THE REAL-WORLD IMPACTS OF DRONE IMPLEMENTATION IN DATA COLLECTION OF FATAL ACCIDENTS

By

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As few doughnuts of acknowledgements…

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Title of Study: THE REAL-WORLD IMPACTS OF DRONE IMPLEMENTATION IN DATA COLLECTION OF FATAL ACCIDENTS

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The objective of this study was to analyze the use of drones and data collected in fatal accident investigations in accident scenes in Austin, Texas. The study compares data pre and post drones being used by the police officers of the Austin Police Department. The study presents a new way to collect evidence for fatal vehicle accidents and the attempts to apply the technology in the real world setting of vehicle investigations. The research findings are intended to be used by other municipalities before they implement the technology for their traffic accident investigations.

The datasets used in this study came directly from the Computer Aided Dispatch (CAD) reports filed by officers in the Austin Police Department. The size of data files came from additional data sources in the records of fatal accident scenes. Time sequences and data file sizes worked to identify how much time was needed for a police officer to establish a full investigation with a drone while working a fatality and helps municipalities understand the data storage requirements for this type of data collection technique.

The study found that when drones are introduced to fatal accident investigations, they increase the duration of the time needed to investigate a scene. The use of drones also increases the use of data for the storage of imaging taken by the drone in this type of case files. Depending on the priorities of a municipality, time and data storage increases, could impact the decision to implement drones as a means to collect data in the field for fatal vehicle accidents.

Small sample size from a single municipality limits inference that could be drawn from results to other cities of the same size and demographic make-up. The study, does however, lead to providing beneficial information on potential impacts of drones in police investigation settings. The data can be used by policy makers to balance the value that drones bring with the burden of their implementation.

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CHAPTER I

Introduction

The following study analyzes the use of drones in fatal accident investigations and the data collected from the accident scenes. The study in this paper compares how data pre and post drones came to be used by the police officers of the Austin Police Department. The study compares time, clarity in evidence, safety for officers, and efficiency of accident investigations. The research study was used to identify changing factors using a comparative analysis in the files of fatal accidents in Austin, Texas, from pre and post the introduction of drone technology to the investigation method used by the Austin Police Department. The study sought to identify how much time was needed for police officers to establish a full investigation with a drone while working a fatality. The research also helps municipalities understand the data storage requirements for this type of data collection technique. The study brings significant understanding of clerical data processing, time and cost of working with and obtaining the drone data for other municipalities before implementing the technology.

Statement of the Problem

The data collecting to ascertain the cause of a traffic incident and contributing factors leading to the fatal traffic accident was not sufficient using old established methods and data collection criteria related to fatal traffic accidents. The contributing factors were the most critical for affixing blame and prevention of future fatal traffic accidents.

The most detrimental and costly traffic collisions involve those having a fatality. Causes of fatality are meticulously documented in accident reports by sworn police officers of the law. Causes of minor incidents are often overlooked. Non-fatal accidents are reviewed casually with much less meticulous observations by the investigators at the scene and are left to be analyzed by insurance companies determining fault and liability. Major and minor accidents would also benefit from the reviewing process offered by drone imagining of accidents. The data collected by drones can be managed in a way that is useable by municipalities and easily studied. Drone data can be utilized for a wide variety of information including timing demonstrations, illustrations, and visualization in 3D renderings. To benefit the reviewing process of fatal accidents, drone data must be included in as many case packages providing an overall view of the traffic accidents in municipalities.

Frequently, minor traffic collisions requiring only an exchange of information by involved drivers mask the need for further investigation. Had the scene been photographed and contributing details documented, the Department of Transportation (DOT) and/or the involved law enforcement (LEF) department had taken corrective action, there is a possibility that another accident could be avoided. The utilization of drone data could help review the leading causes of the most frequent traffic accidents to help identified and implement simple steps taken to avoid additional fatalities. The utilization of drones could help the DOT identify dangerous or fatal intersections and traffic signal timing where the DOT could act to address street intersections and or traffic signal timing. Drones would be useful in monitoring the traffic and traffic patterns during the hours many of the traffic collisions lead to a fatality. Very limited data exist for drone usage in the field of accident investigation, currently they are only for a limited number of fatalities to be studied (Puri, 2005).

Purpose of Study

Although fatalities have increased over the decades, the techniques to study and analyze fatal automobile accidents have not. The Measuring Wheel, invented June 29, 1886, is still the common technology in use today by most police departments. The measuring wheel was patented in Bennington, Texas, by John L. McCaleb (McCaleb, 1886). Policing units began using accident investigations with the aid of the measuring wheel widely in the early 1900's and adopting the practice across the United States (Sparrow, 2015). It is not fully understood why methods have stayed stubbornly similar to those of the early 1900's Low cost of circuitry and energy usage technologies have led to a renaissance of drone usage in the past ten years (Hatfield, 2020). Until the recent addition of new technologies such as drones developed over the last ten years, society has not been able to fully implement the advantages of using drones.

Traffic accident investigations have had little alterations in method or equipment used since the first automobile traffic accident was diagrammed in 1886 in the United States (Seo, 2019). In the past 10 years however, a new method of collecting accident data has begun to be implemented and used in local municipalities. (Karr, 2021) The introduction of drones to collect real time traffic accident data potentially gives much needed advancement in the field of accident investigation. (Karr, 2021)

Fatalities occurring because of an automobile accident is not a new phenomenon. The first recorded automobile fatality occurred in the late summer of 1869. A young female scientific researcher in Dublin, Ireland, climbed onto a home-built steam automobile for a summer joyride (Kean, 2019). Later that afternoon the car would encounter a disturbance in the road later determined to be a pothole (Kean, 2019). The young researcher, by the name of Mary Ward, was thrown from the carriage to the ground where she was crushed by the wheels of the machine breaking her neck and killing her onsite. Mary Ward became the first know automobile fatality in a long line of senseless and tragic deaths (Kean, 2019).

The story of Mary Ward illustrates the pointless tragedy of fatalities that are generated from automobile accidents. Since the mid-1800's millions of individuals have lost their lives prematurely to crashes with automobiles. Over the next hundred-and fifty-years traffic accidents increased with the addition of gasoline powered automobiles into everyday life (Simek, 2019).

The primary purpose of accident reconstruction is to determine the distribution of causes for traffic collisions and insurance companies to assess the percentage of fault attributed to each driver involved (Sparrow, 2015). The fault analysis has the potential to include the determining of the safety issues not already corrected in the area of traffic accident fatalities (Sparrow, 2015).

There have been multiple scientific studies involving the use of drones, documenting how fast the drones can photograph the traffic scene and how accurate the drone data is. However, little effort has been expended on tracking the time involved in the use of drones collecting and disseminating data out in the field. Multiple scientific studies have proven the concept of drone implementation and accuracy before drones were implemented in traffic investigations Khan (2017), Eisenbeiss (2009), and Stáňa (2017).

Few studies have focused on the implementation after the drones were utilized to determine if they had the same real-world effect that was desired or described by the literature (Perez, 2019). The Perez research team generated two geospatial products that could have been used for the documentation of authentic accident scenes from the fictitious traffic accident area. An accuracy assessment was carried out by analyzing the RMSE of the differences between the coordinates of 93 ICPs measured in the orthophotos, with the corresponding ones measured by using Global Navigation Satellite System (GNSS) techniques, but it was not taken into the real world setting for confirmation. (Perez, 2019) Austin, Texas was one of the first cities to implement drones to collect data in traffic accidents involving fatalities in the summer of 2018 (Austin police to use, 2018).

Significance of the Study

All of the traffic investigations, in Texas, require investigators to mark the location of each vehicle in the traffic crash to document the involvement of each according to the State of Texas Instructions to Police for Reporting Crashes, 2016 Edition (TxDOT, 2016). The position of each vehicle involved lends to explaining the sequence of how the crash occurred. The reconstruction of the traffic crash must be articulated in detail to provide a verbal description, along with supporting photographs, to relate each party's involvement for legal and tort consequences (TxDOT, 2016).

Other details documented include the physical condition of each vehicle involved such as brakes, lights, and tires that may have contributed to the traffic crash. The condition of each driver is imperative in determining the cause of the traffic crash (TxDOT, 2016). The officer should state his opinion of what happened in the traffic crash and document that the investigation is pending, or the officer is waiting on facts from the Medical Examiner (TxDOT, 2016). The investigating officer will make notation if the crash report is incomplete, e.g., a Hit and Run or Fatality and information is still pending in the investigation. The field only allows up to 12,000 characters and limits the amount of written data allowed in each report. A small sketch, not necessarily to scale, should be drawn in the space provided on the traffic report. The number of vehicles must be accounted for as reported in the initial diagram of the traffic crash. (TxDOT, 2016).

The diagram will detail all the physical events known at the time of the investigating officer's response. The diagram should detail the events occurring in the crash including direction of travel prior to the impact by use of a solid line, area of the impact, and the path to final positions by use of a dotted line (TxDOT, 2016). The use of photographs will lend to an accurate description of the position of the vehicles involved and factors contributing to the traffic crash (TxDOT, 2016).

Upon receiving the dispatch, the officers of the Austin Police Department now proceed to the fatal accident scene. Once the specially trained office team arrives at the fatal accident scene they begin to collect data needed for the case file. The officers, after marking the fatality accident scene for important pieces, remove the drone from the cruiser drone carrier and deploy the accident investigation drone. The drone flies a predetermined course approximately two hundred feet in the air. The drone guided by remote control and area point markers begins take photos and measure critical evidence. The drone will take between two hundred and five hundred over lapping photos on an average fatal accident scene. Once the data collection is complete, the officers returns the drone to the carrier and return the equipment to the police station for download of information from the drone to the computer system run by the city of Austin, Texas. The photos are retained by Austin Police Department for analyzing and recording. The data is redacted before release to the public by the Office of Open Records in Austin, Texas.

Research Questions

The paired selections from the records of Austin, Texas fatal vehicle accident reports from January 2016 to December 2018 were compared to files from July 2018 to December 2020 (Benningfield, 2021). The pre and post groupings were used to answer the following research questions:

1. How did the addition of drones affect the investigation times and data needs for reports of fatal vehicle accidents in the city of Austin, Texas?
2. What are the possible outcomes for other metropolitan cities of the same size and composition as Austin, Texas, likely to experience with the implementation of drone usage?

Three groups were segregated into different pools of data collection, each included fatal vehicle vs. vehicle accidents, fatal vehicle vs. a stationary object accident, and fatal vehicle vs. pedestrian accidents. The three fatal accident conditions were analyzed for the time duration pre and post drone implementation. Data needs were also collected for the three types of fatal vehicle accidents. Data needs were compared from pre and post the introduction of the drones into the investigations out in the field, as well.

Assumptions & Limitations

Although a large number of studies have been designed and compiled through multiple institutions of research on the duration of accidents occurring on American roadways, no significant consideration of the addition of drones in the investigation techniques while working with real world data have been instituted. An almost complete lack of data and study exist at this time for investigations using drones to facilitate rendering models of fatal vehicle accidents. The current literature today, outside a signal study from the Czech Republic, has not supported alternate means of traffic investigations in the United States.

In communities where drones have been implemented, a serious lack of policies and procedures exist for the use and review of information from the drones. There is a lack of a uniform policy for the usage of drones and drone collected data utilized in the field during accident investigations. The literature for guidance in new communities wanting to adopt this new technology is subjectively lacking. Within the literature there is a distinct lack of understanding data requirements for the larger images that have been produced from the drone image collection such as that collected by the Riegl VZ-400i, Faro Focus S70, Geoslam ZebRevo 3D terrestrial laser scanners and Topcon Falcon 8 drone when used for data collecting that produced large data packages. Currently, methods for collecting data used for 3D modelling has not been reviewed for usage in the court system. Data for 3D models will have to be reviewed for use in sketch making required for fatal traffic accidents in courtrooms. The process will take time and resources that the current literature has not helped to define as yet.

Definition of Terms

The following section provides a definition of terms that are used throughout this research study:

Drone - an un-crewed aircraft or ship guided by remote control or onboard computers

Fatality - the quality or state of causing death or destruction

Flight Plan - a usually written statement (as by a pilot) of the details of an intended flight (as of an airplane or spacecraft) usually filed with an authority

Hit and Run - being or involving a motor-vehicle driver who does not stop after being involved in an accident

Measuring Wheel - a wheel attached to a long handle with a grip and as the wheel turns, it marks off the amount of times it rotates, quickly calculating distance.

Object - something physical that is perceived by an individual and becomes an agent for psychological identification

Pedestrian - a person going on foot: WALKER

Statistical Package for Social Sciences (SPSS) (Version 26) - predictive analytics software was used to analyze frequency distributions and comparative analysis.

3D - a three-dimensional form

Unmanned Aerial Vehicles (UAVs) is an aircraft that carries no human pilot or passengers

Vehicle - a means of carrying or transporting something

CHAPTER II

Literature Review

In the past ten years, drones have entered the world of fatal vehicle accident investigations. Drones have evolved rapidly on multiple fronts in the areas of agriculture, model establishment environments analysis, and 3D model development. All of these areas help with the usage of drones for fatal accident investigations. A clear process of data acquisition has been studied and written about in the literature. The validity and accuracy of drones at accident sites has been studied with modeling and real-world accident scenes. Data usage has been predicted with analysis of Ultra-High Definition Video data requirements. Data usage is directly related to the quality of resolution. The higher the quality of resolution of images the more data is needed for the data file. Extremely defined sharp images that have clear color are between 6K to 8K or also known as Ultra-high Definition Images/Video. Currently, data is being collected in 2k to 4k resolution which has a much smaller number of pixels in each image. The number of pixels decides the quality of the picture (Alsadik, 2022). The data usage requirements of drone images are not yet understood for the use of data management in their day to day application in fatal accident investigations.

Drones Enter Accident Investigation

With the introduction of drones for accident data collection, the models previously developed for accident durations over the past two decades does not suit the new configuration of items that alter time durations at accident scenes. Drones have the potential to dramatically change the time signature of accident investigations according to literature sources (Stáňa, 2017). The use of drones to collect information will change the time devoted to investigations in the field. Traditionally, the officer onsite investigating the accident scene draws photographic depictions of contributing traffic scene variables to photographs from self-flying drones. The investigating officer no longer has to sketch while on scene, but will be programming flight planes, which potentially results in saved time, money, and efforts from police stations.

The data that the drone collects has the potential to reduce the frequency of fatalities at notorious intersections through analyzing the contributing factors identified at the traffic scene (Congress et. al., 2020). Reconfiguring the intersection and improving the driving conditions related to the intersection in question has the possibility of reducing traffic fatalities. The use of the drones can dramatically curtail negative incidents through analyzing the data collected on the ground, supplemented by the aerial photographs provided by the drones (Hatfield, 2020). Understanding how the data from drones is already being used in other industries is critical to future developments for the technology in investigating and analyzing fatal accidents.

The percentage of fault assigned to the involved drivers and/or pedestrians would be facilitated by the information provided by the drone after the redaction requirements were fully understood. Due to the time required by clerical staff to review and process the traffic collision reports, more time will be needed when adding supplements from drone data. The lack of understanding the needs to foster a careful analysis may limit the needed analysis and it might not always take place. The study would bring significant understanding in the clerical data processing, time and cost of working with and obtaining the drone data for other municipalities before they implement the technology.

Texas State Law

> Sec. 552.001. POLICY; CONSTRUCTION. (a) Under the fundamental philosophy of the American constitutional form of representative government that adheres to the principle that government is the servant and not the master of the people, it is the policy of this state that each person is entitled, unless otherwise expressly provided by law, at all times to complete information about the affairs of government and the official acts of public officials and employees. The people, in delegating authority, do not give their public servants the right to decide what is good for the people to know and what is not good for them to know. The people insist on remaining informed so that they may retain control over the instruments

> they have created. The provisions of this chapter shall be liberally construed to implement this policy (Tex., 1993).

Texas State law Title 5 Sec. 552 mandates that all public records, including traffic collisions reports, be made available to the public after the reports are redacted. All the investigations utilizing drones have a tremendous amount of data which must be reviewed, analyzed, categorized, and redacted prior to making them available to the public (Tex., 1993). The review and redaction of material without compromising the integrity and confidentiality of the reports and people involved, requires a tremendous amount of clerical time (Tex., 1993).

Explanation of Drone Development

Compared to manned aircraft, Unmanned Aerial Vehicles (UAVs) are inexpensive, efficient, convenient, reduce casualty rates in the modern war and achieve complex goals when combined with other equipment (e.g., sensors, scanners) in the civil fields (Hu, 2018). Unmanned Aerial System (UAS) basically consists of three parts, (i) the unmanned aircraft, (ii) the ground control station and (iii) data link. In addition, technology requirements and applications, features of payloads, launch and recovery equipment, and ground support equipment are also necessary (Hu, 2018). Unmanned vehicles can be either remotely guided or autonomous vehicles (Avtar and Watanaba, 2019).

Historical UAV systems had limited control over their trajectory because of lack of sophisticated sensor technology (Avtar and Watanaba, 2019). Since 2000, the development of computer sensor and chips needed for these aircrafts has had exponential growth in the market allowing for the wide availability of drones. The term ‘drone’ started to be used to describe pilotless aircrafts in relation to military context, especially for those aircrafts with weapons carrying capabilities (Custers, 2016). However, as time passed by, the term ‘drone’ slowly became a common word that designated any category of unmanned aircrafts in civil or in military usage (Custers, 2016). For now, ‘drone’ has exactly the same meaning as ‘UAV’, the only difference being that ‘UAV’ is more often used in official documents, including legislations, while drone is not used in any kind of legislation (Custers, 2016).

Unmanned Aerial Vehicle (UAV) systems were primarily used for military purposes and were later used for civilian applications (Avtar and Watanaba, 2019). The use of drones has only been expanding in the last decade into the civilian arena. Civilian drone usage is only now becoming expansive and widely used. Drones can now be used for a wide variety of work processes that were not able to be fully evaluated in use for data collection in the field.

Utilization of Drones in Other Industries

In the modern era, due to availability of differential GPS and sophisticated cameras, UAVs are widely used in many aspects of life (Avtar and Watanaba, 2019). The technology has found wide usage in agriculture, industry, transportation, communication, surveillance, and environment applications. Drones are widely used in precision agriculture for crop health monitoring, crop yield, and damage assessment (Avtar and Watanaba, 2019). UAVs have been shown promising contributions in remote sensing data collection for agricultural and forestry applications due to their low cost, lightweight, and low airspeed aircraft capability (Avtar and Watanaba, 2019). Unlike high-altitude aircraft and satellites, UAVs can operate unnoticed and below the clouds. Aerial photographs captured by UAVs can bridge the gap between ground-based observations and remotely sensed imagery captured with conventional aircraft or satellite platforms (Avtar and Watanaba, 2019).

