TRANSPORTATION RESEARCH

CIRCULAR

Number E-C229 February 2018

10th SHRP 2 Safety Data Symposium

From Analysis to Results

October 6, 2017
Washington, D.C.

The National Academies of
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Transportation Research Board
500 Fifth Street, NW
Washington, DC 20001
www.TRB.org

TRANSPORTATION RESEARCH CIRCULAR E-C229
ISSN 0097-8515

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Preface

The purpose of the 10th Strategic Highway Research Project 2 (SHRP 2) Safety Data Symposium was to create a forum for the exchange of ideas about uses and methods for the SHRP 2 Safety Data Program and also identify lessons learned from working with the data. This 10th symposium differed from past symposia in that it moves on from Naturalistic Driving Study (NDS) data collection and management and focuses on safety data analysis, results, and applications. In particular, the Transportation Research Board (TRB) Safety Data Oversight Committee and Safety Data Program staff sponsored this forum so that researchers and practitioners could learn more about current studies that are using the safety data and to gain insight into future potential applications of the data.

In general, the goals of the symposium were to

- Identify what has been done with safety data;
- Explore what has been learned from the research;
- Bring together researchers and practitioners;
- Provide insights to future applications of the data; and
- Provide a forum for the exchange of ideas.

At the symposium, 16 presentations covered a wide variety of safety-related investigations using the SHRP 2 Safety Program Data ranging across vehicle types (e.g., cars and motorcycles), roadway features and infrastructure (e.g., ramps and rail–highway crossings), situations (e.g., work zones and congested traffic), and driver behavior (e.g., speed, teen drivers, and distracted driving). The presentations also explored a range of data integration and analysis approaches and interpretation of results.

PUBLISHER'S NOTE

The views expressed in this publication are those of the authors and do not necessarily reflect the views of the Transportation Research Board or the National Academies of Sciences, Engineering, and Medicine. This publication has not been subjected to the formal TRB peer-review process.

Welcoming Remarks

NEIL PEDERSEN
Transportation Research Board

Neil Pedersen, TRB Executive Director, welcomed the nearly 150 Safety Data Symposium participants on behalf of TRB and the National Academy of Sciences, Engineering, and Medicine. Pedersen welcomed the international attendees from Canada, the United Kingdom, Israel, the Republic of Korea, and Japan. He noted that naturalistic driving and safety data are now truly international in scope. The following is a summary of his welcoming remarks.

Pedersen noted that this is the 10th Safety Symposium and the series began a little over 10 years ago in August 2006. A brief history of the symposium series is useful to put things in context and to show just what a major, long-term effort the whole Strategic Highway Research Program 2 (SHRP 2) Safety Data Program has been.

To begin, Petersen recounted, if one were to go back and take a look at the 2006 symposium agenda, it would be possible to see that after the first symposium and the next few symposia, TRB was getting ready to collect the SHRP 2 Safety Data. For instance, TRB spent much effort understanding the critical research issues that could be better analyzed and better understood by using the safety data. The 150 or more attendees from the 2006 Symposium were instrumental in helping to build the list of critical research issues.

After that, according to Petersen, the symposium agenda began to shift toward helping design the data collection effort, which was very large and very complex. It was to be by an order of magnitude the largest NDS ever conducted with six study sites around the United States, and with thousands of drivers and instrumented vehicles being studied "in the wild." In addition, a very-comprehensive and in-depth geospatial Roadway Information Database (RID) was to be collected using vans and pre-existing data, and assembled to allow for more of the critical research issues to be addressed.

Furthermore, there were many researchers who were involved in the design of the data collection effort, the design of the database, and the actual collection of data. Pedersen thanked those present who had served on one of those research teams. He also noted that those who have used the data for research and were presenting results at the symposium also owe those researchers a debt of gratitude.

By 2010, the symposium agenda had again changed. While there was still much focus on the multiyear data collection effort, the conversation moved on to what would happen after the data were collected and the database was created, specifically to the question of how would qualified researchers access the data once they were available. So, terms like "human research subjects," "personally identifying information," and "institutional review board" started being used much more in the conversations during the symposium.

By 2012, Pedersen noted that something new and interesting was starting to be discussed: pilot projects. A handful of research teams were using the data to research some of the critical issues such as driver distraction, departure from rural curves, and urban intersection safety. (This is a lot like trying to fly a new airplane while it is still under construction! These pilot teams were truly pioneers.) The pilots generated a lot of conversation about the data and needed enhancements for the data.

In the symposia held in 2012 and 2013, TRB staff also started to hear more about international developments. NDSs were underway in Canada, the European Union, Australia, and China because of the recognition that safety is a critical transportation challenge and priority around the globe. Some of the lessons learned and technologies from the SHRP 2 Safety Data Program were being applied in those places. But this is a two-way street. The SHRP 2 Safety Data Program has also learned a great deal from the international NDS programs over the past few years. One example is that naturalistic driving data can help researchers with critical issues well beyond safety such as understanding travel demand, improving system reliability, and making transportation systems more sustainable.

Pedersen went on to say that a lot has happened since the last symposium in July 2014. Data collection and database assembly were completed for both the NDS and the RID—referred to jointly as SHRP 2 Safety Data—in early 2015. In mid-2014, TRB entered into a cooperative agreement with the Federal Highway Administration (FHWA), in association with the American Association of State Highway and Transportation Officials (AASHTO) and the National Highway Traffic Safety Administration (NHTSA) for Phase 1 of SHRP 2 Safety Data Implementation and Oversight. Phase 1 is an experimental program designed to make the Safety Data widely available to qualified researchers to gather information needed to support decisions about implementation and oversight of the data beyond the first 5 years.

Pedersen recognized and thanked the partners from NHTSA, FHWA, and AASHTO for all the support they have given throughout the SHRP 2 Safety Data Program.

The cooperative agreement for Phase 1 of SHRP 2 Safety Data Implementation and Oversight is scheduled to end in mid-2020. A Safety Data Oversight Committee was appointed by the National Academies of Sciences, Engineering, and Medicine to provide strategic direction and oversight for the program during Phase 1. This committee is made up of stakeholders from a diverse set of organizations including state departments of transportation (DOTs), the automobile industry, federal agencies, public health, and big data. The Safety Data Oversight Committee is now considering what should happen in Phase 2, after 2020. TRB and all safety researchers owe the Safety Data Oversight Committee a debt of gratitude.

Pedersen also thanked the Virginia Tech and Iowa State University teams who have had responsibility not only for maintenance of the databases, but supporting all the researchers in accessing and using the data in the databases.

This 10th symposium is a very different one from the previous ones. The focus is no longer on "getting ready." It is squarely on "what has been done with the safety data and what the safety community has learned from the research that has been conducted." TRB did not hold symposia in 2015 and 2016 because it typically takes a year to 18 months to get a research project underway with the safety data and to get results that can be presented. Valuable research takes time to complete. The SHRP 2 Safety Program now has 250 data-use licenses in place for research projects using the SHRP 2 Safety Data. That is a pace of around 100 projects per year. The projects that began in 2015 are now ready to report and many have published results. Those results from the first couple of years of active data availability are what today's symposium is all about.

Focusing on today's symposium, Petersen said its goals are mainly to help researchers learn from each other and to foster interaction in a community of research practice.

The Safety Data Oversight Committee and Safety Data Program staff are sponsoring this forum where researchers and practitioners can learn more about current studies that are using the Safety Data and to gain insight into future potential applications of the data.

The symposium also aims to create a forum for the exchange of ideas about uses and methods for the SHRP 2 Safety Data and also lessons learned from working with the data. As such, there were numerous opportunities for symposium participants to interact with the panelists and with each other. Pedersen encouraged attendees to ask questions after each session and to use the networking times to interact with other researchers.

Pedersen also thanked the TRB Safety Data Program staff who have been involved in both managing the research projects that eventually produced the databases used by the researchers, as well as the TRB staff who have been responsible for the stewardship of the database since it was completed in early 2015.

Pedersen particularly recognized Ann Brach, who has been involved in SHRP 2 since before the program started, has served both as Deputy Director and Director of SHRP 2 during the research phase, and now serves as TRB's director of the Technical Activities Division and is responsible for the stewardship of the safety database. Pedersen thanked Brach for her leadership, and her sweat, blood, and tears over the decade and a half of the SHRP 2 program.

Pedersen encouraged attendees to enjoy the rest of the symposium and he hoped it would be an enjoyable, educational, and productive experience.

Symposium Objectives and SHRP 2 Safety Data Program Update

ANN BRACH
Transportation Research Board

Ann Brach, Director of TRB's Technical Activities Division and previously Director of the SHRP 2 program, welcomed the participants to the symposium. She then provided an update on the SHRP 2 Safety Data Program activities.

In a major step forward for highway safety, the NDS and RID have been successfully developed and implemented (Figure 1).

Data collected to date includes the following:

- 35 million vehicle miles;
- 4,200 crashes and near-crashes;
- 5.5 million trips;
- 12,500 centerline miles of new roadway data collected with mobile van;
- 200,000 highway miles data from agency inventories; and
- Traffic, weather, work zone, safety, and campaigns.

Phase 1 of the SHRP 2 Safety Data Implementation Program runs from March 2015 to August 2020. The objective is to make data accessible to a wide range of researchers. This includes operations, business analysis, and experimentation. The goal is to encourage a high level of actual data use, gather feedback on data use, and to test the market. Another goal is to develop a long-term plan for the operation, governance, and funding of data.

Regarding data use thus far during Phase 1, 256 data use licenses have been issued with over 70 studies published in journals and reports. Thirty-nine papers were submitted to the 96th Annual Meeting of the Transportation Research Board in 2017 with nine sessions that included

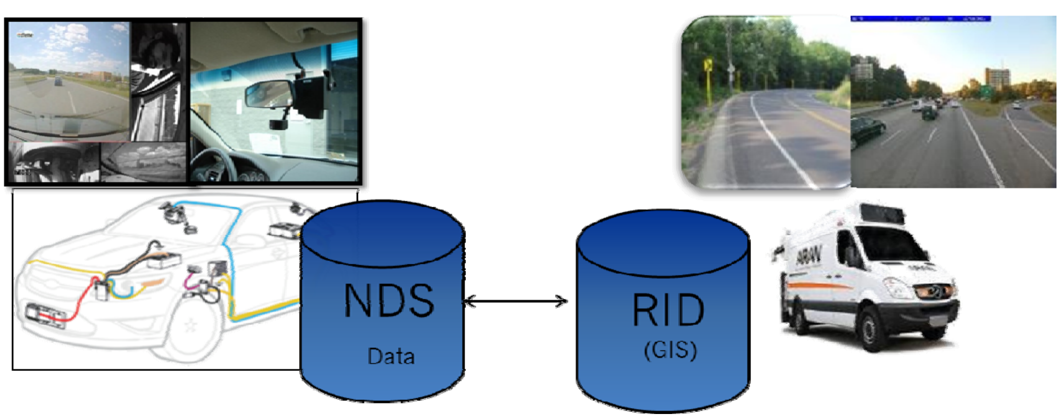

FIGURE 1 NDS and RID.

SHRP 2 NDS topics. For the upcoming 97th Annual Meeting in 2018, researchers have submitted at least 17 papers. The 2018 TRB sessions have not yet been tallied.

Categories of research topics include the following:

- Drowsy and distracted drivers;
- Speed, environment, and driver reaction to slow-moving lead vehicles;
- Differences between older and younger drivers' interaction with roadway features;
- Long-range prediction of danger by drivers;
- Measures of distracted driving;
- Machine learning-based fault determination in crash and near-crash events;
- Safe driver scoring model;
- Effectiveness of high-visibility pedestrian crossings;
- Cruise automation support;
- Study of risk perception using forward video of collisions; and
- Insurance study of driver behaviors leading to crashes.

In 2016, Brach noted that the SHRP 2 Safety Data Implementation Program created "Dataverse" which is an open-source web application to share, preserve, cite, explore, and analyze research data. Dataverse includes 59 user-developed datasets, research data, and documentation. It is available for re-use by other researchers with 40 requests tallied so far. Dataverse is linked to the NDS InSight website.

FHWA also instituted the Safety Training and Analysis Center (STAC) which is a secure data enclave established at FHWA's Turner-Fairbanks Highway Research Center. At STAC, authorized researchers can view and work with SHRP 2 Safety Data, including personally identifying information.

Other U.S. DOT-supported projects through SHRP 2 Solutions include:

- Implementation Assistance Program:
  - State DOT leads with research partners and
  - Administered with AASHTO;
- FHWA Broad Agency Announcements:
  - Research leads with state DOT partners and
  - Administered through FHWA;
- FHWA Exploratory Advanced Research:
  - Automated feature extraction and identity masking and
  - Analytical tool development; and
- NHTSA: seat belt, speeding, medical conditions, and drowsy driving.

Brach remarked that SHRP 2 also sponsors the Safety Data Student Paper Competition. For the 2015–2016 competition, the papers were published in *Transportation Research Circular E-C221: SHRP 2 Safety Data Student Paper Competition*. For the 2017–2018 competition, SHRP 2 is currently soliciting innovative ideas from graduate students for using the SHRP 2 Safety Data.

Brach also highlighted similar international NDS activities including the Canadian NDS, the European NDS (UDRIVE), the Australia NDS Study, and an ongoing effort in China.

The NEST Dataset
Description and Preliminary Results

HUEI-YEN WINNIE CHEN
University of Toronto, presenter

BIRSEN DONMEZ
University of Toronto

MARTINA RISTESKA
University of Toronto

This project utilized the Naturalistic Engagement in Secondary Tasks (NEST) dataset to investigate secondary task engagement in naturalistic driving. Commissioned by the Toyota Collaborative Safety Research Center, the Virginia Tech Transportation Institute (VTTI) reduced the NEST dataset from the SHRP 2 data by sampling a subset of crashes and near-crashes (safety critical events, SCEs) identified as including secondary task engagement as a potential contributing factor (see Owens et al., 2015 for details regarding the creation of NEST dataset).

This research aimed to compare the prevalence of the engagement in single versus multiple types of secondary tasks in distraction-affected SCEs and baselines reported in the NEST dataset, considering driving demands. Earlier descriptive analysis of NEST suggests that drivers engage in more than one type of secondary task in a relatively short time frame (Domeyer et al., 2016). Naturalistic studies also suggest that drivers self-regulate behaviors when engaging in secondary tasks based on-road demands (Funkhouser et al., 2012; Tivesten et al., 2015).

NATURALISTIC ENGAGEMENT IN SECONDARY TASKS DATASET

The NEST dataset includes 236 SCEs (crash–near crash), capturing the majority of the Level I and II severity distraction-relevant crashes in the overall SHRP 2 dataset (Table 1). NEST also includes four baseline epochs for each SCE from the same driver, resulting in a total of 1,180 SCEs and baseline epochs from 205 drivers, of which 147 had at least one crash. Compared to SHRP 2, longer epochs were coded (30 s as opposed to 6 s), and more details were gathered (e.g., frame-by-frame indication of the presence of specific secondary tasks). More specifically, video data were coded for 20 s leading to, and 10 s after, the precipitating event in an SCE, and 20 s for a baseline epoch. Summary data were coded in 10-s segments on the environment (e.g., weather and traffic), driver actions (driver behavior and secondary task engagement), and nature of event (e.g., crash severity). In addition, the study provided frame-by-frame coding (1 Hz) of secondary tasks, including hands-on-wheel information, and eye glance data

TABLE 1 SCEs in NEST Dataset

Safety Critical Events	NEST	SHRP 2
Level I and Level II crashes	**75**	91
Level III and Level IV crashes	84	325
Total crashes	159	416
Near-crashes	77	748
Total distraction–relevant SCEs	**236**	**1,138**

(where the driver was looking at). The present analysis utilized the two 10-s segments leading to the precipitating event in an SCE and both 10-s segments available for a baseline event.

DATA ANALYSIS

The NEST dataset provides an extensive list of variables describing the environment and driver attention around the time of the SCE and the baseline periods. To overcome sample size limitations, the study categorized secondary tasks into nine different types of secondary tasks (Table 2), and grouped variables describing the driving environment by two constructs: motor control difficulty (e.g., alignment) and visual difficulty (e.g., weather or rain).

The study built a logit model to compare the odds of engaging in single vs. multiple types of secondary tasks between SCEs and baselines. The explanatory variables examined were event type (SCE or baseline) and environmental demand (a further combination of lower versus higher level of motor control difficulty and lower versus higher level of visual difficulty). GPS speed at the start of the event and driver age were also included to account for how individual drivers would experience environmental demands. Two-way interactions were included initially but removed due to no significance. Repeated measures were accounted for through generalized estimating equations.

RESULTS

A descriptive analysis was carried out to examine frequency of task types found together in baseline events vs. in SCEs. The most common pairs of task types were found to be the same for baselines and SCEs:

- Dancing/singing + interaction with carried-in device;
- Dancing/singing + outside distraction; and
- Outside distraction + passenger interaction.

The logit model built found that engagement in multiple (versus single) secondary task types was more likely to occur during SCEs compared to baselines (Figure 2). In addition, there was a marginal effect that the age group 65 and over were less likely to engage in multiple

TABLE 2 Aggregated Secondary Task Type and NEST Secondary Tasks

Secondary Task Type	NEST Secondary Tasks
Visual–manual interactions with vehicle integrated device or control	Adjusting and monitoring (a) climate control, (b) radio, and (c) other devices integral to vehicle. Inserting or retrieving CD.
Personal hygiene	Applying make-up. Biting nails or cuticles. Brushing or flossing teeth. Combing, brushing, or fixing hair. Removing or adjusting jewelry. Removing, inserting, or adjusting contact lenses or glasses. Other personal hygiene.
Interaction with carried-in device	Dialing handheld (a) cell phone or (b) cell phone using quick keys. Texting on cell phone. Locating, reaching, or answering cell phone. Cell phone, other. Operating personal digital assistant (PDA) or other handheld device. Locating or reaching for PDA or other handheld device. Viewing PDA or other handheld device. PDA or other handheld device, other.
Talking on handheld cell phone	Talking or listening on hand-held cell phone.
Drinking or eating	Drinking. Eating.
Dancing or singing	Dancing. Talking or singing.
Outside distraction	Looking at (a) an object external to the vehicle, (b) pedestrian, or (c) previous crash or incident. Other external distraction. Distracted by construction.
Reaching or manipulating object	Moving object in vehicle. Object (a) in vehicle, other, or (b) dropped by driver. Reaching for (a) food-related or drink-related item, (b) object that is a manufacturer-installed device, (c) object, other, (d) personal body-related item, or (e) lighting, smoking, or extinguishing cigar or cigarette.
Passenger interaction	Passenger in adjacent or rear seat: interaction. Child in adjacent or rear seat: interaction.

(versus single) types of secondary tasks compared to other age groups. It may be that the older drivers experience cognitive saturation more quickly, compared to their younger counterparts, or there may be generational differences in driving style and technology use. Environmental demand and GPS speed were not significant in this analysis. While sample size and missing data are significant limitations in this analysis, better representation of environmental demands within the NEST or SHRP 2 dataset may also facilitate similar analysis in the future.

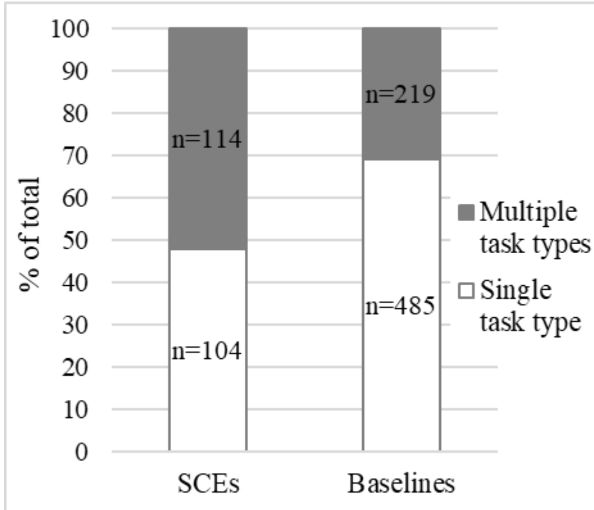

FIGURE 2 Multiple versus single secondary task type engagement.

CONCLUSIONS AND LESSONS LEARNED

These preliminary findings provide insights into the complex relationships between driver distraction, environmental demands, and SCEs. Most crash risk studies to date reported the effects associated with one type of secondary task when it appears that in reality these effects may be confounded by the presence of other secondary tasks. Future research investigating the influence of distraction on crash risk may benefit from considering engagement in multiple secondary tasks and how drivers modulate their behaviors due to various environmental demands.

We note that the results presented here should be interpreted in light of the fact that NEST data only includes drivers who have at least had one distraction-related crash, and they are not necessarily representative of the entire driving population. While SHRP 2 baselines were sampled strategically to approximate crash risk through exposure odds ratios, NEST baselines were not sampled to control for exposure, and may provide biased estimates if crash risk were to be inferred.

RESPONSE TO AUDIENCE QUESTION

In response to a question on the use of devices in vehicles, Chen stated that there were not many advanced vehicular systems in the data, approximately 30 to 40 vehicles. Some had Bluetooth capability.

