Using Worker's Naturalistic Response to Determine and Analyze Work Zone Crashes in the Presence of Work Zone Intrusion Alert Systems

Diwas Thapa [a] and Sabyasachee Mishra [a*]

[a] Department of Civil Engineering, University of Memphis, Memphis, TN 38152, United States

Abstract

Work zone Intrusion Alert Systems (WZIAS) are alert mechanisms that detect and alert workers of vehicles intruding into a work zone. These systems pre-dominantly employ two components, i) sensors placed near the work zone perimeter that detect intrusions, and ii) alarms placed closed to or carried by the workers that them. This study investigates the association between layout of these components for three WZIAS on work zone crashes based on worker reaction. Also, the key determinants of work zone crashes in presence of the WZIAS is identified using survival analysis. The ideal deployment strategy and use case scenarios for the three WZIAS is presented based on the findings of the study. The systems were subjected to rigorous testing that emulated intrusions to record worker reaction and determine occurrence of crashes. Analysis of results indicate that the key determinants of work zone crashes are speed of the intruding vehicle, distance between the sensor and worker, and accuracy of a system in detecting intrusions and alerting workers. Results from field experiments suggest that identification of appropriate use cases for WZIAS is necessary to ensure they work effectively. Based on the findings from this study it is suggested that current guidelines on work zones be modified to standardize WZIAS setup.

Keywords: work zone; transportation; survival analysis; highway crashes; intrusion alert

[*] Corresponding author. Tel.: +1 (901) 678-5043.
E-mail addresses: dthapa@memphis.edu (D. Thapa), smishra3@memphis.edu (S. Mishra)

1. Introduction

A survey of highway construction firms has shown an increase in work zone crashes over the years with 67% of construction firms in the US experiencing at least one work zone crash in 2019 while only 39% of construction firms reported crashes in 2016 ("2019 Highway Work Zone Safety Survey," 2019). A growing statistic can also be seen in work zone injuries and fatalities. In 2010 there were about 37,400 injuries and 586 deaths reported in work zones. The numbers rose to 45,400 injuries and 754 fatalities in 2018 ("Work Zones-Injury Facts-National Safety Council," 2020). The rise in work zone related injuries and deaths can be attributed to an increase in Vehicle Miles Travelled (VMT) across the country. Rising VMT puts additional strain on existing highway infrastructure resulting in an increased demand for highway repair, maintenance, and construction/expansion projects. Increased interaction between workers and motorists on these projects increases the likelihood of work zone crashes unless effective countermeasures are taken. A potential countermeasure that could have notable impact on work zone crashes is the use of alert mechanisms called Work Zone Intrusion Alert Systems (WZIAS) that can detect intrusions and alerts workers. These systems pre-dominantly employ sensors placed near the work zone perimeter to detect intrusions and alarms placed closed to or carried by the workers.

The first prototypes for WZIAS were developed by Stout et al. (1993) under the Strategic Highway Research Program. The program introduced wireless and pneumatic sensor-based systems for use in maintenance work zones. Although the systems developed under the program were never adopted, systems that are currently available in the market are largely based on ideas developed during the project. Present day WZIAS can be broadly divided into two categories based on their detection mechanism. These are; i) advanced warning systems capable of detecting potential intrusions before they occur, and ii) systems capable of detecting intrusions after vehicle enters a predefined work zone perimeter (Eseonu et al., 2018; Marks et al., 2017). Advanced alert systems typically use radar to track speed and trajectory of an incoming vehicle and alert the driver and workers when an intrusion is likely to occur. On the other hand, systems that detect intrusions after a vehicle crosses a predefined work zone perimeter employ sensors that surround a work zone perimeter. These sensors typically detect intrusions based on mechanical impact and can be mounted on traffic channelizers or laid on the ground.

Since the first prototypes were developed in 1993, numerous systems have been developed and tested for potential use, but their adoption has been limited due to unreliable performance and difficult setup. Notably, studies that have found WZIAS to be effective, have based their conclusions on their performance drawn from alarm accuracy, noticeability and work zone coverage (Gambatese and Lee, 2016; Marks et al., 2017; Novosel, 2014). In doing so external factors that are beyond system performance and capabilities have been ignored. For example, speed of an intruding vehicle could have considerable impact on the occurrence and outcome of an intrusion. Furthermore, to avert crashes from high-speed intrusions, WZIA layout (separation between the system and workers) should be duly considered to guarantee the effectiveness of a system. These factors have not been accounted for by past studies. Take for example the studies undertaken by Gambatese and Lee (2016) and Marks et al. (2017), the authors in both studies comprehensively evaluate worker response to system alerts but provide no further analysis of the results or how it could be utilized for planning layouts for WZIAS. In other words, inclusion of system capabilities, intrusion characteristics, and WZIAS layout in investigating work zone crashes is missing in the literature. Identification of appropriate layouts for WZIAS is particularly important considering its impact on system efficacy, and the potential safety implications from its implementation. Currently, no formal guidelines or standards on WZIAS implementation exists, and we believe this is the first study investigating the potential impact of WZIAS layout on work zone crashes using experimental data.

The rest of the paper is organized as follows. In the following section we present an introduction of three systems used in field experiments followed by our review of the literature. In the methodology section, we discuss the experimental setup and the modeling approach used in the study. The data section presents a summary of the experimental data collected from our field experiments. The results from our tests and analyses are presented in the results section followed by the implications of the study and conclusion.

1.1. Overview of WZIAS

A typical work zone layout for a four-lane, two-way road with single lane closure is presented in Fig. 1. Approaching vehicles first arrive at the advance warning area where regulatory and warning signs warn travelers of the work zone downstream. Traffic channelizers are used to separate the work one from adjacent lanes with active traffic. Work zones are comprised of three distinct areas, the transition area, the activity area, and the termination area. The transition area is setup using traffic channelizers laid out at about a 45-degree angle. This area provides travelers with space to adjust their speed and begin merging with the traffic on the adjacent lane. The work area within the activity area is where the actual construction work is undertaken. Buffer spaces are provided on either sides of the work area to provide adequate space for workers and equipment. The termination area downstream of the activity area provides space for vehicles to shift to the adjacent lane after it has crossed the work zone. Traffic channelizers in this portion of the work zone is set at a steeper angle compared to the transition taper. The Manual of Uniform Traffic Control Devices (MUTCD) provides guidelines for the length ofadvanced warning, transition, and termination areas based on the operating speed on the highway. However the guidelines provide no specific recommendations on buffer spaces (Federal Highway Administration, 2009).

In the following section we provide an overview of the three systems used in this study. A schematic presenting the system components is provided in Table 1 with manufacturer recommended deployment strategy in Fig. 2.

1.1.1. Impact Activated System (IAS)

IAS is a wireless radio-based alarm system that comprises of i) cone mountable sensor lamps, and ii) site alarms. The typical deployment strategy for the system is to mount the sensor lamps on traffic cones around the work zone perimeter with the site alarm placed in the work area close to the workers When an errant vehicle intrudes the work zone perimeter, it knocks over down the traffic cones. The sensors mounted on these cones use built in accelerometers to detect the impact and relay alert signals to nearest site alarms. When the alarms are not in range of the sensors, the alerts are relayed

