TRANSPORTATION RESEARCH

CIRCULAR

Number E-C243

April 2019

SHRP 2 Safety Data Student Paper Competition 2017–2019

The National Academies of

SCIENCES · ENGINEERING · MEDICINE

TRB

TRANSPORTATION RESEARCH BOARD

TRANSPORTATION RESEARCH CIRCULAR E-C243

SHRP 2 Safety Data Student Paper Competition
2017–2019

Sponsored by
TRB Oversight Committee for Use and Oversight of SHRP 2 Safety Data, Phase I

January 2019

Transportation Research Board
Washington, D.C.
www.TRB.org

TRANSPORTATION RESEARCH CIRCULAR E-C243
ISSN 0097-8515

The **Transportation Research Board** is one of seven major programs of the National Academies of Sciences, Engineering, and Medicine. The mission of the Transportation Research Board is to provide leadership in transportation innovation and progress through research and information exchange, conducted within a setting that is objective, interdisciplinary, and multimodal.

The **Transportation Research Board** is distributing this E-Circular to make the information contained herein available for use by individual practitioners in state and local transportation agencies, researchers in academic institutions, and other members of the transportation research community. The information in this E-Circular was taken directly from the submission of the authors. This document is not a report of the National Academies of Sciences, Engineering, and Medicine.

Transportation Research Board
500 Fifth Street, NW
Washington, D.C.
www.TRB.org

Foreword

The second Strategic Highway Research Program (SHRP 2) Safety Study, completed in 2015, collected an unprecedented amount of objective data on driver behavior and the driving context. The SHRP 2 Naturalistic Driving Study (NDS captured detailed data on 3,500+ volunteer passenger-vehicle drivers, including continuous driving data and video of the road and the driver over 35 million vehicle miles and more than 4,200 crashes and near-crashes across sites in six states. The SHRP 2 Roadway Information Database (RID collected detailed roadway data on 12,500 centerline miles, compiled existing driving context data on another 200,000 centerline miles, and made it possible to link the roadway data to the driving data. Together, the SHRP 2 NDS and the RID are the "SHRP 2 Safety Data." Phase 1 of SHRP 2 Safety Data Implementation and Oversight is the initial post-data collection phase, begun in March 2015. The objectives of this phase are to make the Safety Data widely available to qualified researchers and to gain experience and data to support decisions about the implementation and oversight of the data beyond the first 5 years. Phase 1 is scheduled to end in August 2020.

2017–2019 SECOND STUDENT PAPER COMPETITION: SHRP 2 SAFETY DATA BONANZA

This e-Circular contains papers submitted to the second Student Paper Competition: SHRP 2 Safety Data Bonanza. The SHRP 2 Safety Data Program and the Transportation Research Board (TRB Oversight Committee for Use and Oversight of SHRP 2 Safety Data, Phase 1 sponsored this competition to promote use of the SHRP 2 Safety Data, to extract new insights and applications of the data, and to foster the next generation of leaders in surface transportation. A call for abstracts was issued in October 2017 to graduate students across the country, soliciting innovative ideas for using the data. The Review Panel for the SHRP 2 Safety Data Student Paper Competition selected eight students to conduct their research proposals; they received a data export, conducted their analysis, and were sponsored to attend the TRB Annual Meeting in January 2019 to present their results at a poster session. The students went on to develop research papers from their analyses.

Four exemplary papers were selected by the Review Panel to be published in this E-Circular. These student papers examine the topics of interchange ramps, a market basket approach to analyzing safety data, risky secondary driving behavior, and pollutant emissions. The variety of these topics is indicative of the broad usefulness of the SHRP 2 safety data.

2015–2016 FIRST STUDENT PAPER COMPETITION: SHRP 2 SAFETY DATA BONANZA

This first student paper competition was published in the *Transportation Research Circular E-C221: SHRP 2 Safety Data Student Paper Competition, 2015–2016* (2017). It can be found on the TRB website at http://www.trb.org/Publications/Blurbs/176065.aspx.

ACKNOWLEDGMENTS

It is important to acknowledge that the SHRP 2 Safety Data Student Paper Competition and this E-Circular is the product of the work of the many individuals, committees, and task groups who volunteered their valuable time and insight. Thanks go to the authors and their faculty sponsors for participating in the second SHRP 2 Safety Data Student Paper Competition.

The TRB Oversight Committee for Use and Oversight of SHRP 2 Safety Data, Phase 1 provided overall leadership of the SHRP 2 Safety Data Student Paper Competition. The Expert Task Group for User Community Development for Safety Data, Phase 1 provided guidance on development and management of the Student Paper Competition. From these two groups was assembled the Review Panel for the SHRP 2 Safety Data Student Paper Competition, who provided valuable reviews and feedback on the abstracts and papers. Special acknowledgement goes to Troy Costales, Joanne Harbluk, Suzie Lee, Tim McDowell, Christopher Melson, Miguel Perez, Norah Ocel, Omar Smadi, Jordan Riddle, and Zongwei Tao. The teams at Virginia Tech Transportation Institute and the Institute for Transportation at Iowa State University also provided data request support. The entire process was managed by TRB staff Steve Andrle, Karen Febey, David Plazak, and Brie Schwartz.

This work was sponsored by the Federal Highway Administration in cooperation with the American Association of State Highway and Transportation Officials. It was conducted in Phase 1 of SHRP 2 Safety Data Implementation and Oversight, which is administered by the Transportation Research Board of the National Academies of Sciences, Engineering, and Medicine.

Contents

Beyond Safety

Utilizing SHRP 2 NDS Data to Model Vehicular Emissions from Passenger Cars at Work Zones Using Vehicle-Specific Power and Operating Mode Distribution Approach

GEORGES BOU-SAAB
SHAUNA HALLMARK
OMAR SMADI
Iowa State University

Transportation sector is a major contributor to air pollution. Therefore, it is essential to monitor vehicular emissions in order to control air quality. Many researchers showed interest in the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS) data to conduct safety and driver distraction studies. One major benefit of using such a dataset is that it represents the overall vehicle fleet, driver population, and traffic conditions in the United States. There is potential to utilize this data in modal emission modeling at project level by acquiring second-by-second speed and acceleration to calculate vehicle-specific power, then assign data to different operating mode bins to estimate emissions. The primary focus of this study was to utilize SHRP 2 NDS data to estimate emissions of criteria pollutants for work zones in four-lane divided principal arterials with different configurations. The analysis also considered work zone principal areas and level of congestion. Overall, results showed that the work zone area type and configuration did not have any impact on emissions, although high congestion levels increased emissions, predominantly within the activity area. Further investigations that compared the different bivariate speed and acceleration distributions using the energy statistics showed that work zone configuration and principal area had a significant impact on vehicle operations.

INTRODUCTION

Work zones are typically employed on roadway networks for restoration, resurfacing, rehabilitation, and reconstruction projects. As a result of lane closure, work zones create bottlenecks reducing capacity and disrupting traffic flow. Congestion due to work zones on a roadway network is nonrecurring since they temporarily interrupt traffic movement. Nonrecurring events also include crashes, severe weather conditions, disabled vehicles, and special planned events and they account for approximately 50% of total congestion. Work zones are responsible for 10% of total congestion (*1*). Impact of work zones is not only limited to mobility, safety, and user cost, it also extends to the environment. Congestion occurring at these particular locations contributes to higher tailpipe vehicular emission including carbon dioxide (CO_2) and criteria pollutants such as carbon monoxide (CO), gaseous hydrocarbons (HC), nitrogen oxides (NO_x), and particulate matter ($PM_{2.5}$ and PM_{10}). Increase in emissions is caused by increases in stop-and-go driving and, in some cases, idling. Besides driving patterns, emissions at work zones are dependent on several significant factors such as facility type, travel demand, and detour plans along with spatial and temporal factors (*2*).

Emission Modeling at Work Zones

Research quantifying the impacts of work zone on emissions is limited. Most related available examined how congestion levels in general impact emissions. A study in Ann Arbor, Michigan, estimated emissions under congested and free-flow conditions from light and heavy duty vehicles on a freeway segment (*3*). This was achieved by collecting instantaneous speed and vehicle position from a permanent traffic recorder. The selected freeway segment experienced congestion due to rush hour and presence of a work zone. Zhang et al. used the comprehensive modal emission model (CMEM) to estimate second-by-second emissions. When the traffic transitioned from free-flow to congested condition, CO, HC, and NO_x emission rates from light-duty vehicles were the highest. On the contrary, lowest rates were recorded for vehicles moving at low speed in the congested work zone. As for CO_2 and fuel consumption, the work zone on the freeway under congested traffic flow yielded highest rates. Results for high-duty vehicles differed, as congested work zones contributed to the highest CO, HC, and CO_2 emission rates as well as fuel consumption. However, NO_x emissions remained unchanged for different traffic conditions (*3*). Salem et al. (*4*) reviewed various lean construction tools to help them understand how the application of this technique can improve sustainability of work zones. Lean construction techniques lowered vehicle operating cost as mobility and traffic flow conditions improved at work zones, which in return reduced emissions.

Researchers and scientists are constantly assessing new technology and techniques that generate positive outcomes and improve quality of life. For instance, the application of wireless communication technology proved to enhance mobility and safety (*5*, *6*). These systems have the ability to adapt driver behavior to various traffic operations and result in lower emissions. A team of researchers at Texas Southern University examined the impact of introducing a driver smart advisory system (DSAS) in a simulated study where a pedestrian crossing was present in a work zone. The implications of the system changed drivers' behavior as they accelerated smoothly in the work zone and made them stop earlier when faced with a safety-related hazardous situation, i.e., pedestrian crossing the street. Consequently, there was a reduction in vehicle emissions for criteria pollutants (*7*). Another simulated study quantified vehicular emissions at network level for a major freeway corridor reconstruction project in Fort Worth, Texas. The work zone was modeled using a series of links. Capacity and free-flow speed on these links were reduced by dropping the number of lanes. The baseline model consisted of events prior to construction of the work zone. Other modeled scenarios assigned calibrated traffic on the links to compute vehicle emissions as travel behavior changed (*8*). Average emission rate of CO_2, CO, HC, and NO_x increased as traffic capacity in the work zone decreased. In a scenario where the capacity was reduced by 50% (i.e., two lanes dropped) with no diversion of traffic, the average inflow volume and emission rate of criteria pollutants upstream and inside the work zone were comparatively higher than downstream of the work zone (*8*). The simulated study was also implemented on a larger-scale regional network in North Carolina which incorporated three major cities: Raleigh, Durham, and Chapel Hill. Only passenger cars and passenger trucks were modeled under single and high-occupancy vehicle demand classes. The baseline scenario in the study considered normal driving conditions with no traffic disturbances. Two other scenarios quantified congestion and diversion patterns by simulating traffic distribution with the presence of work zones on a pavement rehabilitation project on I-40 and I-440 corridors in Raleigh. One of the scenarios considered no diversion (ND) of traffic while the other scenario diverted traffic to major arterials using user equilibrium (UE) traffic assignment technique. Results demonstrated that average speed of vehicles and emission levels were not impacted under the baseline scenario. On the contrary, there was an overall increase in emissions for ND traffic simulation due to drop in average speed as vehicles started to queue upstream of the work zones. As noted previously, traffic was diverted to alternate routes under the UE scenario to reduce congestion upstream and downstream of the work zone. However, when compared to the baseline scenario, Zhou et al. (*8*) noted that emission levels were higher in the UE simulation with the formation of a bottleneck at the work zone.

Effect of Congestion on Emission Levels of Pollutants

Most recently, Texas A&M Transportation Institute investigated the air quality benefits of nighttime construction in urban areas in Texas (*9*). Results from three different case studies suggested that shifting construction activities from daytime to nighttime reduced total emissions at work zones. This should be expected with lower traffic volumes at night. However, researchers showed that for similar emission levels, concentration of pollutants during nighttime might be worsened as a result of changes in meteorological conditions. With limited number of research pertaining to emission modeling at work zones, other similar studies involved comprehending the effect of congestion on emission levels of pollutants. This is considered important while evaluating traffic management strategies. Previous studies analyzed emissions for different roadway types/facilities under varying traffic operation conditions using well-established tools. For instance, freeway air quality was modeled during normal and congested traffic conditions. Salimol Thomas developed a framework to model excess emissions during recurring and nonrecurring congestion conditions in freeways (*10*). A stochastic model was also used to measure the impact of nonrecurring incidents on the local emission inventory. Barth and Boriboonsomsin utilized CMEM to compute carbon dioxide emissions for different level-of-service (LOS) by categorizing velocity of vehicles as a function of congestion levels (*11*). In addition, vehicle emissions on freeways were determined by exploring traffic speeds, freeway capacity, and travel demand (*12*). Papson et al. used time-in-mode (TIM) methodology to estimate emissions at uncongested and congested signalized intersections under three traffic intersection scenarios (*13*). A recent study by Qi et al. obtained emission factors for both freeway and arterial facilities under different congestion levels (*14*). Findings indicated that emissions were negatively impacted as traffic conditions worsened.

Application of SHRP 2 NDS Data in Emission Modeling

Earlier efforts to assess emissions in work zones primarily used average speed and micro-simulated studies to describe vehicle operation which resulted in less reliable results. For increased accuracy in emission modeling at project level, second-by-second speed and acceleration data are required to fully describe the different vehicle operations. These limitations can be addressed with the application of SHRP 2 NDS data. This was the largest naturalistic driving study to date conducted in the United States and included instrumented vehicles with over 3,000 drivers that were recruited from six states: New York, North Carolina, Pennsylvania, Indiana, Florida, and Washington. The study consisted of over 5.5 million trip files with almost 40 million miles of data that can be analyzed extensively by researchers (*15*). A group of researchers intend to apply a new approach to establish optimized representative drive schedules from SHRP 2 NDS data (*16*). Drive cycles, also referred to as drive schedules, are a series of vehicle-speed trajectory points which are essential in modeling since emissions vary with driving patterns (*17*). Other contributing factors include speed limits, traffic conditions, road grade, and curvature. Various countries developed drive cycles to represent their nation's driving conditions. Administrative agencies apply them for federal certification purposes in chassis dynamometer tests to measure tailpipe emissions and fuel economy. In another SHRP 2 NDS, Liu et al. proposed a plan to generate synthesized drive cycles for pick-up trucks that capture the principles of naturalistic driving (*18*). The drive cycles can be used to optimize the design and control of pick-up trucks taking into account the rigorous federal fuel consumption and emission standards. The University of Michigan quantified and characterized fuel consumption rate of different drivers (*19*). This was accomplished with a well-designed SHRP 2 NDS in Michigan where they instrumented 117 identical passenger cars and collected over 210,000 mi of data. Furthermore, North Carolina State University conducted a small-scale SHRP 2 NDS and collected high-resolution data at 1-Hz frequency using a local sample of 35 drivers. They developed eco-driving metrics by inspecting 20 million seconds of naturalistic driving data to extract the different driving styles and measure their impact along with other confounding factors on fuel consumption (*20*).

Current state-of-the-practice illustrated that capacity was reduced on roadways with construction sites which adversely affected vehicle emissions. Exhaust emissions are a function of changes in driver behavior, vehicle kinematics, roadway features, and surrounding environment. Monitoring emissions from every road source is practically and economically not feasible which advanced the development of tools and models to produce reliable emission estimates. Disaggregate speed and acceleration data are required to accurately estimate emissions for an entire state, county, network or at project level. Therefore, there is great potential to apply SHRP 2 NDS data in modeling emissions for different work zone configurations at project level. This will capture differences in driver behavior, roadway geometry, traffic conditions, and their impact on emissions.

Objectives

Emission of criteria pollutants and greenhouse gases from passenger cars can be estimated for work zones at the project level with the application of a modeling system. In the past, predicting emissions for different transportation elements or networks relied on average speed, whereas recent models account for vehicle operating modes, i.e., instantaneous speed and acceleration and time spent idling. Accurate estimation of emissions requires second-by-second data since emission rates are highly sensitive to changes in operating modes (*21*). If average speed was used to describe an element or group of elements, then results can be either overestimated or underestimated.

The application of modal modeling allows for second-by-second estimation of emissions and fuel consumption. A robust database of instantaneous speed and acceleration will be required and SHRP 2 NDS is a prominent source of such data. Roadway and traffic characteristics are linked to the study sites using Roadway Information Database (RID) which makes it possible to include roadway characteristics. The SHRP 2 NDS collected vehicle kinematics at 10-Hz frequency including speed, acceleration, brake status, gas pedal state, etc. The study also recorded forward-view videos and vehicle position at 1-Hz frequency which can be joined with attributes from RID using GPS to determine roadway features such as presence of signs and barriers in work zones.

The primary focus of this research is modeling emissions from passenger cars for different work zone components and configurations while considering changes in congestion level on four-lane divided principal arterials. SHRP 2 NDS data will be applied in a disaggregate approach at project level to examine changes in vehicle operations then acquire emission rates from MOVES–Matrix modeling tool (*22*). The system is configured by a team of researchers at Georgia Institute of Technology and is adapted from the Motor Vehicle Emission Simulator (MOVES) model which is developed by the U.S. Environmental Protection Agency (EPA) to estimate emissions from on-road vehicles in the United States.

PROPOSED STUDY PLAN

The proposed study plan consists of the following tasks that were completed to investigate the impact of various work zone configuration and level of congestion on vehicular emissions.

Task 1. Work Zone Identification

Potential work zones during the implementation of the SHRP 2 NDS were identified using 511 data (*23*). A minimum duration of 3 days was selected for work zones since the probability of finding sufficient NDS time series data was low for short-duration projects. Following the identification of 9,290 potential work zones, the location of work zone trips were then determined by linking the 511 events to RID. This also made it possible to estimate the physical extent of the work zones. The number of traces and unique drivers along with demographic characteristics, such as age and gender, of each driver were requested from Virginia Tech Transportation Institute (VTTI). Road construction projects with at least 15 trips were selected which refined the number of potential work zones to 1,680. Another request was then placed for time–series traces 1.5 mi upstream and downstream of the start of a work zone in addition to front- and rearview video logs (*23*). VTTI provided approximately 9,000 traces. However, traces with at least 90% of speed data were considered for data reduction. Ultimately, the number of traces was reduced to 5,000. For data points with missing speed information, linear interpolation technique was used to construct new data points within the range of a discrete set of known speed points.

Task 2. Data Reduction

The roadway functional class for each trace was determined from RID which facilitated the identification of events used in the data reduction process. A trace is defined as one driver trip through one work zone. Presence of a work zone was validated by reviewing forward videos. Work zone principal area type and configuration along with congestion level were also recorded from forward videos. Some traces did not have a work zone available or were not active. While other traces had traffic signals or nonwork-zone related factors that might have interrupted traffic flow (*23*). As a result, they were excluded from analysis. A total of 532 traces were coded. The sampled traces were represented from three states—New York, Pennsylvania, and Washington—and the fleet consisted of passenger cars. Table 1 provides a description of work zones from every state in terms of unique number of work zones and rural–urban designation.

TABLE 1 Number of Unique Work Zones by State and Rural–Urban Designation

State	Number of Unique Work Zones	Rural–Urban Designation
New York	13	1: Rural and 12: Urban
Pennsylvania	25	20: Rural and 5: Urban
Washington	7	7: Urban

Task 3. Work Zone Classification

Work zones can be categorized according to their structure along with roadway facility, lane closure configuration, and LOS. For emission analysis, work zones are divided into three principal areas:

- Upstream, also referred to as the base condition that represents speed traces of vehicles under normal driving conditions, i.e., before entering the work zone influence area;
- Advanced warning area, the section of the highway between the start of the work zone and the first sign observed on the highway system that informs drivers about any upcoming roadway construction or incident (*24*); and
- Activity area, typically defined as the section of a highway within the vicinity of any roadway construction (*24*). For analysis purposes, the activity area was identified as the location between the start of the shoulder taper and end of a work zone. In few cases, the trace ended within the work zone.

Emissions from advanced warning and activity area will be compared to the baseline condition. Besides area type, the configuration of a work zone that describes the layout of the activity portion of a work zone was classified into three categories:

- Shoulder closure only,
- Shoulder and lane closure, and
- Complex configuration (usually starts with shoulder and lane closure, then traffic is redirected to opposite direction of travel in a head to head configuration).

Congestion has a significant impact on vehicle operation and tailpipe emissions. Therefore, level of congestion for each trace is subjectively determined from forward videos before a vehicle entered the activity area and by grouping traffic density–LOS into three categories. The SHRP 2 dictionary for video reduction is used to define LOS (*25*). The three different classifications for congestion level included

- Noncongested, LOS A (free-flow condition) or LOS B (stable flow with some restrictions due to presence of other vehicles in traffic stream);
- Moderate congestion, LOS C (stable flow with restrictions in speed and maneuverability due to the presence of leading and adjacent vehicles) or LOS D (high traffic density but stable flow with severe restrictions in speed and maneuverability); and
- High congestion, LOS E (unstable flow with traffic operations already at capacity and vehicles are traveling at low speeds with temporary stoppage and inability to maneuver) or LOS F (unstable flow with traffic operations below capacity and vehicles are in stop-and-go condition).

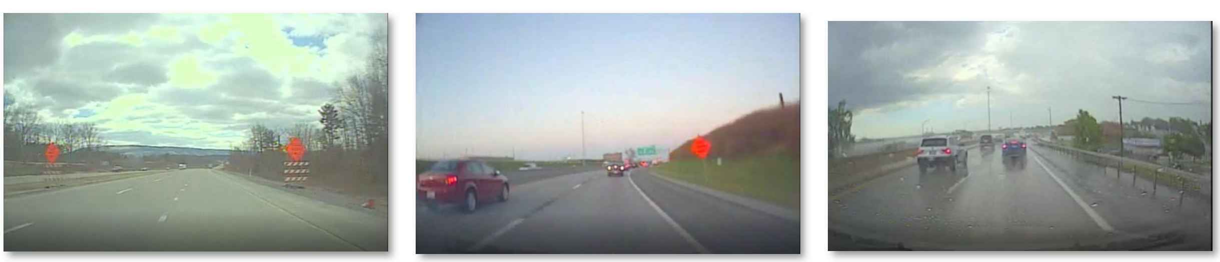
It should be noted that this designation of congestion level differs from traditional definitions of LOS. For this study, LOS can only be estimated for the conditions surrounding each subject vehicle. Therefore, it was more appropriately a measure of activity at one particular location and does not represent LOS for the roadway segment in general. Figure 1 shows an example of how the three different congestion levels were coded.

Taking into consideration that work zones were initially categorized according to their area type, a minimum threshold for distance was set for each section: 500 m (1/3 mi) for upstream section and 800 m (1/2 mi) for both advanced warning and activity area. Not all traces were used to evaluate each section. In other words, a trace might not meet the minimum distance requirement for each principal area. Failure to meet the distance requirement might not essentially capture complete vehicle operation within a particular work zone component. Moreover, emissions will be factored in compliance with the distance limits established. The resulting number of traces for each work zone classification are summarized in Table 2.

Figure 2 illustrates a typical layout of a work zone while Figure 1 shows still images from forward videos as an example of the different congestion levels.

Task 4. Vehicle-Specific Power Computations and Operating Mode Distributions

Average speed, driving schedule, and operating mode distribution are the three conventional techniques used to describe vehicle activity in MOVES (*16*) and it is critical to select an appropriate statistical assessment approach that represents the entire trip. Operating mode distribution accounts for the fraction of time by operating mode which includes different bins defined by vehicle-specific power (VSP) and vehicle activity (speed ranges, idling, braking, and acceleration). This method is more accurate than the other two as it effectively enables users to exploit the capabilities of MOVES in modeling emissions as a function of vehicle activity (i.e., captures all driving behavior). There is a direct correlation between vehicle emissions and instantaneous engine load demand. The engine load is dependent on speed, acceleration, road grade, and air conditioning use. VSP has been used as a proxy variable for power demand or engine load (*26*).



(a) **(b)** **(c)**

FIGURE 1 SHRP 2 NDS still images showing an example of different level of congestion: (*a*) noncongested flow; (*b*) moderate congestion level; and (*c*) high congestion level.

TABLE 2 Number of Traces by Principal Area Type and Congestion Level

Upstream Traces			
	Noncongested	Low Congestion	High Congestion
Shoulder closure	50	144	16
Shoulder and lane closure	77	20	8
Complex configuration	89	29	9
Advanced Warning Area Traces			
	Noncongested	Low Congestion	High Congestion
Shoulder closure	23	37	6
Shoulder and lane closure	98	23	9
Complex configuration	94	34	8
Activity Area Traces			
	Noncongested	Low Congestion	High Congestion
Shoulder closure	29	112	15
Shoulder and lane closure	112	23	8
Complex configuration	106	34	9

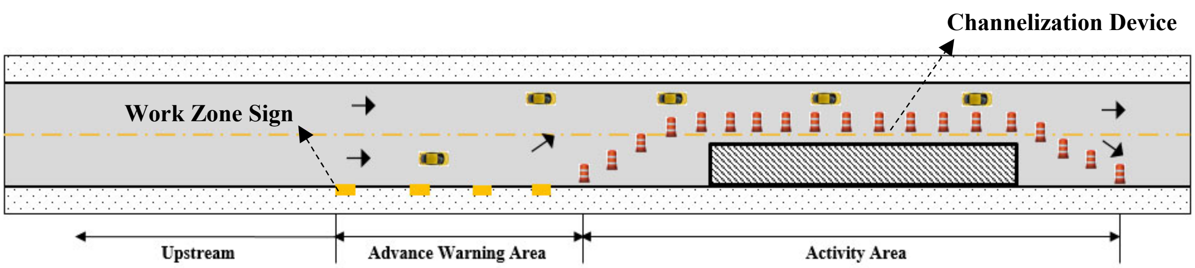


FIGURE 2 Work zone layout defining the three principal areas (adapted from MUTCD).

For consistency in modeling methodology as the one applied in MOVES, the 10-Hz activity data were converted to 1 Hz by averaging speed every 10 consecutive points to determine speed at one second intervals. Instantaneous acceleration was then computed by finding the derivative of speed (difference between the current and previous speed points). The second-by-second vehicle activity data are the inputs for the VSP equation (Equation 1) (*27*):

$$VSP = \left(\frac{A}{M}\right)v + \left(\frac{B}{M}\right)v^2 + \left(\frac{C}{M}\right)v^3 + (a + g\sin\theta)v \quad (1)$$

where

- A = the road load coefficient for rolling resistance (kW-s/m) = 0.1564;
- B = the road load coefficient for rotating resistance (kW-s^2/m^2) = 0.0020;
- C = the road coefficient for drag resistance (kW-s^3/m^3) = 0.00049;
- M = the fixed mass factor for vehicle source type (metric tons) = 1.4788;
- g = acceleration due to gravity (m/s^2);
- v = vehicle speed (m/s);

a = vehicle acceleration (m/s^2); and
sin θ = fractional road grade.

The coefficients for *A*, *B*, *C*, and *M* are obtained either specifically for each vehicle type from the manufacturer or from MOVES 2014 highway vehicle population and activity data guide. Only passenger cars were assumed in the analysis. In addition, road gradient was assumed to be flat (i.e., θ = 0) although the information can be linked from RID. These assumptions will ensure better comparisons in emissions by eliminating differences between vehicle types and roadway terrain.

Task 5. Assignment of Emission Rates to Each Second of Data

Operating mode bins summarized in the MOVES report were generated and emission rates were correlated to vehicle activity using a reference table acquired from MOVES–Matrix for the criteria pollutants and greenhouse gases of interest (*27*). Total running exhaust emissions were calculated by summing the product of driving activities and corresponding emission rates.

The new adapted tool performs similar emissions modeling and yields exact results as the original MOVES interface but at a faster pace. The database in MOVES–Matrix consists of an array of emission rates at multiple levels that resulted by running several iterative MOVES runs. Users can apply scripting techniques to model emissions for every link, in this case every work zone principal area, in the transportation network (*21*, *28*). To save processing time, a matrix table for emission rates in grams per hour was obtained for each operating mode instead of running the model for each work zone principal area and classification. This approach was adopted from Liu et al. (*30*) where they created 23 links covering all operating mode bins for running exhaust. Each link represented 100% of vehicle operation for a specific bin, hence traffic volume, length, and average speed were scaled to 1 h of vehicle operation. For the purpose of this analysis, emission rates from Buffalo, New York, will be applied in a case study. The details of the scenario include:

- Calendar year: 2017;
- Region: Buffalo, New York;
- Transportation links: 23 links to represent all operating mode bins;
- Source type distribution: only passenger cars are considered in the analysis (Source Type ID=21);
- Age distribution: 2017 national default age distribution from MOVES2014 to account for fleet distribution in the United States (*29*); and
- Meteorology: average values for 2017 summer months, i.e., between May and September:
  - Average temperature (in 5°F increment): 70°F and
  - Average relative humidity (in 5% increment): 75%.

The analysis in this paper focused on comparing emissions for CO, NO_x, $PM_{2.5}$, and CO_2. The majority of HC emissions are highly correlated with vehicle cold starts and fuel evaporation. $PM_{2.5}$ is linearly related to PM_{10}, the same applies to the relationship between CO_2 and fuel consumption (*30*).

RESULTS AND DISCUSSION

Speed–Acceleration Plots

The acceleration and speed kernel density plots in Figures 3 through 5 show the changes in vehicle activity for the three work configuration categories as drivers' transition between the different work zone components. Changes in congestion level are also considered. The following inferences can be attained from the plots:

- Across the three different work zone configurations, the distribution of acceleration and deceleration are almost symmetrical, which can be attributed to the fact that there are constant changes in driver behavior. The variation in acceleration is low for noncongested flow at baseline conditions as drivers are operating at higher speeds. When vehicles transition from upstream section of the highway and enter the vicinity of a work zone, lower speeds are noticed with more variability in acceleration. This is expected since drivers have been informed about upcoming roadway construction activity and are advised to lower their speeds using regulatory signs. In addition, as traffic flow becomes more restricted and a queue forms before entering the activity area, drivers travel at lower speeds and higher acceleration–deceleration rate. More braking accompanied by acceleration is induced for congested flow conditions inside work zones.
- The density plots illustrate that vehicles travel within the same speed range in advanced warning area when compared to the baseline condition unless there is high traffic density. However, the range of speed and acceleration increases as vehicles transition to the activity area.
- Lane closure and complex work zone configurations have similar acceleration and speed plots. It can also be observed that the lowest speeds and highest acceleration–deceleration rates occur in the advanced warning area for highly congested traffic flows while there is more variation in speed in the activity area. Congestion level for each trace is determined from forward videos before the driver entered the activity area. In most cases, the formation of a queue started in the advanced warning area and it dissipated inside the activity area.
- For shoulder closure, there is a wide variation in speed and acceleration for highly congested traffic flow condition across all work zone components with more skewness towards higher speeds. This is because slower speeds are not needed in most shoulder closure situations, hence drivers tend to continue traveling at higher speeds. However, when traffic density increases, there are more changes in acceleration–deceleration rate.

