particularly the finding that crowdsourced data provides greatest early warning benefits during off-peak hours when traditional monitoring may be less intensive. This research also contributes to understanding how effective public-private partnerships can help transportation operations by demonstrating how various platforms (like Waze, Active 911, and PulsePoint) can supplement each other. By integrating all these sources into a comprehensive TIM system, major early warning benefits could be obtained.

The developed tools and findings from this project can be immediately implemented by FDOT to improve their TIM practices. Additionally, future research efforts could help further enhance

TIM practices. The future research directions identified from this project include the creation of machine learning models for real-time alert classification that could automatically evaluate incoming alerts based on contextual factors, the integration of the developed TIM toolbox rankings directly into SunGuide operations for real-time decision support, and the development of dynamic algorithms that adjust Waze filtering sensitivity based on current conditions rather than static rules. The research framework established in this project provides a foundation for investigating these emerging opportunities while maintaining focus on proven, cost-effective improvements to current operations. As summarized in Section 4.3.3, a practical next step is to prototype a real-time decision-support layer that evaluates Waze confidence level 3 alerts using a classification model trained on historically matched Waze and CAD incidents. The model would score each new alert and flag those exceeding a predefined probability threshold for operator review, leveraging spatial and temporal variables, alert type and subtype, crowdsourced validation (e.g., reliability scores), and local historical frequency to improve accuracy. With these future efforts, it could be possible to develop a real-time platform which can collect and filter data from multiple TIM data sources and provide the most urgent alerts to TMC operators in a timely manner. This platform would improve traffic safety and operations while improving operator workflow and efficiency, giving operators more time to coordinate response activities. The successful research discussed in this report provides a foundation for such a platform while also allowing FDOT to make immediate improvements and enhancements to their existing TIM systems.

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Appendix A: Developed Codes to Compare TIM Data Sources (Python 3.13)

Comparison and Modeling of Waze and FHP CAD Data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_validate,
StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, roc_auc_score, confusion_matrix, classification_report,
make_scorer
from xgboost import XGBClassifier
from sklearn.utils.class_weight import compute_class_weight
import shap

# Load the final dataset
df = pd.read_csv("processed_pairs_dataset.csv")

# Separate features and target variable
X = df.drop(columns=['earlier_binary'])
y = df['earlier_binary']

# Train-test split before any transformation or resampling
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Compute class weights
class_weights = compute_class_weight('balanced',
classes=np.unique(y_train), y=y_train)
class_weights_dict = {0: class_weights[0], 1: class_weights[1]}

# Chosen hyperparameters
best_params = {
    'colsample_bytree': 0.8,
    'learning_rate': 0.01,
    'max_depth': 7,
    'n_estimators': 200,
    'scale_pos_weight': class_weights_dict[1],
    'subsample': 0.8
}

# Initialize XGBoost model with chosen hyperparameters
best_xgb = XGBClassifier(**best_params, random_state=42)

# Define multiple scoring metrics
scoring = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score),
```

```
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score),
    'roc_auc': make_scorer(roc_auc_score)
}

# Cross-validation strategy
cv = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

# Perform cross-validation with multiple metrics
results = cross_validate(best_xgb, X_train_scaled, y_train, cv=cv,
scoring=scoring, return_train_score=False)

# Print cross-validation results
print("Cross-validation results:")
for metric in scoring.keys():
    print(f"{metric}: {results['test_' + metric].mean()} ±
{results['test_' + metric].std()}")

# Train the XGBoost model with the full training data
best_xgb.fit(X_train_scaled, y_train)

# Predict on test data
y_pred = best_xgb.predict(X_test_scaled)
y_pred_prob = best_xgb.predict_proba(X_test_scaled)[:, 1]

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_prob)

# Print evaluation metrics
print("\nModel: XGBoost with Chosen Hyperparameters")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
print("ROC-AUC Score:", roc_auc)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))

# Plot the performance metrics
performance_xgb = pd.DataFrame([{
    'Model': 'XGBoost',
    'Accuracy': accuracy,
    'Precision': precision,
    'Recall': recall,
    'F1 Score': f1,
    'ROC-AUC Score': roc_auc
}])

fig, ax = plt.subplots(figsize=(14, 8))
performance_xgb.set_index('Model').plot(kind='bar', ax=ax)
```

```
plt.title('XGBoost Model Performance Metrics')
plt.ylabel('Score')
plt.xticks(rotation=45)
plt.ylim(0, 1)
plt.legend(loc='lower right')

# Annotate the bars with the metric values
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}', (p.get_x() * 1.005,
p.get_height() * 1.005))

plt.tight_layout()
plt.show()

# SHAP analysis
explainer = shap.Explainer(best_xgb, X_train_scaled)
shap_values = explainer(X_test_scaled)

# Plot SHAP summary with all features
shap.summary_plot(shap_values, X_test_scaled, feature_names=X.columns)
```

Comparison of Active 911 and FHP CAD Data

```
import pandas as pd

# Load the datasets
traffic_911 = pd.read_csv("traffic_911.csv")
CAD_combined = pd.read_csv("CAD_combined_65m_buffer_roadway_filtered.csv")


# Convert the 'timestamp' columns to datetime with proper time zone
handling
traffic_911['timestamp_911'] =
pd.to_datetime(traffic_911['timestamp_911'])
CAD_combined['timestamp_cad'] =
pd.to_datetime(CAD_combined['timestamp_cad'], utc=True)


# Convert traffic_911 timestamps to UTC after localizing to
America/New_York
traffic_911['timestamp_911'] =
traffic_911['timestamp_911'].dt.tz_localize('America/New_York',
ambiguous='infer', nonexistent='shift_forward').dt.tz_convert('UTC')


# Sort both datasets by their respective timestamp columns
traffic_911 = traffic_911.sort_values('timestamp_911')
CAD_combined = CAD_combined.sort_values('timestamp_cad')


# Perform an asof merge with a tolerance of 30 minutes, keeping only rows
where there is a match
matched_alerts = pd.merge_asof(
    traffic_911,
    CAD_combined,
    left_on='timestamp_911',
    right_on='timestamp_cad',
    direction='nearest',
    tolerance=pd.Timedelta(minutes=30),
    suffixes=('_911', '_cad')
)

# Filter to only include matched alerts (where both 911 and CAD alerts
exist)
matched_alerts = matched_alerts.dropna(subset=['alarm_id_cad'])

# Save the matched datasets to a new CSV file
matched_alerts.to_csv("CAD_911_pairs.csv", index=False)



# Calculate the absolute time difference in minutes
matched_alerts['time_difference'] = (matched_alerts['timestamp_cad'] -
matched_alerts['timestamp_911']).dt.total_seconds().abs() / 60
```

```
# Sort by 'alarm_id_cad' and 'time_difference' to prepare for filtering
the closest matches
matched_alerts_sorted = matched_alerts.sort_values(by=['alarm_id_cad',
'time_difference'])

# Drop duplicates, keeping the entry with the smallest 'time_difference'
for each 'alarm_id_cad'
matched_alerts_filtered =
matched_alerts_sorted.drop_duplicates(subset='alarm_id_cad', keep='first')

print(len(matched_alerts_filtered))
matched_alerts_filtered['cad_earlier'] =
matched_alerts_filtered['timestamp_cad'] <
matched_alerts_filtered['timestamp_911']
matched_alerts_filtered['911_earlier'] =
matched_alerts_filtered['timestamp_cad'] >
matched_alerts_filtered['timestamp_911']

# Calculate the total number of cases
total_cases = len(matched_alerts_filtered)

# Calculate the number of cases where CAD is earlier
cad_earlier_count = matched_alerts_filtered['cad_earlier'].sum()
print("cad earlier:",cad_earlier_count)
# Calculate the number of cases where 911 is earlier
_911_earlier_count = matched_alerts_filtered['911_earlier'].sum()
print('911 earlier:',_911_earlier_count)
# Calculate percentages
cad_earlier_percentage = (cad_earlier_count / total_cases) * 100
_911_earlier_percentage = (_911_earlier_count / total_cases) * 100



# Print the results
print(f"Percentage of CAD alerts earlier: {cad_earlier_percentage:.2f}%")
print(f"Percentage of 911 alerts earlier: {_911_earlier_percentage:.2f}%")
```

Comparison of PulsePoint and FHP CAD Data

```
import pandas as pd
import geopandas as gpd
from shapely.geometry import Point
from geopy.distance import geodesic
import pytz
# Stage 1: Load and Prepare Data
# ------------------------------
# Load cad and pulsepoint alerts data
pp_alerts = pd.read_csv("file_name.csv")
cad_alerts = pd.read_csv("file_name.csv")