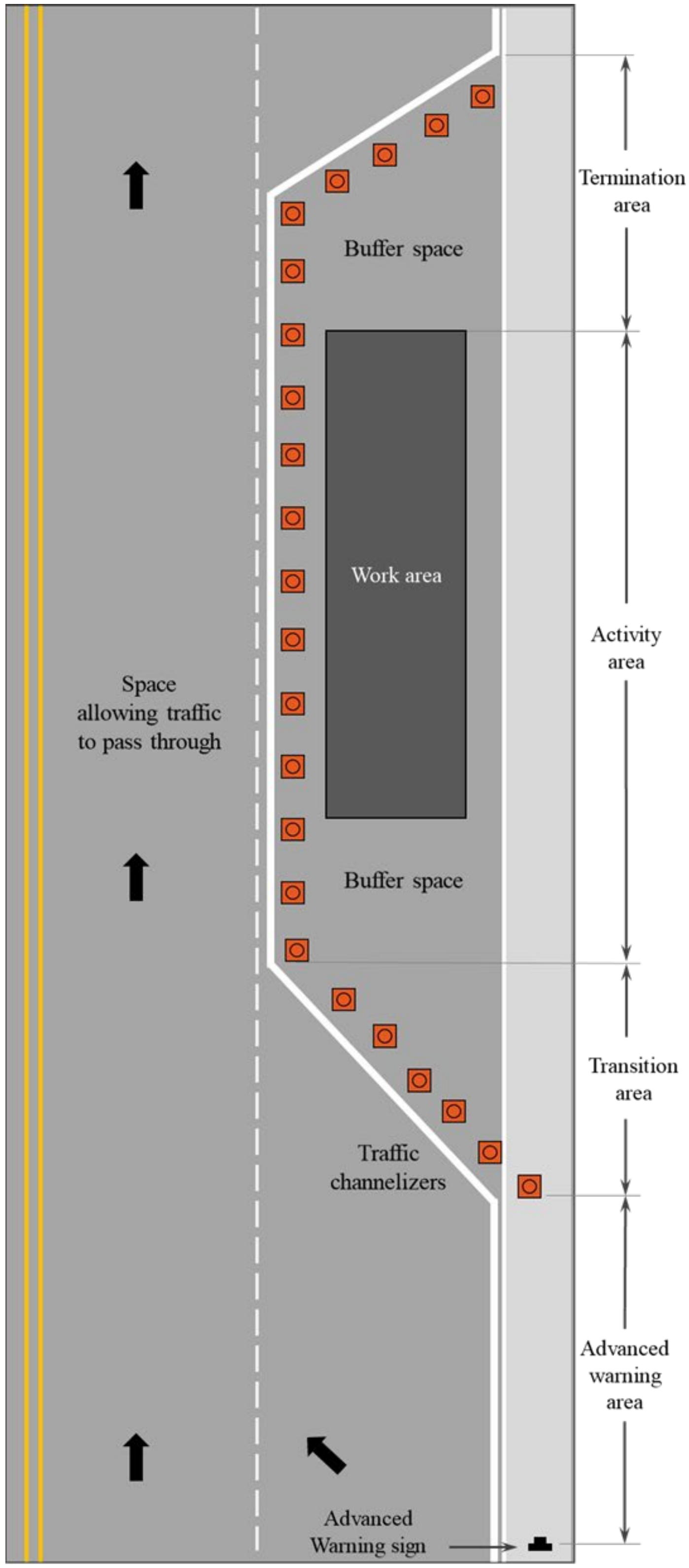
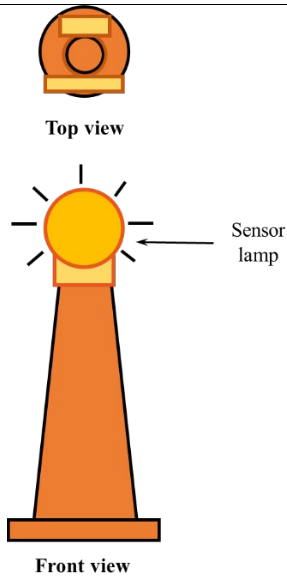
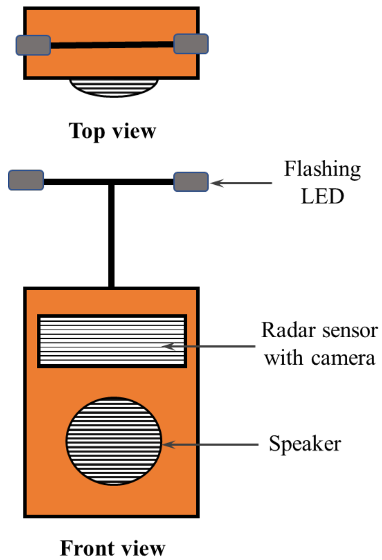
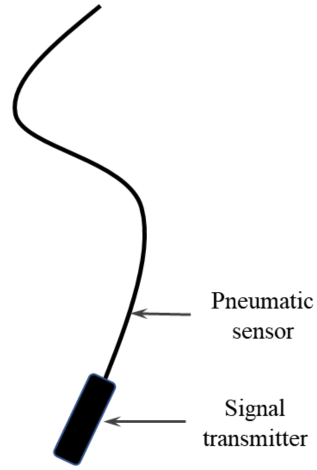


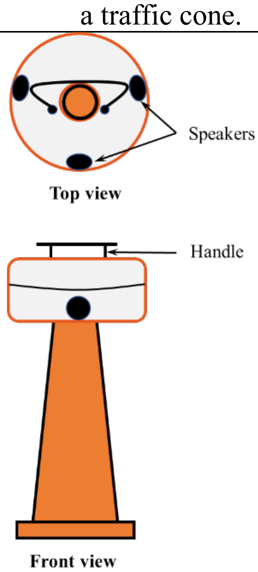
Fig. 1. Typical work zone layout for a single lane closure.

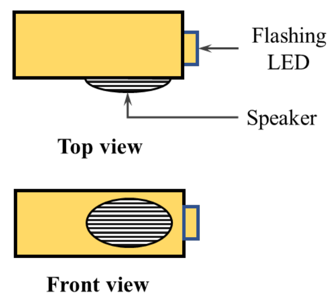
Table 1
Schematic representation of system components

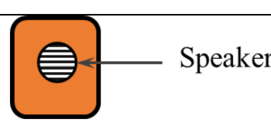
<table>
<tr><th rowspan="2">System components</th><th colspan="3">Systems</th></tr>
<tr><th>IAS</th><th>RAS</th><th>PAS</th></tr>
<tr><td>Sensor</td><td>

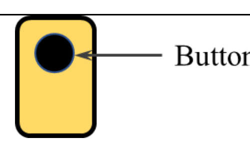
Sensor lamp mounted on a traffic cone.</td><td rowspan="2">

The main assembly that acts as a sensor cum site alarm.</td><td>

Pneumatic sensor with the signal transmitter.</td></tr>
<tr><td>Site alarm</td><td>

Site alarm mounted on a traffic cone.</td><td>

Site alarm with inbuilt alarm and warning LEDs.</td></tr>
<tr><td>Personal alarms</td><td></td><td>

Personal alarm equipped with a speaker</td><td>

Personal alarm equipped with a button for resetting the system after it is triggered</td></tr>
</table>

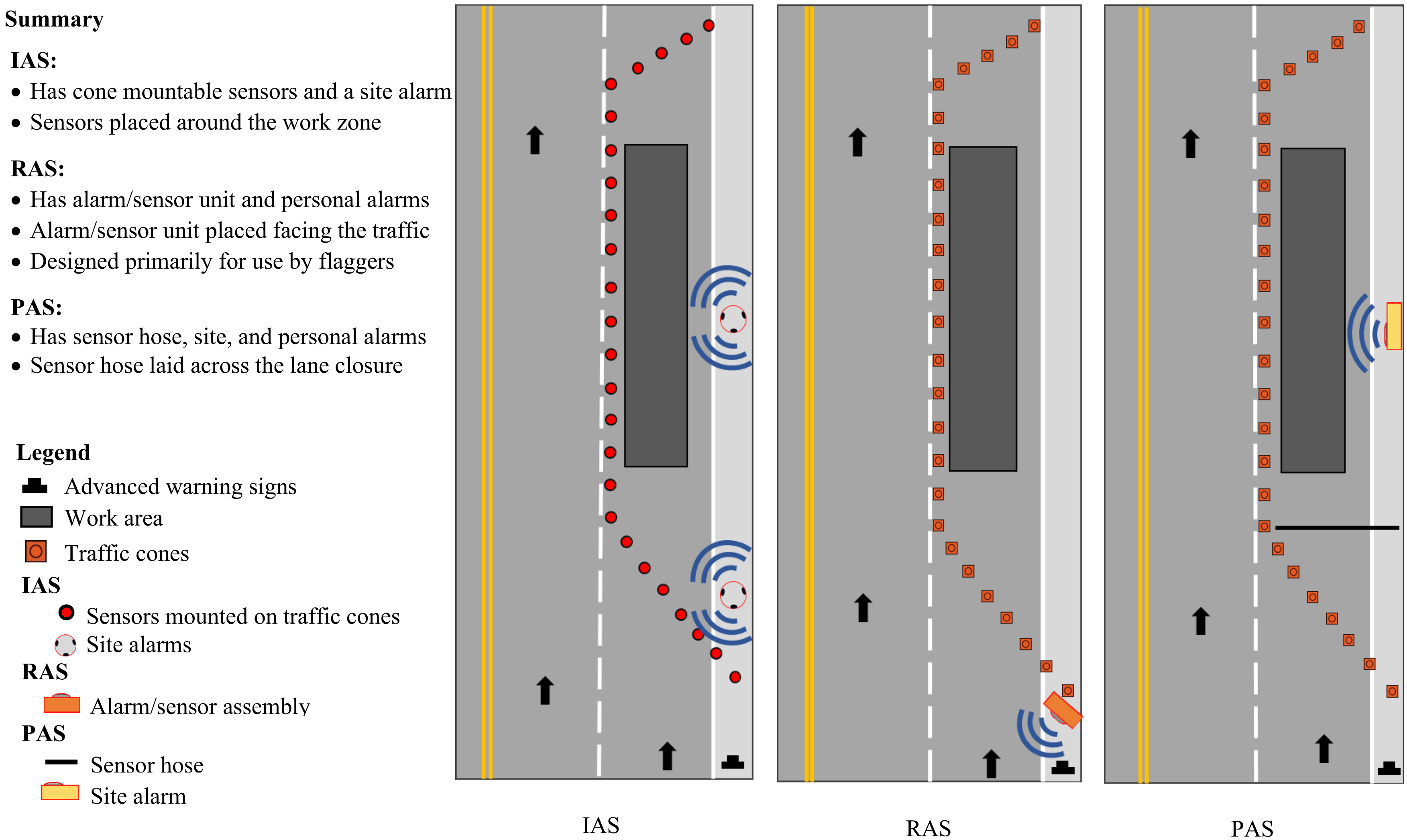


Fig. 2. Manufacturer recommended deployment for the three systems for two-lane, two-way traffic with single lane closure.

from one sensor to another until it reaches the nearest alarm. The site alarm on receiving the alerts produces flashing lights and a high-pitched sound alarm. The system is also capable of transmitting alerts between alarms over long distances. This is achieved by creating a zone of operation for a set of alarms which enables them to communicate over mobile networks. This feature enables the system to be extended over a long distance. For this reason, it is recommended for a site alarm be kept close to the transition taper after it has been connected to alarm(s) placed in the work area. This ensures that alert signals travel from one alarm to another even when the sensors fail to relay the signals over long distances (see Fig. 2).