VSP Distribution

The stacked area plot in Figure 6 shows the VSP distribution for the different work zone configurations and congestion level. VSP is an effective measure of engine load accounting for changes in vehicle activity which is correlated to emissions. It is binned in such a way that three main vehicle operations are represented: deceleration (VSP <0), idling ($0\leq$ VSP <1) and cruising–acceleration (VSP >1). Higher emission rates and fuel consumption (per second) are associated with higher VSP bins. VSP distribution tends to shift to higher modes/bins when vehicles are traveling at higher speeds, or accelerate hard at moderate to high speeds. According

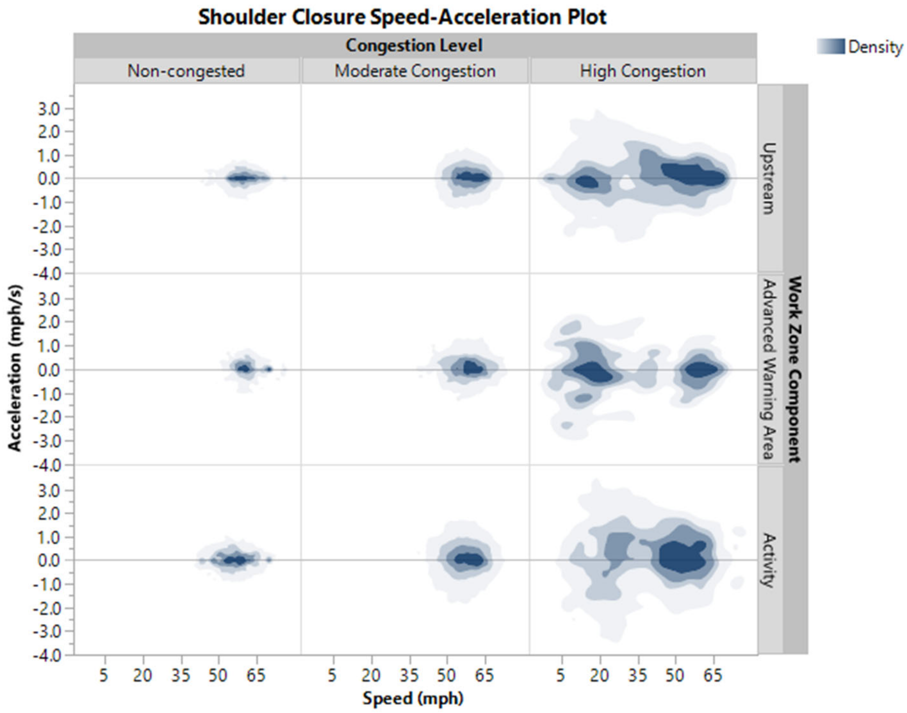


FIGURE 3 Acceleration and speed distribution for shoulder closure zone configuration comparing different congestion level and principal areas.

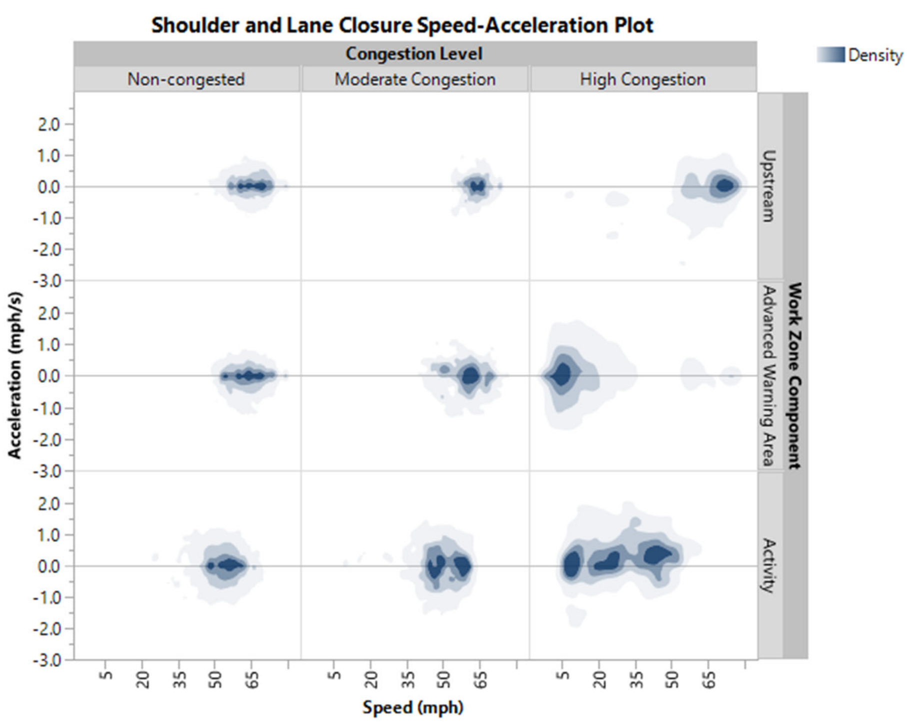


FIGURE 4 Acceleration and speed distribution for shoulder and lane closure zone configuration comparing different congestion level and principal areas.

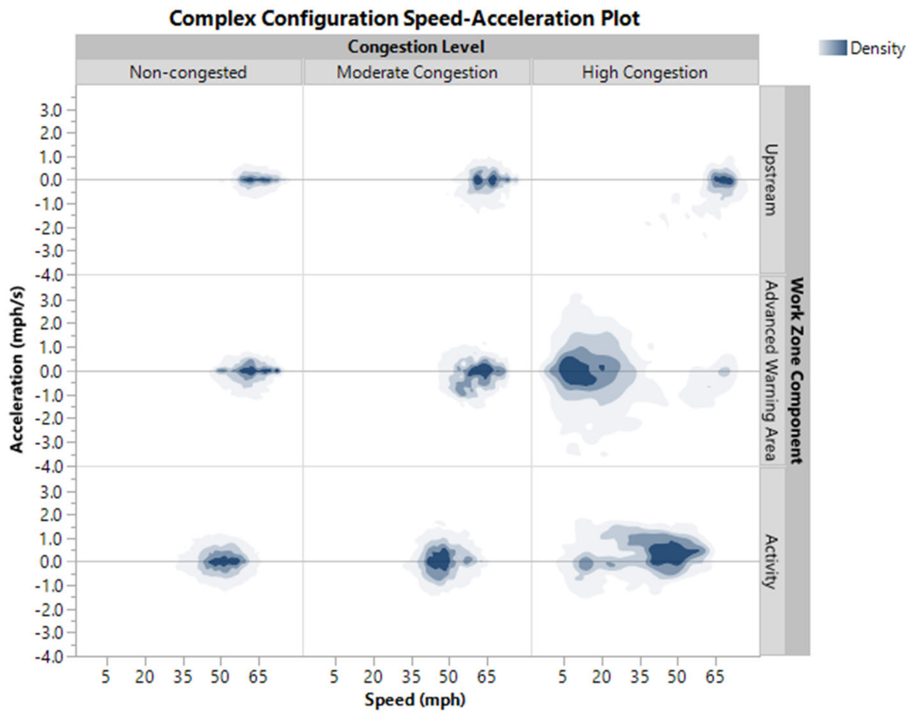


FIGURE 5 Acceleration and speed distribution for complex work zone configuration comparing different congestion level and principal areas.

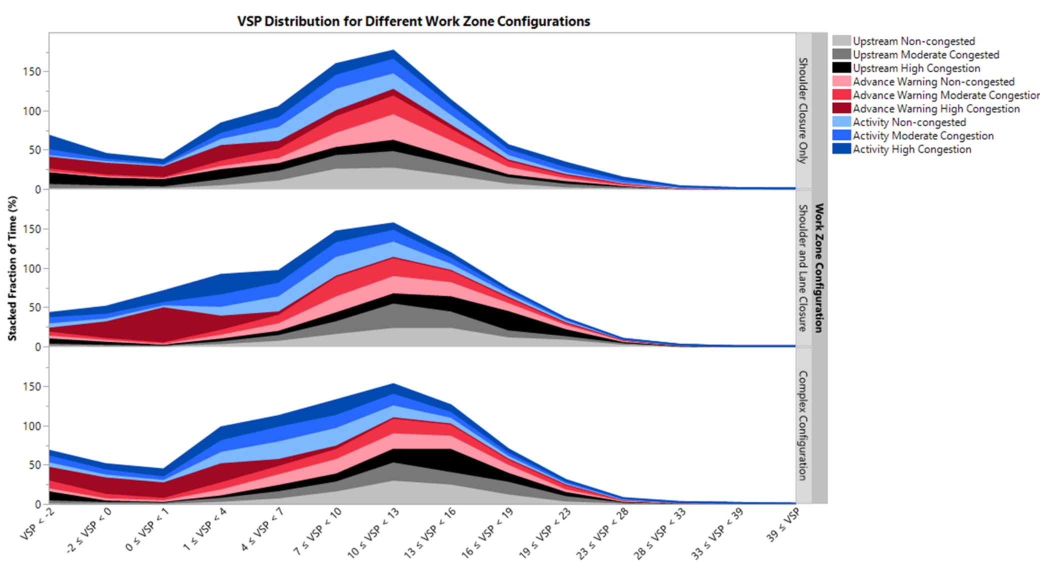


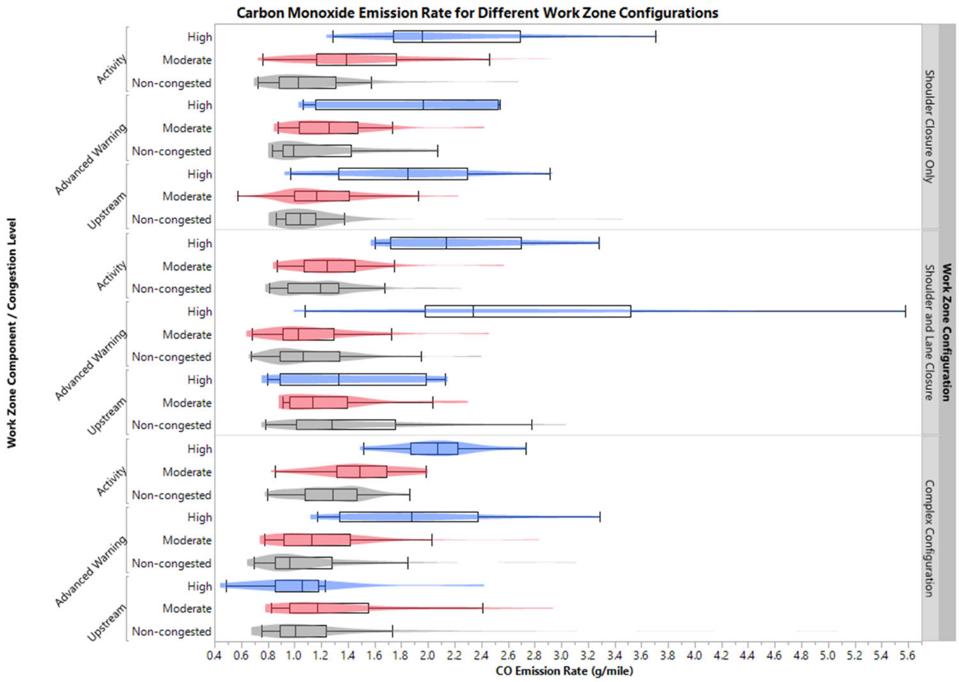
FIGURE 6 Stacked VSP distribution across all different work zone configurations and congestion level.

to the plot, for all work zone configurations, majority of VSP distribution for noncongested and moderately congested traffic flow conditions in the upstream section and advanced warning area of a work zone ranges between 7 and 19 kW/ton. Whereas, the activity area shifts the VSP to lower bins, between 1 and 10 kW/ton. The frequency of VSP in deceleration and idling vehicle operating modes increases as the traffic stream becomes highly congested. This is mostly evident in the advanced warning area. As mentioned previously, vehicles started to queue before a vehicle entered a construction zone for most trips but the queue dissipated within the activity area. As a result, the frequency of VSP is higher in the lower bins for the activity component at high congestion level.

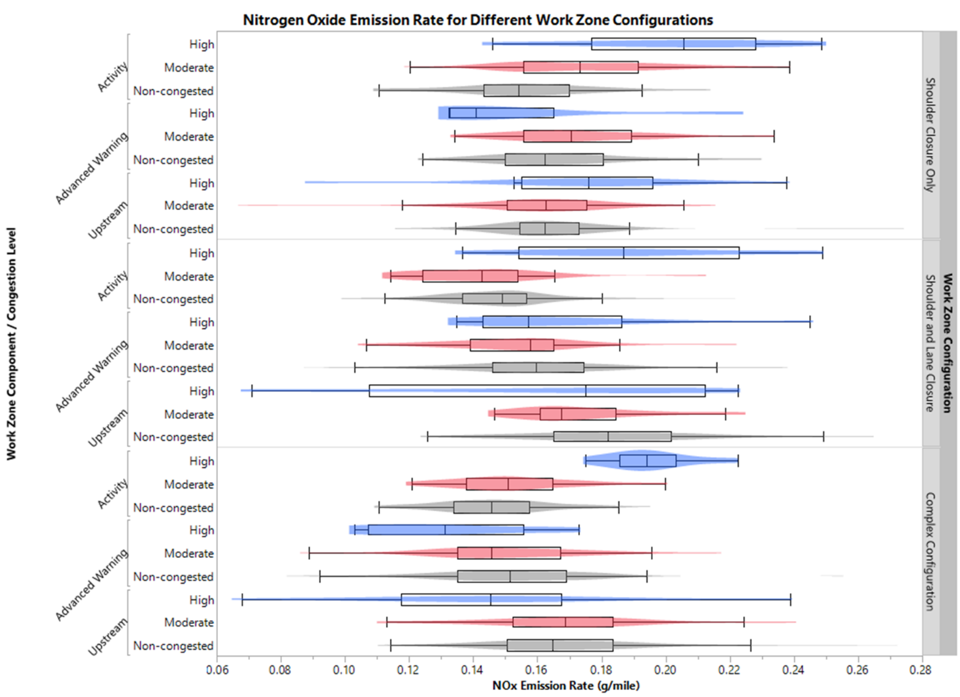
Emissions Comparison

Buffalo is used as a case study to obtain emission factors for CO, NO_x, $PM_{2.5}$, and CO_2 by running MOVES–Matrix at project-level for 2017 calendar year. The factors are assigned to every second of data based on operating mode distribution then the product is summed to find total emissions. Figure 7*a* through 7*d* represent average emission rates per mile for the various work zone principal areas and configurations, including congestion level. There is lack of sufficient evidence indicating that work zone principal area and configuration has an impact on emission rates. On the other hand, congestion level affected emission rates and this is mostly evident in activity portion of the work zone. There is more variability in emission rates for high congestion levels due to the high variation in speed and acceleration. More traces are needed to explore any major differences between area type, configuration and congestion level.

Emission of air pollutants from vehicles are variable due to changes in vehicle technology, vehicle operation on different roadway types, fuel specifications and quality, ambient meteorological conditions, as well as vehicle mileage accumulation (*31*). Estimating emissions using the operating mode distribution methodology basically assigns an emission factor to each second of data which relies on instantaneous vehicle kinematics in terms of speed and acceleration. Emissions analysis of various pollutants for the different work zone categories indicated that higher congestion level increased emissions. Even though it is impractical to assert that work zone configuration and principal area had a major impact on emission rate, the kernel density speed and acceleration plots disclose a different narrative. The shaded contours representing the density of the data points in Figures 3 through 5 illustrate that there are dissimilarities in the operation of vehicles while traveling through the different work zone configurations and principal components at varying traffic density. Subsequently, it is rational to investigate if the differences in vehicle kinematics are statistically significant. Previously, Hallmark and Guensler compared 3-dimensional speed and acceleration profiles from field measurements to output from NETSIM traffic simulation software at signalized intersections (*32*). The intent of the study was to determine if the instantaneous modal vehicle activity output from the simulation adequately represented the field data. However, the only metric used to assess these frequency plots was to compute the percent of time vehicles spent in binned speed and acceleration ranges. Information tends to be lost when data is aggregated or binned (*33*). In recent years, a new nonparametric binning-free goodness-of-fit test for equality of two or more multivariate distributions was proposed (*34*, *35*). The statistical model, known as the energy test is practical and powerful when multidimensional data points are compared to check if the samples belong to the same parent distribution (*36*).

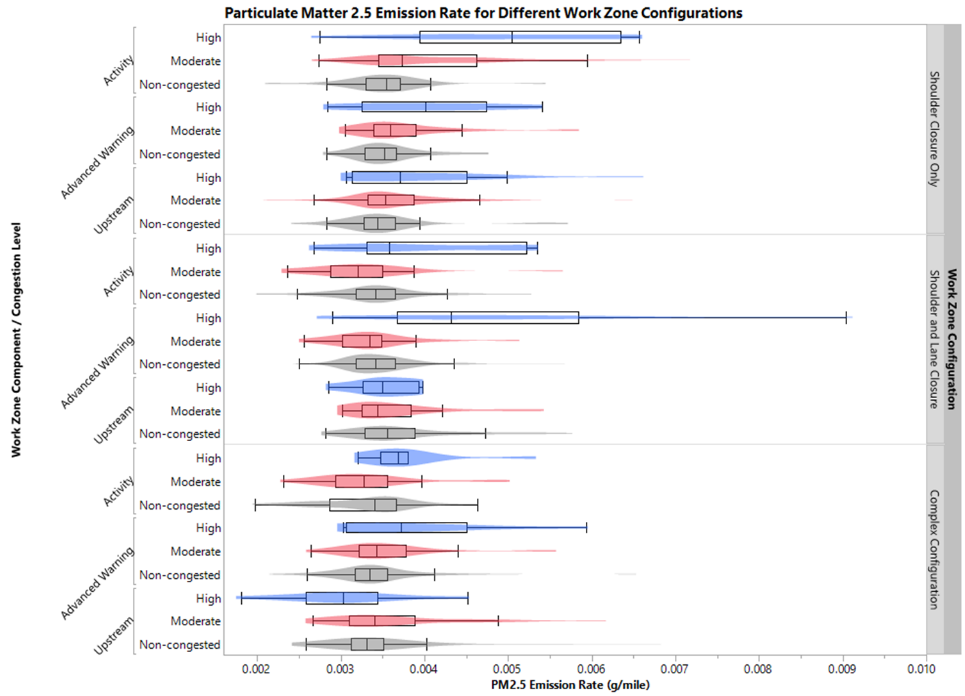


(a)

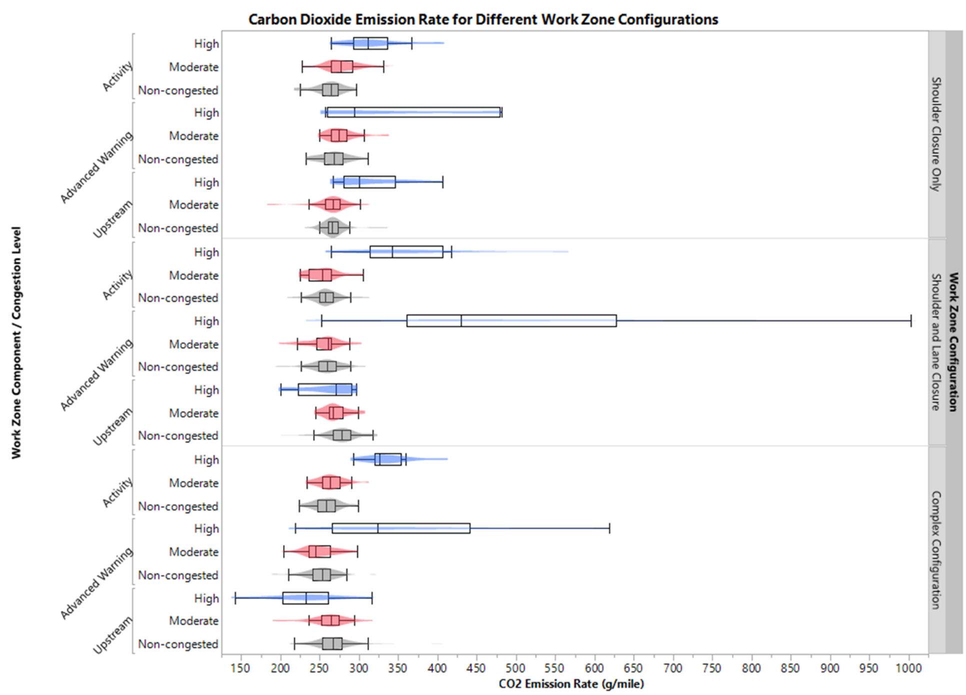


(b)

FIGURE 7 (*a*) CO emission rate per mile for different work zone configurations and congestion level and (*b*) NO_x emission rate per mile for different work zone configurations and congestion level (*continued on next page*).



(c)



(d)

FIGURE 7 (*continued*) (*c*) $PM_{2.5}$ emission rate per mile for different work zone configurations and congestion level and (*d*) CO_2 emission rate per mile for different work zone configurations and congestion level.

Energy of Data: Application of Energy–Statistics to Compare Two-Sample Bivariate Vehicle Kinematics for Equality in Distributions

The development of the energy-statistics eliminates ordering and binning of data to test for equal distribution in high dimensions. It is a multivariate nonparametric test, which means that it does compare the distributions of the samples without forcing a specific shape. The test is a function of the Euclidean distance between observed samples in the variate space (*34*, *37*) and the value of the energy-statistics is an indication of the potential energy of the data for a given data set. This concept was adapted from the notion of Newton's gravitational potential energy between two bodies (*37*). One-dimensional data comparisons based on the empirical distribution functions have been extensively studied in the past with the application of well-known nonparametric tests such as Kolmogorov-Smirnov (KS) and Cramer-von Mises (CM). However, certain issues might emerge when using the KS and other cumulative tests to perform goodness-of-fit comparisons of multidimensional data. This is because in order to obtain the cumulative distribution functions, these statistical methods would depend on ordering the data which results in large number of possible ways to order the data in a multidimensional space (*35*, *36*). In addition, the energy test does not make any assumptions regarding the continuity of the underlying distributions of the samples. Therefore, it is considered to be more generalized in comparison to the tests that are based on ranks of neighbors.

Suppose that $X_1, \dots, X_{n1}$ and $Y_1, \dots, Y_{n2}$ are independent random samples of random vectors with respective distributions F_1 and F_2. The two-sample energy (ε) test statistics for equal distribution consists of three terms corresponding to the energy of each random sample $X\,(\varepsilon_X)$ and $Y\,(\varepsilon_Y)$ along with the interaction energy of the two samples (ε_{XY}) (*38*). Therefore, the two-sample test statistic is equivalent to (Equation 2) (*35*):

$$\varepsilon_{n1,n2} = \varepsilon_X + \varepsilon_Y + \varepsilon_{XY},$$

and (2)

$$\varepsilon_{n1,n2} = \frac{n_1 n_2}{n_1 + n_2}\left(\frac{2}{n_1 n_2}\sum_{i=1}^{n_1}\sum_{m=1}^{n_2}||X_i - Y_m|| - \frac{1}{n_1^2}\sum_{i=1}^{n_1}\sum_{j=1}^{n_2}||X_i - X_j|| - \frac{1}{n_2^2}\sum_{l=1}^{n_1}\sum_{m=1}^{n_2}||Y_l - Y_m||\right)$$

Where, n is the total sample size of the pooled sample. Under the null hypothesis, $H_0\colon F_1 = F_2$ a random permutation of the pooled sample is equal in distribution to a random sample size n. In other words, the two samples are equal in distribution. In the composite alternative, the null hypothesis is rejected when $H_1\colon F_1 \neq F_2$. Typically, larger values of the ε-statistics are significant (*35*).

When considering the bivariate speed and acceleration distributions that are generated for the purpose of this research project, there are three main work zone configurations. For each configuration, the work zone is divided into three principal components and there are three categories for the traffic density. Consequently, this results in 27 speed and acceleration distributions. If two distributions are compared at a time without repetition and the order of selection is not a major concern, then a total of 351 combinations are produced. The multi-sample energy test of equal distribution, "eqdist.etest" function, from the "energy" package in R is used to compare all 351 combinations (*39*). Results from the two-sample energy test for all the combinations implied that the 27 bivariate vehicle kinematic distributions are significantly different. The *p*-value for the ε-statistics for the 351 samples/combinations is less than 0.005, hence there is strong evidence that there are differences in the distributions. The relative scale of speed and acceleration are not the same which might result in one of the projections dominating the value of the energy while the other projection only marginally contributing to it. However, the Euclidean distance between observations is normalized in the ε-statistics.

CONCLUSION

The FHWA reported that roadway construction sites cause traffic flow disruptions in a transportation network. Subsequently, this can have an adverse impact on emissions from vehicles. With limited studies related to emissions modeling at work zones, this research paper examined the impact of work zones on emissions from passenger vehicles at project level using SHRP 2 NDS data. Work zone principal areas and configuration, as well as varying congestion levels were considered in the model. Findings from this study can be implemented in decision-making policies. Transportation officials and engineers will have the ability to decide on the appropriate work zone configuration to implement given roadway and traffic characteristics. Results from a case study in Buffalo demonstrated that level of congestion was the main contributing factor for changes in average emissions for criteria pollutants and CO_2. On the contrary, comparisons between the different bivariate speed and acceleration distributions using the energy statistics showed that work zone configuration and principal area had a significant impact on vehicle operations. Some conclusions are drawn from a limited number of data points. Further investigation is required to show any differences in emissions by rural–urban designation, work zone principal area and configuration. This can be accomplished by reducing more traces or fewer categories can be used to create larger data groups. Furthermore, future research initiatives will include multilane divided highways since this study only analyzed work zones located in four-lane divided principal arterials. Moreover, statistical models will be developed to predict emissions as a function of significant independent variables.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: Georges Bou-Saab, Shauna Hallmark and Omar Smadi, study conception and design; Georges Bou-Sab and Shauna Hallmark, data collection; Georges Bou-Sab and Shauna Hallmark, analysis and interpretation of results; and Georges Bou-Saab, draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

ACKNOWLEDGMENT

We want to acknowledge Minnesota Department of Transportation for providing funding to secure and reduce the data for a related project. VTTI staff were very supportive and co-operative throughout the data request process. We appreciate the efforts of Nicole Oneyear, Amrita Goswamy, and Raju Thapa as they helped with data reduction. Finally, Guillermo Basulto-Elias provided insights on the plots used in the analysis.

REFERENCES

1. Work Zone Management Program. *Facts and Statistics – Work Zone Mobility*. Office of Operation, Federal Highway Administration. https://ops.fhwa.dot.gov/wz/resources/facts_stats/mobility.htm. Accessed November 15, 2017.
2. Tanvir, S., N. M. Rouphail, and B. J. Schroeder. Network Level Impacts of Major Freeway Reconstruction Project on Vehicular Emission. Presented at Air and Waste Management Association 108th Annual Conference and Exhibition, Raleigh, North Carolina, 2015.
3. Zhang, K., S. Batterman, and F. Dion. Vehicle Emissions in Congestion: Comparison of Work Zone, Rush Hour and Free-flow Conditions. *Atmospheric Environmental Journal*, Vol. 45, No. 11, 2011, pp. 1929–1939. https://doi.org/10.1016/j.atmosenv.2011.01.030.
4. Salem, O., S. Pirzadeh, S. Ghorai, and A. Abdel-Rahim. Improving Sustainability of Work-Zones by Implementing Lean Construction Techniques. Presented at International Conference on Architecture and Civil Engineering, Dubai, U.A.E, 2014.
5. Qiao, F. J., J. Jia, L. Yu, Q. Li, and D. Zhai. Drivers' Smart Assistance System Based on Radio Frequency Identification: Enhanced Safety and Reduced Emissions in Work Zones. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2458, 2014, pp. 37–46. https://doi.org/10.3141/2458-05.
6. Li, Q., F. Qiao, X. Wang, and L. Yu. Measures of Performance When Drivers Approaching STOP Sign Intersections with the Presence of Drivers' Smart Advisory System. Presented at 28th Annual Conference of the International Chinese Transportation Professionals Association, Los Angeles, California, 2015.
7. Li, Q., F. Qiao, and L. Yu. Vehicle Emission Implications of Drivers' Smart Advisory System for Traffic Operations in Work Zones. *Journal of Air and Waste Management Association*, Vol. 66, No. 5, 2016, pp. 446–455. https://doi.org/10.1080/10962247.2016.1140095.
8. Zhou, X., S. Tanvir, H. Lei, J. Taylor, B. Liu, N. M. Rouphail, and H. C. Frey. Integrating a Simplified Emission Estimation Model and Mesoscopic Dynamic Traffic Simulator to Efficiently Evaluate Emission Impacts of Traffic Management Strategies. *Transportation Research Part D*, Vol. 37, 2015, pp. 123–136. https://doi.org/10.1016/j.trd.2015.04.013.
9. Farzaneh, R., et al. *Air Quality Benefits of Nighttime Construction in Texas Non-Attainment Counties: Technical Report*. Publication FHWA/TX-17/0-6864-1. Texas Transportation Institute, Texas A&M University, College Station, Texas, 2017.
10. Thomas, S. Modeling of Freeway Air Quality during Recurring and Nonrecurring Congestion Events. Ph.D. dissertation, Purdue University, West Lafayette, Indiana, 2007.
11. Barth, M., and K. Boriboonsomsin. Real-World Carbon Dioxide Impacts of Traffic Congestion. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2058, 2008, pp. 163–171. https://doi.org/10.3141/2058-20.
12. Bigazzi, A. Y., and M. Figliozzi. An Analysis of the Relative Efficiency of Freeway Congestion Mitigation as an Emission Reduction Strategy. Presented at the 90th Annual Meeting of the Transportation Research Board, Washington, D.C., 2011.
13. Papson, A., S. Hartley, and K. L. Kuo. Analysis of Emissions at Congested and Uncongested Intersections with Motor Vehicle Emission Simulation 2010. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2270, 2012, pp. 124–131. https://doi.org/10.3141/2270-15.
14. Qi, Y., A. Padiath, Q. Zhao, and L. Yu. Development of Operating Mode Distributions for Different Types of Roadways Under Different Congestion Levels for Vehicle Emission Assessment using MOVES. *Journal of Air and Waste Management Association*, Vol. 66, No. 10, 2016, pp. 1003–1011. https://doi.org/10.1080/10962247.2016.1194338.