# Convert timestamps into datetime format
florida_tz = pytz.timezone('America/New_York')
pp_alerts['timestamp_pp'] = pd.to_datetime(pp_alerts['timestamp_pp'],
format='%m/%d/%Y
%H:%M').dt.tz_localize(florida_tz).dt.tz_convert(pytz.UTC)
cad_alerts['timestamp_cad'] = pd.to_datetime(cad_alerts['timestamp_cad'],
utc=True)

# Create GeoDataFrames with initial CRS set to WGS84 (EPSG:4326)
cad_alerts['geometry'] = cad_alerts.apply(lambda row:
Point(row['longitude_cad'], row['latitude_cad']), axis=1)
pp_alerts['geometry'] = pp_alerts.apply(lambda row:
Point(row['longitude_pp'], row['latitude_pp']), axis=1)
gdf_cad = gpd.GeoDataFrame(cad_alerts, geometry='geometry',
crs="EPSG:4326")
gdf_pp = gpd.GeoDataFrame(pp_alerts, geometry='geometry', crs="EPSG:4326")



# Stage 2: Buffer and Spatial Join
# -------------------------------
# Set spatial buffer (in miles) and temporal buffer (in minutes)
spatial_buffer_miles = 1
temporal_buffer = 30

# Define a UTM projection
utm_crs = "EPSG:32617"

# Convert GeoDataFrames to the UTM coordinate system
gdf_cad = gdf_cad.to_crs(utm_crs)
gdf_pp = gdf_pp.to_crs(utm_crs)

# Buffer the cad alerts in meters (1 mile = 1609.34 meters)
spatial_buffer_meters = 1609.34 * spatial_buffer_miles
gdf_cad['buffer'] = gdf_cad.geometry.buffer(spatial_buffer_meters)

# Set the buffered geometries as the active geometry
gdf_cad = gdf_cad.set_geometry('buffer')

# Perform spatial join using the buffered geometries
```

```
joined = gpd.sjoin(gdf_pp, gdf_cad, how='inner',
predicate='intersects',lsuffix='pp', rsuffix='cad')

# Convert the joined GeoDataFrame back to the original geographic
coordinate system
joined = joined.to_crs("EPSG:4326")
print(joined.columns)
print(joined.head)


# Stage 3: Calculate Distances and Time Differences
# ---------------------------------------------------
# Function to calculate distance in miles
def calculate_distance(row):
    cad_location = (row['latitude_cad'], row['longitude_cad'])
    pp_location = (row['latitude_pp'], row['longitude_pp'])
    return geodesic(cad_location, pp_location).miles

# Calculate distances and time differences
joined['distance'] = joined.apply(calculate_distance, axis=1)
joined['time_diff'] = (joined['timestamp_cad'] -
joined['timestamp_pp']).abs() / pd.Timedelta(minutes=1)

# Filter by spatial and temporal buffers
filtered_candidates = joined[(joined['distance'] <= spatial_buffer_miles)
& (joined['time_diff'] <= temporal_buffer)]

# Extract results
print(f"Number of alerts within the buffer: {len(filtered_candidates)}")
print(filtered_candidates.head)



# Step 1: Sort the DataFrame by 'alarm_id_pp' and 'distance'
joined_sorted = filtered_candidates.sort_values(by=['alarm_id_pp',
'distance'])

# Step 2: Group by 'alarm_id_pp' and keep the first entry per group (which
is the closest due to sorting)
closest_cad_per_pp =
joined_sorted.groupby('alarm_id_pp').first().reset_index()
# Print the results to verify
print(closest_cad_per_pp.head)



# Stage 4: Which Alert Occurred First
# ------------------------------------
earlier_df= pd.DataFrame()

# Compare timestamps and add columns for verification
earlier_df['cad_earlier'] = closest_cad_per_pp['timestamp_cad'] <
closest_cad_per_pp['timestamp_pp']
```

```
earlier_df['pp_earlier'] = closest_cad_per_pp['timestamp_pp'] <
closest_cad_per_pp['timestamp_cad']

# Count occurrences
pp_earlier_count = earlier_df['pp_earlier'].sum()
cad_earlier_count = earlier_df['cad_earlier'].sum()

# Calculate percentages
total_pairs = len(earlier_df)
pp_earlier_percentage = (pp_earlier_count / total_pairs) * 100
cad_earlier_percentage = (cad_earlier_count / total_pairs) * 100

# Print results
print(f"pp was earlier in {pp_earlier_percentage:.2f}% of the cases.")
print(f"cad was earlier in {cad_earlier_percentage:.2f}% of the cases.")

# Create a list of all pairs with detected timestamps and lat/longs
pairs_list = closest_cad_per_pp[['alarm_id_cad', 'timestamp_cad',
'longitude_cad', 'latitude_cad',
                     'alarm_id_pp', 'timestamp_pp', 'longitude_pp',
'latitude_pp']]

print(closest_cad_per_pp['time_diff'].describe())
print(closest_cad_per_pp['distance'].describe())
```

Evaluation of Adjusted Waze Filtering Protocols

```
## 1- Load CAD and Waze alerts datasets
import pandas as pd
import geopandas as gpd
from shapely.geometry import Point
from geopy.distance import geodesic
import pytz

# Load cad and FHP alerts data
df = pd.read_csv('FTE_WAZE_CAD_RAW.csv')
df2 = pd.read_csv('waze_alerts.csv')
# Ensure 'fetched_at' column is in datetime format
df2['fetched_at'] = pd.to_datetime(df2['fetched_at'])
# Get the first and last timestamps
first_timestamp = df2['fetched_at'].min()
last_timestamp = df2['fetched_at'].max()
print("First timestamp:", first_timestamp)
print("Last timestamp:", last_timestamp)


cad_alerts = df[df['IDS TYPE']=='FHP'].copy()
waze_alerts = df2[df2['alert_confidence'].isin([4,5])].copy()
cad_alerts.columns = cad_alerts.columns.str.lower()
waze_alerts.columns = waze_alerts.columns.str.lower()
cad_alerts.rename(columns={'ids detected
date':'timestamp_cad','longitude':'longitude_cad','latitude':'latitude_cad
'},inplace=True)
waze_alerts.rename(columns={'publish_datetime_utc':'timestamp_waze','longi
tude':'longitude_waze','latitude':'latitude_waze'},inplace=True)
waze_alerts.drop(['reported_by','image','description','country','near_by',
'comments','num_comments'],inplace=True,axis=1)


## 2- Convert timestamp into a datetime object

import pandas as pd

# Convert 'timestamp_cad' to datetime and localize to Eastern Time if it's
naive
cad_alerts['timestamp_cad'] = pd.to_datetime(cad_alerts['timestamp_cad'],
format='%m/%d/%Y %I:%M:%S %p')
if not cad_alerts['timestamp_cad'].dt.tz:
    cad_alerts['timestamp_cad'] =
cad_alerts['timestamp_cad'].dt.tz_localize('US/Eastern',
ambiguous='infer')

# Convert 'timestamp_waze' from UTC formatted string to datetime, then
convert to Eastern Time
waze_alerts['timestamp_waze'] =
pd.to_datetime(waze_alerts['timestamp_waze'], utc=True)
waze_alerts['timestamp_waze'] =
waze_alerts['timestamp_waze'].dt.tz_convert('US/Eastern')
# Format both 'timestamp_cad' and 'timestamp_waze' to the desired string
format for consistency
```

```
cad_alerts['timestamp_cad'] =
cad_alerts['timestamp_cad'].dt.strftime('%m/%d/%Y %I:%M:%S %p')
waze_alerts['timestamp_waze'] =
waze_alerts['timestamp_waze'].dt.strftime('%m/%d/%Y %I:%M:%S %p')
# Ensure timestamp_cad is in datetime format
cad_alerts['timestamp_cad'] =
pd.to_datetime(cad_alerts['timestamp_cad'],format='%m/%d/%Y %I:%M:%S %p')
cad_alerts['timestamp_cad']
# Extract hour of day
cad_alerts['hour_of_day'] = cad_alerts['timestamp_cad'].dt.hour
# Count alerts by hour
alerts_by_hour =
cad_alerts['hour_of_day'].value_counts().sort_index().reset_index()
alerts_by_hour.columns = ['hour_of_day', 'alert_count']
print(alerts_by_hour)
alerts_by_hour.to_csv('FTE_CAD_ALERTS_BY_HOUR_OF_DAY.csv')
waze_alerts['timestamp_waze'].head()
cad_alerts['timestamp_cad'].head()