Agriculture

Drones monitoring in agriculture accounts for a significant proportion of current environmental applications of UAVs. The usage of drones in agriculture is driven by the need for precision agriculture or crop management that uses GPS and other "big data" packages from drones which has been found to be an efficient way to resolve the issue of needed data (Veroustraete, 2015). The usage of green and infrared wavelengths of light from plants can help produce vegetation health assessments and growth / coverage monitoring. Maps of plants from the air can alert farmers to early signed of vegetation being stressed from pest, nutrient, or water pressures (Veroustraete, 2015).

Model Establishment Environments

Investigative authorities can use UAVs for large area investigations and data collection, in order to support model establishment in different fields. For example, the Digital Elevation Model (DEM) is now a popular title, which is a kind of short-, close-range photogrammetry application (de Boer G, 2016). The application can be used in highly dangerous situations such as landslides. The use of high resolution, geo-referenced image monitoring by drone becomes a safe, quick and efficient alternative choice to assessing large unstable landslide areas (de Boer G, 2016).

Drones can now be used to collect detailed information about surfaces at ground level. The great improvement in measurements in atmosphere, cryosphere, ocean, and land surface can be achieved, especially for three-dimensional data (3D) (de Boer G, 2016).

3D Point Cloud Construction

Digital 3D point cloud techniques could be applied in many fields, such as architecture and reconstruction. The data from drones when processed creates a large and accurate point cloud and a textured mesh to help in the reconstruction of buildings and objects (Nex and Remondino, 2014). In aspects of archeology, human touches and operations usually risk damaging the relics, hence building a 3D point cloud that data acquired by drones is necessary, especially for large relics (Nex and Remondino, 2014). In the world of policing, a 3D point cloud reconstruction of an accident can be shown to juries to better understand what happen to cause the accidents (Taylor, 2020).

Drone Usage by Police During Investigations

Aerial drones represent an emergent technology for domestic policing activities (Sakiyama et al, 2016). Policing can use a combination of techniques from agricultural sensing, model establishment environments, and 3D point cloud construction to produce a comprehensive 3D accident scene model for study of an event. Among the different fields of UAS applications, state and local law enforcement agencies seem especially receptive to the adaption and expansion of this technology in their daily work operations (Sakiyama et al, 2016). UAS technology has enormous potential for supporting various policing activities such as search and rescue of missing persons, aerial photography for crime scene investigation, detection of criminal trespass and other criminal activity in public places, identifying traffic violations and responding to automobile accidents, locating hazardous materials without endangering human lives and providing on scene fire or weather conditions to assist rescue workers in emergency situations (Sakiyama et al, 2016).

Using information gathered at road accident scenes has the potential to reduce major loss of life, while increasing economic growth and productivity. Road accidents increase the energy consumption and travel time of vehicles which further disturb the routine activities (Avtar and Watanaba, 2019). Using information gathered from previous accidents fatalities and other lower level accidents involving vehicles could be used to decrease accidents and save human life. Drone increase the quality of information used to be studied (Avtar and Watanaba, 2019).

According to Avtar and Watanaba (2019) drones have the ability to hold a wealth of evidence that could potentially be very useful to assist forensics investigations. The data includes the flight path of the Drone, date and time of flight, altitude, home-point and alerts to inform whether the Drone was near restricted airspace such as airports with no-fly zones (Avtar and Watanaba, 2019). Drones also have the potential to reduce the time for police to be on the scene. Although hypothetical deduction abounds, very few studies have looked at drones in the field when being used by police officers. The goal of this study is to understand data from real world circumstances and add to the literature gap that exist.

Process of Data Acquisition in Drones in Accident Data

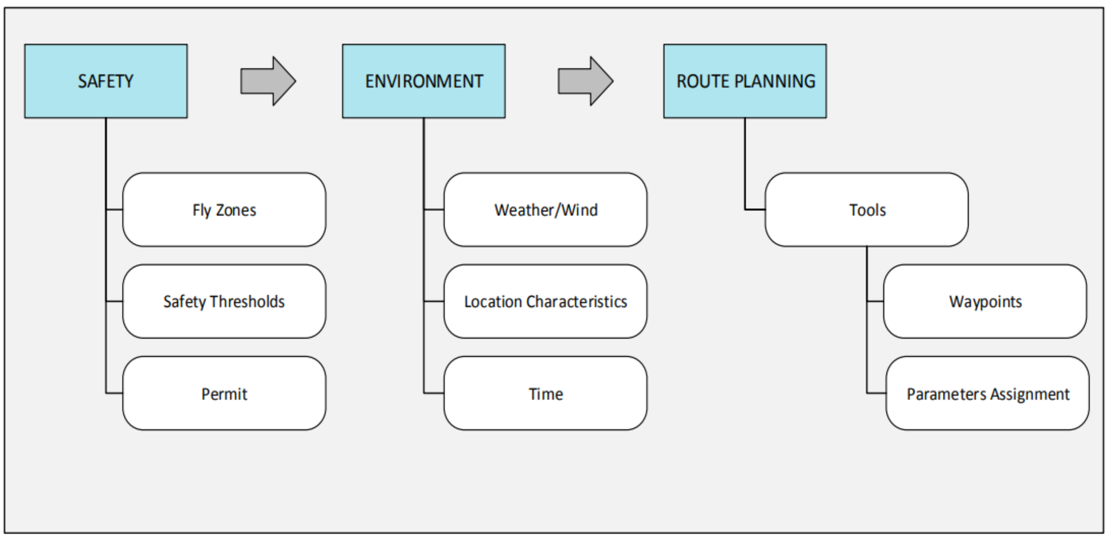
In a growing body of research, drones and unmanned aerial vehicles (UAVs), have been used to prove the accuracy of traffic accident analysis in a laboratory setting. The author Khan gives an extensive yet systematic review of the existing traffic-related UAV studies used in presenting molding from a step-by-step framework (Khan, 2017) Drones have helped to establish, in the literature, an ordered method for investigation at a scene. Drones have also shown promising data for their implementation in real world traffic investigation according to Khan, although they have not yet established a comparison study of pre and post drone deployment to study effects of their usage using these time sequencing methods (Khan, 2017).

In order to conduct a UAV-based traffic study and analysis, an extremely diligent planning period must first be executed followed, by an optimal data analysis, and interpretation procedure. The research by Khan et al. presents a comprehensive universal guiding framework for ensuring a safe and efficient execution of a UAV-based study in traffic analysis.

The framework based on exiting study from Khan et al. is classified into seven main parts. The first part includes, scope definition, which defines the parts that decides what the drone will take images of and where it will travel. The second part encompasses the flight planning which contains the design of the flight such as where the vehicle takes off and lands. Flight planning will also determine where the drone flies and where it takes images so that they are overlapping. The third part includes the flight implementation which is the actual flight. The fourth part contains data acquisition which is the downloading of photos and data to main computer systems. Part five includes the analysis and processing of the data after it is returned to the police station. Part six consist of interpretation of the collected data (photos). Part seven is the optimized traffic application which will include changes made to traffic patterns to prevent future fatalities.

Figure 1

The Flight Planning Steps



Scope Definition

The first module of the studies framework involved the definition of the "Scope of the Study" to be conducted. A clear problem statement with fixed and definite project objectives must be defined during this step according to the authors. The attributes of the workflow through the modules are generated in the first module. The project parameters like object type, output data, camera sensor, type of model helicopter and flight restrictions are designated are defined early. These parameters can vary heavily from one application to another that is why the scope defining stage is necessary. The main objectives of the study are defined and a specific focus is established with respect to the expected results of the study. The objectives of the project may include implementation of a traffic policy program to improve traffic flow or to reduce the traffic conflicts after the study in has been concluded (Khan, 2017).

Flight Planning

The “Flight Planning Stage” involves the preparation for the implementation of the actual UAV flight for the collection of the required data. With the significant increase in the number of UAVs, state laws are now being formulated and implemented in multiple states and countries to avoid major mishaps with drones. The UAV flight planning step has become even more important with the possible damage that drones flight could in tale. In-depth flight planning, based on the project parameters or scope, according the author will become more and more essential (Eisenbeiss, 2009).

UAV flight planning may be classified into three main categories; safety, environment and route planning aspects. The three categories include 1) the flying zone category of the study area must be evaluated with the help of the local flying zone maps, 2) a safe distance has to be maintained from the active airfields and from other sensitive installments, and 3) the process has become easier with the development of UAV flight management platforms which automate a number of steps involved in ensuring safety and attaining flight permits. The location characteristics i.e. infrastructural environment and extents of the built-up area in the study zone must also be considered in quest for an optimal set of flight parameters. A special deliberation towards the weather and wind conditions in the area of study along with the optimal selection for the time of the day. UAV flight planning tools have been developed that enable a more systematic and automated flight operation (Khan, 2017).

Flight Implementation

When the UAV actually flies over an area of interest as per the planned flight path/route, the plan has moved into the "Flight Implementation" section of the strategy. The flight is conducted based on the parameters decided during the flight planning stage. The flight depending upon the user's preference and flying expertise, is controlled either manually via the radio controller or automatically via the auto-pilot function. The author given no preference for either method. One method is not selected over the other for usage in data collection (Khan, 2017).

Data Acquisition

In the 2017, a study conducted by Khan, he noted the importance of the "Data Acquisition" stage by cited work from an earlier study by Barmpounakis et al. in 2016. The Barmpounakis et al. study had acquired high-quality UAV recorded video footage from a regional intersection alongside other data sources attached to the drone flying which included additional sensors (infrared, thermal, ultrasonic etc.) mounted on the

UAV. In some cases, the flight telemetry data (altitude, horizontal speed, vertical speed along with the position and the orientation data) is also attained from the UAV in order to calibrate the recorded video (Khan, 2017).

For police report data, altitude, horizontal speed, vertical speed along with the position and the orientation information is critical for criminal cases and prosecutions. As indicated by Cramer (2001), the integration of position and orientation data generated by the navigation unit of the UAV leads to a reduction of the number of physical control points that are required for the orientation and calibration of the UAV videos. Overall, the scope specific data is acquired from the UAV and is then further treated and processed during the later stages of the framework (Khan, 2017).

Data Processing and Analysis Video Analytics

"Data Processing & Analysis Video Analytics" have attracted significant attention mainly because they enable researchers to easily collect detailed trajectory data and at the same time have a visual observation of the phenomenon (Barmpounakis et al., 2016). Multiple approaches have been employed in the existing literature for the processing and analysis of the UAV based traffic data (Barmpounakis et al., 2016). These approaches can be broadly classified into two categories:

(i) Semi-Automated Video Analysis: The semi-automated video processing and analysis approach has been employed in a number of traffic related UAV studies. Such an approach is easy to set up and ensures a high level of accuracy and reliability. Also, no complex image processing algorithms are required which implies that far less computational power is needed. The approach is more laborious and commonly requires more manpower as it normally involves the establishment of some physical Ground Control Points (GCPs) or have certain lengths accurately measured on the site in order to calibrate the UAV images (Barmpounakis et al., 2016).

(ii) (ii) Automated Video Analysis: An automated analysis of the UAV acquired traffic data involves a series of advanced image processing filters and techniques in order to detect and track the relevant road users. The automated video analysis is gaining popularity especially for the real-time traffic monitoring and tracking applications. Although such an approach is quick and requires minimal manpower, it still has some limitations. Generally, the accuracy of such systems fluctuates dramatically with changes in conditions such as light, climate etc. Additionally, the automated system requires a high computational power and is difficult to initially set up as it involves complex algorithms for each sub-task of the analysis (Barmpounakis et al., 2016).

Data Interpretation

The "Data Interpretation" of the processed video data is the next step in the framework according to Khan. The interpretation is done with the help of different categories of graphs and charts that are generated as an output of the data analysis procedures. The trajectories of the vehicles or other road users extracted during the analysis part are displayed in x-y planar graphs to understand the behavior and trend of the road users. Vehicle trajectories are also represented graphically to illustrate the traffic movement across the intersection or accident scene being studied. Markers can be placed for traffic kinematic parameters i.e. flow and density during the analysis phase of the study (Khan, 2017).

Optimized Traffic Application

The optimized conclusion of the traffic study in accordance with its scope is the final step in Khan's study of UAV based traffic analysis framework. The study-specific traffic parameters determined during the analysis and interpretation phase are employed to improve the existing traffic models which ultimately helps define solutions for solving the real-world traffic situations. The final application is dependent on optimization which may include a number of traffic related objectives such as traffic signal optimization, observation of drivers' behaviors, lane change maneuvers etc. Moreover, a real-time information system can optimize the traffic operation by sending alerts to the concerned departments in case of incidents and emergencies (Barmpounakis et al, 2016).

Validity of Drones in Accident Data

In 2017, a case study was published by Officer Ivo Stáňa et al. from the Police of the Czech Republic, South Moravian Region Police Headquarters, Brno, Czech Republic, detailing the use of Unmanned Aerial Vehicle (UAV) in two different accident investigations. The author also compared averages of several cases of investigation that collected data with drones and without drones. He compared the data in two different categories. Using the two different methods for separation, the first average was of data collected with drones and the second average was of data collected without drones collecting data for evidence (Stáňa, 2017).

To Stáňa, conventionally used surveying wheels seem not only inaccurate, but especially inappropriate with respect of time and accuracy in serious accidents such as the two being studied in the article. The use of conventional methods appears to be insufficient, especially, for accidents involving throwing vehicles off the road with the incidence of inclinations (Stáňa, 2017).

The South Moravian Region Police Headquarters used a combination of the averages for new drone methodology for accident data collection verses the average for the old standard accident data collection methodology and compared the two. Data was collected in cooperation between the Police of the Czech Republic and the Institute of Forensic Engineering in Brno. The two groups were compared using several dozen serious traffic accidents events resulting in at least one person's death or a severe health consequence for at least one victim. Data was collected from a time period of one and a half years for each group (Stáňa, 2017).

The investigator performed comparisons of these two methods within traffic accident data acquisition by showing time savings during the usage of the drone methodology. When documented cases where compared, cases begin investigated with drones had a decrease of 49% compared to the average of traditional investigation events. State averages of cases were used as the preferred method. Cases were not compared in a way that reduced outlining bias in the statistical method (Stáňa, 2017).

Accuracy of Drones in Accident Data

The main objective of accident reconstruction, for law enforcement personnel, is to recreate spatially and temporally the accident event in order to make reasonable assumptions about how and why the accident occurred (Perez, 2019). The Perez study in Merida, Spain verifies the accuracy of using drones for mapping and documenting traffic accident scenes.

Imagery obtained by low cost Unmanned Aerial System (UAS) 4k video in the Perez (2019) used Root Mean Square Error (RMSE) computations, computed from 93 Independent Check Points (ICPs). During the preparation of the study, it was not possible to carry out a previous photogrammetric flight planning, given the specificities required in the documentation of a road accident. The study was composed by two main stages: (i) in the first stage the photogrammetric video acquisition and Processing Workflow (PW) is carried out in order to generate the two main geospatial products (DEM and orthophoto); (ii) in the second stage the Positional Control (PC) is carried out in order to assess the accuracy and effectiveness of the generated orthophoto (Perez, 2019).

Due to the special characteristics and the spontaneity with which road accidents occur, as well as the speed with which it is necessary to carry out the data collection, it is difficult to carry out a conventional photogrammetric flight planning (Perez, 2019). An “in situ” manual flight, with the purpose of replicating real case conditions was employed for the study to simulate real world characteristics as close as possible (Perez, 2019).

The image set was identified manually with the number of images (interval) to be extracted in order to have a required frontal overlap (Perez, 2019). Images were extracted from 729 frames of 4 K video. The drone used a trajectory that followed the axis of the road, assisted at all times by Global Positioning Sensors (GPS) and Unmanned Aerial Vehicle (UAV) sensors (Perez, 2019) over a ten-minute flight. 97.5% overlap was produced for the scene to be analyzed by Perez and his team (Perez, 2019). Blurred images were replaced with the previous images or subsequent frames and placed in the study image collection.