15. Hankey, J. M., J. A. McClafferty, and M. A. Perez. *Description of the SHRP 2 Naturalistic Database and the Crash, Near-Crash, and Baseline Data Sets*. Virginia Tech Transportation Institute, Blacksburg, Va., 2016.
16. Sun, Y., H. Xu, J. Wu, E. Hajj and X. Geng. Data Processing Framework for Driving Cycle Development with Naturalistic Driving Study Data. Presented at the 96th Annual Meeting of the Transportation Research Board, Washington, D.C., 2017. https://doi.org/10.3141/2645-06.
17. Farzaneh et al. *Texas-Specific Drive Cycles and Idle Emissions Rates for Using with EPA's MOVES Model*. FHWA/TX-14/0-6629-1. Texas Transportation Institute, Texas A&M University, College Station, Texas, 2014.
18. Liu, Z., A. Ivanco, and Z. Filipi. Naturalistic Drive Cycle Synthesis for Pickup Trucks. *Journal of Safety Research*, Vol. 54, 2015, pp. 109–115. https://doi.org/10.1016/j.jsr.2015.06.005.
19. LeBlanc, D. J., M. Sivak, and S. Bogard. Using Naturalistic Driving Study Data to Assess Variations in Fuel Efficiency among Individual Drivers. Publication UMTRI-2010-34. Transportation Research Institute, University of Michigan, Ann Arbor, 2010.
20. Tanvir, S., T. Chase and N. M. Rouphail. Heterogeneity and Consistency of Eco-Driving Metrics Using Naturalistic Driving Data. Presented at the 96thAnnual Meeting of the Transportation Research Board, Washington, D.C., 2017.
21. Abou-Senna, H., E. Radwan, K. Westerlund, and C. D. Cooper. Using a Traffic Simulation Model (VISSIM) with an Emission Model (MOVES) to Predict Emissions from Vehicles on a Limited-Access Highway. *Journal of Air and Waste Management Association*, Vol. 63, No. 7, 2013, pp. 819–831. https://doi.org/10.1080/10962247.2013.795918.
22. Guensler, R., H. Liu, X. Xu, Y. Xu and M. O. Rodgers. MOVES-Matrix: Setup, Implementation and Application. Presented at the 95th Annual Meeting of the Transportation Research Board, Washington, D.C., 2016.
23. Hallmark, S., A. Goswamy, O. Smadi, and S. Chrysler. Speed Prediction in Work Zones Using the SHRP 2 Naturalistic Driving Study Data. Presented at the 10th SHRP 2 Safety Data Symposium, Washington, D.C., 2017.
24. Part 6: Temporary Traffic Control. In *Manual on Uniform Traffic Control Devices*. FHWA, U.S. Department of Transportation, 2009, pp. 547–730.
25. *SHRP 2 Researcher Dictionary for Video Reduction Data Version 4.1*. Virginia Tech Transportation Institute, Blacksburg, Virginia. https://vtechworks.lib.vt.edu/bitstream/handle/10919/56719/V4.1_ResearcherDictionary_for_VideoReductionData_COMPLETE_Oct2015_10-5-15.pdf;sequence=1. Accessed July 1, 2018.
26. Frey, H. C., N. M. Rouphail, H. Zhai, T. L. Farias, and G. A. Goncalves. Comparing Real-World Fuel Consumption for Diesel- and Hydrogen-Fueled Transit Buses and Implication for Emissions. *Transportation Research Part D*, Vol. 12, No. 4, 2007, pp. 281–291. https://doi.org/10.1016/j.trd.2007.03.003.
27. Development of Emission Rates for Light-Duty Vehicles in the Motor Vehicle Emissions Simulator MOVES2010. EPA-420-R-11-011. U.S. Environmental Protection Agency. http://www.epa.gov/otaq/models/moves/documents/42r11011.pdf. Accessed August 3, 2018.
28. Guensler, R., H. Liu, Y. A. Xu, A. Akanser, D. Kim, M. P. Hunter, and M. O. Rodgers. Energy Consumption and Emission Modeling of Individual Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2627, 2017, pp. 93–102. https://doi.org/10.3141/2627-11.
29. Default Age Distribution for MOVES2014. http://www.epa.gov/OMSmodels/moves/documents/default-age-distribution-tool-moves2014.xlsx. Accessed August 15, 2018.
30. Liu, H., D. Sonntag, D. Brzezinski, C. R. Fulper, D. Hawkins, and J. E. Warila. Operations and Emissions Characteristics of Light-Duty Vehicles and Ramps. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2570, 2016, pp. 1–11. https://doi.org/10.3141/2570-01.

31. Cai, H., A. Burnham, and M. Wang. Updated Emission Factors of Air Pollutants from Vehicle Operations in GREET^{TM} Using MOVES. Systems Assessment Section. Energy Systems Division. Argonne National Laboratory, 2013.
32. Hallmark, S., and R. Guensler. Comparison of Speed-Acceleration Profiles from Field Data with NETSIM Output for Modal Air Quality Analysis of Signalized Intersections. *Transportation Research Record: Journal of Transportation Research Board,* No. 1664, 1999, pp. 40–46.
33. Schreiber-Gregory, D. N. Data Quality Control: Using High Performance Binning to Prevent Information Loss. Paper No. 2821. *Proc., SAS Global Forum 2018*. https://www.sas.com/content/dam/SAS/support/en/sas-global-forum-proceedings/2018/2821-2018.pdf. Accessed December 16, 2018.
34. Aslan, B., and G. Zech. A New Class of Binning-Free, Multivariate Goodness-of-Fit Tests: The Energy Tests. arXiv e-print, Cornell University, New York. https://arxiv.org/pdf/hep-ex/0203010.pdf. Accessed November 27, 2018.
35. Szekely, G. J., and M. L. Rizzo. Testing for Equal Distributions in High Dimension. *Interstate Journal*, 2004. http://interstat.statjournals.net/YEAR/2004/articles/0411005.pdf. Accessed November 27, 2018.
36. Cohen, E. O., I. D. Reid, and E. Piasetzky. Implementing a 3D histogram version of the Energy-Test in ROOT. *Nuclear Instruments and Methods in Physics Research, Section A, Accelerators, Spectrometers, Detectors, and Associated Equipment*, Vol. 828, 2016, pp. 86–90. https://doi.org/10.1016/j.nima.2016.05.013.
37. Szekely, G. J., and M. L. Rizzo. The Energy of Data. *Annual Review of Statistics and Its Application*: *Extended Review*, Vol. 4, 2017, pp. 447–479.
38. Aslan, B., and G. Zech. A New Test for the Multivariate Two-Sample Problem Based on the Concept of Minimum Energy. arXiv e-print, Cornell University, New York. https://arxiv.org/pdf/math/0309164.pdf. Accessed November 27, 2018. https://doi.org/10.1080/00949650410001661440.
39. M. L. Rizzo. *E-Statistics: Multivariate Inference via the Energy of Data*. Package ‘energy’, Comprehensive R Archive Network, 2018. https://cran.r-project.org/web/packages/energy/energy.pdf. Accessed November 27, 2018.

Identifying Association Between Level of Safety of Events and Driver Characteristics

A Market Basket Analysis

Saleh R. Mousa
Louisiana State University

Sherif Ishak
Old Dominion University

According to the National Highway Traffic Safety Administration (NHTSA), 6 million traffic accidents claim more than 35,000 human lives annually in the United States. These statistics have prompted researchers to investigate the driver characteristics associated with Safety Critical Events (SCEs). Researchers have applied different data-mining approaches to data collected from crash records. Conducting analysis only on crash data could lead to false abstract representation of reality and misleading results. The literature review shows that a well-known technique—the Market Basket Analysis (MBA)—for identifying association relationships among variables has been overlooked. This paper uses the entire set of Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS) events (crash–near-crash and normal–baseline) to perform MBA for identifying the association between the events' safety level and the underlying driver characteristics. The results show that driver impairments (anger, other emotional state, and drugs or alcohol), secondary tasks (reaching for objects and writing or texting), intersection influence (parking lots, driveway entrances and exits, interchanges, signals, and uncontrolled intersections), traffic density [level of service (LOS) C, D, E, and F] and weather conditions (snow or sleet) are the factors most associated with SCE. Results revealed that passenger interactions reduce SCE risk. In addition, drivers have higher SCE risk when traveling on dark, lighted roads compared to when traveling on dark roads that are not lighted. Moreover, males are less associated with SCE compared with females when driving near intersections, in snowy weather, or through congested traffic. Results confirm the increase of association with SCE when driver suffers from Attention Deficit Hyperactivity Disorder (ADHD), cognitive deficit, visual impairment, high sensational seeking tendency, or has poor driving knowledge.

INTRODUCTION

According to the NHTSA, about 6 million traffic accidents claim more than 35,000 human lives annually in the United States (*1*). Despite the growing research interest in traffic safety, the annual motor vehicle accidents and fatalities have increased over the past 3 years (*1*). These statistics have prompted researchers and policymakers to investigate the various factors and driver characteristics associated with SCEs. Traditionally, two different approaches are commonly used to identify the relationship between the SCE likelihood and the investigated contributing factors.

The first approach is the parametric modeling, where the developed models have a certain basic statistical structure, specific assumptions and certain relationships between the input and output variables. For instance, some of these models assume normality of the variables assessed or homogeneity of variance. In one of the early studies implementing parametric approaches, Joshua and Garber (*2*) examined the relationship between the truck crash likelihood and the roadway geometric factors using Poisson and linear regression models separately. Their study concluded that Poisson regression models outperformed the linear regression models in modeling the relationship between truck accidents and the independent variables. Two years later, Miaou et al. used the Poisson regression model to develop an empirical relationship connecting different geometric features with the truck crash likelihood (*3*). It turned out that roadway curvature, longitudinal gradient, and the average annual daily traffic per lane are the most-significant variables that correlate with the truck crash likelihood. However, the Poison model assumes the mean is equal to the variance, and crash data usually violate this assumption when it is overdispersed. To address this drawback, researchers implemented the negative binomial distribution in other studies with different approaches (*4*, *5*). However, due to the assumption of independent observations, both the Poisson and the Negative Binomial models may not be accurate in handling heterogeneous crash data since all observations in the population have different characteristics. Other studies implemented generalized linear models (negative binomial, Poisson regression, etc.) for analyzing crash data (*6*, *7*). However useful these methods are, high dimensionality in crash data leads to an exponential growth in the number of parameters in the developed models and subsequently, invalid results (*8*).

The second approach relies on nonparametric data mining models, which do not assume a fixed structure of the model. Typically, the model grows in size to accommodate the complexity of the data. Recent studies indicate a global shift by researchers towards data-mining techniques as an alternative approach to address traffic safety problems (*9–13*). Classification and Regression Tree (CART) is one of the powerful tools that have been widely used in different studies due to simplicity and ease of interpretation. For instance, Kashani et al. (*10*) implemented a CART algorithm to identify the important factors affecting the severity of crash injuries. Another powerful tool that is widely used in traffic safety research is the Ensemble algorithms, which integrate a group of weak classifiers to obtain one that outperforms any of the weak ones. The Ensemble methodology can be integrated with different model types such as decision trees, neural networks, and Bayesian networks, among others. Out of these models, the tree-based Ensemble algorithms have shown a better performance compared to others (*14*, *15*).

Despite the numerous studies published in traffic safety research, the literature review indicates that most of these studies investigated factors using data collected from either driving simulators or crash reports. In recent years, researchers have tapped into naturalistic driving data to examine the driving behaviors, driver characteristics, and factors associated with SCE occurrence. Some studies evaluate the driver behavior and injury severity in adverse weather conditions (*15*, *16*), another study investigates the association between visual and cognitive abilities and rates of future SCE involvement among older drivers (*17*). Another study predicts crash involvement from a personality measure and a driving knowledge test (*18*). A recent study investigates the relationship between the driver behavior questionnaire, sensation seeking scale, and observed SCE using the SHRP 2 NDS dataset.

Despite the numerous studies that investigate the factors associated with SCE events, most of these studies were limited to investigating SCE (crash or near-crash data only) in the analysis. Excluding the normal–baseline events (BLEs) can sometimes lead to the false abstract representation of reality and misleading results. Moreover, the analysis of most of these studies remains limited to using parametric methods (logistic regression, contingency tables, etc.). When the data dimensionality (number of variables) increases, some imperative assumptions (independence of the input variables) for parametric methods are violated and results from these methods become unreliable. Also, datasets with high dimensionality usually experience multicollinearity (high correlation among the variables), which compromises the accuracy of most statistical and machine learning regression models used. MBA, an advanced data-mining technique for identifying association relationships among variables, appears to have been overlooked. The MBA is a more-generalized tool that is capable of extracting association rules efficiently from datasets with high dimensionality and is considered a more sophisticated and efficient substitute for parametric methods (*19*). In addition, the metrics reported by the MBA (lift and confidence) are robust to multicollinearity. The MBA has been applied in marketing research and can potentially be used as a tool to analyze the naturalistic driving data and to identify the driver characteristics associated with SCE occurrence. To the author's knowledge, the traffic safety literature includes only two studies implementing this technique (*19*, *20*). However, the scope of the analysis in both studies was limited and did not account for any driver characteristics nor naturalistic driving (secondary tasks, driver impairment, etc.) variables. Moreover, data from crash reports were used, and subsequently, the extracted rules were limited only to those including crash among the item set and might be misleading.

The NDS data provided by SHRP 2 provide ample opportunities to identify the association between level of safety of the events and the driver characteristics (*21*). However, the large size of the data and the high dimensionality of the collected data impose additional challenges. To account for all the drawbacks mentioned in the literature, this study uses the SHRP 2 NDS data [crash/near-crash and normal–BLEs) to perform a comprehensive MBA for identifying the association between level of safety of the events and the driver characteristics. The next section summarizes the commonly used Parametric Methods for Detecting Associations and outlines their drawbacks. Next, the Data Description section describes the SHRP 2 NDS data along with a detailed description of the variables used in the analysis. Then, MBA Analysis section, followed by the Discussion of Extracted Rules. Finally, the paper closes with the conclusions.

PARAMETRIC METHODS FOR ASSOCIATION

This section summarizes the commonly used parametric methods for measuring associations among variables and outlines their limitations, compared to MBA, when applied to datasets with high dimensionality as the SHRP 2 NDS dataset.

Binary Logistic Regression

Binary logistic regression is one of the most common parametric methods used for identifying associations between each variable in a set of input variables and a specific dependent binary variable. Association relations are identified through the reported odds ratio and *P*-values. However, applying this technique to datasets with high dimensionality exaggerates the common pitfalls of logistic regression and makes results unreliable for interpretation (*22*). For instance, logistic regression assumes that the input variables are independent. This assumption is most likely violated when the dataset suffers from multicollinearity, which is very common in datasets with is high dimensionality. This makes the *P*-values reported by logistic regression highly unreliable. It is a common practice to consider variables with variance inflation factor (VIF) > 5-10 suffering from multicollinearity. To emphasize, in this study, when all variables were coded into dummy variables of (n – 1) categories, where n is the number of categories of the categorical variable, 37% of the variables had VIF > 10 indicating severe multicollinearity problems and no reliable results from logistic regression except for the quality of the fit. As mentioned earlier, the metrics reported by the MBA (discussed later) are robust to multicollinearity. Finally, logistic regression measures association only between the input variables and a selected binary dependent variable, unlike MBA which is capable of extracting association rules within between a set of input variable.

Contingency Table

Another common tool for identifying association among variables within a dataset is the contingency table. A contingency table shows the distribution of one variable in rows and another in columns. As the dimensionality of the data increases, tracking the association using these tables becomes more tedious. MBA is capable of measuring associations between more than two variables by introducing rules of length greater than two, unlike the contingency tables that can measure associations only between two variables jointly. Consequently, the MBA is a more generalized tool for looking through all possible multiway contingency tables and extracting the most informative rules and can be considered a more sophisticated and efficient substitute for contingency tables (*19*). Moreover, a key assumption for applying the chi-square test in a contingency table is the independence. In traffic safety studies, the same driver can appear as two separate records in both SCE and normal–BLEs. The same driver can even have two separate normal–BLEs which make the data highly correlated and violates a key assumption for chi-square tests.

DATA DESCRIPTION

This study uses the crash, near-crash, and normal–BLEs data collected by the SHRP 2 NDS project. The SHRP 2 NDS contains 3 years data collected from 3,147 drivers from six different sites: New York, Pennsylvania, Florida, Washington, North Carolina, and Indiana. The SHRP 2 NDS data include seven separate records that were used in this study: Visual and Cognitive Tests, Driver Demographic Questionnaire, Barkley's ADHD Screening Test, Driving Knowledge Survey, Sensation Seeking Scale Survey, Driving History Questionnaire, and Event Detail Table. The Visual and Cognitive Tests dataset contains the results of a series of vision tests conducted on drivers. Contrast sensitivity, color perception, visual acuity, and peripheral vision were tested using a multi-purpose vision-testing apparatus. Specialized software programs were also used to assess the useful field of view and ability to Visualize Missing Information (VMI). The Driver Demographic Questionnaire collects socioeconomic characteristics of the 3,147 participants such as family life, gender, income, years driving, and education. Barkley's ADHD Screening Test is a short, clinical, ADHD screening assessment, for identifying ADHD symptoms in terms of specific behaviors. The Driving Knowledge Survey is a test of knowledge of driving laws and appropriate driving behaviors. The Sensation Seeking Scale Survey instruments the participant's sensory stimulation preferences and the degree to which the participant engages in sensation seeking behavior. The Driving History Questionnaire intends to gather information from participants regarding their driving record. The questions evaluate the driving experience, past violations, past crashes, and training received. Finally, the Event Detail Table lists all crashes, near crashes, and baseline events that have been identified and analyzed in SHRP 2 NDS. The Event Detail Table includes information related to the weather, lighting, road conditions, and driving behavior during the event. A more detailed description of the SHRP 2 NDS dataset can be found on the study's data website (*21*). To extract the relevant driver-related and event-related variables, the seven records were merged using the unique Participant ID resulting in a single comprehensive dataset containing all relevant information about the driver characteristics, event characteristics, and level of safety of the event (26 variables per event).

Due to the limited number of crash and near-crash events compared to the normal baseline events, this study combines the crashes and near-crashes into a single level of safety of event named SCE. This practice is common and has been documented in many NDSs (*23*, *24*). To allow MBA extracting useful and reliable association rules that provide insight into driver characteristics associated with SCE, the dataset was reduced and only SCE due to driver's fault were included. The normal–BLEs were kept in the analysis to make the dataset a better representative of the driving population. The final dataset comprised 26,218 events, out of which 7,310 are SCE. Finally, the categories of each of the 26 variables in the dataset were carefully investigated, and the similar categories were collapsed into one homogeneous category. Table 1 summarizes the 26 variables included in the final dataset along with their description and number of levels, after performing the mentioned steps.

The original SHRP 2 NDS dataset includes two secondary task variables, secondary task 1 and secondary task 2. The secondary task 2 variable lists the secondary tasks additional to secondary task 1. Accordingly, in this study, all events with drivers performing more than one secondary task were decoupled as two different events with different secondary tasks. The SHRP 2 NDS original dataset also includes the "Driver Behavior" variable, a very important variable that describes driver behaviors occurring within seconds prior to the event or those resulting from the context of the driving environment, which include what driver did to cause or contribute to the SCE. However, one of the categories of this variable is the "distracted" category, which is only coded for SCE in the original dataset. This limits the usage of this variable whenever BLE are considered. However, this variable is expected to correlate with the secondary tasks and driver impairment variable (used in this study), accordingly, the "Driver Behavior" variable was not used in this study. In order to extract reliable rules, different categories of the secondary task variable were regrouped to create more homogenous categories. For instance, the "Cellphone/Tablet Use" category includes all categories identified by SHRP 2 NDS Insight website that involve using cellphones and tablet except the ones for reaching the devices and texting. Similarly, the "Writing and Texting" category includes the "Cell Phone, Texting," "Tablet device, Operating," and "Writing." Likewise, the "Reaching for Objects" category included the reaching for food, drinks, personal items, tablets, and cellphones categories identified by the SHRP 2 NDS Insight website. In the same way, the "Object in Vehicle" category amalgamates the "Object in the Vehicle, Other," "Moving Object in Vehicle," and "Object Dropped by Driver" categories.

TABLE 1 Summary of the SHRP 2 NDS Variables for MBA

No.	Variable	Description	No. of Levels
1	VMI	Visual Impairment Level based on the results of the VMI test: none, mild, serious	3
2	Visual Impairment (Visual Search)	Visual Impairment Level based on the results of the visual search tests: none, mild, serious	3
3	Age Group	The age group corresponding to the driver's birthdate: 16–19, 20–24, 25–29, 30–39, 40–49, 50–59, … , 80+	9
4	Cognitive Abilities	The score group of the Clock Drawing test which is scored based on a six-point scoring system. Higher scores reflect a greater number of errors and more impairment. A score of ≥3 represents a cognitive deficit, while a score of 1 or 2 is considered normal: 1–2, 3–6	2
5	ADHD Score	Berkley ADHD. When the ADHD total score is greater than or equal to 7, then this is an initial, high-level indication to researchers of possible ADHD in that individual : 0–6, 7–16	2
6	Driving Knowledge	The score group of the driver for a test of knowledge of driving laws and appropriate driving behaviors. The test is scored based on a 19-point scoring system. A score of 19 means answering all 19 questions correct: 0–8, 9–14, 15–16, 17–19	4
7	Sensation Seeking	The score group of the drivers for a survey compiled of questions to gauge the degree to which the driver engages in sensation seeking behavior. The test measures the participant's sensory stimulation preferences. Higher values indicate a greater tendency: 0–9, 10–18, 19–35	3
8	Years Driving	Number of years driving: 0–1, 1–2, 2–3, 3–4, 4–5, +5	6
9	No. Crashes 3 Years	Total number of crashes committed by the driver over the past 3 years: 0, 1, 2+	3
10	No. Violations 3 years	Total number of traffic violations committed by the driver over the past 3 years: 0, 1, 2+	3
11	Marital Status	Single, divorced, married, unmarried partners, widow(er)	5
12	Gender	Male, female	2
13	Work Status	Full-time, part-time, not working outside home	3
14	Income	Under $29,000, $30,000–39,000, $40,000–49,000, … , $150,000+	7
15	Education	High school diploma, college degree, graduate degree	3
16	Business Use of Vehicle	Yes, no	2
17	Insurance	Whether the participant has had auto insurance for the past 6 months: yes, no	2
18	Driver Impairment	Possible reasons for the observed driver behavior(s), judgment, or driving ability: angry, other emotional state; drowsy, sleepy, or fatigued; drugs or alcohol; other; none)	6

Continued on next page.

TABLE 1 (*continued*) Summary of the SHRP 2 NDS Variables for MBA

No.	Variable	Description	No. of Levels
19	Secondary Task	Observable driver engagement in any of the listed secondary tasks during the event: cellphone–tablet use, writing–texting, reaching for objects, passenger interaction, object in vehicle, etc.	17
20	Construction Zone	An indication of whether the precipitating event occurs in or in relation to a construction zone: yes, no	2
21	Intersection Influence	A judgment call as to whether the subject vehicle's safe movement, travel path, and travel speed are under the influence of an intersection at the time of the event: no, yes/traffic signal, yes/stop sign, yes/uncontrolled, yes/interchange, etc.	7
22	Traffic Density	The level of traffic density at the time of the start of the precipitating event: LOSs A, B, C, D, E, F	5
23	Weather	Weather condition at the time of the start of the precipitating event: no adverse conditions, raining, fog, snowing, sleet	5
24	Surface Condition	The type of roadway surface condition that would affect the vehicle's coefficient of friction at the start of the precipitating event: dry, wet, snowy, icy, gravel/dirt road, other	6
25	Lighting	Lighting condition at the time of the start of the precipitating event: darkness-lighted, darkness-not lighted, daylight, dusk, dawn	5
26	LOS	Level of safety of the event, either a SCE or normal–BLE	2

MARKET BASKET ANALYSIS

The MBA is a data mining technique that has been successfully applied to extract association rules from data in marketing research in order to identify the item set of goods a customer prefers to buy together and to investigate the market transactions. In this context, MBA can extract a different set of rules that identify the association between a set of variables within the data. There are many algorithms available for implementing the MBA, among which the a priori is the most commonly used due to its simplicity. The a priori algorithm builds on the following main concept: If an item set is frequent, then all of its subsets must also be frequent, and if an item set is infrequent then all its supersets must also be infrequent (*25*). The a priori algorithm implements this concept in a form of pruning technique for trimming the exponential search space of the candidate rules. Commonly, three main metrics are used to evaluate the extracted rules in the MBA, namely, support, confidence and lift. For a dataset with ***N*** observations, an association rule is defined as 'X→Y or X1, X2→Y, where X's are the antecedents on the left-hand side (LHS) and Y is the consequent on the right-hand side (RHS). In this study, the RHS is either SCE or BLE. The length of the rule is simply the number of elements in an association rule. The formal definitions of the support, confidence, and lift are as follows:

$$\text{Support } (X \rightarrow Y) = \frac{X \cap Y}{N} \quad (1)$$

$$\text{Confidence } (X \rightarrow Y) = \frac{X \cap Y}{X} \quad (2)$$

$$Lift\ (X \rightarrow Y) = \frac{Confidence\ (X \rightarrow Y)}{Support\ (Y)} \quad (3)$$

For a better understanding of these metrics, consider a hypothetical set of 10,000 events shown in Figure 1, wherein 6,000 of these events the driver was male. The hypothetical set of events consists of 2,000 SCE and 8,000 BLE. Out of the total set of events, 1000 only were SCE events involving male drivers. The support of the rule 'X→Y, according to Equation 1, is the frequency measurement of the antecedent and consequent jointly (LHS = X and RHS = Y) in the dataset. Thus, the support of the rule Male→Crash is 1,000/10,000. The higher the support value, the more frequently the item set of the antecedent and consequent occurs. The confidence of the rule, according to Equation 2, is the conditional probability of the consequent (RHS = Y) in an association rule, given the occurrence of the antecedents (LHS = X), and it acts as a reliability measure of a specific association rule 'X→Y. According to Figure 1, the confidence of the rule is 1,000/6,000. Finally, the lift of the rule, according to equation 3, is the ratio between the rules' confidence and the support of the consequent (RHS = Y). According to the figure, the lift of the rule is equal to (1,000*10,000)/ (6,000*2,000). The lift is a measure of the statistical dependence of an association rule. For instance, a lift of value greater than 1 suggests that the presence of the antecedents (LHS = X) increases the probability that the consequent (RHS = Y) also occurs in the transaction. Overall, lift summarizes the strength of association between the products on the left- and right-hand side of the rule, i.e., the larger the lift, the greater the link between the two products (factors). Commonly, in marketing research only rules with lift value greater than one are considered as they imply a positive association between the items bought together. In traffic safety

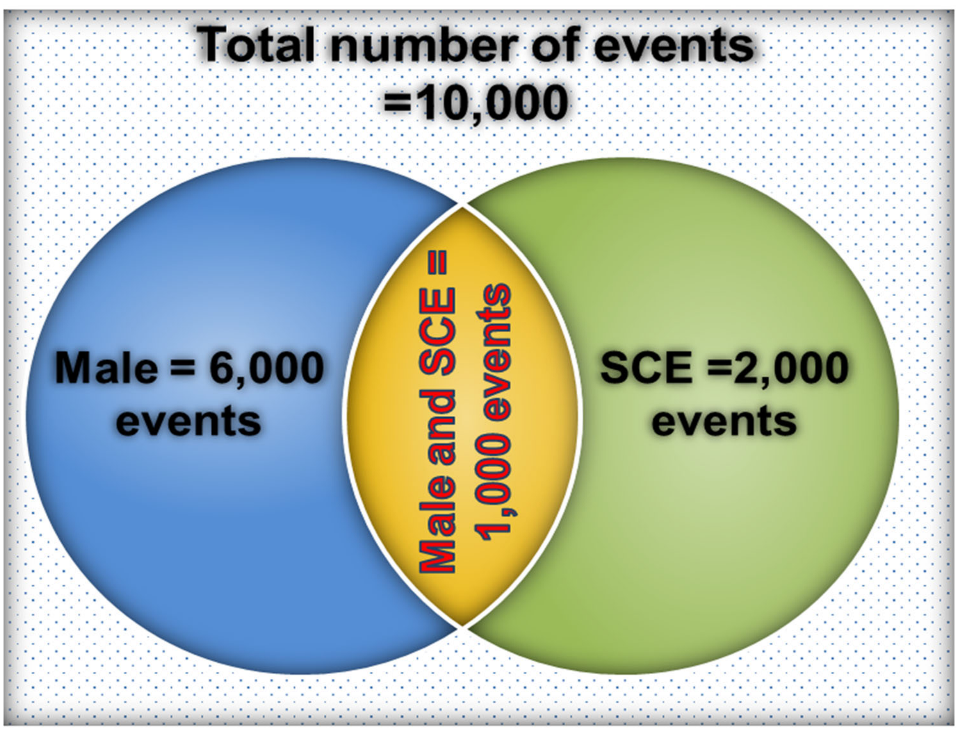


FIGURE 1 Venn diagram presenting the MBA metrics.

research, however, rules with lift value smaller than one imply a negative association between LHS and RHS and can contain useful information. Accordingly, the scope of this study extends to include rules implying negative association.

To perform a comprehensive MBA, all available events in the dataset are treated as shopping baskets in supermarket transactions and an a priori algorithm is applied to the events to extract the association rules between the different variables in the data listed in Table 1. Including a combination of SCE and BLE, provides a better presentation of the real word and offers opportunities for extracting more accurate, reliable, and representative rules. In this context, it is clear that for a specific level of safety of event occurring in the RHS and regardless of the support value of this rule, the confidence is evaluated over the entire data (SCE and BLE). This provides more accurate and more representative results compared to previous studies using only crash reports. However, this makes the data highly unbalanced and whenever a rare event is of interest such as specific driver characteristic associated with SCE instances, the thresholds used for minimum support need to be lowered to allow the analyst to discover associations with such rare events. It is worth mentioning that in marketing research higher support values are favored to extract only rules that are occurring more frequently. However, in traffic safety, any rule that deems to be reliable is of great interest regardless of its support value. Accordingly, there are no specific criteria for setting the support threshold and any small value is acceptable (0.5% used in this study). That said, any rule with a relative frequency of less than 0.5% is not expected to show in the analysis regardless of its confidence and lift values.

Recalling the lift is a measure of the statistical dependence of an association rule, a rule having a lift of 1 would imply that the probability of occurrence of the LHS and that of the RHS is independent of each other. When the RHS and LHS are independent of each other, and irrespective of the high confidence value, no useful rule can be drawn involving the two sides. In this study, to ensure extracting rules with high reliability and usefulness, and to account for the ease of interpretability of the extracted rules, rules were extracted based on these boundary conditions: rule support ≥0.5%; confidence ≥55%; and rule length ≤3.

An a priori algorithm was applied to the data at the mentioned boundary conditions and a total of 3,492 rules were extracted. Considering the high dimensionality within the dataset and the lengths of extracted rules (Length = 2 or 3), these rules are expected to include a large number of redundant association rules that must be removed. An association rule is considered redundant if a more general rule with equal or higher confidence value exists (*25*, *26*). In other words, a more specific rule is considered redundant if it is equally or less predictive than a more general rule. An association rule is considered more general if it has the same RHS but one or more items removed from the LHS. An association rule X→Y is redundant if there is another rule X*→Y where the X* is a subset of X (X* more general) and the confidence of the redundant rule is less than or equal to the nonredundant value. In the view of the high dimensionality of the data and the length of the extracted rules, 2,259 rules out of the extracted ones were deemed redundant. The redundant rules are then removed and the nonredundant rules were further investigated to identify the useful ones. Figure 2 depicts a scatterplot for the support, confidence, and lift values for the complete set of the extracted non-redundant rules (1,233 rules). As shown in the plot, the majority of the rules are clustered within support and lift values in the range of 0.5% to 10% and less than 3%, respectively. The plot also indicates that all the rules with lift value >2 were rare events and had a support value of less than 5%.

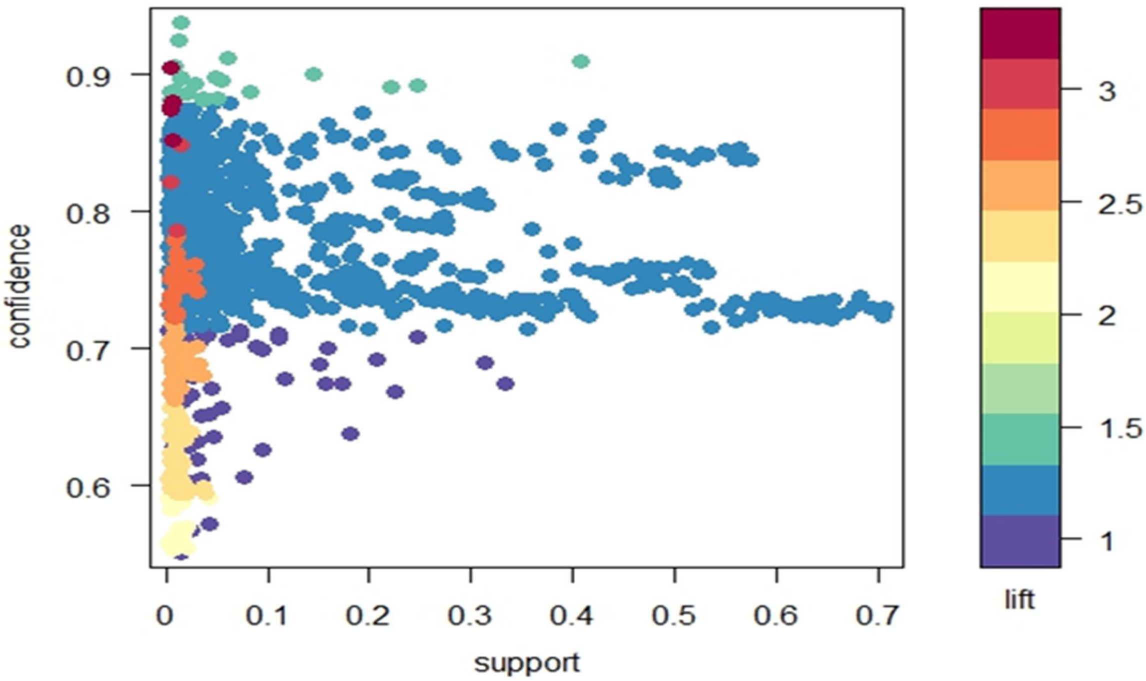


FIGURE 2 Metrics for nonredundant rules.