1.1.2.Radar Activated System (RAS)

RAS is an advanced warning system capable of detecting vehicle speed and tracking its trajectory using radar. The system comprises of two components: i) a sensor/alarm unit consisting of a sensor unit and an alarm housed in a wheeled case, and ii) personal alarms for workers. The sensor/alarm unit has a built-in camera and LEDs. Personal alarms for the system are mobile sized devices that can be strapped onto a worker's arm or carried in pockets. The system is primarily intended to be used by flaggers but can also be used in advanced warning area as a standalone system to detect and warn the drivers and workers of vehicle speeding towards a work zone. As presented in Fig. 2, the recommended setup for the system is to place the system in the shoulder with a flagger. Prior to its deployment, a smartphone application is needed to fully configure the system. The application configures the relative position and orientation of the system with respect to the road, and the threshold speed limit for detecting intrusions. When vehicles approach the work zone at high speed beyond the threshold speed limit, the system marks the vehicle as an intruder and activates alarms on the sensor/alarm unit and personal alarms. The personal alarms produce a high-pitched chirping sound and vibration as alerts.

1.1.3.Pneumatic pressure Activated System (PAS)

The PAS is comprised of three components: i) a pneumatic trip hose sensor with a signal transmitter, ii) a site alarm, and iii) personal alarms for workers. The sensor is designed to detect pressure on the hose after it has been runover by an intruding vehicle. Therefore, it is recommended that it be laid across the lane closure at the end of transition taper where the intruding vehicle is most likely to run over it (see Fig. 2). The site alarm is housed in a hard case which is recommended to be placed in the work area close to the workers. Additionally, workers can also use the mobile sized personal alarms which can be carried on a pocket or strapped onto an arm. These personal alarms also facilitate remote reset of the system after it has been triggered. On detecting pressure, the transmitter attached to the hose sends alerts to the site alarm and personal alarms within its range. The site alarm produces sound alarm with a red blinking light and the personal alarms produce a vibratory alert. A summary of the components, and deployment strategies for the three systems is provided in Table 2.

2. Literature review

2.1. Evaluation of WZIAS

Evaluation of the first WZIAS prototypes developed by Stout et al. (1993) was carried out by the Kentucky Cabinet in 1996 (Agent and Hibbs, 1996). The study concluded that further testing on the systems was necessary before implementation on a large scale. In more recent years, several new systems have been developed and tested, however, the findings from most of these studies have cast doubt regarding effectiveness of systems. In 2010, a cone mountable tilt activated intrusion alarm employing an air horn was tested for its efficacy. The air horn used compressed CO_2 to produce high intensity alarm. The system reportedly was not efficient for use due unsatisfactory performance because of tedious setup, low durability, and frequent misfires during setup and storage. In 2012, the Minnesota Department of Transportation designed a non-intrusive advanced warning system capable of producing audio-visual alarms when vehicles crossed a certain speed limit (Hourdos, 2012). The system was called Intelligent Drum Line (IDL) and it employed a series of modified drums kept about 300 ft apart. These drums could detect the speed of approaching vehicles using radar, communicate this information to other drums and produce warning alert to the driver when certain threshold speed was passed. The warning alerts were also designed to be turned off automatically after the drivers rectified their speed. Limited tests were conducted on the system andthere is no mention of the system being used or tested afterwards. A wireless sensor network-based intrusion alert system using traffic cone mountable sensor nodes and warning devices was developed and tested by researchers for short-term work zone in 2016 (Martin et al., 2016). The system employed a barrier mountable sensor that used ultrasonic waves and a modified wristwatch to detect vehicles and alert workers, respectively. Tests carried out suggested that the system was reliable and accurate.. Among the most studied systems in recent years is a radar based advanced warning system. The system uses a radar sensor to detect vehicle speed and location, and alerts workers in advance when the vehicle approaches at a high speed. The system has been subjected to several studies with promising results (Eseonu et al., 2018; Marks et al., 2017; Theiss et al., 2017; Ullman et al., 2016). The alarm siren produced by the system has been found to be particularly effective due to its resemblance to law enforcement (Ullman et al., 2016). Similarly, the other two systems that have been tested in the past are an impact activated perimeter intrusion detection system and a pneumatic trip hose sensor system (Eseonu et al., 2018; Gambatese et al., 2017; Marks et al., 2017; Novosel, 2014). The impact activated intrusion detection system uses traffic cone mountable sensors to detect impact from an intruding vehicle using built in accelerometers and relays alerts wirelessly to site alarms that produces a high-pitched alarm. Previous evaluations have suggested that the system is ideal for use in high speed highways that require long tapers although specific deployment strategies detailing layout of the system components has not been addressed (Marks et al., 2017; Novosel, 2014). The pneumatic trip sensor system used pneumatic sensors, site and personal alarms. Intruder vehicles are detected by the system only after the sensor hose has been runover. Therefore, positioning of the sensor hose is particularly important when the system is being used. When a vehicle is detected by the sensor, attached wireless transmitter then transmits wireless alert signals to alarm units. Past findings suggest that the system is ideal for short-term maintenance work zones where larger work zone coverage is not required and frequent removal/installation of system is needed (Marks et al., 2017). However, further investigation regarding strategic layout of the system is warranted.

To summarize in brief, although older systems have been proven to be inefficient and difficult to use, newer systems have been found to be more useful and promising. Several studies have been conducted on prospective systems over the years with the objective of evaluating their efficacy. These studies have however omitted any investigations related to practical implications of the system. More specifically answers to questions such as "*How will the layout of the system effect worker response to intrusions*?", and "*How can we deploy the system in the field to guarantee it performs with outmost efficacy*?" has not been communicated by prior studies.

2.2. Highway crash analysis

Studies investigating causal factors influencing highway crashes have heavily relied on count data models and logistic regression to model crash frequency and crash severity respectively (Lord and Mannering, 2010; Ma et al., 2008; Ma and Kockelman, 2006a; Song et al., 2006; Stipancic et al., 2019; Wang et al., 2011; Yang et al., 2015; Ye et al., 2013). These modeling techniques, however, only permit separate investigation of crashes (based on frequency and severity) due to the nature of the response variables. Therefore, in more recent years several multivariate modeling techniques have been employed to simultaneously model crash frequency and severity (Ma et al., 2008; Ma and Kockelman, 2006a, 2006b; Song et al., 2006; Ye et al., 2013). On similar lines, count data and logistic regression models have also been exceedingly used to study the frequency (Khattak et al., 2002; Ozturk et al., 2013; Qi et al., 2005; Venugopal and Tarko, 2000) and severity of work zone crashes (Li and Bai, 2009, 2008; Osman et al., 2019, 2018a, 2018b, 2016; Zhang and Hassan, 2019), respectively. Additionally, application of more novel techniques has gained momentum over the recent years. For example, studies have explored genetic (Hashmienejad and Hasheminejad, 2017; Li et al., 2018; Meng and Weng, 2011) and machine learning algorithms (Chang and Edara, 2018; Mokhtarimousavi et al., 2019; Yahaya et al., 2020; Zeng and Huang, 2014) to model highway and work zone crashes. Similarly, the use of survival or hazard-based models have also gained popularity recently (Keramati et al., 2020; Wu et al., 2020). For example, Keramati et al. (2020) used a survival model to simultaneously account for frequency and severity of crashes occurring on highway-rail grade crossings. The authors modeled crash severities as competitive outcomes with crash as the event of interest. Likewise, Wu et al., (2020) used survival analysis to model crash counts and time interval between crashes and estimate crash modification factors for safety treatments.

Survival analysis is used to model the time until occurrence of an event using a survival or hazard functions (Chang and Jovanis, 1990; Jovanis and Chang, 1989). It is well suited for analyzing time related data where time until occurrence of an event is of interest such as the time until the onset of a disease following some medication, relapse from a disease or even the time interval between highway incidents. In transportation safety research, use of survival analysis has been mostly dominated by its application on experimental data. For example, Sharma et al. (2011) used hazard functions for estimating dilemma zones for drivers in high-speed intersections and proposed an algorithm for reducing conflict on dilemma zones using field data. Similarly, Choudhary and Velaga (2020) and Haque and Washington (2015) used parametric hazard models to model driver stoppage during distraction using driving simulators. On similar lines, Shangguan et al. (2020) investigated the impact of adverse environmental conditions on driver's braking and speed reduction behavior to avoid rear end crashes using data collected from a driving simulator. Parmet et al. (2014) used survival analysis to analyze response time in driver related hazard perception concluding that hazard-based modeling approach was an appropriate approach for investigating hazard perception when using response times generated from simulations. Other safety related studies utilizing survival analysis have investigated lane keeping behavior of cyclists (Guo et al., 2013), crashes at urban intersections (Bagloee and Asadi, 2016), impact of connected vehicle environment on lane-changing behavior using data collected from a driving simulator (Ali et al., 2019), and predicting clearance time for road incidents (Chung, 2010; Nam and Mannering, 2000; Tang et al., 2020). However, its application for investigating work zone crashes and its causal factors is non-existing. Understandably, it is challenging to collect work zone crash data using field experiments and driving simulators considering the safety of the participants and the limitations imposed by simulators.