Figure 2

Flight Planning Steps

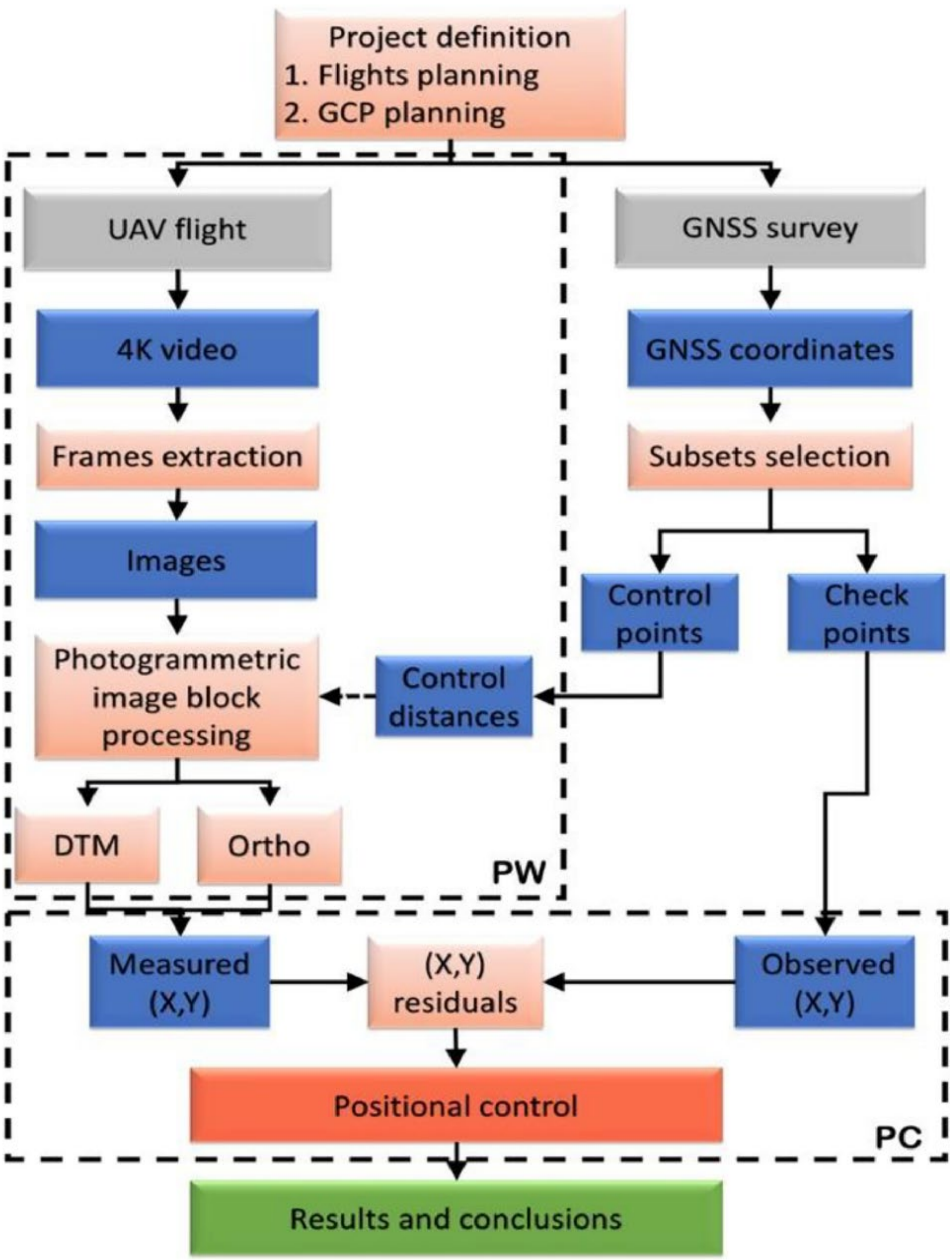
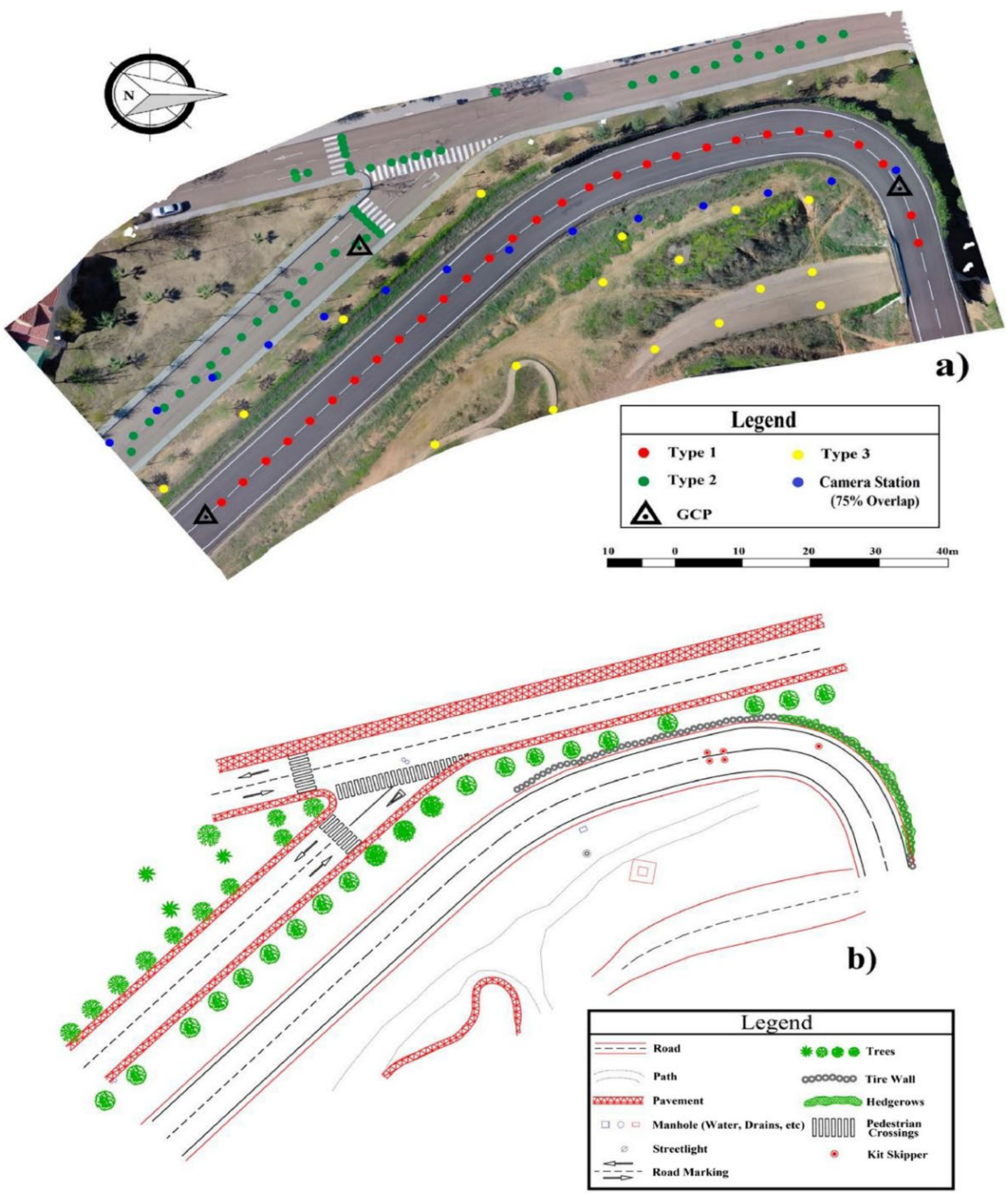


Figure 3

Produces of Perez Study



The results obtained for each of the 9 cases were very similar. The analysis of the 9 case photos had a corresponding overlap of 97.5%. The Perez research team generated two geospatial products that could have been used for the documentation of authentic accident scenes from the fictitious traffic accident area. An accuracy assessment was carried out by analyzing the RMSE of the differences between the coordinates of 93 ICPs measured in the orthophotos, with the corresponding ones measured by using Global Navigation Satellite System (GNSS) techniques (Perez, 2019). Only a small planimetric difference of 2 cm was observed between Case 1, with high processing qualities, and Case 9, where low data processing qualities were used (Perez, 2019).

Once the image processing parameters with the best results were obtained (Case 9), the author proceeded to generate the necessary orthophotos that will serve as basis of the next accuracy assessment. The ICPs were measured and compared with those taken in the field by GNSS procedures, obtaining a new positional control data set for each of these new cases. All cases showed planimetric errors between 10 and 17 cm. Those that present the best behavior, being the cases between 97.5% and 77.5%, with almost identical means of planimetric error of approximately 12 cm (± 2 cm). Nevertheless, the cases of 90%, 85% and 77.5% show small deviations of about 3–4 cm, which are not relevant or significant from the point of view of the final accuracy of the scene under study (Perez, 2019).

For documentation of traffic accidents scenes, it was proven accurate enough to carry out the UAS flights with manual or semi-automatic guidance, using the aircraft sensors through data connections via telemetry radio links or with first person video transmission equipment or First-Person View (FPV) to document traffic accidents for legal purposes. It is also possible to carry out this type of photogrammetric work through small preliminary flight planning, in which it is only necessary to establish a series of basic geometric parameters such as the height of the flight in order to define the final accuracy of the cartographic products (GSD), the start and end positions, as well as those positions where there are changes in the route of the aircraft (Perez, 2019).

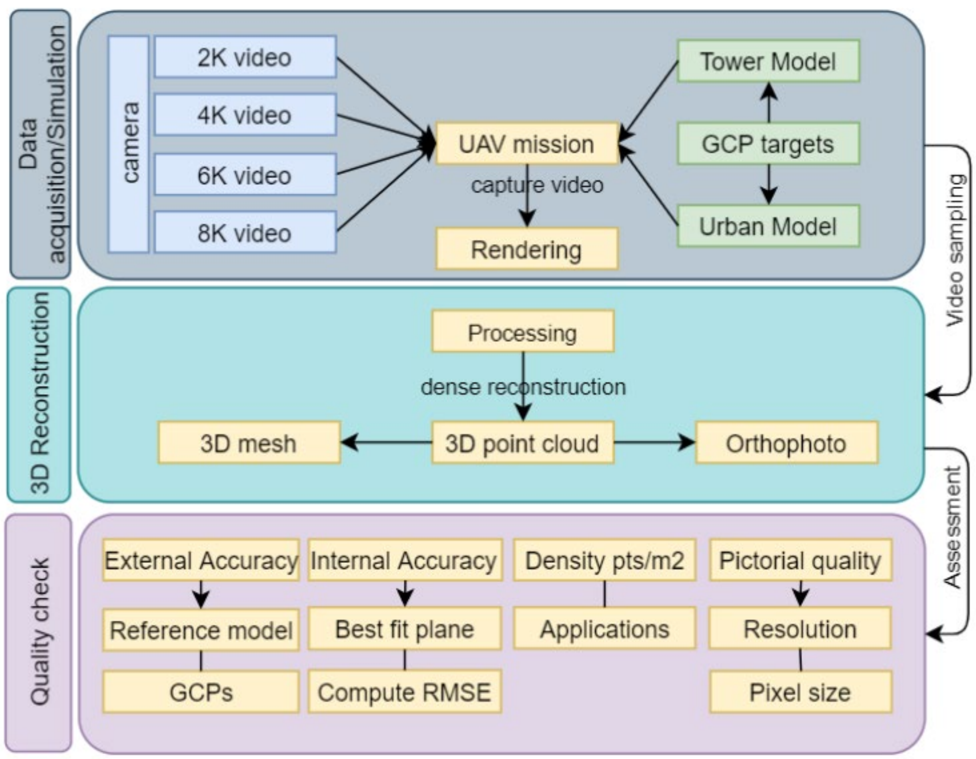
Video and Data Usage Needs of Drones Using Ultra-High-Definition Videos

The methodology followed in the Alsadik (2022) paper used a simulated environment using the Blender tool where it is possible to test the four different video resolutions captured from the same drone at exactly the same flight trajectory (Alsadik, 2022). Sampling the video frames at longer time intervals can help to have a wider baseline configuration and decrease data redundancy according the author Alsadik. The study looked to establish a fair comparison between the produced models of the four different capture speeds to help law enforcement better understand the image processing capability at each resolution level (Alsadik, 2022). Until now, video-based 3D modeling has not been preferred because of the insufficient resolution and very short baseline.

In the Alsadik study, the impact of using UHD video cameras (6K and 8K) onboard drones was investigated on the 3D reconstructed city models. These Ultra High Definition (UHD) video-based models were compared with the same 3D models produced from the currently used High Definition (HD) and 4K cameras. Images were shown to increase in the video resolution not only improved the density but also the internal and external accuracies of the created 3D models when using 6K and 8K cameras. The point density and the reconstruction accuracy were improved up to 90% when using 8K videos compared with the HD videos taken from the same drone. The Ground Sampling Distance (GSD) was improved approximately four times when the 8K image resolution was used compared with the HD resolution while maintaining the same flying height. The improvement of images will guarantee fine details of the reconstructed 3D models and hence opens a wide range of applications for using drones equipped with 8K video cameras for roadway condition assessment, powerline clearance, cultural heritage restoration and documentation, as-built surveying, etc. (Alsadik, 2022).

Figure 4

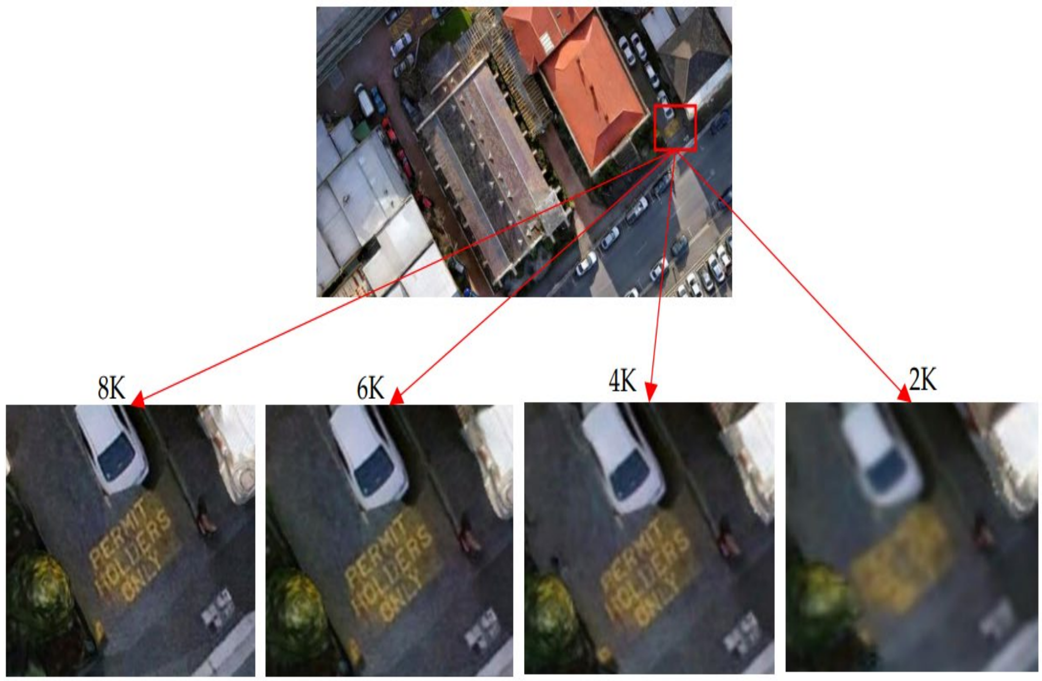
The Workflow of the Methodology of Image Creation



Sampling and filtering of images in investigation are necessary to ensure cost-effective processing and good quality results. Currently, studies show that an accuracy of ∼=1/400 or ∼=5 cm can be achieved when using video frames of 640 × 480 pixels which can be improved to 1 cm with a higher resolution in the best case. 3D image-based modeling is based on taking still shot images where an overlap percentage should be preserved. Research shows that 80% for both end lap and side lap is sufficient to create a 3D model and orthophotos out of the drone images (Alsadik, 2022).

Figure 5

Video Resolutions at 2K, 4K, 6K, and 8K created Orthoimages



3D image-based models can also be created using videos in what is sometimes called videogrammetry, which refers to making measurements from video images taken using a camcorder. A video comprises of a sequence of image frames captured at a certain recording speed. A camera can be used to capture a one-minute video at a speed of 30 frames per second (fps), it means that a total of 1800 video frames are recorded.

It is still a significant challenge when using the UHD videos where memory is required (Alsadik, 2022). The processing power needed for the computations, and the time consumption could be increased by more than 20 times on average, is significant for processing units. The author, Alsadik, recommends to continue the research to find a solution for big data handling and finding on-the-fly or cloud-based solutions to speed up the data handling and the geoinformation data extraction (Alsadik, 2022).

Modeling of Accident Duration

Kamnik Study Model

According to Kamnik (2020), the majority of onsite traffic accident data all over the world is still collected by standard police work. The most traditional approach is by police reports, the investigation of accident sites and vehicles involved, and interviews with the involved road users and witnesses which is discussed in. Police teams collect a mixture of data from on-the-scene investigations (i.e. right after the crash when the vehicles are still in place) and/or on-the-site investigations (visiting the crash site after the scene has been cleared to collect additional data). Also, records from later police interviews with the involved parties are collected (Kamnik, 2020). When all data is compiled, the officers onsite will produce an investigation report for each crash. To complete the dynamics of the investigation, an officer will have a tape and/or measuring wheel to measuring the relations between accident participants and gaining details of the scene. The officer will use a nearby fixed reference point as a selected starting point for measurements. The officer can choose a road sign, corner of a building, or tree near the scene (etc.). Along the road a reference line is measured by the officer and to that line a perpendicular measurement to each detail is obtained (Kamnik, 2020).

The main purpose of the paper by Kamnik was to verify that sketches obtained from the use of a drone using a 3D point cloud program could in the field produce faster and more accurate sketches than classical police measurements. For that purpose, classical police work and sketch making was compared with several different types of drones: Riegl VZ-400i, Faro Focus S70, Geoslam ZebRevo 3D terrestrial laser scanners and Topcon Falcon 8 drone for data collecting. All of the collected data was used for 3D modelling and sketch making. An accuracy comparison was made by using graphical approach. For subsequent visual inspection of the traffic accident scene, the most suitable source is an orthophoto obtained by the Surface from Motion (SfM) method, which is the result of processing a series of georeferenced photographs taken from the UAV. The accident was simulated at a slight curve and inclination involving two cars and a motorcycle (Kamnik, 2020).

For the purpose of comparison of the time for data gathering, accuracy of collected data, sketches made and instrument costs an accident with one death casualty was simulated on the safety driving polygon in Ljubečna, Slovenia. The purpose of the simulation is to investigate how good sketches can we obtain using modern measuring techniques and if the sketch obtained from those methods are good enough as an official input for the Slovenian District State Prosecutor’s Office (SDSPO) (Kamnik, 2020).

A sketch was made showing all the vehicle positions, details markings and measurements. 5 different systems were used for data collection: (1) measurements with a measuring tape, (2) measurements with Riegl, (3) measurements with Faro, (4) measurements with Zeb-Revo and (5) measurements with the Falcon 8 drone (Kamnik, 2020). They marked 14 details and made 19 measurements along the road (abscise axes) and 19 measurements perpendicular to the asphalt verge (ordinate axes) (Kamnik, 2020). The measuring took 64 minutes (not included reconnaissance and marking with white spray paint). The paper presents the comparison of classical police work with Riegl VZ-400i 3D, Faro Focus S70, Geoslam ZebRevo 3D TLS and Topcon Falcon 8 drone measurements (Kamnik, 2020).

Two new police officers were used by the author for each new drone used to collect data on sight. The Riegl VZ-400i scanner scanned the area from nine different standing points (not connected in a geodetic network). The program RiSolve was used for data post-processing. Similar to RiSolve was the program Cloud Compare Software, which was used to obtain 3D models from the Zeb Revo measurements. The Faro Focus S70 scanner scanned on five different standing points (not connected in a geodetic network). Six spherical targets were used also. Geo SLAM ZEB-REVO handheld scanner is very simple to use because no station points are needed. The study did not note that the final drone, the Falcon 8, required standing points. It was noted that the Falcon 8 used Cloud Compare Software (Kamnik, 2020).

Drawing sketches by hand and then redrawing it is a possible source of errors. The drawing by hand method is not good in cases when accidents are categorically complex. Where higher accuracy is needed in small details, the measured data are input into computer systems for accident reconstruction for Slovenian DSPO trials (Kamnik, 2020).

The main focus of this study was to examine methods of investigation that might shorten the time for field work of officers and help clear the traffic scene as soon as possible. Any new method used could not decrease the accuracy of gathered data or its results. Data gathering times in this study were significantly shorter in comparison to classical police work with measurement types and wheels. The use of the Riegl shortened the data collecting time by 77 %, Faro Focus by 49 %, GeoSlam by 97.3 % and Falcon 8 drone by 94.4 %. The dimensions and sketches obtained from point clouds and photos were accurate in average up to 6 cm in comparison to police measurements with measurement type. Accuracy can be even improved when using GeoSlam if more points would be collected. The differences in measurements were in average 4 mm for Riegl, 3 mm for Faro, 6 mm for the GeoSlam, and 3 mm for the Falcon 8 drone. All of the obtained 3D models were similar in the point position accuracy which was also in accordance with the horizontal measured distances (Kamnik, 2020).