## 3- Set the geometry for both alerts as points based on long and lat

# Create GeoDataFrames with initial CRS set to WGS84 (EPSG:4326)
cad_alerts['geometry'] = cad_alerts.apply(lambda row:
Point(row['longitude_cad'], row['latitude_cad']), axis=1)
waze_alerts['geometry'] = waze_alerts.apply(lambda row:
Point(row['longitude_waze'], row['latitude_waze']), axis=1)
# the following conversion is essential or else there will be dispersion
gdf_cad = gpd.GeoDataFrame(cad_alerts, geometry='geometry',
crs="EPSG:4326")
gdf_waze = gpd.GeoDataFrame(waze_alerts, geometry='geometry',
crs="EPSG:4326")

## 4- Create buffers and perform the spatial join

# Set spatial buffer (in miles) and temporal buffer (in minutes)
spatial_buffer_miles = 1
temporal_buffer = 30

# Define a UTM projection
utm_crs = "EPSG:32617"

# Convert GeoDataFrames to the UTM coordinate system
gdf_cad = gdf_cad.to_crs(utm_crs)
gdf_waze = gdf_waze.to_crs(utm_crs)

# Buffer the cad alerts in meters (1 mile = 1609.34 meters)
spatial_buffer_meters = 1609.34 * spatial_buffer_miles
gdf_cad['buffer'] = gdf_cad.geometry.buffer(spatial_buffer_meters)

# Set the buffered geometries as the active geometry
gdf_cad = gdf_cad.set_geometry('buffer')
gdf_cad = gdf_cad.to_crs(utm_crs)
# Perform spatial join using the buffered geometries
```

```
joined = gpd.sjoin(gdf_waze, gdf_cad, how='inner',
predicate='intersects',lsuffix='waze', rsuffix='cad')

# Convert the joined GeoDataFrame back to the original geographic
coordinate system
joined = joined.to_crs("EPSG:4326")
joined.columns
joined.head


## 5- Calculate Distance and time difference between all spatially matched
pairs

joined['timestamp_cad'] = pd.to_datetime(joined['timestamp_cad'])
joined['timestamp_waze'] = pd.to_datetime(joined['timestamp_waze'])

# Function to calculate distance in miles
def calculate_distance(row):
    cad_location = (row['latitude_cad'], row['longitude_cad'])
    waze_location = (row['latitude_waze'], row['longitude_waze'])
    return geodesic(cad_location, waze_location).miles

# Calculate distances and time differences
joined['distance'] = joined.apply(calculate_distance, axis=1)
joined['time_diff'] = (joined['timestamp_cad'] -
joined['timestamp_waze']).abs() / pd.Timedelta(minutes=1)

# Filter by spatial and temporal buffers
filtered_candidates = joined[(joined['distance'] <= spatial_buffer_miles)
& (joined['time_diff'] <= temporal_buffer)]


# Extract results
print(f"Number of alerts within the buffer: {len(filtered_candidates)}")

filtered_candidates.head


## 6- Filter out multiple matched alerts, keep 1 waze alert per matched
CAD

# Step 1: Sort the DataFrame by 'alarm_id_waze' and 'distance'
joined_sorted = filtered_candidates.sort_values(by=['alert_id',
'distance'])

# Step 2: Group by 'alarm_id_waze' and keep the first entry per group
(which is the closest due to sorting)
closest_cad_per_waze =
joined_sorted.groupby('alert_id').first().reset_index()
# Print the results to verify
print(closest_cad_per_waze.head)
closest_cad_per_waze.to_csv('FTE_waze_CAD_pairs.csv',index=False)
closest_cad_per_waze['distance'].describe()
closest_cad_per_waze['distance'].value_counts()
```

```
## 7- Calculate earlier occurrences

closest_cad_per_waze.shape
import pandas as pd
closest_cad_per_waze = pd.read_csv('FTE_waze_CAD_pairs.csv')
closest_cad_per_waze['timestamp_cad']
closest_cad_per_waze.isna().sum()

import pandas as pd
# Convert to datetime, errors='coerce' to catch bad formats
closest_cad_per_waze['timestamp_cad'] =
pd.to_datetime(closest_cad_per_waze['timestamp_cad'])
closest_cad_per_waze['timestamp_waze'] =
pd.to_datetime(closest_cad_per_waze['timestamp_waze'])

# Identify earlier source
closest_cad_per_waze['earlier_source'] = closest_cad_per_waze.apply(
    lambda row: 'waze' if row['timestamp_waze'] < row['timestamp_cad']
    else 'cad' if row['timestamp_waze'] > row['timestamp_cad']
    else 'equal',
    axis=1
)

closest_cad_per_waze['earlier_source'].value_counts()
# Determine which timestamp to use for hour
closest_cad_per_waze['earlier_time'] =
closest_cad_per_waze[['timestamp_waze', 'timestamp_cad']].min(axis=1)
closest_cad_per_waze['earlier_hour'] =
closest_cad_per_waze['earlier_time'].dt.hour

# Time difference in minutes
closest_cad_per_waze['minutes_earlier'] =
(closest_cad_per_waze['timestamp_cad'] -
closest_cad_per_waze['timestamp_waze']).dt.total_seconds().abs() / 60

# Grouped summary with separate averages
summary = closest_cad_per_waze.groupby('earlier_hour').agg(
    cad_earlier_count=('earlier_source', lambda x: (x == 'cad').sum()),
    waze_earlier_count=('earlier_source', lambda x: (x == 'waze').sum()),
    equal_count=('earlier_source', lambda x: (x == 'equal').sum()),
    avg_minutes_earlier_cad=('minutes_earlier', lambda x:
x[closest_cad_per_waze.loc[x.index, 'earlier_source'] == 'cad'].mean()),
    avg_minutes_earlier_waze=('minutes_earlier', lambda x:
x[closest_cad_per_waze.loc[x.index, 'earlier_source'] == 'waze'].mean()),
    total_count=('earlier_source', 'count')
).reset_index()

summary
summary.to_csv('FTE_WAZE_CAD_TABLE.csv')


# Create a DataFrame to store comparison results
```

```
earlier_df = closest_cad_per_waze

# Compare timestamps
earlier_df['cad_earlier'] = earlier_df['timestamp_cad'] <
earlier_df['timestamp_waze']
earlier_df['waze_earlier'] = earlier_df['timestamp_waze'] <
earlier_df['timestamp_cad']
earlier_df['same_time'] = earlier_df['timestamp_waze'] ==
earlier_df['timestamp_cad']

# Count cases
cad_earlier_count = earlier_df['cad_earlier'].sum()
waze_earlier_count = earlier_df['waze_earlier'].sum()
same_time_count = earlier_df['same_time'].sum()

# Total pairs
total_pairs = len(earlier_df)

# Calculate percentages
cad_earlier_percentage = (cad_earlier_count / total_pairs) * 100
waze_earlier_percentage = (waze_earlier_count / total_pairs) * 100
same_time_percentage = (same_time_count / total_pairs) * 100

# Print results
print(f"Waze was earlier in {waze_earlier_percentage:.2f}% of the cases.")
print(f"CAD was earlier in {cad_earlier_percentage:.2f}% of the cases.")
print(f"Both were at the same time in {same_time_percentage:.2f}% of the
cases.")
waze_earlier_count
same_time_count


## 8- Calculate number of Waze matched alerts that had earlier Confidence
Leven 3 (between 21-24)

import pandas as pd
pairs = pd.read_csv('FTE_waze_CAD_pairs.csv')
waze_raw = pd.read_csv('waze_alerts.csv')

pairs.rename(columns={'timestamp_waze':'timestamp','longitude_waze':'longi
tude','latitude_waze':'latitude'},inplace=True)

waze_raw.rename(columns={'publish_datetime_utc': 'timestamp'},
inplace=True)

# Drop specified columns
columns_to_drop = [
    'reported_by',
    'image',
    'description',
    'country',
    'near_by',
    'comments',
    'num_comments'
```

```
]
waze_raw.drop(columns=columns_to_drop, inplace=True)

# Convert 'timestamp_waze' from UTC formatted string to datetime, then
convert to Eastern Time
waze_raw['timestamp'] = pd.to_datetime(waze_raw['timestamp'], utc=True)
waze_raw['timestamp'] = waze_raw['timestamp'].dt.tz_convert('US/Eastern')
waze_raw['timestamp'] = waze_raw['timestamp'].dt.strftime('%m/%d/%Y
%I:%M:%S %p')
pairs['timestamp'] = pd.to_datetime(pairs['timestamp'])
waze_raw['timestamp'] = pd.to_datetime(waze_raw['timestamp'])

filtered_waze = waze_raw[waze_raw['alert_confidence'] == 3]
filtered_waze.shape

# Set the condition for the time range
condition1 = (filtered_waze['timestamp'].dt.hour >= 21) &
(filtered_waze['timestamp'].dt.hour <= 23)