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A Study on the Dynamics of Driver Vision Transitions and Its Impacts on Vehicle Safety

SEHYUN TAK
Presenter

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YEEUN KIM
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BACKGROUND

One of the primary causes of traffic crashes is the driver's inattention and distraction.

According to some reports, approximately 65% to 80% of reported incidents are caused by driver distraction or inattention. Understanding distraction can be the first step to understanding traffic accidents.

Traffic simulations can be a good alternative to perform on-road experiments. However, existing models have limitations since they do not represent crashes. Although distraction is a difficult concept to evaluate quantitatively, previous research has focused on the relationship between eye glance and distraction and also the relationship between eye glance and traffic accident.

This study has two research objectives:

- Analyze driving characteristics, through the driver's eye glance transition, in various driving environments under safe and unsafe situations.
- Describe the concept of a new car-following model that can describe accident situations.

METHODOLOGY

The study used data from the 100-car NDS of VTTI as the primary data source. The released online data includes two types of datasets, a baseline and an event.

The baseline data describes the normal driving situation, and the event database consists of crashes and near-crashes. Both datasets contain eye glance location data and video-reduced data.

The eye glance data records the driver's eye glance location, and the video-reduced data records the driver characteristics and driving environment properties.

The two data sets have different recording times. Baseline data was recorded for 6.1 s at 0.1-s intervals. Event data was recorded for 30 s including 20 s before and 10 s after an impact.

To understand the sequential characteristics of eye glance behavior, the study employed a Markov model which is commonly used for modeling and predicting human behaviors.

There are many examples of using the Markov model for purposes such as modeling speech, gesture, and vision behavior. In addition, the cumulative distribution of eye glance duration is analyzed for use in simulation. This allows maximum duration of gazing at each location. It can be used for forced termination of gazing when it continues too long.

Since baseline data is recorded for 6 s, 6 s right before the event start is used for event data. In addition, to prevent overestimation of keeping the eye glance in same location, data is aggregated in 1-s time steps.

Previous studies typically divided eye glance location into two groups: forward and nonforward or on road and off road. However, since there are limitations on describing distractions such as in passing intersection and lane-change events, the study classified glance locations into four groups: forward, rear view, side, and off road. Rear view represents looking in the rearview mirror, and side consists of right and left forward, mirror, and window. Off road is not looking at the road such as in-vehicle instrument manipulation, using cell phone, speedometer, etc.

As shown in Table 3, the study also focused on three driving environments: relation to junction, traffic density, and time-to-collision (TTC). For relation to junction, data were classified in three groups: nonjunction, intersection, and intersection related. Traffic density was classified as Level of Service (LOS) A to D and LOS E and F. In the analysis process to determine the effect of traffic density, we used only data obtained from nonjunctions in order to minimize the influence of junctions such as intersections. For TTC, transition probability was calculated varying time-to-collision from 0 to 40 s.

Through data analysis using the Markov chain, the study first identified the transition matrix in various driving environments such as traffic density, relations to junction, road geometrics, and lighting conditions. The results show that drivers have a higher probability and duration of distraction and side-looking status at low LOS than high LOS. At the intersection and intersection-related regions, the probability of side-looking shows significantly high and the duration is also long. In addition, at the intersection looking-forward duration is significantly shorter. In the case of road geometrics, without grade, drivers tend to keep their eye glance on and off road and backward in a straight roadway more than a curved roadway. Regarding lighting conditions, the driver showed less off-road movement, which is considered to be related to distraction, in darkness conditions, with or without lighting, as compared to daylight conditions. Also, drivers were more likely to see the side in the darkness condition.

TABLE 3 Sample Size According to Road Environment

Road Environment		**Sample Size**		**Classification**
		Baseline	Event (Accident)	
Relations to junction	Nonjunction Intersection Intersection related	4,015 296 246	413 134 70	Forward, side, off road, rear view
Density	LOS A–D LOS E, F	3,959 56	390 23	Forward, side, off road, rear view
TTC	0~40 (s)		503	Forward, nonforward

On the other hand, the main difference between the normal driving situation and the accident situation is the duration of the inattention and distraction. The transition probability from forward-looking status to distraction status is not significantly different in both situations. But the duration of the inattention and distraction is long in the accident situation compared to that of the normal driving situation. Meanwhile, at the intersection, there are distinctive differences from other situations. In this case, the significant difference between the normal driving situation and the accident situation is the duration of forward-looking status. At the accident situation, drivers maintain their eye glance forward longer than with the normal driving situation.

The effect of speed and TTC was also analyzed using event data. As speed becomes faster, drivers pay greater attention when looking-forward. On the other hand, TTC affects the probability of drivers keeping their eye glance on forward in other ways. The variance of probabilities clearly increases with the increase of TTC. This means shorter TTC forces the driver to pay more attention over threshold probability.

In addition, we proposed a new car-following model by combining driver's eye glance behavior with the existing car-following model. The proposed car-following model describes near-crash and crash situations better than the existing model.

RESULTS

At first, in the analysis with Markov chain, we identified the transition matrix in various driving environments such as traffic density, relations to junction, road geometrics, and lighting conditions. The result shows that drivers have a higher probability and duration of distraction and side-looking status at low LOS than high LOS (Figure 3). At the intersection and intersection-related region, the probability of looking-side shows significantly high and duration is also long. In addition, at the intersection looking-forward duration is significantly shorter. In the case of road geometrics, without grade, drivers tend to keep their eye glance on distraction and backward in a straight roadway more than a curved roadway. During lighting conditions, drivers show less distraction than daylight, and more efforts are made to looking-side with high probability.

On the other hand, the main difference between normal driving situation and accident situation is the duration of the inattention and distraction. The transition probability from forward-looking status to distraction status is not significantly different in both situations. But the duration of the inattention and distraction is long in the accident situation compared to that of the normal driving situation. Meanwhile, at the intersection, there are distinctive differences from other situations. In this case, the significant difference between the normal driving situation and the accident situation is the duration of forward-looking status. At the accident situation, drivers are keeping their eye glance forward longer than that of a normal driving situation.

The effect of speed and TTC is also analyzed using event data. As a result, as speed becomes fast, drivers pay attention more on looking forward. On the other hand, TTC affects the probability of drivers keeping their eye glance on forward in other ways. The variance of probabilities clearly increases with the increase of TTC. It means a shorter TTC forces the driver to pay more attention over threshold probability. In addition, as a result of the validation of the new car-following model, the proposed car-following model is confirmed to better describe driver behavior change in crash and near-crash situations in terms of the time–TTC curve.

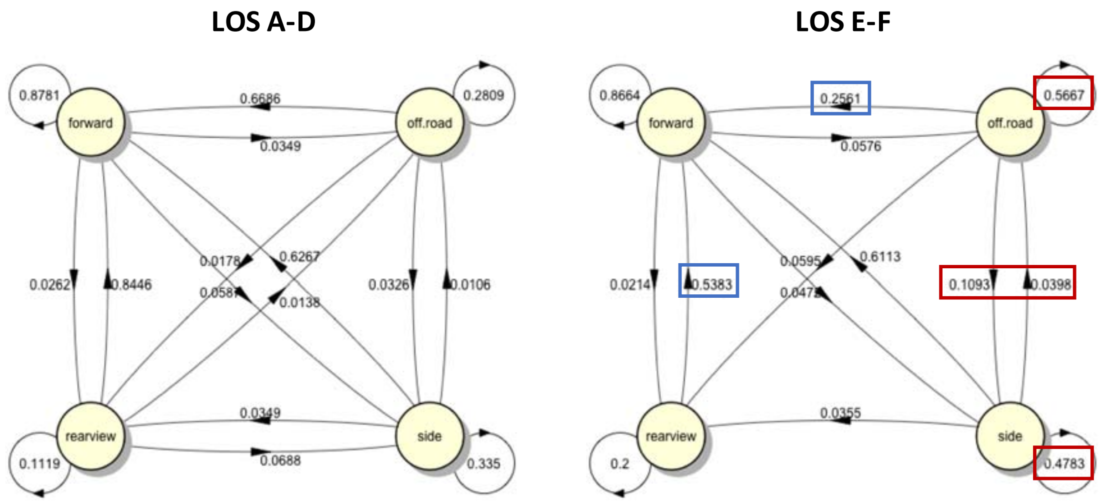

FIGURE 3 Transition matrix with different LOS.

Based on these results, the researchers propose a concept of a new car-following model for accident simulation. The basic concept is simple. When the driver looks forward, it follows the normal car-following model, and when they look nonforward, it keeps the current movement.

The researchers simulated different three cases: (a) normal driving situation, (b) dangerous driving situation, and (c) accident situation (Figure 4). In the normal driving situation, forward-looking and nonforward-looking behavior repeatedly occurred. In this case, since the leader vehicle does not show any adverse action, the eye glance behavior does not have a significant influence on the safety and driving actions.

However, when the leader vehicle reduces the speed, a dangerous situation occurred. When the driver keeps attention, the following vehicle detects this adverse action and reduces its speed appropriately. Fortunately, it did not lead to an accident.

On the other hand, as in accident situation, the accident occurred due to the inattention of the driver.

In this case, the driver does not look forward when the leader vehicle abruptly reduces the speed. As a result, in spite of its maximum braking, the following vehicle crashes into the leader vehicle.

LESSONS LEARNED

This study employed event time series data of crashes and near-crashes to analyze the relationship of TTC and probability of keeping the eye glance on each status. To measure TTC, the study had to distinguish the vehicle in the same lane. Since radar data does not contain lane information of detected objects, the researchers first filtered vehicles considering calculated lateral position of the vehicle compared to recorded lane width. However, in this step, the researchers encountered some difficulties because of the lane width value that is considered inaccurate such as less than 1 m or more than 10 m. Also, the lane width varies continuously

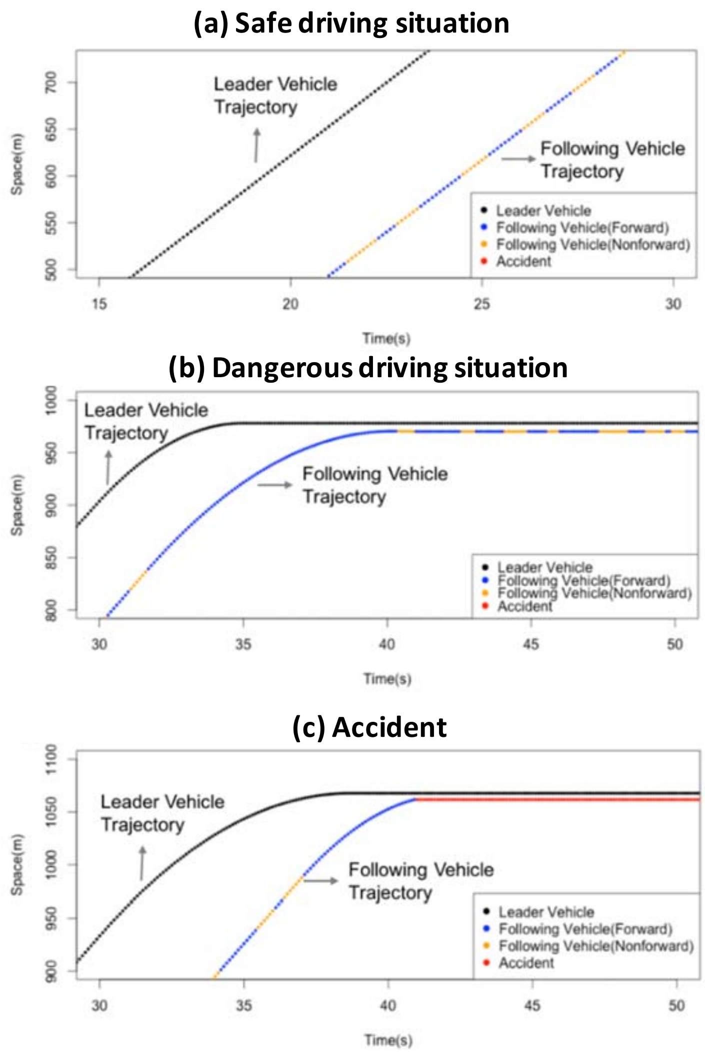

FIGURE 4 Simulation results with eye glance behavior.

during driving. To address these inaccuracies, the researchers used fixed lane width obtained by median value to one file. For those files which had an unacceptable value, the researchers assumed a lane width of 3.2 m.

For future research, it would be beneficial to extend the study to a general driving situation and analyze the behavior change of the individual driver on a daily basis. For this study, the baseline data that is currently available is too short. The researchers believe that behavior changes of the individual driver can be monitored using the current data set.

RESPONSES TO AUDIENCE QUESTIONS

In response to questions, Sehyun Tak verified that the study did not use SHRP 2 data but rather data from the 100-car study from VTTI. Also, the study did not use signal timing data.

Does an Interaction Between Last Glance Duration and Closure Rate Cause Rear-End Crashes?

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BACKGROUND

Rear-end crashes comprise about 1.7 million crashes in the United States, with about 1,700 deaths and 500,000 injuries (NTSB, 2015). An understanding of rear-end crash causes is critical to reducing them. This presentation examines whether an interaction (i.e., mismatch) between vehicle kinematics and last glance duration is the “key mechanism” underlying rear-end crashes.

Closure Rate Metric

Victor et al. (2015) analyzed rear-end crashes and near-crashes (events) from the SHRP 2 NDS. They evaluated the contribution of three factors to events: (1) the last off-path glance duration before an event; (2) the closure rate (i.e., the change in looming rate) between the lead and following vehicle during the last glance; and (3) the interaction between (1) and (2). Using a logistic regression analysis method with matched baseline controls, they concluded that the interaction factor was dominant, with the last glance duration and closure rates by themselves having a minimal effect.

Victor et al. also performed a separate “kinematics” analysis of last glance timing relative to situation kinematics on a subset of the crashes and near-crashes (without considering baseline controls). For a subset of events they called Category 1, their data showed by visual inspection a substantial linear decline in closure rate as last glance duration increased. They claimed their event data thus supported a “mismatch” hypothesis: the predominant cause of the Category 1 rear-end crashes was a short glance with a high closure rate, or a long glance with a low closure rate.

Difference Score Metric

Eiríksdóttir (2016) confirmed the Victor et al. kinematics findings using the same analysis methods on a DriveCam naturalistic driving dataset that included both passenger cars and heavy vehicles, with 100 rear-end events (70 crashes and 30 near-crashes).

Limitations

A major limitation in both studies, however, was an artifact in their definition of the closure rate metric. Specifically, the closure rate was calculated as the slope of a regression line (i.e., the change in looming divided by the glance duration). Because the last glance duration was the denominator of the closure rate metric, a longer glance automatically gives rise to a lower closure rate, and a shorter glance to a higher closure rate, apparently (incorrectly) supporting the mismatch hypothesis.

Two key research questions were investigated:

1. Is there an artifact in the Victor et al. (2015) *closure rate* metric that creates the perfect mismatch between closure rate and last glance duration?
2. Is there also an artifact in the *difference score* metric that creates the mismatch between the *difference score* and last glance duration?

ANALYSIS METHOD

Young (2017) re-analyzed the Victor et al. (2015) event data, but included their matched baseline data as a control, allowing the estimation of odds ratios (ORs) using all the available data points, not just a subset. He then independently tested the Victor et al. findings using two epidemiological methods. First, he stratified the closure rate and last glance duration data. The counts of events and baselines in each stratum were compared to a "just following," no-crash control (short glances <0.5 s and closure rates near 0) to estimate an OR for each stratum. Second, a logistic regression analysis was performed on all the data using a continuous scale to improve statistical power compared to the stratified analysis. The regression model was a linear combination of closure rate, last glance duration, and their interaction. The regression analysis by Young (2017) estimated the ORs of these three risk factors (last glance duration, closure rate, and their interaction), adjusting each risk factor for the influence of the other two.

In the current study, the artifact in the definition of closure rate was partially controlled for by multiplying the closure rate by the last glance duration. The resulting variable of "change in optical looming rate" was the difference (not the ratio) of optical looming between the end of the last glance and its start. This difference metric is no longer divided by the last glance duration, which at least partially reduces the size of the artifact. A simple linear regression for the Category 1 crashes as defined by Victor et al. (2015) was used to directly test the mismatch hypothesis using the closure difference metric. This difference metric was also then compared against the last glance duration, using logistic regression analysis for the dataset of all the data points (crashes, near-crashes, and baseline data).

Similar analysis methods were then applied to the DriveCam dataset of Eiríksdóttir (2016) who had already directly calculated the difference in optical looming between the end of the last glance and its start, to help control for the artifact.

RESULTS

For the original Victor et al. SHRP 2 dataset with the artifact present, the stratification method confirmed a strong interaction effect between closure rate and last glance duration in causing rear-end events, consistent with the Victor et al. (2015) regression analyses. The strong interaction effect occurs because both the effect size and direction (causal or protective) of glance duration are dependent upon closure rate (with the artifact present). At closure rates above a certain minimum positive value, glances increased relative event risk proportional to glance duration, consistent with the mismatch hypothesis. However, at closure rates near zero, long (and short) glances had a protective effect, contradicting the mismatch hypothesis, which says that long glances should cause crashes at low closure rates.

Closure rate by itself (adjusted for last glance duration and interaction effects) had a minimal OR estimate of 0.67 (CI 0.002–182).

Last glance duration by itself (adjusted for closure rate and interaction effects) had a protective OR estimate of 0.40 (CI 0.21–0.76), consistent with the protective OR estimates in the stratification method for glances adjusted for closure rate. The protective effect of glances at closure rates near zero likely arises from improved situation awareness, which reduces crash risk. This protective effect is however inconsistent with at least some statements in Victor et al. that appear to imply that their data shows that eliminating short glances will decrease rear-end events.

New results will be shown for the Victor et al. (2015) and Eiríksdóttir (2016) studies after the partial removal of the artifact in the definition of closure rate. For example, for the Category 1 crashes in Victor et al. (2015), the closure rate as originally defined with the artifact had a negative correlation with last glance duration of –0.85 ($p < 0.0000001$), apparently supporting the mismatch hypothesis. But after partial removal of the artifact by using the difference in closure between last glance start and end rather than the ratio, the correlation was positive (0.49, $p = .02$), inconsistent with the mismatch hypothesis. The logistic regression analysis on the difference metric versus last glance duration for all the data points found that the glances had a protective effect up to a closure difference of about 0.25, inconsistent with the mismatch hypothesis. At higher closure differences than 0.25 (that is, a very rapid closure difference during the last glance), there was a slight upward increase in the probability of a crash as glance duration increased, creating an interaction effect.

CONCLUSIONS

Victor et al.'s (2015) conclusion that "the key mechanism" behind Category 1 rear-end passenger vehicle crashes is due to a "perfect mismatch" between last glance duration and vehicle kinematics is not supported by their SHRP 2 naturalistic driving data after quantitative re-analysis of their data.

A measurement artifact in the closure rate metric causes a dependency of closure rate on last glance duration, which confirms the concern of Eiríksdóttir (2016) and Eiríksdóttir et al. (2017).

The artifact also invalidates Young's (2017) proof of a strong causal interaction between closure rate and glance duration in the Victor et al. data.

There is also an artifact in the difference score metric which causes the observed perfect match between it and last glance duration. Hence, the specific conclusion by Eiríksdóttir (2016) and Eiríksdóttir et al. (2017) that the difference score metric supports a mismatch for short glances is in fact not supported by their data.

LESSONS LEARNED

It logically follows from the current results (both initially and after partial removal of the artifact) that any claim of a rear-end crash being directly caused by a glance per se is incomplete, because the effect of glance duration on rear-end events can only be determined given a specific closure rate (or vice versa). If there were a direct causal effect of last glance duration by itself on rear-end crashes, then the adjusted OR estimate of the last glance duration must be >1, and it was actually <1, a protective effect. It is important in future studies that claims of a main effect on rear-end crashes due to glance duration, closure rate, or any other variable be adjusted for interaction effects from other variables. Furthermore, the assumption that off-road glances are always causal of rear-end crashes is incorrect; they can be protective if the closure rates or closure differences are not quite high.

An inherent limitation of the Victor et al. and Eiríksdóttir data is that their method of measuring the closure rate gave rise to a direct dependency of change rate on last glance duration. A partial removal of this artifact was accomplished with their published data. To avoid this artifact in future studies, the lesson learned is that the closure metric must be derived from an optical looming or radar range rate metric that is independent of glance duration. For example, the data for the looming rate at the end of the last glance could be used, without consideration of the looming rate at the start of the last glance. If the mismatch hypothesis is valid, then the looming rate at that time should be higher as the last glance duration becomes longer. The mismatch hypothesis for the conjoint effect of closure rate and last glance duration for causing rear-end events must be tested with this and other rear-end event metrics that are independent of glance duration before it can be accepted as valid.

RESPONSES TO AUDIENCE QUESTIONS

In response to audience questions, Young noted that the closure rate is higher for crashes versus near-crashes and there is clear heterogeneity between crashes and near-crashes. Visual attention does not necessarily address the capability level of individuals. Young also noted that detecting the looming event is not like other detection tasks but more related to brain reflex.