DISCUSSION OF EXTRACTED RULES

The final set of extracted rules was manually and carefully investigated to extract association relations between the driver characteristics and the LOS of the occurring event. To be more conservative when interpreting the rules, the ones with lift values falling between 0.98 and 1.02 are considered having a lift value equal to 1. Accordingly, these rules are removed from the analysis; recalling this study evaluates rules with lift value greater than or less than 1. Traditionally, the direction and strength of the association between the inspected variables and the LOS of the event are identified by tracking the change in lift values of two or more rules simultaneously. There are two approaches to achieving so. For instance, the lift values can be compared for rules of the same length after one component on either side is changed. Another approach is to compare one rule of length 2 with a rule of length 3 in which the latter introduces a new parameter on the LHS. By tracking the change in lift values accompanying the change in the LHS/RHS elements, inferences can be made about the driver characteristics associated with LOS of the event.

The extracted rules are discussed in two stages. First, all the rules of length two are discussed to identify the direction and strength of the association between the variables in Table 1 and the LOS of the event. Based on these results, specific rules of length three and RHS = SCE are discussed to get better insight into the associations identified in stage 1. It should be noted that some variables did not appear in the final set of the useful rules due to having lift value equal to one or support value less than 0.5%. Therefore, they were omitted from the discussion. Only useful rules that imply an association for meaningful relations are discussed in detail in the following subsections.

MBA Rules of Length 2

This section discusses the rules of length 2 within the final set of extracted rules. These rules and their corresponding lift values are recapitulated in Table 2. Rules 1 to 7 present the association between different age groups and the likelihood of occurrence of BLE. Rules 1 and 2 indicate that age groups (16–19) and (20–24) experience negative association (lift <1) with the BLE which means that these two age groups are more involved in SCE compared to the other age groups. Similarly, rules 8 and 9 show a negative association between BLE and drivers with cognitive deficit (cognitive abilities = 3-6) or ADHD (ADHD score = 7 to 16), respectively. This demonstrates that drivers with cognitive deficit or ADHD are more likely to be involved in SCE. Likewise, rule 10 indicates that drivers with poor driving knowledge (scored 0 to 8 out of 19) are negatively associated with BLE and more vulnerable to SCE compared to other score groups. The increasing lift value for rules 11, 12, and 13 shows that sensational seeking behavior decreases the driver's association with BLE and increases the odds of SCE occurrence. Concerning driving experience, rules 14 and 15 proof that driving experience less than 1 year is negatively associated with BLE, while the +5 years driving experience is associated with BLE and safe driving. Likewise, rules 16 and 18 show that drivers with a driving history of one violation or crash are negatively associated with BLE and more likely to be involved in SCE. The likelihood of being involved in SCE for drivers, with violations–crash history, increases with the increase of the historical number of violations–crashes, as justified by the drop in lift values of rules 17 and 19. Rules 20 and 21 provide an evidence that drivers with single status have a higher possibility of being involved in SCE, unlike drivers with married status who have a higher probability of being involved in BLE.

TABLE 2 MBA Rules of Length 2

No.	LHS	RHS	Lift
1	Age group = (16–19)	LOS = BLE	0.867
2	Age group = (20–24)	LOS = BLE	0.934
3	Age group = (30–39)	LOS = BLE	1.040
4	Age group = (40–49)	LOS = BLE	1.088
5	Age group = (50–59)	LOS = BLE	1.086
6	Age group = (60–69)	LOS = BLE	1.074
7	Age group = (70–79)	LOS = BLE	1.143
8	Cognitive abilities = (3–6)	LOS = BLE	0.972
9	ADHD score = (7–16)	LOS = BLE	0.911
10	Driving knowledge = (0, 8)	LOS = BLE	0.945
11	Sensation seeking = (19, 35)	LOS = BLE	0.928
12	Sensation seeking = (10, 18)	LOS = BLE	1.023
13	Sensation seeking = (0, 9)	LOS = BLE	1.084
14	Years driving = (0, 1)	LOS = BLE	0.840
15	Years driving = 5+	LOS = BLE	1.046
16	No. of crashes 3 year = 1	LOS = BLE	0.957
17	No. of crashes 3 year = 2+	LOS = BLE	0.883
18	No. of violations 3 years = 1	LOS = BLE	0.970
19	No. of violations 3 years = 2+	LOS = BLE	0.842
20	Marital status = married	LOS = BLE	1.092

Continued on next page.

TABLE 2 (*continued*) MBA Rules of Length 2

No.	LHS	RHS	Lift
21	Marital status = single	LOS = BLE	0.934
22	Work Status = part-time	LOS = BLE	0.961
23	Income = under $29,000	LOS = BLE	0.939
24	Education = college degree	LOS = BLE	1.035
25	Education = graduate	LOS = BLE	1.034
26	Education = high school	LOS = BLE	0.957
27	Business use of vehicle = yes	LOS = BLE	0.968
28	Insurance = no	LOS = BLE	0.884
29	Construction zone = yes	LOS = BLE	0.788
30	Driver impairment = angry	LOS = SCE	3.130
31	Driver impairment = other emotional state	LOS = SCE	2.677
32	Driver impairment = drugs and alcohol	LOS = SCE	2.975
33	Driver impairment = drowsy, sleepy, or fatigued	LOS = BLE	0.950
34	Secondary task = no secondary tasks	LOS = BLE	1.115
35	Secondary task = cellphone/tablet use	LOS = BLE	0.793
36	Secondary task = personal hygiene	LOS = BLE	0.882
37	Secondary task = out-of-vehicle distractions	LOS = BLE	0.986
38	Secondary task = vehicle integral devices	LOS = BLE	0.969
39	Secondary task = passenger interaction	LOS = BLE	1.113
40	Secondary task = reaching for objects	LOS = SCE	2.106
41	Secondary task = writing and texting	LOS = SCE	1.614
42	Intersection influence = yes, parking lot, driveway entrance–exit	LOS = SCE	2.442
43	Intersection influence = yes, uncontrolled	LOS = SCE	2.134
44	Intersection influence= yes, interchange	LOS = SCE	1.830
45	Intersection influence = yes, traffic signal	LOS = SCE	1.771
46	Traffic density = LOS C	LOS = SCE	2.123
47	Traffic density = LOS D	LOS = SCE	2.449
48	Traffic density = LOS E,F	LOS = SCE	2.221
49	Weather = fog	LOS = BLE	0.941
50	Weather = sleet	LOS = SCE	1.973
51	Weather = snowing	LOS = SCE	1.880
52	Surface condition = icy	LOS = SCE	2.582
53	Surface condition = snowy	LOS = SCE	1.989
54	Lighting = darkness, lighted	LOS = BLE	0.969
55	Lighting = darkness, not lighted	LOS = BLE	1.153
56	Lighting = dawn	LOS = BLE	0.927
57	Lighting = dusk	LOS = BLE	0.916

Following the same logic for interpreting the rest of the rules, relations and associations can be identified. For instance, part-time workers are more vulnerable to SCE compared to the other working status (rule 22). Also, drivers with income under $29,000 are more associated with SCE compared to the higher income categories that did not appear in the set of extracted rules (rule 23). In addition, drivers with high school education are more affiliated with SCE compared to drivers with college or graduate education who are affiliated with BLE (rules 24 through 26). Moreover, drivers using their vehicles in business activities (rule 27) and drivers with uninsured vehicles (rule 28) are linked with SCE. Rule 29 indicated the lowest lift value in the table, which means that the construction zone is on the top of the factors leading to a strong negative association with BLE and consequently strong association with SCE. Unlike previous rules, rules 30 to 32, 40 to 48, and 50 to 53 have SCE in the RHS and their lift values are very high (>1.5), this indicates that the variables' categories comprised in these rules are the most associated with SCE among all categories listed in Table 1. Consequently, in this study, the most contributing factors to SCE are

1. Driver impairments due to anger or other emotional state or drugs and alcohol;
2. Driver distractions due to reaching for objects, writing, and texting;
3. Influences of parking lots, driveway entrance–exit, interchanges, signals, and uncontrolled intersections;
4. Traffic density of LOS C, D, E, and F; and
5. Snow–sleet weather conditions.

The driver impairment due to being drowsy, sleepy, or fatigued was also associated with SCE (rule 33) but to a lesser extent compared to anger or other emotional state or drugs and alcohol. As expected, performing no secondary tasks increases the association with BLE (rule 34), while cellphone–tablet use, personal hygiene activities, out-of-vehicle distractions, and setting the vehicle's integral devices are associated with SCE, but to a lesser extent compared with reaching for objects, writing, and texting (rules 35 to 38).

The passenger interaction is associated with BLE and decreases the likelihood of SCE (rule 39). This can be attributed to the fact that drivers feel more responsible and cautious when they are not alone in the vehicle. In addition, passenger interaction can to some extent prevent fatigued drivers from falling asleep or get impaired especially for long trips. Regarding weather and lighting conditions, fog, darkness lighted, dawn, and dusk deemed associated with SCE (rules 49, 54, 56, and 57). Surprisingly, rule 55, in opposition to rule 54, implies that dark–not lighted roads are safer compared to the dark–lighted road. A reason for this could be that headlights and taillights of surrounding vehicles are more apparent to the driver in the vehicle's mirrors when traveling on dark–not lighted roads compared to when traveling on lighted roads.

MBA Rules of Length 3

It is worth mentioning that all variable categories showing in rules of length 2 (Table 2) that are having SCE in the RHS (anger, other emotional state, drugs...etc.) are considered the most contributing factors to SCE. Accordingly, these categories are expected to show in many rules of length 3. Similarly, all variable-categories having a negative association with BLE (such as rule 57: lighting = dusk) are by definition associated with SCE, since the LOS is bivariate. Consequently, these variable categories are expected also to appear in numerous rules of length 3 and with SCE in the RHS. However, these variable categories do not require further investigation and are of no interest when investigating the rules of length 3. For making the paper easy to follow, most of these variable categories are omitted from the discussion of the rules of length 3. As shown in Table 2, some variable categories did not appear at all in the table (such as visual impairment, gender, etc.). These variables might still have a significant impact on the driver safety and become associated with SCE when interacting with other variables, i.e., when they occur jointly with another one. For this purpose, the rules of length 3 are included in the analysis and investigated carefully to extract these underlying associations. Table 3 summarizes these rules and their pertinent lift values.

The main concept for investigating rules of length 3 accurate and extracting useful information is tracking the lift value for their pertinent rules (subset rule with SCE in RHS) of length 2 to identify the increase or decrease of association. To illustrate, there are no pertinent age group rules in Table 2 for rules 57 and 58; accordingly, the lift value for association of age group = 16–19 or age group = 25–29 with SCE is considered 1. Therefore, the rise in lift values of rules 57 and 58 justify that serious visual impairment–VMI increases association with SCE. Another approach is inspecting the change in lift value for rules 59 to 61 for the different levels of VMI. In essence, rule 59 has the highest lift value which is evidence that serious visual impairment–VMI increases the association with SCE. Similarly, rules 62 to 64 indicate the increase in association with SCE as the level of visual impairment (visual search) increases. This can be further justified by comparing the lift values of rules 62 and 63 with rule 42. Likewise, rules 65 through 71 confirm that the increase in visual impairment (VMI–visual search) increases the association with SCE.

TABLE 3 MBA Rules of Length 3

No.	LHS	RHS	Lift
57	Age Group = 16–19; VMI = serious	LOS = SCE	1.83
58	Age Group = 25–29; VMI = serious	LOS = SCE	1.74
59	Driver Impairment = angry; VMI = serious	LOS = SCE	3.59
60	Driver Impairment = angry; VMI = mild	LOS = SCE	3.16
61	Driver Impairment = angry; VMI = none	LOS = SCE	3.13
62	Intersection Influence = yes, parking lot, driveway entrance–exit; VMI–Visual Search = serious	LOS = SCE	2.64
63	Intersection Influence = yes, parking lot, driveway entrance–exit; VMI–Visual Search = mild	LOS = SCE	2.48
64	Intersection Influence = yes, parking lot, driveway entrance–exit; VMI–Visual Search = none	LOS = SCE	2.37
65	Intersection Influence = yes, uncontrolled; VMI = serious	LOS = SCE	2.39
66	Intersection Influence = yes, uncontrolled; VMI = mild	LOS = SCE	2.27
67	Intersection Influence = yes, uncontrolled; VMI = none	LOS = SCE	2.12
68	Secondary Task = reaching for objects; VMI–Visual Search = serious	LOS = SCE	2.33
69	Secondary Task = reaching for objects; VMI = serious	LOS = SCE	2.43
70	Secondary Task = writing and texting; VMI–Visual Search = serious	LOS = SCE	2.15
71	Secondary Task = writing and texting; VMI = serious	LOS = SCE	2.39
72	Lighting = darkness, lighted; Age Group = 80+	LOS = SCE	1.72
73	Lighting = dusk; Age Group = 80+	LOS = SCE	1.93
74	Secondary Task = pet interaction; Age Group = 80+	LOS = SCE	2.69
75	Driver Impairment = angry; Cognitive Abilities = 3, 6	LOS = SCE	3.36
76	Driver Impairment = angry; Cognitive Abilities = 1, 2	LOS = SCE	3.07
77	Driver Impairment = drugs and alcohol; Cognitive Abilities = 3, 6	LOS = SCE	3.59
78	Driver Impairment = drugs and alcohol; Cognitive Abilities = 1, 2	LOS = SCE	2.61
79	Intersection Influence = yes, uncontrolled; Cognitive Abilities = 3, 6	LOS = SCE	2.43
80	Intersection Influence = yes, uncontrolled; Cognitive Abilities = 1, 2	LOS = SCE	2.08
81	Secondary Task = reaching for objects; Cognitive Abilities = 3, 6	LOS = SCE	2.33
82	Secondary Task = reaching for objects; Cognitive Abilities = 1, 2	LOS = SCE	2.07
83	Intersection Influence = yes, parking lot, driveway entrance–exit; ADHD Score = 7–16	LOS = SCE	2.60
84	Intersection Influence = yes, parking lot, driveway entrance–exit; ADHD Score = 0–6	LOS = SCE	2.43

Continued on next page.

TABLE 3 (*continued*) MBA Rules of Length 3

No.	LHS	RHS	Lift
85	Intersection Influence = yes, uncontrolled; ADHD score = 7–16	LOS = SCE	2.84
86	Intersection Influence = yes, uncontrolled; ADHD score = 0–6	LOS = SCE	2.07
87	Secondary Task = reaching for objects; ADHD score = 7–16	LOS = SCE	2.31
88	Secondary Task = writing and texting; ADHD score = 0–6	LOS = SCE	1.72
89	Surface Condition = snowy; ADHD score = 7–16	LOS = SCE	2.64
90	Surface Condition = snowy; ADHD score = 0–6	LOS = SCE	1.89
91	Weather = snowing; ADHD score = 7–16	LOS = SCE	2.84
92	Weather = snowing; ADHD score = 0–6	LOS = SCE	1.74
93	Intersection Influence = yes, interchange; Driving Knowledge = 17–19	LOS = SCE	1.85
94	Intersection Influence = yes, interchange; Driving Knowledge = 15–16	LOS = SCE	1.86
95	Intersection Influence = yes, interchange; Driving Knowledge = 9–14	LOS = SCE	1.69
96	Intersection Influence = yes, interchange; Driving Knowledge = 0, 8	LOS = SCE	3.35
97	Intersection Influence = yes, uncontrolled; Driving Knowledge = 17–19	LOS = SCE	2.11
98	Intersection Influence = yes, uncontrolled; Driving Knowledge = 0, 8	LOS = SCE	2.87
99	Secondary Task = reaching for objects; Driving Knowledge = 0, 8	LOS = SCE	2.99
100	Secondary Task = cellphone–tablet use; Driving Knowledge = 0, 8	LOS = SCE	1.99
101	Surface Condition = snowy; Driving Knowledge = 17–19	LOS = SCE	1.92
102	Surface Condition = snowy; Driving Knowledge = 15–16	LOS = SCE	1.92
103	Surface Condition = snowy; Driving Knowledge = 9–14	LOS = SCE	2.03
104	Surface Condition = snowy; Driving Knowledge = 0, 8	LOS = SCE	3.59
105	Construction Zone = yes; Sensation Seeking = 19–35	LOS = SCE	1.75
106	Driver Impairment = angry; Sensation Seeking = 19–35	LOS = SCE	3.38
107	Driver Impairment = angry; Sensation Seeking = 10–18	LOS = SCE	3.13
108	Driver Impairment = angry; Sensation Seeking = 0–9	LOS = SCE	2.56
109	Intersection Influence = yes, interchange; Sensation Seeking = 19–35	LOS = SCE	2.02
110	Intersection Influence = yes, parking lot, driveway entrance–exit; Sensation Seeking = 19–35	LOS = SCE	2.60
111	Intersection Influence = yes, traffic signal; Sensation Seeking = 19–35	LOS = SCE	1.99
112	Intersection Influence = yes, uncontrolled; Sensation Seeking = 19–35	LOS = SCE	2.37
113	Intersection Influence = yes, uncontrolled; Sensation Seeking = 10–18	LOS = SCE	2.04
114	Intersection Influence = yes, uncontrolled; Sensation Seeking = 0–9	LOS = SCE	1.88
115	Secondary Task = cellphone–tablet use; Sensation Seeking = 19–35	LOS = SCE	1.65
116	Surface Condition = icy; Sensation Seeking = 19–35	LOS = SCE	3.03
117	Weather = snowing; Sensation Seeking = 19–35	LOS = SCE	2.08
118	Driver Impairment = angry; Gender = F	LOS = SCE	3.03
119	Driver Impairment = angry; Gender = M	LOS = SCE	3.30
120	Intersection Influence = yes, parking lot, driveway entrance–exit; Gender = F	LOS = SCE	2.51
121	Intersection Influence = yes, parking lot, driveway entrance–exit; Gender = M	LOS = SCE	2.38
122	Intersection Influence = yes, traffic signal; Gender = F	LOS = SCE	1.84
123	Intersection Influence = yes, traffic signal; Gender = M	LOS = SCE	1.70
124	Surface Condition = snowy; Gender = F	LOS = SCE	2.20
125	Surface Condition = snowy; Gender = M	LOS = SCE	1.75
126	Traffic Density = LOS D; Gender = F	LOS = SCE	2.55
127	Traffic Density = LOS D; Gender = M	LOS = SCE	2.34
128	Traffic Density = LOS E, F; Gender = F	LOS = SCE	2.35
129	Traffic Density = LOS E, F; Gender = M	LOS = SCE	2.09
130	Driver Impairment = drowsy, sleepy, or fatigued; Construction Zone = Yes	LOS = SCE	2.19
131	Driver Impairment = drowsy, sleepy, or fatigued; Intersection Influence = yes, interchange	LOS = SCE	2.23

Continued on next page.

TABLE 3 (*continued*) MBA Rules of Length 3

No.	LHS	RHS	Lift
132	Driver Impairment = drowsy, sleepy, or fatigued; Intersection Influence = Yes, Traffic Signal	LOS = SCE	2.57
133	Driver Impairment = drowsy, sleepy, or fatigued; Intersection Influence = Yes, Uncontrolled	LOS = SCE	1.96
134	Driver Impairment = drowsy, sleepy, or fatigued; Lighting = dawn	LOS = SCE	2.15
135	Driver Impairment = drowsy, sleepy, or fatigued; Traffic Density = LOS C	LOS = SCE	2.24
136	Driver Impairment = drowsy, sleepy, or fatigued; Traffic Density = LOS D	LOS = SCE	2.56
137	Driver Impairment = drowsy, sleepy, or fatigued; Traffic Density = LOS E, F	LOS = SCE	3.33
138	Driver Impairment = drowsy, sleepy, or fatigued; Weather = fog	LOS = SCE	1.79
139	Secondary Task = cellphone–tablet use; Intersection Influence = yes, interchange	LOS = SCE	2.42
140	Secondary Task = cellphone–tablet use; Intersection Influence = yes, parking lot, driveway entrance/exit	LOS = SCE	2.75
141	Secondary Task = cellphone–tablet use; Intersection Influence = yes, stop sign	LOS = SCE	1.89
142	Secondary Task = cellphone–tablet use; Intersection Influence = yes, traffic signal	LOS = SCE	2.38
143	Secondary Task = cellphone–tablet use; Intersection Influence = yes, uncontrolled	LOS = SCE	2.84
144	Secondary Task = cellphone–tablet use; Traffic Density = LOS B	LOS = SCE	1.83
145	Secondary Task = cellphone–tablet use; Traffic Density = LOS C	LOS = SCE	2.37
146	Secondary Task = cellphone–tablet use; Traffic Density = LOS D	LOS = SCE	2.95
147	Secondary Task = cellphone–tablet use; Traffic Density = LOS E, F	LOS = SCE	3.00
148	Secondary Task = cellphone–tablet use; Weather = raining	LOS = SCE	1.93
149	Secondary Task = out-of-vehicle distractions; Construction Zone = yes	LOS = SCE	1.86
150	Secondary Task = out-of-vehicle distractions; Intersection Influence = yes, interchange	LOS = SCE	1.84
151	Secondary Task = out-of-vehicle distractions; Intersection Influence = yes, parking lot, driveway entrance–exit	LOS = SCE	2.70
152	Secondary Task = out-of-vehicle distractions; Intersection Influence = yes, traffic signal	LOS = SCE	1.70
153	Secondary Task = out-of-vehicle distractions; Intersection Influence = yes, uncontrolled	LOS = SCE	2.50
154	Secondary Task = out-of-vehicle distractions; Traffic Density = LOS C	LOS = SCE	2.17
155	Secondary Task = out-of-vehicle distractions; Traffic Density = LOS D	LOS = SCE	2.53
156	Secondary Task = out-of-vehicle distractions; Traffic Density = LOS E, F	LOS = SCE	2.39
157	Secondary Task = vehicle integral devices; Intersection Influence = yes, interchange	LOS = SCE	1.69
158	Secondary Task = vehicle integral devices; Intersection Influence = yes, parking lot, driveway entrance/exit	LOS = SCE	2.19
159	Secondary Task = vehicle integral devices; Intersection Influence = yes, traffic signal	LOS = SCE	2.19
160	Secondary Task = vehicle integral devices; Intersection Influence = yes, uncontrolled	LOS = SCE	2.52
161	Secondary Task = vehicle integral devices; Traffic Density = LOS C	LOS = SCE	2.17
162	Secondary Task = vehicle integral devices; Traffic Density = LOS D	LOS = SCE	2.34

Following the same concepts, more useful and relations can be inferred. For instance, drivers in age group 80+ are strongly associated with SCE during darkness and dusk lighting conditions (rules 72 and 73). They are also vulnerable to SCE when interacting with pets (rule 74). Similarly, drivers with cognitive deficit (score = 3–6), have a higher tendency of being involved in SCE when angry, under drugs/alcohol, near uncontrolled intersections, or reaching for objects (rules 75 through 82). Likewise, drivers suffering from ADHD are having higher SCE risk when they are near intersection, reaching for objects, or writing and texting (rules 83 through 88). Drivers suffering from ADHD have higher SCE risk when driving in snow conditions (rules 89 through 92). Another outcome of this study is the substantial increase in the driver's SCE risk with the decrease in driving knowledge survey score (rules 93 through 104) and increase in sensation seeking survey score (rules 105 through 117). Another major finding of this study is the inconsistent variation in association with SCE due to gender. To clarify, taking into consideration the lift value of rule 30, females have less SCE risk compared to males when driving while angry (rules 118 through 119). However, males are less associated with SCE, compared to females, when driving near parking lots, near traffic signals, in snowy weather, or through congested traffic (rules 120 through 129). Finally, rules 130 through 138 confirm the findings of Tables 2 that the driver impairment due to being drowsy, sleepy, or fatigued is associated with SCE. In like manner, rules 139 through 162 confirm the results of Table 2 that cellphone–tablet use, out-of-vehicle distractions, and setting the vehicle's integral devices are associated with SCE.

CONCLUSION

The literature review shows that parametric methods such as logistic regression and contingency tables are the common tools for extracting traffic-safety association relations among variables. However, when these methods are applied to datasets with a large number of variables (high dimensionality), such as the SHRP 2 NDS dataset, the key assumptions related to independence are likely to be violated and the reported results (*p*-values) may become unreliable. In addition, data sets with high dimensionality usually experience multicollinearity (high correlation among the variables), which compromises the accuracy of applied parametric models. Contingency tables also become difficult to track when applied over a dataset with high dimensionality. Accordingly, this study implements the MBA, a more generalized tool for identifying the driver characteristics associated with the involvement in a SCE. MBA is considered one of the best data-mining tool for association analysis, especially for comprehensive datasets with high dimensionality. In addition, the metrics reported by the MBA (lift and confidence) are highly robust to multicollinearity.

Unlike previous studies on extracting associations using crash records only, this study includes normal–BLEs in addition to the SCE to extract more accurate, reliable, and representative rules. The findings of this study render it a long-term reference for traffic safety researchers and SHRP 2 NDS data analysts. For instance, this study identified the following factors as most contributing to SCE: 1) driver impairments due to anger, other emotional state, drugs, and alcohol; 2) driver distractions due to reaching for objects, writing, and texting; 3) influences of parking lots, driveway entrance–exit, interchanges, signals, and uncontrolled intersections; 4) traffic density of LOS C, D, E, and F; and 5) snow–sleet weather conditions. A striking finding of this study is that drivers feel more responsible and cautious when they are not alone in the vehicle. In addition, passenger interaction can to some extent prevent fatigued drivers from falling asleep or get impaired especially for long trips. Another observation is that drivers have lower SCE risk when traveling on dark–not lighted roads compared to when traveling on dark–lighted road. This might be due to the headlights and taillights of surrounding vehicles are more apparent to the driver in the vehicle's mirrors when traveling on dark–not lighted roads compared to the case on lighted roads. Another notable result is the changeable variation in association with SCE due to gender. Specifically, females have lower SCE risk compared to males when driving while angry. However, males are less associated with SCE, compared to females, when driving near parking lots, near traffic signals, in snowy weather, or through congested traffic. Finally, this paper provides a quantitative evidence for the increase of driver association with SCE when he or she suffers from ADHD, experience cognitive deficit, experience visual impairment, has a higher sensational seeking tendency, or has poor driving knowledge.

Overall, this study reveals the effectiveness of the MBA application in safety research as a reliable and accurate tool for analyzing a comprehensive database with high dimensionality such as the SHRP 2 NDS. The results of this paper provide legislators with useful information for developing policies to reduce the likelihood of SCE. The government officials would be interested in the findings of this paper as well. The results will assist in allocating available resources and funds to reduce roadway crashes and improve traffic safety. Furthermore, knowing the driver characteristics (income, gender, age, driving knowledge, etc.) and abilities (visual and cognitive) associated with SCE is of great interest for the auto insurance industry and can assist in the process of determining insurance premiums and policies. Finally, this paper presents a state-of-art methodology for applying the MBA through setting the metrics thresholds, removing redundant rules, and the procedure followed for exploring rules of length 3. Accordingly, the methodology presented in this study can be applied to a wide range of transportation research and this paper serves as a reference for the transportation research community.

ACKNOWLEDGMENT

The authors acknowledge contribution to the paper as follows: Saleh R. Mousa, study conception and design; Saleh R. Mousa, data collection; Saleh R. Mousa and Sherif Ishak, analysis and interpretation of results; and Saleh R. Mousa and Sherif Ishak, draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. National Highway Traffic Safety Administration. 2016 Fatal Motor Vehicle Crashes: Overview. *Traffic Safety Facts: Research Note.* DOT HS 812456. 2017. https://doi.org/DOTHS 812 456.
2. Joshua, S. C., and N. J. Garber. Estimating Truck Accident Rate and Involvements Using Linear and Poisson Regression Models. *Transportation Planning and Technology*, Vol. 15, No. 1, 1990, pp. 41–58. https://doi.org/10.1080/03081069008717439.
3. Miaou, S.-P., P. S. Hu, T. Wright, A. K. Rathi, and S. C. Davis. Relationship Between Truck Accidents and Highway Geometric Design: A Poisson Regression Approach. *Transportation Research Record 1376,* 1992, pp. 10–18.
4. Miaou, S. P. The Relationship between Truck Accidents and Geometric Design of Road Sections: Poisson Versus Negative Binomial Regressions. *Accident; Analysis and Prevention*, Vol. 26, No. 4, 1994, pp. 471–482. https://doi.org/10.1016/0001-4575(94)90038-8.
5. Abdel-Aty, M. A., and A. E. Radwan. Modeling Traffic Accident Occurrence and Involvement. *Accident; Analysis and Prevention*, Vol. 32, No. 5, 2000, pp. 633–642. https://doi.org/10.1016/S0001-4575(99)00094-9.
6. Lord, D., S. D. Guikema, and S. R. Geedipally. Application of the Conway-Maxwell-Poisson Generalized Linear Model for Analyzing Motor Vehicle Crashes. *Accident; Analysis and Prevention*, Vol. 40, No. 3, 2008, pp. 1123–1134. https://doi.org/10.1016/j.aap.2007.12.003.