# Count the number of observations in the specified time range
count = filtered_waze[condition1].shape[0]

print(f'Number of observations between 09:00 PM and 11:59 PM: {count}')
merged_df = pd.merge(pairs, filtered_waze, on='alert_id',
suffixes=('_pairs', '_waze'))
waze_raw['timestamp'].head
pairs['timestamp'].head
merged_df.columns

merged_df['time_diff_3'] = ((merged_df['timestamp_pairs'] -
merged_df['timestamp_waze']).dt.total_seconds() / 60).abs()

# Step 4: Sort by alert_id and time_diff to prepare for selecting the
closest alert
merged_df.sort_values(by=['alert_id', 'time_diff_3'], inplace=True)

# Step 5: Drop duplicates to keep only the closest alert in time for each
alert_id in pairs
closest_alerts = merged_df.drop_duplicates(subset=['alert_id'],
keep='first')

# Step 6: Count the number of unique alert_ids in the result
unique_alerts_count = closest_alerts['alert_id'].nunique()

# Output the count
print(f"Number of unique alerts in pairs with a corresponding alert in
waze_raw with alert_confidence_waze = 3: {unique_alerts_count}")
# Set the condition for the time range
condition = (closest_alerts['timestamp_waze'].dt.hour >= 21) &
(closest_alerts['timestamp_waze'].dt.hour <= 23)
# Count the number of observations in the specified time range
count = closest_alerts[condition].shape[0]
print(f'Number of observations between 09:00 PM and 11:59 PM: {count}')
closest_alerts['num_thumbs_up_waze'].mean()
```

```
### 9- Calculate the average time needed to switch from Confidence Level 3
to Confidence Level 4

import pandas as pd

# Step 1: Load and prepare the data
df = pd.read_csv('waze_alerts_as_of_4-6-2025_1712PM.csv')
df['fetched_at'] = pd.to_datetime(df['fetched_at'])

# Step 2: Get unique fetch times (since each fetch has multiple alerts)
fetch_times =
df[['fetched_at']].drop_duplicates().sort_values('fetched_at').reset_index
(drop=True)

# Step 3: Compute time differences in minutes
fetch_times['time_diff'] =
fetch_times['fetched_at'].diff().dt.total_seconds() / 60

# Step 4: Loop through and check for 10 consecutive ~1-minute intervals
(â‰¤ 1.5 minutes)
for i in range(40, len(fetch_times)):
    recent = fetch_times.loc[i-39:i, 'time_diff']
    if (recent <= 1.5).all():
        switch_time = fetch_times.loc[i-39, 'fetched_at']
        break

# Step 5: Print the result
print("Fetching switched to ~1 minute at:", switch_time)



# Replace this with the actual switch time you found
switch_time = pd.to_datetime(switch_time)
# Filter the full dataset to only include rows from 1-minute fetch period
onward
filtered_df = df[df['fetched_at'] > switch_time].reset_index(drop=True)
# Ensure 'fetched_at' column is in datetime format
filtered_df['fetched_at'] = pd.to_datetime(filtered_df['fetched_at'])
# Get the first and last timestamps
first_timestamp = filtered_df['fetched_at'].min()
last_timestamp = filtered_df['fetched_at'].max()
print("First timestamp:", first_timestamp)
print("Last timestamp:", last_timestamp)
filtered_df.head()
filtered_df.shape
num_unique_alerts = filtered_df['alert_id'].nunique()
print("Number of unique alerts:", num_unique_alerts)


import pandas as pd
```

```
# Convert 'fetched_at' to datetime
filtered_df['fetched_at'] = pd.to_datetime(filtered_df['fetched_at'])

# Sort the DataFrame to ensure correct order processing
filtered_df.sort_values(by=['alert_id', 'fetched_at'], inplace=True)

# Group by 'alert_id' and 'alert_confidence', and get the first occurrence
directly
first_appearances = filtered_df.groupby(['alert_id',
'alert_confidence']).first().reset_index()

# Identify alerts that progress beyond confidence level 2
max_confidence_per_alert =
first_appearances.groupby('alert_id')['alert_confidence'].max()
alerts_with_progression =
max_confidence_per_alert[max_confidence_per_alert >= 3].index

# Filter out alerts that do not meet the criteria
filtered_appearances =
first_appearances[first_appearances['alert_id'].isin(alerts_with_progressi
on)]

# Compute the first time for each alert for later comparison
filtered_appearances['alert_start_time'] =
filtered_appearances.groupby('alert_id')['fetched_at'].transform('min')

# Calculate transition times using shift within groups
filtered_appearances['previous_first_time'] =
filtered_appearances.groupby('alert_id')['fetched_at'].shift(1)
filtered_appearances['transition_time'] =
(filtered_appearances['fetched_at'] -
filtered_appearances['previous_first_time']).dt.total_seconds() / 60

# Initialize a dictionary to store results for plotting
results = {}

# Calculate for time windows from 1 to 12 hours
for hours in range(1, 13):
    filtered_appearances['hours_since_alert_start'] =
    (filtered_appearances['fetched_at'] -
filtered_appearances['alert_start_time']).dt.total_seconds() / 3600
    valid_transitions =
filtered_appearances[(filtered_appearances['alert_confidence'] > 0) &
(filtered_appearances['hours_since_alert_start'] <= hours)]
    mean_transition_times =
valid_transitions.groupby('alert_confidence')['transition_time'].mean()
    results[hours] = mean_transition_times

# Create a DataFrame from the results dictionary
results_df = pd.DataFrame(results)
results_df

import pandas as pd
import matplotlib.pyplot as plt
```

```
# Data from above table, which reflects average transition time per minute
data = {
    '1': [0.221516, 0.694600, 0.795467, 0.842011, 0.905210, 0.928850,
0.942876, 0.961119, 0.961119, 0.961119, 0.984651, 1.037293],
    '2': [5.162423, 5.591605, 5.794740, 5.887781, 5.922202, 5.961849,
6.007315, 6.019804, 6.035527, 6.035527, 6.035527, 6.035013],
    '3': [0.574632, 1.064496, 1.334929, 1.540865, 1.633695, 1.686786,
1.737008, 1.764719, 1.787140, 1.830240, 1.830240, 1.830240],
    '4': [4.144150, 4.584231, 4.777767, 4.950012, 5.041427, 5.099787,
5.165995, 5.196027, 5.219250, 5.229511, 5.252487, 5.270444],
    '5': [1.427360, 2.017455, 2.215813, 2.331149, 2.393793, 2.427489,
2.465705, 2.468474, 2.495729, 2.531232, 2.590685, 2.608894]
}
df = pd.DataFrame(data)
df.columns = ['0 to 1', '1 to 2', '2 to 3', '3 to 4', '4 to 5']

# Plotting
plt.rcParams.update({'font.size': 16})  # Set font size globally

plt.figure(figsize=(12, 8))
for column in df.columns:
    plt.plot(df.index + 1, df[column], label=f'Transition from {column}',
zorder=3)

plt.title('Average Transition Times by Confidence Level for Various
Maximum Thresholds', fontsize=18)
plt.xlabel('Maximum Threshold (hours)', fontsize=16)
plt.ylabel('Average Transition Time (minutes)', fontsize=16)
plt.xticks(range(1, 13), fontsize=14)
plt.yticks(fontsize=14)

# Legend with smaller font size than rest
plt.legend(title='Alert Confidence Transitions', fontsize=14,
title_fontsize=14)
plt.grid(True)
plt.tight_layout()
plt.savefig('average_confidence_level_transition_time.png')
plt.show()
```

TIM Toolbox Ranking Graphs

```
import pandas as pd

df =
pd.read_csv('all_sources_early_detection_by_district_and_hour_of_day.csv)

top_sources = (
    df.loc[df.groupby(['district',
'hour'])['total_early_detection'].idxmax()]
    .pivot(index='hour', columns='district', values='source'))
top_sources


districts = df['district'].unique()
sorted_sources_by_district = {}
for district in districts:
    district_df = df[df['district'] == district]
        # Group by hour and sort sources by total_early_detection in
descending order
    ranked = (
        district_df
        .sort_values(['hour', 'total_early_detection'], ascending=[True,
False])
        .groupby('hour')
        .apply(lambda x: x['source'].tolist())
        .to_dict()
    )