Traditional Modeling of Accidents

A variety of authors have worked to reduce traffic congestion on roadways by understanding the factors that influence incident duration and provide remedial solutions to improve clearance times (Tirtha, 2020). Since 1995, a wide verify research models have been used and designed to determine the equation of accident durations. Models vary from linear regression models used in the mid 90's by Garib to Laman's Copula group-based models introduced in 2018. Among parametric methods that have been developed, the most common methodologies include:

(a) Truncated regression-based time sequential method (Khattak et al., 1995),

(b) Linear regression analysis (Garib et al., 2002),

(c) Parametric hazard-based model (Chung, 2010, Junhua et al., 2013, Tavassoli Hojati et al., 2013, Tavassoli Hojati et al., 2014, Ghosh et al., 2014, Chung et al., 2015, Li et al., 2015),

(d) Binary probit and regression model based joint framework (Ding et al., 2015). In terms of non-parametric methods, approaches employed include (a) Tree based model (Valenti et al., 2010, Zhan et al., 2011), (b) Bayesian networks (Ozbay and Noyan, 2006), (c) Support vector machine (Valenti et al., 2010, Wu et al., 2011),(d) Artificial neural network (Lee and Wei, 2010),

(e) Partial least square regression (Wang et al., 2013),

(f) Copula based grouped ordered response model (Laman et al., 2018).

Tirtha Model for Accident Durations

The methodologies that Tirtha points out have been used in past research are varied and a diverse look at methods used for modeling analysis. Models can be broadly classified into two groups: parametric methods and non-parametric methods according to Tirtha. Based on these models developed by other researchers, the most important independent variables identified in literature include: incident characteristics (such as incident type, number of responders involved, first responder), roadway characteristics (such as functional classification, geometric characteristics, Average Annual Daily Traffic (AADT), Truck AADT), traffic conditions (such as time of the day, weekday/weekend), and weather conditions (such as season, rain, temperature) (Tirtha, 2020).

Tirtha et al. conducted research at the University of Central Florida to define the factors influencing incident duration of accidents in the Orlando, Florida area. Tirtha used the sum of the first three phases to obtain an incident duration time for each of the events being studied. The first three phases together are: Notification time, Response time, and Clearance time followed by a fourth phase Traffic recovery time. The author had the goal of understanding what factors influence incident duration and providing recommendations for improved traffic incident management plans in an independent model. The first three phases are directly affected by the traffic incident and the incident management response infrastructure in the urban roadway setting. The traffic recovery time (fourth phase) is codependent of the first three and is a function of total duration of the first three phases and the traffic demand on the facility. Any improvements in reducing the duration of the first three phases of the incident will contribute to lower traffic recovery time (Tirtha, 2020).

Tirtha jointly modeled incident type and incident duration using a copula-based scaled multinomial logit-group ordered logit model (SMNL-GGOL). The author took information for the study from an incident management dataset compiled by the Florida Department of Transportation (FDOT) collected over six years from 2012 to 2017 for the greater Orlando region as the final dataset for the study. The study is confined to the incidents with an official reported response time compiled by the FDOT. The final dataset, after removing events without a complete response, consisted of 326,348 incident records. In preparation of the sample to be estimated, 2000 incidents were randomly sampled for each year (2012–2017). An estimation was then created using a sample of 12,000 records. For validation test, 2500 records from each year were sampled randomly from the unused data resulting in a validation dataset of 15,000 records. Three incident types indicating crash, debris, and other incidents were used for consideration. The developed model was applied to generate response parameters using duration categories, incident frequencies, and selected independent variables for different incident types (Tirtha, 2020).

Incident Characteristics

Several incident characteristics such as number of responders, category of the first responder, and notified agency were found to influence incident duration. The incident duration was found to be higher with the increased number of responders for all duration models. The increase in the number of responders is representative of the seriousness of the incident (Tirtha, 2020).

Weather Effects

The variables tested for seasonality resulted in a significant parameter for the spring season. The results indicate lower propensity for crash during spring season. The results for the "Rain" variable indicate that in the presence of rain, crash incidences are likely to be higher (Tirtha, 2020).

Built Environment

As the distance from Central Business District (CBD) increases, the time for clearance for crash incidences were found to be higher. The result was indicative of the presence of more incident clearance infrastructure around the CBD (Tirtha, 2020).

Socio-Demographic Variables

As population increases, the model results indicate a reduction in duration for crash and other incidents. Population density and median income in the proximity of incident were found to be significant predictors of incident type. Higher population density increases probability of an incident being debris and reduces the likelihood of an incident being crash relative to other incidents (Tirtha, 2020).

Traffic Characteristic

The model estimation results indicate that incident durations were likely to be higher during 9 pm to 6 am (see (Chung, 2010) and (Laman et al., 2018) for similar findings). On weekdays, duration of crash incidence was likely to be shorter (as is supported by earlier research (Laman et al., 2018). The results are an indication of infrastructure readiness for crash incident clearance (Tirtha, 2020).

Computer Modeling for Accident Duration

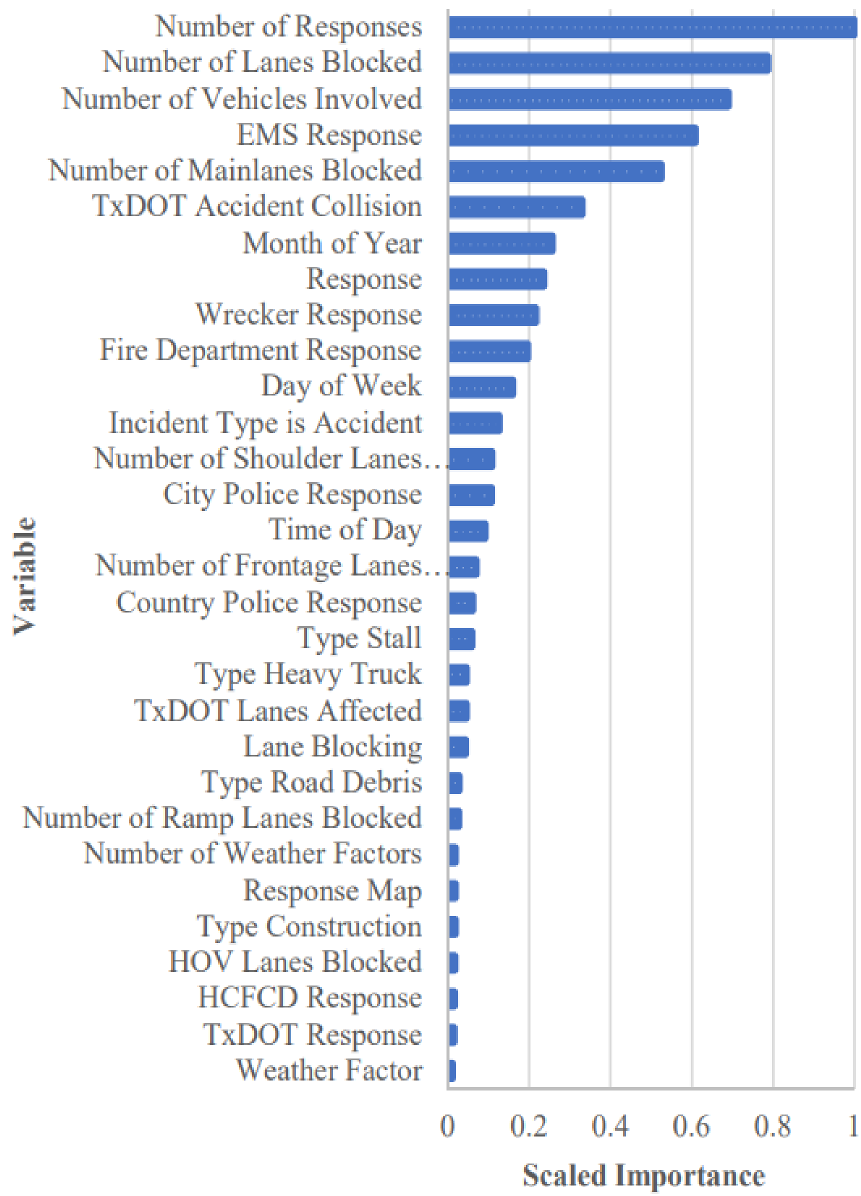
Machine learning (ML) models have been widely utilized in different fields to solve multi-parameter problems. Various studies have developed incident duration models considering multiple independent variables employing different statistical and machine learning (ML) approaches. Hamad et al. (2019) developed four traffic incident duration models using a regression decision tree, support vector machine (SVM), ensemble tree (bagged and boosted), Gaussian process regression (GPR), and artificial neural networks (ANN). Li et al. (2020) developed a deep fusion accident duration prediction model considering spatial-temporal correlations and characteristics of traffic accidents through Restricted Boltzmann Machine (RBM) methods (Rahmat-Ullah, 2021).

Rahmat-Ullah et al. (Rahmat-Ullah, 2021) collected incident data between January 1st, 2004, to December 31st, 2013, for Houston, Texas and retrieved datasets from the TranStar Houston's Transportation Management Center. Fifty-two independent variables were examined in this study to investigate their impacts on incident duration classes. The data sets were divided into 70% training, 15% cross-validation, and 15% validation. Training data sets were used during network simulation, where the modeling program was modified based on a trial-and-error basis. Cross-validation data are utilized to evaluate the training process, which gets terminated when its efficiency stops enhancing. In this study, the incident duration records were classified into four classes: minor, intermediate, major, and severe. Cross-validation data were utilized to evaluate the training process, which gets terminated when its efficiency stops enhancing (Rahmat - Ullah, 2021).

Rahmat-Ullah et al. deployed two different artifical intelligence (AI) models using two diffent approaches 1) Random Forests (RF) is considered as one of ensemble Machine Learning (ML) approaches where multiple decision tree models are combined under a single framework to enhance their individual performance efficiency and 2) Artificial Neural Network (ANN) was a prevalent machine-learning method that is known as the information based-network model. ANN was modeled with two hidden layers of 200 neurons, while the RF model was developed with 50 trees. The concept of such an approach was adopted from human brain operations' behavior in terms of nodes and information processing. The ANN model took a longer running time of 952 seconds, while the RF model was deployed in 152 seconds. The longer training time of the ANN algorithm can be attributed to its complex architecture that consists of two hidden layers of 200 neurons. However, this was not reflected in the model outcomes as the overall prediction accuracy of training and validating RFs was 70 and 71%, respectively, 10% higher than ANN (Rahmat-Ullah, 2021).

Figure 6

Importance Levels of the Examined Independent Variables



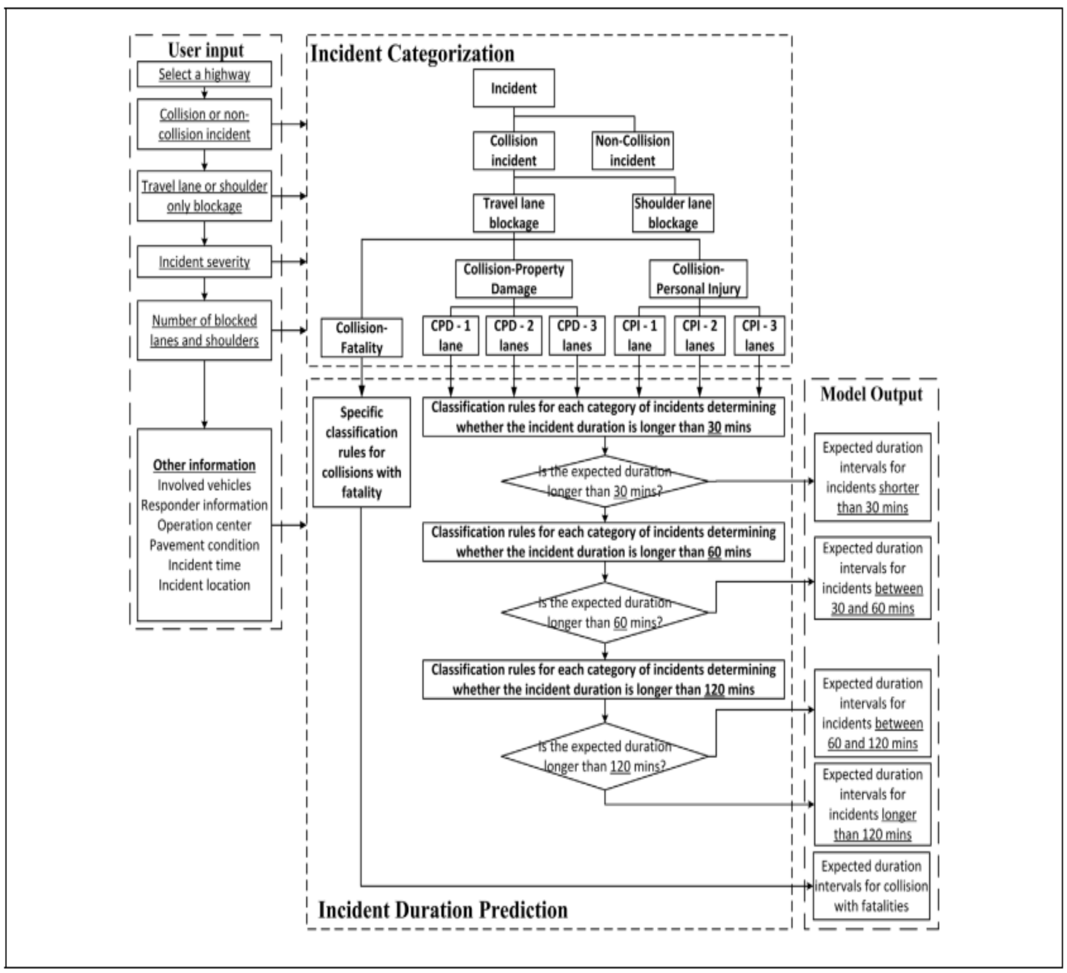
From review of the computer model, can be concluded that there is no linear relationship between model complexity and prediction accuracy. The importance level analysis of independent variables revealed that the top 10 significant parameters affecting the incident duration models are: number of teams responded to the incidents, number of lanes blocked, number of involved vehicles EMS response, number of main lanes blocked, TxDOT accident collision, month of the year, response, wrecker response, and fire department response. According to the authors, compared to similar studies, it was found that the overall prediction accuracy of the examined models in this study was satisfactory (Rahmat-Ullah, 2021).

I-95 Rule-Based Incident Duration System with an Automated Knowledge Transferability Model

Over the past several decades, many U.S. highway agencies have established Traffic Incident Management (TIM) systems to help mitigate impacts of accidents and restore normal traffic conditions. A TIM system typically consists of a coordinated multi-disciplinary process to detect, respond to, and clear traffic incidents. It is expected that such a system can effectively reduce the clearance duration of detected incidents, and reduce the resulting impacts on traffic delay and safety. To do so, a TIM system first needs a reliable and robust model to predict the required duration for incident clearance operations, and then to assess its time-varying traffic queues as well as resulting delays, because such information is essential for determining the proper control strategies and the responsive traffic management tasks (Huang, 2022).

Figure 7

The Application Process of the Developed Incident Prediction Model



The multiple types of already developed incident duration prediction models (IDPMs) include a variety of techniques: continuous statistical models, neural network approaches, discrete / classification methods, and hybrid modeling techniques. The implementation of such an imperative system to contend with non-recurrent congestion remains at the infancy stage. The reason for the unsettling of a consistence model to be used throughout traffic operations is partly because of the large number of factors that are critical to an incident's clearance time but are difficult to collect at a desirable level of accuracy for system development in real time (Huang, 2022).

The study presents by Huang et al. is a knowledge transferability analysis (KTA) model, intending to explore the potential of constructing a new IDPM by transferring some of those prediction rules from existing IDPMs, based on their effectiveness, to the new target highway. The collision with personal injury (CPI), collision with property damage (CPD), and collision with fatality (CF) were formed as the three primaries (Huang, 2022).

CPI and CPD would be first classified into two classes of ‘‘< 30 minutes’’ and ‘‘≥ 30 minutes’’ by using the association rule mining method. The incident data classified in the class of ‘‘≥ 30 minutes’’ are then further divided into two groups of ‘‘< 60 minutes’’ and ‘‘≥ 60 minutes’’ for searching other classification rules. With the same logic, one can then further decompose the incident data group of ‘‘≥ 60 minutes’’ into two clusters of ‘‘<120 minutes’’ and ‘‘≥ 120 minutes.’’ The estimated clearance duration corresponding to the confidence levels of 60%, 70%, and 80% can be produced from the sequential classification process. Notably, compared with CPD and CPI, nearly all highways, by nature, have much fewer incidents resulting in both collisions and fatalities (CF) (Huang, 2022).

Table 1

List of the Incident Duration's Key Contributing Factors Classified by Category

Category	Description	Item
Category-1 (# of responders)	The number of different responders at the incident scene	# of total response units # of arrived CHART # of arrived police # of arrived fireboard # of arrived medical service # of arrived tow service
Category-2 (First arrived responder)	Type of the first-arriving responders	Police first arrived Medical service first arrived Tow service first arrived CHART first arrived Fireboard first arrived
Category-3 (Vehicle status)	The number and the type of vehicles involving in incidents and their damage levels	Overturned, lost load, jack-knife # of total involved vehicles # of involved passenger cars # of involved trucks # of involved motorcycles
Category-4 (Pavement conditions)	Indicators for the pavement conditions	Wet, dry, snow-ice, chemical wet, hazard material related
Category-5 (Lane blockage)	Indicators to denote the lane blockage conditions	# of blocked lanes # of blocked shoulder lanes # of blocked travel lanes # of blocked auxiliary lanes Travel lane blocked in tunnel Travel lane blocked in toll
Category-6 (Operation center)	Indicators reflecting different incident response centers	AOC, TOC3, TOC4, TOC5, SOC
Category-7 (Time)	Temporal-related indicators associated with an incident	Morning peak, evening peak, daytime, night Weekday, weekend Holiday, non-holiday Spring, Summer, Fall, Winter

Note: AOC = Authority Operations Center; SOC = Statewide Operations Center; TOC = Traffic Operations Center; and CHART = Coordinated Highways Action Response Team

As the process for the rule transferability analysis included: (i) generation and update of the Rule Box to include available prediction rules from existing systems; (ii) ranking of key factors for constructing available prediction rules; (iii) identification of the transferring priority for available prediction rules, and (iv) effectiveness assessment with respect to all transferred prediction rules. With the computed importance of each contributing factor, one can do the ranking analysis based on the factor with highest importance in each category (Huang, 2022).

IDPM–I-70 constituted mostly of transferred rules (i.e., 36 out of 54 rules) can achieve the accuracy level of 87% with the training dataset (i.e., 2016–2018) and 82% with the test dataset (i.e., 2019). The model's level of performance is comparable with existing IDPMs, but demands much less resource with an automated computer program and does not need to be constrained by the available size of incident records (Huang, 2022).

Gaps in Literature that Have Not Been Addressed

Although a large number of studies have been designed and compiled, through multiple institutions of research, for the duration of accidents on American roadways, none have considered the addition of drones in the investigation technique while working with real world data. The use of drones has not been included in modeling of traffic event duration in the theoretical data prototyping as well.