7. Zha, L., D. Lord, and Y. Zou. The Poisson Inverse Gaussian (PIG) Generalized Linear Regression Model for Analyzing Motor Vehicle Crash Data. *Journal of Transportation Safety & Security*, Vol. 8, No. 1, 2016, pp. 18–35. https://doi.org/10.1080/19439962.2014.977502.
8. Chen, W.-H., and P. Jovanis. Method for Identifying Factors Contributing to Driver-Injury Severity in Traffic Crashes. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 1717*, 2000, pp. 1–9. https://doi.org/10.3141/1717-01.
9. Shanthi, S., and D. Ramani. Classification of Vehicle Collision Patterns in Road Accidents Using Data Mining Algorithms. *International Journal of Computers and Applications*, 2011.
10. Kashani, A. T., A. Shariat-Mohaymany, and A. Ranjbari. A Data Mining Approach to Identify Key Factors of Traffic Injury Severity. *Preliminary Communication Safety and Security of Traffic*, 2011.
11. Tavakoli Kashani, A., R. Rabieyan, and M. M. Besharati. A Data Mining Approach to Investigate the Factors Influencing the Crash Severity of Motorcycle Pillion Passengers. *Journal of Safety Research*, Vol. 51, 2014, pp. 93–98. https://doi.org/10.1016/j.jsr.2014.09.004.
12. Yu, R., and M. Abdel-Aty. Utilizing Support Vector Machine in Real-Time Crash Risk Evaluation. *Accident; Analysis and Prevention*, Vol. 51, 2013, pp. 252–259. https://doi.org/10.1016/j.aap.2012.11.027.
13. Yu, R., and M. Abdel-Aty. Multi-Level Bayesian Analyses for Single- and Multi-Vehicle Freeway Crashes. *Accident; Analysis and Prevention*, Vol. 58, 2013, pp. 97–105. https://doi.org/10.1016/j.aap.2013.04.025.
14. Wang, J., Y. Zheng, X. Li, C. Yu, K. Kodaka, and K. Li. Driving Risk Assessment Using Near-Crash Database through Data Mining of Tree-Based Model. *Accident; Analysis and Prevention*, Vol. 84, 2015, pp. 54–64. https://doi.org/10.1016/j.aap.2015.07.007.
15. Yu, R., and M. Abdel-Aty. Analyzing Crash Injury Severity for a Mountainous Freeway Incorporating Real-Time Traffic and Weather Data. *Safety Science*, Vol. 63, 2014, pp. 50–56. https://doi.org/10.1016/j.ssci.2013.10.012.
16. Ahmed, M., A. Ghasemzadeh, B. E. Hammit, N. Khan, A. Das, E. Ali, R. Young, H. Eldeeb, et al. *Driver Performance and Behavior in Adverse Weather Conditions: An Investigation Using the SHRP 2 Naturalistic Driving Study Data—Phase 2*, 2018.
17. Huisingh, C., E. B. Levitan, M. R. Irvin, P. MacLennan, V. Wadley, and C. Owsley. Visual Sensory and Visual-Cognitive Function and Rate of Crash and Near-Crash Involvement Among Older Drivers Using Naturalistic Driving Data. *Investigative Ophthalmology & Visual Science*, Vol. 58, No. 7, 2017, p. 2959. https://doi.org/10.1167/iovs.17-21482.
18. Arthur, W., Jr., and D. Doverspike. Predicting Motor Vehicle Crash Involvement from a Personality Measure and a Driving Knowledge Test. *Journal of Prevention & Intervention in the Community*, Vol. 22, No. 1, 2001, pp. 35–42. https://doi.org/10.1080/10852350109511209.
19. Pande, A., and M. Abdel-Aty. Market Basket Analysis of Crash Data from Large Jurisdictions and Its Potential as a Decision Support Tool. *Safety Science*, Vol. 47, No. 1, 2009, pp. 145–154. https://doi.org/10.1016/j.ssci.2007.12.001.
20. Kumar, S., and D. Toshniwal. Analysing Road Accident Data Using Association Rule Mining. *Computing, Communication and Security*, IEEE, 2015. https://doi.org/10.1109/CCCS.2015.7374211.
21. Campbell, K. L. The SHRP 2 Naturalistic Driving Study: Addressing Driver Performance and Behavior in Traffic Safety. *TR News*, No. 282, 2012, pp. 30–35.
22. Ranganathan, P., C. S. Pramesh, and R. Aggarwal. Common Pitfalls in Statistical Analysis: Logistic Regression. *Perspectives in Clinical Research*, 2017. https://doi.org/10.4103/picr.PICR_87_17.
23. Guo, F., S. Klauer, J. Hankey, and T. Dingus. Near Crashes as Crash Surrogate for Naturalistic Driving Studies. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2147*, 2010, pp. 66–74. https://doi.org/10.3141/2147-09.
24. Klauer, S. G., F. Guo, J. D. Sudweeks, and T. A. Dingus. *An Analysis of Driver Inattention Using a Case-Crossover Approach on 100-Car Data*: *Final Report*. National Highway Traffic Safety Administration, 2010.

25. Tan, P.-N., M. Steinbach, and V. Kumar. Association Analysis: Basic Concepts and Algorithms. *Introduction to Data mining*, 2005. https://doi.org/10.1111/j.1600-0765.2011.01426.x.
26. Hahsler, M., C. Buchta, B. Gruen, and K. Hornik. Arules: Mining Association Rules and Frequent Itemsets. *R package version 1.5-0*.

Modeling Determinants of Risky Driving Behaviors and Secondary Task Engagement Using Naturalistic Driving Data

SHIVAM SHARDA
DENISE CAPASSO DA SILVA
KEVIN J. GRIMM
SARA KHOEINI
RAM M. PENDYALA
Arizona State University

Risky driving behaviors (e.g., speeding and reckless driving) and secondary task engagement (e.g., cell phone use and eating–drinking) are associated with an increased probability of crash or near-crash occurrence. With errors in human driver behavior said to be contributing to 94% of traffic crashes on the nation's highways, there is a need to identify and better understand the determinants of risky driving behaviors and secondary task engagement so that appropriate countermeasures and interventions can be implemented. Traditional crash databases provided very little objective information about specific driver behaviors leading up to a crash. As a result, there is little understanding of the determinants of risky driver behavior and secondary task engagement, particularly in the context of events (crashes or near-crashes). The SHRP 2 Naturalistic Driving Study (SHRP 2 NDS) provides a unique database with full information about driver behaviors and secondary task engagement. Using this database, this study aimed to model the determinants of risky driving behaviors and secondary task engagement within a structural equations modeling framework that accounts for endogeneity (interactions among multiple endogenous variables). Results of this study show that risky driving behaviors and secondary task engagement are significantly influenced by demographics, driver knowledge and disposition, and roadway conditions. Therefore, targeted interventions and awareness campaigns could help mitigate unsafe driving behaviors.

INTRODUCTION

Enhancing safety of transportation systems continues to be an issue of much interest and importance to the profession. A major impetus for the development of autonomous vehicles and automated driving assistance systems is that they have the potential to enhance safety by eliminating (or at least greatly reducing) driver error that contributes to 94% of crashes in the United States. Efforts to improve safety also involve regulations to make vehicles safer (e.g., airbags, seatbelts, vehicle designs) and engineering of roadway elements that would improve safety and reduce severity of crash outcomes. However, since driver error contributes to a vast majority of crashes, it is reasonable to expect that the greatest safety benefits can be realized by targeting driver behaviors and minimizing any unsafe driver actions that may contribute to adverse outcomes on the nation's roadways.

Previous research studies have mainly focused on modeling frequencies of crashes by type, probability of crash occurrence by type, and probability of crash severity based on a number of explanatory factors that include vehicle attributes, driver's demographic characteristics, environmental conditions and roadway aspects. However, these studies do not include any detailed information about driver behaviors because such variables are rarely, if ever, available in crash reports.

Naturalistic driving studies (SHRP 2 NDS) provide data on human behaviors and actions in the course of driving a vehicle, and provide the detailed driving behavior information needed to address the limitations of traditional crash databases. Indeed, a spate of recent studies using SHRP 2 NDS data has documented the influence of different driving behaviors on crash occurrence and severity. For example, Dingus et al. (2016) studied driver performance and behaviors that contribute to crash events. They found that overall impairment, driver performance error, driver judgement error, and distraction increased crash risk by 5.2, 18.2, 11.1, and 2.0 times respectively (when compared to ideal driving behavior).

Previous studies have essentially shown that unsafe driving behaviors and distracted driving contribute significantly to increasing the probability of an event, which may be defined as a crash or a near-crash where an evasive action averted what would have been a crash (Young et al., 2008). However, literature examining the factors that contribute to risky and unsafe–distracted driving behaviors in the first place is quite limited. In order to improve safety, it is necessary to understand the determinants of drivers' risky behaviors; such an understanding will help in the identification of appropriate countermeasures and interventions. Rather than modeling the probability of a crash or near-crash occurring (as a function of driver behaviors), this paper presents an integrated model of risky driving behaviors and secondary task engagement. By doing so, the paper offers a basis to identify potential strategies that could help reduce risky driving behaviors at the outset.

The remainder of this paper is organized as follows. In the next section, a brief review of the literature is provided. The third section presents an overview of the data and the fourth section presents the modeling framework and methodology. The fifth section presents model estimation results and concluding remarks are offered in the sixth and final section.

DRIVING BEHAVIOR AND CRASH OUTCOMES

There is a large body of literature devoted to examining the association between driving behaviors and crash risk but limited literature examining factors that contribute to risky driving behaviors and secondary task engagement in the first place. Moreover, there is a plethora of safety studies that directly relate traffic, roadway, and environmental factors to crash frequency and severity (Mannering, 2018; Ramos et al., 2016; Ye et al., 2009). However, these studies are not able to account for the effects of driver behaviors because such variables are largely unobserved and cannot be objectively and accurately measured after an event has occurred.

There is ample evidence that risky driving behaviors and risk-taking attitudes contribute to a higher probability of crash occurrence (Elander et al., 1993). Sensation-seeking, aggression, and social deviance are significantly related to traffic crash involvement (Jonah, 1997). Studies examining the implications of cell phone use have generally concluded that phone usage contributes to increased crash risk. Owens et al. (2018) found that visual–manual interactions with the phone increased odds of crashing by two times, but handheld phone conversations did not significantly increase odds of a crash. In a driving simulator study, Young et al. (2008) found that increased driver workload due to eating or drinking increased crash risk significantly.

Overall, the literature has shown that risky driving behaviors and secondary task engagement increase crash risk. However, the literature does not comprehensively explore the determinants of such unsafe driver behaviors, and only a few studies have attempted to address this research gap. Parker et al. (1998) measured the attitudes of drivers towards four driving violations (driving under the influence, speeding, following closely, and dangerous passing or overtaking). They found that younger drivers and males are less aware of or concerned with the negative outcomes of such behaviors (for themselves or others). Gershon et al. (2018) examined SHRP 2 NDS data to identify predictors of kinematic risky driving (KRD) and found that teenagers who had their own car were more likely to engage in KRD. Driving during the day and driving alone was also associated with KRD. Ahmed and Ghasemzadeh (2018) found that environmental conditions significantly affect driver behavior and performance; for example, the probability of reducing speed by more than 5 km/h was between 23% and 29% depending on the severity of rain. Additionally, middle-aged and older drivers exhibited more conservative and safe driving behaviors compared to younger drivers.

Overall, the literature has established that risky and distracted driving behaviors contribute to adverse safety outcomes. It is therefore desirable to determine the factors that contribute to such unsafe behaviors so that risky driving behaviors and secondary task engagement can be reduced through effective countermeasures. By clearly identifying those contributing factors, it will be possible to deploy interventions, awareness campaigns, and strategies that would reduce or eliminate such behaviors in the first place, thereby leading to reduced crash occurrence and severity in the longer term.

DATA DESCRIPTION

NDSs constitute an innovative and intensive method for observing driver behavior and traffic safety phenomena in the real world. SHRP 2 NDS databases include detailed information about the trips undertaken by drivers in their vehicles, driver behaviors, secondary task engagement, driver condition (e.g., drowsy), and driver attributes. The SHRP 2 NDS involved collecting such data for 3 years from 3,500 volunteer subjects aged 16–98 years across six states. Continuous recording of high-resolution data for crashes, near crashes, and normal driving conditions allows a rich interpretation and investigation of the relationships among factors that contribute to adverse safety events and outcomes. Complete details about the SHRP 2 NDS and the resulting database may be found in SHRP 2 (2015).

Table 1 presents a detailed description of risky driving behaviors and secondary task engagement, with each of the behaviors or secondary task engagement depicted as one possible nominal outcome.

Table 2 presents a detailed descriptive analysis of the data. Because risky driving behaviors and secondary task engagement are strongly associated with event (crash or near-crash) occurrences, the baseline no-crash events were not included in the final analysis dataset. After extensive cleaning of the dataset, the final analysis dataset includes 7,824 events (crashes or near-crashes) involving 2,074 unique drivers. Among the 7,824 events, 1,643 are actual crashes while 6,181 are near-crashes. In the case of risky driving behaviors, 90.4% of baseline no-crash events (27,484 events) are associated with no risky driving behaviors, whereas for near-crash events, only 52.1% involved no risky driving behaviors; for crash events, the percentage drops to 26.8. In the two adverse event columns (crash and near-crash), just over 21% involved distracted driving. Where a crash occurred, 37.6% involved improper driving while 7.73% involved speeding. These percentages are higher compared to corresponding percentages in the other columns.

TABLE 1 Definition of Risky Driver Behaviors and Secondary Task Engagement

Risky Driver Behavior	Definition of the Category
None	No risky behavior shown.
Distraction	Subject driver not maintaining acceptable attention to the driving task.
Signal violation	Stop sign violation (rolling, ran stop sign, and did not see sign); signal violation (disregarded, tried to beat signal change, did not see signal); non-signed crossing violation; and other signs (e.g., yield).
Following too close	Following the front vehicle at an unsafe distance.
Improper or reckless driving	Improper turn (cut corner on right/left, wide left/right turn); improper signal; improper backing; improper turn; other improper/unsafe passing; driving slowly—below speed limit; passing on right; illegal passing; wrong side of road; making turn from wrong lane; sudden or improper braking; failed to signal; sudden or improper braking; right-of-way error in relation to other vehicle—apparent recognition/decision failure; drowsy, asleep, or fatigued; and disregarded officer or watchman.
Aggressive driving	Aggressive driving: directed menacing action or other action.
Speeding	Exceeded speed limit; speeding or unsafe action in work zone; and driving slowly in relation to other traffic but not below speed limit.
Other	Other; avoiding vehicle/animal/pedestrian; apparent unfamiliarity with roadway/vehicle; and inexperience in driving.
Secondary Task Engagement	**Definition of the Category**
None	No secondary task.
Cellphone–tablet use	Texting, holding, listening, location, browsing, operating, dialing, hand-held, viewing.
Interacting with someone	Interacting with the passenger and child.
Distraction external to vehicle	Looking at an object, pedestrian, previous crash or incident, construction, animal, or other external distraction.
Eating or drinking	Eating or drinking with or without utensil, lid, or straw.
Distraction internal to vehicle	Moving object in vehicle; inserting or retrieving CD (or similar); insect in vehicle; adjusting or monitoring radio or climate control; pet in vehicle; and other nonspecific internal eye glances.
Other activities pursued	Writing, shaving, applying make-up, reading, dancing, combing–brushing–fixing hairs, smoking cigar/cigarette or lighting cigar/cigarette, or biting nails/cuticles.
Reaching for something	Reaching for object, food, personal body item, cigar.
Unknown	Unknown.

When it comes to secondary task engagement, it appears that driver's exhibit a fairly high level of driving skill. The percent of events that involved no secondary task engagement does not differ dramatically across the three event-type columns. For the no-crash events, 47.8% involved no secondary task engagement. The corresponding percentages are 38.2 and 40.2 for near-crash and crash events respectively, suggesting that there is fairly high level of secondary task engagement even during baseline events when nothing adverse is taking place. One-in-five near-crash events involves cell phone or tablet use; 14.1% of near-crash events involve distraction internal to vehicle. Overall, crash occurrence (relative to a near-crash occurrence) does not seem to be associated with a greater level of secondary task engagement; rather it is associated with a greater level of risky driving behaviors.

Table 2 also shows the influence of exogenous attributes on crash events. Care should be exercised when trying to interpret patterns of association between exogenous variables and event types. Because driving may occur more in certain conditions than others (in other words, there is different levels of exposure to different exogenous conditions), the statistical patterns may depict the effects of exposure as opposed to a correlation or association per se. In addition, there may be other confounding factors that mediate the nature of the association. For example, drivers may be more risk-taking under certain favorable environmental and traffic conditions (e.g., dry surface conditions, low traffic volumes) than under adverse conditions. These types of self-correcting behaviors play a role in shaping the influence of the exogenous attributes on crash occurrence.

In general, the patterns depicted are quite consistent with expectations. Crashes (in comparison to no-crash or near-crash events) are more likely to occur during adverse lighting and weather conditions and when surface conditions are slippery and wet. In comparison to no-crash or near-crash events, crashes are more likely to occur on undivided highways, when there are no lanes clearly demarcated, and under free-flow conditions [presumably because drivers take more risks under Level-of-Service (LOS) A1]. Moreover, crashes are more likely to occur in the presence of traffic control signal (dynamic or static), relative to no-crash or near-crash events. Driver impairment is a more prevalent factor in crash events. However, it can be seen that impairment, in general, is present for under 5% of events, regardless of event type. It appears that near-crashes are more likely to occur (relative to no-crash and crash events) in business or industrial areas, possibly due to the visual distractions in such areas.

An analysis of the socioeconomic and demographic characteristics of the drivers (exogenous factor in the study) shows that there is an equal split between males and females. For the sake of brevity, a detailed table of socioeconomic characteristics is not furnished. About one-quarter of drivers are 20–24 years of age and about one-fifth of drivers in the study are 65 years or over. Nearly one-half of the drivers are single and 34% are married. Nearly three-quarters of the drivers reside in homes that they own and 31% indicated that they do not work outside the home. Nearly one-in-four drivers reported a household income greater than or equal to $100,000 per year.

About 18% reported household income less than $30,000 per year. Nearly 90% of the drivers obtained their driver's license between the ages of 15 and 18 years; only 9.5% obtained their driver's license after attaining 18 years of age.

Overall, the SHRP 2 NDS data provides a rich set of information for analyzing the factors contributing to risky driving behaviors and secondary task engagement in a crash or near-crash context.

TABLE 2 Risky Driver Behavior, Secondary Task Engagement, and Transportation—Location Attributes by Event Type

Endogenous Variable: Risky Driver Behaviors	No Crash (*N* = 27,484) (%)	Near Crash (*N* = 6,181) (%)	Crash (*N* = 1,643) (%)
None	90.4	52.1	26.8
Distracted	0.00	21.7	21.1
Signal violation	1.10	2.56	3.04
Following too close	0.10	2.12	0.11
Improper driving	3.50	12.1	37.6
Aggressive driving	1.20	1.40	0.21
Speeding	3.30	6.81	7.73
Other	0.40	1.23	3.41
Secondary Task Engagement			
No secondary tasks	47.8	38.2	40.2
Cell phone/tablet use	14.8	20.9	17.1
Interacting with Someone	14.5	8.77	12.6
Distraction external to vehicle	8.20	8.09	8.58
Eating/drinking	2.40	1.86	2.07
Distraction internal to vehicle	6.20	14.1	9.19
Other activities pursued	5.30	6.05	6.82
Reaching for something	0.70	1.83	2.86
Unknown	0.10	0.20	0.61
Exogenous Variable: Transportation Attributes			
Lighting (darkness/dusk/dawn)	22.4	20.7	26.8
Lighting (daylight)	77.6	79.3	73.2
Weather (no adverse condition)	90.8	90.4	85.9
Weather (adverse condition)	9.20	9.60	14.1
Surface condition (wet/snow/icy)	15.7	16.1	24.1
Surface condition (dry)	84.3	83.9	75.9

Exogenous Variable: Transportation Attributes	No Crash (*N* = 27,484) (%)	Near Crash (*N* = 6,181) (%)	Crash (*N* = 1,643) (%)
Divided (median strip or barrier)	41.8	50.7	20.6
Not divided, simple 2-way traffic way	43.5	34.7	50.0
No lanes	2.80	3.30	19.2
Not divided, center 2-way left-turn lane	8.40	6.40	4.60
One-way traffic	3.40	4.90	5.50
LOS A1	38.2	14.5	52.8
LOS A2	30.6	15.5	17.2
LOS B	25.3	43.1	21.2
LOS C	4.10	17.0	5.90
LOS D/E/F	1.90	9.90	2.90
No traffic control	83.2	71.3	68.3
Dynamic traffic control sign	6.50	12.1	12.7
Static traffic control sign	10.3	16.6	19.0
Exogenous Variable: Driver Impairment			
Impaired	1.90	3.60	4.40
Not impaired	98.1	96.4	95.6
Exogenous Variable: Location Attributes			
Business–industrial	32.9	48.8	35.4
Interstate, bypass, divided highway with no traffic signals	25.8	6.80	35.0
Moderate–open residential	25.3	25.9	14.3
Urban location	2.10	5.10	4.40
Bypass–divided highway with traffic signals or open country	5.40	2.40	2.50
Church, playground, school	8.40	11.0	8.30
Other	0.20	0.10	0.10

MODELING FRAMEWORK

This study aimed to use SHRP 2 NDS data to identify contextual factors that influence risky driving behaviors and secondary task engagement that may lead to adverse safety outcomes. In trying to model such a complex phenomenon, a number of considerations need to be taken into account. Risky driving behaviors and secondary task engagement represent endogenous variables with nominal outcomes as depicted in Table 1. Given the presence of multiple endogenous variables, it would be advisable to adopt a simultaneous equations modeling framework that can incorporate a multitude of relationships among various explanatory and dependent variables. The structural equations modeling (SEM) methodology is very suited to analyzing such complex behavioral phenomena (characterized by the presence of multiple endogenous variables with nominal outcomes). In addition, the data set contains information at distinct levels. As mentioned earlier, there are 2,074 unique drivers with 7,824 events (crashes or near-crashes). In other words, there are multiple records per driver; in the presence of such repeated observations for the same behavioral unit (driver), it is advisable to adopt a methodology that is able to account for the fact that observations belonging to the same driver are correlated and have identical values for driver attributes that do not change across events (for the same driver). To account for repeated observations, this study adopts a multilevel modeling framework to account for two distinct levels of analysis: person level and event level. Multilevel models provide more accurate results than traditional models by introducing random effect terms, which account for the unobserved heterogeneity among different drivers (Chin and Quddus, 2003). Another advantage of the multilevel modeling framework is its ability to incorporate variables at the level where their impacts occur. Many studies have employed multilevel models to analyze crashes (Xie et al., 2014).

Figure 1 shows the overall modeling framework. At the person (driver) level, the SHRP 2 NDS data offers a number of attributes that describe driver capabilities and attitudes (proclivity to engage in different types of behaviors and actions). The dataset includes many indicators that describe driving history and knowledge or awareness. These descriptors are likely to be affected by socioeconomic and demographic variables. The SEM framework provides a mechanism to define latent variables or constructs that represent the underlying aspect of interest. Thus, in Figure 1, a latent variable called Driver Cognition is defined; this latent variable is unobserved and not measured explicitly in the dataset. However, a number of indicators measuring driving history and driver knowledge or awareness are combined in a factor analysis to represent the latent Driver Cognition factor. Similarly, the dataset includes many variables representing the tendency of an individual to engage in various types of driving behaviors, take risks while driving, and engage in sensation-seeking behaviors. All of these indicators are likewise combined through a factor analysis approach to define a latent variable or construct representing Driver Disposition. The Driver Cognition and Driver Disposition (latent) factors are now endogenous variables that are themselves affected and influenced by socioeconomic and demographic characteristics, but are also affecting the endogenous variables of interest for this study, namely, risky driver behavior and secondary task engagement.

At the observation level, driver impairment, trip duration, and transportation system and location attributes are assumed to influence the driver behavior outcomes of interest including risky driving behaviors and secondary task engagement. The model system therefore has a multitude of components and offers a comprehensive depiction of the phenomenon under study. In addition to the latent factor models, there are four components for the multilevel SEM defined by the two nominal outcome variables (risky driving behaviors and secondary task engagement)

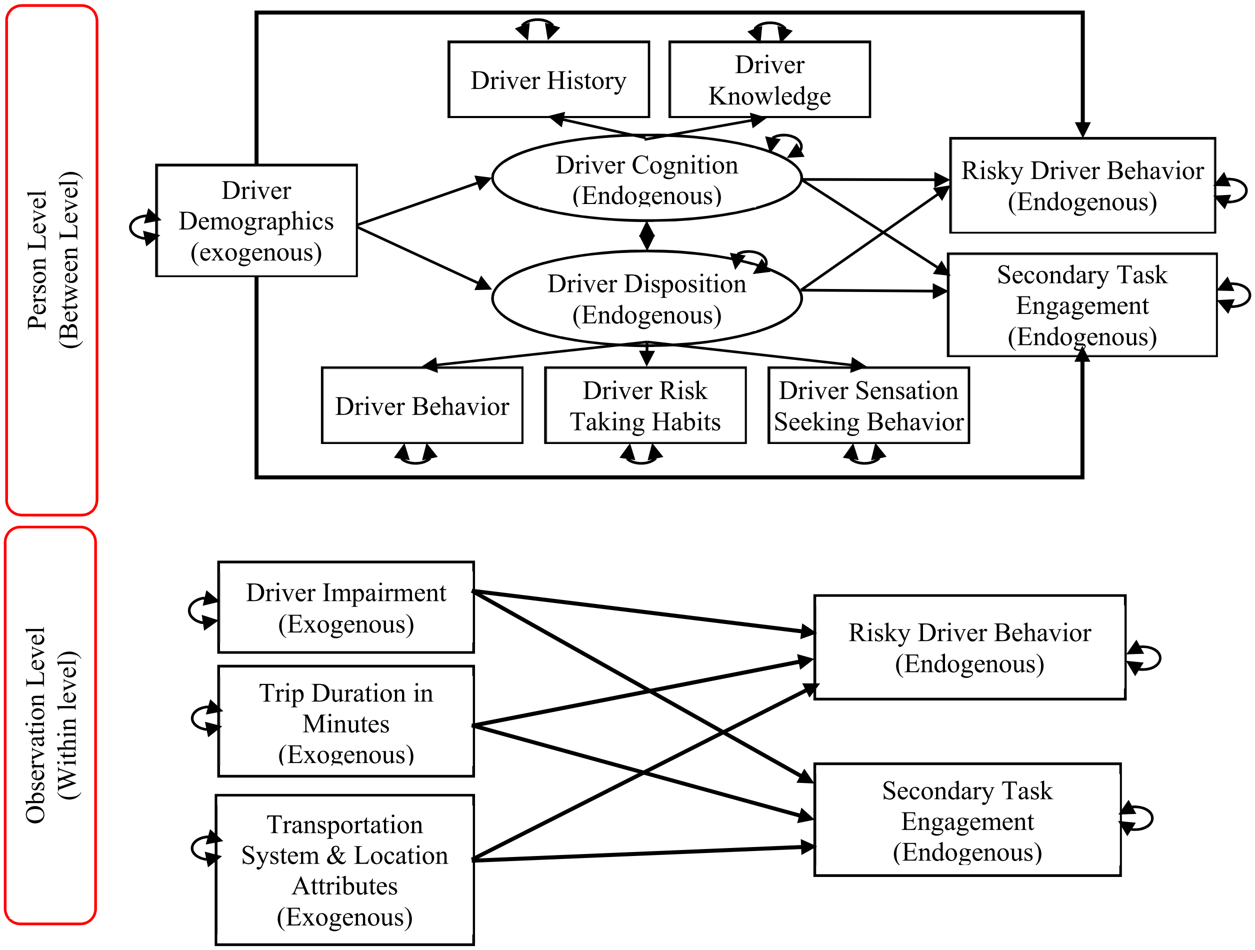


FIGURE 1 Multilevel structural equation modeling framework.

and two levels (person level and event level). Within the scope of this paper, it is difficult to present the estimation results for all components of the model system. Hence the paper depicts selected results in tabular form with additional results described in text.

The results of the factor analysis are shown in Table 3. Driver Cognition is described by driving history (number of years of driving and number of traffic violations in the past year) and driving knowledge or awareness. The driving knowledge–awareness is measured by the ability of the individual to correctly identify road signs, traffic control devices, and signs of being drowsy.

Table 3 also shows the descriptive statistics for each of the indicators that loaded onto a latent variable (Driver Cognition and Driver Disposition) in the factor analysis. The factor loadings and corresponding standard errors are shown in the last column of the table.

TABLE 3 Driver Latent Factors and Factor Loadings

Driver Cognition (Factor)	Indicators for Driver Cognition	Min.	Max.	Std. Dev.	Factor Loadings (Std. Error)
Driving history (indicators)	Year of Driving	0	74	19.9	1.00 (base)
	Categories	Zero	One	Two or more	
	Number of Violation	59.1	24.6	16.3	–0.228 (0.093)
		Incorrect Response	**Correct Response**		
Driver Knowledge Questionnaire (indicators)	Merge Sign	1.06	98.9		2.550 (1.251)
	Right of Way	1.24	98.8		0.975 (0.260)
	Traffic Control	3.35	96.7		0.465 (0.161)
	Yellow Lane	21.3	78.7		0.625 (0.116)
	Drowsy	9.05	91.0		0.407 (0.193)
Driver Disposition (Factor)	**Indicators for Driver Disposition**	**Never (%)**	**Occasionally (%)**	**Often (%)**	**Factor Loadings (Std. Error)**
Driver Behavior Questionnaires (Indicators)	Passing on right	50.5	44.2	5.36	1.00 (base)
	Tailgating	76.2	21.8	1.93	1.485 (0.048)
	Passing turn vehicle	91.4	8.00	0.61	1.435 (0.061)
	Forgot where car is parked	70.6	27.0	2.43	0.478 (0.030)
	No Recollection	84.0	15.3	0.69	0.993 (0.042)
	Running red light	92.7	6.90	0.43	1.489 (0.066)
	Miss Pedestrian	95.4	4.61	0.00	0.869 (0.062)
	Often road rage	95.0	4.41	0.55	1.232 (0.067)
	Wrong way	98.4	1.56	0.08	0.755 (0.091)
	Disregard speed limit	74.6	23.0	2.39	1.483 (0.047)
	Driving above alcohol limit	97.9	1.90	0.17	1.227 (0.095)
	Roadway aversion	97.9	1.87	0.19	1.205 (0.092)
	Underestimate speed of oncoming traffic	96.3	3.64	0.08	1.166 (0.073)
	Wrong destination	87.0	12.6	0.36	0.686 (0.040)
	Wrong lane at intersection	83.9	16.1	0.06	0.629 (0.037)
	Involved in racing	97.9	1.96	0.19	1.724 (0.108)
	Aggressive braking	94.8	5.22	0.00	0.976 (0.061)
Driver Risk Taking Questionnaires (Indicators)	Drive Sleepy	40.4	58.7	0.84	1.039 (0.035)
	Changes lane suddenly	34.1	62.5	3.40	1.628 (0.047)
	Run stop signs	70.4	27.3	2.28	0.946 (0.035)
	Speed for thrill often	72.5	26.2	1.32	1.212 (0.041)
	Fail to yield often	73.0	26.5	0.51	0.858 (0.035)
	Make illegal turns	56.8	42.5	0.75	1.068 (0.036)
	Follow emergency vehicle	95.1	4.70	0.22	1.010 (0.065)
	Failure to adjust	33.1	61.7	5.14	0.969 (0.032)
	Accelerate at yellow light	15.0	78.8	6.16	1.706 (0.051)
	Adjust CD player	14.1	77.5	8.40	1.544 (0.046)
	Eyes off road to passenger	25.9	72.5	1.55	1.000 (0.036)
	Not use belt	87.3	11.6	1.12	0.560 (0.039)
	Not use signal	50.0	48.3	1.67	0.507 (0.027)
		Min.	**Max.**	**Std. Dev.**	**Factor Loadings (Std. Error)**
Sensation Seeking Score (Indicator)	Driver Sensation Seeking Behavior	0	35	6.83	2.861 (0.079)

MODEL ESTIMATION RESULTS

The multilevel structural equations modeling framework applied in this study is well documented in the literature (Muthen, 1994; Ratanavaraha et al., 2016). The complete methodology is not provided here in the interest of brevity; also, only an illustrative tabulation of the driver profile model is provided, while driver behavior and secondary task engagement model results are described in text form.

Models of Driver Cognition and Driver Disposition (Latent Factors)

Table 4 shows the models of Driver Cognition and Driver Disposition. In Figure 1, these factors are essentially influenced by socioeconomic and demographic attributes. Although this table is depicted in stand-alone format, it should be noted that the results in this table are part of a larger comprehensive multilevel structural equations model system in which all coefficients are estimated simultaneously. The other model components depicting the influence of explanatory variables and factors on risky driving behaviors and secondary task engagement will be explained in subsequent subsections.