This study was in part inspired by the evident gap in the published literature concerned with the investigation of work zone crashes using survival analysis. To our knowledge no previous studies have applied survival analysis to work zone crashes. Furthermore, the goal of this study is to identify and recommend guidelines on WZIAS layout which has potentially huge implications for WZIAS implementation. In view of these gaps, we present the three main research needs addressed by this study in the following section.

Table 2

Summary of systems specifications.

	IAS	RAS	PAS
System components	• Cone mounted sensor lamps, and • Site alarm	• Sensor/alarm unit consisting of radar-based sensor, flashing LEDs and alarm speaker, and • personal alarms	• Pneumatic trip hose sensor, • site alarm, and • personal alarms
Alert mechanism	• Motion detection from vehicular impact on the traffic cones	• Radar based vehicle tracking	• Pressure exerted by vehicle running over the trip hose
Type of alert	• Sound and flashing lights	• Sound and flashing LED on the sensor unit, and • vibratory and sound alert on personal alarms	• Sound and flashing lights on site alarm, and • vibratory alert on personal alarms
Deployment	• Sensors mounted on traffic cones placed around the work zone perimeter, and • site alarm close to the workers	• Main unit placed on the shoulder outside the transition taper facing the oncoming traffic, and • personal alarms carried by the worker	• Pneumatic sensor laid across the closed lane in transition area, • site alarm within the work area, and • personal alarms carried by the workers

2.3. Research gap and study objectives

Based on the review of literature, we identify and rid of the following gaps with this study.

i. Past studies investigating the efficacy of WZIAS have been based solely on their performance (Gambatese et al., 2017; Marks et al., 2017). Therefore, causal factors that are extrinsic to the systems have not been considered in these studies. Two of such factors are considered in this study, i) speed of intrusion, and ii) layout of WZIAS. In doing so we recommend best practices for choosing and deploying systems in the field. The impact of high-speed intrusions on work zone crash could be partially negated by devising appropriate system deployment strategies that facilitates quicker worker response. Since the deployment strategy is unique to each system, the relative position of the system components with respect to the work zone perimeter and workers is likely to vary based on choice of the system and work zone closure. Considering this, it is imperative to identify ideal use case scenarios for each system and establish best deployment strategies for their implementation. Although a prior study has made recommendations on selection of systems (Marks et al., 2017), we go a step further and recommend ideal deployment strategies as a means to translate theoretical knowledge on system characteristics and performance into work zone standards for real world application using experimental data.

ii. Our study analyzes workers' naturalistic response to system alerts to investigate the occurrence of work zone crashes. While the analysis of naturalistic response by itself is not new to the literature, analysis of worker responses is rather novel since published research almost in its entirety has been centered around drivers (Choudhary and Velaga, 2020; Dingus et al., 2016; Haque and Washington, 2015; Shangguan et al., 2020). These studies have analyzed drivers' braking response collected using driving simulators. In contrast, our approach aims to imitate work zone crashes to collect worker response in the field for two main reasons. First, it allows us to collect the response time, i.e., the time taken by workers to perceive and react to an alarm (move out of the way to safety). The exact time taken by a worker to react reactcannot be collected without field experiments. Second, collection of worker response using driving simulators is particularly challenging. Although driving simulators are effective in studying driver behavior, they provide limited to no scope for incorporating WZIAS and recording the worker response. Furthermore, unexpected problems that are frequently exhibited by WZIAS in the real world, such as false alarms and delayed activation are best studied using field experiments.

iii. We employ non-parametric and semi-parametric survival models to analyze worker response and occurrence of crashes in presence of WZIAS using field experiments. To our knowledge, application of survival analysis to this end has not been done in the literature.

3. Method

As previously mentioned, this study utilized field experiments to collect and analyze workers' naturalistic response to work zone intrusion alerts produced by WZIAS. Various WZIAS layouts and intrusions speeds were used to emulate different scenarios for work zone intrusions. Worker response to the alerts produced by WZIAS upon detection of these intrusions were then used to determine potential crashes. Determination of crash was based on worker response and alerts produced by the systems. In the following sections we discuss the experimental arrangements, procedures, and explain the methodology used to determine crashes.

3.1. Pilot testing

Field experiments for the study was conducted in two phases. In the first phase a pilot test was conducted to determine the maximum signal transmission range for the system components. This was important to ensure that the layout of the system components in our experiments was such that they were not too far apart to result in a loss of signal during transmission. The transmission range was determined as follows. The distance between the system components, sensor and alarm units, were gradually increased at 50 feet intervals. At each interval four attempts were made to activate the alarms by triggering the sensors. If all four attempts were successful, the transmission was assumed to be complete. The maximum distance beyond which complete transmission ceased was considered as the maximum transmission distance (Novosel, 2014). This methodology was applied to find the transmission range for the following system components.

- IAS: Sensor to site alarm.
- RAS: Main assembly (sensor/alarm) to personal alarms.
- PAS: Pneumatic sensor to personal alarm.

As expected, different transmission ranges were obtained for the systems. For IAS, the transmission range from sensor to site alarm was 300 ft while for RAS the transmission range between the main assembly and personal alarms was about 400 ft. For PAS, complete transmission between sensor and site alarm was limited to 150 ft.

Transmission range can provide a reasonable estimate of response time needed to avert a crash. For example, when using systems with greater ranges, the sensor and alarm can be placed further apart which would provide workers with more time to react to an intrusion as the vehicle entering the perimeter will have to traverse longer distance before reaching the work area. This knowledge can aid in determining system layouts. This is particularly relevant for systems based on mechanical impact and pressure detection such as IAS and PAS. However, the same is not applicable to advanced warning systems like RAS since they are capable of alerting workers in advance. In such a case, detection range of the system can be used as a surrogate measure to estimate optimal layout of the system. Detection range can be defined as the minimum distance between intruder vehicle and the system needed to trigger an alarm.

In this study, the detection range for RAS was tested for different test speeds. In these experiments, test vehicles were driven towards the RAS main assembly at predetermined test speeds and the moment of alarm activation was recorded using video cameras. Using the recordings, the exact point at which the alarms were triggered was identified and the distance of the point from the main assembly was measured. Results suggested that the detection range was comparable to the standard Stopping Sight Distance (SSD) for the respective test speeds. Table 3 presents the results from pilot testing for transmission and detection range. The standard values of SSD for the test speeds are also provided within parenthesis.

IAS and PAS were selected for the next phase of testing wherein worker response post intrusion was collected. RAS was excluded from the second phase of tests considering advanced detection and warning.

3.2. Field testing

The field tests were conducted in a controlled facility that was closed to traffic and pedestrians. A typical lane closure identical to Fig. 1 was setup using traffic channelizers to imitate a work zone. Five highway maintenance workers from TDOT were recruited as test subjects for the study. National demographic of highway construction workers suggested that only about 2.5% of the highway maintenance workers in the US were female and the average age of workers was about 44 years ("Data USA: Highway Maintenance Workers," 2018). The workers were selected to represent this demographic. All participants in the study, driver, and workers, were certified and experienced in highway construction and maintenance. They were also informed regarding the methodology and objective of the study before the field tests began.

Table 3

Results from pilot testing.

Tests	**IAS**	**RAS**	**PAS**
Transmission range			
Sensor to site alarm	300 ft	NA	NA
Sensor to personal alarms	NA	400 ft	150 ft
Median detection range (n=3)	**Observed range (Standard SSD)**		
Test speed			
30 mph	175 ft (200 ft)		
45 mph	350 ft (360 ft)		
60 mph	500 ft (570 ft)		

During the experiments, the systems were setup in the lane closure following manufacturer recommendations presented in Table 2. The workers were then positioned close to a hypothetical work area and asked to engage in an activity of their choosing in a sitting position facing away from the incoming test vehicle. To obtain naturalistic response to the intrusion, workers were not provided prior information on when an intrusion would occur. They were also instructed to react only to the alerts produced over the devices (site or personal alarms). Test vehicles were then driven into the lane closure at various speeds to imitate intrusions. Several safety precautions were adopted to ensure safety of the participants. Drivers of the test vehicles were instructed not to deviate from the course of their trajectory and travel on the same lane while the workers were positioned away from the trajectory of the intruding vehicles on the adjacent lane. The workers were also asked to respond by moving away from the lane closure towards the shoulder upon receiving alerts from the system being tested. To counterbalance order effects, workers were randomly chosen for experiments. A randomly chosen worker would participate on tests for a certain configuration of a system. After completion of tests on the configuration, next worker was then chosen at random to participate on the same experimental configuration and so on. After completion of tests for a certain configuration the system being tested was switched and the tests were then carried out in a similar manner.