    # Convert to DataFrame where each source gets a rank column (1st, 2nd,
etc.)
    max_len = max(len(v) for v in ranked.values())
    district_matrix = pd.DataFrame({
        hour: pd.Series(sources + [None] * (max_len - len(sources)))
        for hour, sources in ranked.items()
    }).T
    district_matrix.columns = [f"{i+1}st" if i == 0 else f"{i+1}nd" if i
== 1 else f"{i+1}rd" if i == 2 else f"{i+1}th" for i in range(max_len)]
    district_matrix.index.name = "hour"

    sorted_sources_by_district[district] = district_matrix



# View matrix for District 1, for example
sorted_sources_by_district['District 2']

final_result = []
for district, matrix in sorted_sources_by_district.items():
    # Reset index to get 'hour' as a column
    df_sorted = matrix.reset_index()

    # Create a column with tuple of the top 4 sources to check for
identical patterns
```

```
    df_sorted['combo'] = df_sorted[['1st', '2nd', '3rd',
'4th']].apply(tuple, axis=1)

    # Identify breaks in the pattern using a cumulative ID
    df_sorted['group'] = (df_sorted['combo'] !=
df_sorted['combo'].shift()).cumsum()

    # Group by pattern group
    grouped = df_sorted.groupby('group')

    for _, group in grouped:
        start_hour = group['hour'].min()
        end_hour = group['hour'].max()
        top_sources = group[['1st', '2nd', '3rd', '4th']].iloc[0].tolist()

        final_result.append({
            'district': district,
            'start_hour': start_hour,
            'end_hour': end_hour,
            '1st': top_sources[0],
            '2nd': top_sources[1],
            '3rd': top_sources[2],
            '4th': top_sources[3],
        })

# Convert to final DataFrame
merged_source_ranges = pd.DataFrame(final_result)
merged_source_ranges

import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import pandas as pd

# === CONFIGURATION OPTIONS ===
SAVE_FIGS = True         # Set to False to disable saving
DPI = 600                 # Resolution of saved figures
SAVE_DIR = "./"           # Change this if you want to save to a subfolder
TITLE_FONT = 18           # Font size for plot title
LABEL_FONT = 15           # Font size for axis labels and ticks

# Abbreviated labels for sources
label_map = {
    'active911': 'A911',
    'pulsepoint': 'PP',
    'waze': 'WZ',
    'waze_3': 'WZ3'
}

# Fixed color assignment
color_map = {
    'active911': '#d62728',  # red
    'pulsepoint': '#2ca02c', # green
    'waze': '#1f77b4',       # blue
    'waze_3': '#ff7f0e'      # orange
```

```
}

# Extract relevant sources from top 4 ranks
top_sources = pd.unique(merged_source_ranges[['1st', '2nd', '3rd',
'4th']].values.ravel())
top_sources = [src for src in top_sources if pd.notna(src)]

# Plot each district separately
districts = merged_source_ranges['district'].unique()

for district in districts:
    df = merged_source_ranges[merged_source_ranges['district'] ==
district]

    fig, ax = plt.subplots(figsize=(16, 8))

    for _, row in df.iterrows():
        start = row['start_hour']
        end = row['end_hour'] + 1  # inclusive end hour

        for i, rank in enumerate(['1st', '2nd', '3rd', '4th']):
            source = row[rank]
            if pd.isna(source):
                continue

            width = end - start
            color = color_map.get(source, '#cccccc')
            label = label_map.get(source, source)

            ax.barh(
                y=i,
                width=width,
                left=start,
                color=color,
                edgecolor='k'
            )

            ax.text(
                x=start + width / 2,
                y=i,
                s=label,
                va='center',
                ha='center',
                fontsize=LABEL_FONT - 2,
                color='white' if color in ['#1f77b4', '#d62728'] else
'black',
                weight='bold'
            )

    ax.set_yticks(range(4))
    ax.set_yticklabels(['1st', '2nd', '3rd', '4th'], fontsize=LABEL_FONT)
    ax.set_title(f"Ranked TIM Sources by Hour Block - {district}",
fontsize=TITLE_FONT)
    ax.set_xlabel("Hour of Day", fontsize=LABEL_FONT)
```

```
    ax.set_xlim(0, 24)
    ax.set_xticks(range(0, 24))
    ax.tick_params(axis='x', labelsize=LABEL_FONT)

    # Legend with full source names
    handles = [mpatches.Patch(color=color_map[src], label=src) for src in
top_sources]
    ax.legend(
        handles=handles,
        loc='lower center',
        bbox_to_anchor=(0.5, -0.28),
        fontsize=14,
        title_fontsize=14,
        ncol=len(handles),
        title="Source"
    )

    plt.tight_layout(rect=[0, 0.12, 1, 1])

    if SAVE_FIGS:
        filename = f"{SAVE_DIR}top_sources_{district.replace(' ',
'_').lower()}.png"
        plt.savefig(filename, dpi=DPI)

    plt.show()
```

Appendix B: TSS Classification Model (Python 3.13)

TSS Data Preparation

```
import pandas as pd

CAD_22_23 = pd.read_csv('fhp_alerts_FY22_23_limited_access.csv')
CAD_24 = pd.read_csv('fhp_alerts_24.csv')
CAD_25 = pd.read_csv('FHP_25.csv')

tss_22_23 = pd.read_csv('tss_alerts_FY22_23.csv')
tss_24 = pd.read_csv('tss_alerts_24.csv')
tss_25 = pd.read_csv('tss_25.csv')


# Define renaming map
rename_map = {
    'alarm_id_cad': 'alarm_id',
    'alarm_id_tss': 'alarm_id',
    'EVENT ID': 'alarm_id',
    'latitude_cad': 'latitude',
    'latitude_tss': 'latitude',
    'LATITUDE': 'latitude',
    'longitude_cad': 'longitude',
    'longitude_tss': 'longitude',
    'LONGITUDE': 'longitude',
    'timestamp_cad': 'detected_timestamp',
    'timestamp_tss': 'detected_timestamp',
    'IDS DETECTED DATE': 'detected_timestamp',
    'resolved_timestamp_cad': 'resolved_timestamp',
    'resolved_timestamp_tss': 'resolved_timestamp',
    'IDS RESOLVED TIME': 'resolved_timestamp',
    'ACTION TAKEN': 'action_taken',
    'action_taken_cad': 'action_taken',
    'action_taken_tss': 'action_taken'
}

# Final columns to keep
final_columns = ['alarm_id', 'latitude', 'longitude',
'detected_timestamp', 'resolved_timestamp', 'action_taken']

# Function to rename and keep only desired columns
def standardize_columns_only(df, name):
    df.rename(columns=rename_map, inplace=True)
    for col in final_columns:
        if col not in df.columns:
            df[col] = pd.NA
    df.drop(columns=[col for col in df.columns if col not in
final_columns], inplace=True)

# Apply in-place to each dataset
datasets = {
    'CAD_22_23': CAD_22_23,
    'CAD_24': CAD_24,
    'CAD_25': CAD_25,
```

```
    'tss_22_23': tss_22_23,
    'tss_24': tss_24,
    'tss_25': tss_25,
}

for name, df in datasets.items():
    standardize_columns_only(df, name)


# Step 1: Convert to datetime
CAD_25['detected_timestamp'] =
pd.to_datetime(CAD_25['detected_timestamp'], format='%m/%d/%Y %I:%M:%S
%p')
CAD_25['resolved_timestamp'] =
pd.to_datetime(CAD_25['resolved_timestamp'], format='%m/%d/%Y %I:%M:%S
%p')

# Step 2: Localize and convert to UTC (forcing first DST interpretation)
CAD_25['detected_timestamp'] =
CAD_25['detected_timestamp'].dt.tz_localize('America/New_York',
ambiguous='first', nonexistent='shift_forward').dt.tz_convert('UTC')
CAD_25['resolved_timestamp'] =
CAD_25['resolved_timestamp'].dt.tz_localize('America/New_York',
ambiguous='first', nonexistent='shift_forward').dt.tz_convert('UTC')
CAD_24[CAD_24['alarm_id']==2299134]


# Manually fix alarm_id 2299134 by changing the raw string
CAD_24.loc[CAD_24['alarm_id'] == 2299134, 'detected_timestamp'] = '11/3/24
2:04 AM'
CAD_24.loc[CAD_24['alarm_id'] == 2299134, 'resolved_timestamp'] = '11/3/24
2:04 AM'

# Step 1: Convert to datetime
CAD_24['detected_timestamp'] =
pd.to_datetime(CAD_24['detected_timestamp'], format='%m/%d/%y %I:%M %p')
CAD_24['resolved_timestamp'] =
pd.to_datetime(CAD_24['resolved_timestamp'], format='%m/%d/%y %I:%M %p')