Results shown in Table 4 are intuitive and consistent with the findings reported previously in the literature. In the Driver Cognition model, a positive coefficient implies that the individual is more knowledgeable and has a better driving history and track record. In the Driver Disposition model, a positive coefficient depicts a more risky driving proclivity and attitude. In the Driver Cognition model, it is found that females have a better driving record, knowledge, and history than males, as evidenced by the positive coefficient. This finding is consistent with that reported in the literature (Al-Balbissi, 2003).

TABLE 4 Model Results for Driver Profile
(*N* = 7,824 events; number of drivers = 2,074

Explanatory Variable	Driver Cognition Coefficient (*t*-stat)	Driver Disposition Coefficient (*t*-stat)
Intercept	–0.071 (–1.91)	–0.418 (–5.65)
Gender: Female	0.030 (1.76)	—
Age ≥20, ≤24 years	—	0.329 (6.24)
Age ≥25, ≤34 years	—	0.220 (3.85)
Age ≥35, ≤54 years	0.039 (1.80)	—
Age ≥55, ≤64 years	—	–0.433 (–6.35)
Age ≥65 years	—	–0.566 (–10.54)
Married	0.041 (2.13)	—
Income <50k	–0.044 (–2.27)	—
Income ≥70k, <100k	—	0.076 (1.53)
Income ≥100k	0.034(1.70)	0.131 (2.85)
College degree	0.037 (1.79)	—
Professional degree	0.055 (2.44)	—
Work status, part-time	–0.046 (–2.25)	0.087 (2.12)
Rent home	—	0.131 (2.76)
Licensed at age 15–18 years old	0.062 (1.91)	0.238 (3.99)
Own vehicle 1–6 years old	—	0.061 (1.42)

Younger adults are more likely to exhibit a proclivity towards risky driving habits, as evidenced by the positive coefficients in the Driver Disposition model (Castec et al., 2011). Higher income individuals have a higher level of risky driving disposition when compared with lower income individuals. It is possible that this reflects their greater amount of driving, higher levels of car ownership, larger travel distances, and possible self-compensating behavior that comes with owning higher performance newer cars. Shinar et al. (2001) reported that speeding behavior increases with income thus suggesting that affluent individuals judge the merits of risk taking habits themselves. Married individuals have a better driving history and knowledge; the same can be said for individuals in the highest income category as evidenced by positive coefficients in the Driver Cognition model. It is likely that these individuals have a greater level of knowledge and awareness, and have life-cycle stage circumstances (dependents in household) that motivate them to be more cautious in their driving. Similarly, those with a higher level of education show better Driver Cognition than those with lower levels of education (Vaez and Laflamme, 2005).

Other variables in the model show that those who work part time and rent their home are more likely to engage in risky driving habits. It is possible that these individuals, by virtue of their more temporary living and working arrangements, do not feel a strong sense of community and engage in more sensation-seeking driving behaviors (Leeman et al., 2013). Those who obtained a driver's license at a young age are more knowledgeable, but also more risk taking. Those with newer vehicles (between 1 and 6 years old) are also more prone to engage in risky and sensation-seeking driving behavior, a finding consistent with the notion that people are likely to try and enjoy their newer vehicle while also subconsciously engaging in self-compensatory behavior confident in the safety features available in newer vehicles (i.e., they engage in more risky behaviors based on the notion that the vehicle has advanced safety features that will protect them in the event of a crash).

Models of Risky Driving Behaviors

There are two model components for risky driving behaviors. One corresponds to the person level and the other corresponds to the event level. This multilevel modeling framework provides key insight on the influence of person attributes and the influence of contextual attributes on the propensity to engage in various risky driving behaviors. In the interest of brevity, detailed model estimation result tabulations are not presented.

The model results show that, at the person level, Driver Cognition is associated with a lower level of distracted driving, signal violation, following too close, improper–reckless driving, and speeding. On the other hand, Driver Disposition (risk-taking tendency) is associated with a higher level of distraction, signal violation, following too close, and speeding (consistent with Delhomme et al., 2009). These findings suggest that interventions and campaigns that aim to change driver habits, awareness, knowledge, and proclivities may be successful in reducing risky driving behaviors. Females appear more prone to distraction and following too close, possibly because of the secondary task engagement associated with chauffeuring passengers and children, but they are less prone to improper and reckless driving, aggressive driving, and speeding (as reported previously by Ozkhan et al., 2005).

Older drivers (65 years and above) are more prone to signal violation and improper–reckless driving, suggesting the onset of diminished driving skills. They are, however, less likely to speed when compared to younger drivers. Those with a higher level of education (college degree or professional degree) are less likely to engage in distractions, following too closely, speeding, improper/reckless driving, or aggressive driving. It appears that a higher level of education brings about awareness of the risks of undesirable driving behaviors (as noted by Noland and Laham, 2018). Those who are single are more likely to engage in risky driving behaviors, consistent with the notion that these individuals are likely to be young adults and have no dependents (Jonah, 1986). Of note, those who obtained their driver's license early, i.e., between the ages of 15 and 18 years, are less likely to engage in improper–reckless driving or aggressive driving but are more likely to speed. It is possible that these individuals feel confident in their driving abilities and feel comfortable speeding without engaging in reckless driving.

At the event level, it is found that favorable conditions are generally associated with less-risky driving behaviors. Driving during the day in daylight or on divided highways with a median is associated with less distractions, signal violations, improper and reckless driving, and aggressive driving. However driving in the daylight is associated with speeding, while driving on a divided highway with median is associated with following too closely. It is possible that drivers are comfortable navigating at high speeds in daylight conditions when visibility is good; similarly, there may be a greater acceptance of smaller headways on divided highways where traffic in the opposite direction is separated physically by a barrier and where there are likely to be multiple lanes allowing lane shifts in the event of unexpected braking. On undivided highways, drivers tend to be distracted, but less prone to engaging in any other risky driving behavior. The presence of a static traffic control sign is associated with more risky driving behaviors such as signal violation, improper–reckless driving, and speeding – suggesting that drivers are more likely to ignore such signs and may find them an unnecessary annoyance. Driving through business–industrial areas is associated with distraction, signal violation, and improper/reckless driving, reflecting the busy nature of the streets in such areas. However, these areas are associated with reduced behaviors involving following too closely, aggressive driving, and speeding—all findings that are consistent with expectations as drivers may try to be cautious in busy streets filled with distractions.

Drivers tend to speed on longer trips (greater than 20 min in length) and in free-flow travel conditions. At LOS C (stable, but dense flow) drivers tend to follow front vehicle too closely but do not engage in reckless driving, speeding, or signal violations. Driving impairment caused by anger, sadness, drug use, or alcohol use is associated with higher levels of all risky driving behaviors, suggesting that countermeasures addressing impairment are likely to see considerable benefit in reducing risky driving behaviors.

Models of Secondary Task Engagement

As with the models for risky driving behavior, there are two models of secondary task engagement —one at the person level and one at the event level. It should again be recognized that all model components comprise a single framework and are all estimated in a single step using the multilevel structural equations methodology. As in the case of risky driving behaviors, Driver Cognition and Driver Disposition (latent) factors are important determinants of secondary task engagement that could essentially lead to distractions. Those with higher levels of driver awareness and knowledge and better driving history are less likely to use cell phone or tablet, get distracted, or pursue other activities in the vehicle. On the other hand, those with a proclivity for engaging in risky driving habits and be sensation-seeking are more likely to use a cell phone or tablet, eat or drink, and pursue other activities inside the vehicle. Clearly, personality traits are important determinants of unsafe driving behaviors and secondary task engagement that could lead to adverse safety outcomes.

Females are more likely to engage in secondary tasks, perhaps because they engage in more of the child–passenger chauffeuring activities in a household (Ozkhan et al., 2005). They are more likely to use cell phone, be distracted with something inside the vehicle, pursue other activities while driving the vehicle, and reach for something inside the vehicle. Those who are single are more prone to using a cell phone and pursuing other activities while driving, consistent with the notion that they are likely to be more risk taking. Younger drivers are more likely than older drivers to use cell phone and interact with someone in the vehicle; likewise, older drivers are less likely to be distracted by something internal to the vehicle, pursue other activities, or reach for something inside the vehicle. Older drivers are, however, distracted (more so than younger drivers) by external stimuli. The ability to stay focused on the driving task in the midst of myriad external stimuli may diminish with age and hence older drivers may refrain from engaging in activities that could take their focus away from the driving task. Older drivers may choose nonfreeway routes and are more likely to be distracted by more activity on city streets. Lower-income individuals generally depict greater levels of secondary activity engagement, especially with cell phone use, eating or drinking, and distraction internal to vehicle. A greater awareness of the dangers of secondary task engagement is likely to exist among higher income and more educated individuals. One finding is that those who obtained their driver's license between the ages of 15 and 18 years (early in life) are more likely to engage in a range of secondary tasks including cell phone use, interacting with someone, eating or drinking, distraction internal to vehicle, and pursuing other activities. It appears that these individuals, by virtue of the accumulated experience in driving from an early age, feel confident in their ability to drive while multitasking.

At the event level, it is found that drivers are more prone to using the cell phone or tablet and less prone to being distracted by something external to the vehicle when traveling on divided highways. It is possible that drivers feel more comfortable using the cell phone when on a divided highway without the danger of any oncoming vehicles in their path. Similarly, on a divided highway, there are likely to be fewer external distractions that could affect driver task engagement. On an undivided highway, on the other hand, there is a greater likelihood of distractions external to vehicle as such streets likely pass through business–industrial areas. Indeed, it is found that business–industrial areas engender higher levels of distraction and cell phone use. Driving in residential areas is associated with higher levels of cell phone uses, distractions internal to vehicle, reaching for something, and pursuing other activities. It is possible that drivers feel more comfortable multitasking in a slower speed residential environment; they may also be distracted with household related communications and activities in the vicinity of their home. On longer trips greater than or equal to 30 min in duration, drivers show a greater proclivity to use cell phone or tablet, interact with someone, and reach for something inside the vehicle. They are, on the other hand, less likely to eat/drink on a longer trip, possibly because longer trips involve greater levels of high speed freeway travel. Finally, lower levels of visibility (i.e., during snow or rain) are associated with a lower likelihood of engaging in secondary task engagement or risky driving behaviors, suggesting that individuals are more cautious in such environmental conditions.

The model provided excellent goodness-of-fit, given the nature of the phenomenon under study. The log likelihood at convergence is –27,029.50 with 322 parameters while the log likelihood for the constants only model is –69,933.09. The adjusted ρ^2 is 0.613, which is quite reasonable for a model of this nature.

DISCUSSION AND CONCLUSIONS

This study uses the SHRP 2 NDS data to examine the influence of various factors in contributing to risky driving behaviors and secondary task engagement, i.e., driver actions that could increase probability of a crash or near-crash events. The multilevel structural equations modeling framework accounts for correlation across repeated observations for the same individual, thereby providing more accurate statistical inferences regarding the effects of different factors on risky driving behavior and secondary task engagement.

Overall, it is found that young adults, males, lower income individuals, those without a college degree, and those who are less embedded within the community (such as renters and part-time workers) are more likely to engage in risky driving behaviors and secondary task engagement. In addition, those who obtained their driver's licenses early in their life, between the ages of 15 and 18 years, were more likely to engage in secondary task engagement. These findings provide valuable insights on the demographic groups that could be targeted for educational campaigns and special interventions. Perhaps those who received their driver's license at a very young age can be asked to complete one or more refresher training modules on safe driving. It was also found that individuals who had a poorer knowledge and awareness of various signs or had a history of traffic violations were more likely to engage in risky driving behaviors and secondary task engagement. Whenever individuals get cited for traffic violations, it may help to provide educational materials that explain good driving practice and the consequences of exercising poor driving behaviors. Such awareness campaign materials could be sent to the homes of those who received a violation or who are more likely to be error-prone in their interpretation of traffic signs and controls. By targeting these demographic groups, it may be possible to bring about real changes in the risky driving behaviors and secondary task engagement of high-risk groups. In addition, understanding the factors causing risky driver behavior can help inform in-vehicle technology decisions and enhance safety feature (e.g., antilock brake system, forward collision warning systems, pre-crash systems, lane departure warnings).

From a transportation system standpoint, special attention should be paid to busy business–industrial areas where drivers are prone to getting distracted and engage in a number of secondary tasks. A number of countermeasures may be implemented to mitigate the adverse effects of such locations. The amount of visual clutter and distracting elements may be reduced in an effort to reduce the number of distractions. The speed of travel can be reduced, pedestrian-only areas can be defined to separate pedestrians from traffic, and dynamic message signs imploring drivers to pay attention may be strategies worth considering. Interventions may also be worthwhile in the context of free flow travel. Artificially lowering speed limits may be undesirable in many jurisdictions; but including dynamic message signs with safety messages and key reminders of good driving behaviors may help advance safety. In addition, dividing highways using a median strip or barrier appears to have beneficial impacts; driving on divided highways is found to be associated with lower levels of risky driving behaviors and secondary task engagement (except for cell phone use). A key finding within the secondary task engagement model is that females are more likely to be distracted in the vehicle, reach for something, interact with a passenger, or use the cell phone. Given that they are more likely to chauffeur children and passengers, this finding is not surprising.

In summary, vehicle designs that are more forgiving and able to accommodate such distractions should be advanced. Awareness campaigns to improve driver knowledge about safe following distances and best practices to avoid road rage may help drivers practice safer driving behaviors. By implementing customized strategies and interventions that reduce engagement in risky driving behaviors and secondary task engagement for different market segments, it will be possible to bring about more favorable safety outcomes and reduce the risk of crash or near-crash events.

ACKNOWLEDGMENT

The authors would like to thank Transportation Research Board, Iowa State University, and Virginia Tech for providing the SHRP 2 NDS dataset used in this research and for supporting the student paper competition.

REFERENCES

Al-Balbissi, A. H. Role of Gender in Road Accidents. *Traffic Injury Prevention*, Vol. 4, No. 1, 2003, pp. 64–73. https://doi.org/10.1080/15389580309857.

Ahmed, M. M., and A. Ghasemzadeh. The Impacts of Heavy Rain on Speed and Headway Behaviors: An Investigation Using the SHRP 2 Naturalistic Driving Study Data. *Transportation Research Part C, Emerging Technologies*, Vol. 91, 2018, pp. 371–384. https://doi.org/10.1016/j.trc.2018.04.012.

Cestac, J., F. Paran, and P. Delhomme. Young Drivers' Sensation Seeking, Subjective Norms, and Perceived Behavioral Control and Their Roles in Predicting Speeding Intention: How Risk-Taking Motivations Evolve with Gender and Driving Experience. *Safety Science*, Vol. 49, No. 3, 2011, pp. 424–432. https://doi.org/10.1016/j.ssci.2010.10.007.

Chin, H. C., and M. A. Quddus. Applying the Random Effect Negative Binomial Model to Examine Traffic Accident Occurrence at Signalized Intersections. *Accident Analysis and Prevention*, Vol. 35, No. 2, 2003, pp. 253–259. https://doi.org/10.1016/S0001-4575(02)00003-9.

Delhomme, P., J. F. Verlhiac, and C. Martha. Are Drivers' Comparative Risk Judgments About Speeding Realistic? *Journal of Safety Research*, Vol. 40, No. 5, 2009, pp. 333–339. https://doi.org/10.1016/j.jsr.2009.09.003.

Dingus, T. A., F. Guo, S. Lee, J. F. Antin, M. Perez, M. Buchanan-King, and J. Hankey. Driver Crash Risk Factors and Prevalence Evaluation Using Naturalistic Driving Data. *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 113, No. 10, 2016, pp. 2636–2641. https://doi.org/10.1073/pnas.1513271113.

Elander, J., R. West, and D. French. Behavioral Correlates of Individual Differences in Road-Traffic Crash Risk: An Examination of Methods and Findings. *Psychological Bulletin*, Vol. 113, No. 2, 1993, pp. 279–294. https://doi.org/10.1037/0033-2909.113.2.279.

Gershon, P., J. Ehsani, C. Zhu, F. O'Brien, S. Klauer, T. Dingus, and B. Simons-Morton. Vehicle Ownership and Other Predictors of Teenagers Risky Driving Behavior: Evidence from a Naturalistic Driving Study. *Accident Analysis and Prevention*, Vol. 118, 2018, pp. 96–101. https://doi.org/10.1016/j.aap.2018.06.001.

Jonah, B. A. Accident Risk and Risk-Taking Behaviour among Young Drivers. *Accident Analysis and Prevention*, Vol. 18, No. 4, 1986, pp. 255–271. https://doi.org/10.1016/0001-4575(86)90041-2.

Leeman, R. F., R. A. Hoff, S. Krishnan-Sarin, J. A. Patock-Peckham, and M. N. Potenza. Impulsivity, Sensation-Seeking, and Part-Time Job Status in Relation to Substance Use and Gambling in Adolescents. *Journal of Adolescent Health*, Vol. 54, No. 4, 2014, pp. 460–466. https://doi.org/10.1016/j.jadohealth.2013.09.014.

Mannering, F. Temporal Instability and the Analysis of Highway Accident Data. *Analytic Methods in Accident Research*, Vol. 17, 2018, pp. 1–13. https://doi.org/10.1016/j.amar.2017.10.002.

Muthén, B. O. Multilevel Covariance Structure Analysis. *Sociological Methods & Research*, Vol. 22, No. 3, 1994, pp. 376–398. https://doi.org/10.1177/0049124194022003006.

Naderi, H., H. Nassiri, and S. Sahebi. Assessing the Relationship between Heavy Vehicle Driver Sleep Problems and Confirmed Driver Behavior Measurement Tools in Iran. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 59, 2018, pp. 57–66. https://doi.org/10.1016/j.trf.2018.08.007.

Noland, R. B., and M. L. Laham. Are Low Income and Minority Households More Likely to Die from Traffic-Related Crashes? *Accident Analysis and Prevention*, Vol. 120, 2018, pp. 233–238. https://doi.org/10.1016/j.aap.2018.07.033.

Owens, J.M., B. Tefft, F. Guo, Y. Fang, M. Perez, J. McClafferty, and T. Dingus. Crash Risk of Cell Phone Use While Driving: Case-Crossover Study of SHRP 2 Naturalistic Driving Data. *AAA Foundation for Traffic Safety Report*, Washington, D.C., 2018b. http://aaafoundation.org/wp-content/uploads/2018/01/CellPhoneCrashRisk_FINAL.pdf. Accessed September 13, 2018.

Özkan, T., and T. Lajunen. Why Are There Sex Differences In Risky Driving? The Relationship between Sex and Gender-Role on Aggressive Driving, Traffic Offences, and Accident Involvement among Young Turkish Drivers. *Aggressive Behavior: Official Journal of the International Society for Research on Aggression*, Vol. 31, No. 6, 2005, pp. 547–558. https://doi.org/10.1002/ab.20062.

Parker, D., T. Lajunen, and S. Stradling. Attitudinal Predictors of Interpersonally Aggressive Violations on the Road. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 1, No. 1, 1998, pp. 11–24. https://doi.org/10.1016/S1369-8478(98)00002-3.

Ramos, A., H. Teng, and Y. Fu. Estimating Crash Rate of Freeway Segments Using Simultaneous Equation Model. *Journal of Transportation Technologies*, Vol. 6, No. 05, 2016, pp. 327–338. https://doi.org/10.4236/jtts.2016.65029.

Ratanavaraha, V., S. Jomnonkwao, B. Khampirat, D. Watthanaklang, and P. Iamtrakul. The Complex Relationship Between School Policy, Service Quality, Satisfaction, and Loyalty for Educational Tour Bus Services: A Multilevel Modeling Approach. *Transport Policy*, Vol. 45, 2016, pp. 116–126. https://doi.org/10.1016/j.tranpol.2015.09.012.

Shinar, D., E. Schechtman, and R. Compton. Self-reports of safe driving behaviors in relationship to sex, age, education and income in the US adult driving population. *Accident Analysis and Prevention*, Vol. 33, No. 1, 2001, pp. 111–116. https://doi.org/10.1016/S0001-4575(00)00021-X.

The Second Strategic Highway Research Program (2005–2015). http://www.trb.org/StrategicHighwayResearchProgram2SHRP 2/Blank2.aspx. Accessed September 13, 2017.

Vaez, M., and L. Laflamme. Impaired Driving and Motor Vehicle Crashes among Swedish Youth: An Investigation into Drivers' Sociodemographic Characteristics. *Accident Analysis and Prevention*, Vol. 37, No. 4, 2005, pp. 605–611. https://doi.org/10.1016/j.aap.2005.03.001.

Xie, K., X. Wang, K. Ozbay, and H. Yang. Crash Frequency Modeling for Signalized Intersections in A High-Density Urban Road Network. *Analytic Methods in Accident Research*, Vol. 2, 2014, pp. 39–51. https://doi.org/10.1016/j.amar.2014.06.001.

Ye, X., R. M. Pendyala, S. P. Washington, K. Konduri, and J. Oh. A Simultaneous Equations Model of Crash Frequency by Collision Type for Rural Intersections. *Safety Science*, Vol. 47, No. 3, 2009, pp. 443–452. https://doi.org/10.1016/j.ssci.2008.06.007.

Young, M. S., J. M. Mahfoud, G. H. Walker, D. P. Jenkins, and N. A. Stanton. Crash Dieting: The Effects of Eating and Drinking on Driving Performance. *Accident Analysis and Prevention*, Vol. 40, No. 1, 2008, pp. 142–148. https://doi.org/10.1016/j.aap.2007.04.012.

Interchange Deceleration Lane Design Based on Naturalistic Driving Speeds and Deceleration Rates

Dan Xu
Huaguo Zhou
Chennan Xue
Auburn University

The objective of this study is to determine the minimum lengths of freeway deceleration lanes based on naturalistic driving speeds and deceleration rates from the Naturalistic Driving Study (SHRP 2 NDS) database. SHRP 2 NDS has the distinct advantage of providing insight into driver behavior based on a wide-ranging collection of data regarding the driver, the vehicle, and the environment, whereas previous studies of this subject relied primarily on crash data, radar data, computer simulations, and driving simulators. Ten study locations that are located on I-75 in Florida with varying deceleration lane lengths and off-ramp lengths were used. The analysis included (1) speed distribution on different lengths of freeway deceleration lanes and off-ramps based on polynomial regression models; (2) drivers' behavior, including brake pedal usage, critical speed change point detection, and the distribution of deceleration rates compared with the American Association of State Highway and Transportation Officials (AASHTO) *Green Book* assumptions; and (3) a new method to determine the minimum deceleration lane lengths based on naturalistic driving speeds and deceleration rates. The results revealed that (1) typically, vehicle speeds reduced by 10% to 25% on deceleration lanes while 75% to 90% on off-ramps; (2) deceleration rates on deceleration lanes and off-ramps before critical speed change points are lower than assumptions from the *Green Book*; and (3) deceleration lanes can be shorter when off-ramps are long at diamond interchanges (e.g., greater than 1,550 ft).

INTRODUCTION

The freeway diverge area including deceleration lanes and off-ramps provides exits for vehicles from freeway mainline via off-ramps to adjacent crossroads. It aims at offering vehicles an effective, safe, and smooth transition from high speed to low speed. However, crashes occur more frequently in the diverge area than other freeway segments. In 2012, a National Cooperative Highway Research Program (NCHRP) study reported that the average crash rate on freeway deceleration lanes in the state of Washington was 0.68 crashes per million vehicle-miles traveled (MVMT) (*1*). It was three times higher than the average crash rate of acceleration lanes (0.16 MVMT) and 15.3% higher than that of the mainline segment before the next off-ramp (0.59 MVMT). Moreover, it is important to note that 42.4% of freeway deceleration lane crashes were rear-end crashes due to the speed differential (*1*). In Alabama, similarly, 201 crashes occurred on freeway deceleration lanes were rear-end crashes, accounting for 71.28% of total freeway deceleration lane crashes from 2012 to 2016 (*2*). Therefore, there is an urgent need to reduce crash rates on freeway deceleration lanes.

Previous studies revealed that crash rates can be related to the deceleration lane length (*3–7*). In other words, crash rates would be reduced with an optimal length of the deceleration lane. Referring to the deceleration lane design, three aspects that determine the deceleration lane length are recommended by the AASHTO *Green Book* (*8*). The first is drivers' speeds while they initially diverge onto the auxiliary lane. Second is drivers' speeds at the end of the deceleration lane. Third is their manners of deceleration. Additionally, it requires the consideration of the speed differential between vehicles on the mainline and the ramp. However, the *Green Book* only provides the minimum lengths of deceleration lanes according to the design speed differential from the freeway mainline and off-ramp. Moreover, similarities of recommended design lengths were found in the 2011 *Green Book* and 1965 edition. Data that was used in both editions were collected in the 1930s. Thus, recent data and research are required to update the design guide.

Considering the safety issues on the deceleration lane and outdated design guides, this study is to determine minimum lengths of freeway deceleration lanes and help update design guides based on the current drivers' diverging behavior and vehicle braking mechanisms. Conventional studies heavily rely on field data collection (e.g., radar gun). They have been either time-consuming or labor-intensive tasks, which may also result in erroneous conclusions due to intrinsic biases. To fill this gap, using the SHRP 2 NDS data is a new approach to investigate the driver behavior during daily trips through unobtrusive data gathering equipment and without experimental control (*9*). Data including speed, acceleration–deceleration rate, brake status, traffic condition, pavement markings, etc., can provide insight into the interrelationship among drivers, vehicles, and deceleration lane designs.

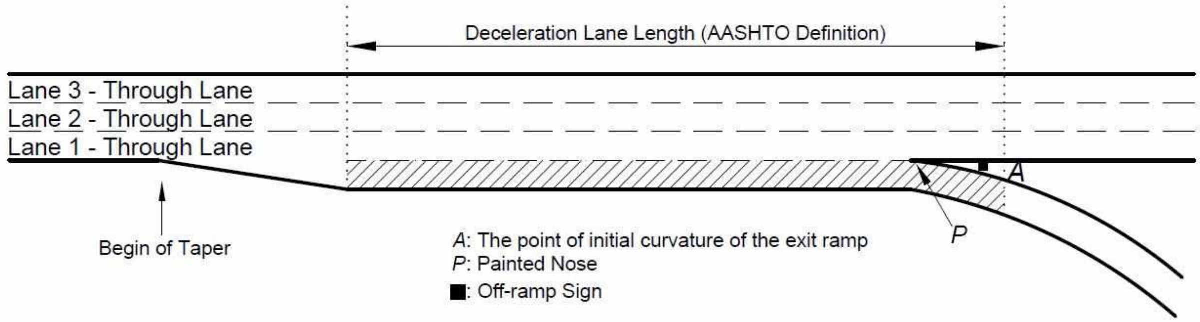
The detailed objectives of this work are (1) to explore speed distributions on different lengths of deceleration lanes and off-ramps; (2) to investigate drivers' braking behaviors on deceleration lanes and off-ramps; and (3) to determine minimum lengths of parallel and tapered deceleration lane designs. The rest of the paper summarizes the data collected, the methodology, analytical details, and results, followed by conclusions that place the results in the context of engineering practice.

LITERATURE REVIEW

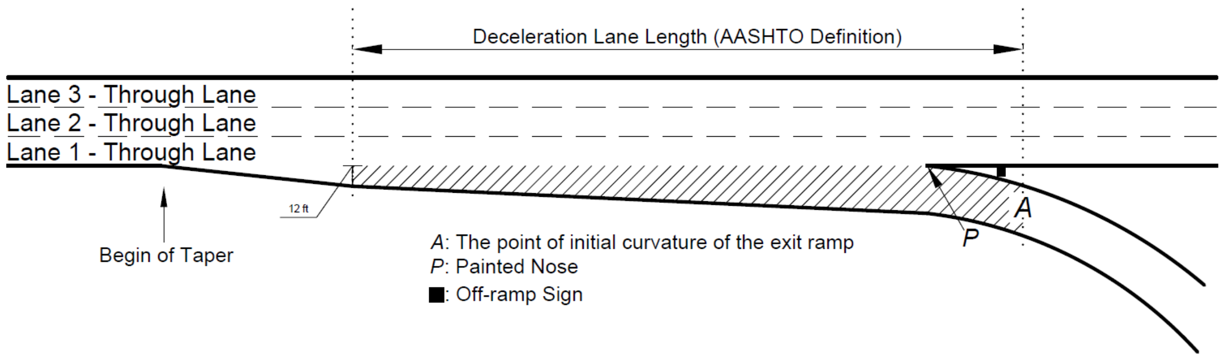
Previous studies on deceleration lane design mainly focused on design policy, operational and safety effects, and driver behavior.

AASHTO Design Policy

According to the *Green Book* definition, a deceleration lane is a speed-change lane that intends to minimize conflicts between vehicles on the mainline and diverging area (*8*). There are two general forms of declaration lane (as shown in Figure 1): the parallel-design which has an added lane for changing speed and the tapered design which provides a direct exit at a flat angle (*8*). The length of a deceleration lane is measured from the point of a 12-ft right-tapered wedge or a 12-ft added parallel lane to the point of the exit ramp curvature beginning (*8*). In practice, it is hard to control and measure the beginning of the exit ramp alignment. Thus, this study measured the deceleration lane length from the same starting point defined by AASHTO to the point of the physical gore (after the painted nose).



(a)



(b)

FIGURE 1 Definition of deceleration lane length: (*a*) parallel-design deceleration lane and (*b*) tapered-design deceleration lane.

Equations 1 and 2 present the procedure of calculating the minimum deceleration lane length in the 1965 *Blue Book* (*10*). The length is primarily determined by the speed differential between the average speed on the mainline and the off-ramp.

$$L_{Decel} = 1.47V_h t_n - 0.5d_n(t_n)^2 + \frac{(1.47V_r)^2 - (1.47V_a)^2}{2d_{wb}} \qquad (1)$$

$$V_a = \frac{1.47V_h + d_n t_n}{1.47} \qquad (2)$$

where

L_{Decel} = deceleration lane length, ft;
V_h = highway speed, mph;
V_a = speed after t_n s of deceleration without brakes, mph;
V_r = entering speed for controlling exit ramp curve, mph;
t_n = deceleration time without brakes (assumed to be 3 s);
d_n = deceleration rate without brakes, ft/s^2;
d_{wb} = deceleration rate with brakes, ft/s^2.

Two assumptions were made during calculation (*11*) that

1. Most vehicles travel at the average speed instead of the design speed when traffic volumes are low (e.g., on a freeway with a 70-mph design speed; the assumption is that a driver will enter the auxiliary lane at 58 mph); and
2. A 3-s deceleration before braking is applied on the taper section, which results in two deceleration rates (d_n and d_{wb}).

The only difference between the 2004 *Green Book* and the 1965 *Blue Book*, regarding minimum lengths of freeway deceleration lanes, is that the taper length is included in the deceleration lane length in the 1965 *Blue Book* while being listed separately in the 2004 *Green Book*. Comparing two recent versions of the *Green Book*, parameters in Equations 1 and 2 turn out to be the same in both the 2011 and 2004 editions.

Operational and Safety Impact of Freeway Deceleration Lane

A number of studies utilized regression models to optimize the deceleration lane length and the configuration of off-ramps (*3–7*). However, the results were inconsistent due to the quality of the data. Some studies suggested that increasing the deceleration lane length would reduce crash rates while some others implied it would increase. Twomey et al. identified that deceleration lane of 900 ft or more can reduce traffic friction on through lanes, therefore, reducing crash rates (*12*). Wang et al. also addressed that a longer deceleration lane is more likely to reduce injury severity (*13*). On the contrary, crash predictive models developed by Chen et al. revealed that the crash frequency increases with the lengthening of the deceleration lane (*14*). A recent study indicated the optimal deceleration lane length between 500 and 700 ft significantly reduces the crash severity (*15*). Considering different types of off-ramps, parallel-designed sites with a one-lane exit had the lowest crash frequency and crash rate (*16*).