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Framework for Identifying Speed-Related Crashes in the SHRP 2 Naturalistic Driving Study Driving Event Dataset

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BACKGROUND

Speeding-related crashes are a serious problem in the United States. In 2014, there were 9,696 fatalities in speeding-related crashes, representing 28% of all fatal crashes (NHTSA, 2016). The SHRP 2 NDS data provide a unique data source to investigate pre-crash factors and for understanding the role of the driver, vehicle, and environment in these crashes. The current research examined speed-related driving events within the SHRP 2 driving event dataset using forward video data and vehicle data from the InSight website (insight.shrp2nds.us).

Initial InSight record queries indicated that there were 437 events coded as having "exceeding the speed limit" or "driving too fast for conditions" as driver behaviors immediately preceding a driving event. (Note: Additional Driving Events became available in September 2017. These new events became available too late to include in the analyses.) This speed-related subset, in conjunction with the nonspeeding baseline events, has the potential to provide unique insight into driver speeding behaviors that precede safety-relevant events. However, closer inspection of the driving events indicated that the range of driving events coded as speed-related included many events that were not of interest from the perspective of understanding the effects of speeding on safety. Specifically, many of these driving events represented scenarios that could not lead to crashes of the type typically targeted by policy and countermeasures, while in other cases speed was completely incidental.

The purpose of this presentation is to describe methodological limitations associated with using SHRP 2 driving event data as surrogates for real crashes, and to outline a framework for using driving event data in a way that maintains the validity and generalizability of the findings.

METHOD

The objective of the analysis was to examine events that were relevant to safety and policy regarding speeding. This goal framed what aspects of events were important. Specifically, event severity had to be applicable to other national data [e.g., Fatality Analysis Reporting System (FARS), Crashworthiness Data System (CDS)], and speed needed to play a causal role, rather than being incidental. Accordingly, the driving events were examined and recoded in terms of new dimensions that better reflected the safety-focused objectives.

The starting point for identifying surrogate events was in terms of kinematic values, such as deceleration level, TTC, etc. The SHRP 2 driving events already incorporate this approach, so the basic level of filtering for severity had already been accomplished by the data provider. Crash severity was redefined along a scale that mapped to more severe crashes recorded in national data (Council et al., 2010). Consequently, it was necessary to identify and exclude irrelevant events, such as curb strikes, parking lot conflicts, etc. For example, recoded crashes shared key characteristics with high-severity crashes, such as roll-overs and collisions with substantial objects. The scope of near-crashes was also refocused so that they aligned better with these crash types. The crash mechanism was also investigated based on speeding crash typologies and observation of the driving events. For example, was there an immediately precipitating aspect that could be plausibly attributed to a consequence of speeding?

Observers reviewed event data and coded multiple variables, including the following:

- Subjective assessment of speeding: Ranged from clearly driving above the posted speed limit (PSL) to too fast for conditions (TFFC) to clearly not speeding.
- Contribution of speed in the event ranged from speed directly precipitated to speed was not a factor.
- Crash mechanism (described below).
- Other contributing factors:
  - Level of driver impairment (e.g., intoxicated, distracted);
  - Driver decision making (occurrence of obvious driver decision errors, including deliberately dangerous or aggressive actions); and
  - How avoidable the event was (would this have happened without speeding?).
  - Degree to which others precipitated the event (i.e., other driver, animal, bicyclist).
- Other InSight driving event variables provided contextual other information.

A key challenge for identifying speed-related surrogate events was to ensure that they could plausibly be caused by speeding. Researchers developed an initial taxonomy of speed-related crash mechanisms and refined it based on observed data. The primary mechanisms included the following.

1. High speed makes it difficult to control the vehicle in a way that keeps it within intended path (vehicle momentum overcomes handling).
2. High speed overcomes tire friction (involves skidding), which directly causes crash or diminishes the effectiveness of the driver's evasive response.
3. Drivers have reduced time and distance to execute an avoidance maneuver.
4. Because of the high speeds, driver perception or interpretation of the driving situation may be compromised.
5. Violates expectations of other drivers (e.g., "appearing out of nowhere").

Researchers reviewed the driving event videos on Insight and coded each event using the new variables and criteria. Figure 5 shows a framework for describing how the variables coded from the driving events could contribute to the nature and severity of the event.

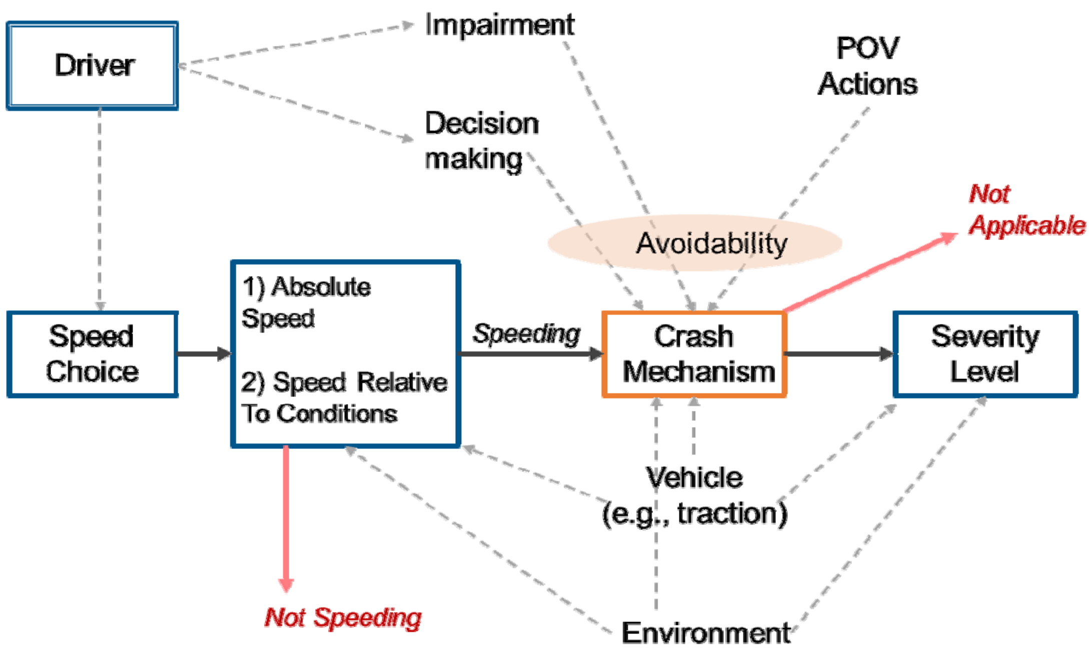

FIGURE 5 Anatomy of a speeding crash.

RESULTS

The recoding exercise substantially changed the nature of the speed-related driving events relative to the existing SHRP 2 coding. With the recoded data, the ratio of near-crashes to crashes was 12:1, compared to a ratio of approximately 2:1 in the original data.

Recoding the events also changed the distribution of crash severity ratings across events. Of the SHRP 2 crashes originally rated as having the highest severity level, 12% remained coded as crashes, 42% were recoded as near-crashes, and the remaining 46% were judged to be too minor to be applicable to the safety scope defined in the objectives. Similarly, with near-crashes, 43% retained this severity level, while 57% of near-crashes were recoded as nonconflicts (i.e., no possibility of collision). Recoding these events substantially changed the distributions of a wide range of event aspects within the sample, such as role of speeding, conflict/crash configuration, and avoidability of the events, among others. Importantly, recoding driving events to meet a specific objective has implications for the conclusions that could be drawn from the samples and generalizability of the findings.

Of the crash and near-crash events that involved clear speeding, the most common mechanisms were: loss of vehicle control (44%), loss of tire friction (28%), and reduced response time (24%) (Table 4). The distribution of crash types was different from previous taxonomies based on fatalities (Council et al., 2014). However, this is expected given that all SHRP 2 collisions were non-fatal. Additionally, a new type of conflict was identified in which the speeding vehicle seemed to violate the expectations of another vehicle, leading to a conflict.

Although the classifications are subjective to some degree, only 13% of crashes and near-crashes appeared to be mostly due to driving at high speeds and 26% of the events were due to driving "TFFC," typically involving adverse weather. In 35% of events, speed appeared to be a contributing factor, exacerbating other primary crash causes, and in the remaining 26% of events, speed was incidental to other solely precipitating factors (i.e., texting).

Table 5 shows how the crash mechanisms were involved in different types of crash events. For roadway departure events, the most common mechanism was low traction followed by loss of control. The primary crash mechanism in rear-end conflicts was low available response time. For turn-into-path and side-swipe incidents, low response time was also the most common mechanism, followed by violations of the expectations of other drivers. Side-swipe conflicts typically occurred when the subject vehicle was traveling at a high speed relative to the principle other vehicle (POV) initiating a lane change into the subject vehicle's lane.

LESSONS LEARNED

The findings have important implications for conclusions about crashes using SHRP 2 driving events. This dataset comprises a unique, detailed view of driving conflicts and crashes that provides information about factors present at the time of safety-relevant events. It is tempting

TABLE 4 Role of Speeding by Mechanism, Crashes, and Near-Crashes Combined

Mechanism:		1	2	3	4	5	
	N	Loss of Control	Low Traction	Low RT	Impaired Perception	Violated Expectations	
Clearly Speeding	25	44%	28%	24%	0%	4%	100%
TFFC	49	6%	86%	8%	0%	0%	100%
Speeding Contributed	69	3%	14%	64%	6%	13%	100%
Speeding was Incidental	49	8%	6%	76%	2%	8%	100%

TABLE 5 Event Type by Mechanism, Crashes, and Near-Crashes Combined

Mechanism:		1	2	3	4	5	
	N	Loss of Control	Low Traction	Low RT	Impaired Perception	Violated Expectations	
Road departure (left or right)	70	24%	63%	10%	3%		100%
Rear-end, striking	56		13%	73%	2%	13%	100%
Turn into Path (both directions)	13	8%	8%	62%		23%	100%
Sideswipe, same direction (L or R)	12		8%	67%		25%	100%
Animal-related	9			100%			100%
Turn across path	8			100%			100%
Other	8	13%	88%				100%

for researchers to conduct queries that return subsets of driving events related to different types of "crash" events and simply conduct analyses on the resulting sample. However, this is a potential trap that can lead to invalid conclusions if the events are not proper surrogates for the target crash types, both in terms of the severity and involvement of relevant causal factors.

The reality is that identifying an initial event dataset is only the starting point. The onus is on researchers to examine and understand exactly what the sample contains. Some events will be relevant to the research objectives, but many may not. Researchers should develop an approach for distinguishing between relevant and irrelevant driving events within a sample. Specifically, events must be selected so that they are linked to plausible antecedent mechanisms and predefined outcomes in a logical way. There are multiple approaches for accomplishing this linkage. However, researchers must understand the implications of their chosen approach, and conclusions and generalizations must conform to the associated limitations.

It must be stated that this analysis is not a criticism of the SHRP 2 driving event dataset. The way the dataset is coded serves an important function for facilitating identification of a relevant pool of events that meet established kinematic criteria (i.e., Wu and Jovanis, 2012). To accommodate research, the driving events are coded to apply to a broad range of issues that are of interest to the transportation research community. However, researchers must acknowledge the specifics of each event and take responsibility for further refining their sample data to focus on only the relevant events.

RESPONSES TO AUDIENCE QUESTIONS

In response to a question on how speeding was determined, Richard Christian stated it was subjective based on a 15-s window by comparison with other vehicles and with consideration of the road type. Speeding was generally categorized as being 10 mph above the PSL, with the additional requirement that the vehicle be going faster than the traffic stream. For many driving events speeding was not determined based on the PSL because it was unavailable.

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Effect of Speed Variance on Crash Frequency on Freeways Using the SHRP 2 Safety Database

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HAO XU
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BACKGROUND

Speed variance is the expectation of the squared deviation of the driving speed from the average speed in a time range. In 2010, AASHTO published the first edition of the *Highway Safety Manual* (HSM) to provide safety knowledge and tools to facilitate improved decision making based on safety performance. The HSM states that a greater change of speed leads to a more severe outcome, which clearly clarified the impact of speed variance on crash severity. But the relationship between speed variance and the probability of crashes is unclear as speed variance is difficult to obtain for previous years. Because of this unclear relationship, speed variance was not readily used in crash prediction models. Also, speed variance information is not a data element in state DOTs' highway datasets and state DOTs are not required to collect and maintain speed variance data. To address the influence of speed variance on crash frequency and to improve the accuracy of the existing prediction models, practitioners need a simple and economic method to collect speed variance. Also, speed variance should be studied in depth. This study addresses the following two questions:

1. How significant is the influence of speed variance on crash frequency compared to road characteristics?
2. How do you describe the influence of speed variance on crash frequency?

METHOD

Driving cycles have been developed to provide a single speed–time profile that is representative of driving. Figure 6 is an example of a driving cycle. Driving cycles are widely used for estimating vehicle emissions and fuel consumption. The detailed speed information of driving cycles—including average speed, speed variance, maximum speed, and minimum speed—can be extracted from driving cycles, which can be used for crash analysis.

In this research, the crash data, roadway characteristics, and driving cycles were generated from SHRP 2 Safety Database. The driving cycle procedure considered the roadway properties of functional class, access control, area, through lane number, speed limit, horizontal curve level, and grade level. This research also considered the influence of LOS to driving cycles as drivers are supposed to have different driving cycles under different LOSs. Speed variance was then extracted for each driving cycle. Crash data on freeways from 2006 to 2012 in five sites

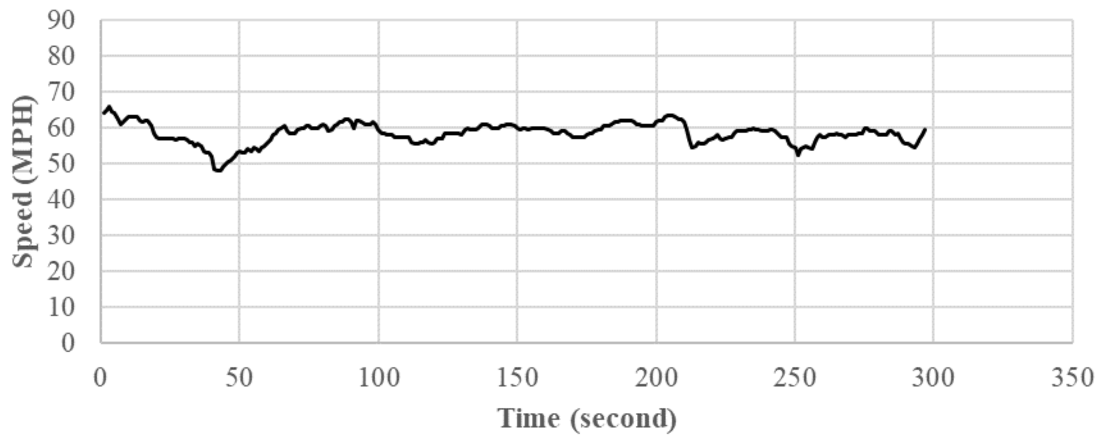

FIGURE 6 An example of a driving cycle.

in the RID supplemental database were taken into consideration in this research. Crash data in different years in each site were first combined into one crash layer based on linear reference system (LRS). The generated crash layers were then matched with roadway features and driving cycle based on LRS. As a result, speed variance, roadway features, and crash data were linked together. Negative binomial regression was selected to analyze the correlation between crash frequency and different factors. The impact of different speed variances on crash rate was also explored based on a power regression model.

RESULTS

The study presents an economical method of extracting speed variance data from driving cycles generated by the SHRP 2 Safety Database. By using negative binomial regression, the importance of different factors on crash frequency was examined. Speed variance is identified as an important influencing factor that is not covered in the HSM. A power equation was generated to reveal the relationship between speed variance and crash rate (Figure 7). The results indicate the crash rate will increase as the speed variance becomes larger.

Speed variance could potentially be added as crash modification factor (CMF) into HSM crash prediction models given this strong relationship with crash frequency. Speed variance can also be considered in real-time crash risk prediction systems for autonomous vehicles technology to provide crash risk warnings to drivers to pay more attention to the current driving situation, which could reduce the potential crash risk. This research focused on analyzing the relationship between crash frequency and speed variance on full-access–control freeways. For partial-access–control and no-access–control highways, speed variance is expected to be larger than freeways as through traffic movement is affected by cross traffic movement. The influence of speed variance on crash frequency of no or partial access control will be studied in future research by the authors.

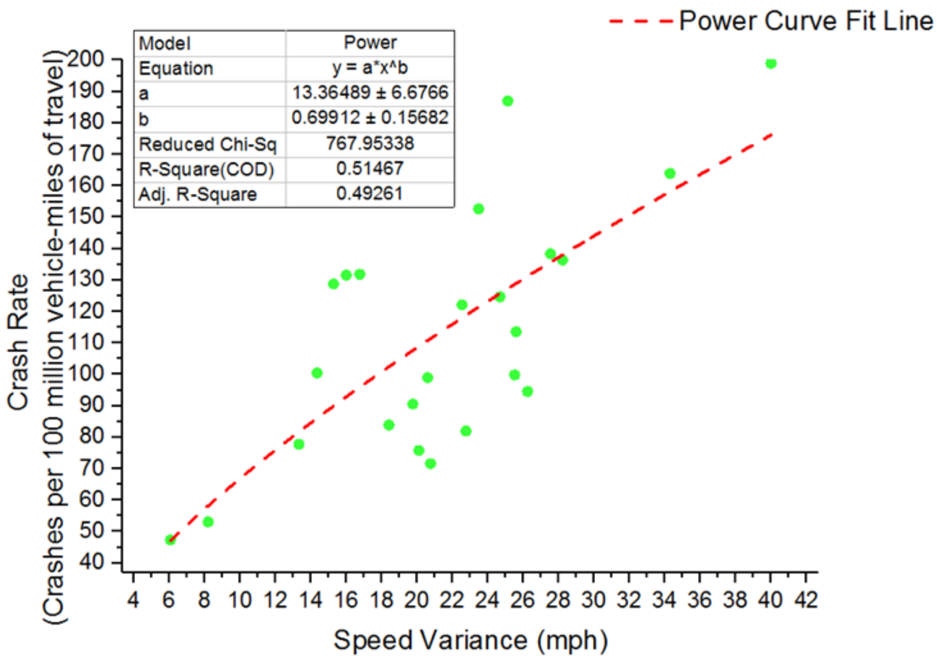

FIGURE 7 The relationship between speed variance and crash rate.

LESSONS LEARNED

Speed variance data collection is traditionally performed by setting up data collection stations which is a laborious effort. In this research, the speed variance is generated from driving cycles using SHRP 2 Safety Database, which is an extension of driving cycle application. State DOTs can potentially extract speed variance data from existing driving cycles. This paper explored the relationship between speed variance and crash rate and recommended to add speed variance as a CMF in the HSM crash prediction model. This could improve the accuracy of the current crash prediction model. The original purpose of this project is to develop methods to extract driving cycles from the SHPR2 Safety Database. But the authors extended the research into the safety area by deep analysis of the data. This paper is directed at researchers who want to extend their current research results into other areas to better use the SHPR 2 Safety Database.

RESPONSES TO AUDIENCE QUESTIONS

In response to questions, Jianqing Wu stated the study did not include data on whether the cruise control was engaged. Further studies should consider the influence of cruise control on speed variance. In this research, other factors were considered but speed variance was the most relevant.

Speed Prediction in Work Zones Using the SHRP 2 Naturalistic Driving Study Data

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BACKGROUND

More than 60,000 crashes and approximately 600 fatalities occur in work zones annually. Work zone crashes are a problem not only for the traveling public but also for highway workers who are injured or killed by errant vehicles. More than 100 worker fatalities occur in work zones each year in the United States.

Work zone crashes are caused by a variety of factors. Driver errors, including distraction and speed, are the main contributors, but the role of speed and distraction in work zones crashes has not been well quantified. Now, however, the availability of NDS data collected by SHRP 2 offers an opportunity for a first-hand observation of work zone safety and of actual driver behavior.

The study evaluated driver behavior in a variety of work zone types to assess which work zone countermeasures and configurations were the most effective in getting driver attention and encouraging speed compliance. Work zones were identified using the RID and confirmed through forward video for driving traces. Speed, acceleration, and pedal position were sampled at various positions upstream and through the work zone. Driver behavior, such as distraction, texting, and glance location as well as corresponding work zone characteristics such as presence of a worker, type of traffic control, number of lanes closed were also coded. A linear mixed-effects model was utilized to model the impact of driver behavior and work zone features on speed throughout work zones.

METHODOLOGY

Work zones were identified using 511 data and then locations confirmed by requesting and reviewing forward videos for several NDS time series traces through the location of interest using the following steps.

Step 1: Identify Potential Work Zones Using 511 Data

The RID contains 511 information for most states and was queried for each of the 3 years the NDS was active (2011 to 2013). The resulting data included around 2 million records. Because 511 data were not available for Indiana, this state was not included.

The 511 files contain information about any traffic event occurring within the study state, including construction. Potential work zones were identified using an attribute query in ArcGIS that was specific to each state. Key words such as “construction,” “lane closure,” “road work,” or “maintenance” were used.

Some information about the duration of the event was usually available, and potential work zones in place for more than 3 days were identified. Three days was used as a threshold because it was unlikely that a sufficient number of NDS time series traces would be available for short-duration work zones. Ultimately, 9,290 potential work zones were identified.