The experiments were varied by intrusion speeds, and relative position of the system sensors to the workers. Intrusion speeds ranging from 30-60 mph at 5 mph increments were considered for the study. The relative position between sensors and worker were varied from 100-300 ft for IAS and 100-150 ft for PAS considering their transmission range as shown in Fig. 3. Besides predefined speed and sensor-to-worker spacing, data was collected on i) activation of alert; ii) noticeability of alarms measured using sound intensity; and iii) worker reaction time during each experimental trial. A description of the data collected is provided in Table 4 and the various experimental configurations is summarized in Table 5. Consequently, the outcome of the intrusion, i.e., if an intrusion resulted in a crash, was decided based on activation of alert and worker reaction recorded using video cameras (see section 3.3 for detailed explanation).

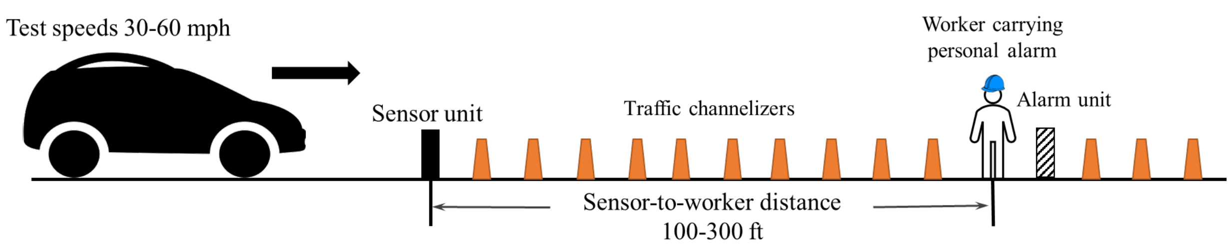


Fig. 3. Schematic representation of worker relative to the system components.

3.3. Crash determination and hypothesis formulation

Determination of whether an intrusion would result in a crash was based on three possible outcomes following an intrusion. These outcomes were based on worker reaction time (t_w), critical time (t_c), and activation of alarms. Worker reaction time for each experiment was determined from video recordings while the critical time was calculated based on test speed and sensor-to-worker distance (see variable description in Table 4). The three possible outcomes from experiments considered are as follows.

- Outcome 1: Alarms activate and $t_w < t_c$ = No crash

In case the alarms activate, and a worker's response time is less than the critical time we assert that the intrusion is unlikely to result in a crash since the worker would have adequate time to get to safety.

- Outcome 2: Alarms activate and $t_w > t_c$= Crash

When this outcome is observed, we assert a crash is imminent since the intruding vehicle would have traversed the distance between the sensor and the worker before the workers would have adequate time to react to the alarms.

- Outcome 3: Alarms fails to activate = Crash

Under this outcome we assume that workers would be unaware of the intrusion as system fails to register any intrusion and therefore a crash would be imminent.

Table 4

Description of variables.

Variables	**Description**
Speed [u, mph]	Speed of the intruding vehicle
Sensor-to-worker [D_w, ft]	Distance between the sensor and the worker for tested system (see Fig. 3)
Alert (1=Yes, 0=No)	Binary variable indicating whether the alarms activated
Sound_int (dB)	Sound intensity of the site alarm at worker location used as a measure of alarm noticeability
Worker_react [t_w, s]	Time taken by a worker to perceive and react to alarms by initiating an evasive motion to move away from the work area towards the shoulder
Critical_time [t_c, s]	Measure of time taken by the test vehicle to reach the worker after it has entered the work zone perimeter, mathematically calculated as $t_c = \frac{D_w}{u*1.47}$
Crash (1=Yes, 0=No)	Binary variable indicating if an intrusion resulted in a crash determined as follows: Alert =1 and $t_w < t_c$ then 0 Alert =1 and $t_w > t_c$ then 1

	Alert = 0 then 1

It is noteworthy that our approach in determining the outcome of the intrusion is based on workers' response. Drivers upon hearing alarms or striking traffic barriers, may often be able to break, stop or steer the vehicle to safety. Since our experiments were based on real world interaction between an intruding vehicle and workers this limitation could not be eliminated due to safety concerns. Four hypotheses are formulated to test the effect of the variables on work zone crashes. These hypotheses are as follows:

H1: With increase in sensor-to-worker distance, the probability of work zone crashes will decrease since the critical time increases.

H2: Greater latency in signal transmission increases the probability of work zone crashes as worker.

Since worker reaction time is dependent on the latency of signal transmission, system with shorter latency could be better able to reduce work zone crashes. Latency in signal transmission is defined as the time between intrusion detection and alerts.

Table 5

Summary of experimental configurations for the systems.

Variables	**Experimental configurations**
Speed	Between 30-60 mph at 5 mph intervals
Sensor-to-worker	
IAS	Set at 100 ft, 200 ft and 300 ft
PAS	Set at 100 ft, and 150 ft

Note: There were a total of 7(Speed) x *(2+3)(Sens_to_alr) = 35 experimental configurations for the two systems.*

H3: With the increase in speed of the intruding vehicle, the probability of work zone crashes will increase. As the speed of the intruding vehicle increases the critical time decreases and quicker responses from workers will be required to avoid crashes. Therefore, with higher intrusion speeds, crashes are more likely to occur.

3.4. Survival analysis

Survival analysis is popularly used in many areas of research such as epidemiology, engineering, and economics to model the time until occurrence of an event. In this study, the event is occurrence of a work zone crash. In other words, our analysis models work zone crashes considering the time until its occurrence measured since intrusion of the work zone perimeter. It is worth mentioning that this study assumes any possible contact between a worker and intruding vehicle as a crash regardless of its severity.

The survival function then gives the probability of non-crash intrusion occurring at time *T* which is longer than some specified time *t.* Assuming *f(t)* is the probability density function and *F(t)* is the cumulative distribution function of the continuous random variable *T,* the probability that no crashes occur after time *t* is given by the survival function $S(t)$ as follows:

$$S(t) = P(T > \ t) = 1 - F(t) \tag{1}$$

Another concept that is related to survival function is the hazard function. Hazard function *h(t)* also called the hazard rate gives the instantaneous probability of occurrence of an event (crash) conditional on no events having occurred until the time *t*. Mathematically, it can be written as:

$$h(t) = \frac{f(t)}{S(t)} = \lim_{\Delta t \to 0} \frac{P(T\pounds\ t + Dt|T > \ t)}{Dt} \tag{2}$$

Survival analysis collectively refers to three main survival models. These models are Kaplan-Meier (KM) estimator, Cox Proportional Hazards (Cox PH) model, and Accelerated Failure time (AFT) model which belong to non-parametric, semi-parametric, or parametric family of models, respectively.

3.4.1.Kaplan Meir estimator

KM estimator is a non-parametric estimator of the survival function for small time intervals. It can be written as:

$$S_{KM}(t) = \prod_{i:t_i \leq t}(1 - \frac{e_i}{n_i}) \tag{3}$$

where t_i represents time at which at least one crash is observed, e_i is the number of crashes that occurred at t_i and n_i is the number of intrusions that did not results in a crash. A notable limitation of KM estimator is its ability to incorporate variable effects. Since only the time and occurrence of crashes are include in the estimator, it cannot be used to model the effects of variables. Regardless, they can be used to compare the probability of crashes between separate groups of variables using the log rank test statistic. For example, to compare the likelihood of crashes between two different intrusion speeds, KM estimators can be used to estimate the survival functions for each speed separately and test if they are statistically different. The log rank test statistic tests the null hypothesis that the survival functions for the two groups (in this case intrusions speeds) being compared is not statistically different. The test statistic is calculated as:

$$c^2 = \frac{\sum_{j=1}^{J}(O_j - E_j)}{\sqrt{\sum_{j=1}^{J} V_j}} \sim N(0,1) \text{ under } H_0 \tag{4}$$

where O_j and E_j are the observed and expected number of crashes, respectively for distinct time of crashes $t_1 < t_2 < t_3 \ldots . < t_j$, and V_j is the variance of observed number of crashes.

Semi-parametric and fully parametric models that can address the effect of variables are often preferred over KM estimators.

3.4.2. Cox proportional hazard model

Due to the inability of KM estimators to include variables in estimating survival functions, use of semi-parametric Cox PH and fully parametric AFT models is often preferred. Cox PH model assumes multiplicative effect of variables on some baseline hazard to study variable effects on the time until an event. The model is based on two assumptions, i) the functional form for survival function exponential, and ii) hazard rate is constant over time. Mathematically, it can be written as follows:

$$h(t|X) = h_o(t)\exp(-bX) \tag{5}$$

where for a vector of variables X, $h(t|X)$ is the hazard function, $h_o(t)$ is the baseline hazard function and $\exp(-bX)$ is the functional form of the variables with a vector of coefficients, b. The underlying proportional hazard assumption however might not hold true for all variables in a model. Test for the assumption is particularly important when the effect of variable is of interest (i.e., test whether the effect of variable is constant overtime or not). In case the assumption is violated, the variables violating the assumption can be controlled by stratification while simultaneously including remaining variables in the model. Such a model is referred to as stratified Cox PH model. Assuming the variable violating the proportional hazard assumption has *K* levels, the modified hazard function can be mathematically expressed using the following equation.

$$h_k(t|X) = h_{ok}(t)\exp(-bX) \quad (6)$$

Here, $h_k(t|X)$ and $h_{ok}(t)$ are the hazard and baseline hazard functions respectively for k^{th} stratum with $k = 1, 2, 3 \ldots, K$ levels of the variable that is being stratified. Note that unlike in Eq. (5) where there is a single baseline hazard function, Eq. (6) results in a different baseline hazard function for each level of the stratified variable.