# Step 2: Localize and convert to UTC
CAD_24['detected_timestamp'] =
CAD_24['detected_timestamp'].dt.tz_localize('America/New_York',
ambiguous='NaT', nonexistent='shift_forward').dt.tz_convert('UTC')
CAD_24['resolved_timestamp'] =
CAD_24['resolved_timestamp'].dt.tz_localize('America/New_York',
ambiguous='NaT', nonexistent='shift_forward').dt.tz_convert('UTC')



# Step 1: Convert to datetime
tss_24['detected_timestamp'] =
pd.to_datetime(tss_24['detected_timestamp'], format='%m/%d/%y %I:%M %p')
tss_24['resolved_timestamp'] =
pd.to_datetime(tss_24['resolved_timestamp'], format='%m/%d/%y %I:%M %p')
```

```
# Step 2: Localize to Eastern Time and convert to UTC
tss_24['detected_timestamp'] =
tss_24['detected_timestamp'].dt.tz_localize('America/New_York',
ambiguous='first', nonexistent='shift_forward').dt.tz_convert('UTC')
tss_24['resolved_timestamp'] =
tss_24['resolved_timestamp'].dt.tz_localize('America/New_York',
ambiguous='first', nonexistent='shift_forward').dt.tz_convert('UTC')


# Step 1: Convert to datetime
tss_25['detected_timestamp'] =
pd.to_datetime(tss_25['detected_timestamp'], format='%m/%d/%Y %I:%M:%S
%p')
tss_25['resolved_timestamp'] =
pd.to_datetime(tss_25['resolved_timestamp'], format='%m/%d/%Y %I:%M:%S
%p')

# Step 2: Localize to Eastern Time and convert to UTC
tss_25['detected_timestamp'] =
tss_25['detected_timestamp'].dt.tz_localize('America/New_York',
ambiguous='first', nonexistent='shift_forward').dt.tz_convert('UTC')
tss_25['resolved_timestamp'] =
tss_25['resolved_timestamp'].dt.tz_localize('America/New_York',
ambiguous='first', nonexistent='shift_forward').dt.tz_convert('UTC')


# Step 1: Identify the index of the invalid row and drop it
bad_idx = CAD_22_23[CAD_22_23['resolved_timestamp'] == "0001-01-01
00:00:00+00:00"].index
CAD_22_23.drop(index=bad_idx, inplace=True)

# Step 2: Parse and convert to UTC
CAD_22_23['detected_timestamp'] =
pd.to_datetime(CAD_22_23['detected_timestamp'],
utc=True).dt.tz_convert('UTC')
CAD_22_23['resolved_timestamp'] =
pd.to_datetime(CAD_22_23['resolved_timestamp'],
utc=True).dt.tz_convert('UTC')


tss_22_23['detected_timestamp'] =
pd.to_datetime(tss_22_23['detected_timestamp'], format='ISO8601',
utc=True).dt.tz_convert('UTC')
tss_22_23['resolved_timestamp'] =
pd.to_datetime(tss_22_23['resolved_timestamp'], format='ISO8601',
utc=True).dt.tz_convert('UTC')


tss_22_23[['longitude','latitude']].describe()
tss_24['action_taken'].value_counts()
TSS_combined = pd.concat([tss_22_23, tss_24, tss_25], ignore_index=True)
CAD_combined = pd.concat([CAD_22_23, CAD_24, CAD_25], ignore_index=True)
CAD_combined['action_taken'].value_counts()
```

```
TSS_combined['action_taken'].value_counts()


## Clean up CAD

# Step 1: Drop any group that contains 'False Alarm' or 'Already Created'
excluded_actions = {'False Alarm', 'Already Created'}

CAD_filtered = CAD_combined.groupby('alarm_id').filter(
    lambda g: not g['action_taken'].isin(excluded_actions).any()
)

# Step 2: From the remaining, keep only groups with at least one valid
action
valid_actions = {'New Event', 'Associated', 'Acknowledged', 'System
Resolved'}

CAD_prep = CAD_filtered.groupby('alarm_id').filter(
    lambda g: g['action_taken'].isin(valid_actions).any()
)


CAD_prep['action_taken'].value_counts()
CAD_prep['alarm_id'].value_counts().value_counts().sort_index()
CAD_prep = CAD_prep.sort_values('detected_timestamp').groupby('alarm_id',
as_index=False).first()
CAD_prep['action_taken'].value_counts()
CAD_prep = CAD_prep[(CAD_prep['latitude'] != 0.0) & (CAD_prep['longitude']
!= 0.0)]


import pandas as pd
import numpy as np
from tqdm import tqdm

# Ensure datetime
CAD_prep['detected_timestamp'] =
pd.to_datetime(CAD_prep['detected_timestamp'])

# Sort by time
CAD_prep = CAD_prep.sort_values('detected_timestamp')

# Track indices to keep
keep_indices = []

# Group by (latitude, longitude)
for (lat, lon), group in tqdm(CAD_prep.groupby(['latitude', 'longitude']),
desc="Processing locations"):
    group = group.sort_values('detected_timestamp')
    times = group['detected_timestamp'].values
    indices = group.index.values

    last_kept_time = pd.Timestamp.min
```

```
    for i in range(len(group)):
        if times[i] > last_kept_time + pd.Timedelta(hours=1):
            keep_indices.append(indices[i])
            last_kept_time = times[i]

# Keep only earliest alerts in each 1-hour spatial window
CAD_prep = CAD_prep.loc[keep_indices]
CAD_prep.shape

# Convert to string first to ensure consistent comparison
CAD_prep['alarm_id'] = CAD_prep['alarm_id'].astype(str)

# Check for duplicates
duplicates = CAD_prep['alarm_id'].duplicated()
print(f"Number of duplicate alarm_ids: {duplicates.sum()}")

# To see which alarm_ids are duplicated
duplicate_ids =
CAD_prep[CAD_prep['alarm_id'].duplicated(keep=False)]['alarm_id'].unique()
print(f"Unique alarm_ids that appear more than once:
{len(duplicate_ids)}")

# To see the actual duplicate rows
duplicate_rows =
CAD_prep[CAD_prep['alarm_id'].duplicated(keep=False)].sort_values('alarm_i
d')
print(f"\nFirst few duplicate rows:\n{duplicate_rows.head(10)}")

# If you want to see how many times each alarm_id appears
alarm_id_counts = CAD_prep['alarm_id'].value_counts()
duplicated_counts = alarm_id_counts[alarm_id_counts > 1]
print(f"\nAlarm IDs appearing more than once:\n{duplicated_counts}")
CAD_prep.head()
CAD_prep['action_taken'].value_counts()
TSS_combined.head()

# Fix only rows where lat > 90 or lon > 180 (likely microdegrees)
TSS_combined.loc[TSS_combined['latitude'].abs() > 90, 'latitude'] /= 1e6
TSS_combined.loc[TSS_combined['longitude'].abs() > 180, 'longitude'] /=
1e6


# Check for values outside typical Florida longitude range
invalid_longs = TSS_combined[TSS_combined['longitude'] > -60]
print(invalid_longs[['detected_timestamp', 'latitude', 'longitude']])
print(f"Total bad longitude entries: {len(invalid_longs)}")


TSS_combined[['latitude', 'longitude']].describe()
TSS_combined.head()
TSS_combined['action_taken'].value_counts()
TSS_combined.to_csv('tss_22-25.csv',index=False)
CAD_prep.to_csv('cad_22-25_LA.csv',index=False)
```

TSS Alerts Labeling

```
## 1- Load CAD and TSS alerts datasets

import pandas as pd
import geopandas as gpd
from shapely.geometry import Point
from geopy.distance import geodesic
import pytz
# Load cad and tss alerts data
tss_alerts = pd.read_csv("tss_22-25.csv")
cad_alerts = pd.read_csv("cad_22-25_LA.csv")

# Check for values outside typical Florida longitude range
invalid_longs = tss_alerts[tss_alerts['longitude'] > -60]
print(invalid_longs[['detected_timestamp', 'latitude', 'longitude']])
print(f"Total bad longitude entries: {len(invalid_longs)}")

# Fix latitude (all need ×100)
mask_lat = tss_alerts['latitude'].abs() < 1
tss_alerts.loc[mask_lat, 'latitude'] *= 100

# Fix longitude based on magnitude
mask_lon_100 = tss_alerts['longitude'].abs().between(0.1, 1)
mask_lon_1000 = tss_alerts['longitude'].abs() < 0.1

tss_alerts.loc[mask_lon_100, 'longitude'] *= 100
tss_alerts.loc[mask_lon_1000, 'longitude'] *= 1000