Step 2: Determine the Locations of Potential Work Zone Events and Obtain the Number of Likely Trips

The next step was to link the identified 511 events to the RID data. In some cases, the 511 data were in the form of a single point for each event, which did not indicate work zone extent, or in the form of a line, which provided some indication of work zone boundaries.

When 511 events were related to a link, they were mapped to the corresponding link ID in the RID. When 511 events were provided as a point, they were mapped to the RID, and the nearest corresponding link ID was extracted. Locations for the 9,290 potential work zones were sent to VTTI, and the number of time series traces and unique drivers and the drivers’ age–gender information for the links of interest were requested. Potential work zone trips were determined by identifying the trips falling within the dates indicated in the 511 data. VTTI provided a list of potential trips and unique drivers and the age–gender of each driver.

Step 3: Refine the Extents of Potential Work Zones

The data set resulting from Step 2 was reviewed by the team, and work zones with at least 15 potential trips were selected, resulting in 1,680 potential work zones. In order to request time-series traces, it was necessary to make some estimate of the physical extent of each potential work zone. When 511 data were presented as a link, the link was mapped to the RID, and the corresponding link IDs were extracted. Dynamic segmentation was used to add links approximately 0.5-mi upstream and downstream of each identified work zone to increase the likelihood that the actual work zone was included. When 511 data were presented as a point, dynamic segmentation was used to extract links 2-mi upstream and downstream of the point.

Step 4: Confirm Work Zone Presence and Duration

A list of link IDs and work zone dates was submitted to VTTI. Time-series traces sampled across the duration of the work zone were desired because exact start and end times were not known. Even if these times were recorded in maintenance or other records, work zones did not always start or end on time and records were not always updated. As a result, if a work zone was present at some points and not others within the start–end dates, as observed in the forward video, some attempt could be made to narrow the work zone duration. Several time-series traces and associated forward videos were requested for each work zone. The forward video was reviewed to determine whether a work zone was actually present. The type of work zone and the work zone characteristics were also coded when a work zone was present.

In some cases, no work zone was present. In other cases, barrels were present along the side of the roadway, but the work zone was not considered to be active. These locations were excluded. Additionally, work zones that contained signals or other non-work-zone–related interruptions in traffic flow were also excluded because predicting speed or reaction would have been difficult when external stimuli were present.

Step 5: Request Work Zone Data

A set of 118 work zones on four- or two-lane roadways with shoulder or lane closures was selected. The beginning and end points of each work zone, initially identified in Step 3, were adjusted based on a review of the forward video and corresponding spatial location from the time series data. Once beginning and end points were established, a distance of 1 mi upstream and downstream of each work zone was determined using dynamic segmentation. All link IDs associated with the work zone and the upstream–downstream segments were extracted. Next work zone features, such as work zone signage and the start of the work zone, were identified in the forward video and then spatially located by noting the nearest video time stamp. The time stamp was selected in the time series data and physically located using the most proximate GPS (latitude and longitude) records and interpolation. As a result, the vehicle's position relative to each work zone feature was calculated for each 0.1-s interval (representing one row within the time series trace) for each work zone trip.

Using vehicle position within the work zone, vehicle speed was sampled at 100-m increments from a point 804 m upstream (0.5 mi) to a point 1,207 m within the work zone (approximately 0.75 mi). The work zone beginning point was taken as the reference position (0). This resulted in an equal number of sample points (21) for every time-series trace. Work zone characteristics, such as type of median, number of closed lanes, type of channelizing devices, or presence of a lane shift, were reduced from the forward view video.

Driver distraction, glances, and number of passengers were coded at the VTTI secure data enclave. Weather and road surface conditions were coded using the forward video for each trace. A linear mixed-effects (LME) model was used to predict drivers' speeds at various points in the work zone. LME provides a linear relationship between a dependent variable and fixed effects. Mixed-effects models incorporate both fixed effects parameters and random effects. A random effects variable was included for each driver to account for repeated measurements. Speed (in mph) was the dependent variable.

RESULTS

The final model indicated that speeds decrease as a driver progresses into the work zone but speed becomes reasonably static around 300 m inside the work zone. Different distractions (e.g., using a cell phone, eating) were modeled separately, but an effect for each could not be isolated. As a result, all distractions were combined into one model. The results show that when drivers are engaged in a distraction, their predicted speed is 3.88 mph higher than when a distraction is not present. Female drivers drove 1.99 mph slower on average than male drivers. Drivers who drive more miles annually have higher speeds in work zones.

Drivers traveled on average 17.90 mph slower during nighttime conditions with lighting present than in other lighting conditions. Speeds were lower when cones (6.2 mph) or concrete barriers as opposed to other types of channelizers were present. The effects of dynamic message signs could not be isolated in the present model but will be investigated further.

Additional findings include the following:

- Signing:
  - No impact of first work zone sign,
  - –2.0 mph for variable message sign (VMS), and
  - Decrease at static lane merge (–3.5 mph).
- Driver characteristics:
  - Speed negatively correlated with age,
  - –0.6 mph lower when driver glance is on roadway task,
  - 0.7 m/s higher when interacting with cell phone, and
  - Lower for other types of distraction (interacting with in-vehicle controls, eating or smoking, interacting with passenger). (Note: cell phone users tend to drive faster.)
- Work zone configuration (compared to shoulder closure):
  - Head to head: –10.2 mph slower,
  - Right lane/shoulder closer: –12.5 mph slower, and
  - Left lane/shoulder closer: –0.2 mph slower.
- Channelizing device (compared to cones):
  - Concrete + cones: –3.0 mph,
  - Barrels: –0.7 mph,
  - Vertical panels: –1.8 mph, and
  - Concrete barrier + barrels: –2.0 mph.
- Location:
  - Begins to decrease ~500 m upstream and
  - Levels out ~500 m downstream.

LESSONS LEARNED

A significant contribution of this work was to demonstrate that work zones can be located within 511 data and then matched to work zones identified in the SHRP 2 NDS data. Around 1,680 work zones were located that had at least 15 time series traces. This result suggests that other 511 data can be mined to find situations of interest.

Limitations and challenges for this study include

- Significant data reduction;
- Difficult to read work zone signs from the video;
- Work zones are complex environments;
- Need to account for the impact of multiple work zone devices;
- Sample size (results are from an interim model); and

- Need to develop machine visioning techniques to identify and extract work zone features

Next steps for future research include a need to account for the impact of multiple work zone devices and to develop models for additional work zone types including two -lane and multi-lane work zones.

The expected results of this research are to determine which work zone features or configurations are most likely to encourage appropriate behavior for merging practices and speed. Results should also address the impact of cell phone use on driver behavior and support states implementing cell phone restrictions.

Motorcycle Crash Patterns in Florida

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BACKGROUND

In 2015, 4,693 motorcyclists were killed, representing 13% of the total traffic fatalities, which has raised to the level comparable to pedestrians and bicyclists (known as vulnerable road users or VRUs) fatalities combined. Like VRUs, motorcyclists are not protected by hard shells; but unlike VRUs who generally cannot harm others in traffic crash, motorcyclists can cause serious harm to other road users (including vehicle drivers) due to the heavier weight and higher speed of motorcycles. In most parts of the United States, riding a motorcycle is not a necessity but a personal choice. People who choose to ride motorcycles tend to exhibit aggressive behaviors on the road, such as speeding, unsafe passing, riding in groups, and snaking in traffic. Their behaviors endanger not only themselves, but also other road users. In recent years, the issue of motorcycle crashes has been elevated to the top priority of U.S. DOT and many state DOTs. This study aims at identifying the patterns of motorcycle crashes in Florida.

METHODOLOGY

Florida is a top state of motorcycle crashes in the United States; understanding the patterns of motorcycle crashes in Florida and the major causation factors can help decision makers more efficiently use their safety resources. In 2015, Florida had 550 motorcycle fatalities, the most of any state.

The objective of this research was to

- Offer a methodology that enables a quick grasp of the motorcycle crash patterns in a region, from big picture view down to location specific causation factors.
- Derive actionable information that allow data-driven decision making at both planning and project levels on when, where, and how to invest safety funds.
- Provide leads of what data properties to look into when studying SHRP 2 NDS and other safety data.

This study analyzed Florida's motorcycle crash data from 2011 to 2012 that is included in the SHRP 2 RID. Prior to 2011, Florida's crash records did not contain data fields indicating involvement of motorcycles in a traffic crashes. This study utilized time-series analyses, pivot charts, spatial screening techniques, and site investigations.

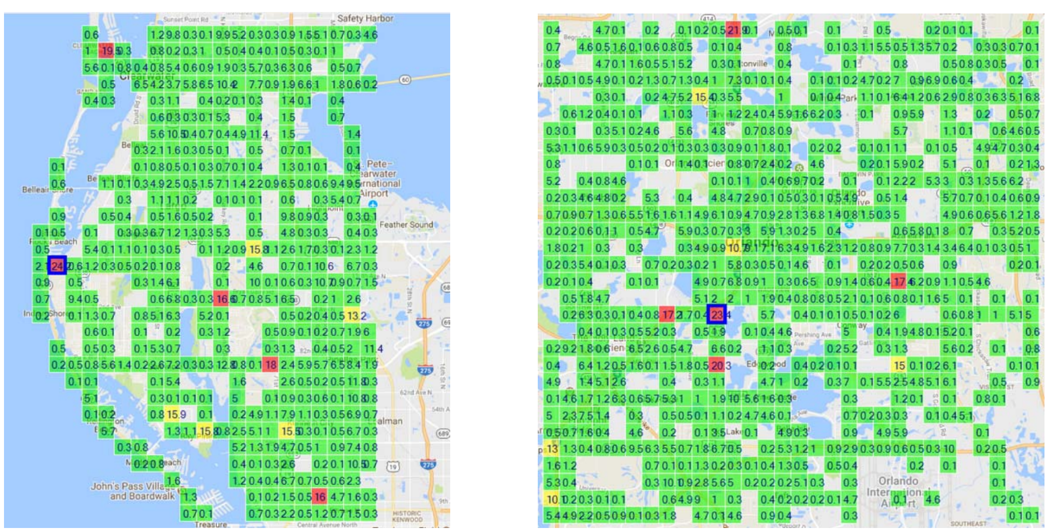
RESULTS

This study utilized time-series analyses and pivot charts to capture the patterns and major causations of Florida's motorcycle crashes. The researchers also used spatial screening techniques to identify high-risk locations of motorcycle crashes, and synthesize the site features of the high-risk locations. For example, the top five motorcycle crash sites identified varied in characteristics by geographic region. Figure 8 illustrates high motorcycle crash locations by crash cost for Clearwater and Orlando. The results are specific enough to allow responsible agencies to take immediate actions to alleviate the motorcycle crashes in their jurisdictions. The methods used in this study are applicable to other states.

CONCLUSIONS

The study identified the following motorcycle crash characteristics in Florida.

- Peak months: March and October.
- Peak days of week: Friday, Saturday, and Sunday.
- Peak hours of day: 15:00 to 18:00.
- Motorcycle crash rate on the state highway system is more than 10 times that of county or city roads.
- More than 50% of crashes are intersection or interchange related.
- Approximately 35% of crashes occur under dark conditions.
- "Careless driving" and "failed to yield right-of-way" are leading motorcycle crash factors.



(a) (b)

FIGURE 8 High motorcycle crash locations by crash costs (red cells): (*a*) Clearwater and (*b*) Orlando.

In addition, the spatial screening technique can help identify high-value locations with more-severe crashes, providing a pool of candidate sites for safety improvements. The map-based site investigation approach provides many clues of what might contribute to the documented crashes. This combined with site-specific crash data analysis can narrow down the causation factors. Large intersections and complex interchanges impose more danger to motorcyclists. Many high-crash sites have schools, hotels, apartments, restaurants, and pawn shops nearby.

RESPONSES TO AUDIENCE QUESTIONS

In response to questions, Zhang stated that motorcycle traffic data is not routinely collected in Florida. Infrastructure and exposure were mentioned as motorcycle crash contributors.

The Association Between Secondary Task Engagement and Crash Risk by Age Group

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BACKGROUND

Driver distraction is associated with engaging in a subsidiary, secondary task that diverts driver attention from the primary driving task. While secondary task engagement is associated with increased crash risk, distraction and resulting crash risk may vary depending on the type of task, driver characteristics, and the driving environment. Essentially, not all secondary task engagement increases crash risk in the same manner for all driver age groups. While distracted driving is risky for drivers of all ages, it is of particular concern among teen drivers. Teen drivers engage in a wider variety of secondary tasks and are more susceptible to distraction by these tasks compared to older and more experienced drivers. According to the NHTSA, 9% of the fatal crashes that occurred in 2015 involving 15- to 19-year-old drivers were attributed to driver distraction, the highest proportion of any other driver age group. However, more information is needed regarding secondary task engagement among novice teenage drivers. The current study uses the SHRP 2 Naturalistic Driving Dataset to evaluate secondary task prevalence and associated crash risk among novice teenage drivers compared to other driver age groups.

RESEARCH GOALS AND METHODOLOGY

The goals of this research are to

- Assess the prevalence of secondary tasks engagement among young and other drivers age groups and
- Identify tasks that are associated with increased crash risk for each drivers' age group

The analysis included a sample of 831 participants from SHRP 2 study, age 16 to 55 years who were recruited from six different states (Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington) and assessed for periods of 3 to 24 months. The entire sample of drivers 16 to 17 years old (*n* = 248; average age 16.6, SD = 0.46; 54% female) and random samples of drivers 18 to 20 years old (*n* = 194; average age 19.2, SD = 0.84; 50% female), 21 to 25 years old (*n* = 196; average age 23.1, SD = 1.5; 55% female), and 35 to 55 years old (*n* = 193; average age 45.4, SD = 6.09; 59% female) were included in these analyses. Data were collected using data acquisition systems installed in participants' vehicles that included multi-axis accelerometers, GPS, and video cameras to monitor the driver's face, hand, and body positioning; drivers' forward and rear views; and the vehicle dashboard (Dingus et al., 2016).

Crash Data Set

A crash event was operationally defined as any physical contact between the driver's vehicle and another object. The threshold value used to detect crashes in the data was gravitational units ≥ .65 *g*-force. The analysis yielded 432 at-fault crash events (determined by coders who viewed each event) across four the driver age groups: 16 to 17 years old (*n* = 195); 18 to 20 years old (*n* = 89); 21 to 25 years old (*n* = 79); and 35 to 55 years old (*n* = 69). To generate a baseline that represented normal driving conditions, random baseline road segments (i.e., data epochs) were sampled for each driver, proportionally to distance traveled. Crash rates for each age group were calculated as the number of crash events per 10,000 mi driven.

Secondary Task Data

Secondary tasks were identified and coded for crashes and baseline data. Each secondary task was assigned one of the 11 following categories: texting, dialing, or browsing cell phone; talking or listening to cell phone; reaching for object(s) (other than phone); interacting with object(s) in the vehicle; interacting with in-vehicle system(s); interaction with a passenger; singing or dancing or talking to self; food and drink intake; self-grooming; smoking; and external distraction.

Statistical Analysis

ORs comparing secondary tasks by type in crash events relative to baselines were estimated using a mixed-effects logistic regression model that included participant specific random effects to capture the between-participant variability.

RESULTS

The crash rate for 16- to 17-year-old drivers was 4.7 times higher than the crash rate of drivers aged 21 to 25 and 35 to 55, and 1.4 times higher than 18- to 20-year-old drivers (data not shown). Next, we examined secondary task prevalence.

As shown in Table 6, the overall tendency to engage in secondary tasks while driving was highest for the 16 to 17 age group and lowest for the 35 to 55 age group (62% and 52% respectively).

TABLE 6 Secondary Task Prevalence[a]

Category	16-17 (%)	18-20 (%)	21-25 (%)	35-55 (%)
Total secondary task	62	58	58	52
Interaction with a passenger	22	16	15	15
Interacting with in-vehicle systems	5	4	4	4
Interacting with objects in the vehicle	2	2	2	2
Reaching	1	1	1	2
Cellphone dialing/texting/browsing	8	9	9	3
Cellphone talking	2	3	6	3
Singing/Dancing and Talking to self	2	1	2	0
External distraction	9	9	8	12
Personal hygiene	5	5	5	4
Food and drink intake	3	3	4	5
Smoking	0	1	1	3

[a] Presence of the task in sampled road segments.

Interacting with a passenger was the most prevalent type of secondary task for all age groups, ranging from 15% in the 35 to 55 age group and up to 22% in the 16 to 17 age group. Manual cell phone use dialing, texting, or browsing, a high-risk secondary task, was highly common among drivers in age groups 16 to 25. The prevalence of cell phone dialing among the teens was about 2.5 times higher than the oldest drivers group (35 to 55 years old). In contrast, the prevalence of food and drink intake and attending external stimulation not relating to driving (external distraction) were highest for the oldest drivers group compared to the three other age groups.

For young drivers (16 to 25 years old), attending external distraction; manual use of cell phone including dialing, texting, or browsing; interacting with objects in the vehicle; and reaching types of secondary tasks were associated with significantly increase in crash risk (OR = 1.49, CI = 1.06–2.09; OR = 1.64, CI = 1.17–2.3; OR = 2.99, CI = 1.71–5.24; OR = 3.09, CI = 1.58–6.06, respectively). Within the young drivers group, the youngest age group of 16- to 17-year-old drivers, crash likelihood when engaging in cell phone including dialing, texting, or browsing was significantly elevated (OR = 1.80, CI = 1.14–2.84). Among 18- to 20-year-old drivers, the likelihood of a crash when reaching and when interacting for objects while driving were OR = 6.14, CI = 2.10–17.96; OR = 5.44, CI = 2.30–12.85, respectively. Operating in-vehicle systems, interacting with object(s) in the car, reaching, and cell phone dialing, texting, or browsing type of tasks were significantly associated with increased crash risk among the 21- to 25-year-old drivers (OR = 3.33, CI = 1.38–8.08; OR = 3.88, CI = 1.11–13.59; OR = 4.47, CI = 1.21–16.44; OR = 2.11, CI = 1.09–4.07, respectively). Interestingly, crash risk estimates for engaging in secondary tasks were not significant for the 35 to 55 age group.

In summary, engaging in secondary tasks was highly prevalent across all drivers' age groups. However, both engagement in specific tasks and their association with crash risk varied across driver age groups. Similar to findings from previous NDS (Klauer et al., 2014), this study shows that for younger drivers certain secondary tasks, including cell phone dialing, can cause distraction and dramatically increase crash risk. Many secondary tasks associated with increased crash risk rely on the visual channel, forcing the driver to look away from the road. Given the high prevalence of secondary tasks reported here, and their likely association with SCEs, policies and practices are needed that limit high-risk secondary task engagement, particularly among young drivers.

LESSONS LEARNED

The extensive data included in SHRP 2 dataset provides a unique opportunity to assess distracted driving in real-world settings, across representative samples of the driver population (Dingus et al., 2016). Our findings are consistent with previous research demonstrating that young drivers are more distracted and at greater crash or performance risk when engaging in secondary task relative to older drivers (Klauer et al., 2014; Lee et al., 2006). The results emphasize the need to distinctly address each driver age group in terms of propensity to engage in secondary tasks and the crash risks associated with this behavior. Future research is needed to determine if young drivers are at an elevated crash risk due to longer duration of glances off road when engaging in secondary tasks while driving, engaging during complicated driving situations, or simply failing to safely divide their attention between secondary tasks and driving.

NDSs could benefit from a more comprehensive assessment of secondary task engagement. Currently, the baseline data set is derived from a random sample of noncrash epochs that provide a useful comparison of second task engagement in "usual" driving. In sufficiently large studies this method provides reasonable estimates of the population prevalence of secondary task engagement. However, these estimates cannot be understood to reflect usual driving in all its complexity. Although this has not been empirically evaluated, the random sampling approach could be biased by the driver group variability in exposure to driving conditions such as night, inclement weather task duration, execution, and frequency. Possibly, machine vision could eventually evolve to automate the analysis of larger numbers of baseline driving epochs (video clips).

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Computer Vision Tools for Automated Feature Extraction in Naturalistic Driving Studies

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BACKGROUND

NDSs that include video and time-series sensor data can encompass literally millions of driving hours. Finding events of interest to a transportation researcher often requires a kinematic trigger. In addition, characterizing driver behavior in the absence of such triggers requires labor-intensive manual coding. Computer vision combined with machine learning can automate the process of feature extraction, where a feature is a behavior or condition of interest to a transportation researcher. Such automated feature extraction (AFE) can lead to knowledge discovery in previously unattainable data streams. In this presentation we show capabilities developed by various parties for the SHRP 2 NDS video data under the auspices of the FHWA's Exploratory Advanced Research Program. These capabilities can detect secondary events of interest as well as characterize driver behavior aspects such as presence of front seat passengers, head pose, body pose, and environmental conditions and surroundings.