Diverge Speed and Maneuver

Generally, conventional studies employed field observation to monitor driving behaviors of diverging drivers on deceleration lanes and off-ramps. Garcia and Romero concluded that the drivers start to decelerate before exiting the mainline with a speed reduction of 10.5 mph even on a long deceleration lane (*17*). Based on an NCHRP project, vehicles that diverge early on the deceleration lane are likely to diverge at speeds that are close to freeway speeds while late-diverging vehicles have lower diverging speeds (*3*). Calvi et al. did two studies on diverging performance on deceleration lanes with a driving simulator (*18–19*). This study revealed that lower traffic volumes result in higher existing speeds, higher average and maximum deceleration rates, and earlier braking on the mainline. Findings from the follow-up study indicated that the taper type of deceleration lane contributes to the significantly higher speed difference. Furthermore, lower traffic volumes lead to higher deceleration rates.

The literature review illustrated that none of the previous studies used SHRP 2 NDS data to study speed and deceleration rates on freeway deceleration lane and off-ramp. As SHRP 2 NDS data consists of various information such as the driver’s interaction with the vehicle, the traffic environment, and roadway characteristics, it provides an opportunity to conduct a first-ever study on determining deceleration lane lengths based on distributions of naturalistic driving speeds and deceleration rates on freeway diverge areas.

METHODOLOGY

Data Description

SHRP 2 conducted a naturalistic driving study to address the role of driver performance and behavior in traffic safety (*20*). It involves understanding how the driver interacts with and adapts to the vehicle, environmental condition, roadway geometric characteristics, and traffic control devices (*20*). In this study, all data used was acquired from the SHRP 2 NDS dataset, which aims at improving safety and reliability for motorists and providing answers to key traffic- and safety-related questions (*21*).

This subset of the SHRP 2 NDS dataset includes a video clip of the forward-view and rear-view videos of traffic conditions on the roadway. The time-series report for each video contains speeds (km/h), acceleration–deceleration rates (*g*), the brake pedal status (0 or 1), etc. The report also involves driver assessment (driving crash history, physical assessment, and risk perception scale) and vehicle information (model year, brand, and classification). The time-series report of each traversal provides the speed data at 0.1-s intervals when the vehicle is traveling through the freeway diverge area. By reviewing the forward-view videos, which were taken from cameras mounted inside the vehicles to provide drivers' views, the traffic condition (free flow or non-free flow), environmental condition (lighting and weather), roadway geometric features (freeway diverge area layout), and the presence of traffic control devices (traffic sign and pavement marking) can be identified to assist with understanding driver behavior negotiating the freeway deceleration lane and off-ramp. The video of each trip was reviewed to ensure that it is a complete traversal beginning before the deceleration lane and ending after the off-ramp terminal. At the bottom left corner of the forward-view video, the continuous timestamp is offered to refer to the corresponding time-series report, where details of the vehicle maneuver were provided at 0.1-s intervals. These details include the vehicle speed from the speedometer, the longitudinal acceleration rate, and the brake pedal status.

The original dataset contained 971 trips from 10 locations, but some reports were incomplete. Further, some trips began after the off-ramp or ended before the terminal were filtered. Finally, 709 complete trips driven by 272 unique drivers were used for analysis in this study as presented in Table 1.

Site Description

Ten study locations, five one-lane exit with parallel-design deceleration lane locations (Locations 1P through 5P), and five one-lane exit with tapered-design deceleration lane locations (Locations 1T through 5T), are located on I-75 in Florida as shown in Figure 2. The 2011 *Green Book* design criterion for minimum deceleration lane lengths was compared with study locations to determine if they met the minimum requirement. Table 1 lists site information, the type of interchange design, the type of deceleration lane design, the divergence angle, the length of every section (taper, deceleration lane, and off-ramp) in the diverge area, the minimum length determined in the *Green Book*, the number of trips, and the number of unique drivers.

Eight of 10 locations are diamond interchanges with relatively straight off-ramps. Two others are partial cloverleaf interchanges (Locations 3P and 5P) where the straight off-ramps were selected for reducing the impact on the speed by horizontal curvature (as presented in Figure 2*e* and 2*i*). The divergence angle ranges from 2 degrees to 7 degrees for all locations. For parallel-design locations, taper lengths are from 165 to 270 ft. Taper lengths of tapered-design locations were found to be shorter (130 to 205 ft). Deceleration lane lengths are in the range of 645 to 990 ft for parallel-design locations, which are longer than lengths in tapered-design locations (320 to 445 ft). For both types, off-ramp lengths vary from 940 to 1,725 ft. Most of the locations' off-ramp terminals are signalized intersections while three of them are under yield control (Locations 1T, 3P, and 5T). The speed limit on the freeway mainline is 70 mph for all locations. Off-ramp advisory speeds of 35 mph were posted at four locations (Locations 1P, 2P, 3P, and 4T). It should be noted that limited information is available on establishing advisory speeds for off-ramps that do not have horizontal curvatures (*22*). After comparing the actual deceleration lane length of each location with *Green Book* requirements, lengths of deceleration lane from parallel-design locations are longer than the minimum length, while tapered-design locations are shorter.

TABLE 1 Site Description, Minimum Deceleration Lane Length, and Number of Trips and Drivers

Site Locations	Interchange Design	Divergence Angle	Taper Length (ft)	Deceleration Lane Length (ft)	Off-Ramp Length (ft)	Green Book Minimum Deceleration Length (ft)	Design Status Compared to Green Book	Number of Trips	Number of Drivers
Location 1P: I-75/SW Archer Rd	Diamond	4°	190	645	1475	490	**GREATER**	92	45
Location 1T: I-75/Clark Rd	Diamond	4°	200	425	1595	615	**LESS**	102	30
Location 2P: I-75/SW County Highway 484	Diamond	5°	195	735	990	490	**GREATER**	23	23
Location 2T: I-75/US 98	Diamond	7°	150	320	940	615	**LESS**	59	48
Location 3P: I-75/FL 326	Parclo	5°	165	775	1030	490	**GREATER**	46	32
Location 3T: I-75/US 98	Diamond	4°	205	420	1170	615	**LESS**	202	56
Location 4P: I-75/CR 768	Diamond	3°	200	700	1180	615	**GREATER**	28	6
Location 4T: I-75/SW College Rd	Diamond	4°	150	445	1340	490	**LESS**	16	13
Location 5P: I-75/CR 765	Parclo	2°	270	990	1690	615	**GREATER**	120	9
Location 5T: I-75/CR 769	Diamond	4°	130	365	1725	615	**LESS**	21	10

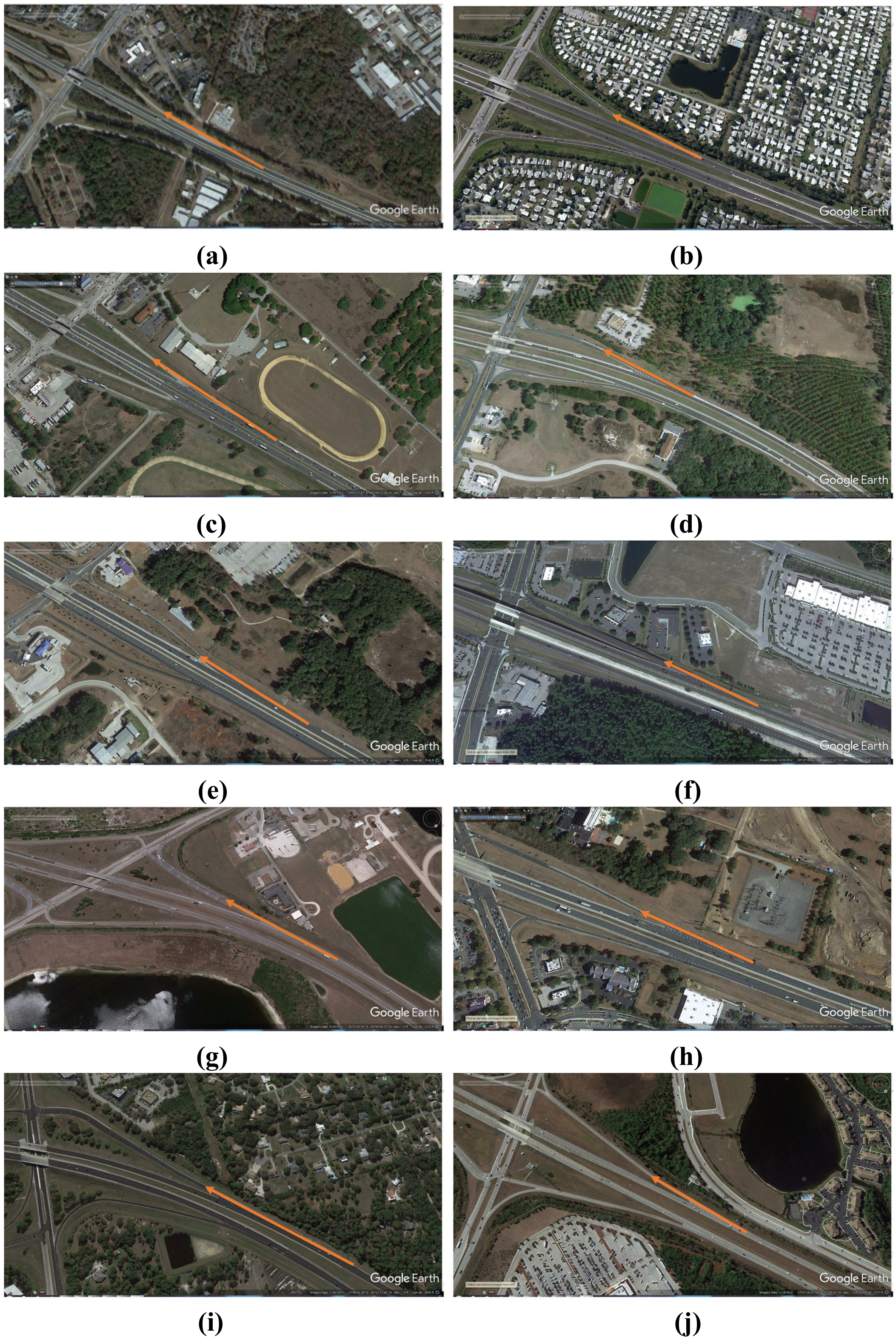


FIGURE 2 Aerial photos of study locations: (*a*) Location 1P; (*b*) Location 1T; (*c*) Location 2P; (*d*) Location 2T; (*e*) Location 3P; (*f*) Location 3T; (*g*) Location 4P; (*h*) Location 4T; (*i*) Location 5P; and (*j*) Location 5T.

Data Analysis

Data analysis was performed from three aspects: (1) speed distributions on deceleration lanes and off-ramps of 10 locations; (2) driver behaviors in terms of the brake pedal usage and the deceleration rate compared with the *Green Book* assumption, and (3) determinations of minimum deceleration lane length based on naturalistic speeds and deceleration rates.

Reviewing videos was the first step in the data analysis necessitated. Observers recorded the video frame number (the timestamp) at critical points in the video. Taper start point, deceleration lane start point, deceleration lane endpoint (physical gore), and off-ramp endpoint (stop bar at the terminal) on each location were considered critical points for this analysis. The frame number allowed for correlation to the data in the time-series report (speed, acceleration–deceleration rate, brake pedal status, etc.). Thus, the timestamp of each critical point in the time-series table was tagged to help determine the speed distribution (i.e., maximum, 85th percentile, mean, and minimum speed; and their standard deviations) of every section on the deceleration lane and off-ramp. In Table 1, the lengths of different sections (taper, deceleration lane, and off-ramp) at each study location are presented.

Polynomial Regression

The speed distributions on the taper, the deceleration lane, and the off-ramp were calculated by applying polynomial regression models, which were estimated using the SHRP 2 NDS trips and speed data at 0.1-s intervals. The polynomial regression method minimizes the sum-of-squared residuals between measured and simulated quantities. The least squares method is used to estimate unknown parameters (*23*):

$$v = \beta_0 + \beta_1 L + \beta_2 L^2 + \beta_3 L^3 + \cdots + \beta_n L^n + \varepsilon \qquad (3)$$

where

L = the distance from the starting point of the taper along the deceleration lane and off-ramp (ft),
v = vehicle speed (mph),
β_n = estimated parameters,
ε = the error of the specification.

Four best-fitted models using SHRP 2 NDS speed data, maximum speed, 85th percentile speed, mean speed, and minimum speed distributions, were developed for each study location by using the statistical computing software R. R software provides a variety of statistical (linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering, etc.) and graphical techniques (*24*). The residual standard error was used as a measure of goodness-of-fit to evaluate and determine the quality of the fitted model.

Critical Speed Changepoint Detection

The changepoint detection estimates the point at which the statistical properties of a sequence of observations change (*25*). It has been widely used in various application areas, including climatology, bioinformatic applications, finance, oceanography, and medical imaging (*26-30*). By applying this method, speed time series data is defined as: $V_{1:n} = (V_1, V_2, \ldots V_n)$. A changepoint may occur within this set when there exists a time, $\tau \in \{1, \ldots, n-1\}$, where the statistical properties of $\{V_1, \ldots, V_\tau\}$ and $\{V_{\tau=1}, \ldots, V_n\}$ are different in some way (*24*). The aim of the analysis is to estimate the location of the changepoint efficiently and accurately by minimizing the following equation:

$$\sum_{i=1}^{m+1}\left[C\left(V_{(\tau_{i\_1}+1):\tau_i}\right)\right]+\beta f(m) \tag{4}$$

Where C is a cost function for a segment, e.g., negative log likelihood; m is the number of changepoints; and $\beta f(m)$is a penalty to guard against over fitting (*25*). This method is used to identify the driver speed change position on the deceleration lane and off-ramp, so that the location where drivers take action to decelerate can be determined.

Driver behavior was identified by brake pedal usage and deceleration rate. Brake pedal status was coded as 0 or 1 in the time-series reports. The value of 0 indicates that the driver did not apply the brake at the certain 0.1 s, while 1 means he or she did. To find where drivers applied brakes most often, brake pedal usage was evaluated by the percentage of the drivers applying brakes in certain sections.

The time-series reports provided deceleration rates which can be used to calculate the mean and 85th percentile deceleration rates on the taper, deceleration lane, and off-ramp sections. The rates can also be determined by converting the distance-based speed model to the time-based one. The deceleration rate distribution was executed to find out the section where drivers mostly reduce their speeds so that the effective decelerating section could be found. When calculating deceleration rates, the *Green Book* recommended two methods (*8*): one is based on a two-step process of deceleration, coasting (assumed 3 s) and braking; the other is based on a constant decelerating behavior on the deceleration lane which was validated by El-Basha et al. (*31*). In this study, the deceleration rate was compared with the *Green Book* rates based on a constant decelerating behavior over the entire deceleration process. The minimum deceleration lane length can then be estimated based on the deceleration rate from SHRP 2 NDS data and polynomial regression models by using Equation 5.

$$D=\frac{v_i^2-v_f^2}{2d} \tag{5}$$

where

D = deceleration distance (ft),
v_i = initial speed (ft/s),
v_f = final speed (ft/s),
d = deceleration rate (ft/s^2).

RESULTS

The results were categorized into three parts: (1) polynomial regression of speed distribution on the deceleration lanes and off-ramps; (2) driver behavior in terms of brake pedal usage, deceleration rates, and a comparison with the *Green Book* assumptions; and (3) minimum lengths of deceleration lanes based on naturalistic driving speed and deceleration rates.

Speed Distribution

Examples of fitted four speed distribution profiles by polynomial regression are presented in Figure 3, which shows speed distribution on the deceleration lane and the off-ramp in Locations 1P and 1T. The x-axis is the length (ft) and the y-axis is the speed (mph). The light blue lines are the speed data from SHRP 2 NDS time-series reports, one trace coming from one traversal. The other four lines in the figure are fitted polynomial regression models, including the maximum speed distribution (Maroon), the 85th percentile speed distribution (Red), the mean speed distribution (Orange), and the minimum speed distribution (Pink). The critical points are also marked with estimated speeds.

For example, the 85th percentile speed distribution in Location 1P (Figure 3*a*), the speed at the beginning of the taper was 74.02 mph. It was reduced to 72.67 mph when the vehicle entered the deceleration lane. The speed was further reduced to 63.39 mph after driving through the 645-ft deceleration lane, resulting in a 9.28-mph speed reduction on the deceleration lane. However, it was found that a great speed reduction occurred on the off-ramp, especially close to the off-ramp terminal where a signalized intersection exists. Finally, the 85th percentile speed was reduced to 23.88 mph. As for Location 1T as shown in Figure 3*b*, the speed distribution was slightly different from Location 1P. Before the taper in Location 1T, an extra 210-ft segment before the taper section was counted to make the length equal to the total length of taper and deceleration lane in Location 1P. It was found that, in Location 1T, drivers decelerated on the mainline before entering the taper section. The 85th percentile speed at the taper start point was 69.64 mph, which is nearly 5 mph lower than that in Location 1P. When entering the deceleration lane, the speed was 68 mph. The 425-ft deceleration lane only helps reduce 3 mph considering the speed at the off-ramp start point being 64.49 mph. Similar to Location 1P, a significant speed reduction of 33.58 mph was observed on the off-ramp.

Polynomial regression models of 85th percentile speed and mean speed distributions for Locations 1P and 1T are summarized as follows:

For Location 1P:

$$v_{1P-85^{th}} = -9.767 \times 10^{-12} {L_{1P}}^4 + 3.38 \times 10^{-8} {L_{1P}}^3 - 3.462 \times 10^{-5} {L_{1P}}^2 - 1.703 \times 10^{-3} L_{1P} + 74.02 \quad (6)$$

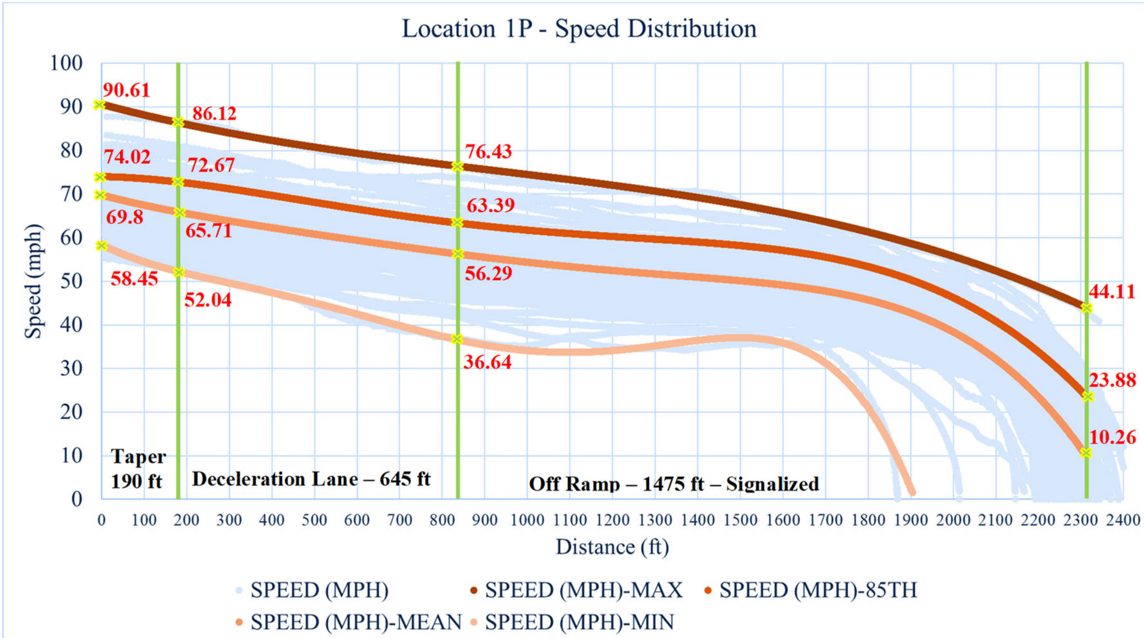
$$v_{1P-Mean} = -6.646 \times 10^{-15} {L_{1P}}^5 + 2.697 \times 10^{-11} {L_{1P}}^4 - 3.978 \times 10^{-8} {L_{1P}}^3 + 2.997 \times 10^{-5} {L_{1P}}^2 - 2.594 \times 10^{-2} L_{1P} + 69.80 \quad (7)$$

For Location 1T:

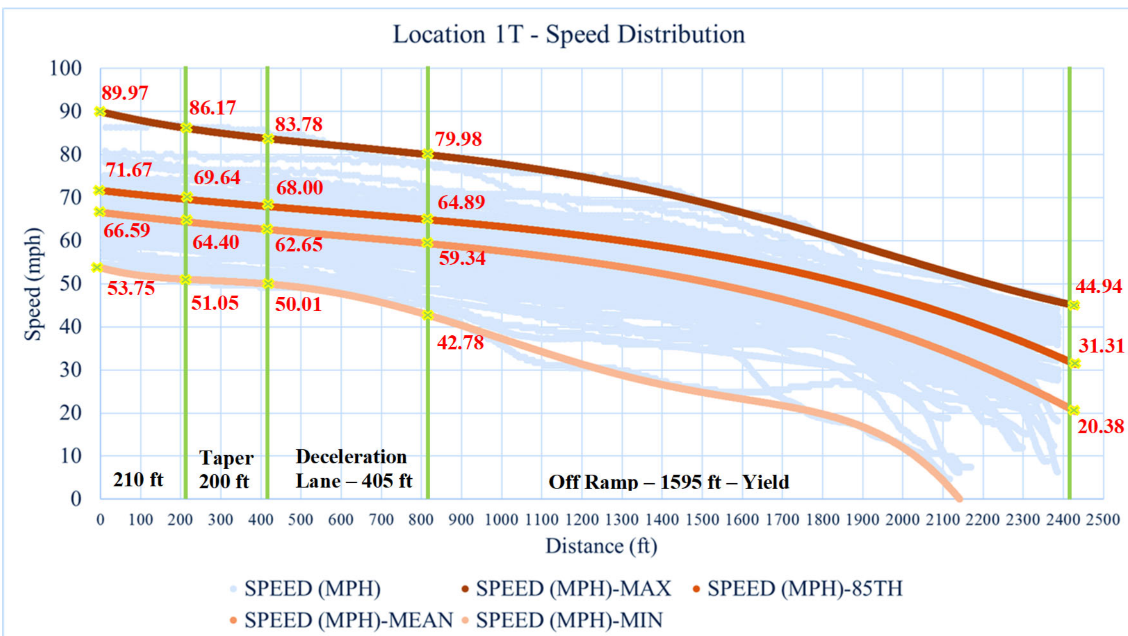
$$v_{1T-85^{th}} = -3.32 \times 10^{-9} {L_{1T}}^3 + 5.64 \times 10^{-6} {L_{1T}}^2 - 1.071 \times 10^{-2} L_{1T} + 71.67 \quad (8)$$

$$v_{1T-Mean} = -3.968 \times 10^{-9} {L_{1T}}^3 + 6.61 \times 10^{-6} {L_{1T}}^2 - 1.165 \times 10^{-2} L_{1T} + 66.59 \quad (9)$$

All study locations performed four regressions. It should be noted that all estimated parameters are statistically significant at the 99% confidence level. *L* is defined as the distance from the starting point of the taper to any points on the taper, deceleration lane or off-ramp; *v* is the speed downstream from the taper start point.



(a)



(b)

FIGURE 3 Speed distribution examples: (*a*) parallel-design, Location 1P and (*b*) tapered design, Location 1T.

From the models developed, only 85th percentile speeds and mean speeds at the taper start point, deceleration lane start point, deceleration lane endpoint, and off-ramp endpoint were summarized in Table 2. The speeds at parallel-design locations were 1 to 2 mph higher than that at tapered-design locations in taper and deceleration lane sections. However, the speeds upon vehicles entering the off-ramp for Locations 1T to 5T were typically 3 mph higher than parallel-design locations. When an advisory speed was posted on the off-ramp, the operating speeds were not significantly affected by the advisory speed which is 35 mph for Locations 1P, 2P, 3P, and 4T. The mean speed for a 35-mph advisory speed location was approximately 55 mph, and the approximate speed was 58 mph without the advisory speed sign.

TABLE 2 A Comparison of Speed Distribution and Speed Reduction Percentage on the Deceleration Lane and Off-Ramp: (*a* Parallel-Design Locations and (*b* Tapered-Design Locations

Site		Speed (mph)				Speed Reduction Percentage*		
		Taper Start	Deceleration Lane Start	Deceleration Lane End	Off-Ramp End	Taper	Deceleration Lane	Off-Ramp
Location 1P	85th	74.02	72.67	63.39	23.88	2.69%	18.51%	78.80%
645 ft	Mean	69.80	65.71	56.29	10.26	6.87%	15.82%	77.31%
Location 2P	85th	72.53	70.14	60.04	31.48	5.82%	24.60%	69.57%
735 ft	Mean	64.59	65.70	53.14	17.71	-2.37%	26.79%	75.58%
Location 3P	85th	68.09	65.12	55.92	19.31	6.09%	18.86%	75.05%
775 ft	Mean	61.97	58.84	47.13	11.50	6.20%	23.20%	70.60%
Location 4P	85th	69.47	70.76	63.29	19.14	-2.56%	14.84%	87.72%
700 ft	Mean	63.03	64.57	55.95	13.95	-3.14%	17.56%	85.57%
Location 5P	85th	75.07	73.87	69.81	29.00	2.60%	8.81%	88.58%
990 ft	Mean	69.26	68.36	62.18	22.50	1.92%	13.22%	84.86%
*Note: Speed reduction percentage=speed reduction/total speed reduction from deceleration lane start point to the off-ramp end point								

(a)

Site		Speed (mph)				Speed Reduction Percentage*		
		Taper Start	Deceleration Lane Start	Deceleration Lane End	Off-Ramp End	Taper	Deceleration Lane	Off-Ramp
Location 1T	85th	69.64	68.00	64.89	31.31	4.28%	8.11%	87.61%
425 ft	Mean	64.40	62.65	59.34	20.38	3.98%	7.52%	88.51%
Location 2T	85th	72.55	70.62	65.46	20.81	3.73%	9.97%	86.30%
320 ft	Mean	64.37	62.52	57.06	15.82	3.81%	11.25%	84.94%
Location 3T	85th	67.14	65.47	61.58	28.29	4.30%	10.01%	85.69%
420 ft	Mean	61.30	59.45	54.59	19.62	4.44%	11.66%	83.90%
Location 4T	85th	68.19	68.37	64.85	7.47	-0.30%	5.80%	94.50%
445 ft	Mean	64.37	63.63	58.75	0.00	1.15%	7.58%	91.27%
Location 5T	85th	73.20	71.98	68.26	37.05	3.37%	10.29%	86.33%
365 ft	Mean	66.65	65.82	62.61	28.18	2.16%	8.34%	89.50%
*Note: Speed reduction percentage=speed reduction/total speed reduction from deceleration lane start point to the off-ramp end point								

(b)

The speed reduction percentage is the percentage of speed reduced at the taper, deceleration lane, and off-ramp section. As shown in Table 2, the high percentage of the speed reduction occurred on off-ramps, which revealed that speed reduction was more significant on off-ramps than deceleration lanes. However, the *NCHRP Report 730* made a different indication (*1*). It should be mentioned that the *NCHRP Report 730* did not include the speed and deceleration along the entire deceleration lane and off-ramp but only several points (*1*). The authors indicated that drivers were completing much of the required deceleration in the freeway lane upstream of the beginning of the taper when they found field-measured deceleration rates were less than the *Green Book* assumptions (*1*). This indication is very different from our results. For example, our results showed that Location 1P only had a 16% speed reduction in mean speed distribution on deceleration lanes and approximately 77% on off-ramps. When comparing parallel-design locations with tapered-design locations, it was found that tapered-design locations have higher speed reduction percentages on off-ramps in the range of 84% to 95%, while parallel-design locations have 70% to 88% speed reduction. The speed- reduction percentage on the deceleration lane and off-ramp indicated that drivers decelerated more on an off-ramp than on the deceleration lane. Also, some negative speed reduction percentages were observed, which implied that drivers may have accelerated on the taper section at three out of five parallel-design locations.

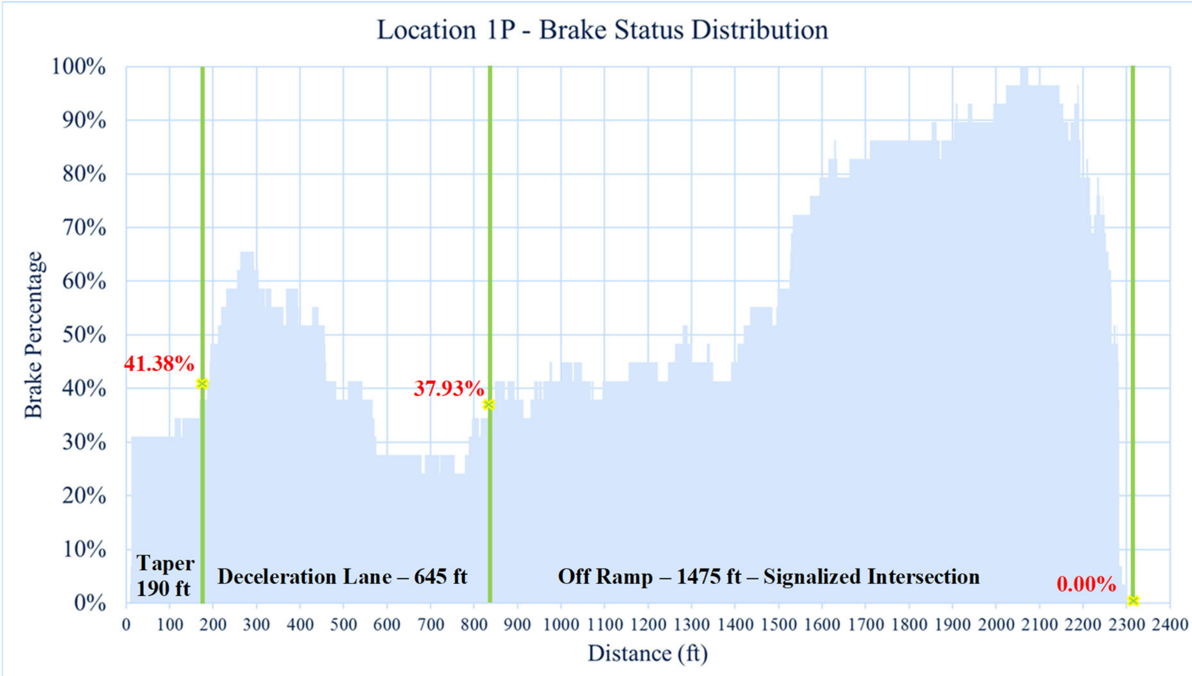
Moreover, longer deceleration lanes may not lead to higher speed reduction percentages. For both types of locations, the study sites with the longest deceleration lanes have the lowest speed reduction percentages. Location 5P with a 990-ft deceleration lane only had 8.81% speed reduction on it. Location 4T with a 445-ft deceleration lane only had 5.80% speed reduction on it. However, shorter deceleration lanes do not result in higher speed reduction percentages either. The locations with highest speed reduction percentages are median lengths – Location 2P (735-ft deceleration lane) and Location 3T (420-ft deceleration lane).