# Create a copy to avoid modifying original data
cad_alerts = cad_alerts.copy()

# Fix latitude: if abs(lat) > 90, it's likely in microdegrees
cad_alerts.loc[cad_alerts['latitude'].abs() > 90, 'latitude'] /= 1e6

# Fix longitude: if abs(lon) > 180, it's likely in microdegrees
cad_alerts.loc[cad_alerts['longitude'].abs() > 180, 'longitude'] /= 1e6



tss_alerts.to_csv('tss_alerts_for_plot.csv',index=False)
cad_alerts.to_csv('cad_alerts_for_plot.csv',index=False)
print(tss_alerts[['latitude', 'longitude']].describe())
print(cad_alerts[['latitude', 'longitude']].describe())


## 2- Convert timestamp into a datetime object


import pandas as pd

# the format should be based on how the timestamp is viewed in jupyter
notebook, not excel
```

```
cad_alerts['detected_timestamp'] =
pd.to_datetime(cad_alerts['detected_timestamp'],format='ISO8601',
utc=True)
cad_alerts['resolved_timestamp'] =
pd.to_datetime(cad_alerts['resolved_timestamp'],format='ISO8601',
utc=True)

tss_alerts['detected_timestamp'] =
pd.to_datetime(tss_alerts['detected_timestamp'],format='ISO8601',
utc=True)
tss_alerts['resolved_timestamp'] =
pd.to_datetime(tss_alerts['resolved_timestamp'],format='ISO8601',
utc=True)
cad_alerts['detected_timestamp'].head()
tss_alerts['detected_timestamp'].head()


## 3- Set the geometry for both alerts as points based on long and lat



import pandas as pd
import geopandas as gpd
from shapely.geometry import Point
from geopy.distance import geodesic

# Step 1: Create geometry from lat/lon
cad_alerts['geometry'] = cad_alerts.apply(lambda row:
Point(row['longitude'], row['latitude']), axis=1)
tss_alerts['geometry'] = tss_alerts.apply(lambda row:
Point(row['longitude'], row['latitude']), axis=1)

# Step 2: Create GeoDataFrames with WGS84 CRS (EPSG:4326)
gdf_cad = gpd.GeoDataFrame(cad_alerts, geometry='geometry',
crs="EPSG:4326")
gdf_tss = gpd.GeoDataFrame(tss_alerts, geometry='geometry',
crs="EPSG:4326")

# Step 3: Save original point geometry (to use later for accurate lat/lon
extraction)
gdf_cad['point_geometry'] = gdf_cad['geometry']
gdf_tss['point_geometry'] = gdf_tss['geometry']

# Step 4: Define spatial/temporal thresholds
spatial_buffer_miles = 1
temporal_buffer = 30  # minutes
utm_crs = "EPSG:32617"  # UTM zone for Florida
cad_alerts['geometry'].head()


## 4- Create buffers and perform the spatial join


# Step 4: Project to UTM for accurate distance buffering
```

```
gdf_cad = gdf_cad.to_crs(utm_crs)
gdf_tss = gdf_tss.to_crs(utm_crs)

# Step 6: Buffer CAD alerts in meters (1 mile ≈ 1609.34 m)
spatial_buffer_meters = 1609.34 * spatial_buffer_miles
gdf_cad['buffer'] = gdf_cad.geometry.buffer(spatial_buffer_meters)

# Step 7: Set the buffer as the active geometry
gdf_cad = gdf_cad.set_geometry('buffer')

# Step 8: Perform spatial join (TSS inside buffered CAD)
joined = gpd.sjoin(gdf_tss, gdf_cad, how='inner', predicate='intersects',
lsuffix='tss', rsuffix='cad')
joined.columns
joined.shape
joined.head()


# Optional: Confirm TSS date range
print(tss_alerts['detected_timestamp'].min(),
tss_alerts['detected_timestamp'].max())

# Optional: Confirm CAD date range
print(cad_alerts['detected_timestamp'].min(),
cad_alerts['detected_timestamp'].max())



## 5- Calculate Distance and time difference between all spatially matched
pairs

import numpy as np
import pandas as pd

# STEP 9: Reproject to WGS84 (do only if it's not already EPSG:4326)
joined = joined.to_crs("EPSG:4326")

# STEP 10: Extract lat/lon from geometries
joined['latitude_cad'] = joined['point_geometry_cad'].y
joined['longitude_cad'] = joined['point_geometry_cad'].x
joined['latitude_tss'] = joined['point_geometry_tss'].y
joined['longitude_tss'] = joined['point_geometry_tss'].x

# STEP 11: Vectorized haversine formula (miles)
def haversine_np(lat1, lon1, lat2, lon2):
    R = 3958.8  # Earth radius in miles
    lat1, lon1, lat2, lon2 = map(np.radians, [lat1, lon1, lat2, lon2])
    dlat = lat2 - lat1
    dlon = lon2 - lon1
    a = np.sin(dlat/2)**2 + np.cos(lat1) * np.cos(lat2) *
np.sin(dlon/2)**2
    return 2 * R * np.arcsin(np.sqrt(a))

joined['distance'] = haversine_np(
```

```
    joined['latitude_cad'].values,
    joined['longitude_cad'].values,
    joined['latitude_tss'].values,
    joined['longitude_tss'].values
)

# STEP 12: Vectorized time difference in minutes
joined['time_diff'] = (
    (joined['detected_timestamp_cad'] -
joined['detected_timestamp_tss']).abs()
    / np.timedelta64(1, 'm')
)

# STEP 13: Apply spatial & temporal thresholds
filtered_candidates = joined[
    (joined['distance'] <= spatial_buffer_miles) &
    (joined['time_diff'] <= temporal_buffer)
]

# STEP 14: Output
print(f"Number of alerts within the buffer: {len(filtered_candidates)}")
print(filtered_candidates.head())


filtered_candidates['time_diff'].describe()
filtered_candidates['distance'].describe()


## 6- Filter out multiple matched alerts, keep 1 tss alert per matched CAD


# Step 1: Sort the DataFrame by 'alarm_id_tss' and 'distance'
joined_sorted = filtered_candidates.sort_values(by=['alarm_id_tss',
'distance'])

# Step 2: Group by 'alarm_id_tss' and keep the first entry per group
(which is the closest due to sorting)
closest_cad_per_tss =
joined_sorted.groupby('alarm_id_tss').first().reset_index()
# Print the results to verify
print(closest_cad_per_tss.head)
closest_cad_per_tss.to_csv('tss_CAD_pairs.csv',index=False)
closest_cad_per_tss['distance'].describe()
closest_cad_per_tss['distance'].value_counts()
closest_cad_per_tss.columns


## 7- Calculate earlier occurrences


earlier_df= pd.DataFrame()

# Compare timestamps and add columns for verification
```

```
earlier_df['cad_earlier'] = closest_cad_per_tss['detected_timestamp_cad']
< closest_cad_per_tss['detected_timestamp_tss']
earlier_df['tss_earlier'] = closest_cad_per_tss['detected_timestamp_tss']
< closest_cad_per_tss['detected_timestamp_cad']

# Count occurrences
tss_earlier_count = earlier_df['tss_earlier'].sum()
cad_earlier_count = earlier_df['cad_earlier'].sum()

# Calculate percentages
total_pairs = len(earlier_df)
tss_earlier_percentage = (tss_earlier_count / total_pairs) * 100
cad_earlier_percentage = (cad_earlier_count / total_pairs) * 100

# Print results
print(f"tss was earlier in {tss_earlier_percentage:.2f}% of the cases.")
print(f"cad was earlier in {cad_earlier_percentage:.2f}% of the cases.")