METHODOLOGY

Four data sets were utilized for the analysis presented in this work. The first, the VTTI Training dataset, consists of three drivers sharing three vehicles instrumented with SHRP 2 data acquisition systems. The dataset was used with computer vision AFE tools, consisting of two face detectors and head pose estimators with associated confidence values; a hand camera anomaly detector; a body pose estimator; a traffic signal light and state detector; and a vehicle detector with associated brake light detector. The tools were executed across the entire data set (~130 h of video) and anomalies were selected based on threshold criteria tuned for each particular feature extractor. The detected features included proximity of hands to face in the body pose feature extractor; head pose deviation from the median value for the trip (assumed to be facing forward); reconstruction error for the hand anomaly detection; traffic light detection; and vehicle and brake light detection. The analysis consisted of sampling the data at the points of interest to manually confirm event detection.

The second data set consisted of a set of blurred cabin view images from the SHRP 2 data set, selected based on the September 2015 version of the Event Detail Table. Using assumptions about the relationship between the driver seat and passenger seat, a convolutional neural network was trained to differentiate between a passenger in the front seat and no passenger. The third set was the "head pose validation set," developed by VTTI, which contains manual annotated faces.

This set was used to quantify levels of face detection. Finally, a fourth set developed at Oak Ridge National Laboratory (ORNL) with the VTTI loaner data acquisition system was used to test elements of performance that were not easily found in the other data sets, such as head pose, body position, and to measure additional feature extractors such as mouth openness.

RESULTS

Generally, the tools were able to identify events that would not be discovered without intense manual review. Hand motion could be detected but not tracked and was sometimes confounded by overall changes in the scene lighting. The detection of hand-to-face events was successful in that multiple events could be found quite easily. Instances of the driver looking away from the road were also detected fairly easily, with the constraints of a positive face detection required. Coarse head pose could be measured with the tools given the constraints of positive face detection.

Other body pose events of interest were characterized well using the staged data set collected at ORNL. The vehicle detectors were not as accurate as desired and would require additional work to meaningfully augment the radar systems employed in the SHRP 2 study. The traffic light detection was successful in many cases with good agreement with manual selection of the signalized intersections, but sometimes had issues with nearby signals that were not in the field of view due to the geolocation method used. With some of the data sets it is currently impossible to assemble true receiver operating characteristics due to a lack of ground truth, but studies that benefit from finding select, key examples of different behaviors could benefit from these tools.

LESSONS LEARNED

The feature extraction tools could offer a good deal of efficiency improvements for some kinds of transportation research. In particular, for secondary behaviors the hand anomalies, head pose detection, and upper body tracker could prove very valuable for identifying regions of video where researchers could focus further manual data reduction. There is not currently sufficient resolution to distinguish eye gaze. The vehicle detectors did not offer significant benefits over the radar signals available in the study, but with some changes they could offer additional insight into behavior and environment such as vehicle type. The final recommendation is for additional studies to be undertaken to utilize the tools for particular transportation research questions; our sample sets here are primarily for training and computer vision evaluation. Nevertheless, the tools show promise for exploring some aspects of NDS data analysis and knowledge discovery.

AREAS UNDER DEVELOPMENT

ORNL is compiling tools into an “Ensemble Tool” that can run in the FHWA’s Safety Training Analysis Center. ORNL is also working to make improvements to vehicle detection and real-world measurements through the use of the camera model plus radar to spatially locate vehicles in videos. Additional work is progressing on Automated Identity Masking (AIM) including improved data sets, more testing, modified methods and comparison with manually coded videos.

RESPONSE TO AUDIENCE QUESTION

In response to a question, Karnowski said identifying merging actions would be another useful area to investigate.

Using Principal Components Analysis to Characterize Safety in Work Zones

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BACKGROUND

Road work zones are a safety issue for road users as well as road workers. In 2014, 669 deaths, 2% of all road fatalities in the United States for that year, occurred in work zones. Migletz et al. (1998) showed that the safest work zones are those with the smallest increase in the upstream to work zone speed variance. Thus, a particular challenge of work zones is selecting appropriate speed limits and assessing speed variance (and safety in general) dynamically. The objective of this work is to develop a method to characterize "normal" driving in a way to distinguish deviations from normal that are safety relevant. This method is intended to be used in real time. While this approach could be used for any application, we have applied it to work zone driving because of its greater variability and sensitivity to changing conditions. The new insights that are produced by these methods will help identify new or improved counter measures to enhance safety for both drivers and road workers.

METHODOLOGY

This study uses data from the SHRP 2 NDS. The data includes 420 baseline and 243 SCEs—consisting of crashes, near-crashes, crash-relevant conflicts—in work zones, of 20- and 30-s duration, respectively. To limit the overall variability in the events due to different road types and types of work zone treatment, only events that occurred on an interstate highway are used for analysis, i.e., 249 baseline events and 71 safety-related events (12 crashes and 59 near-crashes). These data records were previously confirmed by the Iowa State University Institute for Transportation as occurring within a true work zone. Additional coding of the forward video was implemented in our project to make sure all events have the same categorical variables.

The study used principal components analysis (PCA) with continuous data to reduce and orthogonalize dimensions. In this case, 10-Hz time series of speed and acceleration for 1.5-s periods of driving can be described efficiently with only three principal components (PCs). PCs are linear combinations of the original variables. For each 1.5-s period of driving, speed and acceleration could be described as a point in three-dimensional space. The collection of such points across the 249 baseline events creates a cloud of points in that space that can be thought of as normal driving. SCEs were used to contrast safety-relevant driving to normal driving (Figure 9).

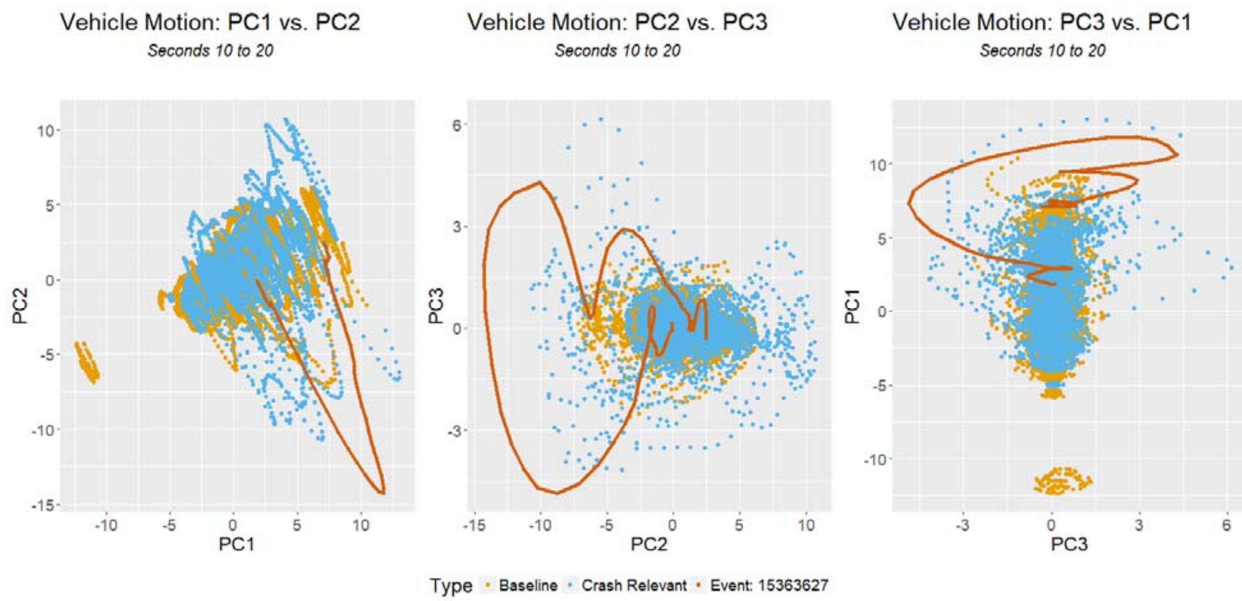

FIGURE 9 PCA, 2-D views (brown is baseline; blue is SCEs; 10 s prior to the precipitation event).

RESULTS

Using three PCs, we were able to develop a distribution of normal driving based on baseline epochs. Over the course of each baseline event, the PC scores for one or more 1.5-s sample within the event fell outside of the normal distribution 34.4% of the time, compared to 100% of the time for SCEs. Even when we consider only the portion of the SCEs that occurred before the precipitating event, over 70% of SCEs had one or more 1.5-s samples that were outside of normal driving. Following this encouraging result, we developed a set of prediction models using the PCs to distinguish between baselines and SCEs. Just before the precipitating event, the performance of the models was well above chance. In particular, increased variability in the three PCs was a key indicator that an event was safety critical. The pilot work suggests that this method can be useful in distinguishing between SCEs and baselines, even shortly before the precipitating event. In particular, we think that PCA might help identify traffic conditions (i.e., driving behavior) that falls outside of normal bounds and thus might represent higher-risk conditions, even without the presence of a SCE. Such a method might also be used to dynamically change work zone speed limits or messaging.

LESSONS LEARNED

About Data

One data element that would be useful for this approach is proximity (e.g., range), but for many of the cases it was not available, or it was unreliable. Lateral proximity was not available in the dataset. Thus, the method can only rely on driver behavior in the form of speed and acceleration.

About the Method

We chose to limit our analysis sample to events on Interstates with the goal of reducing complexity and making the baselines and SCEs more comparable (since they were from different work zones). However, this also reduced the overall variance in the data, which is what PCA is meant to capture. Thus, we may have made the task harder and the results more specific to interstate driving. In a follow-on study, we will use a wider range of conditions and may need more PCs to explain the larger variability.

Insight from the Analysis

One of the unexpected results was that the same three PCs explain variance in speed and acceleration regardless of when the 1.5-s epoch occurred, even relative to SCEs. Thus, this approach, if extended to a larger sample, can be broadly generalized to efficiently describe driving in many conditions. We have only scratched the surface of potential analysis approaches and applications if our results hold on the larger dataset.

NEXT STEPS

Next steps to advance this research include:

- Finalize PCs for more road types and including proximity measures (if possible);
- Improve pilot models to include time sequence indicating impending issues (events starting to leave the normal space);
- Relate PCA normal driving distribution to speed limit and road type, as well as any other key variables (e.g., work zone treatment);
- Develop model of different scenarios to recommend speed limits given work zone conditions; optimize throughput and safety; and
- Consider applications:
  - Dynamic speed limits for work zones based on conditions and
  - Monitoring traffic in work zones for V2X applications (e.g., warnings, dynamic message signs).

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Migletz J., J. L. Graham, and B. D. Hess. Effectiveness and Implementation of Procedures for Setting Work Zones Speed Limits. NCHRP Report 3-41, 1998.

Extracting Association Rules from the SHRP 2 Naturalistic Driving Data
A Market Basket Analysis

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BACKGROUND

According to the NHTSA, more than 6 million traffic crashes claimed more than 35,000 human lives in the United States in 2015. This statistic has promoted researchers and policy makers to investigate the various factors associated with crashes. Over the past few decades, such factors have been studied with data collected from either driving simulators or crash reports. In recent years, researchers have tapped into naturalistic driving data to examine driving behaviors and understand the likely causes of crashes. A few recent studies attempted to identify the significant factors leading to crashes using naturalistic driving data. However, most of the studies relied on traditional analytical techniques that may have limited ability to evaluate crash-causing factors. One of the advanced well-known techniques for identifying association relationships among different variables is the Market Basket Analysis (MBA), which has been applied in marketing research. This technique can potentially be used as a tool to analyze the naturalistic driving data and to understand the impact of driving behavior on crash and near-crash risk.

In essence, this study will (1) extract the association relationships between different variables in the data, and (2) identify the significant factors that impact crash/near-crash risk, and distracted driving likelihood.

METHODOLOGY

This study extracted 23,000 events with 20 different variables from the NDS database. Additionally, the study uses the socioeconomic characteristics of drivers associated with every event. The events and socioeconomic characteristics data are linked through the unique IDs provided in the NDS database (Table 7).

TABLE 7 Event Details and Driver Demographics Data

Variables per each event			
Age	Years of Driving	Annual Miles Traveled	Relation to Junction
Gender	Training	Event Duration	Intersection Influence
Income	License Age	Secondary Task 1	Alignment
Education	State	Secondary Task 2	Grade
Working Status	Vehicle	Front seat passengers	Occupied lane
Marital Status	Driver Behavior	Rear seat passengers	Locality

The data were first cleaned and reduced to eliminate redundancy among variables. For instance, the variables identified as "signal violation, tried to beat signal change," "signal violation, intentionally disregarded signal," and "signal violation, apparently did not see signal" were combined into one category namely "signal violations."

To apply the MBA, the different events were treated as shopping baskets in supermarket transactions. An a priori algorithm was then applied to the different events to extract significant association rules between the different variables in the data. This includes the driving behavior and secondary tasks, and their impact on event severity (crash/near-crash, or normal baseline event). An association rule is defined as ''$X \rightarrow Y$'' or "$X1$, $X2 \rightarrow Y$", 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 association rules are extracted based on three boundary conditions: rule support > 3%, confidence > 75%, and length ≤ 4. The formal definitions of the support, confidence, and lift are as follows:

$$\text{SUPPORT}(X \rightarrow Y) = \frac{\sigma(X \cap Y)}{N} \tag{1}$$

$$\text{CONFIDENCE}(X \rightarrow Y) = \frac{\sigma(X \cap Y)}{\sigma(X)} \tag{2}$$

$$\text{LIFT}(X \rightarrow Y) = \frac{\text{CONFIDENCE}(X \rightarrow Y)}{\text{SUPPORT}(Y)} \tag{3}$$

For a better understanding of these metrics, consider the Venn diagram shown in Figure 10, where the area of the rectangle N is the set of all available observations. The support of the rule ''$X \rightarrow Y$'', 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 defined by the orange are in Figure 10, is interpreted as a percentage of the area of N. 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 10, the confidence of the rule (orange area) is interpreted as a percentage of the summation of both the blue and orange areas. 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 the confidence of the rule divided by the percentage of the green and orange areas from the total area of *N*. The significant rules are then sorted based on a descending lift and the redundant rules are then removed and the nonredundant rules are further investigated to identify the useful ones. An association rule “*X*→*Y*” is redundant if there is another rule “*X**→*Y*”, where the *X** is a subset of *X*, and the confidence and the lift values of the redundant rule are less than or equal to the nonredundant value.

RESULTS

A preliminary sample of the extracted association rules includes the following:

- Rule 1. “{DRIVERBEHAVIOR1=“Drowsy, sleepy, asleep, fatigued”} → {EVENTSEVERITY1=Crash}” Support (0.045), confidence (0.78), lift (4.48).

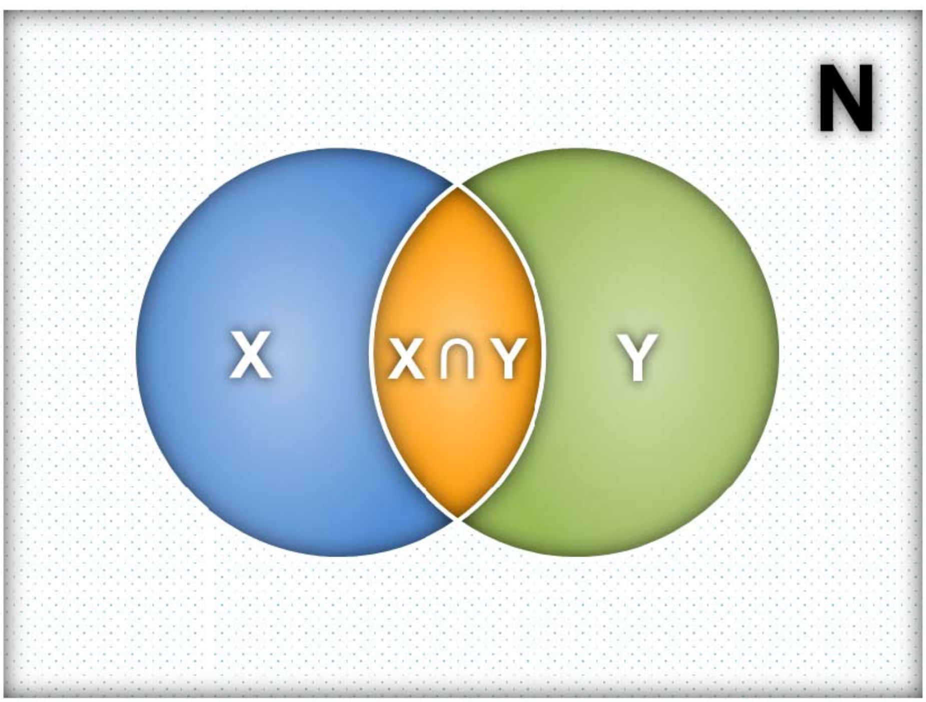

FIGURE 10 Venn diagram presenting the MBA metrics.

- Rule 2. "{DRIVERBEHAVIOR1=None} → {EVENTSEVERITY1=Balanced-Sample Baseline}" 0.74, 0.92, 1.11.
- Rule 3. "{AgeGroup=70-74} → {DRIVERBEHAVIOR1=None}" 0.038, 0.87, 1.069.
- Rule 4. "{MarStat=married} → {DRIVERBEHAVIOR1=None}" 0.32, 0.85, 1.04.
- Rule 5. "{LOCALITY=Residential, EVENTSEVERITY1=Crash} → {REARSEATPASSENGERS=0}" 0.037, 0.96, 1.044.

These rules give an indication of which variables have a significant association with others, what factors increase crash risk, and what factors increase the likelihood of engaging in risky driving behavior. For instance, Rule 1 indicates that drowsy, sleepy, asleep, or fatigued drivers are more likely to get involved in a crash with support and confidence values of 4.5% and 78%, respectively. On the other hand, Rule 2 indicates that normal driving, where no violations are committed and no secondary tasks are performed, increases safety with a support and confidence values of 74% and 92%, respectively.

These association relationships are of importance to decision makers as they give an insight into the type of driving behavior that is more likely to increase crash risk. These association rules also provide insights into the factors that increase the likelihood of risky types of driving behavior. For instance, Rules 3 and 4 indicate that older and married drivers are more likely to drive safely and to avoid risky tasks or behaviors. Rule 5 indicates that for crashes occurring in residential areas, the number of rear seat passengers is most common to be zero. This rule is in accordance with Rules 3 and 4, as nonmarried and young drivers are most likely to have no rear seat passengers for trips through residential areas. However, this rule can also be interpreted as drivers are more cautious when there are rear passengers than when driving alone. Further investigation is needed to verify these findings. The developed association rules will help legislators identify factors of significant impact on crash risk and drivers' compliance to traffic regulations and hence provide effective solutions. These results indicate the effectiveness of the MBA application in safety research, especially with a comprehensive database such as that of the NDS.

Further, the analysis of rules shows an association between the vehicle occupancy and the likelihood of performing improper driving actions, engaging in cell phone texting, reading, or writing, or getting distracted. Whenever the driver is alone in the front seat or there are no rear seat passengers, the likelihood of performing the aforementioned actions increases. Furthermore, all these highly correlated factors are deemed to be highly associated with the likelihood of occurrence of a crash/near-crash event.

In addition, whenever the driver has fewer than 20 years of experience, the driver is more likely to get involved in cell phone texting, reading, or writing activity. Also, there is an increased likelihood of crash/near-crash event occurrence if the driver gets distracted.

Moreover, the normal driver behavior and normal/baseline events show an association with each of the following factors: presence of a passenger in front seat; presence of a passenger in the rear seats; driving on an Interstate, highway, or residential road; driver being married; and crash not being near any intersection.

LESSONS LEARNED

The preliminary results of this study show the effectiveness of MBA in safety research, especially with a comprehensive database such as that of the NDS. To extract association rules in safety research, contingency tables are usually constructed where the different variables are organized in a matrix form to study the relationships between them. As the size of data increases, contingency tables become less efficient to extract association rules, especially when looking at multidirectional relationships between the different variables. The MBA, on the other hand, is a faster and more generalized tool to look through all possible contingency tables that can be constructed for a dataset and extract the useful association rules. Following this fast and more effective way of extracting useful and critical association rules, legislators will have the necessary information to develop policies for reducing the likelihood of crashes or distracted driving, and researchers will have a tool in hand that can be used for applications in safety research. In addition to the usefulness of the MBA, this study also demonstrates the use of NDS data in extracting useful association relationships. This ongoing research will continue to extract all possible non-redundant association rules in the NDS data using the MBA.

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NHTSA. Quick Facts 2016. DOT HS 812 451. National Highway Traffic Safety Administration, U.S. Department of Transportation, Washington, D.C., October 2017.