An almost complete lack of data and study exist at this time for investigations using drones to rendering models of fatal vehicle accidents. The current literature today, outside a signal study from the Czech Republic, has not been investigated. Time sampling of the use of drones has not been published inside the United States. The Police of the Czech Republic and the Institute of Forensic Engineering in Brno's study made no efforts to eliminate bias in cases their studies and simply compared average means from two accident groups.

In communities were drones have been implemented, a serious lack of policies and procedures exist for the use and review of information from the drones. There is a lack of a uniform policy of the usage of drones while in the field during accident investigations in the literature for guidance of new communities that want to adopt this new technology. Texas State law Title 5 Sec. 552 mandates that all public records, including traffic collisions reports, be made available to the public after the reports are redacted, but not how to use the drones at the accident scene.

Within the literature there is a distinct lack of understanding data requirements for the larger images that will be produced from the image collection. The Riegl VZ-400i, Faro Focus S70, Geoslam ZebRevo 3D terrestrial laser scanners and Topcon Falcon 8 drone when used for data collecting produce large data packages. All of the collected data used for 3D modelling will then be used for sketch making. The process will take time and resources that the literature has not helped to define yet.

CHAPTER III

Methodology

In an average year, approximately 70 to 120 individuals will lose their lives in a vehicular accident on Austin, Texas roads (The Official, 2022). The Austin Police Department began using drone imaging after the acquisition of departmental drones capable of taking photographic evidence in mid-2018 to present day. Every two years, any state agency in the State of Texas must produce a report identifying each use of a drone by a government employee. (Tex., 1993) The report used was titled, "Compliance Report for the Use of Small Unmanned Aircraft Systems by a Law Enforcement Agency; Texas Government Code 423.008" (Benningfield, 2021). Using these records 29 cases were identified as possible study selections to be studied in comparison to 29 other cases from before the introduction of the drones (Benningfield, 2021).

Both sets of cases, from pre and post the implementation of drones, were matched as closely as possible to line the configurations of the fatal accidents with one another using the primary components of models by those of researchers such as Khan and Rahmat-Ullah. Configurations included if a fatality occurred, type of vehicle, and what item was hit (i.e. human, vehicle, or object). Additional pairing items for comparison included weather, season, precipitation, and time of day.

The paired selections from the records of Austin, Texas fatal vehicle accident reports from January 2016 to December 2018 were compared to files from July 2018 to December 2020 (Benningfield, 2021). The pre and post groupings were used to answer the research questions:

1. How did the addition of drones affect the investigation times and data needs for reports of fatal vehicle accidents in the city of Austin, Texas?
2. What are the possible outcomes for other metropolitan cities of the same size and composition as Austin, Texas, likely to experience with the implementation of drone usage?

Three groups were segregated into different pools of data collection, each included fatal vehicle vs. vehicle accidents, fatal vehicle vs. a stationary object accident, and fatal vehicle vs. pedestrian accidents. The three fatal accident conditions were analyzed for the time duration pre and post drone implementation. Data needs were also collected for the three types of fatal vehicle accidents. Data needs were compared from pre and post the introduction of the drones into the investigations out in the field, as well.

Description of Research Instrument

The following research study was designed to identify changing factors using a comparative analysis in the files of fatal accidents in Austin, Texas from pre and post the introduction of drone technology to the investigation method of the Austin Police Department. Time signatures in computer aided dispatches (CADs) were used to analyze the pre and post to see if there is a statistically significant change in time in cases that used drones compared to those that did not use drones. Cases were paired together based on characteristics of the accidents such as type of collision resulting in a fatality, time of day, and vehicles involved. The size measurement of the individual data files was recorded for each data image and compared for a statistically significant change. The time needed to form redactions on data files were to be calculated and reported in the analysis report. Although, it was found no redaction time was required for these images according to the Austin PD open record division.

Quantitative indicators were used to test the efficiency of the new technique with the measurements of time, size of data collected for hard drive usage, and staff time for analysis. Pre and post data averages were used in a standardized paired “T-Test” for statistical validity due to the normal distribution of the data. Normality was tested using the Kolmogorov–Smirnov Test. Reliability was tested using linear regression for each set of data. Cases remained linked using multiple factor correlation of cases. Experimental findings did not help support the declination of drone-based data collection timed in police investigations involving fatal accidents and other lower lever vehicle accidents. In the third condition (vehicle vs. pedestrian), where normality was not established with the Kolmogorov–Smirnov test, the Wilcoxon Signed Ranks Test was used to test the condition. Data usage was described with descriptive statistics between pre and post paired cases.

Reliability and Validity

The paired “T-Test” was utilized for this study for the inferential statistics to study in the completion times of fatal accident investigations in Austin, Texas. Three types of fatal vehicle accidents were paired by primary descriptive factors that included time of day, type of fatal accidents, type of vehicles, and descriptive characteristics from pre and post the introduction of drone data collection. A normal distribution was tested for using Kolmogorov–Smirnov Test. The paired t-test was used on the first two conditions after testing for normality. The third used the Wilcoxon Signed Ranks Test because normality could not be established. A linear regression test was used on each condition to determine the reliability of the study. All paired types of fatal vehicle accidents were found to have a reliable regression test. The goodness of fit was described and tested for the validity of the study groups obtained.

Data Collection

The collection of data for the propose of this research study involved a three-step process of collecting data from the Austin Police Department (PD). The researcher analyzing this study with prior consent to the Oklahoma State IRB (IRB-22-137) contacted the Austin Police department in Austin, Texas to communicate and release data for this study. IRB consent letter can be found in the Appendix. The Austin PD supplied the data through there office of open records. With the help of the Austin PD, 28 cases were identified for the study in three condition areas. Each case came from a list of publicly published fatalities and were narrowed down to 29 pre and 29 post drone usage began.

The Austin PD uses a Computer Aided Dispatch System referred to as CAD. The Austin PD supplied the requested information from the CAD System. The CAD system logs in the first office onsite to the last officer leaving the site and all dispatches in-between. The beginning and ending times for each case used in the study came from review of the CAD reports of the Austin PD. The time of reviewing each file in the Austin Police Department case files came from the Department of Open Records. All data was public files able to be seen by the community and was not involved in an ongoing court case at time of the study.

Analysis Approach

Statistical Package for Social Sciences (SPSS) (Version 26) predictive analytics software was used to analyze frequency distributions and comparative purposes among time signatures of data collected from pre and post the introduction of drones in three different variable groups. The following research study was designed to investigate the effect of time signatures of the investigations of fatal vehicle accidents in the city of Austin, Texas. The study was secondarily designed to understand Austin, Texas's experience with the implementation and use of data and information request in correlation to drone usage. Time signatures were analyzed to see if corrections in predictive properties existed in time sequences to see if time sequences changed after the adoption of drones. Variant groups included vehicle vs. vehicle, vehicle vs. object, and vehicle verses pedestrian. Mean, median, standard deviation, skewness and Kurtosis were derived from the time signature according to the variant group classification. A linear regression test was used on each condition to determine the reliability of the study. The Kolmogorov-Smirnov test was used to decide if a sample comes from a population with a normal distribution. For paired sets that were normal according to the Kolmogorov-Smirnov test, the pair were calculated with the paired T-Test statistical test. For the non-normally distributed pair sets, a non-parametric test was used.

Study Timeline

The subject for the studies were selected from the fatalities that occurred 2.5 years before the introduction of the drone systems for data and the 2.5 years after drones were introduced for the usage of data collection from 2018-2020 to see the effect of time signatures of the investigations of fatal vehicle accidents in the city of Austin, Texas and the implementation and use of data and information request in correlation to drone usage. In accordance with Texas state law at the time, all drone usage by a governmental entity has to be published bi-annually (Bennington, 2021). The report was used to identify specific accident investigation that could be paired with earlier accidents from before the usage of drones (Bennington, 2021). First, all fatal accidents investigated that contain a motorcycle or bicycles was removed from the pool of possible data selection. The motorcycle grouping was found to be smaller and have fewer constant numbers of fatalities than other data groups. Motorcycle fatalities could not easily be put in other groups so it was decided that they would be excluded from the three primary study groups. Motorcycle accidents characteristics did not follow the mass distribution of vehicle vs vehicle or the vehicle vs. pedestrian format. Many of the motorcycle fatalities were also still in the court system for possible criminal charges which made them unaccusable for this study. Cases that remained were found to be challenging to pair with another case using details. Details of motorcycle cases are much more diversified then that of their vehicle involved counter parts with what and how they are hit to cause a fatal accident (Bennington, 2021).

Only nine cases where vehicles killed a pedestrian were found to be usable in the data set. One pedestrian vs. vehicle case was found to be out of the jurisdiction to the responding police unit. So, although, it appeared on the list of data, it was not completed and could not be used for the study. Out of the remaining data items ten paired vehicle vs. vehicle and ten paired vehicle vs. object cases were identified and matched to a case with the same characteristics in the 2016-2018 data pool from that of the 2018-2020 pool cases using drones for data.

It is important to note that not all fatalities were documented with drones in the first two years of their usage by the department. At the time of this research study the only cases identified from the department to have used drones where from the time frame of 2018 -2020. Not all fatalities from the time from 2018 – 2020 had a drone collecting data for the investigation. Weather and flying conditions such as high winds played a role in the decisions to use the drone in accident investigation (Bennington, 2021). When weather did not permit the use of drones for investigation official accidents, the more traditional method was used during the introduction of the drone program.

Implication of Research

The research in this paper quantifies the duration of investigations compared to that of investigation for fatal accidents that did not use drones for evidence gathering. Data in this paper can be used to give broad expectation for municipalities in the United States that have similar attributed and characteristics as Austin, Texas when implementing drones for fatal accident investigations. Potentially most impactful, this paper will identify how much time is needed for police officer to establish a full investigation with a drone while working a fatality. The paper will also help municipalities understand the data storage requirements for this type of data collection technique.

CHAPTER IV

Results

Texas Government Code Chapter 552 mandates that all public records of drone usage be made available. Biannually, the state of Texas, requires the publishing of records of any drone usage by state governmental employees. State records were reviewed to identify cases in three categories that could be paired with accident that occur just prior to the introduction of the drones as standard data collection methodology: vehicle vs. vehicle, vehicle vs. object such as pole or tree, and vehicle vs. pedestrian. Ten cases were selected for each group. Nine were collected for the vehicle vs. pedestrian since that was all that was available from the study time period. One vehicle vs. pedestrian was withdrawn from the study because it was found that the data had not been collected due to a jurisdictional issue although the Austin PD was called to the scene.

Each case selected was paired with a case matching its description from before the use of drones in the year 2016-2018. The pair couples were matched based on characteristics such as type of fatal accident, vehicles involved, time, weather, and season. After each pairing was complete, the Austin PD supplied the CAD report times for the accident investigation and the size of the data file produced. All files were reviewed and released by the Open Records Department of the Austin City Government.

The purpose of the study was to describe and to assess the differences, if any, of the initial and exiting times during fatal vehicle investigations if drones were used instead of tradition methods for evidence collection by the Austin PD. Other municipalities can review this document to better understand what challenges and additions a drone program for fatal accident investigation could mean for their local areas. The secondary purpose was to describe if the data requirements from accident scenes would change given the addition of the new technology for the Austin PD. The study collected two sets of data: times of investigations and data file sizes for each pairing of cases.

The population consisted of ten vehicle vs. vehicle pairs, ten vehicle vs. object such as pole or tree pairs, and eight vehicle vs. pedestrian pairs. Paired T-Testing was used to analyze the data of the initial and exiting times. Vehicle vs. vehicle pairs demonstrated that a 20 percent increase occurred in the average time of field investigations compared to their paired investigation counterparts from when drones were not available. The mean score for investigation with drones was 442.70 minutes with a standard deviation of 50.54 compared to 354.50 minutes for the investigations without drones that had a standard deviation of 127.12.

Vehicle vs. object pairs demonstrated that a 20 percent increase occurred in the average time of field investigations compared to their paired investigation counterparts from when drones were not available. The mean score for investigation with drones was

506.10 minutes with a standard deviation of 211.33 compared to 424.50 minutes for the investigations without drones that had a standard deviation of 261.28.

Vehicle vs. pedestrian pairs demonstrated that a 25 percent increase occurred in the average time of field investigations compared to their paired investigation counterparts from when drones were not available. The mean score for investigation with drones was 321.38 minutes with a standard deviation of 149.99 compared to 431.00 minutes for the investigations without drones that had a standard deviation of 178.72. A Wilcoxon Signed Ranks Test was performed to compare the mean score for investigations with drones compared to the mean score for investigation without drones because sampling was found to not be parametric in nature. Matched Pairs were found to not have statistically significant differences in time signatures from before the addition of drones ($n = 8$, $M = 321.38$, $SD = 149.99$) $z = -1.400$, $p = [0.161]$, $r = -0.495$, compared to after the adoption of the drones for fatal car accidents.

Data usage results revealed that an average of 3.43 gigabytes were used for investigations after the implementation of drones for fatal car accidents of all three types compared to an average usage of 0.096 gigabytes before the implementation of drones for investigation. Data usage for investigation with drones in vehicle vs. vehicle fatal accidents was 5.263 gigabytes with a standard deviation of 8.899 compared to 0.003 gigabytes for the investigations without drones that had a standard deviation of 0.008. The mean data usage for investigation with drones in vehicle vs. object fatal accidents was 2.641 gigabytes with a standard deviation of 1.536 compared to 0.268 gigabytes for the investigations without drones that had a standard deviation of 0.847. The mean data usage for investigation with drones in vehicle vs. pedestrian fatal accident was 2.137

gigabytes with a standard deviation of 1.396 compared to 0.0 gigabytes for the investigations without drones that had a standard deviation of 0.0.

The follow section describes the analysis conducted and displays the empirical results of the data collected from January 2016- December 2020.

Data Screening

Figure 8

Code Information for Type of Accidents

The following information is the code for each type of traffic fatal accident and the year period that it comes from.

1a	Vehicle vs. Vehicle without Drone data 2016 - 2018
1b	Vehicle vs. Vehicle with Drone Images from 2019 - 2020
2a	Vehicle vs. Object without Drone data 2016 - 2018
2b	Vehicle vs. Object with Drone Images from 2019 - 2020
3a	Vehicle vs. Pedestrian without Drone data 2016 - 2018
3b	Vehicle vs. Pedestrian with Drone Images from 2019 - 2020

Table 2

Time Pairs in Investigation According to Type of Fatal Accident in Minutes

The following is the listed times in minutes for each member of the pairs pre and post the addition of drones.

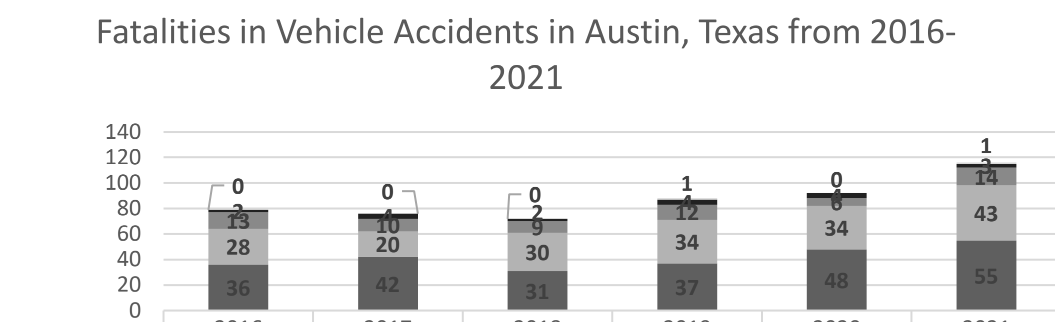
Variable Pairs	1a	1b	2a	2b	3a	3b
Pair 1	505	532	1033	892	377	355
Pair 2	338	395	210	519	275	332
Pair 3	432	493	200	603	209	379
Pair 4	272	371	610	504	295	492
Pair 5	297	473	259	419	667	527
Pair 6	262	444	456	323	299	154
Pair 7	382	426	269	246	0*	395 *
Pair 8	477	471	291	322	215	771
Pair 9	98	388	601	812	234	438
Pair 10	482	434	316	421		

*Pairing number 7 in category 3 was removed from the group due to data being withdrawn at site because of jurisdiction.

In Figure 9, *Fatalities from Vehicle Accidents in Austin, Texas from 2016-2021,* Austin, Texas fatalities divided by type of accident. Information was obtained from a data base and website operated by the City of Austin. All information presented in this figure can be found at www.data.austintexas.gov. For this study, motorcycle and bicycle accidents were removed from the groups studied. Study cases were pulled from the Pedestrian and Motorist groups after reviewing details and finding matches for each case used from before the introduction of drones for data collection. Not all cases from 2018 – 2020 used drones for data collection. (The Collection, 2022)

Figure 9

Fatalities from Vehicle Accidents in Austin, Texas from 2016-2021



	2016	2017	2018	2019	2020	2021
Other	0	0	0	1	0	1
Bicyclist	2	4	2	4	4	3
Motorcyclist	13	10	9	12	6	14
Pedestrian	28	20	30	34	34	43
Motorist	36	42	31	37	48	55

Figure 10, *Fatal Accident Pairings for Vehicle vs. Vehicle,* pairs were matched using a set of conditions. The first condition was that the accidents must include a fatality at the scene as a result of the accident. Second, the type of accident must match for this set the accident must be a Vehicle vs. Vehicle collision. Next, the types of vehicles were matched. A car vs. car was matched with another accident that had Car vs. Car. C-T represented a car vs. truck. Only on pair mixed a car vs. truck with a car vs. car. The truck in the Car vs. truck was found to have similar mass to that of a car so it was used as a pairing. Only passenger trucks were used for this study. No tractor trailer fatalities were included. Lastly, Pairs had to match on one of the following conditions time within a three-hour window, weather (precipitation), or season.

Figure 10

Fatal Accident Pairings for Vehicle vs. Vehicle

	Fatality	Type of Accident	Type of Vehicle	Time	Weather	Season
Pair 1	X	V vs. V	C-C	X		X
Pair 2	X	V vs. V	C-C	*	X	
Pair 3	X	V vs. V	C-C	X		X
Pair 4	X	V vs. V	C-T	X		
Pair 5	X	V vs. V	C-C	X		
Pair 6	X	V vs. V	C-C	X	X	
Pair 7	X	V vs. V	C-T	X	X	X
Pair 8	X	V vs. V	C-C	X		
Pair 9	X	V vs. V	C-T and C-C	X	X	
Pair 10	X	V vs. V	C-T	X	X	

*Both cases came from the morning time period although they were outside the three-hour window.

Notes: V-V stands for Vehicle vs. Vehicle. C-C is a car interacting another car. C-T is a car interacting with a truck. All trucks are not tractor-trailers in this study.

