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Evaluation of Work Zone Mobility by Utilizing Naturalistic Driving Study Data, Phase II

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ABSTRACT

The objective of this research was to study work zone mobility by utilizing the second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) data. The NDS data provides a unique opportunity to study car-following behaviors for different driver types in various work zone configurations, which cannot be achieved through traditional field data collection. The complete NDS work zone trip data of 200 traversals by 103 individuals, including time-series data, forward-view videos, radar data, and driver characteristics, was collected at four work zone configurations (two-to-one and three-to-two lane closure, and two-to-two and three-to-three shoulder closure), which encompasses nearly 1,100 vehicle miles traveled (VMT), 19 vehicle hours traveled (VHT), and over 675,000 data points at 0.1-s intervals. First, the gap and headway were analyzed for different drivers (gender, age group, and risk perceptions) to develop the gap and headway selection tables. Furthermore, the speed profiles for different work zone configurations were established to explore the speed change through the entire work zones. The generalized additive model (GAM) was used to develop the best-fit curves of time headway and speed distributions. The change point detection method was used to identify where significant changes in mean and variance of speeds occur. The research results provided additional information on potential impact of human factors on car-following models at work zones that have been implemented in current work zone planning and simulation tools. Additionally, the findings of this work can also be helpful to the automotive industry to improve Adaptive Cruise Control (ACC) gap spacing setting at work zones.

Keywords (up to 5):

Naturalistic Driving Study, Work Zone Mobility, Gap and Headway, Speed Profile, Driving Behavior

EXECUTIVE SUMMARY

As maintenance and construction work increase, work zone mobility has become a major concern for transportation agencies. The second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) data provides a unique opportunity to study car-following models for different driver types under different work zone configurations. However, driver characteristics, such as gender, age group, and risk perception are typically not available using the traditional roadside data collection methods. Current work zone mobility studies (simulation-based methods or field study) generally do not consider driver characteristics. Driver characteristics can be a very important factor contributing to work zone capacity because different types of drivers react differently to work zones. Although there have been several work zone studies that applied NDS data, none of them have focused on work zone mobility. In the first phase of the project, researchers ascertained the NDS data can be used to develop new (or update existing) capacity and traffic flow models for three types of work zones, based on a small data sample. Collecting more complete trip information that traverse the entire work zone (500 ft upstream, advance warning area, transition area, activity area, termination area, and 500 ft downstream) is recommended to support further study. Thus, this project collected the complete NDS work zone trip data of 200 traversals by 103 individuals at four work zone configurations (two-to-one and three-to-two lane closure, and two-to-two and three-to-three shoulder closure), which encompasses nearly 1,100 vehicle miles traveled (VMT), 19 vehicle hours traveled (VHT), and over 675,000 data points at 0.1-s intervals. The gap and headway selection tables, and speed profiles, were developed for different types of drivers in four freeway work zone configurations.

Key findings are summarized as follows:

- Gap and headway selection tables revealed that car-following behaviors are significantly different among different driver characteristic groups at different areas of work zones.
- Speed distribution analysis indicated that speeds decrease at the transition area and increase near the termination area for lane closure conditions, while for shoulder closure conditions, significant speed reduction was only found at locations where concrete barriers appeared and narrowed shoulder clearance.

This is the first study that applies SHRP 2 NDS data to study the impact of driver characteristics on gap and headway selection and speed distribution during the entire work zone areas. Current SHRP 2 NDS database contains limit trips and work zone configurations. It is suggested to collect more NDS data to further validate the headway selection and speed distribution by different driver types for more work zone configurations.

1.0 INTRODUCTION

The number of work zones has been increasing to address the growing needs for highway maintenance and construction as the National Highway System (NHS) is aging. According to the Federal Highway Administration (FHWA), work zones accounted for an estimated 10% of overall congestion and 24% of unexpected freeway delays, which was equivalent to about 888 million vehicle-hours in 2014 (FHWA Work Zone Facts and Statistics 2019). Due to reduced operating speeds, narrowed lane widths, and smaller shoulder clearances, the capacity per lane in work zone is lower than that in the non- work zone (Yeom, Rouphail and Rasdorf 2015). Thus, in order to arrange for the construction work on the freeway and mitigate the delay issues, State Departments of Transportation (DOTs) and local transportation agencies have applied various simulation models and planning tools to estimate or predict work zone capacity (Yeom, Rouphail and Rasdorf 2015, Weng and Meng 2015, Weng and Meng 2011, Transportation Research Board 2016, Weng and Meng 2012, Heaslip, et al. 2009, Kan, Ramezani and Benekohal 2014). Traffic simulation software, for example, CORSIM (developed by the University of Florida, USA) and VISSIM (developed by PTV Group, Karlsruhe, Germany), have been used to estimate the operational capacity of work zones with different configurations for decades (Heaslip, et al. 2009, Chatterjee, et al. 2009, Heaslip, Jain and Elefteriadou 2011). The calibration of these simulation models requires field data to ensure the accuracy of the estimated results. Meanwhile, the planning-level work zone simulation tools such as QUEWZ (University of Florida, USA) and QuickZone (FHWA, USA) are also popular among DOTs although it was reported that the QUEWZ and QuickZone were inaccurate due to outdated field data and parameters (Benekohal, Kaja-Mohideen and Chitturi 2003, Ramezani and Benekohal 2012, Ishimaru and Hallenbeck 2019, Trask, et al. 2015).

The second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS) data has shown the potential to provide various information, which can be used to refine the estimated results from these models and tools. The SHRP 2 NDS data is a new approach to investigate driver behavior during daily trips through unobtrusive data gathering equipment and without experimental control (Van-Schagen, et al. 2011). Compared with traditional field data collection techniques, the NDS data offers a unique opportunity to observe actual work zone layouts, traffic conditions, and driver performance while negotiating freeway work zones (Dingus, et al. 2015). In Phase I, the researchers utilized the NDS data to evaluate capacity, car-following characteristics, and driver types in three freeway work zone configurations [two-to-one lane closure (LC 2-1), two-to-two shoulder closure (SC 2-2), and three-to-three shoulder closure (SC 3-3)] (Zhou, Turochy and Xu 2019). It was the first attempt to apply NDS data to study the headway distribution at work zones based on driver characteristics. In the second phase of this study, the researchers collected more complete trips that traverse the entire work zone (500 ft upstream, advance warning area, transition area, activity area, termination area, and 500 ft downstream) for further study.

1.1 OBJECTIVE

The study objectives were set to:

1. Develop gap and headway selection tables based on different driver characteristics (i.e., gender, age group, and risk perception) at four work zone configurations; and
2. Perform a speed analysis to develop speed distribution models and identify key speed change points at work zones.

1.2 SCOPE

The scope of the study was limited to four types of work zone configurations on freeways, including two-to-one lane closure (LC 2-1), three-to-two lane closure (LC 3-2), two-to-two shoulder closure (SC 2-2), and three-to-three shoulder closure (SC 3-3). NDS data used includes time-series (e.g., speed and acceleration rate), forward roadway videos, radar data, and driver risk perceptions.

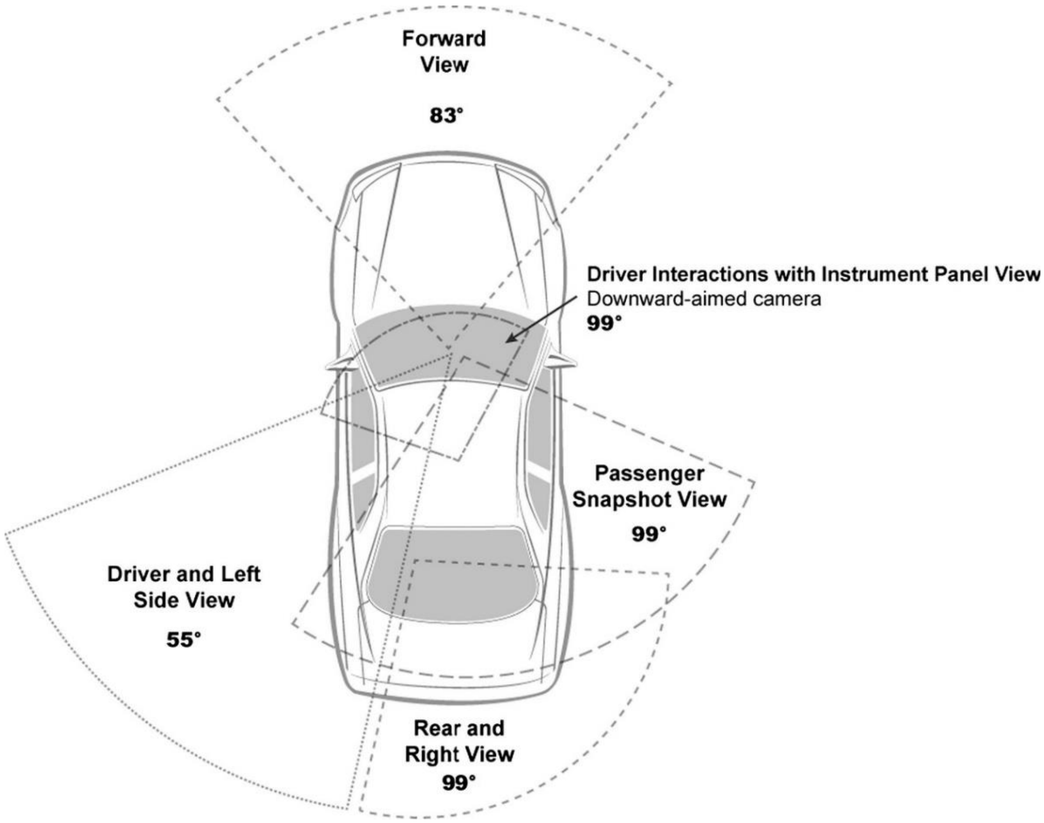
2.0 LITERATURE REVIEW

The literature review is divided into seven sections to summarize the related past studies on SHRP 2 NDS data, freeway work zone capacity estimation, work zone simulation models, headway and gap distribution, and speed studies. These sections are followed by a brief review of other SHRP 2 NDS applications in work zones and a summary of findings and gaps identified in the literature review.

2.1 SHRP 2 NDS Data Overview

SHRP 2 NDS aims to improve safety and reliability for motorists and providing answers to key traffic- and safety-related questions (Dingus, et al. 2015). Extensive data collection was conducted to achieve the goal of SHRP 2, which offers a unique opportunity to address different research questions that were not able to be studied before. To fulfill the critical gap in data about driver behavior, the SHRP 2 Safety Program conducted the most comprehensive NDS that collected large-scale data from six states, including Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington (Strategic Highway Research Program 2014). The NDS database contains comprehensive video and vehicle sensor data collected from drivers and their vehicles over a three-year period. More than 3,500 volunteer drivers from the six study sites participated in this study with their everyday or “natural” driving behavior recorded. From 2010 to 2013, over five million trips with nearly 50 million miles of driving were monitored with more than 4 petabytes of naturalistic information. The volunteer drivers were balanced with approximately equal numbers of male and female in all age groups. Six data collection areas were selected to represent a mix of road types and weather conditions. The participants were recruited through call centers and traditional methods (Campbell 2012).

The vehicles from the participating drivers were instrumented with a data acquisition system (DAS) capable of collecting high-resolution data including vehicle kinematics, lane tracking, forward radar data, and video recordings of the forward and rear roadway. The complete data collection procedure was established by the Virginia Tech Transportation Institute (VTTI) (Hankey, Perez and Mcclafferty 2016). **Figure 1** presents the video camera views. Each participant’s vehicle was equipped with forward view (upper left), driver and left side view (upper right), instrument panel view (lower left), and rear and right view (lower right) cameras to record both the in-vehicle and out-of-vehicle environment. Data were continuously recorded while the participant’s vehicle was operating.



(*a*)

(*b*)

FIGURE 1. VIDEO CAMERA VIEWS: (*A*) FIELDS OF VIEW FOR THE DAS (ANTIN, LEE AND PEREZ, ET AL. 2019); (*B*) QUAD IMAGE OF FOUR VIDEO CAMERA VIEWS (DINGUS, ET AL. 2015).

The NDS data were divided into two portions (InSight and InDepth) regarding their nature. The InSight data are divided into four categories: vehicle, drivers, trips, and events. The information provided under each category is summarized in **Table 1**. The data was either directly captured by the DAS during data collection period, or through questionnaire surveys.

TABLE 1. SUMMARY OF INSIGHT DATA CATEGORIES.

Vehicles	Vehicle types (car, truck, van, etc.)
	Vehicle ages and condition
	Amount of data collected per vehicle
	Quantities of vehicles installed
	Vehicle technologies and equipment
Drivers	Numbers of participating drivers
	Amount of data collected per driver
	Driver demographics and driving history
	Driver physical and psychological state
	Driver participation experience
Trips	Summary measures describing trips
	Trip length, duration, start time, stop time
	Min, max, mean for speed, acceleration
	Trip summary record table
	Trip density maps
Events	Crashes, near crash, and baseline event records
	Events by type and severity
	Event viewer

The second portion of NDS data is known as InDepth, which data includes information that may potentially result in identifying the participants. These data contain time series data and video data, which are not available on InSight database.

The SHRP 2 NDS data offers a unique opportunity to observe actual work zone layouts, traffic conditions, and driver performance while negotiating freeway work zones. NDS data provides driver demographic information that could not be obtained in the traditional field data collection.

2.2 Capacity Estimation

Numerous studies have focused on work zone capacity issues, including several methods that have been proposed to estimate and predict work zone capacity. These methods can be divided into parametric and nonparametric methods (Weng and Meng 2015).

The parametric method uses a predetermined form to predict work zone capacity based on the field data so that the coefficients of predictors can be determined (Lu, et al.

2018). It has been widely used to estimate both the short-term and long-term work zone capacity by considering parameters such as work intensity, number of closed lanes, lateral distance to the lane closure, work zone length, presence of ramps, heavy vehicle adjustment factor, the day of the week, and weather conditions (Krammes and Lopez 1994, Kim, et al. 2000, Al-Kaisy, Zhou and Hall 2000). In addition, the 6th edition of the Highway Capacity Manual (HCM) offered detailed guidance on determining work zone capacity by including lane closure severity index, barrier type, area type, lateral clearances, and day-or nighttime work conditions. It defined capacity as "the maximum sustainable hourly flow rate at which persons or vehicles reasonably can be expected to traverse a point or a uniform section of a lane or roadway during a given time period under the prevailing roadway, environmental, traffic, and control conditions" (Transportation Research Board 2016). Another way to estimate the work zone capacity is to derive the capacity from speed-flow curves. Over the years, some researchers adopted this method to derive information from the prediction model (Weng and Meng 2015, Sarasua, et al. 2006, Racha, et al. 2008, Avrenli, Benekohal and Ramezani 2011, Bharadwaj, et al. 2018).

When estimating the work zone capacity, sometimes it is not feasible to describe the capacity by mathematical functions due to nonlinear relationships and complex interactions between a large number of variables and capacity (Adeli and Jiang 2003). Therefore, several non-parametric methods, such as neural-fuzzy logic, decision tree, and ensemble tree models, have been applied to provide work zone capacity estimations (Weng and Meng 2011, Weng and Meng 2012, Adeli and Jiang 2003, Karim and Adeli 2003, Weng and Meng 2013). The nonparametric method is a technique that does not assume that the structure of a model is fixed (Corder and Foreman 2014). Because of fewer assumptions being made by nonparametric methods, these models are more flexible, robust, and applicable to nonquantitative data (Yau 2013). However, it was also pointed out that nonparametric approaches typically require generous historical traffic data to provide accurate and reliable predictions (Karim and Adeli 2003).

2.3 Simulation Models

According to the use of traffic analysis tools and simulation models in the FHWA Traffic Analysis Toolbox, simulation tools have been widely applied in much traffic analysis research (Dowling, Skabardonis and Alexiadis 2004). From the most generalized to the most complex, simulation tools can be grouped into four categories: sketch-planning tools; macroscopic simulation models; mesoscopic simulation model; and microscopic simulation models.

Sketch-planning methodologies and tools produce general order-of-magnitude estimates of travel demands and traffic operations in response to transportation changes (Zhang, et al. 2012). The planning level work zone simulation tools include software such as QUEWZ (University of Florida, USA), QuickZone (FHWA, USA), FREEVAL-WORK ZONE

(North Carolina State University, USA), etc. (Alexiadis, Jeannotte and Chandra 2004). As high-level planning applications, these deterministic tools aid in simpler approaches in that data requirements, calibration, and interpretation of the results are highly aggregated. Thus, they cost the least time or money in which to facilitate rapid analysis. These advantages, however, are coupled with the weakness in that the network complexity, potential network impacts, vehicle interactions, and high-level analysis are limited. It was found that the QUEWZ and QuickZone were not accurate in past studies (Trask, et al. 2015, Bharadwaj, Edara and Sun 2019). The inaccurate results were caused by outdated parameters or models. For example, the QUEWZ models were developed based on the 1965 HCM general speed-flow relationship and regression based on field data (Ishimaru and Hallenbeck 2019).

Macroscopic simulation models are based on the deterministic relationships of the flow, speed, and density of the traffic stream that treat traffic flows as an aggregate quantity without analyzing individual vehicle movement (Zhang, et al. 2012). These simulation models include software such as the TRANSYT-7F (University of Florida, USA) package within the Highway Capacity Software (HCS) from McTrans (Alexiadis, Jeannotte and Chandra 2004). While these models have the ability to model a large geographic area and provide slightly more details than the sketch-planning tools, they are still limited to their simple representations of traffic movement and do not account for the stochasticity of work zone environments.

Mesoscopic simulation models are a combination of both microscopic and macroscopic simulation models (Zhang, et al. 2012). While they still model at an aggregate level and the focus is on the movement of a platoon of vehicles, their unit of traffic flow is the individual vehicle; further, different platoons' interactions are considered. These models are able to model both large geographic areas and corridors, but their primary limitation is their inability to model detailed operational strategies. Thus, these tools may not be helpful for individual work zones.

Microscopic models simulate the movement of every vehicle in the network based on car-following, lane-changing, and gap-acceptance theories (Zhang, et al. 2012). These tools are based on a stochastic process, and every vehicle in the network can be tracked over short time-intervals so that the result of each run is unique. Popular microscopic simulation software includes CORSIM and VISSIM, which are developed by FHWA and the PTV Group, respectively (Alexiadis, Jeannotte and Chandra 2004). These models aim to represent transportation systems accurately at the individual vehicle level and are effective in modeling plenty of scenarios such as heavily congested conditions, complex geometric configurations, and system-level improvement impacts. CORSIM and VISSIM have been used in several studies to estimate the capacity of work zones with different lane closure configurations (Heaslip, et al. 2009, Chatterjee, et al. 2009, Heaslip, Jain and Elefteriadou 2011). However, the detailed and comprehensive analysis requires a substantial amount of roadway geometry, traffic control, and traffic pattern data. In addition, to represent real-world traffic conditions, it was suggested that further calibration work is needed to address other issues with specific work zone configurations (Yeom, Rouphail and Rasdorf 2015). This calibration process is usually tedious and expensive.

2.4 Headway and Gap Distribution

Vehicle time headway is a critical traffic flow characteristic that affects the level of service (LOS) and capacity (May 1990). Time headway or headway is defined as the time between two consecutive vehicles (in seconds) when they pass a single point on a roadway (Mathew and Rao 2006). Thus, in work zones, this factor is of utmost importance to analyze so that accurate vehicle dynamics in work zones can be generated. Headway distribution modeling has been studied for decades (Ye and Zhang 2009). Many vehicle headway distribution models have been proposed to model the vehicle headway at various traffic flow levels, including exponential distribution, Weibull distribution, gamma distribution, lognormal distribution, Erlang distribution, and inverse Gaussian distribution (Cowan 1975, Sun and Benekohal 2006, Greenberg 1966). These studies only fit the models in the mixed vehicular traffic without consideration of vehicle headways for different types of vehicle following patterns. Thus, researchers began to disaggregate vehicle headways into various types as the leader and follower vehicle pairs, such as the car-truck pair, truck-car pair, truck-truck pair, and car-car pair (Ye and Zhang 2009, Hoogendoorn and Bovy 1998, Weng, Meng and Fwa 2014). However, as work zone traffic has unique characteristics, few studies explored vehicle headway distribution in work zones (Sun and Benekohal 2006, Weng, Meng and Fwa 2014). Moreover, none of the past studies considered the effects of driver characteristics on headway in work zones, despite the fact that different drivers exhibit various influences due to their unique driving behaviors. Therefore, there is a need to develop headway selection tables based on driver characteristics in work zones.

Gap spacing is the distance between two consecutive vehicles during vehicle following, which is the core of adaptive cruise control (ACC) systems (Swaroop and Rajagopal 2001). There are two major gap spacing categories in the previous research, including constant spacing policy and variable spacing policy (Swaroop and Huandra 1998). The constant spacing policy always keeps a constant spacing between two consecutive vehicles which is independent of driving environment (Gerdes and Hedrick 1996, McMahon, Hedrick and Shladover 1990, Chehardoli and Homaeinezhad 2018) If a small spacing is chosen, a high traffic capacity will be provided (Darbha, Rajagopal and Tyagi 2008). However, no ACC systems have adopted the constant spacing policy on the market in practice (Xiao, Gao and Wang 2009, Sheikholeslam and Desoer 1990, Seiler, Pant and Hedrick 2004, Farnam and Sarlette 2019, Căilean and Dimian 2017).