Application of Cox PH model for independent and identically distributed random variables are straightforward. However, for individuals in a study that are subjected to repeated measures (i.e., when measurements are in clusters) it is necessary to account for unobserved heterogeneities arising from different clusters that may expose individuals to different levels of hazard (Haque and Washington, 2015; Wang et al., 2020). Unobserved heterogeneities can be accounted for in Cox PH model by adding a frailty parameter assuming that every cluster of individuals has a different frailty, and among them the frailest would die first. The frailty parameter is essentially a random effect term that multiplicatively modifies the hazard function for each cluster. The resulting modified Cox PH model is called shared frailty Cox PH model and is of the form:

$$h_{ij}(t|u_i) = h_o(t)u_i\exp(-bX_{ij}) \quad (7)$$

where, h_{ij} represents the hazard function for i^{th} individual (worker) in the j^{th} measure (experiment); b is a vector of coefficients for the variables X_{ij} and u_i is the shared frailty with mean 1 and variance θ following a gamma distribution (for example, see Therneau et al. (2003)).

It is worth mentioning here that a third member of the family of survival models are fully parametric AFT models. These models assume that variables have multiplicative effect on the survival time. Exponential, Weibull, log-logistic, lognormal and loglogistic are some of the commonly used parametric distributions in AFT models. There are notable limitations to AFT models. Selection of appropriate distributions for AFT models is often difficult unless the underlying distribution can be identified with certainty (Kleinbaum and Klein, 2012). Also, AFT models cannot handle zero values in the response variable (Zhang and Thomas, 2012). For these reasons, Cox PH and stratified Cox PH were used for statistical analyses in study. All analyses in this study were done using R v3.5.1, and R package *survival* which utilizes penalized partial loglikelihood for model fitting (Therneau, 2020; Therneau et al., 2003).

4. Data

A total of 525 observations (35(experimental configurations) x 5(workers) x 3(trials) were recorded from the experiments which comprised of 315 observations for IAS and 210 observations for PAS. Descriptive statistics of variables used in our analysis is shown in Table 6. The descriptive statistics for workers are presented here to provide the reader a summary of test subjects.

5. Results and discussion

KM estimators are useful in determining the change in probability of survival and testing the independence of groups in absence of variable effects. Therefore, KM estimators were used for the two systems, different test speeds and sensor-to-worker distances to test the independence of survival probability. Fig. 4 (a) presents the result from KM estimator for cumulative probability of work zone crashes with 95% confidence interval. A large confidence interval was observed at the end of the curve which is indicative of most crashes occurring within the first seven seconds of intrusion. Similarly, the KM estimators for different groups namely systems (Fig. 4(b)), test speeds (Fig. 4(c)), sensor-to-alarm distance (Fig. 4(d)) are also presented. The tick marks in these plots represents censored data for which no crashes were observed. Log-rank test was conducted to test independence of groups. Results from log-rank test suggested difference in survival functions across groups (Chi-square = 72.3, p-value < 0.01 for systems; Chi-square = 97.6, p-value < 0.01 for test speeds; and Chi-square = 432, p-value < 0.01 for sensor-to-worker distances).

In comparing the estimators for IAS and PAS for the same time, IAS was observed to result in greater probability of survival compared to PAS after three seconds. This suggested that for longer tapers, IAS would be safer. This is because for longer tapers vehicles will have to travel for a longer duration downstream after intrusion. In such events IAS would likely result in a higher survival probability. Among the estimators for different speed groups, lower speeds displayed longer horizontal leveling. This suggested that the probability of survival remained constant for a longer period when the intruding vehicles were traveling at a lower speed. That is to say, compared to intrusions that occur at low speed, intrusions that occur at higher speeds had more noticeable impact on occurrence of work zone crashes over a shorter period. The

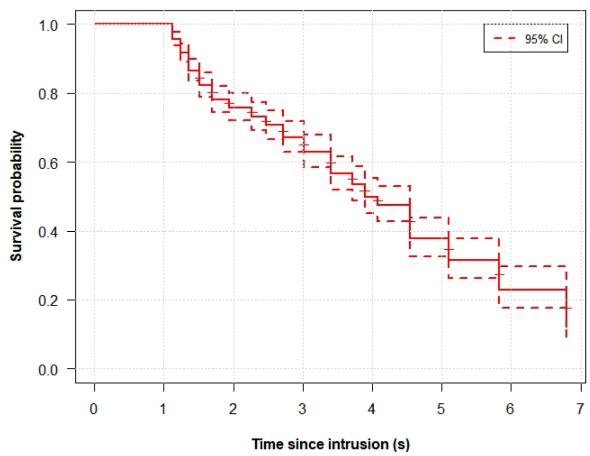
Table 6

Descriptive statistics.

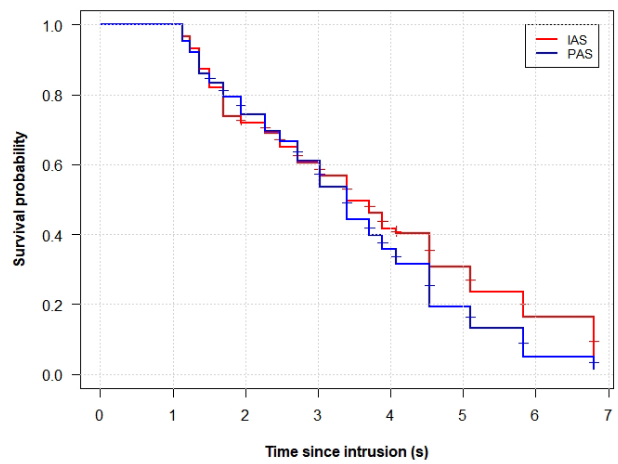
Category or Variables	**Mean**	**Std. deviation**
Worker_react		
IAS	1.98	0.38
PAS	1.96	0.41
Sound_int		
IAS		
100 ft	68.51	1.48
200 ft	57.25	1.47
300 ft	51.98	1.54
PAS		
100 ft	75.36	1.62
150 ft	69.67	1.59
Workers	**Frequency**	**Proportion (%)**
Age		
Mid-age (30≤ age ≤55)	4	80
Young (age ≤ 30)	1	20
Gender		
Male	4	80
Female	1	20
System alerts and crash	**Frequency**	
IAS		
Alert (1=Yes, 0=No)	212	
Crash (1=Yes, 0=No)	120	
Total experimental trials	315	
PAS		

Alert (1=Yes, 0=No)	160
Crash (1=Yes, 0=No)	74
Total experimental trials	210

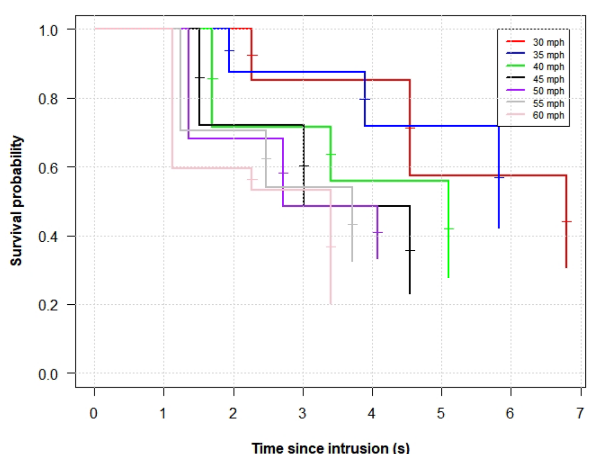
estimators suggest that for the same difference in time the change in survival probability for high-speed intrusions (greater than 35 mph) was higher versus low-speed intrusions. These findings hint that for high-speed intrusions, even a small increase in critical time would have measurable impact on work zone crashes. Parallel results can be drawn for the estimators on sensor-to-worker distance.



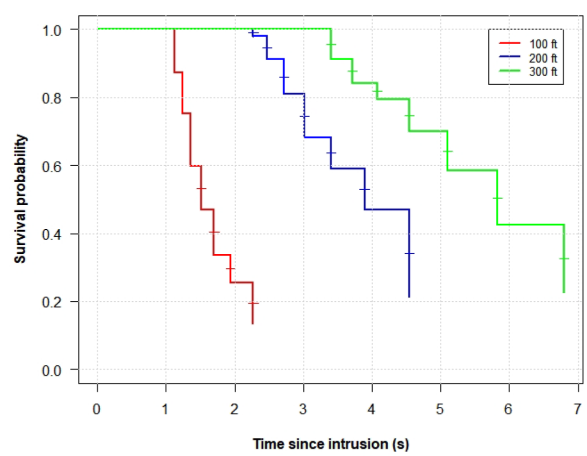
(a) Null estimator with 95% CI.



(b) Estimators for IAS and PAS.