Time was based on a three-hour window around the occurrence of the drone fatal investigation to be matched with the investigation that did not have a drone. Weather matches were based on perception amounts. Season was in the three-month period around the occurrence of the drone fatal investigation to be matched with the investigation that did not have a drone.

Pairs were matched using a set of conditions in Figure 11, *Fatal Accident Pairings for Vehicle vs. Object*. The first condition was that the accidents must include a fatality at the scene as a result of the accident. Second, the type of accident must match for this set the accident must be a Vehicle vs. Object collision. Next, the type of objects must be a match. “P” stands for a vehicle hitting a pole. “T” stands for a vehicle hitting a tree. Only passenger trucks were used for this study. No tractor trailer fatalities were included. Lastly, Pairs had to match on one of the following conditions time within a three-hour window, weather (precipitation), or season.

Figure 11

Fatal Accident Pairings for Vehicle vs. Object

	Fatality	Type of Accident	Type of Vehicle	Time	Weather	Season
Pair 1	X	V vs. Object	P-P	X		X
Pair 2	X	V vs. Object	P-P	X	X	X
Pair 3	X	V vs. Object	T-T	X	X	
Pair 4	X	V vs. Object	P-P	X	X	
Pair 5	X	V vs. Object	T-T			X
Pair 6	X	V vs. Object	P-P	X		
Pair 7	X	V vs. Object	P-P		X	
Pair 8	X	V vs. Object	P-P			X
Pair 9	X	V vs. Object	T-T	X		
Pair 10	X	V vs. Object	P-P	X		X

Notes: V vs. Object stand for a vehicle interacted with an object to cause a fatality. P-P stands for both cases hit a pole. T-T both cases hit a tree. All trucks are not tractor-trailers in this study.

Time was based on a three-hour window around the occurrence of the drone fatal investigation to be matched with the investigation that did not have a drone. Weather matches were based on precipitation amounts. Season was in the three-month period around the occurrence of the drone fatal investigation to be matched with the investigation that did not have a drone.

Pairs were matched using a set of conditions in Figure 12, *Fatal Accident Pairings for Vehicle vs. Pedestrian*. The first condition was that the accidents must include a fatality at the scene as a result of the accident. Second, the type of accident must match for this set the accident must be a Vehicle vs. Pedestrian collision. Next, the type of vehicle hitting the pedestrian must be a match. “C” stands for a car. “T” stands for a truck. “H + R” stands for a hit and run. Only passenger trucks were used for this study.

No tractor trailer fatalities were included. Lastly, pairs had to match on one of the following conditions time within a three-hour window, weather (precipitation), or season.

Figure 12

Fatal Accident Pairings for Vehicle vs. Pedestrian

	Fatality	Type of Accident	Type of Vehicle	Time	Weather	Season
Pair 1	X	V vs. Ped.	C-P	X		X
Pair 2	X	V vs. Ped.	T-P	*	X	
Pair 3	X	V vs. Ped.	C-P	X	X	X
Pair 4	X	V vs. Ped.	C-P	X	X	X
Pair 5	X	V vs. Ped.	H+R	X	X	X
Pair 6	X	V vs. Ped.	C-P	X	X	X
Pair 7	Drone unit was called back for jurisdictional reasons - time was not usable.					
Pair 8	X	V vs. Ped.	C-P	X	X	
Pair 9	X	V vs. Ped.	C-P	X	X	

Notes: V vs. Ped. stands for a vehicle interacting with a pedestrian to cause a fatality. C-P stands for car hitting a pedestrian. T-P stands for a truck hitting a pedestrian. All trucks are not tractor-trailers in this study. H+R are "hit and runs" with a vehicle of approximately the same mass.

Time was based on a three-hour window around the occurrence of the drone fatal investigation to be matched with the investigation that did not have a drone. Weather matches were based on perception amounts. Season was in the three-month period around the occurrence of the drone fatal investigation to be matched with the investigation that did not have a drone.

*Both cases came from the morning time period although they were outside the three-hour window.

*Pairing number 7 in category 3 was removed from the group due to data being withdrawn at site because of jurisdiction.

Reliability

Table 3

Configurations of Mean and Distribution of Variable Pairs

Mean and median were calculated for each group of items. The standard deviation, skewness, and kurtosis were found for each group. Means were used in paired t-testing.

Variable of Pairs	1a	1b	2a	2b	3a	3b
Mean	354.50	442.70	424.5	506.10	321.38	431.00
Median	360.00	439.00	303.5	462.50	285.00	408.50
Standard Deviation	127.12	50.54	261.28	211.33	149.99	178.72
Skewness	-0.718	0.262	1.589	0.82	2.147	0.588
Kurtosis	0.258	-0.588	2.484	-0.183	5.012	1.648

Regression Line Data

Table 4

Linear Regression of Paired Data Groups

Regression line were used to demonstrate the reliability of the samples for the study from each group. R squared, intercept, and X variables were calculated for each line.

Variable of Pairs	1a	1b	2a	2a2*	2b	3a	3b	3b2*
R squared	0.929	0.975	0.782	0.869	0.917	0.884	0.677	0.916
Intercept	131.933	352.067	4.733	85.722	138.533	22.214	94.714	167.286
X Variable	40.467	6.479	76.321	54.233	66.830	68.619	50.369	26.179

*A statistical outliner was taking out of 2a2 and 3b2 and ran again using SPSS.

Figure 13

Regression Line for Vehicle vs. Vehicle Pre-Drone Usage

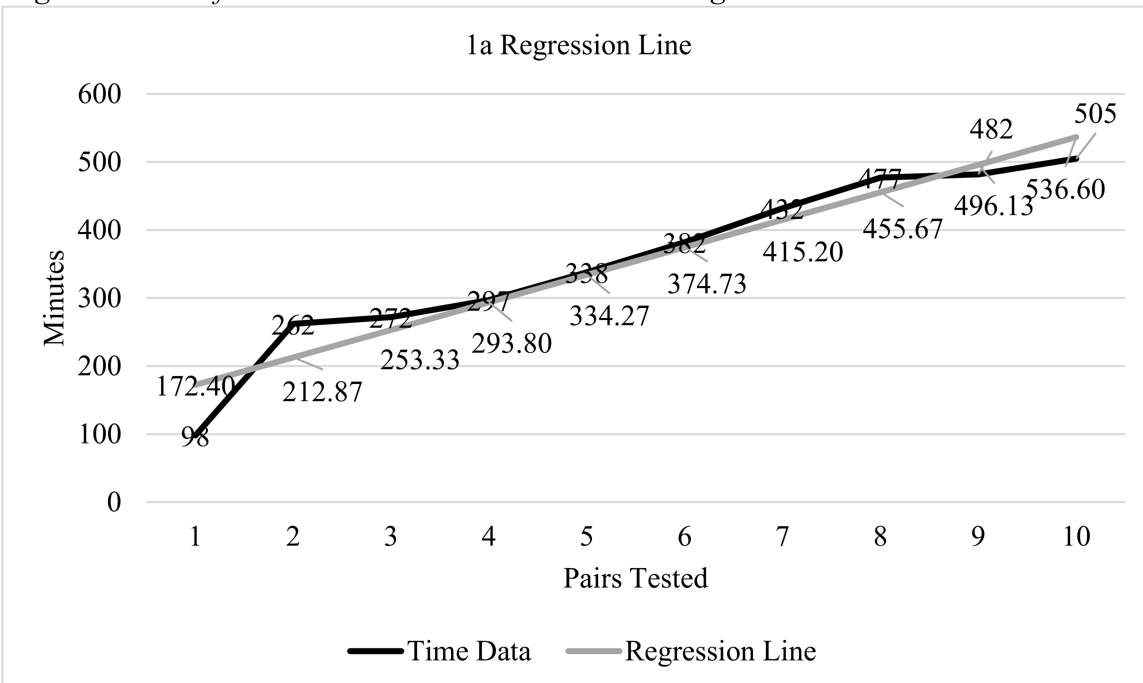


Figure 14

Regression Line for Vehicle vs. Vehicle Post-Drone Usage

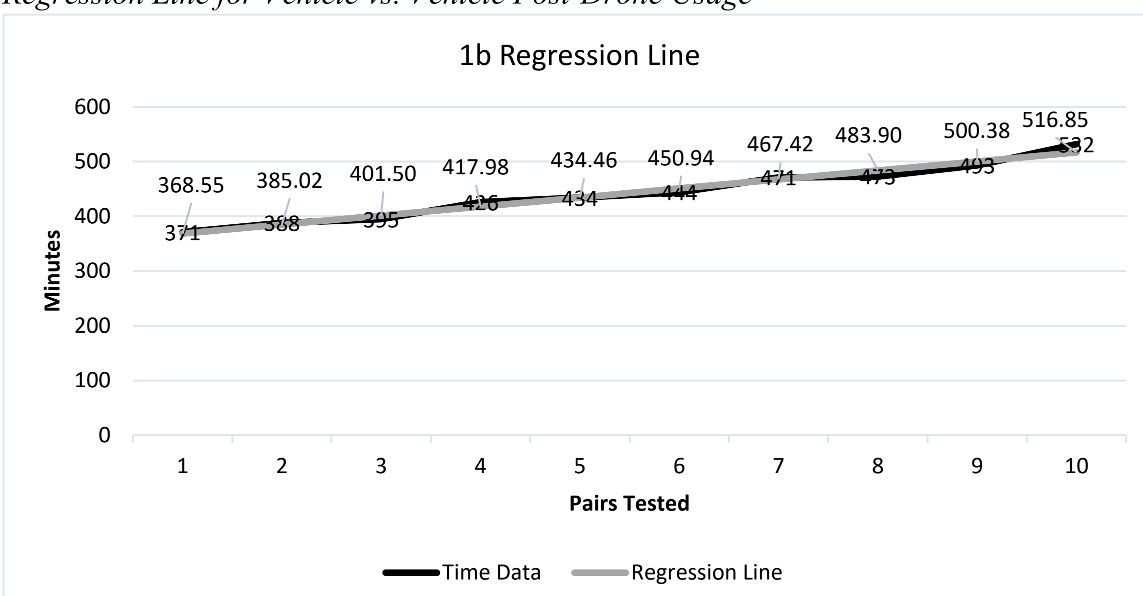


Figure 15

Regression Line for Vehicle vs. Objects Pre-Drone Usage

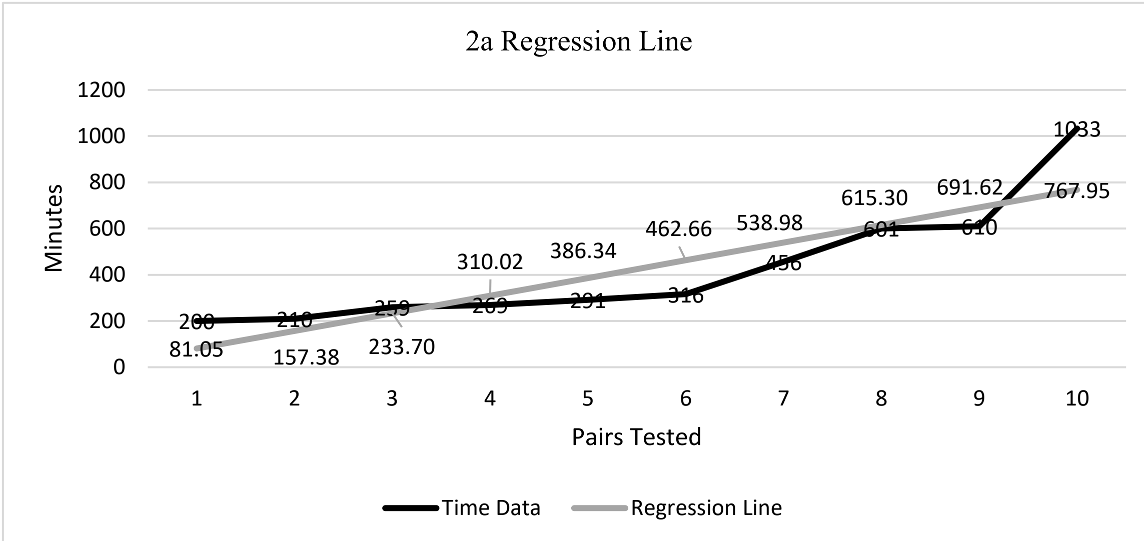


Figure 16

Regression Line for Vehicle vs. Objects Post-Drone Usage

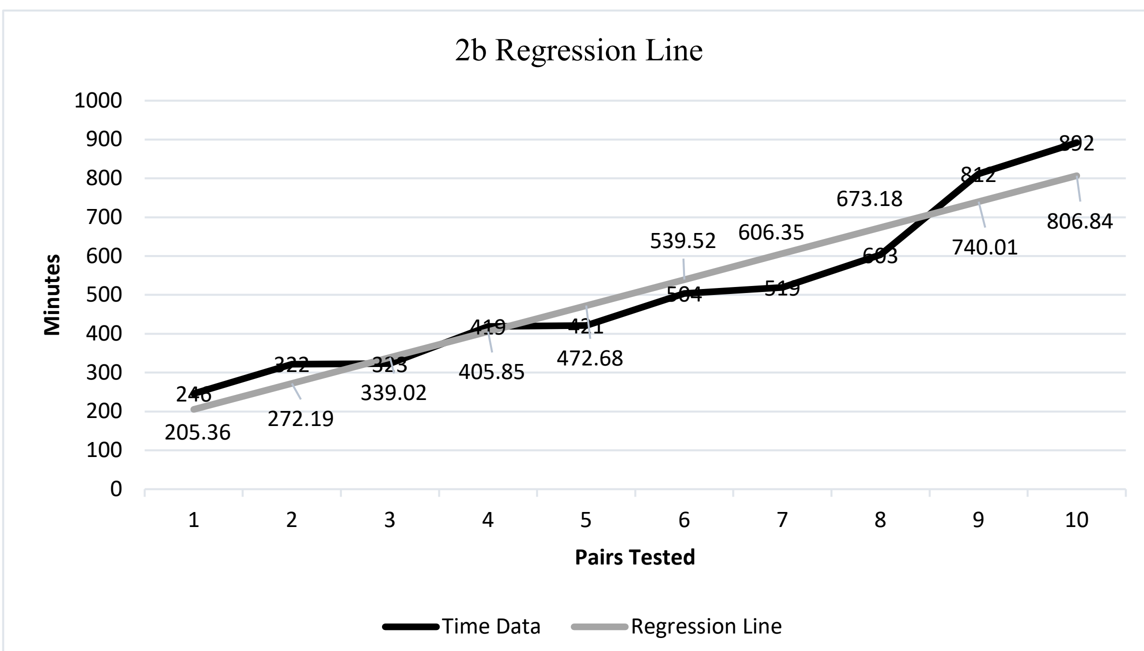


Figure 17

Regression Line for Vehicle vs. Pedestrian Pre-Drone Usage

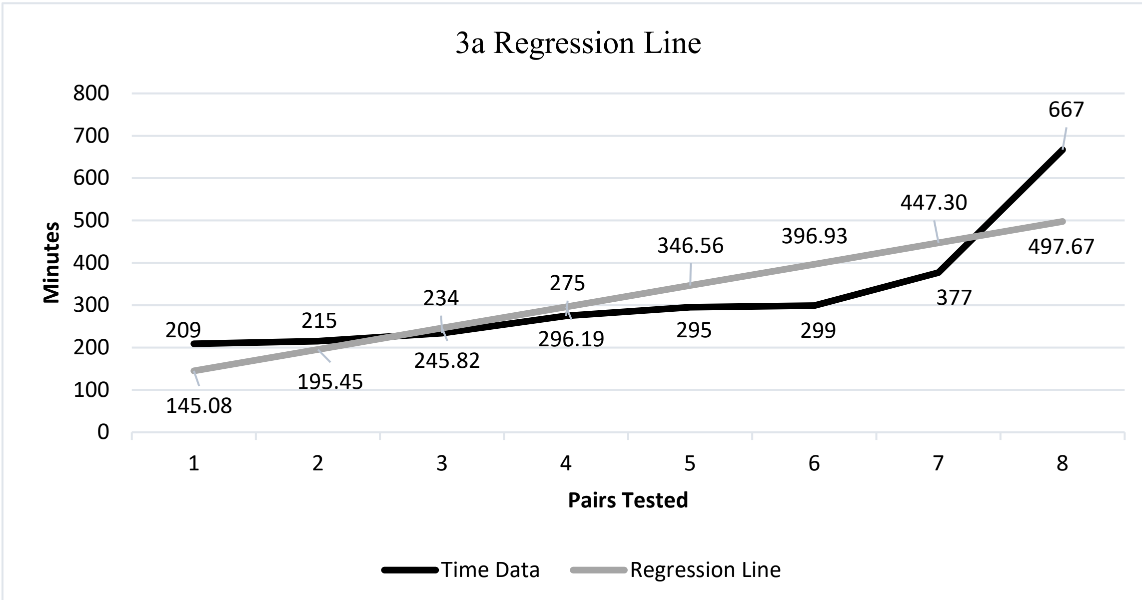
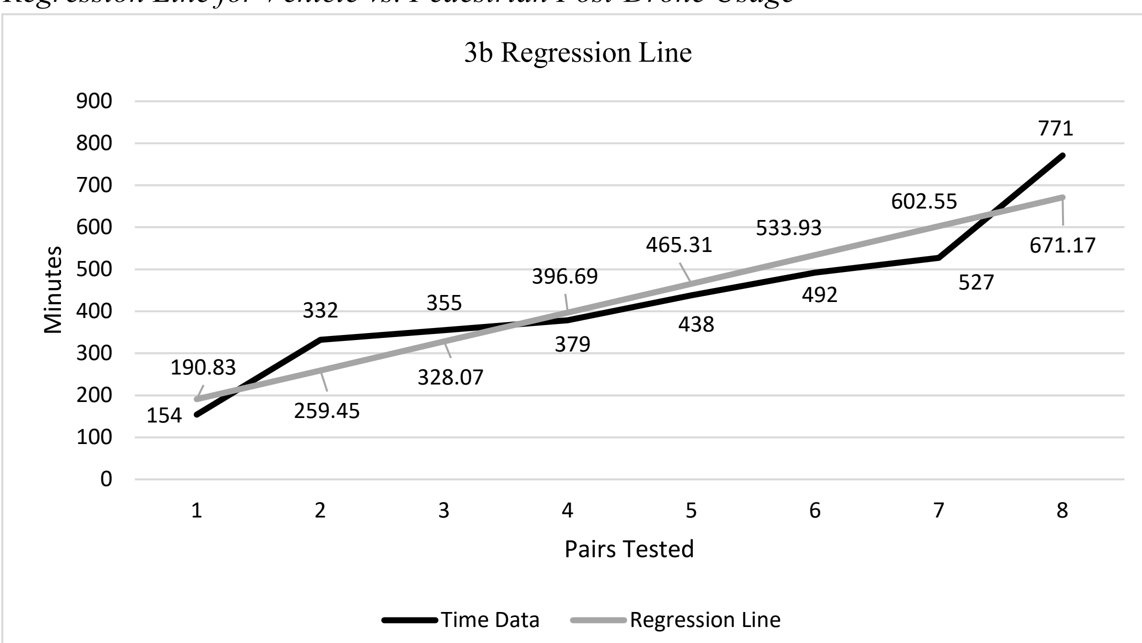