The variable spacing policy treats the desired spacing between consecutive vehicles as a function of the ACC vehicle's speed, which includes the time headway-based, traffic flow stability, constant safety factor and human driving behavior spacing policies. The most common spacing policy in both academia and automotive industry is the time headway-based spacing (Wang and Rajamani 2004). In the previous studies, the term "time gap" was used instead of "time headway" (van der Heijden, Lukaseder and Kargl 2017, Căilean and Dimian 2017, Lin, et al. 2008, Moon, Kang and Yi 2010, Bageshwar, Garrard and Rajamani 2004). "Time gap" refers to the time between the rear bumper of the leading vehicle and the front bumper of the following vehicle when passing a fixed position, while "time headway" refers to the time between the front bumper of the leading vehicle and the front bumper of the following vehicle when passing a fixed position. "time gap" and "time headway" are different in quantity, but they lead to the same vehicle behavior based on the qualitative perspective (Stüdli, Seron and Middleton 2017). In automotive industry, ACC systems normally select the range of time gap between 1 to 2 seconds (Naranjo, et al. 2006). However, the time headway-based spacing is not suitable for high density traffic conditions due to the failure of traffic flow stability (Marsden, cDonald and Brackstone 2001, Darbha and Rajagopal 1999, Wang and Rajamani 2004).

Thus, the traffic flow stability spacing is introduced to solve this problem. One of the traffic flow stability spacing policies was designed based on the Greenshield's model, which was proven to maintain traffic flow stability and ensure safety (Wang and Rajamani 2004, Swaroop and Huandra 1998, Zou and Levinson 2002). The other one was developed based on the traffic volume flow rate curve with the desired spacing being a nonlinear function of the speed of the following vehicle (Santhanakrishnan and Rajamani 2003).

Constant safety factor spacing was proposed to improve safety as safety is one of the major concerns in ACC systems (Xiao and Gao 2010, Shladover, et al. 2015). This policy can be obtained by analyzing the emergency braking process (Mackinnon 1975). However, the safety factor spacing emphasizes more on the safety perspective and it is more conservative safety-wise (Tomizuka and Karl- Hedrick 1995).

The fourth gap spacing is human driving behavior spacing, which is to enhance driver comfort and take human driving behaviors into consideration for ACC systems (Fancher, Bareket and Ervin 2001). It was stated that the ACC spacing should be similar to human driver's spacing behavior (Zhou and Peng 2005) and real human driving data was employed to develop ACC systems (Moon and Yi 2008, Kesting and Treiber 2008, Fancher, Bareket and Peng, et al. 2003). In a previous study, Peng *et al*. recorded 107 drivers' driving behaviors to develop a human driving behavior spacing policy. It was proved that this spacing policy can improve customer acceptance and system utilization by introducing driver characteristics (Gao, et al. 2015). However, more research is needed to further expand and develop the human driving behavior spacing policy that is similar to human drivers to reflect their physical and mental capabilities. From this perspective, the SHRP 2 NDS data offers the potential for developing the human driving behavior spacing policy for ACC systems in the automotive industry.

2.5 Speed Studies

There are various factors that affect the speed of vehicles passing through a work zone, including roadway geometrics, such as the number of lanes, lane width, horizontal and vertical curvature, lateral clearance; traffic warning signs (variable speed limit signs, speed monitoring and display, flaggers), and law enforcement (Noel, et al. 1988). Previous work zone speed studies mainly addressed factors affecting speed limits, driver compliance with speed limits, enforcement, and safety issues (J. Migletz, J. Graham, et al. 1998, Bham and Mohammadi 2011, Benekohal, Kaja-Mohideen and Chitturi 2004, J. Migletz, J. L. Graham, et al. 1999, Pesti and McCoy 2001, Li and Bai 2008).

It was found that narrowed lane widths contributed to greater speed reduction (Chitturi and Benekohal 2005). Another study evaluated the effectiveness of signs usage to reduce speed of traffic through work zones. As recommended by the NCHRP, the normal posted speed is typically reduced by 10 mph for work zones (J. Migletz, J. Graham, et al. 1998). It was stated that Changeable Message Sign (CMS), speed display trailers or CMS with radar, innovative signs, flagging treatments, lane narrowing, late merge, transverse striping, and rumble strips are the commonly used speed reduction methods and strategies (Bham and Mohammadi 2011, Benekohal, Kaja-Mohideen and Chitturi 2004). For driver compliance, it was found that compliance was the greatest where the speed limit was not reduced, and compliance decreased where the speed limit was reduced by 10 mph or more (J. Migletz, J. L. Graham, et al. 1999). In a recent study, Adeli evaluated driver speed variations according to speed limits and road work signs based on driving simulator data (A. Adeli 2014). The results found that driver’s age, road familiarity, and experience had a noteworthy impact on speed limit compliance. However, research has shown that once the enforcement tool (police vehicle patrolling or a speed feedback trailer) is out of sight, vehicle speeds will return to their previous levels (Pesti and McCoy 2001). As for safety issues, it was revealed that the greatest number of fatal crashes occurred on highways with speed limits between 61 and 70 mph, which confirmed that high speeds increase the severity of work zone crashes (Li and Bai 2008). Furthermore, the previous speed studies in work zones did not provide a full picture of speed profiles when utilizing spot-measured data. Thus, it would be useful to perform a speed analysis that explores the speed distribution and speed change in the form of time series at work zones.

2.6 Other Work Zone Studies that Utilizing NDS Data

There have been a few studies utilizing NDS data to study work zone safety. Goswamy used NDS data to investigate work zone safety, especially the role of speed and distraction in work zone crashes and near-crashes (Goswamy 2019). Another work zone study used statistical descriptions of normal driving behavior to identify abnormal behavior as the basis for countermeasures by utilizing NDS data (Flannagan, et al. 2019). Bharadwaj *et al*. investigated risk factors and developed a binary logistic regression model to estimate the crash risk in work zones (Bharadwaj, Edara and Sun 2019). The authors also quantified the risk of different contributing factors. For instance, it was found that the odds ratio of driver inattention is 29, which is the most critical behavioral factor contributing to crashes. Chang and Edara applied four machine-learning algorithms to work zone events with NDS data to predict the occurrence of a safety-critical event by using pre-event variables (Chang and Edara 2017). These algorithms included the random forest, deep neural network, multilayer feed forward neural network, and t-distributed stochastic neighbor embedding. It was concluded that the random forest algorithm performed the best in classifying different safety-critical events with a prediction accuracy of 97.7%.

2.7 Gaps between the Previous Research and Proposed Work

In summary, the comprehensive review of the available literature indicated that very few work zone studies in the past considered driver characteristics and their car-following behaviors. The NDS data can provide this unique information that could not be obtained from field data collection or traffic simulation models. The driver types and their gap and headway distributions in work zones would be helpful to identify how driver behaviors affect work zone capacity. Moreover, the NDS data can be used to develop gap spacing policies for ACC systems based on human driving behavior in work zones. The literature review also revealed that none of the previous studies that applied SHRP 2 NDS data investigated the work zone mobility. The impact of driver characteristics on gap and headway selection and speed distribution during the entire work zone areas has never been studied. Furthermore, the results can be used to enhance work zone planning and simulation models by considering different headway distributions based on driver characteristics and their speed profiles traversing the entire work zone.

3.0 METHODOLOGY

This section provides the methods to perform SHRP 2 NDS data collection and reduction, headway and gap distribution, and speed analysis.

3.1 Data Collection and Reduction

A conference call was scheduled with Virginia Tech Transportation Institute (VTTI) staff for requesting proper work zone NDS data. First, over 58-hour sample video clips were delivered to identify work zone start and end mileposts, so that the trips that traversed the same locations during the same time periods can be exported. The exported time interval covers at most 20 weeks (10 weeks before and 10 weeks after the identified sample trips occurred). However, as work zone activity proceeded, the configuration changed very quickly. For example, although work zone start and end milepost were identified from the first step, work zone configuration might have changed within 2 weeks (1 week before and 1 week after the identified sample trips). Thus, all received NDS videos were reviewed to assure that they were categorized into the proper work zone configuration.

The time-series data (i.e., speed), radar data (i.e., time gap), and video clips of the forward roadway were obtained for each trip. All the time-series data and radar data were collected at 0.1-s intervals. **Table 2** provides the data dictionary in time-series reports. As the radar data dictionary file stated, the headway collected from radar is actually gap in seconds which equals to the distance between target rear bumper and participant vehicle front bumper divided by the participant's vehicle speed. Space headway is defined as the distance between the same points of two consecutive vehicles following each other (Mathew and Rao 2006) Thus, an average vehicle length of 15 ft (Sellén 2021) was added to such distance, so that the time headway was counted from the lead vehicle's front bumper to the participant vehicle's front bumper. It should be noted that when there is no (or close enough) target vehicle in front of participant vehicle, headways become unavailable. The example data is provided in **Figure 2**.

TABLE 2. NDS TIME-SERIES DATA DICTIONARY.

Variable Name	Description
vtti_timestamp	Time since beginning of trip, in milliseconds
vtti_speed_network	Vehicle speed indicated on speedometer collected from network, in km/h
vtti_accel_x	Vehicle acceleration in the longitudinal direction versus time, in *g*
vtti_pedal_brake_state	On or off press of brake pedal, 0 = off; 1 = on
LEADVEHICLE_HEADWAY	Headways which equal to the distance between target rear bumper and participant vehicle front

	bumper divided by the participant's vehicle speed, in seconds

vtti.timestamp	vtti.file_id	vtti.accel_x	vtti.pedal_brake_state	vtti.pedal_gas_position	vtti.speed_network	vtti.video_frame	LEADVEHICLE_HEADWAY
1182800	27185101	0	0	14.75	86.5475	17695	1.059582
1182900	27185101	0.0087	0	15.875	86.5675	17696.5	1.060143
1183000	27185101	0.0319	0	16.3	86.545	17698	1.059526
1183100	27185101	0.0087	0	16.875	86.6425	17699.5	1.059962
1183200	27185101	0.0232	0	17	86.6275	17701	1.060723
1183300	27185101	0.0406	0	17	86.572	17702.5	1.062516
1183400	27185101	0.0058	0	17.3	86.63	17704	1.060484
1183500	27185101	0.0232	0	17.25	86.475	17705.5	1.062394
1183600	27185101	0.0058	0	17	86.445	17707	1.064325
1183700	27185101	-0.0029	0	17	86.455	17708.5	1.064268
1183800	27185101	0.0203	0	17	86.45	17710	1.066142
1183900	27185101	0.0145	0	16.5	86.4125	17711.5	1.066949
1184000	27185101	0.0203	0	16.5	86.318	17713	1.069653
1184100	27185101	0.0203	0	16.5	86.34	17714.5	1.070163
1184200	27185101	0.0087	0	16.6	86.3025	17716	1.072527
1184300	27185101	0.0261	0	17	86.3125	17717.5	1.072611
1184400	27185101	0.0058	0	17.75	86.32	17719	1.073194
1184500	27185101	0.0145	0	20.125	86.3575	17720.5	1.073753

(*a*)

(*b*)

FIGURE 2. NDS EXAMPLE DATA FOR FREEWAY WORK ZONES: (*A*) TIME-SERIES REPORT; AND (*B*) FORWARD-VIEW VIDEO.

The forward-view video can be linked to time-series data and radar data so that the corresponding speed and time gap at certain 0.1 s can be acquired. Driver risk perception and driver demographics data were also requested. Driver risk perceptions were calculated based on self-reported measures, which indicated their perceptions of risk associated with different driving behaviors. Higher scores indicate greater risk perceptions. The driver risk perception was collected from the questionnaire designed to gauge the participant's perception of dangerous or unsafe driving behaviors or scenarios (Transportation Research Board of the National Academies of Science 2020). This questionnaire includes 32 driving-behavior-related questions. For example, how would the participant evaluate the risk when not yielding the right-of-way, the participant's associated risk with passing other cars on the right side or the shoulder of the road, the participant's associated risk with turning without signaling, etc. Each question was assigned a score from 1 (No Greater Risk) to 7 (Much Greater Risk). Therefore, the total scores range from 32 to 224.A higher score indicates that the driver is more cautious or obedient to traffic rules. The total risk perception score of drivers is the sum of all the scores from questions in the questionnaire.

To eliminate the potential distraction or impact by non- work zone elements, only trips that occurred during daylight time with clear vision in good weather condition on the dry pavement were selected. To reduce the impact of interchanges near work zones that might potentially influence driver performance, trips near interchanges were also filtered to exclude the effects of merging and diverging maneuvers on driver behaviors. A total of 200 complete work zone trips traversed the entire work zone (500 ft upstream, advance warning area, transition area, activity area, termination area, and 500 ft downstream) driven by 103 unique drivers were finally selected at four locations. Each represents one work zone configuration. According to the FHWA, lane closure and shoulder closure are the most common types of construction in work zones (FHWA 2020). Meanwhile, four- and six-lane divided highways are the most common types of roadways that occupy over 90% of the Interstate System mileage (FHWA 2017). Thus, four work zone configurations were selected in this study as presented in **Figure 3**. They are lane closure with lane reduction from two lanes to one lane (LC 2-1), lane closure with lane reduction from three lanes to two lanes (LC 3-2), shoulder closure with two lanes (SC 2-2), and shoulder closure with three lanes (SC 3-3), which encompass nearly 1,100 VMT, 19 VHT, and over 675,000 data points at 0.1-s intervals. A work zone typically consists of four consecutive sections: advance warning area, transition area, activity area, and termination area. In lane closure work zones (**Figure 3*a*** and **Figure 3*b***), it is easy to define these four sections. But in shoulder closure work zones, the borders among transition area, activity area, and termination area are not clear. In this study, only two areas were defined for shoulder closure work zones: advance warning area and work zone area. It should be noted that the distances between traffic control devices noted in each part of Figure 3 are based on application of the principles in Part 6 of MUTCD.

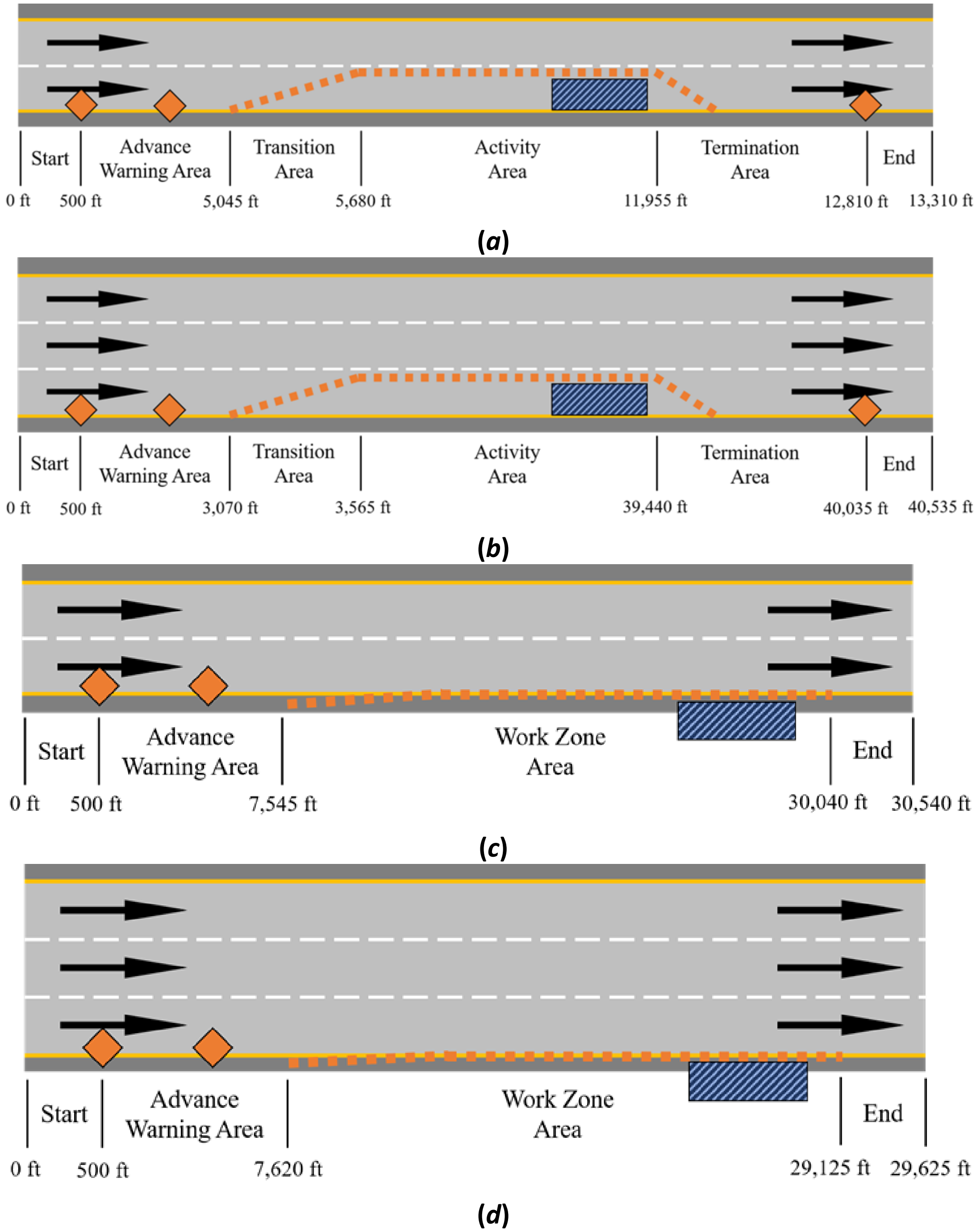


FIGURE 3. FOUR WORK ZONE CONFIGURATIONS: (*A*) LC 2-1; (*B*) LC 3-2; (*C*) SC 2-2; AND (*D*) SC 3-3.

The speed control methods were only applied at lane closure configurations with portable changeable message signs at the beginning of transition area. Work zone speed limits that affect speed choice were only appeared in the LC 2-1 locations. There was no other law enforcement to affect speed reduction in the other three work zone locations.

Only SC 2-2 appeared concrete barriers while other three work zone configurations were all used drums. **Table 3** summarizes numbers of unique drivers and trips at each work zone configuration (location), and their geographic locations. One LC 2-1 work zone is in New York State, and the other three work zones are geographically located in Florida.

TABLE 3. SUMMARY OF FINAL DATASET

Work Zone Configuration (Location)	Geographically Located	Number of Unique Drivers			Number of Trips
		Female	Male	Total	
LC 2-1	New York	11	9	20	50
LC 3-2	Florida	10	10	20	50
SC 2-2	Florida	10	14	24	50
SC 3-3	Florida	21	17	38	50

3.2 Headway and Gap Distribution

The headway and gap distributions through the entire work zone were explored for the four different configurations. To identify the relationships between headway/gap selection and driver characteristics, all drivers were categorized into different age groups: young, middle-aged, and senior groups.

3.2.1 Generalized Additive Model

To explore the driver's headway distribution through the entire work zone, the generalized additive model (GAM) was used to predict the best-fitted curve of headway profile of work zone consecutive sections to provide a better understanding of how driver negotiating the entire work zone, given the headway data from NDS. When compared with other techniques, GAM has three key advantages: (1) easy to interpret; (2) flexible predictor functions can uncover hidden patterns in the data; and (3) regularization of predictor functions help avoid overfitting (Larsen 2015). The GAM (Hastie and Tibshirani 1990, Wood 2017) allows non-linear functions of each variable, while maintaining the additivity of the model. This is achieved by replacing each linear component $\beta_j x_{ij}$ by a smooth non-linear function $f_j(x_{ij})$. A GAM can be written as **Equation 1**:

$$y_i = \beta_0 + \sum_{j=1}^{n} f_j(x_{ij}) + \varepsilon_i = \beta_0 + f_1(x_{i1}) + f_2(x_{i2}) + \cdots + f_n(x_{in}) + \varepsilon_i \qquad (1)$$

Where,

y_i = Dependent variable

x_{in} = Predictor variable

$f_n(x_{in})$ = Smooth non-linear function

GAM allows fitting a non-linear function f_j to each x_j that one does not need to manually try out numerous transformations on each of the predictor variables. Since GAM is an additive model, one can examine the impact of each x_j on y_i individually. In this model, the smoothness of function f_j for the variable x_j is summarized via degrees of freedom. In GAM, the linear predictor predicts a known smooth monotonic function of the expected value of the response, and the response may follow any distribution (Wood 2017). To compare GAM with the other models such as the polynomial regression model, the Akaike information criterion (AIC) is an estimator of the relative quality of models for a given set of data. AIC uses a model's maximum likelihood estimation (log-likelihood) as a measure of fit. Typically, lower AIC values indicate a better-fit model. The R package 'mgcv' (Wood and Wood 2021) with the 'gam' function was applied to develop the GAM models.

3.3 Speed Analysis

A speed analysis was performed to explore the speed distribution and speed change over the entire work zone. To achieve this goal, GAM and change point detection techniques were applied.