(c) Estimators for different test speeds.



(d) Estimators for sensor-to-worker distances.

Fig. 4. KM estimators.

The vertical drop in survival probability was less frequent for great distances indicative of its positive impact on the occurrence of crashes. Therefore, for the same difference in time, the probability of survival can be expected to vary less when the separation between the sensors and workers is more. The time at which the survival probability approaches the minimum value is also noteworthy. At 100 ft, most crashes occurred within 2 seconds of intrusion while for 300 ft almost all crashes were observed between 3-7 seconds of intrusion. Based on these results it can be concluded that when workers are close to the work zone perimeter (sensor-to-worker distance is less) even small increment in the critical time would have measurable impact on the occurrence of crashes.

Next, three variations of the Cox PH model were fit to the experimental data obtained from both systems to investigate the effect of variables on occurrence of crashes. The first model was a Cox PH model. The second was a stratified Cox PH model that stratified variables violating the proportional odds assumption. The third model was a shared frailty Cox PH model incorporating random effects to account for heterogeneity in the data from repeated trials on the same individuals. Backward elimination approach was used to develop the models by first removing variables with high multicollinearity based on Variation Inflation Factor (VIF) followed by removal of variables that did not contribute towards model goodness of fit. Two model goodness of fit were considered while selecting variables, namely, AIC and C-statistic. Additionally, the stratified Cox PH model was developed by administering Schoenfeld test for proportional hazards assumption on the variables and then stratifying variables violating the assumption. In the shared frailty Cox PH model, a frailty term with gamma distribution (mean 1 and variance θ) was added to the Cox PH model to account for mixed effects. Summary of the three models is presented in Table 7. The shared frailty model was found to be a slightly better fit compared to the other models. Further, high values of C-statistic for all three models is indicative of their good discriminatory power (Hosmer and Lemeshow, 2000).

Results from the stratified Cox model is shown in Table 8. The table presents variable coefficients with their standard errors within parentheses, and their hazard ratios and VIFs. Hazard ratios provided here can be used to quantify the change in outcome (here the probability of crash) with the change in the predictor variables. VIF for the variables in the model were close to 1 suggesting low correlation between one other (Kock and Lynn, 2012). In the initial model, the variables *Sensor-to-worker*, *Worker_react* and *Speed* were found to be statistically significant. Variable *Speed* was however later removed from the model due to high VIF (VIF=11). The sign of the variable coefficients gives an idea of its influence on the outcome. A negative coefficient, and hazard ratio less than 1 for a variable implies that the variable is inversely associated with the outcome. On the contrary, a positive coefficient, and a hazard ratio greater than 1 implies direct relationship between the variable and outcome. For example, a negative coefficient for *Sensor-to-worker* implies that, controlling for other factors, with an increase in sensor-to-worker distance the probability of crash decreases. More precisely the model predicts that probability of crash decreases by about 3% with every 1 ft increase in distance. The finding is intuitive since with greater separation between the worker and the sensor, intruding vehicles will need to travel further downstream after the intrusion providing additional time for the workers to react to the intrusion. This finding supports our first hypothesis H1.

Table 7

Summary of the Cox models for overall survival function.

Model fit measure	Cox model	Stratified Cox model	Shared frailty Cox model
Partial loglikelihood at zero	-1379	**-1276**	-1379
Partial loglikelihood at convergence	-1163	**-986**	-1161
AIC	2335	**1978**	2234
C-statistic	0.83	**0.84**	0.83

Table 8

Result from stratified Cox model.

Variables	Coefficients (SE)	Hazard ratio	VIF
Sensor-to-worker	-0.025 (0.002)***	0.97	1.30
Sound_int	0.010 (0.01)	1.01	1.33
Worker_react	0.311 (0.15)*	1.37	1.06

Number of crashes = 383

Level of significance: ***0.001, **0.01, *0.05, # 0.1

Similarly, a positive coefficient and hazard ratio more than 1 for *Worker_react* suggests that the variable is causally related to the work zone crashes and with unit increase in worker reaction time, probability of crash can be expected to increase by about 37%. It is obvious that work zones crashes are more likely to occur when workers fail to react timely to intrusions. Considering that the primary reason for worker's delayed response in our experiments can be attributed to greater latency in signal transmission we support

Table 9

Results from Cox models for the systems.

Variables	Coefficients (SE)		
	Cox model	**Stratified Cox model**	**Shared frailty model**
IAS			
Speed	0.22 (0.02)***	**0.25 (0.02)*** **	0.22 (0.02)***
Sound_int		**0.64 (0.05)*** **	0.58 (0.05)***
Alert (1=Yes, 0=No)			
Yes	-2.10 (0.29)***	**-**	-2.10 (0.29)***
C-statistic	0.96	**0.96**	0.97
Likelihood ratio test	342.30	**323.80**	342.7
AIC	537.6	**434.9**	537.6
Variance of gamma frailty			0.003
Number of crashes = 198			
PAS			
Speed	0.20 (0.11)***	4.08 (355.06)	**0.20 (0.02)*** **
Alert (1=Yes, 0=No)			
Yes	-1.02 (0.27)***	-	**-1.07 (0.27)*** **
Sound_int	0.56 (0.04)***	-0.01 (0.06)	**0.57 (0.04)*** **
C-statistic	0.95	0.99	**0.95**
Likelihood at convergence	-345.92	398.2	**335**
AIC	697.83	268.9	**697.2**
Variance of gamma frailty			**0.002**

Number of crashes = 185

Level of significance: ***0.001, **0.01, *0.05, $^{\#}$ 0.1

Note: "-" indicates the variable stratified in the model.

hypothesis H2. Therefore, we can assert that a system's quickness in producing alert after detection is imperative towards reducing crashes. The variable *Sound_int* although statistically insignificant improved the model goodness of fit and was therefore included in the model. These results in general indicate that for any work zones regardless of the system being used, the two key factors that need consideration are separation between the sensors and the worker and the system's ability to alert the workers in time. Among the three hypotheses, no specific findings could be reported to support or oppose H3 from the model.

The aforementioned models analyzed aggregated data for both the systems. However, to study the influence of variables on each system, system specific analysis was needed. Therefore, the three variations of the Cox PH model were applied to crash data on IAS and PAS separately. The same modeling technique described in the preceding paragraphs were applied. We present the model results with parameters estimates, standard error, and model goodness of fit parameters for the models in Table 8. Note that the variable *Alert* was stratified for the stratified Cox models for both the systems. The magnitude of coefficients for the models were comparable except for stratified Cox model for PAS. Of the three models for IAS, the stratified model was found to the superior fit. Similarly, the shared frailty Cox model was the best fit for PAS. Although model goodness of fit indicated that the stratified model was the best fit for PAS, the model was discarded due to its inconsistent estimates compared to other models. The variances of gamma frailty for IAS and PAS were found to be 0.002 and 0.003, respectively. Low magnitude of variances is indicative of small variability between the workers which can be attributed to relatively small sample size. Although accounting for mixed effects is recommended when the number of participants (workers in this case) is larger than five, interpretation of causal effects from mixed models for smaller number of participants is still considered safe (Gelman and Hill, 2007). Due to the difficulty in recruitment, this study was limited to five workers. This can be expanded further as a potential avenue for future research. In contrast to the findings in Table 7, the influential variables for both systems were found to be

Speed, Sound_int, and *Alert*. As expected, the coefficient for *Speed* for both the systems was positive indicating direct relationship between speed of the intruding vehicle and work zone crashes. This provided evidence to our hypothesis H3. Further, results from the frailty model for PAS resulted in a high magnitude negative coefficient for *Alert* suggesting an inverse and prominent relationship of the variable with work zone crashes.

6. Research implications and recommendations

The results from tests and analyses highlighted the influence of system performance and layout on work zone crashes. Results from pilot testing provided with essential information on system's transmission range and analyses of experimental data using non-parametric KM estimators and semi-parametric Cox PH models highlighted the impact of variables (i.e., *Speed, Sensor-to-alr, Sound_int, Alert, Worker_react*) on crashes. We discuss the implications of the findings in parallel with our recommendations as follows.

i. System selection

Based on the results from pilot testing and model analysis we recommend using IAS in construction work zones that require long term use of stationary traffic channelizers over long tapers. The system's transmission range allows it to be used in long tapers and therefore can used effectively in facilities where the posted speed limit is more than 30 mph. However, the time needed to setup each individual sensor makes it impractical for use in projects that require frequent repositioning. RAS is recommended for use in projects that requires flagging. In our review of the literature, we could find no other systems that facilitates flagging operation and advanced intrusion detection. Further, it can be used in facilities with operating speed less than 40 mph. The 400 ft transmission range of the system makes it ideal for covering work zone perimeters with medium length tapers (Fig. 5(c)). When flagging operation is needed on facilities with speed limit greater than 40 mph, we recommend the system to be used alongside IAS to overcome the limitation imposed by its transmission range. When used with IAS, the system can be used primarily for enforcing speed limit while utilizing IAS for alerts. Finally, PAS despite having a relative short transmission range, is easy to deploy. It is best suited for short term maintenance or mobile work zones and on facilities with speed limit less than 30 mph since the system's 150 ft range is