# Create a list of all pairs with detected timestamps and lat/longs
pairs_list = closest_cad_per_tss[['alarm_id_cad',
'detected_timestamp_cad', 'longitude_cad', 'latitude_cad',
                     'alarm_id_tss', 'detected_timestamp_tss',
'longitude_tss', 'latitude_tss']]

print(closest_cad_per_tss['time_diff'].describe())
print(closest_cad_per_tss['distance'].describe())


## 8- Place unmatched TSS alerts in a saperate dataset

unmatched_alerts =
tss_alerts[~tss_alerts['alarm_id'].isin(closest_cad_per_tss['alarm_id_tss'
])]
umatched_alerts.to_csv('umatched_tss_alerts.csv',index=False)
unmatched_alerts.head()
```

Modeling of TSS Alerts

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

df = pd.read_csv('df_train.csv')
df_test = pd.read_csv('df_test.csv')
df = df[df['action_taken'] != 'Responder Arrival']
# Convert detected_timestamp to datetime with mixed format handling
df['detected_timestamp'] = pd.to_datetime(df['detected_timestamp'],
format='ISO8601', utc=True)
df_test['detected_timestamp'] =
pd.to_datetime(df_test['detected_timestamp'], format='ISO8601', utc=True)
df_test_metadata = df_test.copy()


# Compute correlation matrix
corr_matrix = df.corr(numeric_only=True)
```

```
# Plot heatmap
plt.figure(figsize=(12, 10))
plt.imshow(corr_matrix, cmap='coolwarm', interpolation='none')
plt.colorbar(label='Correlation')
plt.xticks(range(len(corr_matrix.columns)), corr_matrix.columns,
rotation=90)
plt.yticks(range(len(corr_matrix.columns)), corr_matrix.columns)
plt.title("Correlation Matrix - df_test")
plt.tight_layout()
plt.show()


# Extract hour of day and one-hot encode
df['hour'] = df['detected_timestamp'].dt.hour
df = pd.get_dummies(df, columns=['hour'], prefix='hour')
# Drop detected_timestamp
df = df.drop(columns=['detected_timestamp'])
# One-hot encode action_taken
df = pd.get_dummies(df, columns=['action_taken'], prefix='action')
# Extract hour of day and one-hot encode
df_test['hour'] = df_test['detected_timestamp'].dt.hour
df_test = pd.get_dummies(df_test, columns=['hour'], prefix='hour')
# Drop detected_timestamp
df_test = df_test.drop(columns=['detected_timestamp'])
# One-hot encode action_taken
df_test = pd.get_dummies(df_test, columns=['action_taken'],
prefix='action')

import xgboost as xgb
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import train_test_split

# Define the features you want to use
feature_cols = [
    'alerts_per_day',
    'minutes_since_last_alert',
    'sensor_predictability',
    'wighted_alert_density',
    'hour_0', 'hour_1', 'hour_2', 'hour_3',
    'hour_4', 'hour_5', 'hour_6', 'hour_7',
    'hour_8', 'hour_9', 'hour_10','hour_11',
    'hour_12', 'hour_13', 'hour_14', 'hour_15',
    'hour_16','hour_17', 'hour_18', 'hour_19',
    'hour_20', 'hour_21', 'hour_22','hour_23',
  ]

# Split X and y from training and test sets using the feature list
X_train = df[feature_cols]
y_train = df['target']

X_test = df_test[feature_cols]
y_test = df_test['target']
```

```
# Handle class imbalance
pos = (y_train == 1).sum()
neg = (y_train == 0).sum()
scale_pos_weight = neg / pos

params = {
        'objective': 'binary:logistic',
#        'eval_metric': 'aucpr',  # Better for imbalanced data
        'scale_pos_weight': 8.7,
        'max_depth': 5,
        'learning_rate': 0.025,
        'n_estimators': 670,

    }

# Initialize XGBoost with imbalance handling
xgb_model = xgb.XGBClassifier(**params)

# Train the model
xgb_model.fit(X_train, y_train)

# Predict on test
y_pred_test = xgb_model.predict(X_test)

# Optionally store predictions
df_test_metadata['y_pred'] = y_pred_test
df_test_metadata['y_prob'] = xgb_model.predict_proba(X_test)[:, 1]

# Basic evaluation
auc = roc_auc_score(y_test, xgb_model.predict_proba(X_test)[:, 1])
print(f"Test ROC AUC: {auc:.4f}")


from sklearn.metrics import (
    f1_score, precision_score, recall_score,
    confusion_matrix, classification_report, roc_auc_score
)

# Get predicted probabilities and labels
y_prob = xgb_model.predict_proba(X_test)[:, 1]
y_pred = xgb_model.predict(X_test)

# Compute metrics
f1 = f1_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_prob)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred, digits=3)

# Print results
print(f"Model Evaluation Metrics:")
print(f"ROC AUC      : {roc_auc:.4f}")
print(f"F1 Score     : {f1:.4f}")
```

```
print(f"Precision   : {precision:.4f}")
print(f"Recall      : {recall:.4f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(report)


import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Prepare data
df_metadata = df_test_metadata.copy()
df_metadata['hour'] =
pd.to_datetime(df_metadata['detected_timestamp']).dt.hour
df_metadata['day_of_week'] =
pd.to_datetime(df_metadata['detected_timestamp']).dt.day_name()

# Calculate metrics for each hour-day combination
results = []
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',
'Saturday', 'Sunday']

for day in day_order:
   for hour in range(24):
       # Filter data for this day-hour combination
       block_data = df_metadata[(df_metadata['day_of_week'] == day) &
(df_metadata['hour'] == hour)]

       if len(block_data) > 0:
           y_true = block_data['target']
           y_pred = block_data['y_pred']

           # Calculate confusion matrix
           tn, fp, fn, tp = confusion_matrix(y_true, y_pred, labels=[0,
1]).ravel()

           # Calculate metrics
           detection_rate = tp / (tp + fn) if (tp + fn) > 0 else np.nan  #
Recall for nonrecurring
           false_alarm_rate = fp / (fp + tn) if (fp + tn) > 0 else np.nan
# FPR for recurring

           results.append({
               'day': day,
               'hour': hour,
               'detection_rate': detection_rate,
               'false_alarm_rate': false_alarm_rate
           })

results_df = pd.DataFrame(results)
```

```
# Create pivot tables for heatmaps
detection_pivot = results_df.pivot(index='day', columns='hour',
values='detection_rate')
detection_pivot = detection_pivot.reindex(day_order)

fpr_pivot = results_df.pivot(index='day', columns='hour',
values='false_alarm_rate')
fpr_pivot = fpr_pivot.reindex(day_order)

import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Font settings
title_font = {'family': 'Arial', 'size': 14, 'weight': 'bold'}
axis_label_font = {'family': 'Arial', 'size': 12, 'weight': 'bold'}
tick_fontsize = 12
annot_fontsize = 12
cbar_label_fontsize = 12

#Plot 1: Detection Rate
fig, ax1 = plt.subplots(figsize=(12, 8))
sns.heatmap(detection_pivot, annot=True, fmt='.2f', cmap='RdYlGn',
            vmin=0, vmax=1, ax=ax1, cbar_kws={'label': 'True Positive
Rate'})

ax1.set_title('True Positive Rate by Hour and Day of Week',
fontdict=title_font, pad=20)
ax1.set_xlabel('Hour of Day', fontdict=axis_label_font)
ax1.set_ylabel('Day of Week', fontdict=axis_label_font)
ax1.set_xticks([i + 0.5 for i in range(24)])
ax1.set_xticklabels(range(24), fontsize=tick_fontsize)
ax1.set_yticklabels(detection_pivot.index, fontsize=tick_fontsize)
ax1.collections[0].colorbar.ax.tick_params(labelsize=cbar_label_fontsize)

plt.tight_layout()
plt.savefig('detection_rate_heatmap.png', dpi=1200, bbox_inches='tight')
plt.show()

#Plot 2: False Alarm Rate
fig, ax2 = plt.subplots(figsize=(12, 8))
sns.heatmap(fpr_pivot, annot=True, fmt='.2f', cmap='RdYlGn_r',
            vmin=0, vmax=0.5, ax=ax2, cbar_kws={'label': 'False Positive
Rate'})

ax2.set_title('False Positive Rate by Hour and Day of Week',
fontdict=title_font, pad=20)
ax2.set_xlabel('Hour of Day', fontdict=axis_label_font)
ax2.set_ylabel('Day of Week', fontdict=axis_label_font)
ax2.set_xticks([i + 0.5 for i in range(24)])
ax2.set_xticklabels(range(24), fontsize=tick_fontsize)
ax2.set_yticklabels(fpr_pivot.index, fontsize=tick_fontsize)
ax2.collections[0].colorbar.ax.tick_params(labelsize=cbar_label_fontsize)
```

```
plt.tight_layout()
plt.savefig('false_alarm_rate_heatmap.png', dpi=1200, bbox_inches='tight')
plt.show()

#Overall Metrics
y_true_all = df_metadata['target']
y_pred_all = df_metadata['y_pred']

tn_total, fp_total, fn_total, tp_total = confusion_matrix(y_true_all,
y_pred_all, labels=[0, 1]).ravel()

overall_detection_rate = tp_total / (tp_total + fn_total)
overall_false_alarm_rate = fp_total / (fp_total + tn_total)

print(f"\ OVERALL PERFORMANCE METRICS:")
print("="*50)
print(f"Overall Detection Rate: {overall_detection_rate:.3f}
({overall_detection_rate:.1%})")
print(f"Overall False Alarm Rate: {overall_false_alarm_rate:.3f}
({overall_false_alarm_rate:.1%})")
```