3.3.1 Change Point Detection

To identify whether vehicle speeds significantly varied before, during, and after work zone, a change point analysis was conducted. The change point detection, also known as breakpoint analysis, is an algorithmic approach using maximum-likelihood estimation to quantify the point at which the statistical properties of a sequence of observations change. Multiple change points were detected using a nonlinear asymptotic model listed in **Equation 2**:

$$y = a - be^{-cx} \tag{2}$$

Where, x = Distance from the forest edge
y = Variable of interest

If multiple statistically significant change points are detected, the change point that most accurately represented a visible change in the data trend will be selected. The R package 'changepoint' (Killick and Eckley 2014) with the 'cpt.meanvar' function was used to examine concurrent changes in the mean and variance of each speed data sequence.

4.0 RESULTS

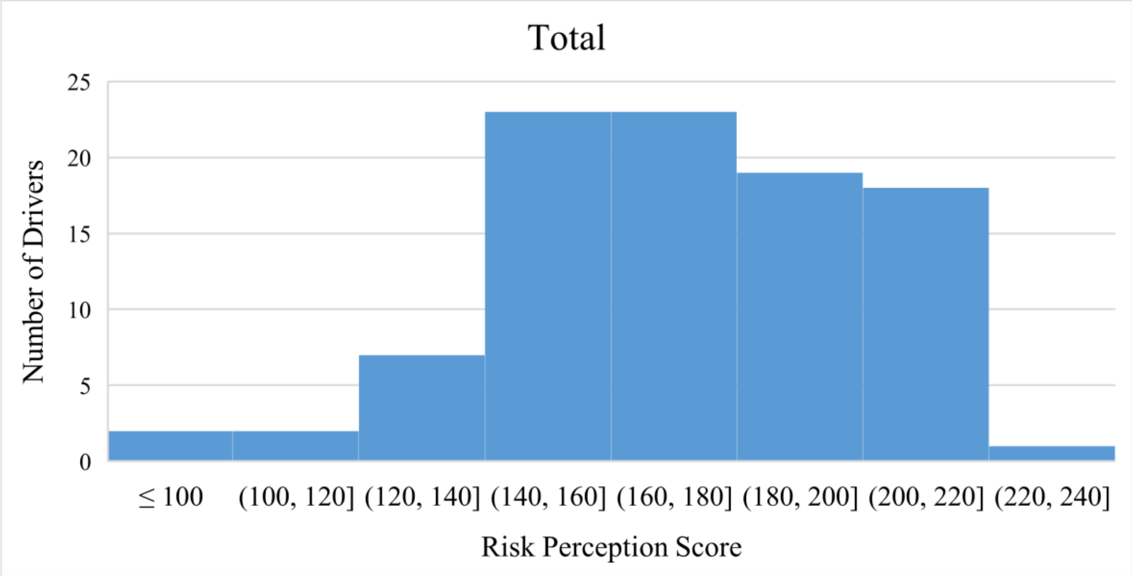
This section describes how the SHRP 2 NDS data led to the freeway work zone mobility evaluation. First, the gap and headway selection tables based on the driver characteristics and work zone configurations were developed. Second, speed analysis in terms of speed distributions and speed changepoint detection along the entire work zone consecutive sections was performed.

4.1 Gap and Headway Distribution

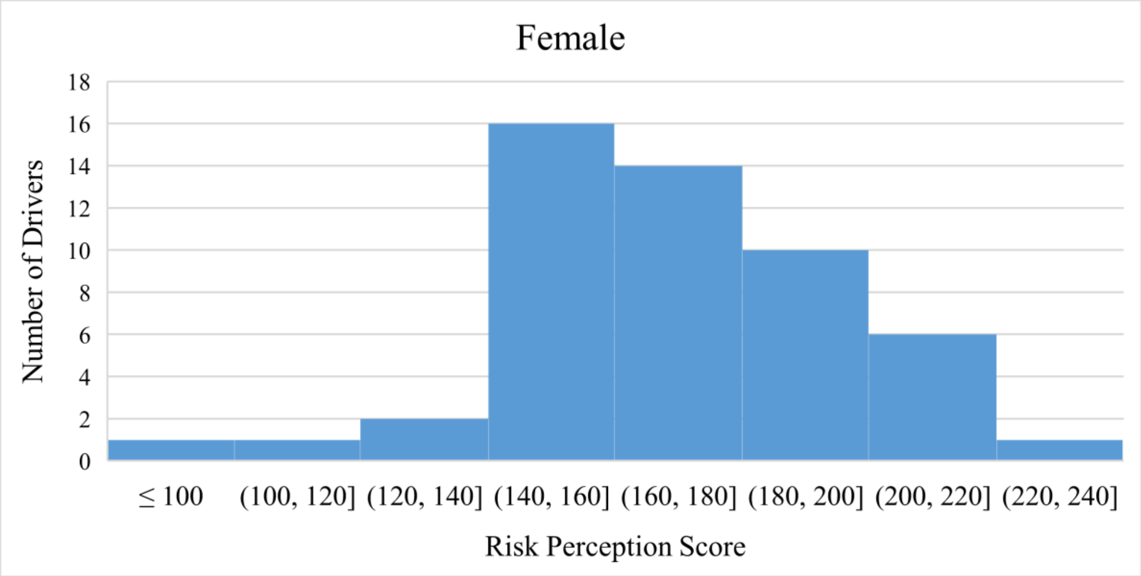
In this section, time and space gap together with time headway distribution were studied based on driver characteristics (i.e. gender, age group, and risk perception) at four work zone configurations.

4.1.1 Driver characteristics

Driver characteristics include gender (female and male), age group (younger than 24, 25 to 59, and older than 60), and mean of total risk perception score. A higher perception score indicates that the driver is conservative and a lower score represents an aggressive driver. As presented in **Figure 4*a***, 60% of drivers in the dataset have a risk perception score greater than 160, which indicates that these participants have good risk perceptions and tend to be cautious and obedient to traffic rules. It was found that risk perception distribution in female and male drivers are very different in **Figure 4*b*** and **Figure 4*c***. Approximate 80% of female drivers' risk perceptions fall into the interval between 140 and 200, while only 55% of male drivers scored within that interval. 25% of male drivers' risk perceptions fall into the interval between 200 and 220. In other words, male drivers were self-reported to have higher risk perceptions than the participating female drivers. In total, there were 52 female drivers and 50 male drivers. As shown in **Table 4**, the numbers of young, middle-aged, and senior drivers are 52, 28, and 22, respectively. Despite two cases with very low risk perceptions, risk perceptions of female and male drivers range from 120 to 220. Female drivers obtain higher risk perception scores than the male drivers in the same age group. It is interesting to find that regardless of gender, the risk perception score increases with the increase of driver's age. Please noted that there was one participant left demographic info blank, and thus it was not included in the headway distribution analysis.


Total
25
20
15
10
5
0
Number of Drivers
≤ 100
(100, 120]
(120, 140]
(140, 160]
(160, 180]
(180, 200]
(200, 220]
(220, 240]
Risk Perception Score

(*a*)


Female
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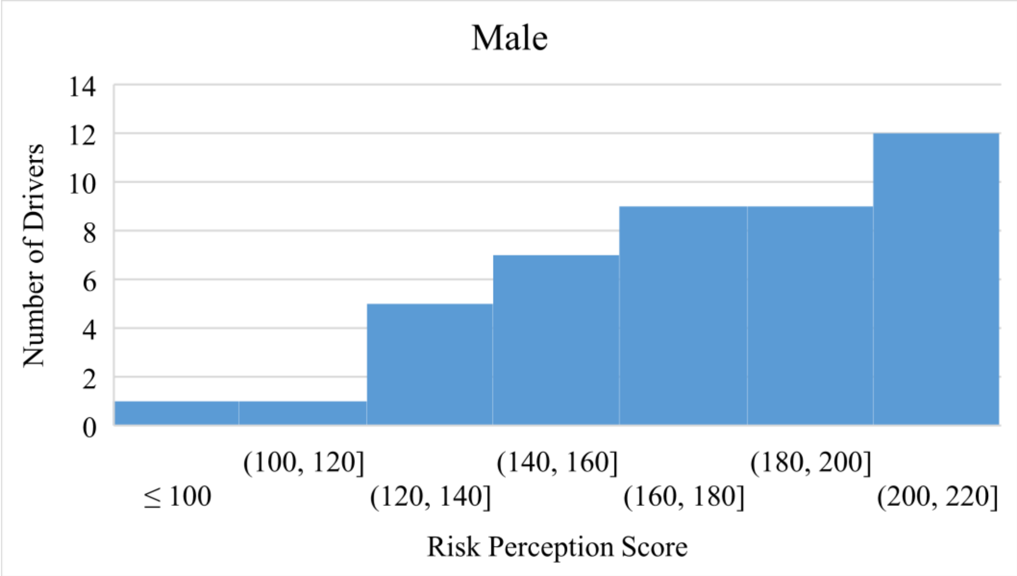
16
14
12
10
8
6
4
2
0
Number of Drivers
≤ 100
(100, 120]
(120, 140]
(140, 160]
(160, 180]
(180, 200]
(200, 220]
(220, 240]
Risk Perception Score

(*b*)



(*c*)

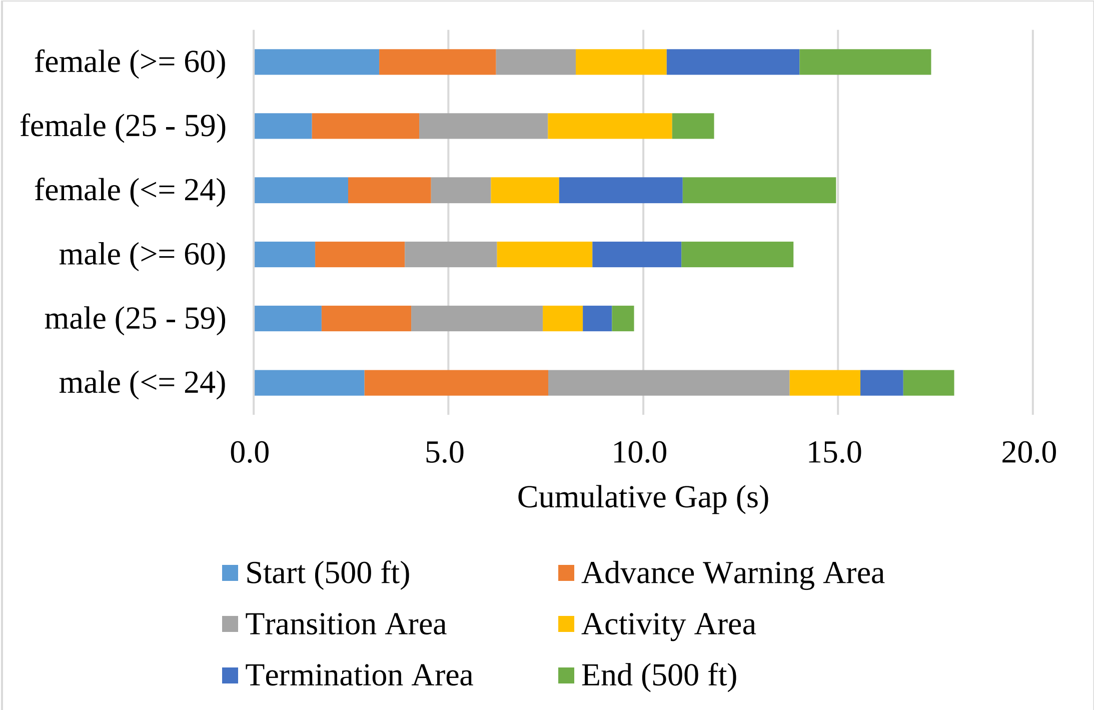
FIGURE 4. DRIVER RISK PERCEPTION DISTRIBUTION: (*A*) TOTAL DRIVERS; (*B*) FEMALE DRIVERS; AND (*C*) MALE DRIVERS.

TABLE 4. SUMMARY OF DRIVER RISK PERCEPTION AND DEMOGRAPHIC INFO

Age	Female		Male	
	Sample Size	Risk Perception*	Sample Size	Risk Perception*
≤ 24	32	(120, 198)	20	(112, 192)
25 - 59	11	(150, 205)	17	(123, 206)
≥ 60	9	(164, 221)	13	(147, 219)
*Note: a higher risk perception score indicates a higher cautious level.				

4.1.2 Gap and headway profiles by driver types

Figure 5 presents the gap and headway profile by driver types at four work zone configurations, which contains time gaps in seconds, space gaps in feet, time headway in seconds, and space headway in feet. It was stated that young drivers are more aggressive and have higher risks to be involved in fatal crashes when compared with other age groups (Lambert-Bélanger, et al. 2012), which is consistent with lower risk perception score (more aggressive driver) from young drivers. Interestingly, young drivers maintained a longer gap and headway than middle-aged drivers. From four work zone configurations in this study, middle-aged drivers typically maintained the shortest time gap and headway among all age groups. Space headway equals to gap spacing plus 15 ft (which is the assumed average vehicle length). Thus, space headway was not presented in **Figure 5**.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female (25 - 59)
female (<= 24)
male (>= 60)
male (25 - 59)
male (<= 24)
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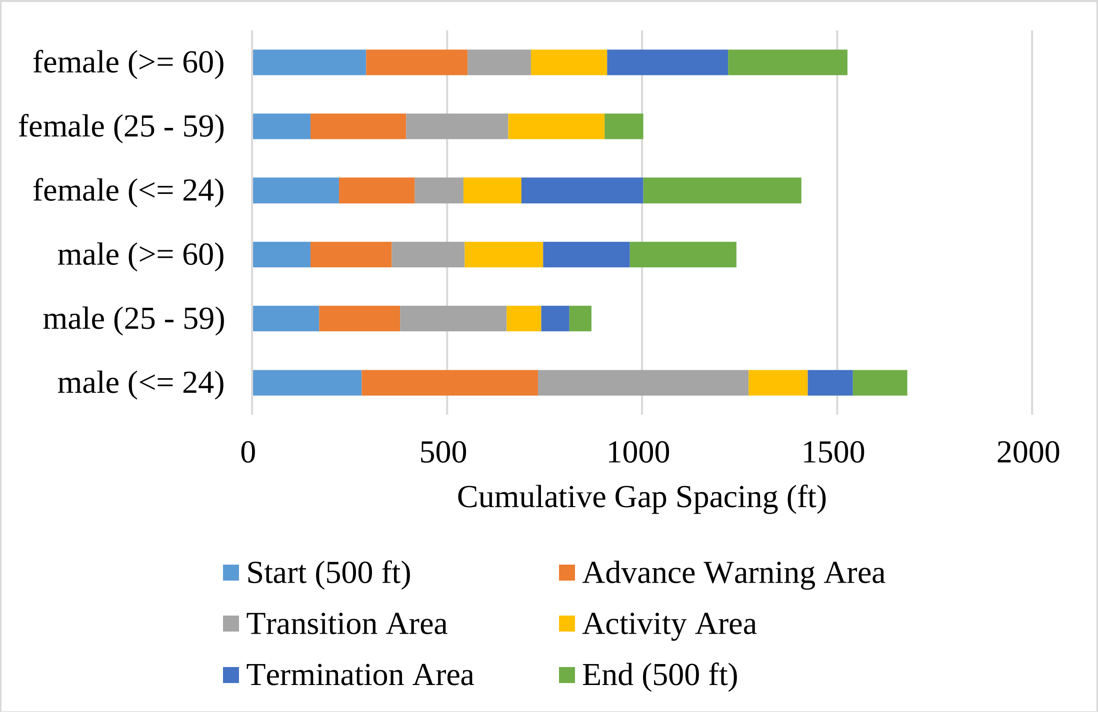
10.0
15.0
20.0
Cumulative Gap (s)
Start (500 ft)
Advance Warning Area
Transition Area
Activity Area
Termination Area
End (500 ft)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female (25 - 59)
female (<= 24)
male (>= 60)
male (25 - 59)
male (<= 24)
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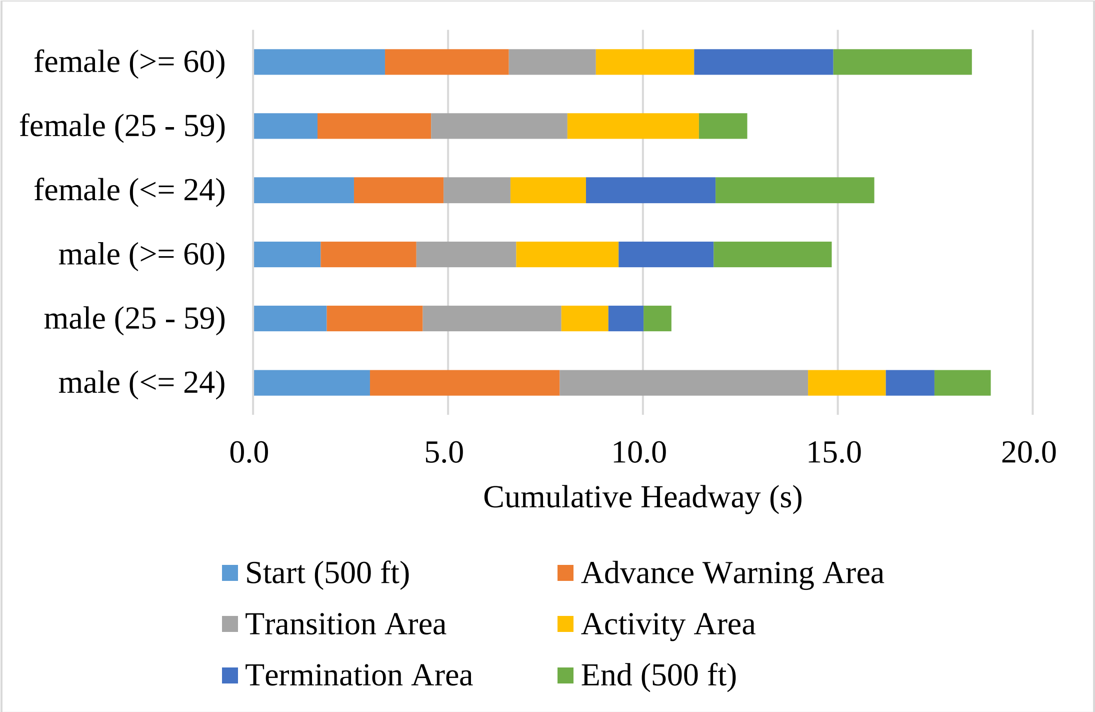
1000
1500
2000
Cumulative Gap Spacing (ft)
Start (500 ft)
Advance Warning Area
Transition Area
Activity Area
Termination Area
End (500 ft)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female (<= 24)
male (>= 60)
male (25 - 59)
male (<= 24)
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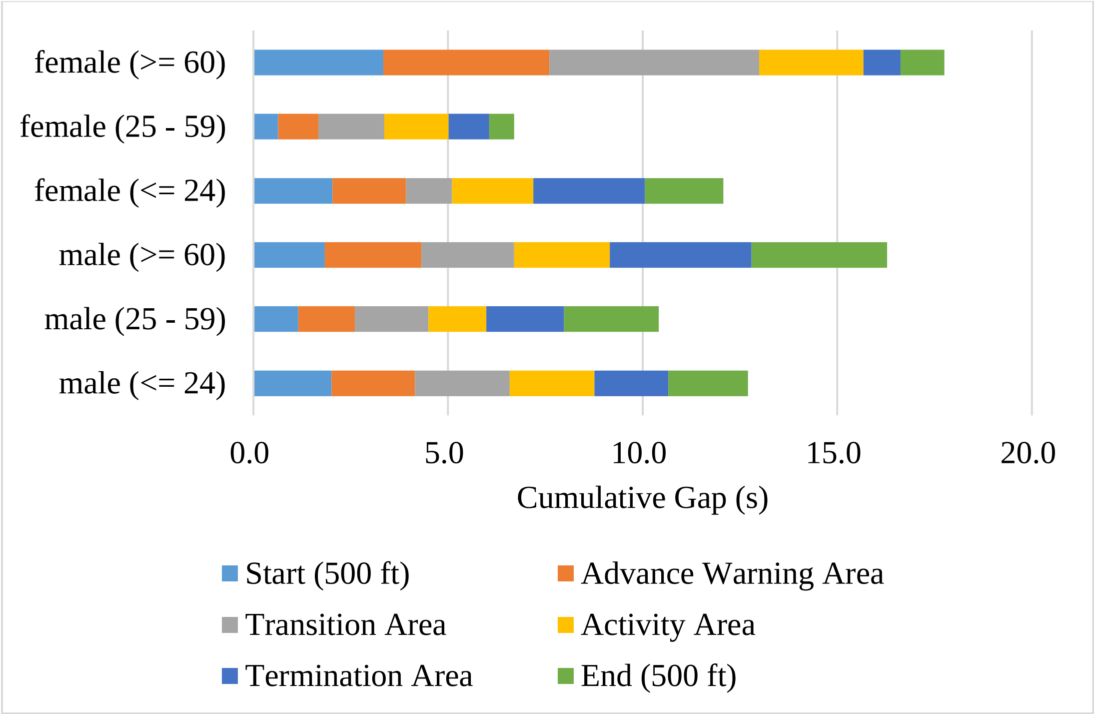
20.0
Cumulative Headway (s)
Start (500 ft)
Advance Warning Area
Transition Area
Activity Area
Termination Area
End (500 ft)