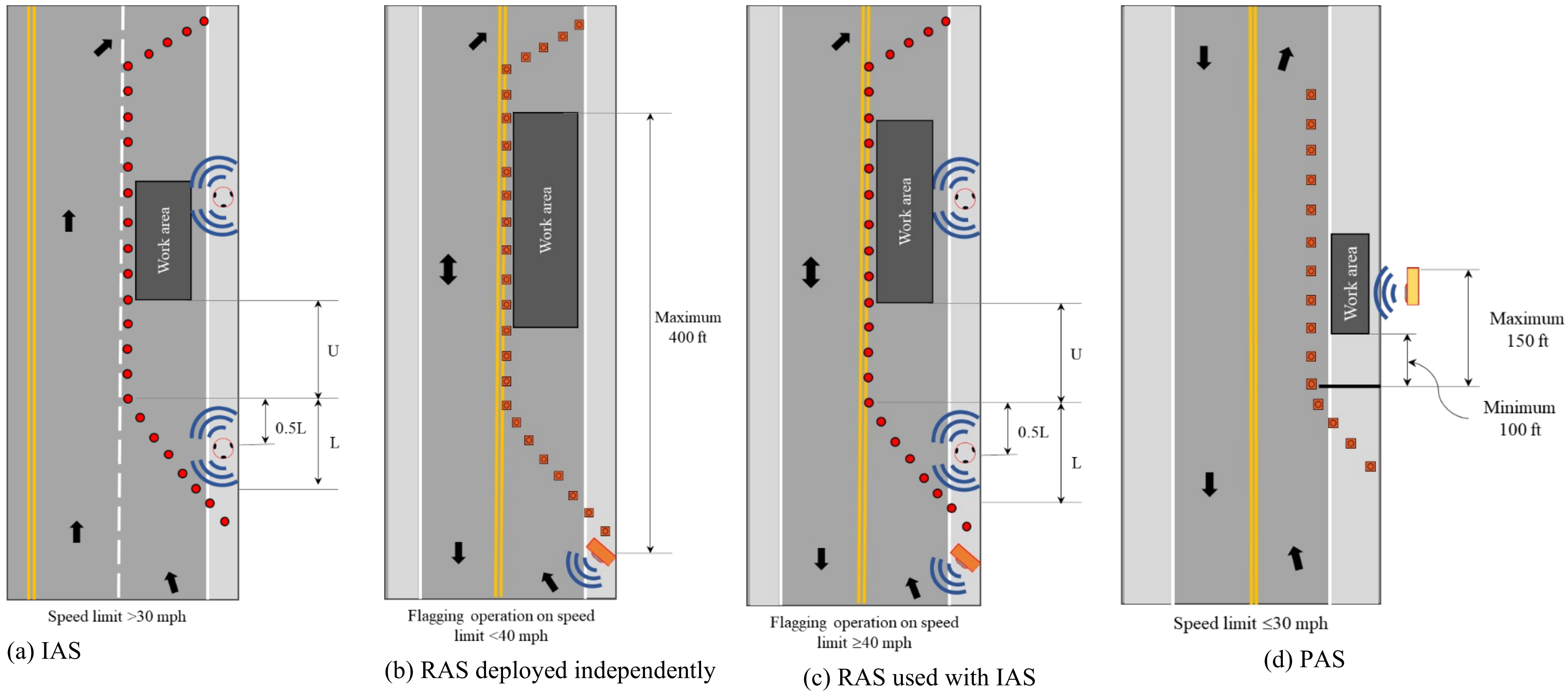


Fig. 5. Recommended setup for work zone and system components.

Table 10
Work zone taper and system deployment

Speed limit (mph)	**Revised speed limit (mph)**	**Minimum taper length as per MUTCD, L (ft)**	**Recommended minimum buffer space, U (ft)**
35	35	245	155
40	35	125	155
45	40	480	180
50	45	540	200
55	50	600	225
60	50	600	225
65	55	720	245
70	60	800	290

adequate for work zones on facilities operating at less than 30 mph. The system is well suited for work zones on shoulders with little or no lane encroachment as shown in Fig. 5(d). A summary of our recommendations is presented in Table 11.

ii. Speed limit

Results from our regression models in Table 9 suggests, with unit increase in operating speed the probability of crash increases by about 22% *((exp(0.2)-1)x100%)*. Since reduction in the operating speed limit could have measurable impact on crashes, we recommend reducing the speed limit near work zones whenever WZIAS are being used. Reduction in existing speed limit will reduce the probability of crash and shorten length of lane closure needed which will provide a greater opportunity for the systems to cover the work zone (Mishra, 2013). However, reduction in speed limit should be done after careful consideration since the general practice on reduction of speed limit across the US varies with states (Bham and Mohammadi, 2011). We recommend a conservative approach that agrees with existing practices. We recommend a 5-mph and 10-mph reduction in speed limits for highways operating at 40-55 mph and 60+ mph respectively. Work zones can be set up on facilities based on their operating speed as provided in MUTCD 2009. However, appropriate guidelines and standards will need to be established for the buffer area.

iii. Buffer space and system deployment

The transmission range of the system components should be given due consideration while determining the length of buffer space. We present a schematic for the recommended layout of system components based on our findings in Fig. 5. In case of IAS, based on results from from KM estimators (Fig. 4(c)), we recommend providing minimum buffer space that in numerically equal to *revised speed limit in ft/s x 3 seconds* as most crashes above 40 mph occur within 3 seconds of intrusion. We recommend using at least two site alarms while using the system, one placed close to the transition taper and the other placed next to the work area (see Fig. 5(a)). The alarm unit placed near the transition taper can be placed midway between the taper length. This configuration will ensure that intrusions detected by the sensors in the transition area is communicated to all site alarms regardless of their separation. Additionally, the spacing between the sensors in the transition taper should be based on engineering judgement such that vehicles would not be able to pass through the perimeter without striking the cones/sensors. It is noteworthy that as per MUTCD guidelines, the spacing between the traffic barriers should be limited to 40 ft on highways operating at 40 mph speed limit. Simlar guideline can be followed for the cones/sensors placed in rest of the work zones on all highways. In case of RAS, the primary objective while using the system should be to place it within transmission range of the work area as shown in Fig. 5(b). Since the system is recommended primarily for flagging, the MUTCD recommendation is to set transition taper at maximum of 150 ft for which the 400 ft transmission range of the system is adequate. When used with IAS, the layout for both the systems should be dictated by IAS and since the goal of RAS will be primarily to alert the drivers of the speed limit around a work zone. The layout for PAS should also be based on its transmission due to its comparatively limited range. We recommend buffer space for the system should be at least 100 ft with the sensor-to-alarm distance limited to 150 ft to ensure transmission and meet the MUTCD guidelines (Fig. 5(d)). It is worth noting that this recommendation also satisfies our finding demonstrated in Fig. 4(d) where a minimum time of at least 2 seconds is desirable for sensor-to-alarm distance of 100 ft since the system is recommended for use in facilities with operating speed less than 30 mph.

Table 11

System selection.

System	Type of work	Taper length	Type of facility
IAS	i. Long term construction with stationary traffic channelizers	Long tapers > 150 ft	Speed limit >30 mph
RAS	i. Flagging operation ii. Short term mobile work zone requiring speed enforcement	Medium tapers < 400 ft	Used in conjunction with IAS in facilities with speed limit > 40 mph
PAS	i. Short term mobile Construction and maintenance work zones ii. Work zones with minor encroachment	Short	Posted speed limit < 30 mph

	Tapers < 150 ft

7. Conclusion

This study employed non-parametric and semi-parametric survival analysis to investigate the influence of external variables associated with WZIAS on work zone crashes. The study used three WZIAS and subjected them to field tests wherein intrusions were imitated by driving test vehicles into a work zone with workers in a controlled setting. The activation of system alarms and worker reaction were then used to determine occurrence of crashes. The study contributed to the literature in the following manner.

i. Identification of WZIAS related external factors influencing work zone crashes

Previous studies evaluating WZIAS have focused entirely on their characteristics and performance. As per our knowledge, this is the first study that addresses the influence of external factors on the effectiveness of WZIAS. The manner of system deployment, more specifically the layout of systems components and intrusion speed has not been accounted for by previous studies while evaluating system efficacy.

Our findings highlight the influence of intrusion speed, sensor-to-worker spacing, and system accuracy on occurrence of work zone crashes. We conclude that among all these factors intrusion speed and adequate spacing between the system sensors and workers is imperative to reducing crashes since appropriate measures pertaining to these factors can be adopted in the field. This can be achieved by reducing speed limits and standardizing the length of the buffer space to provide adequate separation.

ii. Standardization of deployment strategies for systems

Although current literature recommends appropriate use cases for systems based on field experiments (Marks et al., 2017) specific recommendations that translate theoretical knowledge derived from field tests to standardized field practice is missing.

In this study we recommend appropriate use case scenarios for systems based on their transmission range and ease of installation. Additionally, we also present ideal deployment strategies for the system with revisions to existing MUTCD guidelines. Revisions recommended to existing guideline include standards for buffer space and appropriate placement location of system components within a work zone.

Declaration of competing interests

Authors declare no competing interests.

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