Driver Braking Behavior

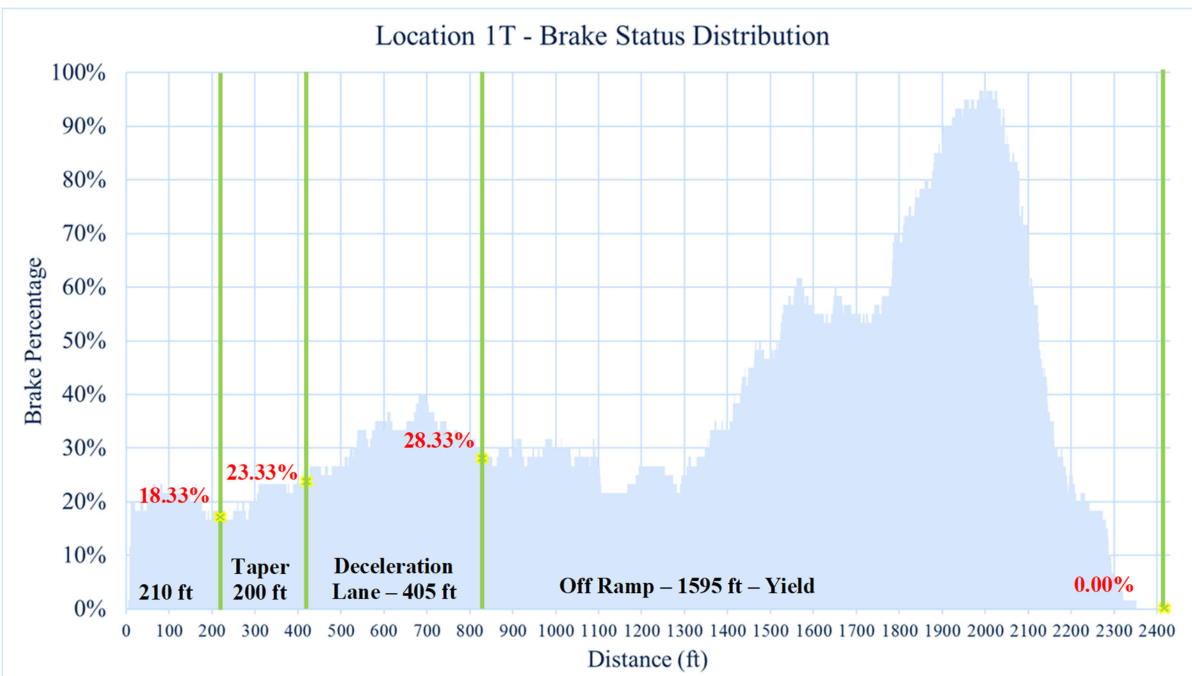
Driver braking behavior was interpreted by the brake pedal usage and deceleration rate distribution on the deceleration lane and off-ramp.

Brake Pedal Usage

The brake status (0 or 1) indicates whether the driver was applying the brake at the certain 0.1 seconds. The brake status distribution was performed based on the percentage of drivers who applied brakes at certain sections on the deceleration lane and off-ramp. Figure 4 shows two examples of brake status distribution. At Location 1P, only 30% of drivers applied brakes when entering the taper section. An increase to 60% of drivers applied brakes when entering the deceleration lane while a decrease back to 30% happened after traversing the first half of the deceleration lane. More braking behavior was observed after the vehicle approached the off-ramp terminals. Similar results from Location 1T were presented in Figure 4*b*. From 10 study locations, the average brake percentages for taper, deceleration lane, and off-ramp sections are 21.42%, 30.30%, and 63.67% in parallel-design locations, respectively, and 25.23%, 32.51%, and 57.69% in tapered-design locations, respectively.



(a)



(b)

FIGURE 4 Brake status distribution examples: (*a*) parallel-design, Location 1P and (*b*) tapered-design, Location 1T.

Deceleration Rate Distribution

To calculate the deceleration rates, the speed-distance-based model, for example, Equations 6 to 9, was first converted to the speed-time-based model as time can be calculated from the distance and speed. Then, the first derivative of this speed-time-based model was determined. This first derivative is the deceleration rate from speed regression. The mean and 85th percentile deceleration rates were summarized in Table 3. An extra step was taken to identify the critical speed changepoint on the off-ramp. As greater speed reductions and higher brake percentages were observed upstream from the off-ramp terminal, change point models were used to identify driver reaction point where most drivers decelerate very hard when approaching the ramp terminal. Two examples of critical speed change point analysis are presented in Figure 5. In Location 1P, drivers adjusted their speed 469-ft upstream of the off-ramp terminal (1,841 ft after the taper start point) from the 85th percentile speed distribution. For Location 1T as shown in Figure 5*b*, this number was increased to 764 ft (1,666 ft after the taper start point). The average reaction points for parallel-design locations are 540.4 ft in 85th percentile speed and 541.6 ft in mean speed. For tapered-design locations, the critical speed change points are 646.8 ft in 85th percentile speed and 652.2 ft in mean speed upstream from the ramp terminal.

TABLE 3 Deceleration Rates at Study Locations

Deceleration Rate (ft/s^2)		Taper	Deceleration Lane d_D	Off Ramp d_R		GB Decel Rate* (ft/s^2)
				Before Changepoint	After Changepoint	
Location 1P	85th	-1.63	-2.34	-2.12	-5.72	-5.41
645 ft	Mean	-3.61	-2.24	-1.88	-5.19	
Location 2P	85th	-2.47	-2.41	-2.32	-6.46	-5.41
735 ft	Mean	-0.35	-2.57	-2.55	-4.52	
Location 3P	85th	-2.87	-1.79	-2.76	-3.53	-5.41
775 ft	Mean	-2.67	-1.91	-2.20	-2.47	
Location 4P	85th	0.18	-1.93	-2.89	-5.09	-5.88
700 ft	Mean	0.17	-1.95	-2.20	-4.20	
Location 5P	85th	-0.98	-0.92	-2.15	-5.45	-5.88
990 ft	Mean	-0.52	-1.01	-1.77	-4.55	
Location 1T	85th	-1.28	-1.12	-2.06	-2.94	-5.88
425 ft	Mean	-1.26	-1.10	-2.12	-2.69	
Location 2T	85th	-2.08	-2.53	-3.77	-5.22	-5.88
320 ft	Mean	-1.78	-2.46	-3.35	-3.61	
Location 3T	85th	-1.23	-1.27	-2.28	-4.48	-5.88
420 ft	Mean	-1.37	-1.48	-1.90	-4.12	
Location 4T	85th	0.08	-1.90	-2.60	-7.03	-5.41
445 ft	Mean	-0.88	-1.63	-3.08	-5.40	
Location 5T	85th	-1.50	-1.55	-1.50	-3.24	-5.88
365 ft	Mean	-0.96	-1.36	-1.62	-2.87	
Parallel-	85th	-1.55	-1.88	-2.45	-5.25	Note: *GB Decel Rate is the deceleration rate recommended in the Green Book.
Design	Mean	-1.40	-1.94	-2.12	-4.19	
Tapered-	85th	-1.20	-1.67	-2.44	-4.58	
Design	Mean	-1.25	-1.61	-2.41	-3.74	

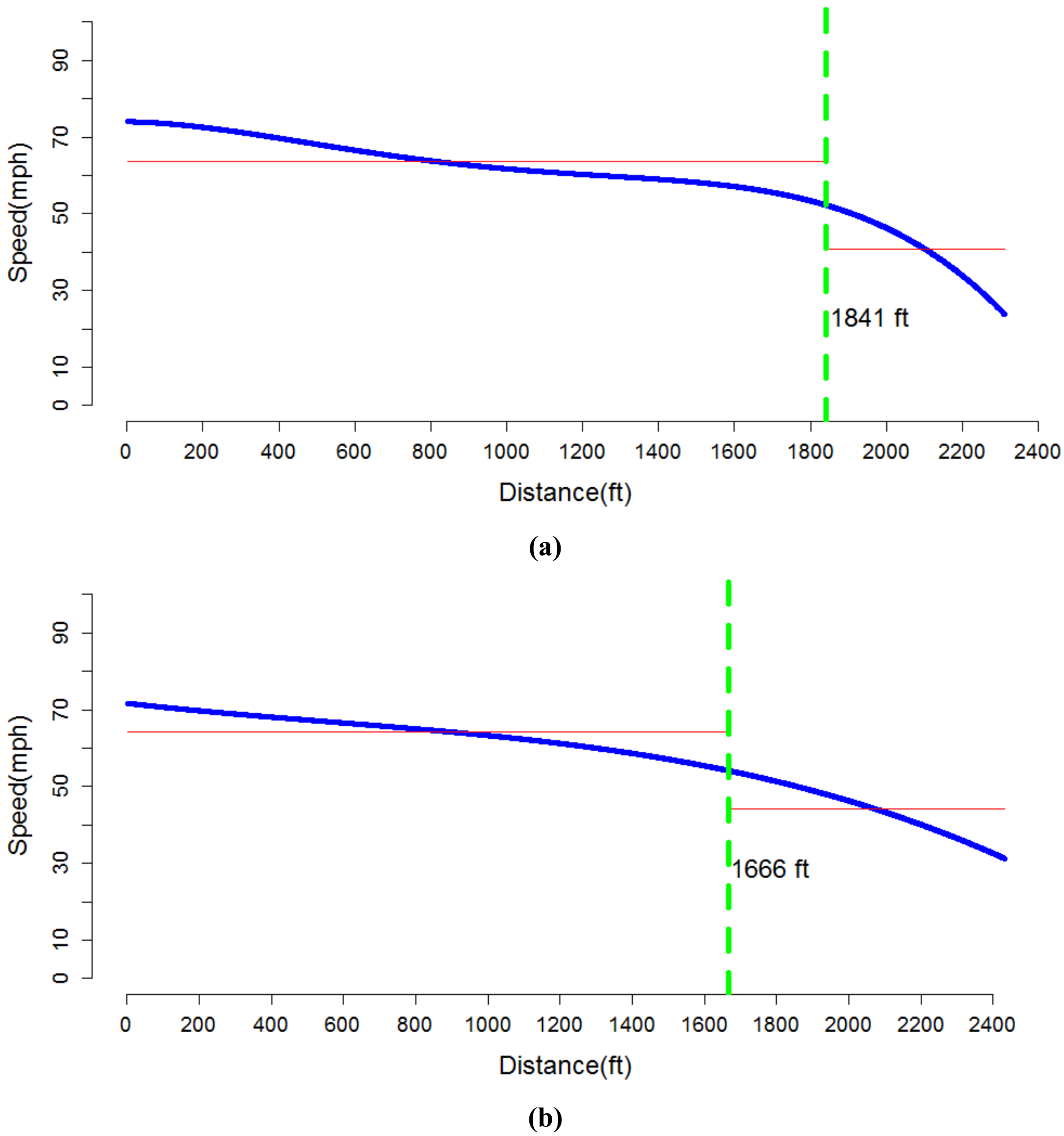
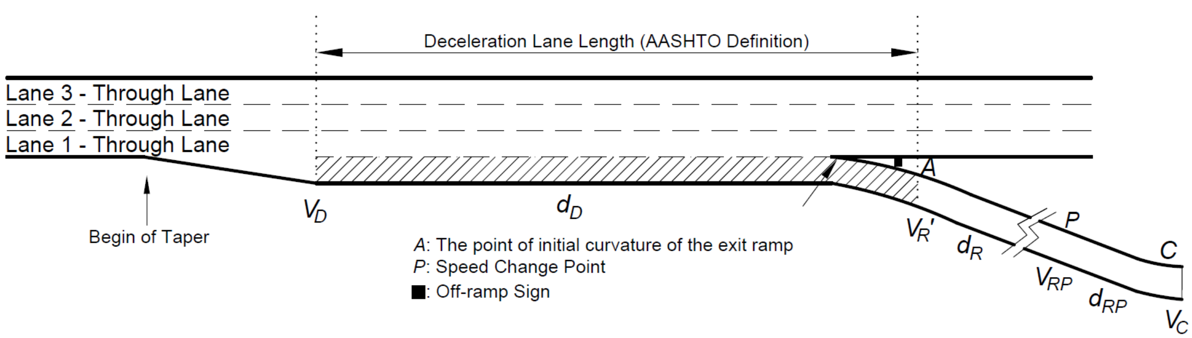


FIGURE 5 Critical speed changepoint examples: (*a*) parallel-design, Location 1P and (*b*) tapered-design, Location 1T.

The R statistical package of change point was utilized for critical speed change point detection based on binary segmentation algorithms. After the changepoints are detected, the deceleration rate before and after the changepoint on the off-ramps can also be obtained. The mean and 85th percentile deceleration rates were compared with the *Green Book* criterion which assumes a constant deceleration (*8*). The *Green Book* deceleration rates were derived from recommended minimum deceleration lane lengths as summarized in *NCHRP Report 730* (*1*). As shown in Table 3, most of the naturalistic driving deceleration rates were lower than the design deceleration rates in the *Green Book*. However, the deceleration rates after the change point on the off-ramp were relatively higher than other sections, and some of them were even greater than the design rates. For parallel-design deceleration lanes, the deceleration rates on the deceleration lane were slightly higher than that on the tapered-design locations. In *NCHRP Report 730*, however, the authors observed that parallel deceleration lanes had a substantially higher deceleration rate of more than twice than tapered-design ones especially on straight ramps (*1*). All deceleration rates on the deceleration lane were much smaller than the *Green Book* criterion. The mean deceleration rates on certain sections of parallel-design and tapered-design locations were summarized in the last four rows in Table 3. It can be found that the *Green Book* assumes that drivers are exiting the freeway with a constant deceleration rate, while the results of this study indicate that drivers' braking behavior on the taper section, deceleration lane section, and off-ramp section are different with different deceleration rates.

Determination of the Minimum Length of Deceleration Lane

Equations 10 to 12 were developed to estimate the minimum deceleration lane length. The general idea of determining the minimum length for deceleration lane is to calculate the deceleration distance needed to decelerate from mainline speeds to ramp terminal speeds and subtract the certain off-ramp length. In other words, the minimum deceleration lane length is equal to the deceleration distance deducted by the off-ramp length. The minimum deceleration length can be determined by plugging in the deceleration rates from the deceleration lanes (d_D) and off-ramps (d_R and d_{RP}) sections in Table 3, entering speed for the deceleration lane (V_D), and estimating entering speed for the exit ramp (V_R'), the change point on the off-ramp (V_{RP}), and the first controlling feature on off-ramp (V_C) from regression models. The controlling feature represents whether ramp curvature or the crossroad terminal is the design element that controls vehicle deceleration (*1*). On the relatively straight ramps at locations described in this study, the first controlling feature usually is the crossroad terminal (signalized intersection).



$$\begin{cases} L_{Decel} = L_Q,\, V_D \le V_R' \\ L_{Decel} = \dfrac{(1.47V_R')^2 - (1.47V_D)^2}{2d_D} + L_Q, V_D > V_R' \end{cases} \tag{10}$$

$$V_R' = \frac{\sqrt{(1.47V_{RP})^2 - 2d_R L_R}}{1.47} \tag{11}$$

$$V_{RP} = \frac{\sqrt{(1.47V_C)^2 - 2d_{RP} L_{RP}}}{1.47} \tag{12}$$

where

L_{Decel} = Deceleration lane length, ft;
L_Q = Queue length at the off-ramp terminal, ft;
L_R = Length from deceleration lane endpoint to the critical speed change point upstream from the first controlling feature on the off-ramp, ft;
L_{RP} = Length from the critical speed change point to the off-ramp terminal, ft;
V_C = Speed at the first controlling feature on the off-ramp, mph;
V_D = Entering speed for deceleration lane, mph;
V_R' = Estimated entering speed for the off-ramp, assuming drivers decelerate on L_R with a constant deceleration rate on exit ramps (d_R), mph;
V_{RP} = Speed at the change point on the off-ramp, mph;
d_D = Deceleration rate on deceleration lane, ft/s^2;
d_R = Deceleration rate on exit ramp, ft/s^2; and
d_{RP} = Deceleration rate after the critical speed change point on the off-ramp, mi/h.

To determine the deceleration lane length, the key parameters are summarized in Table 4. For example, at parallel-design locations, the speed at stop bar of the off-ramp terminal (V_C) should be 0 mph and the deceleration rate (d_{RP}) is estimated to be –5.25 ft/s^2 on the off-ramp after the changepoint. The distance between the stop bar and the changepoint (L_{RP}) is 540 ft as mentioned previously. By applying Equation 12, the speed at the changepoint (V_{RP}) is 51.22 mph. When the total length of the off-ramp is 1,550 ft ($L_R = 1550 - 540 = 1010$ ft), drivers would be able to comfortably reduce all the required speed on the off-ramp ($V_R' = 70\text{mph} = V_D$). For tapered-design locations, the final speed should also be 0 mph ($V_C = 0$ mph) and the deceleration rate is –4.58 ft/s^2 after the change point ($d_{RP} = -4.58$ ft/s^2). Following the same steps, it can be determined that no deceleration lane will be required for decelerating purpose with a 1,540 ft off-ramp. The proposed minimum deceleration lane lengths of study locations are presented in Table 5. As a result, Locations 1T, 5P, and 5T do not require a deceleration lane serving decelerating functions.

TABLE 4 Summary of Key Parameters to Determine the Deceleration Lane Length

Key Parameters		Parallel-Design		Tapered-Design	
		Minimum (85th)	Mean	Minimum (85th)	Mean
Deceleration Lane (ft/s^2) d_D		-1.88	-1.94	-1.67	-1.61
Off Ramp	Before Changepoint (ft/s2) d_R	-2.45	-2.12	-2.44	-2.41
	After Changepoint (ft/s2) d_{RP}	-5.25	-4.19	-4.58	-3.74
Speed Entering Dec.Lane (mph) V_D		70.00	65.00	69.00	63.00
Speed at the Changepoint on Off-Ramp (mph) V_{RP}		51.22	45.74	52.49	47.43
Speed at the 1st Controlling Feature (mph) V_C		0.00	0.00	0.00	0.00
Length from Changepoint to Off-Ramp terminal (ft) L_{RP}		540		650	

TABLE 5 Comparison of Proposed Deceleration Lane Length and Design Length

Site Locations	Proposed Minimum Length (ft) (85th) L_{Decel}	Actual Deceleration Lane Length (ft)	Green Book Minimum Deceleration Length (ft)	Off-Ramp Length (ft) L_R+L_{RP}
Location 1P: I-75/SW Archer Rd	75	645	490	1475
Location 1T: I-75/Clark Rd	NA[1]	425	615	1595
Location 2P: I-75/SW County Highway 484	560	735	490	990
Location 2T: I-75/US 98	600	320	615	940
Location 3P: I-75/FL 326	520	775	490	1030
Location 3T: I-75/US 98	370	420	615	1170
Location 4P: I-75/CR 768	370	700	615	1180
Location 4T: I-75/SW College Rd	200	445	490	1340
Location 5P: I-75/CR 765	NA[1]	990	615	1690
Location 5T: I-75/CR 769	NA[1]	365	615	1725
Note: [1]NA indicates that the deceleration lane is not required for decelerating purpose.				

CONCLUSIONS

This study applied SHRP 2 NDS data to explore freeway deceleration lane and off-ramp designs based on naturalistic driving speeds and deceleration rates. Some key findings that were concluded are as follows:

(1) The operating speeds were much higher than the *Green Book* assumptions. The *Green Book* indicates that on a freeway with a 70-mph design speed, drivers will enter the deceleration lane at 58 mph. In the five parallel-design locations, the speed distribution, however, showed that the speed was 65 mph on average when vehicles entered the deceleration lane. The *Green Book* also assumed that the speed reached the end of deceleration lane with a ramp of 35 mph design speed should be 30 mph, which instead was 55 mph on average based on this study.

(2) Drivers were not effectively using the deceleration lane regarding the speed reduction. From speed distribution results, for parallel-design locations, the speed reduction on the deceleration lane is approximately 15% to 25%. The percentage of the speed reduced on the off-ramp is 75% to 85% which indicates that the speed reduced much more after vehicles approached the off-ramp terminal. For tapered-design locations, the speeds reduced on the

deceleration lane were even lower, 10% speed reduction on deceleration lanes and 85% to 90% on off-ramps.

(3) The brake status distribution further emphasized that the effective deceleration segment is on the off-ramp rather than the deceleration lane. The average brake pedal usage on off-ramps is higher than that on deceleration lanes on average (26.01% for taper section, 36.83% for the deceleration lane section, and 53.72% for the off-ramp section).

(4) The results from critical speed change point models also implied that drivers' reaction points of sharp deceleration were on the off-ramp upstream the ramp terminal. The average distances of reaction points from the terminal are 540 ft for parallel-design locations and 650 ft for tapered-design locations.

(5) The calculated mean and 85th percentile deceleration rates were dynamic while the *Green Book* criterion assumes constant values for the entire decelerating maneuver. It was found that the deceleration rates on the deceleration lane were much lower than those on the off-ramp after the critical speed change point. Most of the deceleration rates on the deceleration lane and off-ramp at study locations were lower than constants provided by the *Green Book*, however, some were higher after the critical speed change point.

(6) Based on the speed and deceleration rate distribution, a new method was developed to determine the minimum length of the deceleration lane. The results indicated that a deceleration lane may not be required for serving decelerating purpose on both parallel- and tapered-design deceleration lane locations when the ramp length is more than 1,550 ft. This number is specific to the diamond interchange (or interchanges with relatively straight off-ramps) with 70 mph speed limit on the mainline with the assumption of a stop is required at the off-ramp terminal.

In addition to the original objectives of this work, this study enabled the following observations. The advisory speeds posted on off-ramps were not able to significantly impact on drivers' operating speeds. For locations with a 35-mph advisory speed, the average 85th percentile speed and mean speed are 63 mph and 55 mph, respectively. For those without advisory speeds, the 85th percentile speed is 65 mph and the mean speed is 58 mph.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: Dan Xu, Huaguo Zhou, and Chennan Xue, study conception and design; Dan Xu and Chennan Xue, data collection; Dan Xu and Chennan Xue, analysis and interpretation of results; and Dan Xu, Huaguo Zhou, and Chennan Xue, draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

ACKNOWLEDGMENT

The research described here was funded by the Auburn University Intramural Grants Program. The authors would like to thank students who help with the data cleaning: Yukun Song, Pingzhou "Lucas" Yu, Shanshan Ma, and Meredith Ayers.

REFERENCES

1. Torbic, D. J., J. M. Hutton, C. D. Bokenkroger, D. W. Harwood, D. K. Gilmore, M. M. Knoshaug, J. J. Ronchetto, M. A. Brewer, K. Fitzpatrick, S. T. Chrysler, and J. Stanley. *NCHRP Report 730: Design Guidance for Freeway Mainline Ramp Terminals*, 2012. https://doi.org/10.17226/22743.
2. Critical Analysis Reporting Environment. *Center for Advanced Public Safety*. The University of Alabama, Tuscaloosa, AL, 2012.
3. Cirillo, J. A. The Relationship of Accidents to Length of Speed-Change Lanes and Weaving Areas on Interstate Highways. *Highway Research Record 132*, 1970, pp. 17–32.
4. Chen, H., P. Liu, J. J. Lu, and B. Behzadi. Evaluating the Safety Impacts of the Number and Arrangement of Lanes on Freeway Exit Ramps. *Accident Analysis and Prevention*, Vol. 41, No. 3, 2009, pp. 543–551. https://doi.org/10.1016/j.aap.2009.01.016.
5. Bauer, K. M., and D. W. Harwood. *Statistical Models of Accidents on Interchange Ramps and Speed-Change Lanes*. Publication FHWA-RD-97-106. FHWA, U.S. Department of Transportation, 1997.
6. Bared, J., G. L. Giering, and D. L. Warren. Safety of Evaluation of Acceleration and Deceleration Lane Lengths. *ITE Journal*, Vol. 69, 1999, pp. 50–54.
7. Lord, D., and J. A. Bonneson. Calibration of Predictive Models for Estimating Safety of Ramp Design Configurations. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1908, No. 1, 2005, pp. 88–95. https://doi.org/10.1177/0361198105190800111.
8. American Association of State Highway and Transportation Officials. *A Policy on Geometric Design of Highways and Streets*, Washington, D.C., 2011.
9. Van Schagen, I., R. Welsh, A. Backer-Grondahl, M. Hoedemaeker, T. Lotan, A. Morris, F. Sagberg, and M. Winkelbauer. *Towards a Large-Scale European Naturalistic Driving Study: A Final Report of PROLOGUE*. SWOV Institute for Road Safety Research, Leidschendam, Netherlands, 2011.
10. American Association of State Highway and Transportation Officials. *A Policy on Geometric Design of Rural Highways*. Washington, D.C., 1965.
11. Fitzpatrick, K., S. T. Chrysler, and M. Brewer. Deceleration Lengths for Exit Terminals. *Journal of Transportation Engineering*, Vol. 138, No. 6, 2012, pp. 768–775. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000380.
12. Twomey, J. M., M. L. Heckman, J. C. Hayward, and R. J. Zuk. Accidents and Safety Associated with Interchanges. *Transportation Research Record 1385*, 1993, pp. 100–105.
13. Wang, Z., H. Chen, and J. J. Lu. Exploring Impacts of Factors Contributing to Injury Severity at Freeway Diverge Areas. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2102*, 2009, pp. 43–52. https://doi.org/10.3141/2102-06.
14. Chen, H., H. Zhou, J. Zhao, and P. Hsu. Safety performance evaluation of left-side off-ramps at freeway diverge areas. *Accident Analysis and Prevention*, Vol. 43, No. 3, 2011, pp. 605–612. https://doi.org/10.1016/j.aap.2010.08.019.
15. Chen, H., H. Zhou, and P. S. Lin. Freeway deceleration lane lengths effects on traffic safety and operation. *Safety Science*, Vol. 64, 2014, pp. 39–49. https://doi.org/10.1016/j.ssci.2013.11.007.
16. Lu, J. J., L. Lu, P. Liu, H. Chen, and T. Guo. *Safety and Operational Performance of Four Types of Exit Ramps on Florida's Freeways.* Final Report. University of South Florida, Florida Department of Transportation, 2010.
17. Garcia, A. and M. A. Romero. Experimental Observation of Vehicle Evolution on a Deceleration Lane with Different Lengths. Presented at 85th Annual Meeting of the Transportation Research Board, Washington, D.C., 2006.
18. Calvi, A., A. Benedetto, and M. R. De Blasiis. A Driving Simulator Study of Driver Performance on Deceleration Lanes. *Accident Analysis and Prevention*, Vol. 45, 2012, pp. 195–203. https://doi.org/10.1016/j.aap.2011.06.010.
19. Calvi, A., F. Bella, and F. D'Amico. Diverging Driver Performance Along Deceleration Lanes. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2518,* 2015, pp. 95–103. https://doi.org/10.3141/2518-13.

20. Campbell, K. L. The SHRP 2 Naturalistic Driving Study: Addressing Driver Performance and Behavior in Traffic Safety. *TR News*, No. 282, 2012, pp. 30–35.
21. Dingus, T. A., J. M. Hankey, J. F. Antin, S. E. Lee, L. Eichelberger, K. E. Stulce, D. McGraw, M. Perez, and L. Stowe. *Naturalistic Driving Study: Technical Coordination and Quality Control*. SHRP 2 Report S2-S06-RW-1. Transportation Research Board, 2015.
22. Venglar, S. P., R. J. Porter, K. O. Obeng-Boampong, and S. Kuchangi. *Establishing Advisory Speeds on Non Direct-Connect Ramps: Technical Report*. Publication FHWA-TX-09-0-6035-1. Texas Transportation Institute, Texas Department of Transportation, 2008.
23. Gill, P. E., W. Murray, and M. H. Wright. *Practical Optimization*. Emerald Group, Wash. and UK, 1981.
24. *What Is R?* https://www.r-project.org/about.html. Accessed July 2nd, 2018
25. Killick, R., and I. Eckley. Changepoint: An R Package for Changepoint Analysis. *Journal of Statistical Software*, Vol. 58, No. 3, 2014, pp. 1–19. https://doi.org/10.18637/jss.v058.i03.
26. Reeves, J., J. Chen, X. L. Wang, R. Lund, and Q. Q. Lu. A Review and Comparison of Changepoint Detection Techniques for Climate Data. *Journal of Applied Meteorology and Climatology*, Vol. 46, No. 6, 2007, pp. 900–915. https://doi.org/10.1175/JAM2493.1.
27. Erdman, C., and J. W. Emerson. A fast Bayesian Change Point Analysis for the Segmentation of Microarray Data. *Bioinformatics (Oxford, England)*, Vol. 24, No. 19, 2008, pp. 2143–2148. https://doi.org/10.1093/bioinformatics/btn404.
28. Zeileis, A., A. Shah, and I. Patnaik. Testing, monitoring, and dating structural changes in exchange rate regimes. *Computational Statistics & Data Analysis*, Vol. 54, No. 6, 2010, pp. 1696–1706. https://doi.org/10.1016/j.csda.2009.12.005.
29. Killick, R., I. A. Eckley, K. Ewans, and P. Jonathan. Detection of Changes in Variance of Oceanographic Time-Series Using Changepoint Analysis. *Ocean Engineering*, Vol. 37, No. 13, 2010, pp. 1120–1126. https://doi.org/10.1016/j.oceaneng.2010.04.009.
30. Nam, C. F., J. A. Aston, and A. M. Johansen. Quantifying the Uncertainty in Change Points. *Journal of Time Series Analysis*, Vol. 33, No. 5, 2012, pp. 807–823. https://doi.org/10.1111/j.1467-9892.2011.00777.x.
31. El-Basha, R. H. S., Y. Hassan, and T. A. Sayed. Modeling Freeway Diverging Behavior on Deceleration Lanes. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2012, 2007, pp. 30–37. https://doi.org/10.3141/2012-04.

The National Academies of

SCIENCES • ENGINEERING • MEDICINE

The **National Academy of Sciences** was established in 1863 by an Act of Congress, signed by President Lincoln, as a private, non-governmental institution to advise the nation on issues related to science and technology. Members are elected by their peers for outstanding contributions to research. Dr. Marcia McNutt is president.

The **National Academy of Engineering** was established in 1964 under the charter of the National Academy of Sciences to bring the practices of engineering to advising the nation. Members are elected by their peers for extraordinary contributions to engineering. Dr. C. D. Mote, Jr., is president.

The **National Academy of Medicine** (formerly the Institute of Medicine) was established in 1970 under the charter of the National Academy of Sciences to advise the nation on medical and health issues. Members are elected by their peers for distinguished contributions to medicine and health. Dr. Victor J. Dzau is president.

The three Academies work together as the **National Academies of Sciences, Engineering, and Medicine** to provide independent, objective analysis and advice to the nation and conduct other activities to solve complex problems and inform public policy decisions. The National Academies also encourage education and research, recognize outstanding contributions to knowledge, and increase public understanding in matters of science, engineering, and medicine.

Learn more about the National Academies of Sciences, Engineering, and Medicine at **www.national-academies.org**.

The **Transportation Research Board** is one of seven major programs of the National Academies of Sciences, Engineering, and Medicine. The mission of the Transportation Research Board is to increase the benefits that transportation contributes to society by providing leadership in transportation innovation and progress through research and information exchange, conducted within a setting that is objective, interdisciplinary, and multimodal. The Board's varied committees, task forces, and panels annually engage about 7,000 engineers, scientists, and other transportation researchers and practitioners from the public and private sectors and academia, all of whom contribute their expertise in the public interest. The program is supported by state transportation departments, federal agencies including the component administrations of the U.S. Department of Transportation, and other organizations and individuals interested in the development of transportation.

Learn more about the Transportation Research Board at **www.TRB.org**.

TRB
TRANSPORTATION RESEARCH BOARD
500 Fifth Street, NW
Washington, DC 20001