(a)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female (<= 24)
male (>= 60)
male (25 - 59)
male (<= 24)
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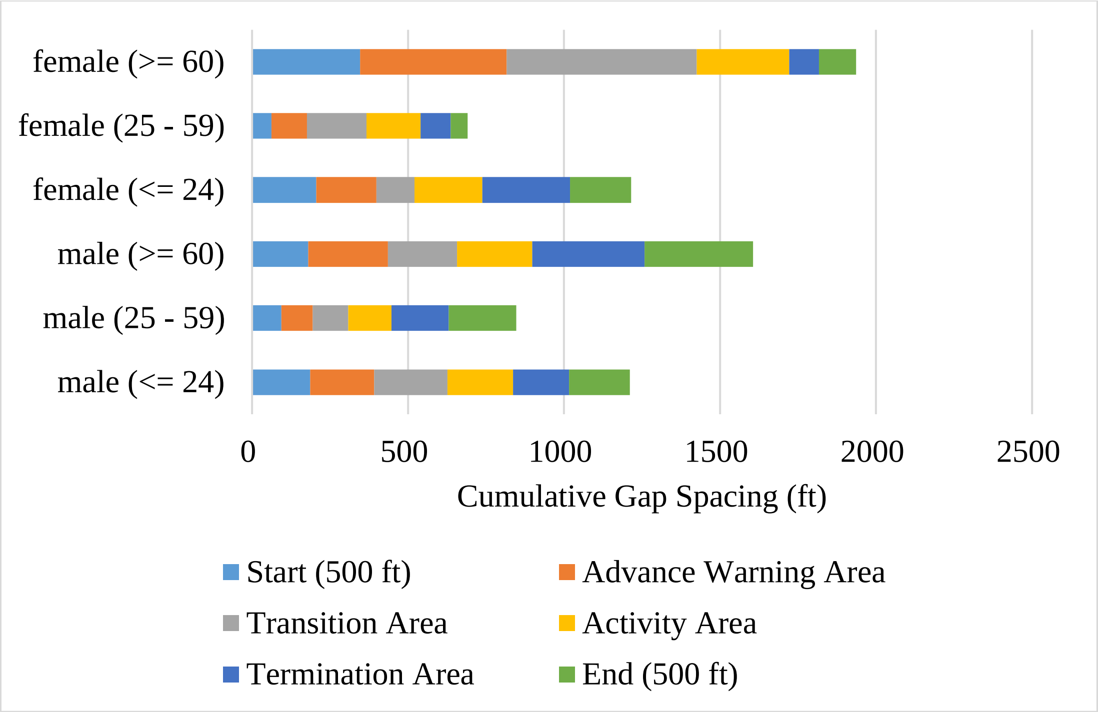
20.0
Cumulative Gap (s)
Start (500 ft)
Advance Warning Area
Transition Area
Activity Area
Termination Area
End (500 ft)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male (<= 24)
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500
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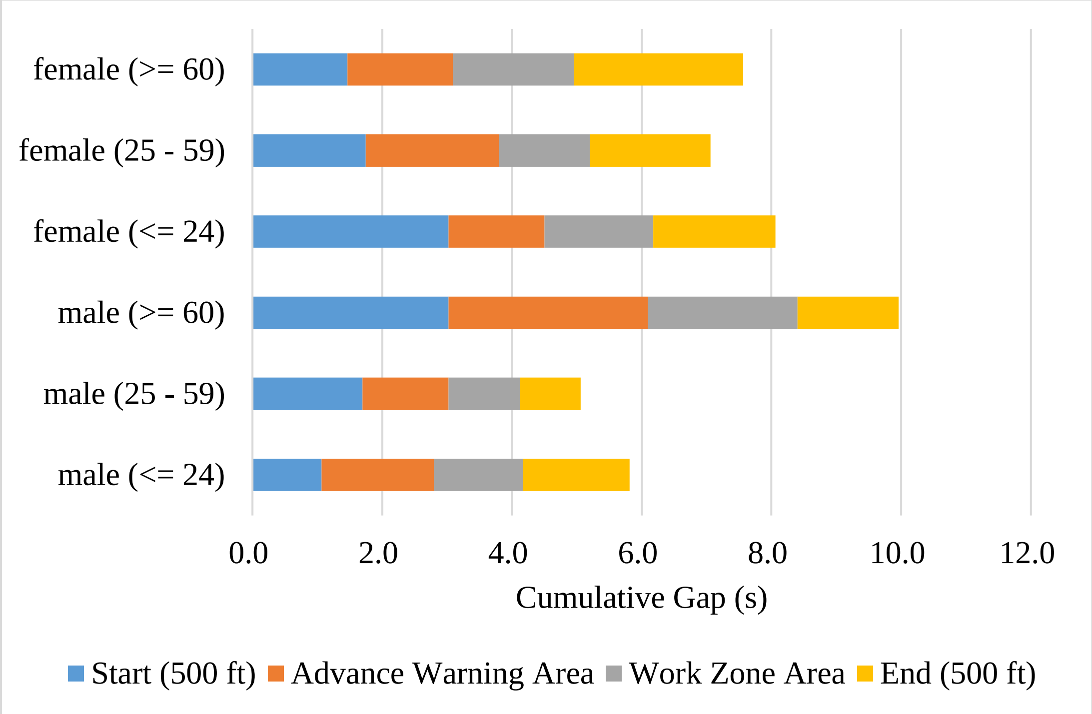
1500
2000
2500
Cumulative Gap Spacing (ft)
Start (500 ft)
Advance Warning Area
Transition Area
Activity Area
Termination Area
End (500 ft)

(b)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male (>= 60)
male (25 - 59)
male (<= 24)
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2.0
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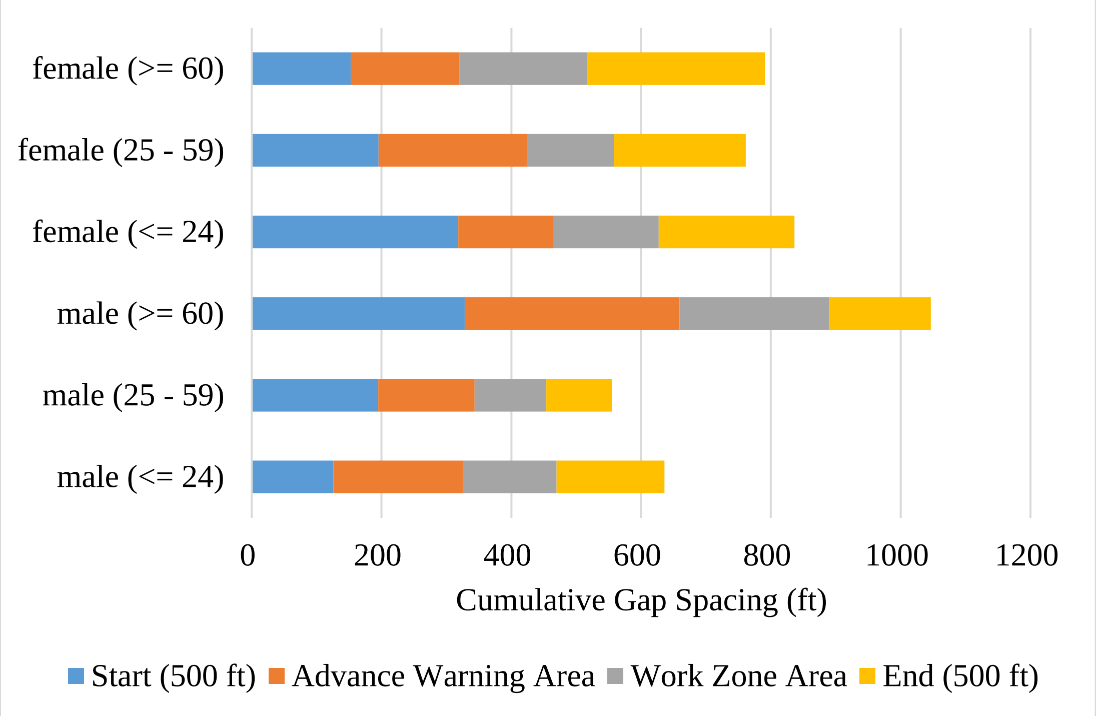
8.0
10.0
12.0
Cumulative Gap (s)
Start (500 ft)
Advance Warning Area
Work Zone Area
End (500 ft)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male (25 - 59)
male (<= 24)
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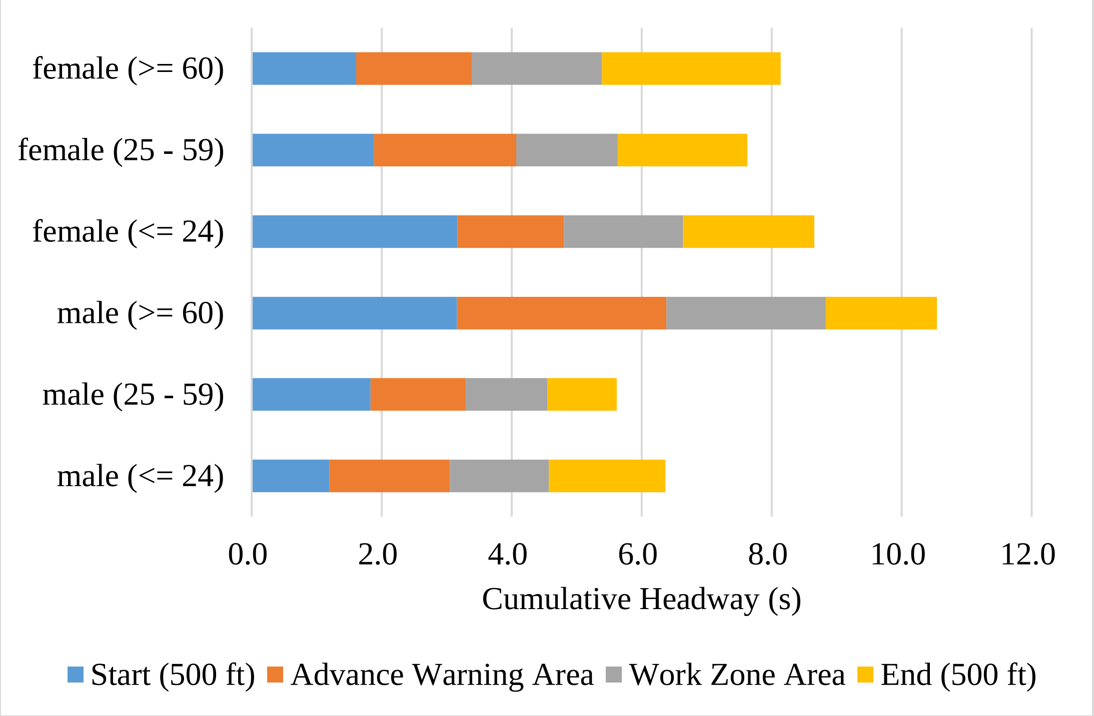
600
800
1000
1200
Cumulative Gap Spacing (ft)
Start (500 ft)
Advance Warning Area
Work Zone Area
End (500 ft)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female (<= 24)
male (>= 60)
male (25 - 59)
male (<= 24)
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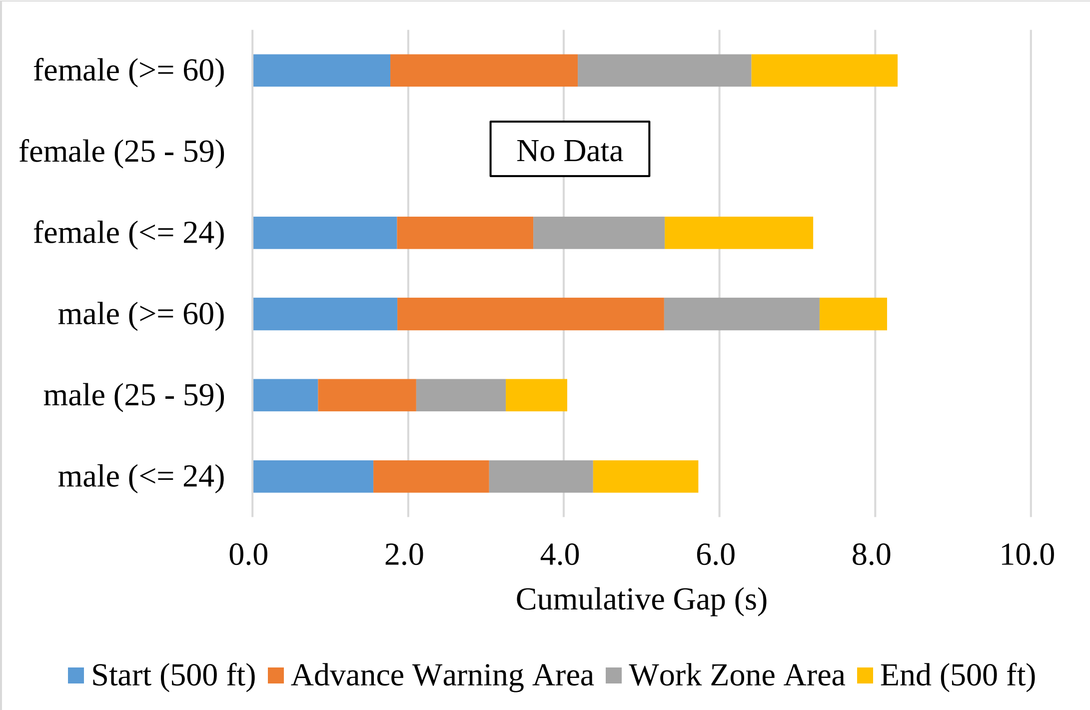
4.0
6.0
8.0
10.0
12.0
Cumulative Headway (s)
Start (500 ft)
Advance Warning Area
Work Zone Area
End (500 ft)

(c)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female (25 - 59)
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male (>= 60)
male (25 - 59)
male (<= 24)
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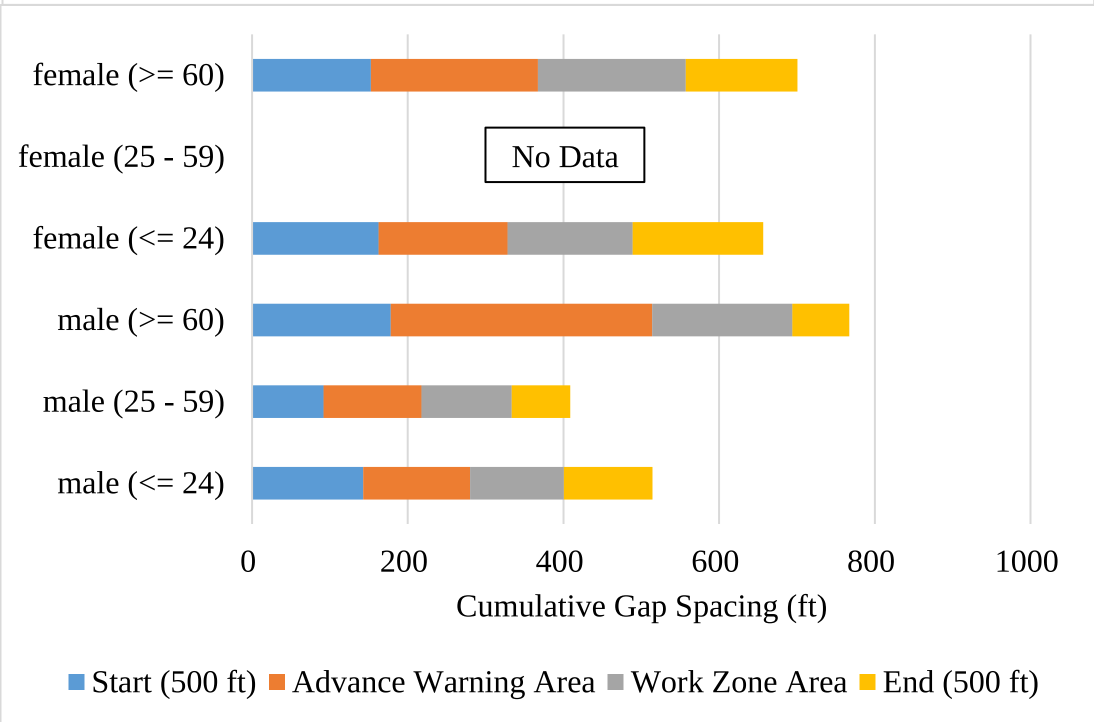
Work Zone Area
End (500 ft)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female (25 - 59)
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male (25 - 59)
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600
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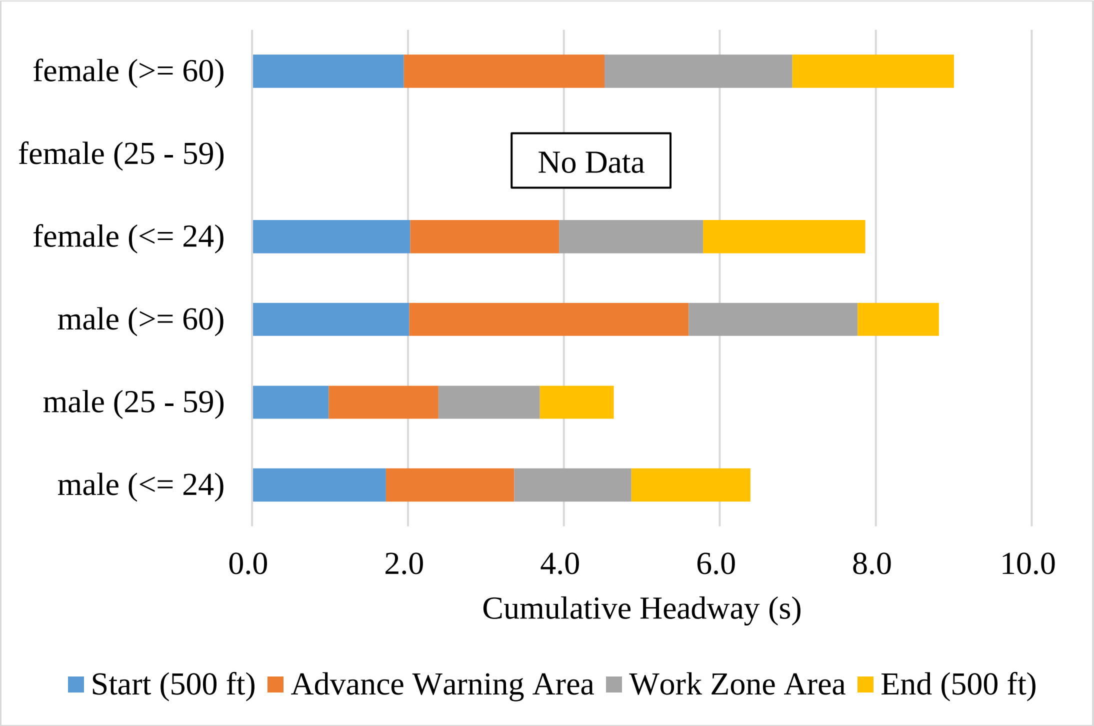
1000
Cumulative Gap Spacing (ft)
Start (500 ft)
Advance Warning Area
Work Zone Area
End (500 ft)



(***d***)

FIGURE 5. GAP AND HEADWAY PROFILE BY DRIVER TYPES: (*A*) LC 2-1; (*B*) LC 3-2; (*C*) SC 2-2; AND (*D*) SC 3-3.

Gap and headway selection tables before, during, and after work zone by different driver types at four selected work zone configurations (LC 2-1, LC 3-2, SC 2-2, and SC 3-3) were developed. **Table 5** to **Table 8** summarize the details of gap and headway distribution and driver characteristics (gender, age group, and driver risk perceptions). It includes the 95% confidence interval, mean values of risk perception scores, and gap and headways from drivers by age group and gender.

The time and space gap distributions from different drivers traversing various work zones can improve ACC spacing policies for automotive industry. Taking driver characteristics into consideration when developing spacing policies contributes to the similarity of human driver's spacing behavior in the ACC systems, and thus, would be able to enhance comfort for drivers. It can further improve driver's acceptance and system utilization by introducing driver characteristics.

The headway distributions from different drivers traversing various work zone can improve work zone capacity models. The desired time headway parameter (CC1) in VISSIM is static through all work zone consecutive sections, although it was suggested that desired time headway should be modeled as a distribution rather than a static value when data are available (Dong, et al. 2015). Thus, if headway distribution models built for different driver characteristics are used in lieu of a static value in VISSIM, a more accurate capacity estimation can be captured.

TABLE 5. GAP AND HEADWAY SELECTION TABLE BY DRIVER CHARACTERISTICS AT LC 2-1.