Figure 18

Regression Line for Vehicle vs. Pedestrian Post-Drone Usage



Time Comparisons

Figure 19

Time Comparison of Accident Duration in Vehicle vs. Vehicle

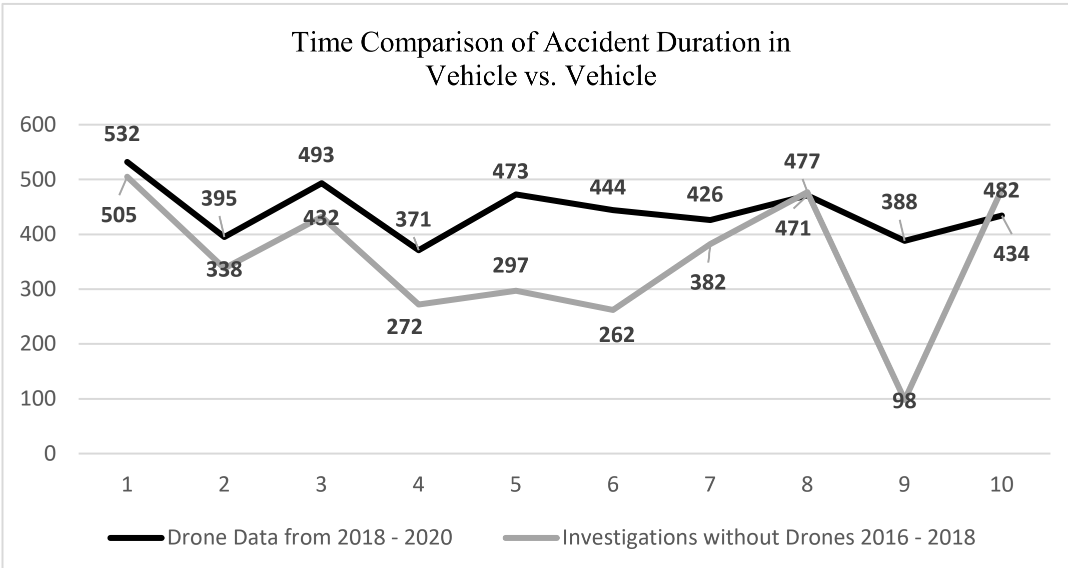


Figure 20

Time Comparison of Accident Duration in Vehicle vs. Object

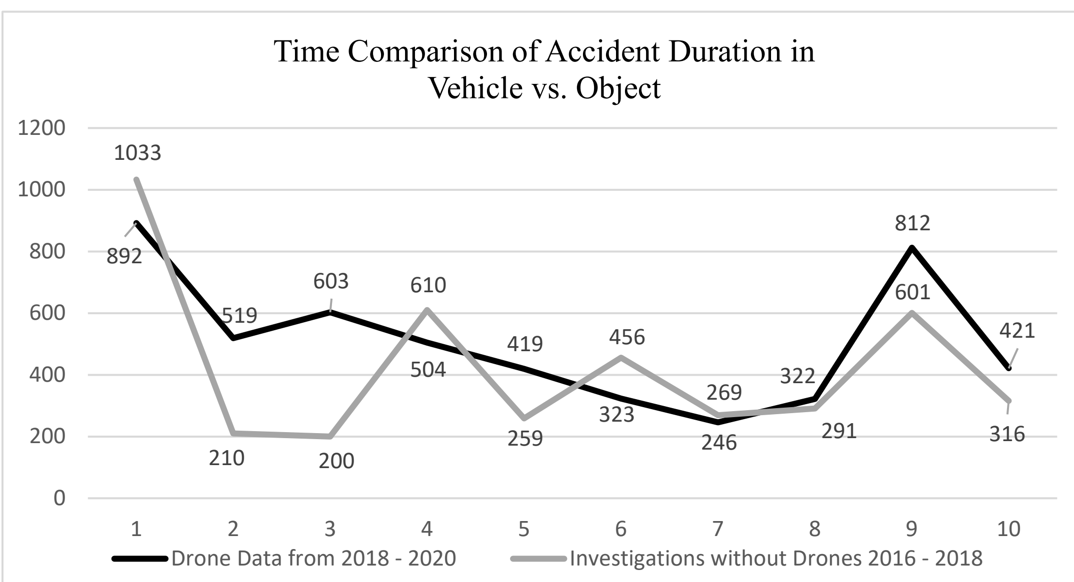
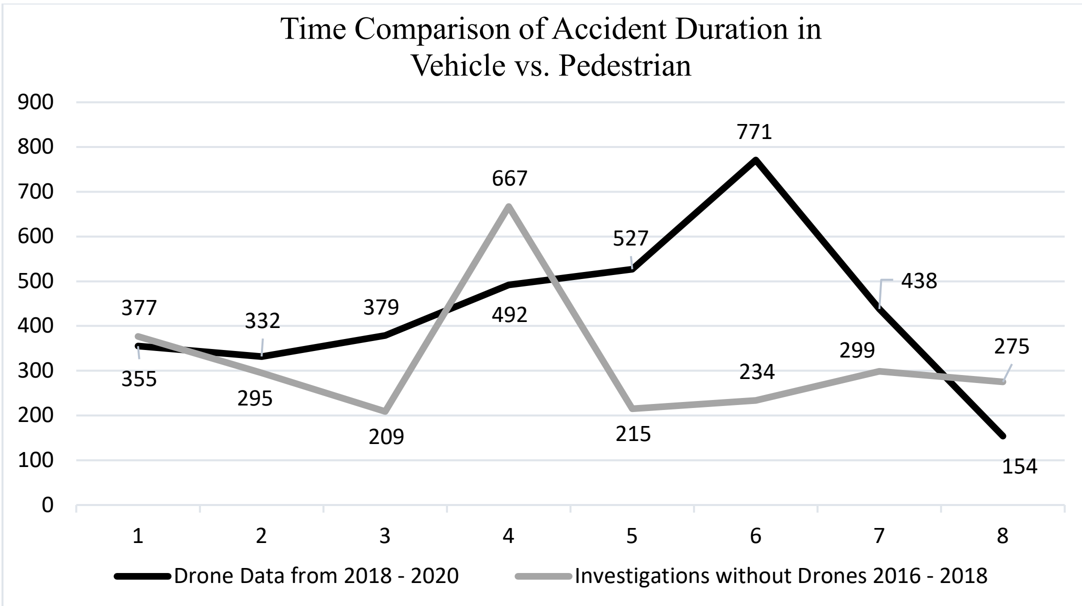


Figure 21

Time Comparison of Accident Duration in Vehicle vs. Pedestrian



Kolmogorov-Smirnov Test Assessment of Normality

Table 5

Kolmogorov-Smirnov Test for Normality

Variables of Pairs	1a	1b	2a	2b	3a	3b
Kolmogorov-Smirnov Test	0.200	0.200	0.052	0.200	0.200	0.023
Degrees of Freedom	10	10	10	10	8	8

Paired T-Test

The pair 1a – 1b were found to have a normal distribution in both units so the pair were annualized using a Paired T-Test Ranks Test to determine statistical significance.

1a compared to 1b with a paired T-Test.

Table 6

1a compared to 1b with a paired T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	onea	354.5000	10	127.10822	40.19515
	oneb	442.7000	10	50.53942	15.98197

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	onea & oneb	10	.939	.000

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	onea - oneb	-88.20000	81.53363	25.78320	-146.52565	-29.87435	-3.421	9	.008

Paired Samples Effect Sizes

					95% Confidence Interval	
			Standardizer[a]	Point Estimate	Lower	Upper
Pair 1	onea - oneb	Cohen's d	81.53363	-1.082	-1.855	-.272
		Hedges' correction	85.13960	-1.036	-1.777	-.261

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

The pair 2a – 2b were found to have a normal distribution in both units so the pair were annualized using a Paired T-Test Ranks Test to determine statistical significance.

Table 7

2a compared to 2b with a paired T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 2	twoa	424.5000	10	261.27944	82.62381
	twob	506.1000	10	211.33252	66.82921

Paired Samples Correlations

		N	Correlation	Sig.
Pair 2	twoa & twob	10	.930	.000

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 2	twoa - twob	-81.60000	100.86977	31.89782	-153.75789	-9.44211	-2.558	9	.031

Paired Samples Effect Sizes

				95% Confidence Interval	
		Standardize[a]	Point Estimate	Lower	Upper

Pair 2	twoa - twob	Cohen's d	100.86977	-.809	-1.514	-.072
		Hedges' correction	105.33091	-.775	-1.449	-.069

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Wilcoxon Signed Ranks Test

The pair 3a – 3b were found to have a non-parametric unit in the pair so a Wilcoxon Signed Ranks Test was used to determine statistical significance.

Table 8

3a compared to 3b with a Wilcoxon Signed Ranks Test

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
threea	8	321.3750	149.98851	209.00	667.00
threeb	8	431.0000	178.72405	154.00	771.00

Ranks

		N	Mean Rank	Sum of Ranks
threeb - threea	Negative Ranks	3[a]	2.67	8.00
	Positive Ranks	5[b]	5.60	28.00
	Ties	0[c]		
	Total	8		

a. threeb < threea
b. threeb > threea
c. threeb = threea

Test Statistics[a]

	threeb - threea
Z	-1.400[b]
Asymp. Sig. (2-tailed)	.161

a. Wilcoxon Signed Ranks Test
b. Based on negative ranks.

Data Usage

Data usage by each case is listed in gigabytes in Figure 22, *Data Collection in Gigabytes*. Often before the use of drones, no data was included in the files and did not require addition space. Mean and median were calculated for each group of items. The standard deviation, skewness, and kurtosis were found for each group.

Figure 22

Data Collection in Gigabytes

Data Collection in Gigabytes

	1a	1b	2a	2b	3a	3b
Pair 1	0	2.04	2.68	2.42	0	0.687
Pair 2	0.000004	2.56	0	1.41	0	2.66
Pair 3	0	0.767	0	2.6	0	0
Pair 4	0	2.01	0	3.0	0	4.42
Pair 5	0.001	1.02	0	0.966	0	1.41
Pair 6	0	12.3	0	1.56	0	2.3
Pair 7	0	28.6	0	3.83	0	2.72
Pair 8	0.0000152	1.53	0	6.33	0	2.9
Pair 9	0	1	0	1.99		
Pair 10	0.026	0.8	0	2.3		
Mean	**0.003**	**5.263**	**0.268**	**2.641**	**0.000**	**2.137**
Median	**0.000**	**1.770**	**0.000**	**2.360**	**0.000**	**2.480**
Standard Deviation	**0.008**	**8.899**	**0.847**	**1.536**	**0.000**	**1.396**
Skewness	**3.154**	**2.481**	**3.162**	**1.679**	**NA**	**-0.036**
Kurtosis	**9.959**	**6.138**	**10.000**	**3.466**	**NA**	**-0.086**

*Pairing number 7 in category 3 was removed from the group due to data being withdrawn at site because of jurisdiction.

Figure 23

Vehicle vs. Vehicles Pairing for Data Storage Usage in Gigabytes

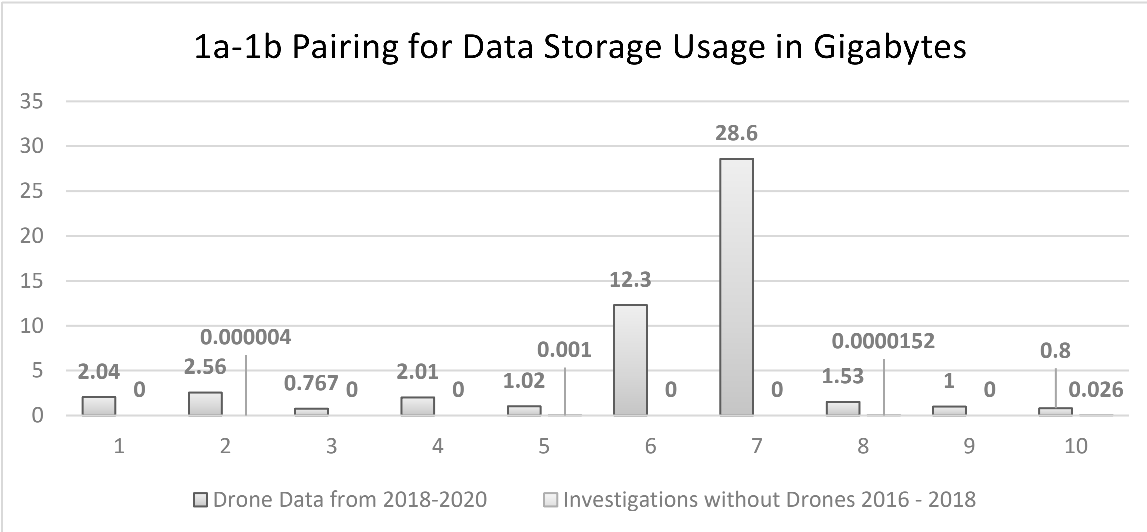


Figure 24

Vehicle vs. Objects Pairing for Data Storage Usage in Gigabytes

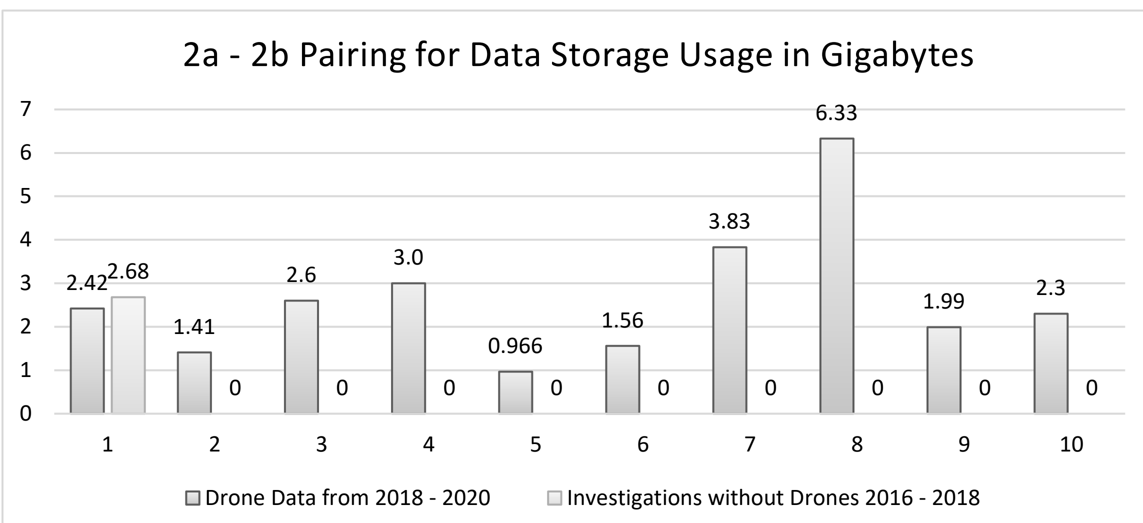


Figure 25

Vehicle vs. Pedestrian Pairing for Data Storage Usage in Gigabytes

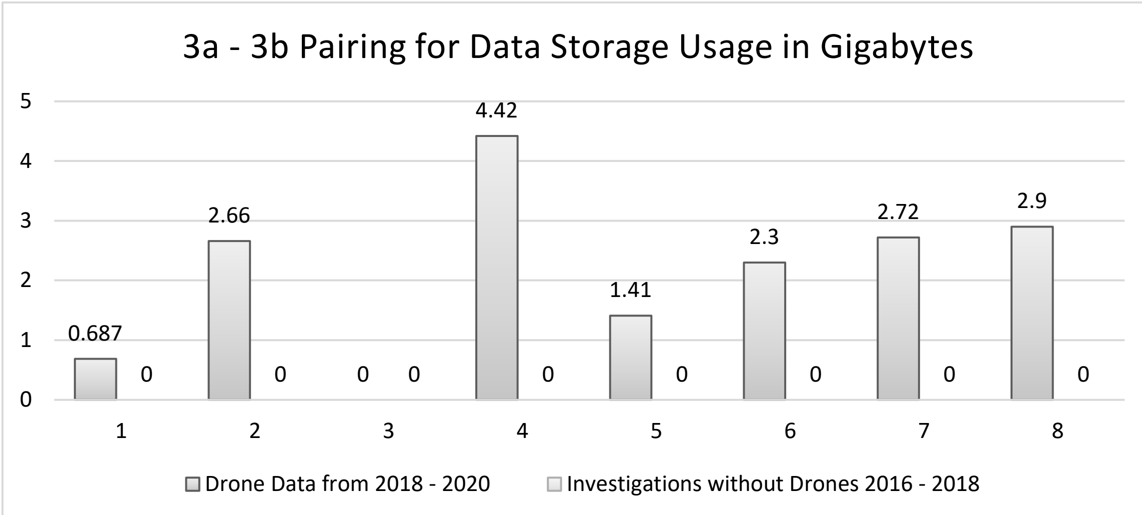


Figure 26

Gigabytes used by Fatal Accident Investigations Post-Drones were used (Ranked Smallest to Greatest)