Development and Validation of Post-Processing Methods for the SHRP 2 MASK Head Pose Data

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MYOUNGHOON JEON
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BACKGROUND

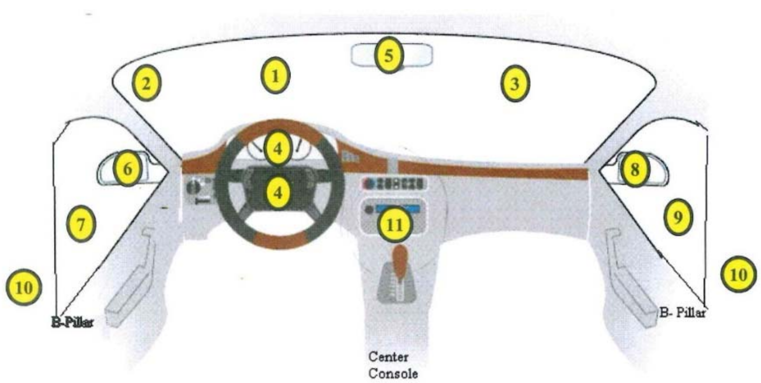
Many highway research initiatives require the use of coarse visual scanning behavior of drivers to evaluate driver response to visual cues or distractions along the roadway. The SHRP 2 NDS data set includes the VTTI head pose estimation system, MASK, derived from the autonomous machine vision processing of the study participant's face video. The MASK head pose data provided by the NDS consists of a machine vision recording for the dynamic pitch, yaw, and roll orientation of the participant's head. The original intent of the data set was to provide researchers the ability to estimate driver looking behavior without using readily identifiable participant video.

However, in a preliminary validation report by VTTI, the MASK data was found to significantly lack the necessary precision and accuracy to estimate driver head pose. The VTTI researchers recommended that the available MASK data not be used for analyses. However, they also indicated that additional post-data collection processing might improve the result. This project explored techniques that can be used to post-process the MASK head pose data and allow it to be more useful for research purposes. In the study, additional post-processing methods are utilized to create a data set that will be capable of discriminating coarse scanning movements to the left and right. An algorithm was also developed that allows for the rapid evaluation of these coarse head scanning movements over thousands of individual trip segments. This will allow future researchers to study a participant looking to the left side or right side of the roadway for potential hazards.

METHODOLOGY

There are two types of data available from the SHRP 2 dataset that could be used to determine coarse driver scanning behavior: the machine vision head pose (MASK) (Figure 11) or a frame-by-frame narrative for the driver eyeglance behavior seen in the participant video (Figure 12). While the machine vision head pose data would be the least-expensive alternative, due to the uncertainty of the machine vision data (as expressed previously), it is necessary to look for a more accurate representation of the driver looking behavior so that it can be compared to the MASK data. In the MASK validation report from VTTI, researchers used an eye glance reduction narrative of the participant video as a statistical comparison to the MASK data (Figure 13). They used this narrative to determine if thresholds are present for a clear discrimination between the different eye

FIGURE 11 Participant video.



782982	Forward
783048	Transition
783116	Transition
783183	Transition
783249	Right Window/Mirror
783316	Right Window/Mirror
783383	Right Window/Mirror
783449	Transition
783517	Transition
783583	Transition
783649	Forward
783716	Forward
783783	Transition
783850	Left Windshield
783916	Left Windshield
783983	Left Windshield
784050	Left Windshield
784117	Left Windshield
784183	Left Windshield
784251	Transition
784317	Right Windshield
784383	Right Windshield
784450	Transition
784518	Forward

FIGURE 12 Eye glance locations and narrative sample.

MACHINE VISION HEAD POSE		*EYEGLANCE REDUCTION*	
LESS EXPENSIVE	✓	MORE EXPENSIVE	✗
LESS INVASIVE	✓	MORE INVASIVE	✗
RAPIDLY EVALUATED	✓	TIME CONSUMING	✗
NOT VERY ACCURATE	✗	MOST ACCURATE	✓

FIGURE 13 Comparison of MASK versus eye glance narrative data.

glance locations. While VTTI determined that no such thresholds are present, it was found in this project that the eye glance narrative could be used as a reference to validate various post-processing methods to systematically increase the confidence of the MASK head pose data.

In this study, to be able to compare the qualitative eye glance narrative with the quantitative MASK data, the individual glance locations for the eye glance narrative were coded. This was accomplished with a measured angle of head rotation recorded for each eye glance location using a wearable orientation sensor (Figure 14). Three participants were asked to sit in a stationary vehicle (both sedan and truck type) while wearing the orientation sensor mounted to their head. In a controlled lab environment, the participants were instructed to look in each of the predetermined glance locations. As they looked at those locations, angles of rotation were recorded for both the pitch and rotation axes. The measurements were collected and averaged from the participants, and from the two vehicle types. The qualitative eye glance narrative data was then replaced with the quantitative angle measurements. This allowed the original MASK head pose data to be compared with the eye glance reduction in a more direct, quantitative manner (Figure 15).

FIGURE 14 Eye glance head rotation measuring.

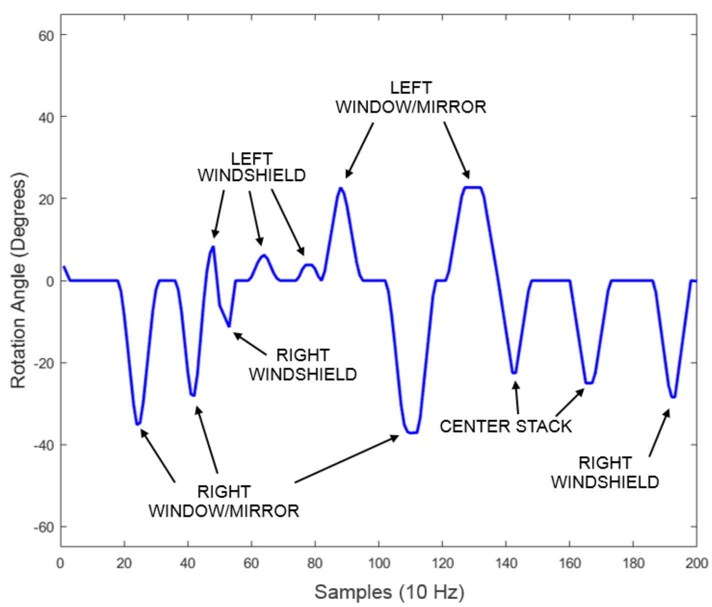


FIGURE 15 20-s sample of quantified eye glance narrative.

After initially comparing the MASK and reduced narrative data for 50 individual trips segments, the MASK data appeared to match the eye glance narrative in contour, but consistently appeared biased with respect to the reference (Figure 16). This could be attributed to the fact that the baselines given by the NDS are averaged over 2 to 3 min, while the samples in this study are only 20 to 30 s long. The provided baseline may not allow the MASK data to accurately represent the driver head rotation behavior.

Now, it can be assumed that for a significant driving period, the driver should be looking at the forward roadway most of the time. Based on this assumption, and the fact that the origin for this data should be centered about the forward-looking position, new baselines could be produced by evaluating the trip sample and determine at what angles did the driver maintain the same head position for most of the trip. To accomplish this, a 2-D bivariate probability distribution of the yaw and pitch data was used (Figure 17). The process uses the kernel density estimation function in MATLAB to produce a 2-D density estimate of the combined pitch and yaw data. The resulting graph shows a peak (or peaks) at the head pose locations occurring most frequently in both the pitch and yaw over the sample period (Figure 18). This peak (or the highest peak if there is more than one) can be used to determine the baseline values over the sample period. This process helped to remove the apparent bias found when comparing the MASK data with the eye glance narrative. Additionally, missing data points were interpolated and a data smoothing process was also implemented to smooth the noisy machine vision data. For this study, a LOESS (local regression) smoothing technique was used, but other methods may be explored in the future. These processing techniques helped to significantly improve the correlation of the MASK and narrative data over the entire sample.

After being able to greatly improve the output of the MASK, an algorithm was developed that would allow for the rapid evaluation of visual scanning behavior over thousands of trip segments. According to past research, if a driver's head pitch (up and down) is within 8 degrees from either side of the origin, but at the same time, their head rotation (left and right) is outside

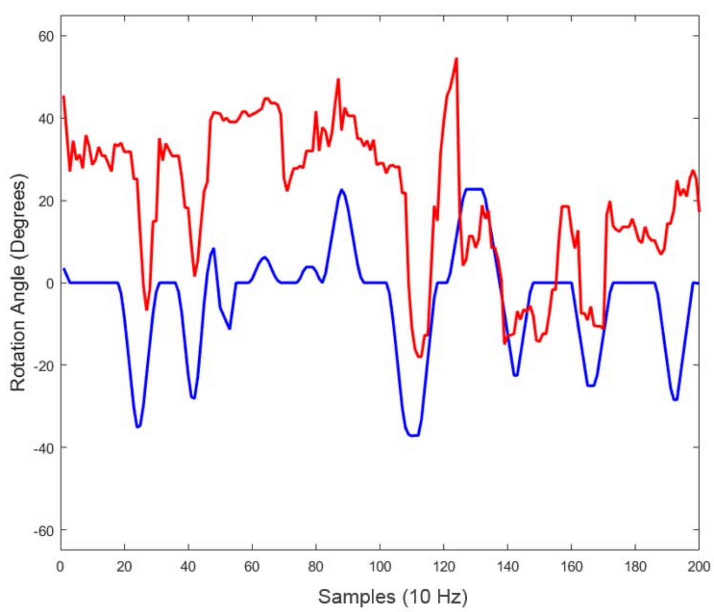


FIGURE 16 Initial comparison of MASK (red) versus quantified narrative (blue).

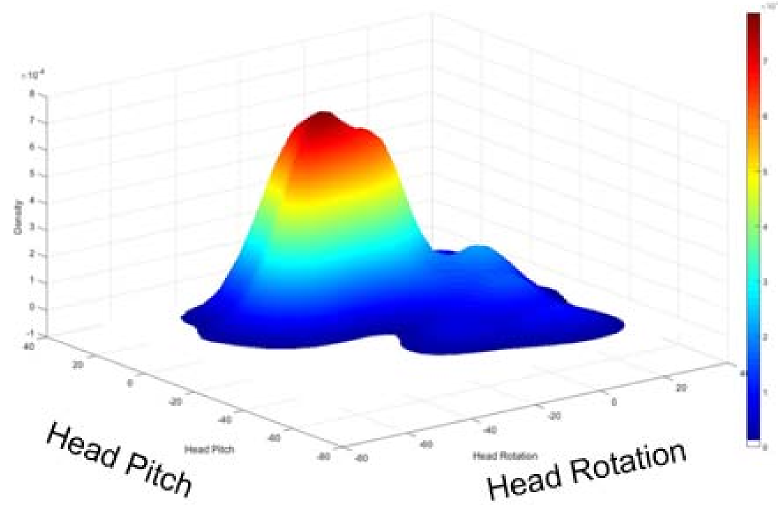


FIGURE 17 Example of probability density function used to determine new baselines.

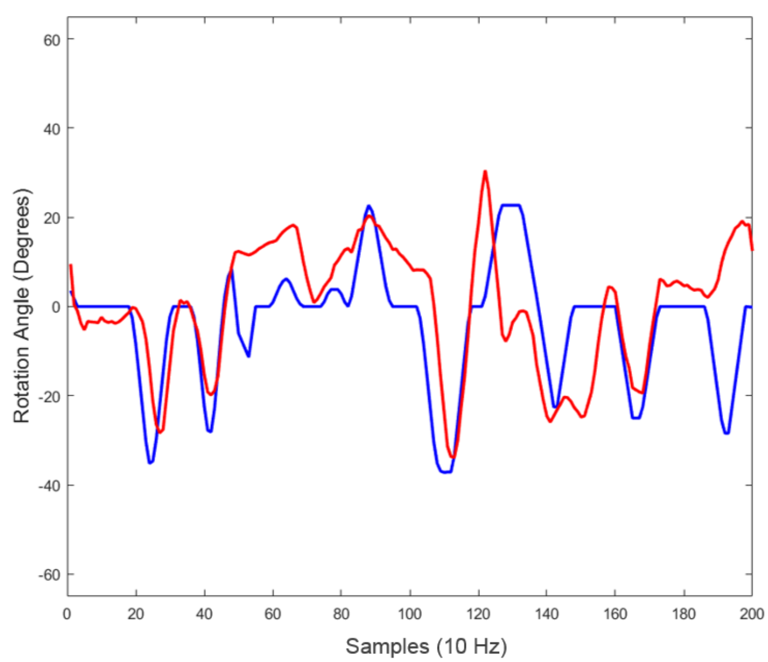


FIGURE 18 Improved data through post-processing (MASK: red; narrative: blue).

of 8 degrees from either side of the origin, then the driver is most likely looking out the left or right windshield–window (Figure 19). Knowing when a driver is looking in this direction can be critical, especially in the case of a distracted driving study. Using this assumption, an algorithm was developed in MATLAB that can distinguish data points meeting these criteria from the rest, and classify them as a left or right glance.

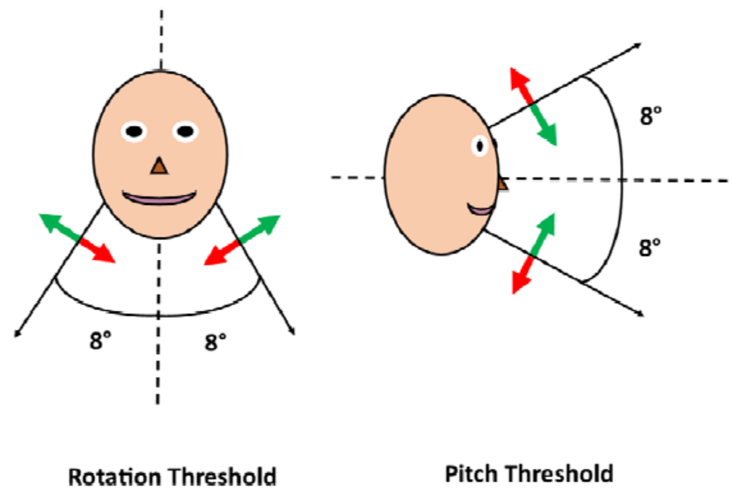


FIGURE 19 Visual scanning criteria for head pose data.

RESULTS

Using the post-processing methods described previously, for the head rotation, an overall 34% decrease was found in the absolute error between the MASK head pose data and the coded eye glance reduction narrative. The head pitch yielded a 12% improvement. Also, using the algorithm to classify left–right scanning behavior described previously, the sample for this study was evaluated for both the processed and unprocessed head pose data. Comparing these results with the eye glance narratives allowed for the determination of the number of true forward and left–right glances that exist within those meeting the criteria, as determined by the algorithm. The goal would be to reduce the number of forward glances that are classified, while increasing the number of left–right glances. The processing techniques described earlier have a positive effect on how the data is classified in the algorithm (Figure 20).

This research shows that the NDS MASK data can potentially be used to establish looking behavior, at least at a rudimentary level. Post-processing techniques are needed to smooth and interpolate the data, and to improve the baseline for the time segment under consideration. Use of the MASK head pose data allows for a much faster and less costly means of evaluating this looking behavior.

Looking behavior could be used to evaluate distracted driving issues and help evaluate compliance with traffic control devices that require drivers to observe traffic conditions. It could also be used to help evaluate driver behavior before traffic incidents or near-miss incidents. In our application, we will use the driver behavior to help evaluate driver compliance with traffic control devices at highway–rail grade crossings. The looking behavior will be combined with speed, brake, and throttle position data from the NDS to create a behavioral score for each crossing traversal. This score will allow us to compare driver behavior between different types of crossings and different individual crossings within a crossing type. The impact of environmental variables like time of day, weather, and driver demographics will also be evaluated.

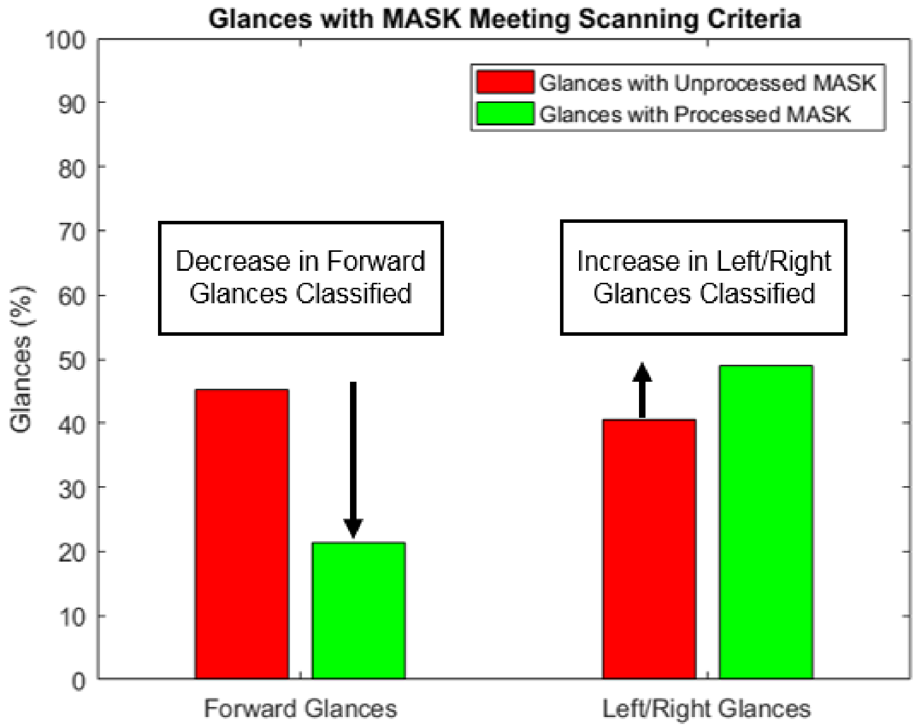


FIGURE 20 Comparison of classified MASK data before and after processing.

LESSONS LEARNED

Analysis techniques developed here can be used in other research efforts to rapidly characterize driver looking behavior. Although this research effort was limited to 20- to 30-s segments, it could be easily adapted to accommodate much longer time periods. Creating a quantitative reference from the trip segment eye glance narrative to use in comparing the MASK data has allowed for the evaluation and implementation of various post-processing methods.

One critical lesson learned is the existence of data discrepancies between the MASK and eye glance narrative data. The MASK data has a varying sampling rate in the range from 2 to 15 Hz, so when scaling it to the constant sampling rate of the narrative, the MASK data was stretched in some areas and blank data points were then interpolated as a result.

Another topic is the uncertainty in the threshold value of 8 degrees for the left–right glance classifying algorithm. Further work may involve evaluating better scanning thresholds using optimization programming for the sample of MASK data used in this research.

Toward Naturalistic Driving Crash Representativeness

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Safety for the Long Haul, Inc.

BACKGROUND

Heterogeneity is seen pervasively in motor vehicle crashes. Crashes have many different scenarios and physical configurations, and each vehicle in a multivehicle crash plays a distinct role. Both conventional and NDS of crash occurrence and causation involve samples of events meant to represent a target population of harmful crashes. Yet crash populations vary significantly from one another, making generalizations from part-to-part or part-to-whole potentially spurious. This is even more true when sampled events are not even crashes but rather are noncrash conflicts.

"External validity" is the extent to which any study generalizes beyond its specific conditions to phenomena of broader importance (*1*). Practitioners could improve naturalistic driving (ND) external validity by more mindful event sampling and by exercising greater caution in extrapolations of ND findings to important target populations. Representativeness might also be improved by differentially weighting objective event profiles to corresponding profiles of target populations. This would treat ND datasets as one might treat an unrepresentative survey sample taken from a population. Potential parameters for indexing include those describing the "who," "when," "where," and "how" of crashes. This treatment would retain the ND advantage of providing videos and other dynamic data to answer "why" questions about individual events.

METHODOLOGY

This presentation was based on ND critiques published by the author including a 2017 TRB Annual Meeting and *Transportation Research Record* paper, Crash Heterogeneity: Implications for Naturalistic Driving Studies and for Understanding Crash Risks (*2*). The presentation also briefly addressed the representativeness of ND studies intended to assess crash and driver fatigue risks associated with commercial truck driver hours-of-service (HOS) rules, based on a 2017 conference paper (*3*).

Both new and previously reported crash and ND statistics were presented. This included statistics from major in-depth "conventional" crash causation investigations including the National Motor Vehicle Crash Causation Survey (NMVCCS). NMVCCS employed stratified sampling and case weighing to generate nationally representative prevalence estimates. Trained researchers investigated 5,471 crashes, each of which involved a light passenger vehicle. Sampled crashes included all five police-reported KABCO severity levels. Crash investigation studies are relevant to ND and to the larger goals of safety research because they reveal basic "who," "when," "where," and "how" characteristics of the target population of ND inference, i.e., crashes causing actual human harm. Such distributions are termed "auxiliary variables" in survey research because they capture objective attributes of target populations which should be matched by samples seeking to accurately represent those target populations.

Judgmentally determined "why" variables seek to explicate crash causation. Of the hundreds of variables coded for each case in NMVCCS, perhaps the most heuristic was the critical reason (CR). The CR is the "immediate reason" for the destabilizing event which became the crash. The human factors-based CR taxonomy employed in NMVCCS and past causation studies is an important paradigm for understanding crash genesis.

Crash statistics show that motor vehicle crashes are heterogeneous in their conditions of occurrence, risk factors, and causal scenarios. ND statistics presented included comparisons of crash configuration distributions of SHRP 2 crashes of different severities, also demonstrating heterogeneity. SHRP 2 crashes were further disaggregated by number of vehicles and fault, with comparisons to similar NMVCCS breakdowns.

Addressed also was the discontinuity inherent in ND capturing of crashes with actual impact forces versus noncrash conflicts where sampling is from dynamic perturbations of various types. Researchers themselves determine the latter based on their event choices. Discontinuity is seen in crash–conflict differences described.