	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
Start (500 ft)	Female	Subtotal	2.7	(1.3, 4.2)	251	(121, 380)	2.9	(1.4, 4.3)	176
		≤ 24	2.4	(2.3, 2.5)	223	(218, 228)	2.6	(2.5, 2.7)	142
		25 - 59	1.5	(1.2, 1.8)	150	(120, 180)	1.6	(1.3, 2.0)	161
		≥ 60	3.2	(1.7, 4.7)	293	(155, 431)	3.4	(1.9, 4.9)	186
	Male	Subtotal	1.9	(0.8, 2.9)	181	(81, 281)	2.0	(0.9, 3.1)	191
		≤ 24	2.8	(2.0, 3.7)	281	(191, 371)	3.0	(2.1, 3.9)	146
		25 - 59	1.7	(1.0, 2.5)	172	(99, 244)	1.9	(1.1, 2.7)	190
		≥ 60	1.6	(0.5, 2.6)	150	(58, 241)	1.7	(0.7, 2.8)	208
	Grand Total		2.4	(1.0, 3.8)	225	(101, 349)	2.6	(1.2, 3.9)	182
Advance Warning Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	2.9	(1.5, 4.2)	249	(125, 374)	3.0	(1.6, 4.4)	174
		≤ 24	2.1	(1.7, 2.5)	194	(149, 240)	2.3	(1.9, 2.7)	142
		25 - 59	2.8	(1.7, 2.5)	245	(126, 364)	2.9	(1.4, 4.4)	167
		≥ 60	3.0	(1.6, 4.4)	259	(128, 391)	3.2	(1.8, 4.6)	182
	Male	Subtotal	2.6	(1.3, 4.2)	240	(94, 386)	2.8	(1.2, 4.4)	185
		≤ 24	4.7	(3.6, 5.8)	453	(356, 549)	4.9	(3.8, 6.0)	146
		25 - 59	2.3	(0.7, 3.9)	207	(72, 342)	2.5	(0.8, 4.1)	167
		≥ 60	2.3	(1.0, 3.6)	208	(93, 323)	2.5	(1.2, 3.7)	207
	Grand Total		2.8	(1.3, 4.2)	246	(114, 378)	2.9	(1.5, 4.4)	178
Transition Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	2.4	(1.1, 3.7)	190	(88, 292)	2.6	(1.3, 3.9)	170
		≤ 24	1.5	(1.5, 1.6)	124	(122, 127)	1.7	(1.7, 1.8)	142
		25 - 59	3.3	(1.4, 5.2)	262	(112, 412)	3.5	(1.6, 5.4)	165
		≥ 60	2.0	(1.5, 2.6)	163	(120, 206)	2.2	(1.7, 2.8)	177
	Male	Subtotal	3.1	(0.8, 5.4)	253	(60, 445)	3.3	(1.0, 5.6)	192
		≤ 24	6.2	(5.9, 6.5)	539	(513, 566)	6.4	(6.1, 6.7)	146
		25 - 59	3.4	(0.8, 6.8)	273	(68, 542)	3.6	(0.9, 7.0)	174
		≥ 60	2.4	(1.0, 3.8)	188	(77, 299)	2.6	(1.1, 4.0)	207
	Grand Total		2.7	(0.9, 4.4)	213	(68, 359)	2.8	(1.1, 4.6)	179
Activity Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score

	Female	Subtotal	2.4	(1.0, 3.9)	200	(79, 322)	2.6	(1.2, 4.1)	174
		≤ 24	1.8	(0.6, 3.4)	149	(53, 297)	1.9	(0.8, 3.6)	142
		25 - 59	3.2	(0.8, 5.5)	247	(62, 432)	3.4	(1.0, 5.7)	163
		≥ 60	2.3	(1.4, 3.3)	195	(107, 282)	2.5	(1.5, 3.5)	181
	Male	Subtotal	2.1	(0.6, 3.6)	174	(54, 294)	2.3	(0.8, 3.8)	196
		≤ 24	1.8	(0.5, 3.2)	152	(37, 268)	2.0	(0.6, 3.4)	146
		25 - 59	1.0	(0.8, 1.2)	88	(69, 108)	1.2	(1.0, 1.4)	202
		≥ 60	2.4	(0.9, 4.0)	201	(77, 325)	2.6	(1.1, 4.2)	207
	Grand Total		2.3	(0.8, 3.8)	191	(70, 313)	2.5	(1.0, 4.0)	181
Termination Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	3.4	(1.8, 5.0)	310	(162, 459)	3.5	(1.9, 5.1)	177
		≤ 24	3.2	(2, 4.40)	313	(196, 429)	3.3	(2.1, 4.5)	141
		25 - 59	NA	NA	NA	NA	NA	NA	NA
		≥ 60	3.4	(1.8, 5.1)	310	(158, 462)	3.6	(1.9, 5.2)	182
	Male	Subtotal	1.7	(0.4, 3.1)	163	(31, 297)	1.8	(0.5, 3.3)	191
		≤ 24	1.1	(1.0, 1.2)	115	(105, 126)	1.2	(1.2, 1.3)	146
		25 - 59	0.8	(0.4, 1.2)	73	(30, 119)	0.9	(0.5, 1.4)	202
		≥ 60	2.3	(0.5, 4.0)	222	(65, 379)	2.4	(0.7, 4.2)	204
	Grand Total		2.8	(1.1, 4.6)	262	(103, 422)	3.0	(1.2, 4.7)	181
End (500 ft)	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	2.9	(1.2, 4.6)	267	(108, 425)	3.1	(1.4, 4.8)	181
		≤ 24	3.9	(3.9, 4.0)	405	(403, 408)	4.1	(4.0, 4.1)	141
		25 - 59	1.1	(0.9, 1.2)	99	(81, 116)	1.2	(1.1, 1.4)	171
		≥ 60	3.4	(1.7, 5.0)	306	(154, 458)	3.5	(1.9, 5.2)	186
	Male	Subtotal	2.1	(0.5, 3.9)	198	(49, 364)	2.2	(0.6, 4.1)	191
		≤ 24	1.3	(1.3, 1.3)	139	(135, 144)	1.4	(1.4, 1.5)	146
		25 - 59	0.6	(0.5, 0.6)	56	(52, 60)	0.7	(0.7, 0.7)	202
		≥ 60	2.9	(0.8, 5.0)	273	(91, 455)	3.0	(0.9, 5.1)	203
	Grand Total		2.6	(0.8, 4.4)	242	(78, 407)	2.8	(1.0, 4.6)	185

TABLE 6. GAP AND HEADWAY SELECTION TABLE BY DRIVER CHARACTERISTICS AT LC 3-2.

Start (500 ft)	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	2.3	(1.0, 3.5)	230	(96, 364)	2.4	(1.1, 3.7)	170
		≤ 24	2.0	(0.9, 3.2)	206	(84, 328)	2.2	(1.0, 3.4)	150
		25 - 59	0.6	(0.6, 0.6)	62	(62, 63)	0.8	(0.8, 0.8)	196
		≥ 60	3.3	(2.7, 3.9)	346	(272, 420)	3.5	(2.9, 4.1)	203

	Male	Subtotal	1.7	(1.0, 2.3)	150	(78, 221)	1.8	(1.2, 2.5)	148
		≤ 24	2.0	(1.3, 2.7)	186	(115, 258)	2.2	(1.5, 2.9)	152
		25 - 59	1.2	(0.9, 1.4)	94	(59, 128)	1.3	(1.1, 1.6)	165
		≥ 60	1.8	(1.8, 1.9)	180	(177, 184)	2.0	(1.9, 2.0)	192
	Grand Total		1.8	(0.9, 2.7)	172	(72, 271)	2.0	(1.1, 2.9)	154
Advance Warning Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.8	(0.5, 3.2)	192	(51, 332)	2.0	(0.6, 3.4)	172
		≤ 24	1.9	(0.6, 3.2)	192	(63, 322)	2.0	(0.7, 3.4)	163
		25 - 59	1.0	(0.2, 1.8)	114	(23, 205)	1.2	(0.4, 2.0)	196
		≥ 60	4.3	(3.9, 4.6)	470	(413, 527)	4.4	(4.0, 4.8)	203
	Male	Subtotal	1.9	(1.0, 2.8)	165	(60, 270)	2.1	(1.2, 3.0)	152
		≤ 24	2.1	(1.3, 3.0)	205	(117, 293)	2.3	(1.4, 3.2)	153
		25 - 59	1.5	(0.7, 2.2)	101	(17, 190)	1.8	(0.9, 2.7)	165
		≥ 60	2.5	(1.8, 3.1)	255	(191, 319)	2.6	(2.0, 3.3)	104
	Grand Total		1.9	(0.8, 2.9)	173	(56, 289)	2.1	(1.0, 3.1)	158
Transition Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.4	(0.3, 2.6)	152	(25, 280)	1.6	(0.4, 2.7)	164
		≤ 24	1.2	(0.4, 2.0)	122	(37, 206)	1.3	(0.5, 2.2)	156
		25 - 59	1.7	(1.0, 2.4)	190	(127, 253)	1.8	(1.1, 2.5)	196
		≥ 60	5.4	(5.4, 5.4)	609	(606, 612)	5.5	(5.5, 5.6)	203
	Male	Subtotal	2.2	(0.2, 4.2)	174	(49, 300)	2.4	(0.4, 4.4)	162
		≤ 24	2.4	(1.4, 3.5)	235	(130, 340)	2.6	(1.5, 3.6)	147
		25 - 59	1.9	(0.5, 4.5)	114	(13, 225)	2.2	(0.6, 4.9)	170
		≥ 60	2.4	(0.9, 3.8)	221	(88, 355)	2.5	(1.1, 4.0)	190
	Grand Total		1.9	(0.3, 3.7)	166	(39, 293)	2.1	(0.5, 3.9)	163
Activity Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	2.0	(0.7, 3.4)	212	(73, 351)	2.2	(0.8, 3.5)	169
		≤ 24	2.1	(0.7, 3.5)	217	(73, 361)	2.2	(0.8, 3.6)	158
		25 - 59	1.7	(0.7, 2.6)	173	(75, 272)	1.8	(0.9, 2.7)	193
		≥ 60	2.7	(1.2, 4.2)	295	(130, 461)	2.8	(1.3, 4.3)	203
	Male	Subtotal	1.9	(0.8, 3.0)	181	(66, 295)	2.1	(0.9, 3.2)	154
		≤ 24	2.2	(1.1, 3.3)	210	(100, 321)	2.3	(1.3, 3.4)	140
		25 - 59	1.5	(0.5, 2.5)	139	(34, 244)	1.7	(0.6, 2.7)	167
		≥ 60	2.5	(1.4, 3.5)	241	(135, 347)	2.6	(1.6, 3.6)	156
	Grand Total		1.9	(0.7, 3.1)	190	(67, 314)	2.1	(0.9, 3.3)	159

	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
Termination Area	Female	Subtotal	1.6	(0.7, 2.6)	161	(63, 259)	1.8	(0.8, 2.8)	184
		≤ 24	2.9	(2.4, 3.3)	281	(228, 333)	3.0	(2.6, 3.5)	158
		25 - 59	1.0	(0.5, 1.5)	97	(52, 142)	1.2	(0.7, 1.7)	191
		≥ 60	1.0	(0.6, 1.3)	96	(65, 127)	1.1	(0.8, 1.4)	203
	Male	Subtotal	2.0	(0.8, 3.3)	190	(69, 312)	2.2	(0.9, 3.4)	141
		≤ 24	1.9	(0.8, 3.0)	180	(63, 296)	2.1	(1.0, 3.2)	138
		25 - 59	2.0	(0.6, 3.4)	183	(63, 304)	2.2	(0.8, 3.5)	164
		≥ 60	3.6	(3.6, 3.7)	360	(356, 365)	3.8	(3.7, 3.8)	192
	Grand Total		1.9	(0.7, 3.1)	183	(66, 299)	2.1	(0.9, 3.3)	160
End (500 ft)	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.5	(0.9, 2.1)	151	(96, 206)	1.7	(1.1, 2.3)	180
		≤ 24	2.0	(1.6, 2.5)	196	(155, 237)	2.2	(1.7, 2.6)	154
		25 - 59	0.6	(0.6, 0.7)	54	(53, 56)	0.8	(0.8, 0.8)	179
		≥ 60	1.1	(0.8, 1.4)	119	(90, 147)	1.3	(1.0, 1.6)	203
	Male	Subtotal	2.2	(0.9, 3.5)	205	(74, 336)	2.4	(1.1, 3.7)	154
		≤ 24	2.1	(0.7, 3.4)	195	(62, 328)	2.2	(0.9, 3.6)	146
		25 - 59	2.4	(1.2, 3.7)	217	(90, 343)	2.6	(1.4, 3.9)	164
		≥ 60	3.5	(3.4, 3.6)	347	(341, 353)	3.6	(3.6, 3.7)	192
	Grand Total		2.0	(0.8, 3.2)	188	(73, 303)	2.1	(1.0, 3.3)	162

TABLE 7. GAP AND HEADWAY SELECTION TABLE BY DRIVER CHARACTERISTICS AT SC 2-2.

	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
Start (500 ft)	Female	Subtotal	2.1	(0.7, 3.6)	226	(81, 371)	2.3	(0.9, 3.7)	177
		≤ 24	3.0	(1.2, 4.9)	318	(132, 505)	3.2	(1.3, 5.0)	154
		25 - 59	1.7	(1.6, 1.9)	196	(183, 208)	1.9	(1.8, 2.0)	192
		≥ 60	1.5	(1.2, 1.7)	152	(121, 184)	1.6	(1.3, 1.9)	193
	Male	Subtotal	2.0	(0.8, 3.1)	222	(91, 352)	2.1	(0.9, 3.3)	185
		≤ 24	1.1	(1.0, 1.1)	126	(121, 131)	1.2	(1.2, 1.2)	191
		25 - 59	1.7	(0.7, 3.0)	195	(76, 349)	1.8	(0.8, 3.1)	201
		≥ 60	3.0	(2.9, 3.2)	328	(300, 357)	3.2	(3.0, 3.3)	156
	Grand Total		2.1	(0.7, 3.4)	225	(84, 365)	2.2	(0.9, 3.6)	179
Advance Warning Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.6	(0.9, 2.3)	166	(89, 242)	1.8	(1.1, 2.4)	181

		≤ 24	1.5	(0.8, 2.2)	147	(65, 229)	1.6	(0.9, 2.4)	158
		25 - 59	2.1	(1.2, 2.9)	229	(136, 322)	2.2	(1.4, 3.0)	192
		≥ 60	1.6	(1.0, 2.2)	168	(102, 233)	1.8	(1.2, 2.4)	192
	Male	Subtotal	1.8	(0.5, 3.1)	200	(59, 342)	1.9	(0.7, 3.2)	194
		≤ 24	1.7	(0.9, 2.6)	200	(107, 292)	1.9	(1.0, 2.7)	188
		25 - 59	1.3	(0.5, 2.2)	149	(41, 256)	1.5	(0.6, 2.4)	201
		≥ 60	3.1	(1.4, 4.8)	331	(140, 522)	3.2	(1.5, 4.9)	188
	Grand Total		1.7	(0.7, 2.6)	179	(71, 288)	1.8	(0.9, 2.8)	186
Work Zone Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.8	(0.7, 2.8)	183	(72, 294)	1.9	(0.9, 3.0)	181
		≤ 24	1.7	(0.5, 2.8)	162	(44, 280)	1.8	(0.7, 3.0)	158
		25 - 59	1.4	(0.7, 2.1)	134	(71, 196)	1.6	(0.8, 2.3)	192
		≥ 60	1.9	(0.8, 2.9)	197	(87, 307)	2.0	(1.0, 3.0)	192
	Male	Subtotal	1.4	(0.5, 2.3)	141	(43, 238)	1.5	(0.6, 2.5)	194
		≤ 24	1.4	(0.5, 2.3)	144	(41, 246)	1.5	(0.6, 2.4)	188
		25 - 59	1.1	(0.4, 1.8)	111	(34, 187)	1.3	(0.5, 2.0)	188
		≥ 60	2.3	(1.4, 3.2)	230	(140, 321)	2.5	(1.5, 3.4)	201
	Grand Total		1.6	(0.6, 2.6)	162	(55, 268)	1.7	(0.7, 2.7)	187
End (500 ft)	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	2.4	(1.5, 3.4)	255	(158, 352)	2.5	(1.6, 3.5)	181
		≤ 24	1.9	(1.4, 2.4)	209	(146, 272)	2.0	(1.5, 2.5)	158
		25 - 59	1.9	(1.8, 1.9)	203	(202, 204)	2.0	(1.9, 2.0)	192
		≥ 60	2.6	(1.6, 3.6)	274	(168, 379)	2.8	(1.7, 3.8)	192
	Male	Subtotal	1.2	(0.6, 1.9)	125	(64, 192)	1.3	(0.7, 2.0)	194
		≤ 24	1.6	(1.4, 1.8)	166	(155, 177)	1.8	(1.6, 2.0)	188
		25 - 59	0.9	(0.6, 1.4)	101	(64, 148)	1.1	(0.7, 1.5)	201
		≥ 60	1.6	(0.9, 2.8)	157	(86, 284)	1.7	(1.0, 2.9)	188
	Grand Total		1.7	(0.7, 2.8)	184	(79, 289)	1.9	(0.9, 2.9)	183

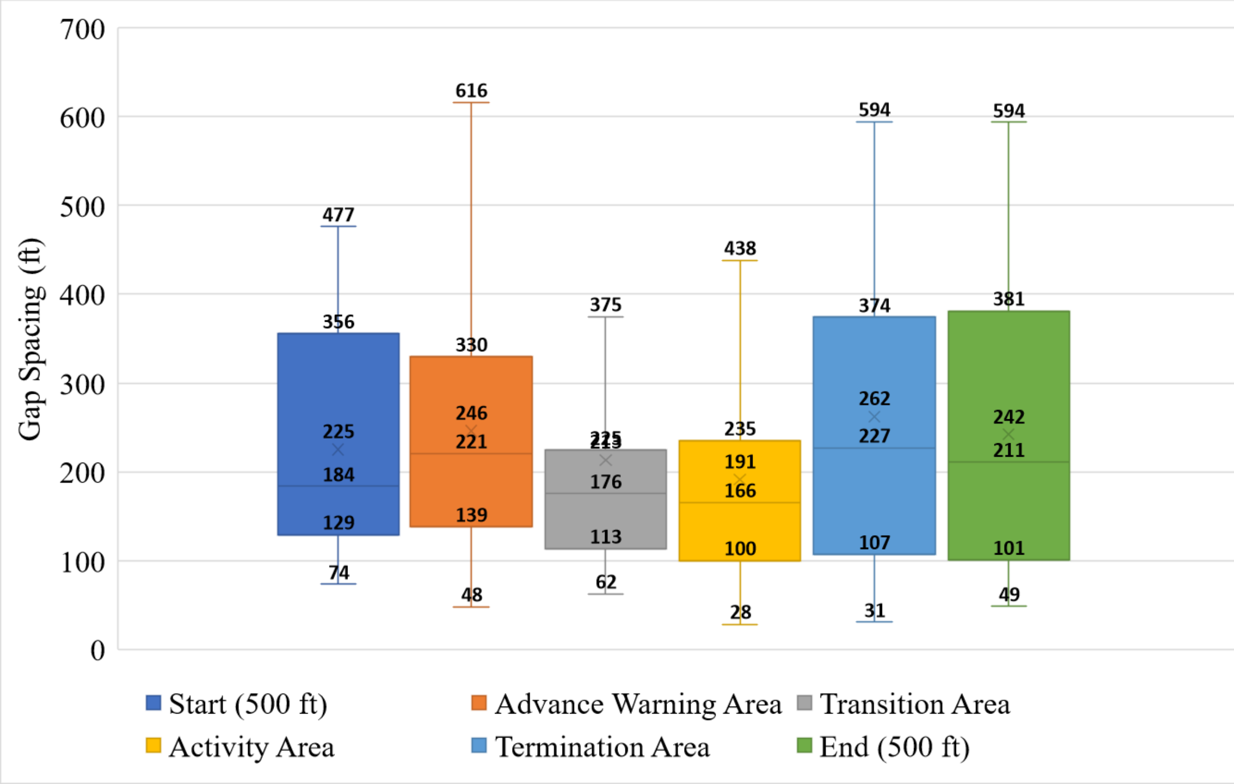
TABLE 8. GAP AND HEADWAY SELECTION TABLE BY DRIVER CHARACTERISTICS AT SC 3-3.