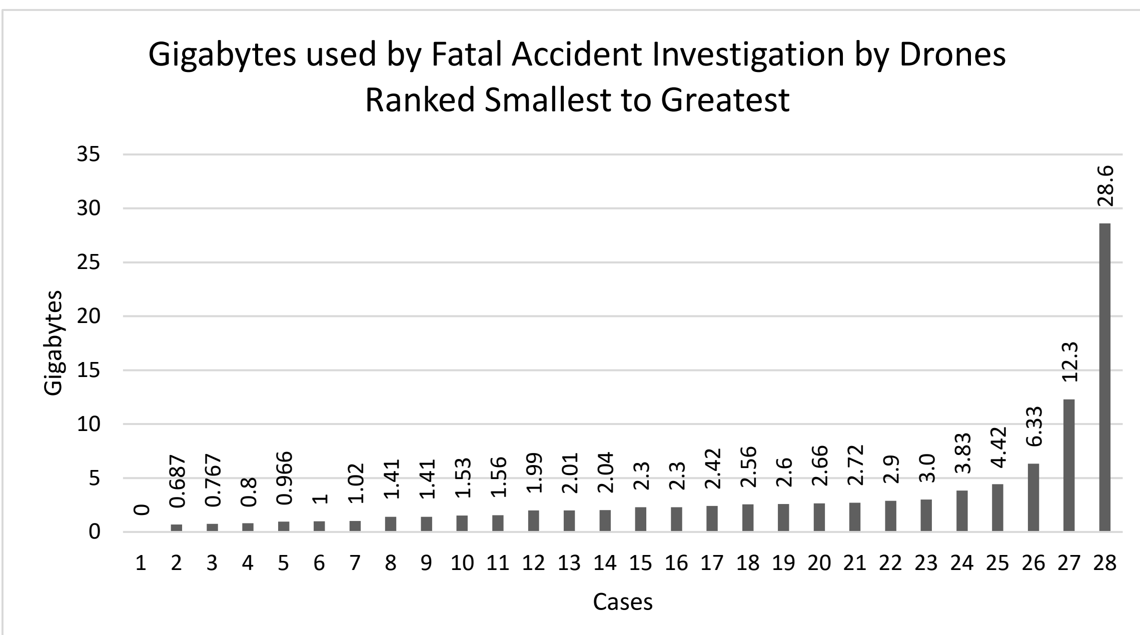
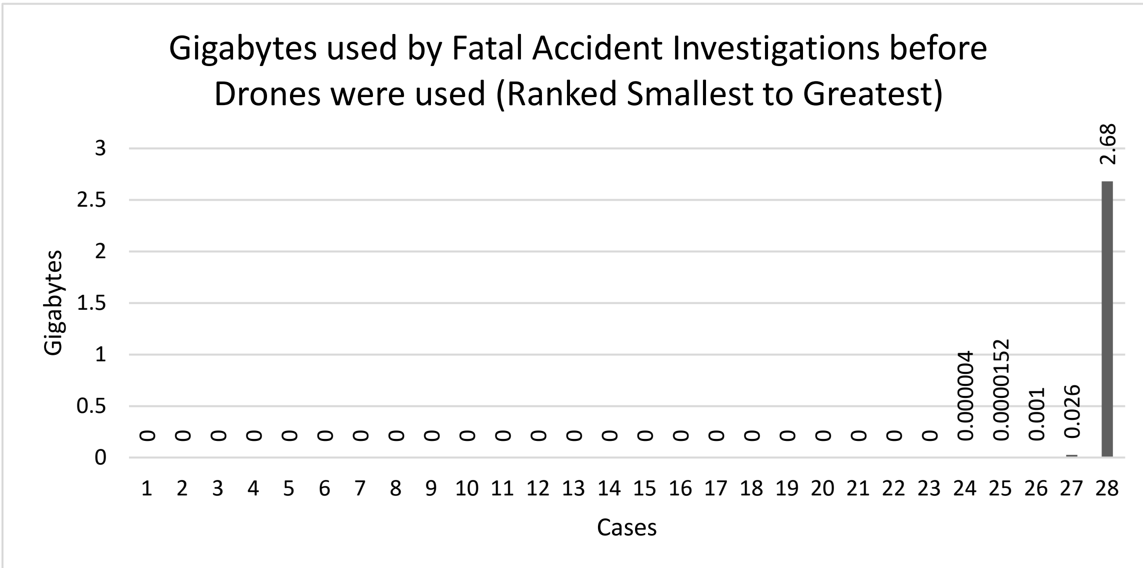


Figure 27

Gigabytes used by Fatal Accident Investigations Pre-Drones were used (Ranked Smallest to Greatest



Ethical Concerns

All initial data files with the raw times from the CAD reports were reviewed for release by the City of Austin Texas Open Record Department in conjunction with the Austin Police Department in Austin, Texas. All efforts were made to address any ethical considerations or sources of bias in the study model. Reviewers from the Office of Open Records compiled all data before release from CAD reports in police electronic files. All images were reviewed of redactable content. No redactable content was found to be in any of the images from pre or post the transition to drone usage for data collection.

File sizes were also complied by the City of Austin Texas Open Record Department. File and images themselves were not released for review of content. Data was handled in a respectful and conscientious way for the families and friends of the fatalities involved in the accident's cases used for this studies' data review. Cases were studied by the number on the file not by the victim's names and personal information.

CHAPTER V

Discussion and Conclusions

Limited studies have been conducted to evaluate the impact of adapting drones into fatal accident investigations for evidence gathering. Most scientific research studies have tried to quantify the length of accidents and have been derived from the collection of already collected data compiled by municipalities within the United States. Quantification studies include those completed by Kamnik (2020), Tirtha (2020), and Ullah (2021).

The implementation of drone usage has been attempted to be modeled on closed tracks to study how police officers would interact with the drones' verses tradition methods used by Perez and Khan. The Police of the Czech Republic in cooperation with the Institute of Forensic Engineering in Brno performed comparisons of two methods including drones and a method without drones within traffic accident data acquisition to demonstrate time savings during the usage of the drone methodology. The single study looking at time signatures, in the Czech Republic, was attempted without the aid of pairing data or other statically useful method to eliminate bias. Time studies in the laboratory settings and simulated work environments do not seem to correlate with the preliminary work in the real world (Stáňa, 2017).

Vehicle vs. Vehicle

Research Question One: What is the difference, if any, between the time signature on CAD reports that used traditional methods of investigation from before the use of drones were available in fatal accident investigations when compared to the time sequences of investigations that have used drones to collect evidence in fatal car accidents from investigations involving vehicle vs. vehicle crashes? Hypothesis 1. There is no significant difference between the means of the initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones involving vehicle vs. vehicle crashes. Dependent Variable: Time of investigation. Independent Variables: Pair couples based on characteristics: type of fatal accident, vehicles involved, time, weather, and season.

A paired sample T-Test was used to test whether the means of the initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones (ten pre and ten post). In 20 reports the times of fatal accident investigations were compared. In looking at the relationship of the initial times and the times after drones were introduced, the means were tested to see if there was a significant difference. The mean, standard deviation, and analysis of variance were calculated to determine if there was any significance. The paired T-Test was utilized to compare the means initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones and a paired sample correlation was conducted to determine any statistical significance.

Findings: The study of time sequence results revealed that a 20 percent increase occurred in the average time investigation took in the field compared to their paired investigation counterparts from when drones were not available. The mean score for investigation with drones was 442.70 minutes with a standard deviation of 50.54 compared to 354.50 minutes for the investigations without drones that had a standard deviation of 127.12. There was a significant difference in initial and exiting time signatures of the investigation done with drones compared to that of investigation done without drones ($M = [442.70]$, $SD = [50.54]$) and [time signatures of the investigation group done without drones] ($M = [354.50]$, $SD = [127.12]$); $t(20) = -3.421$, $t(df) = [9]$, $p = [0.008]$.

A paired samples T-Test was performed to compare the mean score for investigation with drones compared to the mean score for investigation without drones. Matched Pairs were found to have significant differences in time signatures from before the addition of drones ($n = 10$, $M = 354.50$, $SD = 127.12$), compared to after the adoption of the drones for fatal car accidents. ($n = 10$, $M = 442.70$, $SD = 50.54$) $t(20) = -3.421$, $p = [0.008]$, $d = 9$. The indicators are that investigations without drones had significantly fewer numbers of minutes compared to investigation with drones in fatal vehicle vs. vehicle accidents. Police would experience longer investigation times and have a need to be at the accident scene for more of their shift. The police would also be in the route of traffic for a longer period of time which increases the risk of harm to the police officer.

Vehicle vs. Object

Research Question One: What is the difference, if any, between the time signature on CAD reports that used traditional methods of investigation from before the use of drones were available in fatal accident investigations when compared to the time sequences of investigations that have used drones to collect evidence in fatal car accidents from investigations involving vehicle vs. object crashes? Hypothesis 2. There is no significant difference between the means of the initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones involving vehicle vs. object crashes. Dependent Variable: Time of investigation. Independent Variables: Pair couples based on characteristics: type of fatal accident, vehicles involved, time, weather, and season.

A paired sample T-Test was used to test whether the means of the initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones (ten pre and ten post). In 20 reports the times of fatal accident investigations were compared. In looking at the relationship of the initial times and the times after drones were introduced, the means were tested to see if there was a significant difference. The mean, standard deviation, and analysis of variance were calculated to determine if there was any significance. The paired T-Test was utilized to compare the means initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones and a paired sample correlation was conducted to determine any significance. Police would experience longer investigation times and have a need to be at the accident scene for more of their shift. The police would also be in the route of traffic for a longer period of time which increases the risk of harm to the police officer.

Findings: The study of time sequence results revealed that a 20 percent increase occurred in the average time investigation took in the field compared to their paired investigation counterparts from when drones were not available. The mean score for investigation with drones was 506.10 minutes with a standard deviation of 211.33 compared to 424.50 minutes for the investigations without drones that had a standard deviation of 261.28. There was a significant difference in initial and exiting time signatures of the investigation done with drones compared to that of investigation done without drones ($M = [424.50]$, $SD = [261.28]$) and [time signatures of the investigation group done without drones] ($M = [506.10]$, $SD = [211.33]$); $t (20) = -2.558$, $t(df) = [9]$, $p = [0.031]$.

A paired samples T-Test was performed to compare the mean score for investigation with drones compared to the mean score for investigation without drones. Matched Pairs were found to have significant differences in time signatures from before the addition of drones ($n = 10$, $M = 506.10$, $SD = 211.33$), compared to after the adoption of the drones for fatal car accidents. ($n = 10$, $M = 424.50$, $SD = 261.28$) $t (20) = -2.558$, $p = [0.031]$, $d = 9$. The indicators are that investigations without drones had significantly fewer numbers of minutes compared to investigation with drones in fatal vehicle vs. vehicle accidents.

Vehicle vs. Pedestrian

Research Question One: What is the difference, if any, between the time signature on CAD reports that used traditional methods of investigation from before the use of drones were available in fatal accident investigations when compared to the time sequences of investigations that have used drones to collect evidence in fatal car accidents from investigations involving vehicle vs. pedestrian crashes? Hypothesis 3. There is no significant difference between the means of the initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones involving vehicle vs. pedestrian crashes. Dependent Variable: Time of investigation. Independent Variables: Pair couples based on characteristics: type of fatal accident, vehicles involved, time, weather, and season.

A paired sample T-Test was not able to be used because one of the pairs failed to prove to have a normal distribution because of an outlier. A Wilcoxon Signed Ranks Test was used in SPSS to determine if the means were significantly different for the initial and exiting time signatures of the investigation done with drones compared to that of investigations done without drones (eight pre and eight post). In 16 reports of the times of fatal accidents, investigations were compared. One pair was removed from the data set because the drone incident of the marked pair was found to be outside of the jurisdiction of the Austin Police Department so data was not collected. Originally, 18 cases were to be used for analysis. A tenth drone case was not available for the service area being studied during the time dates used for the study.

In looking at the relationship of the initial times and the times after drones were introduced, the means were tested to see if there was a significant difference. The mean, standard deviation, and analysis of variance were calculated to determine if there was any significance. The Wilcoxon Signed Ranks Test was utilized to compare the means initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones and a paired sample correlation was conducted to determine any significance.

Findings: The study of time sequence results revealed that a 25 percent increase occurred in the average time investigation took in the field compared to their paired investigation counterparts from when drones were not available. The mean score for investigation with drones was 431.00 minutes with a standard deviation of 211.33 compared to 321.38 minutes for the investigations without drones that had a standard deviation of 149.99. There was not a statistically significant difference in initial and exiting time signatures of the investigation done with drones compared to that of investigation done without drones according to the Wilcoxon Signed Ranks Test performed to compare the mean score (M = [431.00], SD = [211.33]) and [time signatures of the investigation group done without drones] (M = [321.38], SD = [149.99]); z = -1.400, p = [0.161], with a small effect size (r = -0.495).

A Wilcoxon Signed Ranks Test was performed to compare the mean score for investigations with drones compared to the mean score for investigation without drones because sampling was found to not be parametric in nature. Matched Pairs were found to not have statistically significant differences in time signatures from before the addition of drones (n = 8, M = 321.38, SD = 149.99), compared to after the adoption of the drones for fatal car accidents. (n = 8, M = 431.00, SD = 211.33) z = -1.400, p = [0.161], r = -0.495. The indicators are that investigations without drones did not have significantly different numbers of minutes compared to investigation with drones in fatal vehicle vs. pedestrian accidents.

Data Usage for Documentation

Research Question One: What is the difference, if any, between the data usage from reports that used traditional methods of investigation from before the use of drones were available in fatal accident investigations when compared to the data usage of investigations that have used drones to collect evidence in fatal car accidents from investigations involving three types of crashes? Hypothesis 4. There is no significant difference between the means of the initial and exiting time signatures of the investigation done with drone compared to that of investigation done without drones for all three major types of fatal accidents. Dependent Variable: Data usage of investigation files. Independent Variables: Pair couples based on characteristics: type of fatal accident, vehicles involved, time, weather, and season.

Findings: The study of data usage results revealed that an average of 3.43 gigabytes were used for investigations after the implementation of drones for fatal car accidents of all three types compared to an average usage of 0.096 gigabytes before the implementation of drones for investigation. Eighty nine percent of cases studies remained under 5 gigabytes for the data used in investigation while drones were being used. Only 3 individual cases went above 5 gigabytes for data usage from the drone investigation data group. Eighty two percent of cases had no data usage recorded before the use of drones were put in place.

The mean data usage for investigation with drones in vehicle vs. vehicle fatal accidents was 5.263 gigabytes with a standard deviation of 8.899 compared to 0.003 gigabytes for the investigations without drones that had a standard deviation of 0.008. The mean data usage for investigation with drones in vehicle vs. object fatal accidents was 2.641 gigabytes with a standard deviation of 1.536 compared to 0.268 gigabytes for the investigations without drones that had a standard deviation of 0.847. The mean data usage for investigation with drones in vehicle vs. pedestrian fatal accident was 2.137 gigabytes with a standard deviation of 1.396 compared to 0.0 gigabytes for the investigations without drones that had a standard deviation of 0.0

Conclusions

The following conclusions are based on the findings to answer the research questions did the introduction of drones by the Austin, Texas Police Department effect of time signatures of the investigations of fatal vehicle accidents in the city of Austin, Texas. Secondarily, did the addition of drones have implications on the implementation and use of data and information request in Austin, Texas.

The following research questions guided this study for analyzing fatal accident records in the city of City of Austin, Texas:

1. How did the addition of drones affect the investigations of fatal vehicle accidents in the city of Austin, Texas with their time signatures?
2. What are the possible outcomes for other metropolitan cities of the same size and composition as Austin, Texas, likely to experience with the implementation of drone usage with use of data and information request?

In both vehicle vs. vehicle and vehicle vs. object fatal accidents, the time on scene increased by approximately 20%. The increase in time is found to be in contradiction of previous studies in the literature. Vehicle vs. pedestrian fatalities were found to have a 25% increase in time of investigation although it was found to not be statically significant at this time possibly due to outliers and small sample size.

Although the times of both vehicle vs. vehicle and vehicle vs. object fatal accidents were found to have increased, the standard deviation for both decreased. The consolidation of the standard deviation could be a demonstration of the standardization of the method being used to investigate fatal accidents. The use of drones seems to have brought a more uniform time period for fatal accident investigations.

Data usage significantly increased with the usage of drones for data collection in all three types of fatal investigations. The study of data usage results revealed that an average of 3.43 gigabytes were used for investigations after the implementation of drones for fatal vehicle accidents of all three types compared to an average usage of 0.096 gigabytes before the implementation of drones for investigation. Eighty nine percent of data analyzed for this study remained under 5 gigabytes for the data used in investigation while drones were being used. Only 3 individual cases went above 5 gigabytes for data usage from the drone investigation data group. Eighty two percent of cases had no data usage recorded before the use of drones were put in place. At the average year total of 84 death per year, the department would use 288.12 gigabytes annually. With the introduction of more intensive data camera with 6k and 8k, the data requirements could become extensively more (Alsadik, 2022).

When the Austin, Texas, Office of Open Record was asked to review the images to identify any material that would need to be redacted before the images were released to the public and the what time was needed for redactions to be completed, the office concluded that no additional time for redactions was required at this time with the current technology. With further improvements in visual capablities, image redactions might become a significant issue as cameras on the drones move from 4K to 6k and 8K technology. More detail will become viewable as higher definition images are used in the accident investigation process.

Recommendations

Results of this study suggest that the placement of drones in the assistance of officers in fatal accident investigations increase the time duration of the investigation out in the field. Further study is recommended to understand why the discrepancy from previous studies published. Additional studies need to undertake into the methods used by the police departments. A standardization of methods might explain differences seen in the research. Methodology of the usage of the drone could be a key item in the time sequence demonstrated.

There is a great need for research and study in the use and evaluation of drones in fatal accident investigations. Data from a variety of jurisdiction throughout the United States would help to define best practices in the implementation of this new technology.

Additional recommendations include:

1. Review of methodology of drone usage and standardization throughout the United States and the State of Texas.
2. Have policy makers review accident needs from time signatures to better understand congestion patterns on the roadways they serve.
3. Further recording of accidents to see if time sequences change as experience is gained with uniformed officers out in the field.
4. Review of data compacity, for storage and in production devices out on the market and that can be obtained for use, to understand data needs.

5. Review of data needs and transfer requirements in relation to audience.

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APPENDICES

Oklahoma State University Institutional Review Board

Date:	03/30/2022
Application Number:	IRB-22-137
Proposal Title:	THE REAL-WORLD IMPACTS OF DRONE IMPLEMENTATION IN DATA COLLECTION OF FATAL ACCIDENTS
Principal Investigator:	Amanda Brown-Harvey
Co-Investigator(s):	
Faculty Adviser:	Mallory Casebolt
Project Coordinator:	
Research Assistant(s):	
Processed as:	Not Human Subjects Research

Status Recommended by Reviewer(s): Closed

Based on the information provided in this application, the OSU-Stillwater IRB has determined that your project does not qualify as human subject research as defined in 45 CFR 46.102 (d) and (f) and is not subject to oversight by the OSU IRB. Should you have any questions or concerns, please do not hesitate to contact the IRB office at 405-744-3377 or irb@okstate.edu.

Sincerely,
Oklahoma State University IRB

VITA

Amanda M. Brown

Candidate for the Degree of

Doctor of Education

Thesis: **THE REAL-WORLD IMPACTS OF DRONE IMPLEMENTATION IN DATA COLLECTION OF FATAL ACCIDENTS**

Major Field: Applied Educational Studies

Biographical:

Education:

Completed the requirements for the Doctor of Education in Applied Educational Studies at Oklahoma State University, Stillwater, Oklahoma in December, 2022.

Completed the requirements for the Master of Public Health in Industrial Hygiene at University of Alabama, Birmingham, Birmingham, Alabama in 2006.

Completed the requirements for the Bachelor of Science in Environmental Health Science and the Bachelor of Independent Studies in Aviation Human Factors with a minor in Chemistry at Eastern Kentucky University, Richmond, Kentucky in 2005.

Experience: Instructor - Southeastern Oklahoma University, Southeastern Louisiana University, Eastern Kentucky University, Western Kentucky University

Professional Memberships: ASSP, AIHA