RESULTS

Concerns about the external validity (crash representativeness) of ND mixed conflict datasets include the following:

- Origin, definition, and derivation. Conflicts are dynamic events defined by dynamic criteria, while crashes are defined by material consequences. Conflict typologies (e.g., hard braking, swerves) do not correspond to crash typologies so there is no reason to believe that they would be representative of them.
- Horizontal crash heterogeneity. Crashes are heterogeneous both "horizontally" and "vertically." Horizontal heterogeneity refers to the variety of scenarios seen within any crash severity level. For example, NMVCCS data show sharply different causal profiles for different crash types. Figure 21 depicts the distributions of seven CR types and other factors for four crash involvement types from NMVCCS (*4*). The first five factors are CRs assigned to these vehicles–drivers. The last two factors (alcohol and vehicle) are associated factors which likely contributed to the involvement. Each of the four types shows a distinctive pattern of causal and contributing factors. Even the two rear-end-striking subtypes have notable differences. Conversely, the prevalence of the seven factors varies across the four involvement types.

Vertical Crash Heterogeneity

Similarly, crash causality varies "vertically" with severity, as seen in both SHRP 2 crashes and those in national databases. A 2015 NHTSA report by Blincoe et al. (*5*) (Figure 22) shows the varying presence of six factors in crashes (including both police-reported and non-police-reported) of different severities. NHTSA estimated factor presence for the years 2008 to 2010 based on its National Automotive Sampling System (NASS) and related extrapolations. The severity scale used was the maximum abbreviated injury scale (MAIS), which ranges from

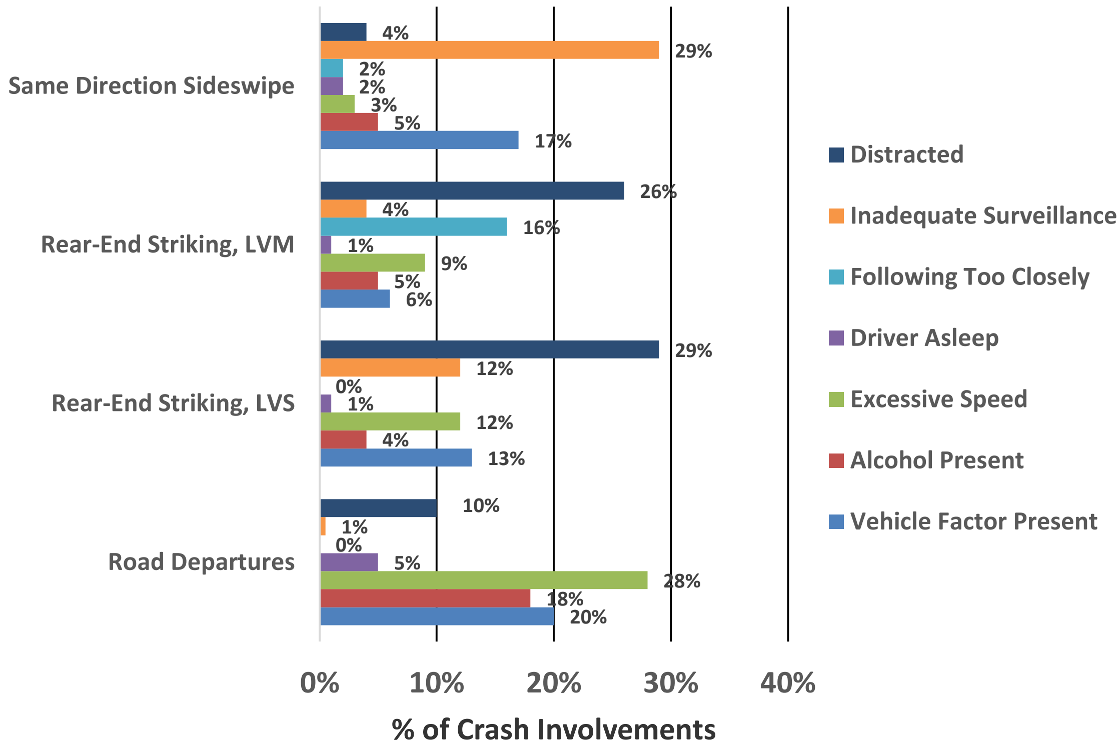

FIGURE 21 Weighted distributions of selected CRs for four crash involvement types in NMVCCS (LVM = lead vehicle moving, LVS = lead vehicle stopped). Distraction includes two types: internal and external. Excessive speed includes three: excessive speed for conditions, to be able to respond, and for a curve–turn. Alcohol and vehicle percentages exclude cases coded as unknown or unreported.

property damage-only (PDO) up to MAIS 6 (fatal) based on the most severe injury in the crash. Crash heterogeneity complicates the representation of specific crash populations, even when using samples of crashes. The challenge faced by noncrash datasets is even greater.

Theoretical Foundation

The historic roots of the ND conflict paradigm are in the writings of H. W. Heinrich. Based on studies of industrial accidents (not traffic crashes), Heinrich formulated the premise that “the predominant causes of no-injury accidents are, in average cases, identical with the predominant causes of major injuries, and incidentally of minor injuries as well.” This foundational assumption ignores the fact of heterogeneity across and up and down the crash triangle. Although Heinrich’s theory assumes otherwise, there is no empirical or analytic link between miscellaneous ND “SCEs and crashes, especially serious crashes where most human harm resides” (Figure 23).

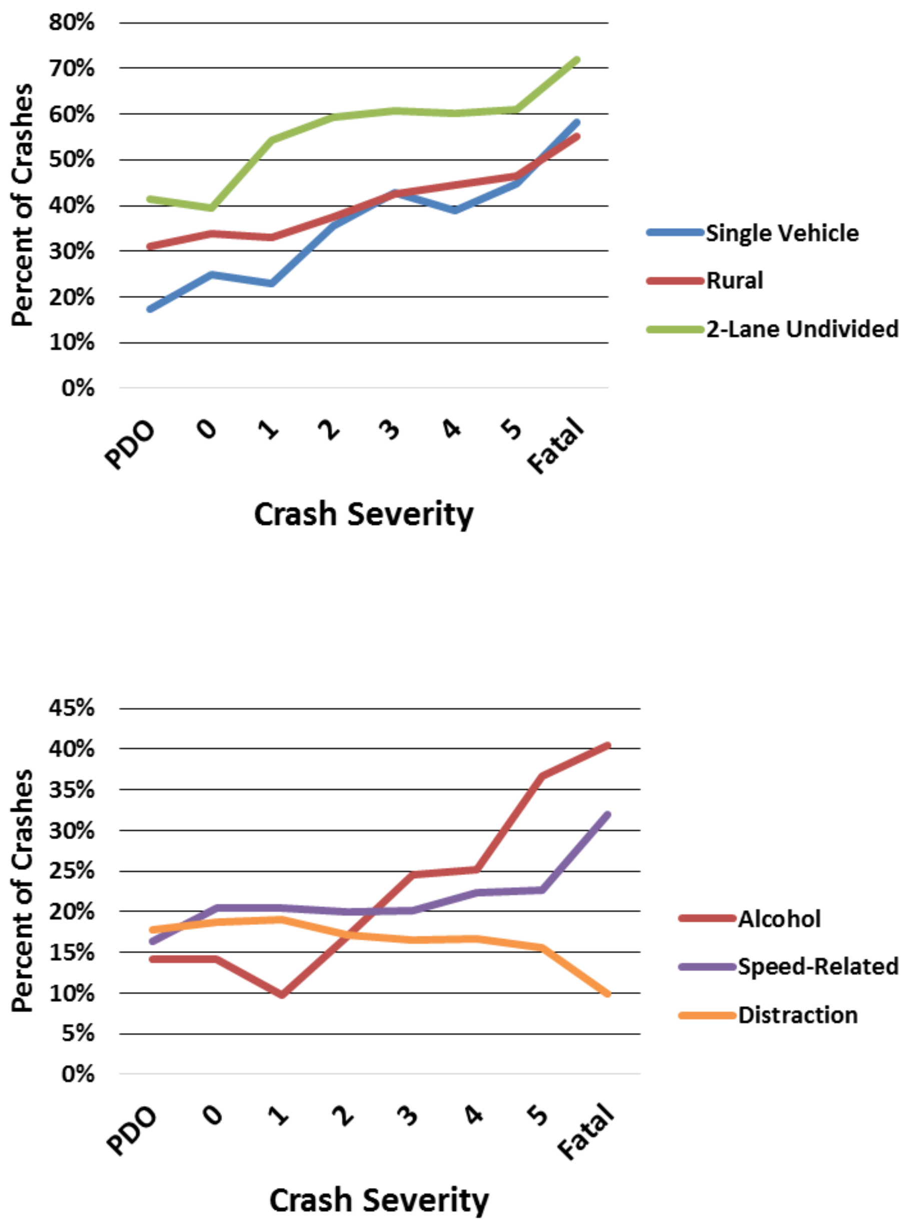

FIGURE 22 Trends in crash (*a*) conditions of occurrence and (*b*) causation-related factors with increasing severity. Note: Data for two-lane undivided includes rural crashes only.

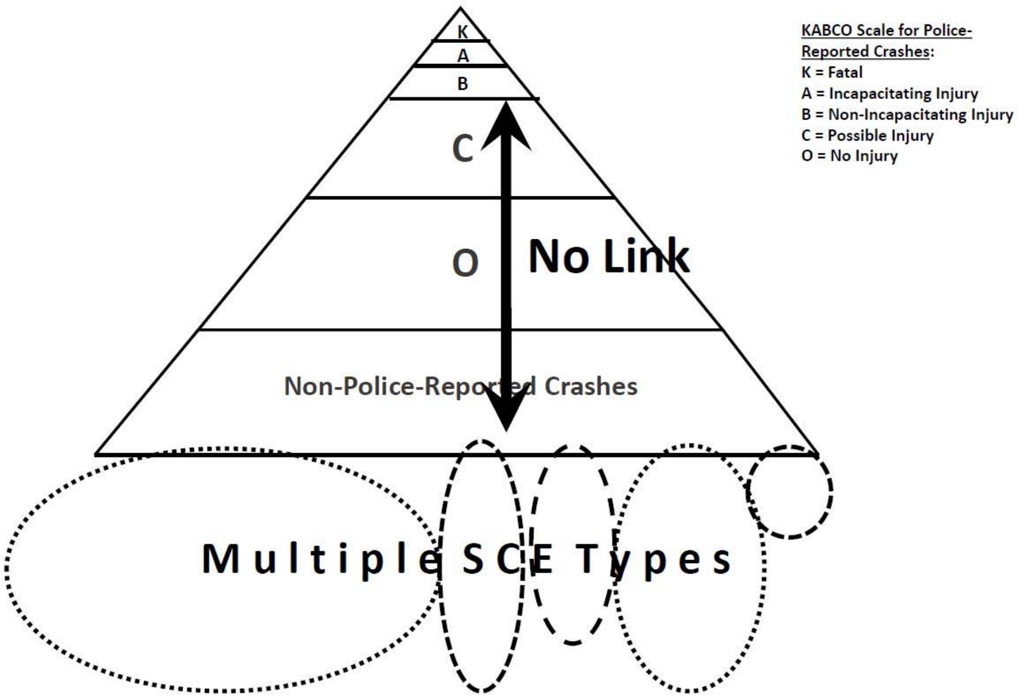

FIGURE 23 Crash triangle for crashes plus multiple ND SCE types constituting many ND event datasets (*6*).

- Conflict-crash contrasts. Studies show sharp causal differences between non-crash conflicts and crashes, even within the same ND study.
- Even weaker links to serious crashes, the most important target population. The vast majority of ND events are not crashes, and, further, the vast majority of ND crashes are extremely minor. Neither noncrashes nor minor crashes represent serious crashes, which, per NHTSA, account for 70% of economic costs and more than 90% of total societal harm (*7*).

Crash involvements can be parsed into three causal categories: (1) multivehicle not-at-fault;(2) multivehicle at-fault; and (3) single-vehicle and at-fault. Percentages for SHRP 2 crash involvements were 18%, 22%, and 60%, respectively. This SHRP 2 distribution contrasts with that of NMVCCS (44%, 39%, 17%). Relative to NMVCCS, SHRP 2 oversampled single-vehicle involvements while under-sampling not-at-fault involvements. This appears to be related to the large number of extremely minor SHRP 2 single-vehicle impacts. The threshold for "nonreportable" SHRP 2 crashes appears to be much lower than that in national survey studies of nonreported crashes.

Commercial truck driver HOS rules are intended to reduce driver fatigue and crash risk by limiting driving and other work hours. Major HOS studies in the past decade have employed ND SCEs as their principal surrogate measures (*8*). Analysis of the events employed, however, indicate that a high majority of these SCEs are not demonstrably fatigue-related in their causation. Moreover, the "how" characteristics of SCEs differ markedly from those of serious large truck crashes (*9*).

LESSONS LEARNED

The following are lessons learned from the results of this investigation:

- The Heinrich Law positing identical causal mechanisms across accidents of different severities is not true in regard to traffic crashes.
- Abstract phrases like “crash risk” have no definite meaning without an accompanying crash population referent.
- Narrow (e.g., within a crash type) are likely to be more valid than broader extrapolations. For example, ND conflict and crash data on a specific involvement type such as “rear-end, striking vehicle, lead vehicle moving” is likely to extrapolate much more validly than the same data encompassing a variety of involvement types.
- ND event datasets combine data from disparate sources: impact forces for crashes and miscellaneous dynamic triggers for noncrash conflicts.
- Mixed ND conflict datasets are not likely to be externally valid in relation to crash populations because they are not derived from those populations. Post hoc numeric indexing might improve validity somewhat.
- All-crash ND datasets such as that within SHRP 2 potentially capture samples representative of the universe of physical contacts experienced by motorists. This does not, however, make their prevalence estimates applicable to crashes deemed important by society.
- The SHRP 2 crash dataset should not be taken as representing U.S. crash populations documented in public records and major crash research databases.
- “Minor nonreportable contacts” within SHRP 2 should not be taken as representing nonreported crashes as defined by NHTSA.
- The validity of large truck ND SCE datasets employed in truck driver HOS-related studies is questionable, both in capturing driver fatigue (construct validity) and in representing overall truck crash risk (external validity).
- NDS is unchallenged in its capabilities to provide “why” answers for individual events captured and recorded by its sensors. Direct observation of individual events does not in itself make prevalence extrapolations accurate, however.
- Comparing NDS event data to the “who,” “when,” “where,” and “how” distributions of important crashes and crash involvements might provide more meaningful insights from this innovative research technology. Such indexing is a standard procedure in survey research and could be applied comprehensively to SHRP 2 and other ND data to improve external validity (*10*).

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Driver Behavior Near Urban Interchanges with Closely Spaced Ramps

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R. J. PORTER
VHB

BACKGROUND

The primary goal of this research is to better understand behavior contributing to crashes occurring in vicinity of closely spaced freeway interchanges through the use of NDS data to quantify differences in driver behavior as a function of ramp spacing and auxiliary lane presence.

The overall project objective is to identify implementable countermeasures that address observed behaviors. By identifying measures of driver behavior that can serve as safety surrogates, countermeasures can be directed at targeting such behaviors to reduce crash frequencies and severities.

The researchers have made significant progress toward achieving the primary goal which is the primary focus of this symposium presentation. Specifically, this presentation describes methodologies developed to quantify the behavior of drivers making merging, diverging, and through movements at freeway interchanges using SHRP 2 NDS data. Measures of driver behavior include those related to lane-change location, lane-change duration, and speed differential, or the difference in speed between entering or exiting drivers and surrounding traffic. Driver behavior differences were analyzed as a function of ramp spacing and the presence of an auxiliary lane between the entrance and exit ramps. Database quality issues, such as correction of maneuver type classifications (e.g., entering, exiting, and through), are currently being addressed and may also result in interesting findings transferable to a range of related applications using the NDS data.

METHODOLOGY

A thorough site selection process was completed and resulted in 56 locations in the states of Washington and North Carolina. The sites were selected to provide a distribution of ramp spacing with and without an auxiliary lane. A sampling algorithm was then used to select 15,825 traversals from an initial set of 244,371 available trips traversing the study sites. Work completed to date has focused on quantifying locations of "entering" and "exiting" maneuvers, durations of lane-change movements, speed differences between maneuvering vehicles and other surrounding vehicles, and estimating traffic conditions at the time that the traversals occur. To summarize:

- Merge–diverge locations. The longitudinal position of each vehicle over the elapsed time of each traversal was estimated by matching the GPS coordinates to a common edge line for each study site. Discontinuities in estimated distances between the vehicle center and adjacent lane markings were used to indicate when a lane change occurs.
- Lane-change durations. Thresholds unique to each traversal were used to measure lane-change durations. This threshold was established by estimating the typical second-to-second variation in the lateral lane position along the entire vehicle trajectory, and identifying when the vehicle's change in lateral lane position exceeds its range of typical fluctuations.
- Merging speed differentials. The speed differential between the instrumented merging vehicle and nearby vehicles is based on radar data and the instrumented merging vehicle's estimated speed. The speeds of nearby vehicles are estimated by combining the instrumented vehicle's estimated speed at a given timestamp with radar range rates.
- Traffic conditions. Time series radar data and instrumented vehicle data (e.g., speed data) are used to estimate traffic conditions occurring in the immediate operating environment near the subject vehicle. Estimates of vehicle speeds and headways will help in understanding some of the effects of traffic conditions on driver behavior and their further impact on safety.

RESULTS

The results of this project continue to evolve as the team explores the data, improves algorithms, and integrates updated analyses into overall findings. As shown in Figure 24, the analysis so far shows most entering vehicles merging into through lanes before traveling 40% to 50% of the distance between the physical ramp gores, with a higher number of drivers waiting longer to merge when auxiliary lanes are present. For exiting traffic, locations with auxiliary lanes show much earlier lane changes than locations without auxiliary lanes. Sites without auxiliary lanes are displaying some detection errors, indicating that the lane-change detection algorithm is more effective at sites with auxiliary lanes.

Analysis also shows low sensitivity of lane-change durations to ramp spacing and auxiliary lane presence (Figure 25). However, data quality issues and lane-change algorithm improvements will be further explored to confirm these trends. Most lane changes require between 3 and 9 s to complete, with an average duration of approximately 6 s, reinforcing other findings in the literature.

It appears that the speed differential does not vary much as a function of ramp spacing or auxiliary lane presence, although sites with longer ramp spacing show fewer cases with merging vehicles traveling slower than other nearby vehicles (Figure 26). Ongoing work is currently examining the impact of other geometric attributes (e.g., ramp length, cross-street elevation, terminal type) to help identify potential countermeasures.

Ten near-crash events were identified across all 56 locations, and included vehicles performing a "through" maneuver, approaching a queue of exiting vehicles, and merging from the entrance ramp. Algorithms to quantify rapid deceleration events and short following distances are part of ongoing analysis. Analyzing both near-crash events and expected crash frequencies as a function of ramp spacing and auxiliary lane presence is expected to help verify behaviors as useful safety surrogates to select or design countermeasures.

Entering Vehicles
Exiting Vehicles

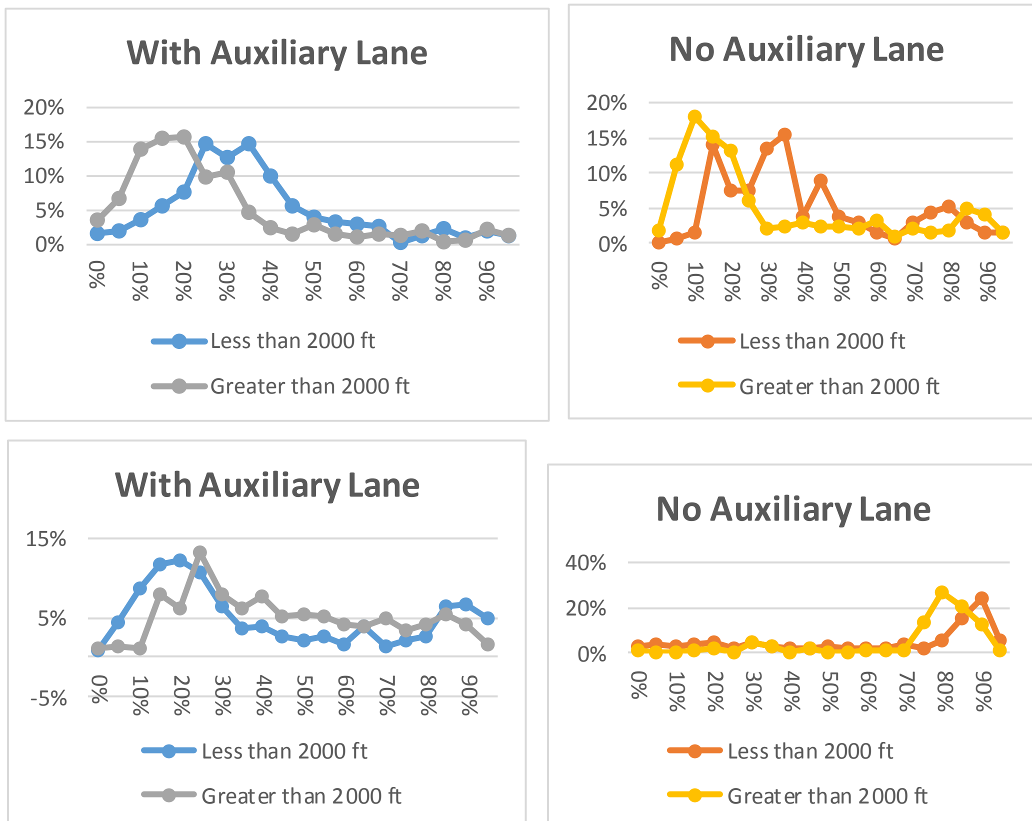

FIGURE 24 Merge location: entering and exiting traversals.