Start (500 ft)	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.8	(0.9, 2.8)	160	(73, 247)	2.0	(1.0, 3.0)	171
		≤ 24	1.9	(1.0, 2.8)	163	(83, 243)	2.0	(1.1, 2.9)	168
		25 - 59	NA	NA	NA	NA	NA	NA	NA
		≥ 60	1.8	(0.6, 3.0)	153	(48, 258)	1.9	(0.7, 3.1)	181
	Male	Subtotal	1.5	(0.7, 2.3)	143	(70, 216)	1.7	(0.9, 2.5)	162

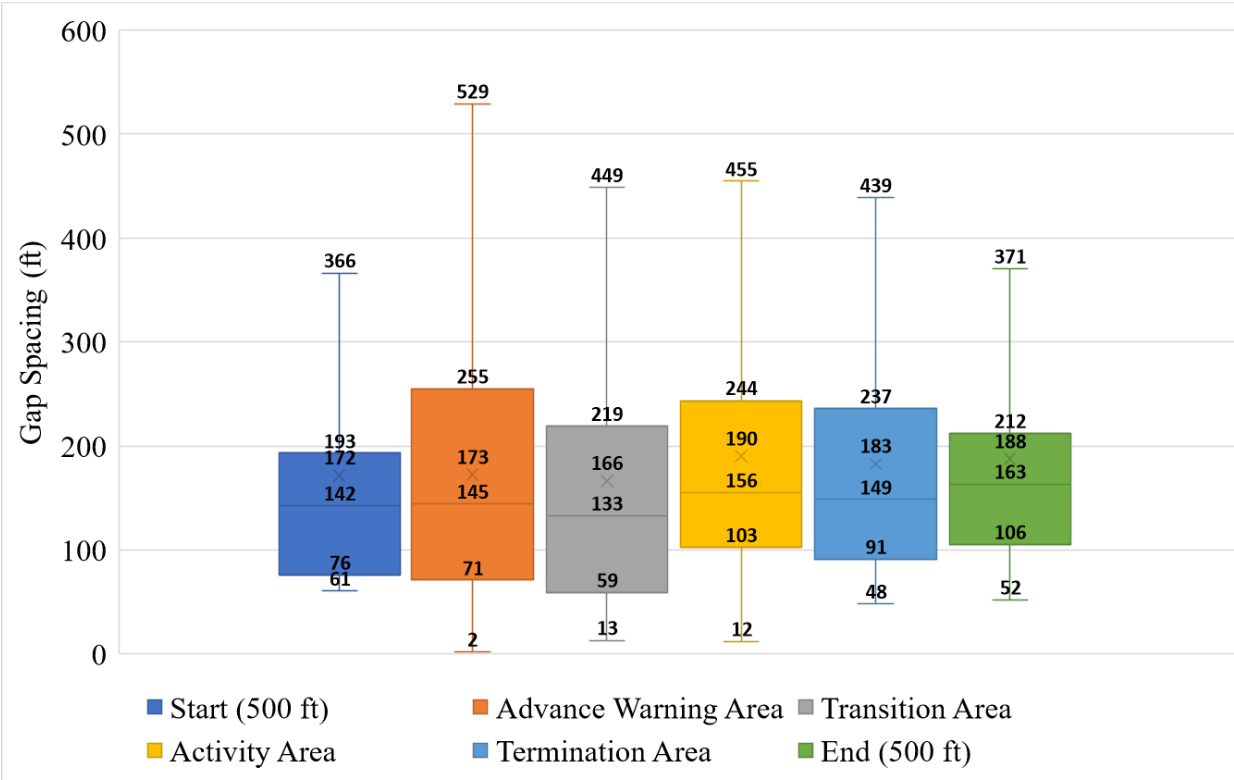
		≤ 24	1.6	(0.7, 2.4)	143	(68, 218)	1.7	(0.9, 2.6)	153
		25 - 59	0.8	(0.5, 1.6)	92	(57, 176)	1.0	(0.6, 1.7)	166
		≥ 60	1.9	(1.8, 1.9)	178	(169, 187)	2.0	(1.9, 2.1)	189
	Grand Total		1.7	(0.8, 2.6)	153	(71, 235)	1.9	(0.9, 2.8)	167
Advance Warning Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.9	(0.7, 3.2)	179	(63, 296)	2.1	(0.9, 3.3)	174
		≤ 24	1.8	(0.6, 2.9)	166	(58, 273)	1.9	(0.8, 3.1)	170
		25 - 59	NA	NA	NA	NA	NA	NA	NA
		≥ 60	2.4	(1.1, 3.7)	215	(85, 345)	2.6	(1.2, 3.9)	184
	Male	Subtotal	1.6	(0.5, 2.8)	152	(44, 264)	1.8	(0.6, 2.9)	166
		≤ 24	1.5	(0.7, 2.3)	137	(68, 207)	1.6	(0.9, 2.4)	158
		25 - 59	1.3	(0.4, 2.7)	126	(44, 265)	1.4	(0.5, 2.8)	193
		≥ 60	3.4	(1.6, 5.3)	336	(187, 518)	3.6	(1.7, 5.4)	194
	Grand Total		1.8	(0.6, 3.1)	172	(56, 288)	2.0	(0.8, 3.2)	172
Work Zone Area	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.8	(0.6, 3.0)	167	(58, 276)	2.0	(0.8, 3.1)	173
		≤ 24	1.7	(0.5, 2.9)	160	(45, 276)	1.8	(0.7, 3.0)	168
		25 - 59	NA	NA	NA	NA	NA	NA	NA
		≥ 60	2.2	(1.4, 3.1)	190	(112, 268)	2.4	(1.5, 3.3)	191
	Male	Subtotal	1.4	(0.6, 2.2)	128	(55, 201)	1.6	(0.8, 2.3)	168
		≤ 24	1.3	(0.6, 2.0)	120	(55, 185)	1.5	(0.8, 2.2)	161
		25 - 59	1.2	(0.4, 1.9)	116	(40, 191)	1.3	(0.6, 2.0)	170
		≥ 60	2.0	(1.1, 2.9)	180	(95, 266)	2.2	(1.3, 3.1)	198
	Grand Total		1.7	(0.6, 2.7)	154	(54, 255)	1.8	(0.8, 2.9)	171
End (500 ft)	Gender	Age	Mean Gap (s)	95% CI of Gap (s)	Mean Gap Spacing (ft)	95% CI of Gap Spacing (ft)	Mean Headway (s)	95% CI of Headway (s)	Mean Risk Score
	Female	Subtotal	1.9	(1.0, 2.8)	166	(79, 253)	2.1	(1.2, 3.0)	175
		≤ 24	1.9	(1.0, 2.8)	168	(82, 254)	2.1	(1.2, 3.0)	173
		25 - 59	NA	NA	NA	NA	NA	NA	NA
		≥ 60	1.9	(0.7, 3.1)	144	(50, 237)	2.1	(0.9, 3.3)	198
	Male	Subtotal	1.1	(0.4, 1.8)	92	(35, 150)	1.2	(0.5, 1.9)	173
		≤ 24	1.3	(0.9, 1.8)	114	(77, 150)	1.5	(1.1, 2.0)	168
		25 - 59	0.8	(0.6, 0.9)	75	(58, 93)	0.9	(0.8, 1.1)	171
		≥ 60	0.9	(0.2, 1.9)	73	(16, 161)	1.0	(0.4, 2.1)	181
	Grand Total		1.6	(0.7, 2.6)	142	(56, 228)	1.8	(0.9, 2.8)	174

4.1.3 Gap Comparison

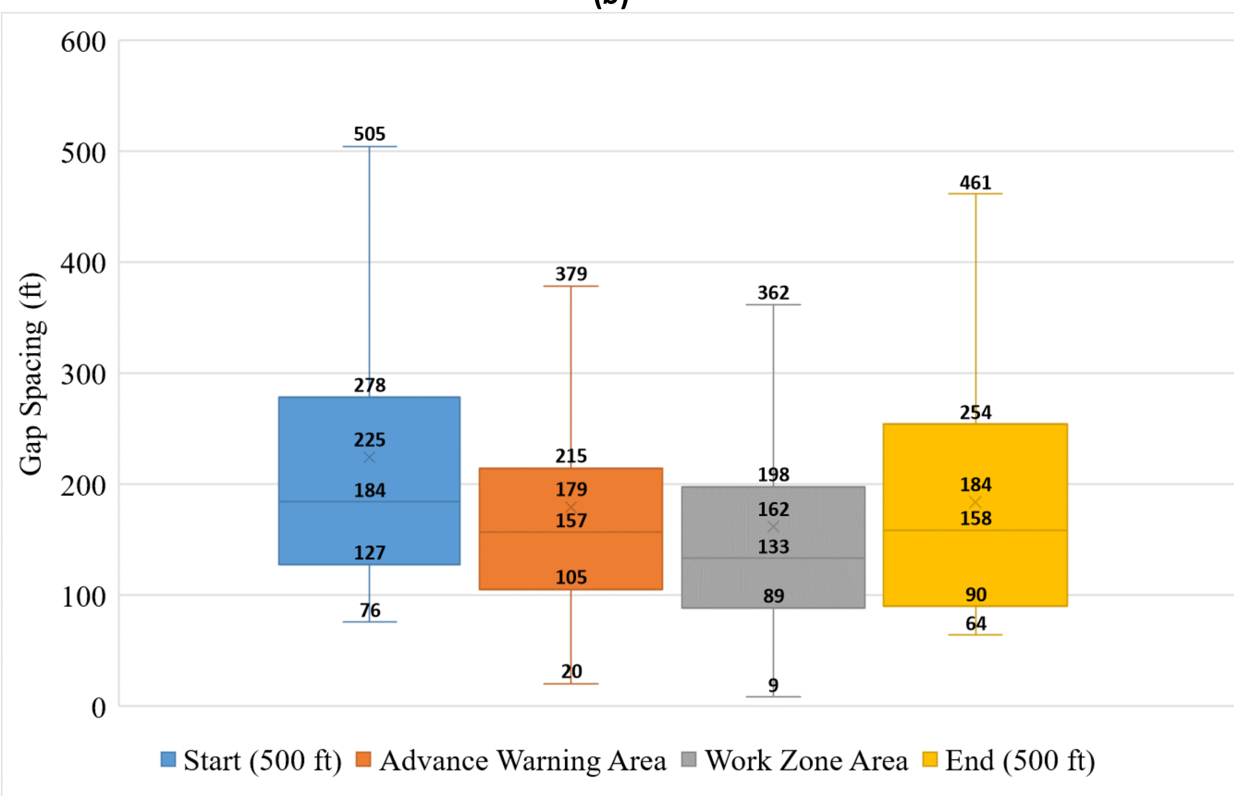
The gap spacing distributions by different work zone consecutive sections are illustrated in **Figure 6**. Boxplots were utilized to detect potential outliers, which were filtered if they were beyond the upper limit or lower limit. It can be found that vehicles maintain different gap spacings in different work zone sections and configurations. For instance, at work zone configuration LC 2-1 as presented in **Figure 6*a***, the mean gap spacings from start section to end section (**Table 5**) are 225, 246, 213, 191, 262, and 242 ft, respectively. The lower quartile (25%) can be treated as the critical gap spacing that most driver would maintain a gap that are longer than that. From the boxplots, the range of the upper quartile (75%) and lower quartile (25%) in mean gap spacing have the tendency to decrease as vehicles moving from start section to transition area. The mean gap spacing began to increase after traversing activity area. While for LC 3-2 (**Figure 6*b***), the mean gap spacing throughout the entire work zone remains consistent– from 166 to 190 ft (**Table 6**). As for shoulder closure, the mean gap spacings from the start to the end at SC 2-2 are 225, 179, 162, and 184 ft (**Table 7**). At SC 3-3, headways were stable with minor changes ranging from 142 to 172 ft traversing work zones (**Table 8**). This might be indicating that with more through lanes, work zone activity will have fewer impacts on drivers.



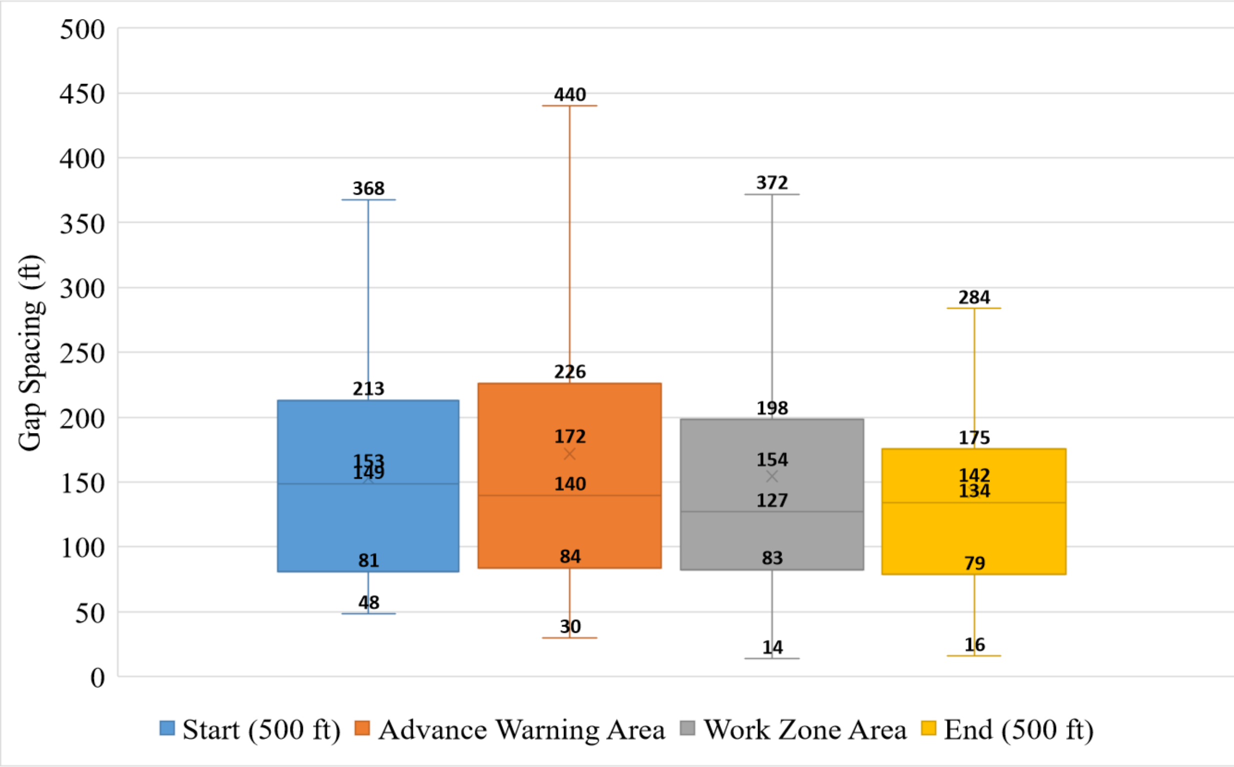
(*a*)


600
500
400
300
200
100
0
Gap Spacing (ft)
366
193
172
142
76
61
529
255
173
145
71
2
449
219
166
133
59
13
455
244
190
156
103
12
439
237
183
149
91
48
371
212
188
163
106
52
Start (500 ft)
Advance Warning Area
Transition Area
Activity Area
Termination Area
End (500 ft)

(b)


600
500
400
300
200
100
0
Gap Spacing (ft)
505
278
225
184
127
76
379
215
179
157
105
20
362
198
162
133
89
9
461
254
184
158
90
64
Start (500 ft)
Advance Warning Area
Work Zone Area
End (500 ft)

(c)



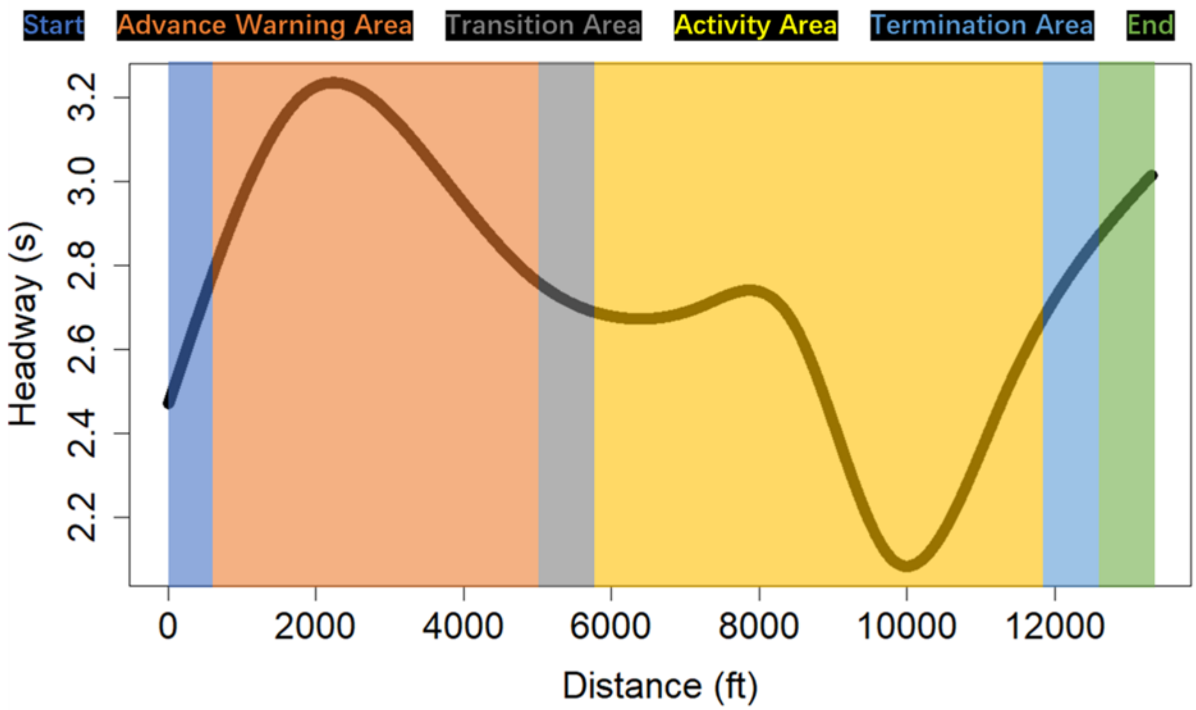
(*d*)

FIGURE 6. GAP SPACING DISTRIBUTION BY WORK ZONE AREAS: (*A*) LC 2-1; (*B*) LC 3-2; (*C*) SC 2-2; AND (*D*) SC 3-3.

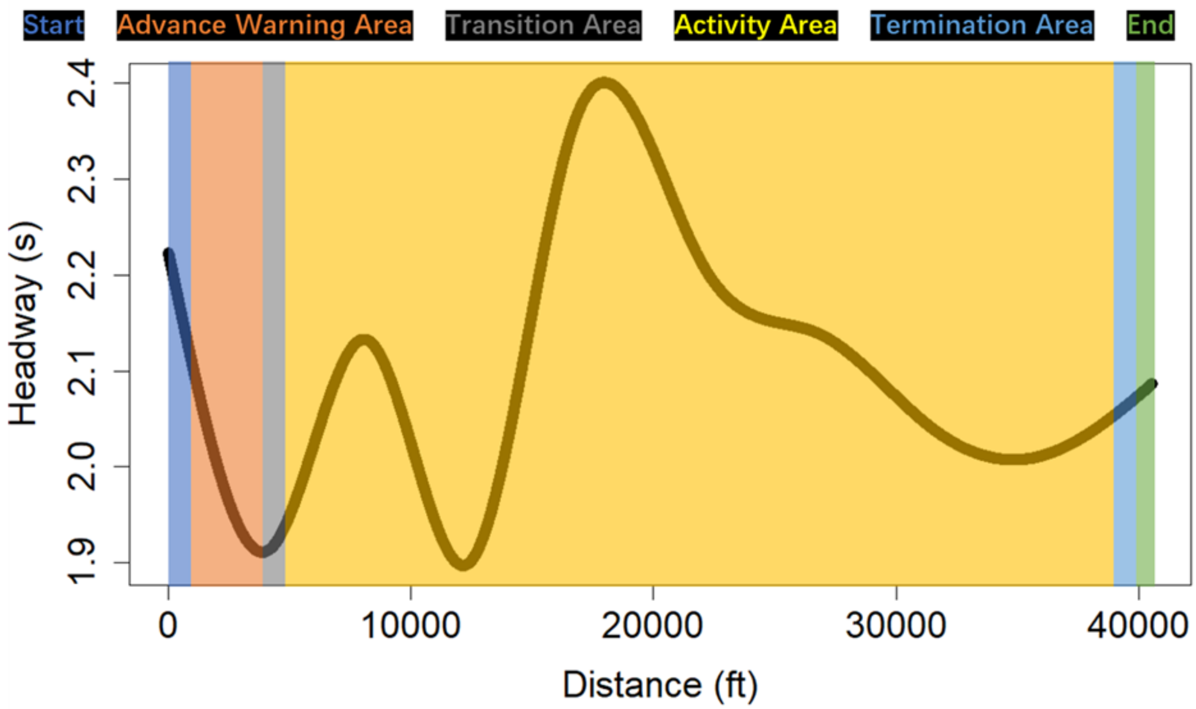
4.1.4 Headway Estimation

As shown in **Figure 7**, GAM estimated the best-fitted curves of time headway throughout work zone at four work zone configurations. **Figure 7*a*** presents the time headway estimation for LC 2-1. The time headway tends to increase when drivers approach advance warning area. It starts to decrease when drivers are in the advance warning area. The decreasing trend continues until drivers are at the end of activity area. The smallest time headway occurs in activity area. The time headway quickly increases after drivers enter termination area. For LC 3-2 (**Figure 7*b***), fluctuations are expected before activity area. The time headway tends to consistently decrease when drivers approach activity area. The smallest headway was estimated in activity area. The time headway started to increase in termination area where drums are removed.

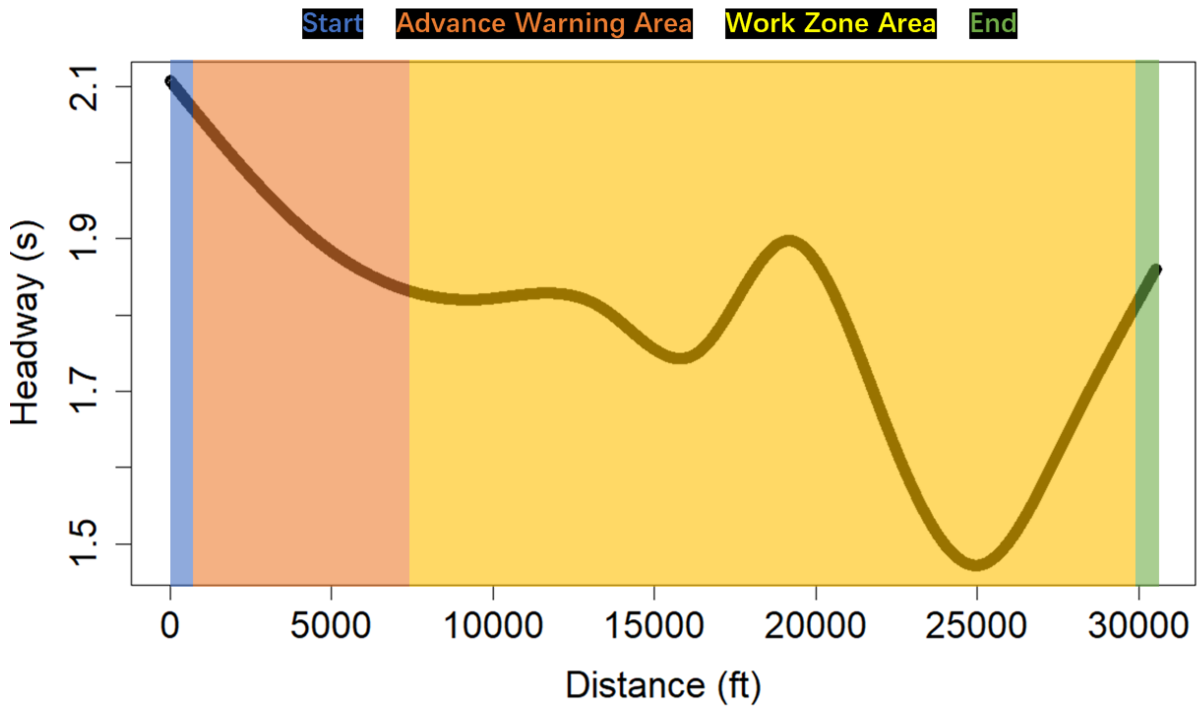
Figure 7*c* presents the estimated headway for SC 2-2. The overall trend illustrates that time headway decreases until drivers start to leave the work zone. For SC 3-3 (**Figure 7*d***), two smallest headway points were observed. The first one occurs at where the shoulder has been fully closed with limited shoulder clearance. The second one can be found where drivers approach activity area. A decreasing trend in time headway can be noticed before these two points and an increasing trend shows up after.


Start
Advance Warning Area
Transition Area
Activity Area
Termination Area
End
Headway (s)
2.2
2.4
2.6
2.8
3.0
3.2
0
2000
4000
6000
8000
10000
12000
Distance (ft)

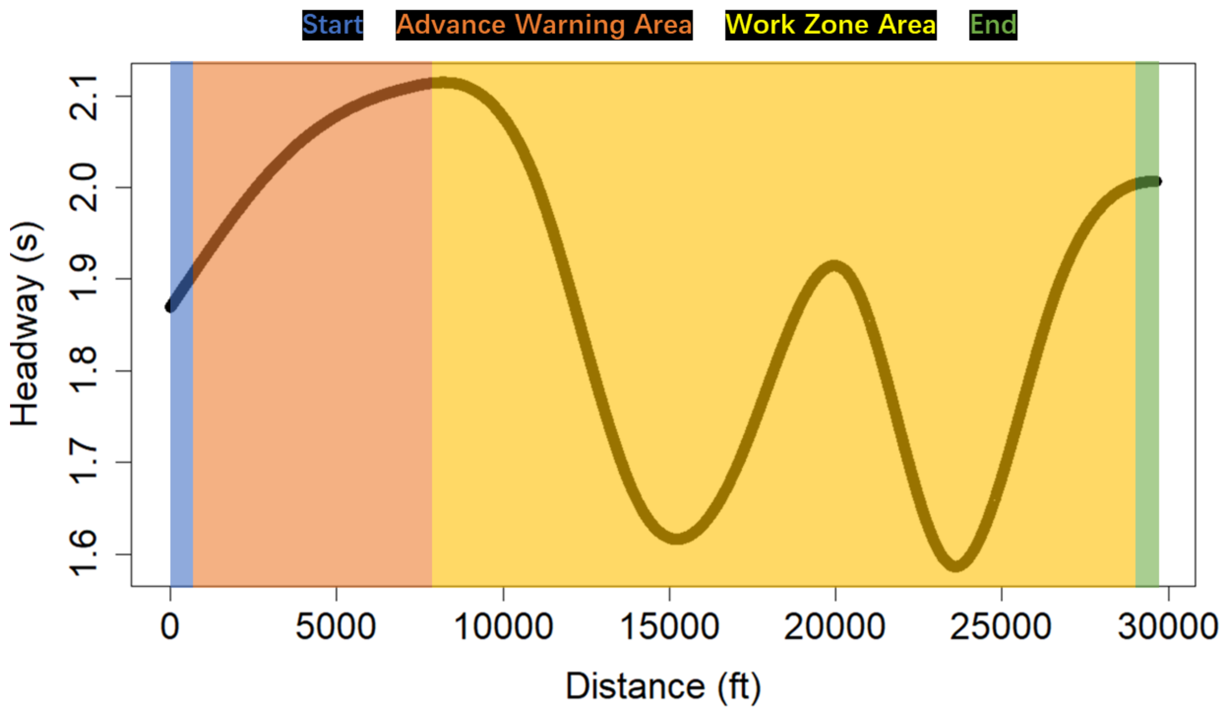
(a)


Start
Advance Warning Area
Transition Area
Activity Area
Termination Area
End
Headway (s)
1.9
2.0
2.1
2.2
2.3
2.4
0
10000
20000
30000
40000
Distance (ft)

(b)


Start
Advance Warning Area
Work Zone Area
End
Headway (s)
1.5
1.7
1.9
2.1
0
5000
10000
15000
20000
25000
30000
Distance (ft)

(c)


Start
Advance Warning Area
Work Zone Area
End
Headway (s)
1.6
1.7
1.8
1.9
2.0
2.1
0
5000
10000
15000
20000
25000
30000
Distance (ft)

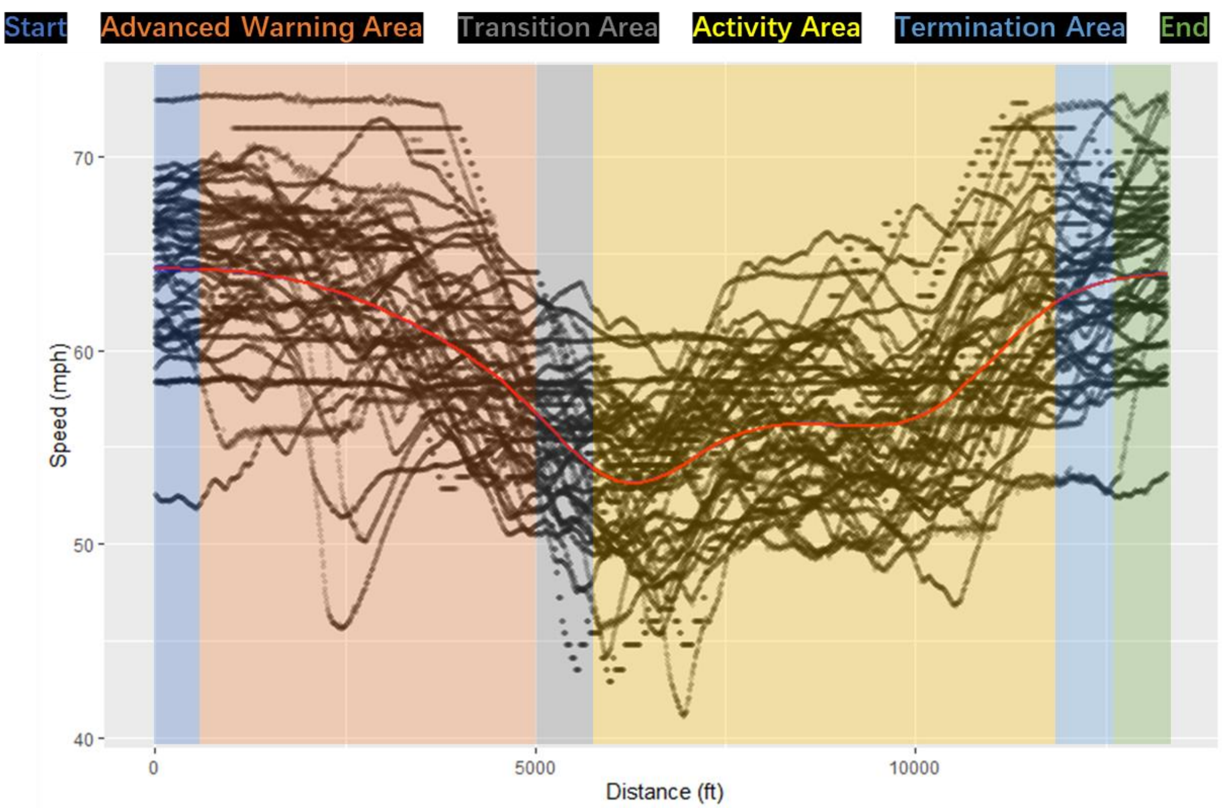
(*d*)

FIGURE 7. HEADWAY ESTIMATION BY WORK ZONE SECTIONS: (*A*) LC 2-1; (*B*) LC 3-2; (*C*) SC 2-2; AND (*D*) SC 3-3.

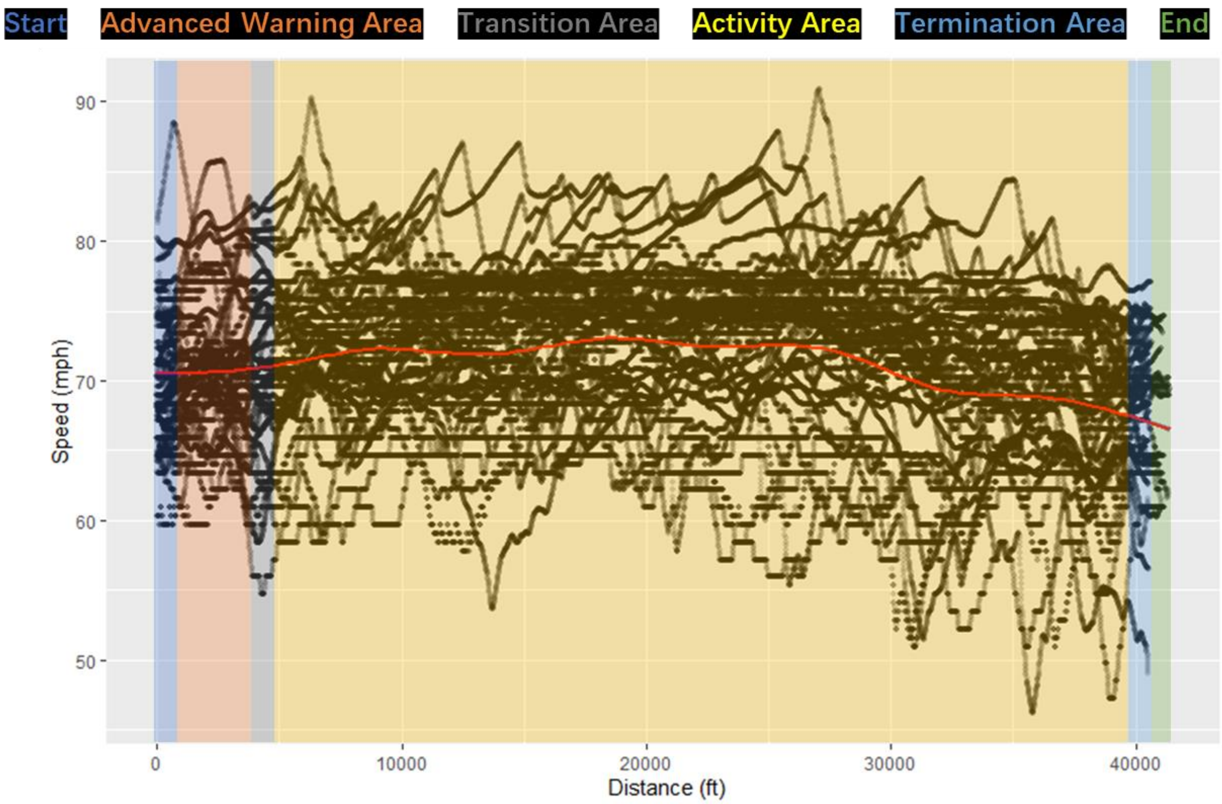
4.2 Speed Analysis

4.2.1 Speed profile

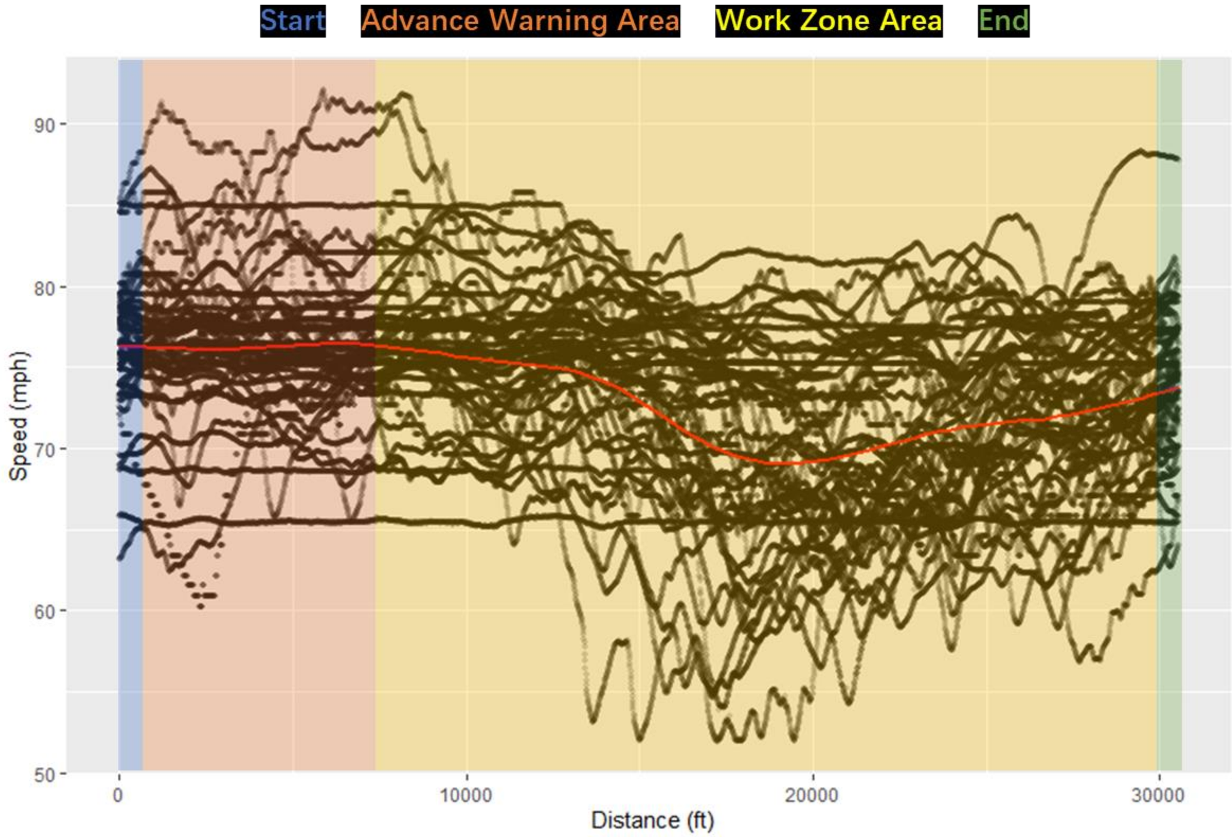
Speed profiles by GAM are presented in **Figure 8**, which shows speed distributions in the entire work zone at four configurations. The x-axis is the length (ft) and the y-axis is the speed (mph). The black dots are the speed data from SHRP 2 NDS time-series reports, one trace coming from one traversal. The red lines are the best-fitted curves by using GAM. After reviewing the forward-view videos, it was found that the reduced speed limit sign (55 mph) only appeared at LC 2-1 configuration. From **Figure 8*a***, it is observed that at LC 2-1 work zone, speeds decreased when approaching work zone, but drivers were only compliant with 55 mph speed limit during transition area. Their speeds increased when entering the activity area. At SC 2-2 work zone, there is a speed reduction between 10,000 and 20,000 ft, which was due to the presence of concrete barriers instead of drums. The other two configurations did not observe significant speed changes during the entire work zone traversal.



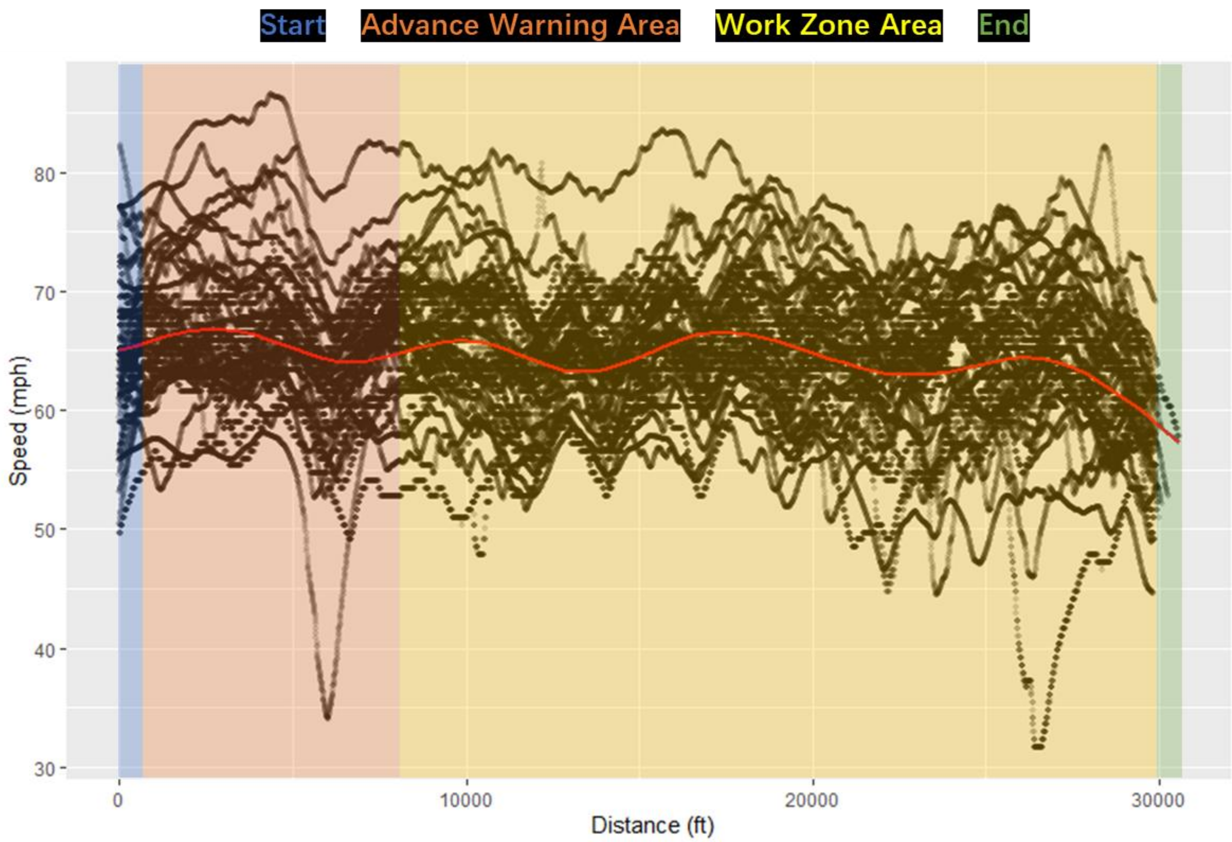
(*a*)


Start
Advanced Warning Area
Transition Area
Activity Area
Termination Area
End
Speed (mph)
Distance (ft)
90
80
70
60
50
0
10000
20000
30000
40000

(b)


Start
Advance Warning Area
Work Zone Area
End
Speed (mph)
90
80
70
60
50
0
10000
20000
30000
Distance (ft)

(*c*)

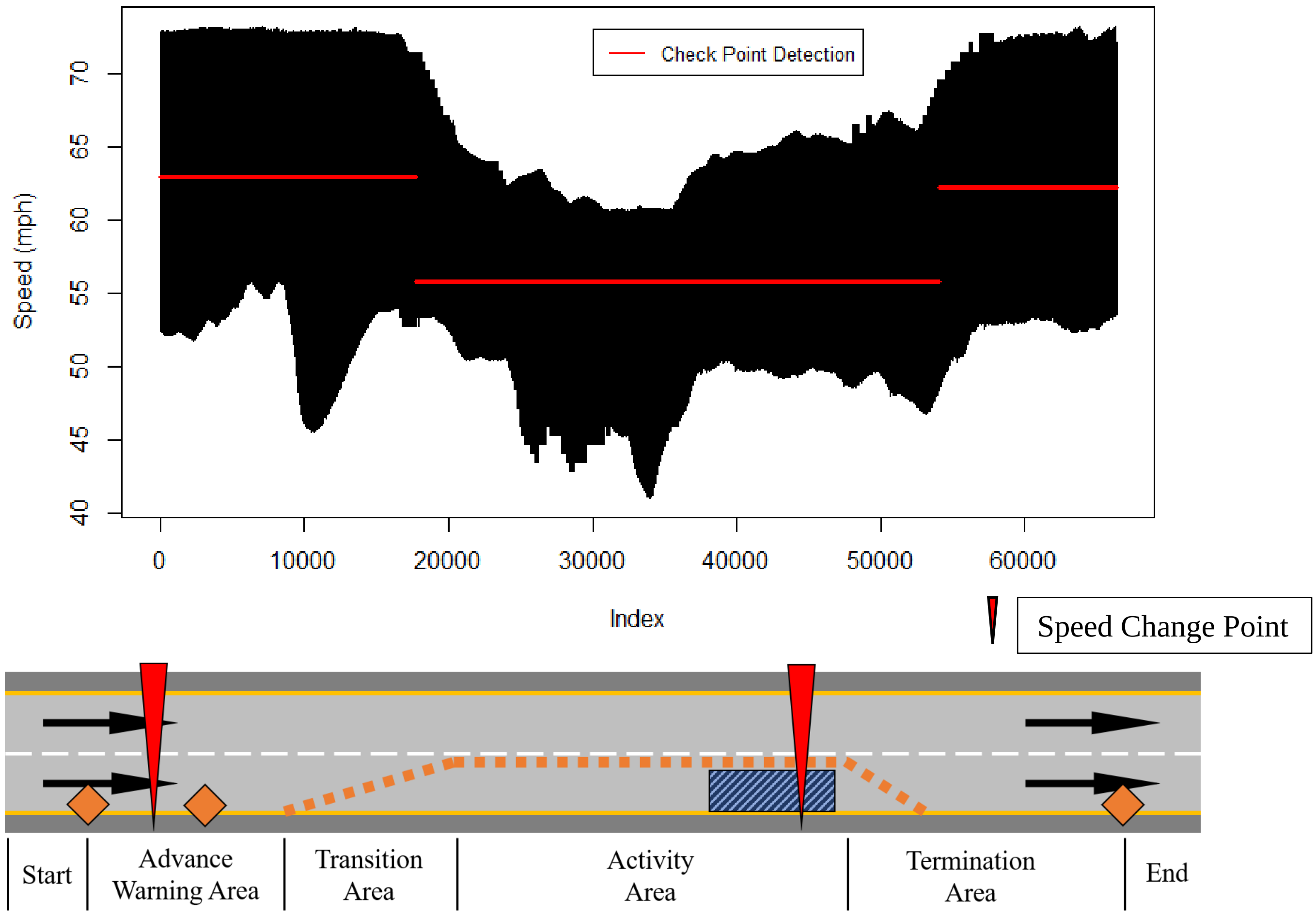


(d)

FIGURE 8. SPEED DISTRIBUTION: (A) LC 2-1; (B) LC 3-2; (C) SC 2-2; AND (D) SC 3-3.

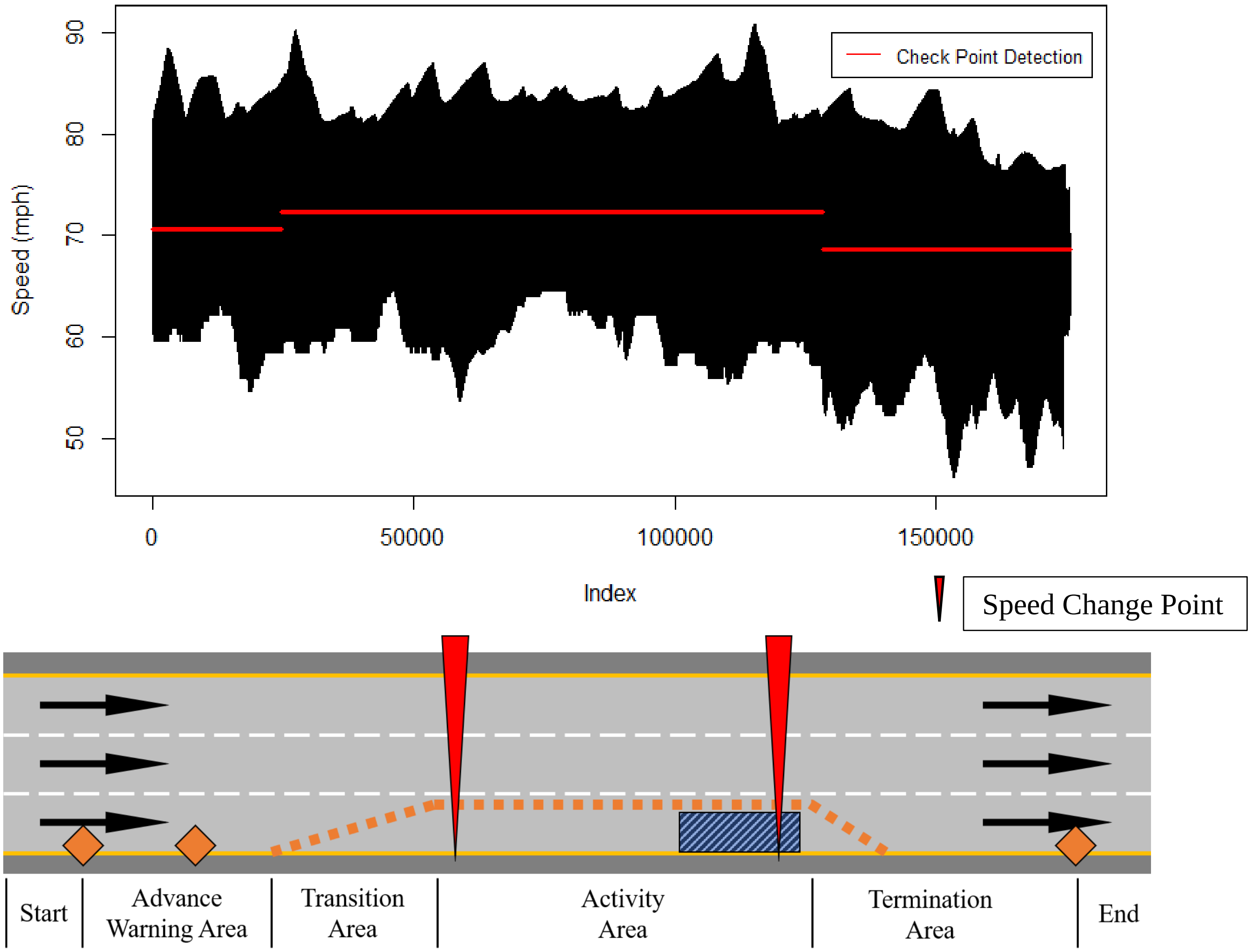
4.2.2 Speed change point

The speed change point detection concept was used to identify points where both mean and variance of speeds had significant changes. **Figure 9** presents speed change points at four work zone configurations. The x-axis is the data point index and the y-axis is the speed (mph). The red arrow indicates the location of a speed change point in work zones. As aforementioned, only LC 2-1 presented the speed reduction requirement from the reduced speed limit sign. It was found, in **Figure 9*a***, that the mean speed began to decrease by 8 mph after entering advance warning area and increased back to initial speeds after drivers saw the end of work zone drums. At LC 3-2 (**Figure 9*b***), it was observed a slight speed increase (2 mph on average) after the transition area. This might be caused by driver accelerating to merge to the left two lanes. The mean speed then decreased by 4 mph when drivers reached the activity area. No reduced speed limit sign was installed at the LC 3-2 location. For SC 2-2 (**Figure 9*c***), the mean speed was significantly reduced by 5 mph where concrete barriers narrowed shoulder clearance. It increased by 2 mph near the end of work zone area. The slight speed decreases (2-3 mph) at SC 3-3 (**Figure 9*d***) were observed which was likely led by the downstream merging behavior from downstream freeway on-ramps.

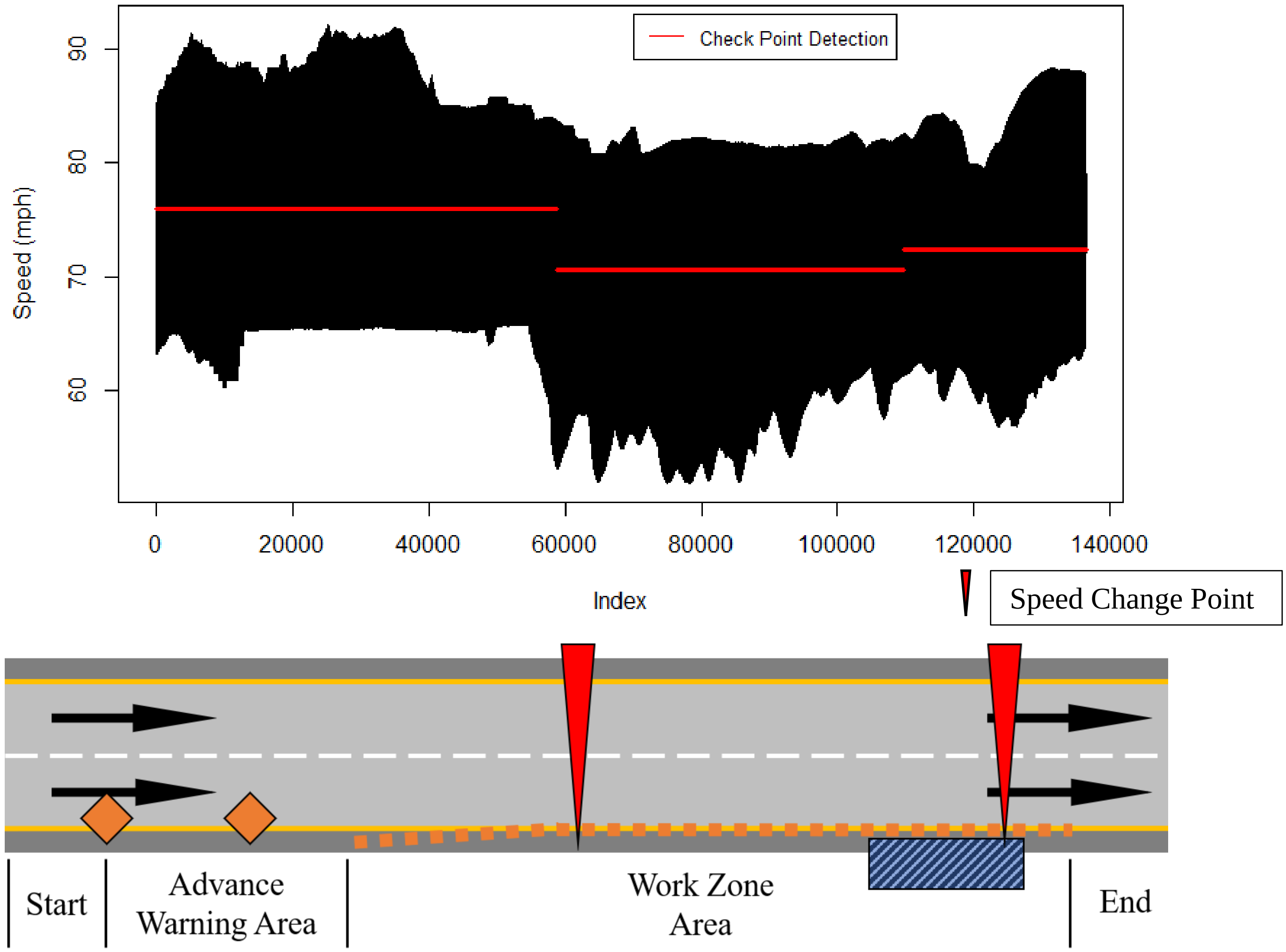


Check Point Detection
Speed (mph)
40
45
50
55
60
65
70
0
10000
20000
30000
40000
50000
60000
Index
Speed Change Point
Start
Advance Warning Area
Transition Area
Activity Area
Termination Area
End

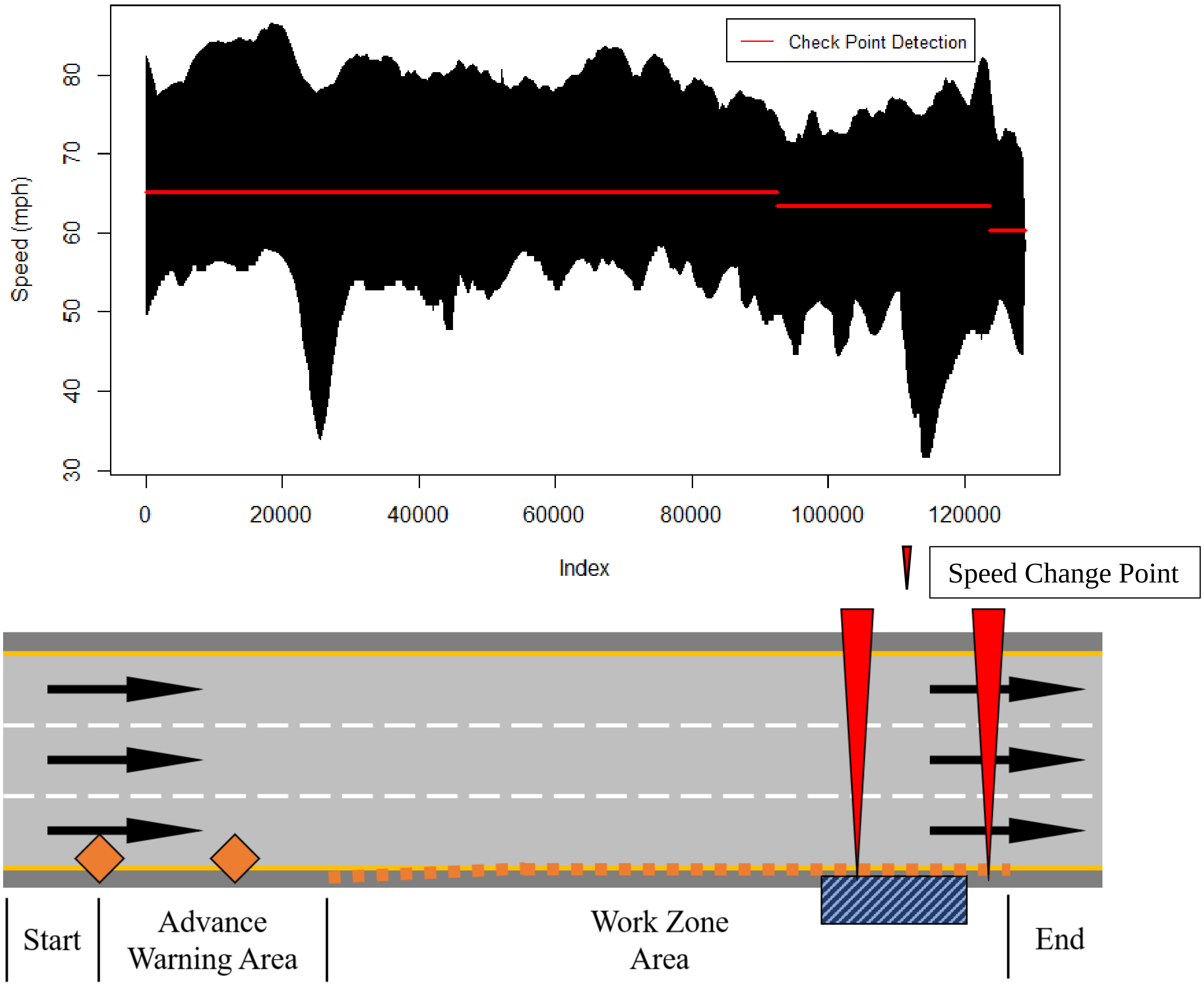
(a)


Check Point Detection
Speed (mph)
90
80
70
60
50
0
50000
100000
150000
Index
Speed Change Point
Start
Advance Warning Area
Transition Area
Activity Area
Termination Area
End

(b)


Check Point Detection
Speed (mph)
90
80
70
60
0
20000
40000
60000
80000
100000
120000
140000
Index
Speed Change Point
Start
Advance
Warning Area
Work Zone
Area
End

(c)



(d)

NOTE: RED ARROW = SPEED CHANGE POINT

FIGURE 9. SPEED CHANGE POINT DETECTION: (*A*) LC 2-1; (*B*) LC 3-2; (*C*) SC 2-2; AND (*D*) SC 3-3.

5.0 CONCLUSION

This study utilized SHRP 2 NDS data to develop gap and headway selection tables based on driver characteristics and establish speed profiles in four freeway work zone configurations. The results can be used to enhance work zone planning and simulation models and improve ACC spacing policies in work zones. Key findings are summarized as follows:

- The gap and headway selection tables revealed that car-following behaviors are highly variable among different drivers. The time and space gap distributions from different drivers traversing various work zone areas can be useful to improve ACC spacing policies for automotive industry. Further studies are needed to understand driver's acceptance of current ACC gap setting at work zones. This study found that mean headways vary among the different component parts of a work zone. These findings suggest that separate headway distributions should be used for different work zone areas when modeling work zone traffic control using simulation or planning tools.
- The speed data analysis indicated that speed decrease when drivers approach transition area and increase when they are near termination area for lane closure conditions. The mean speed at LC 2-1 was reduced by 8 mph from 63 mph to 55 mph (the reduced speed limit) when entering advance warning area and the speed increased back to initial speeds after activity area. At LC 3-2, the 4 mph mean speed reduction from 72 mph to 68 mph was observed when drivers were approaching activity area. For SC 2-2, the mean speed was reduced by 5 mph from 76 mph to 71 mph by the concrete barriers that narrowed shoulder clearance. The shoulder closure typically does not have significant impacts on speeds under non-breakdown conditions. There was no significant speed change at SC 3-3.

6.0 RECOMMENDATIONS

This study applied SHRP 2 NDS data to study the impact of driver characteristics on gap and headway selection and speed distribution during the entire work zone areas. Future studies could investigate the headway and gap distributions under other types of weather and lighting conditions. It is also suggested to collect more NDS data to further validate the gap and headway selection and speed distribution by different driver types for more work zone configurations with additional work zone trips by more unique drivers. This would also be helpful for understanding drivers' acceptance of current ACC gap settings at work zones.

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8.0 APPENDICES

8.1 Appendix A – Acronyms, abbreviations, etc.

ACC	Adaptive Cruise Control
AIC	Akaike Information Criterion
CMS	Changeable Message Sign
DAS	Data Acquisition System
DOT	Department of Transportation
FHWA	Federal Highway Administration
GAM	Generalized Additive Model
HCM	Highway Capacity Manual
HCS	Highway Capacity Software
LC	Lane Closure
MUTCD	Manual on Uniform Traffic Control Devices
NDS	Naturalistic Driving Study
NHS	National Highway System
SC	Shoulder Closure
SHRP 2	The Second Strategic Highway Research Program
TTC	Temporary Traffic Control
VHT	Vehicle Hours Traveled
VMT	Vehicle Miles Traveled
VTTI	Virginia Tech Transportation Institute

8.2 Appendix B – Associated websites, data, etc., produced

N/A

8.3 Appendix C – Summary of Accomplishments

Date	**Type of Accomplishment** *(select from drop down list)*	**Detailed Description** *Provide name of person, name of event, name of award, title of presentation, location and any links to announcements if available* *Please attach any abstracts, summaries, high quality photos, or additional details as an appendix.*
8/7/2020	Conference Presentation	Dan Xu, ITE Annual Meeting/McTrans Virtual Booth, Analysis of Headway and Speed based on Driver Characteristics and Work Zone Configurations Using Naturalistic Driving Study Data
1/7/2021	Student Accomplishment or Award	Dan Xu & Dr. Hugo Zhou, 2020 Best Paper Award by TRB's Standing Committee on Human Factors or Infrastructure Design and Operations (ACH40), Analysis of Headway and Speed based on Driver Characteristics and Work Zone Configurations Using Naturalistic Driving Study Data
1/12/2021	Conference Presentation	Dr. Hugo Zhou & Dan Xu, TRB ACH40 Committee Meeting, Analysis of Headway and Speed based on Driver Characteristics and Work Zone Configurations Using Naturalistic Driving Study Data
3/17/2021	Student Accomplishment or Award	Dan Xu & Dr. Hugo Zhou, Second Place Winner of the General Member Technical Paper Competition by SDITE, Analysis of Headway and Speed based on Driver Characteristics and Work Zone Configurations Using Naturalistic Driving Study Data
3/24/2021	Publication	Dan Xu & Dr. Hugo Zhou, accepted for publication by TRR, Analysis of Headway and Speed based on Driver Characteristics and Work Zone Configurations Using Naturalistic Driving Study Data

8/5/2021	Conference Presentation	Dr. Hugo Zhou, Joint ALSITE/DSITE 2021 Annual Meeting, Applications of Naturalistic Driving Study Data to Improve Highway Design and Traffic Operation
10/6/2021	Conference Presentation	Dr. Hugo Zhou & Dan Xu, STRIDE Webinar, Evaluation of Work Zone Mobility by Utilizing Naturalistic Driving Study Data, Phase II