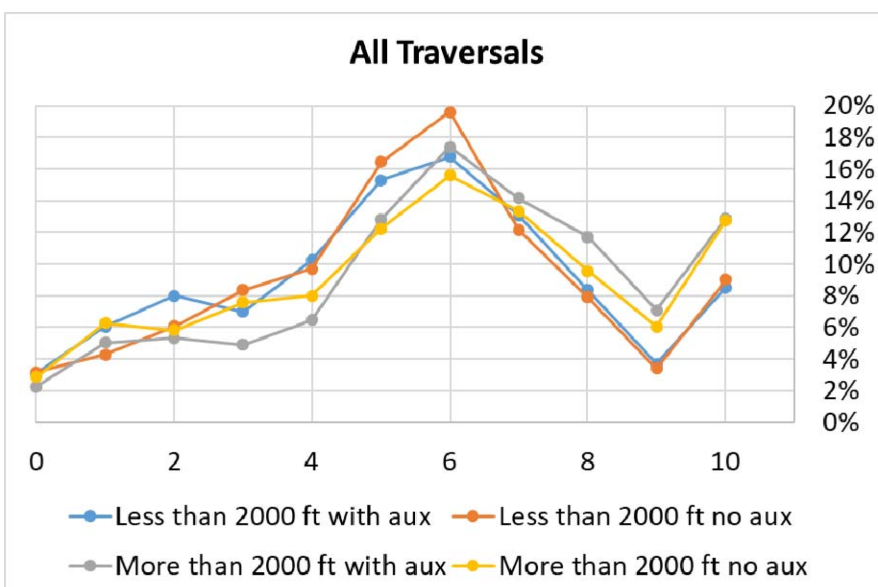

FIGURE 25 Land change duration.

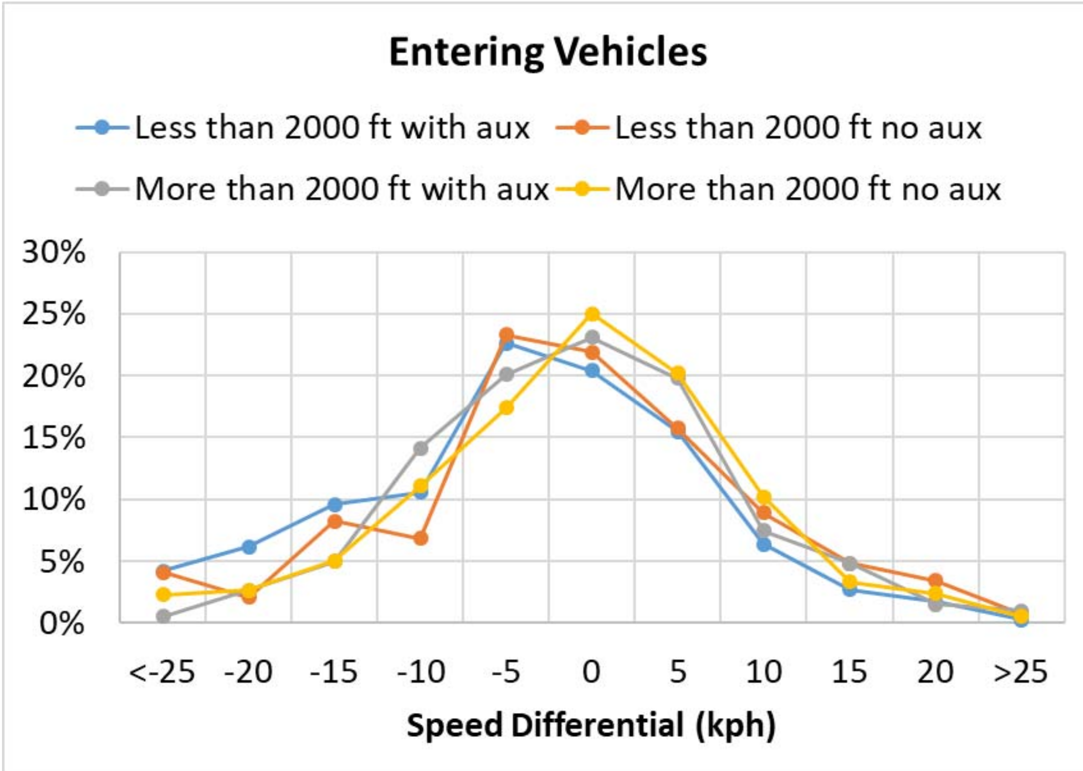

FIGURE 26 Speed differentials.

The research so far resulted in the following preliminary conclusions:

- With an auxiliary lane present, most weaving occurs before reaching half the distance to the exit ramp.
- Most lane changes require 3 to 9 s.
- Slightly faster lane changes were observed at locations with shorter ramp spacing.
- Few effects were observed on merging speed differentials, but there were more negative speed differentials at locations with shorter ramp spacing.

LESSONS LEARNED

This project proposes a range of analysis methods that can be used to quantify driver behavior at urban interchanges with closely spaced ramps with the ultimate objectives of finding valid safety surrogates and designing effective countermeasures. The resulting algorithms and methods, however, are applicable to different facility types, opening new avenues for research to improve our understanding of driver behavior using NDS data. Efforts ranging from site selection, to data requests, time series sampling, and data exploration and analysis are transferable to a variety of research projects.

Through exploring a number of NDS variables, their accuracy, and logical variable combinations to produce reliable measures of driver behavior, the team has gained valuable knowledge useful to other researchers. For example, we created an effective transformation to find vehicle positions that can be compared between sites by referencing GPS traces to a position relative to lane markings, and then finding a percentage distance between known points (e.g., gores of entrance and exit ramps). Contributions and lessons learned from assessing variable reliability show accuracy strengths and issues with specific variables when used for our purposes. For example, attempts to improve maneuver classification accuracy (e.g., entering, exiting, and through) using lane position variables have not been not very successful, but have resulted in promising approaches using statistical analyses of combinations of speed and GPS traces.

Integrating data from different sources for this research has been essential and leaves a number of important lessons. Construction, roadway changes, and incident data collected from aerial photography, street view imagery, and the RID were checked against candidate sites during site selection and sampling to try to minimize confounding factors in our analysis. Aerial imagery was also used to collect additional geometric data (e.g., ramp types, interchange types), which can be included in analyses of driver behavior.

Research conducted in this study is sponsored by FHWA and SHRP 2's Implementation Assistance Program and the Utah DOT, and it is expected to be completed by May 2018.

Using NDS Data to Evaluate Driver Behavior at Highway–Rail Grade Crossings

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DAVID NELSON
MYOUNGHOON JEON
MODESTE MUHIRE
Michigan Technological University

BACKGROUND

Incidents between highway vehicles and trains at highway–rail grade crossings have long been one of the greatest sources of injuries and fatalities related to rail transportation. Although the volume of incidents has decreased significantly since the 1990's it has plateaued in recent years (Figure 27). While the leading cause of crossing accidents is human (driver) behavior, observing that behavior is a challenging task, as crossing traversals tend to take place in "randomized" fashion and infrequently. Our expectation for drivers centers on the traffic control devices (TCDs) in place at the crossing, and on common sense.

The NDS data with its 5 million trips provided an unprecedented opportunity to collect direct observations of drivers negotiating crossings, and to see how they react to the crossing environment, including the TCDs currently used to warn drivers as they approach railway tracks.

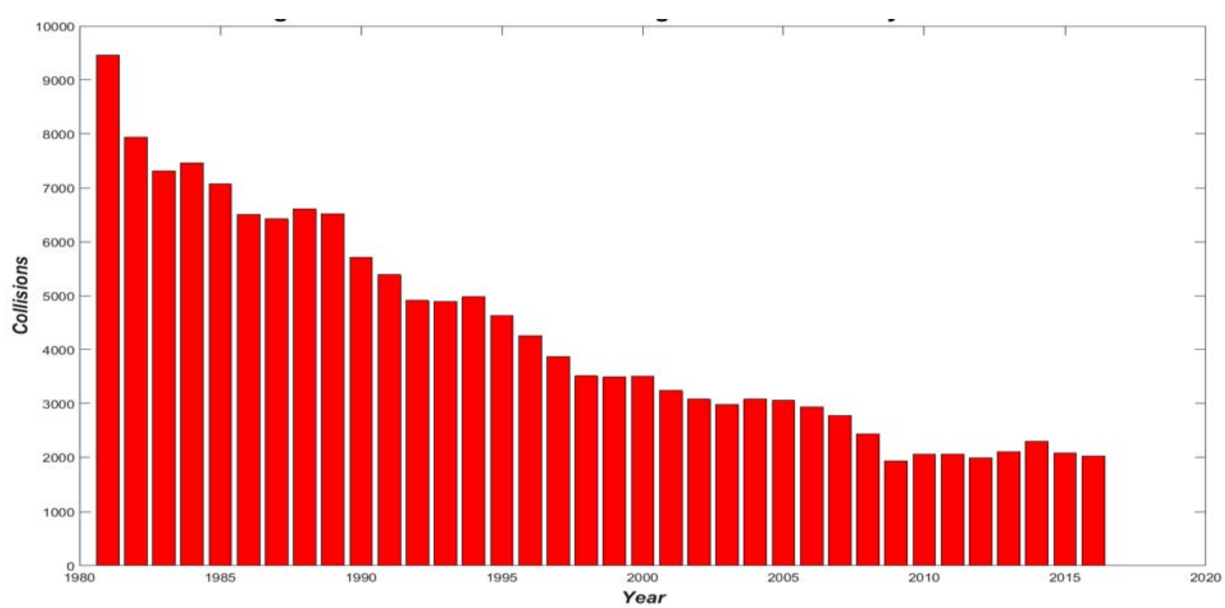

FIGURE 27 Collisions at rail–highway crossings.

The NDS data set includes trip data that can be used to observe driver behavior, and relate it to vehicle position during a traversal of a given crossing. Analysis of that behavior is complicated by the fact that traversals occur at different speeds, and that actions taken by drivers may occur in a different order at any given crossing.

Our analysis combines a variety of sensor inputs to create a compliance score that can be used to compare behaviors across different crossings and drivers. The compliance score focuses on looking behavior and speed profile, including driver preparations to slow and the actual speed and acceleration of the traversing vehicle. We also categorize the crossings based on selected locational parameters and the type of warning devices present. Crossings utilize two broad categories of TCDs: active and passive. Passive measures utilize a crossbuck sign, sometimes combined with a Stop or yield sign. The yield, however, is somewhat redundant, as the official meaning of the crossbuck is essentially the same as a yield. All railroad crossings (not necessarily true for transit crossings) have a crossbuck posted, so that all drivers approaching a crossing should be prepared to stop before reaching the crossing. Our expectation then, is that a driver will prepare by letting up on the throttle, slowing the car a bit (possibly by touching the brake), and visually scanning the area for a train.

METHODOLOGY

We primarily used data from the trip time series for our initial analysis. Brake and throttle positions are used to help assess driver preparation, and are indexed to both time and position during the crossing. Speed and acceleration are available from both GPS and in-vehicle sensors, and again can be indexed to time and position. Finally, head rotation data is available and can be used to assess the looking behavior. However, initial work with the head rotation data revealed some issues that had been previously identified by VTTI. Additional post-processing work allowed us to more reliably assess this behavior.

The selection of crossings to use in our analysis, and of the traversals for each crossing selected, required a separate procedure, so statistical significance could be secured for analysis. Our research team first acquired a copy of the RID from the Iowa State University Center for Transportation Research and Education (CTRE), along with a list of 1,017 crossings from the RID that had traversals in the NDS. We combined this list with information from the Federal Railroad Administration (FRA) Crossing Inventory and Accident databases to create an access database with relevant crossing information about all of the NDS crossings. We used Google Earth and Maps to review conditions at all of these crossings, and included aerial and street-view photos in our access data base for further review. For our initial investigations we devised a method for selecting crossings that involved the type of crossing (active or passive), the crossing configuration, and accident information from each crossing. We used the resulting crossing list to request two datasets of approximately 12,000 traversals of 300 crossings, primarily from the states of New York, Florida, and Indiana. An additional 3,000 traversals will be requested later in the research.

With the data in hand, we used a set of custom designed interfaces and MatLab scripts to pull information about the driver and vehicle speed and acceleration, brake and throttle positions, and driver looking behavior out of our data set. We used this information to develop a compliance score for each crossing traversal, aggregated those scores to analyze driver behavior at the crossings, and compared it to the behavior expected from the TCDs in place.

RESULTS

In general, results suggest that drivers are not behaving as expected at crossings. A crossbuck has essentially the same meaning as a yield sign, so drivers should actively look for a train approaching from either direction, and should prepare to slow down and stop if needed to avoid a conflict with an approaching train. Drivers are not generally looking for a train, and are not preparing to stop except when active measures are in place and active, or when a stop sign is included at the crossing.

There are difficulties with data available from NDS. The NDS MASK data was intended to provide direct input on the looking behavior of drivers. However, the process used to prepare the MASK had difficulty picking up facial features in some situations. There is missing data in some areas, and data with lower confidence in others. Post-processing procedures can be used to fill some of the gaps and smooth the data. The result cannot be used to definitively locate the eye glance, but can be used reliably to establish general looking behavior.

Environmental conditions sometimes mask behavior. Although we can tell when a driver is slowing down, when the brake is applied and the throttle released, and when the driver looks in the direction of a potential train, we cannot know exactly why that is happening. We can control for some potential problems, for example we have forward facing video that can tell us what the vehicle in front of our test vehicle is doing. This lets us remove situations where the driver is responding to traffic in front and not the TCDs. In some cases, the crossing surface is rough, which can cause drivers to slow down, but not necessarily because of the TCDs. We can control for this by evaluating the vertical acceleration of the vehicle with the NDS data. Interestingly, slowing because of roughness could lead to use of tactile TCDs in addition to the visual ones currently in place.

The research team may use results to help develop better TCDs. With an understanding of how drivers are reacting to current TCDs we will be able to propose new devices, or improvements to the existing ones that correct those behaviors.

The research team will use results to validate simulator work, and create faster, more-targeted methods for evaluating TCDs. As part of our ongoing research program we will coordinate the results of our NDS study work with an ongoing driving simulator program at Michigan Tech. We will build simulator scenarios that match the conditions found at crossings included in the NDS data set, and then compare driver behavior between the simulator and real-life environments. Hopefully we can validate the use of the simulator environment to fast track evaluation of proposals for future improvements to the crossing environment.

LESSONS LEARNED

Analysis techniques developed here can be used in other research efforts to rapidly characterize driver looking behavior. Although our research effort was limited to 20- to 30-s segments, it could be easily scaled up to accommodate much longer time periods. Using Google Earth and Google Maps provides a relatively easy method of verifying roadway condition data. Using the MASK data to evaluate looking behavior has shortcomings. We learned how to interpolate and smooth the sometimes incomplete MASK data to achieve a general idea of where a participant was looking. We also developed a technique to find a baseline head position for each of the short traversals we used in our study. A small investigation within our larger study explored how the

MASK data head rotations related to directions a driver needed to look for a train, and found that with some manipulation the data became a more reliable tool. However, further research is still needed to increase the confidence in using the head rotation data for looking behavior.

We found that environmental conditions of the crossing and traversal make it challenging to create general trends of driver behavior. For example, obstructions around crossings may affect timing requirements for visual scanning and speed reductions. In addition, when a driver slows approaching a crossing it could be because the crossing surface is rough, or because of a nearby driveway, or other traffic. Further breakdown of crossings to more finely tuned categories and drivers' response to other environmental and demographic data will be the focus of future research efforts with this data set.

RESPONSES TO AUDIENCE QUESTIONS

In response to questions, Lautala expressed that in crossings with active warning devices, it is clear that almost all drivers rely on their warnings, despite the fact that they are still supposed to be preparing to stop, even without the active warning. On passive crossings, adding stop signs with crossbucks resulted in more compliant behavior that yield signs, but adding yield improved behavior when compared to cross bucks only. It is speculated that this is due to drivers' better understanding on what yield and stop signs mean. These findings could have policy implications in the future.

Impact of Deceleration Lane Length on Vehicles' Speed and Deceleration Rates Based on NDS Data

HUAGUO ZHOU
Auburn University, presenter

DAN XU
Auburn University

BACKGROUND

Freeway crashes occur more often in the diverging area on the freeway. According to 2012 NCHRP Report 730 the average crash rate at freeway deceleration lanes was 0.68 crashes per million vehicle miles traveled (MVMT) which is three times higher than crashes in acceleration lanes (0.18 MVMT). Furthermore, 42.4% of the crashes that occurred at freeway deceleration lanes were rear-end crashes resulting from speed differentials.

The objectives of this study are:

- To determine the speed distribution on the deceleration lane and off-ramp for diamond and partial cloverleaf (parclo) designs;
- To determine deceleration behavior by analyzing deceleration rates and average brake pedal usage; and
- To potentially update standards for the minimum deceleration lane length by utilizing speed and deceleration distribution.

METHODOLOGY

Speed data were used to perform the speed distribution based on the length of deceleration lane and off-ramp by applying nonlinear least squares (NLS) regression models. The NLS regression method minimizes the sum-of-squared residuals between measured and simulated quantities, and the method of least squares is used to estimate the values of the unknown parameters:

$$v = f(L; \beta) + \varepsilon \quad (1)$$

where

f = a given nonlinear function of the explanatory variables L and the parameters β,
L = the length of taper, deceleration lane, and off-ramp (ft),
v = vehicle speed (mph),
β = estimated parameters, and
ε = the error of the specification.

The statistical computing software R was used to develop a best-fitted nonlinear regression model for each study location to perform a speed distribution profile so that the ND speed of drivers along the deceleration lane and off-ramp could be obtained.

Speed data also were marked and analyzed at specific points, including taper start point, deceleration lane start point, deceleration lane endpoint, and off-ramp endpoint. The speed profile along the deceleration lane and off-ramp in terms of the 85th percentile speed, maximum speed, minimum speed, average speed, and standard deviation were summarized from the NDS data to compare the values that were predicted by the NLS model.

Driver braking behavior was identified by brake pedal usage and deceleration rate distribution. Brake pedal usage evaluated the percentage of the drivers who were braking at certain sections, which implied the segments where drivers applied brakes most often. Deceleration rate was determined by taking the derivative of the speed–time based model converted from the NLS model, which is a speed-distance based model. Deceleration rate was also obtained from NDS dataset. Deceleration rate distribution on the deceleration lane and off-ramp was identified to determine the effective deceleration segment.

RESULTS AND CONCLUSIONS

Drivers were not effectively using the deceleration lane as would be expected. By using the speed data predicted from the nonlinear regression model, the speed reduction on the deceleration lane is approximately 20% to 25%, while the percentage of speed reduced on the off-ramp is 75% to 80% with most speed reduced after entering the storage lane at the off-ramp (as shown in Table 8*a* and 8*b*). Although the speed reduction on the longer deceleration lane (2,265 ft) is not as notable as that on the shorter deceleration lane, it is still found to have more speed reduction on the off-ramp than on the deceleration lane. Thus, the off-ramp is more effective for drivers to decelerate than the deceleration lane.

TABLE 8*a* Comparison of Speed Distribution and Speed Reduction Percentage of the Deceleration Lane and Off-Ramp: Speed Distribution Based on NLS Regression Model

<table>
<tr><th rowspan="2">Site</th><th colspan="5">Speed (mph)</th></tr>
<tr><th>Taper Start</th><th>Deceleration Lane Start</th><th>Deceleration Lane End</th><th colspan="2">Off-Ramp End</th></tr>
<tr><td>Location 1-735ft</td><td>72.07</td><td>65.37</td><td>55.37</td><td colspan="2">6.29</td></tr>
<tr><td>Location 2-755ft</td><td>68.32</td><td>64.2</td><td>53.84</td><td colspan="2">1.34</td></tr>
<tr><td>Location3-1380ft</td><td></td><td>60.52</td><td>57.36</td><td>Merge to WB (Left)</td><td>Merge to EB (Right)</td></tr>
<tr><td>Location3-1860ft</td><td></td><td>65.16</td><td>61.16</td><td rowspan="2">43.66</td><td rowspan="2">47.86</td></tr>
<tr><td>Location3-2265ft</td><td></td><td>66.81</td><td>57.81</td></tr>
</table>

TABLE 8*b* Comparison of Speed Distribution and Speed Reduction Percentage of the Deceleration Lane and Off-Ramp: Speed Reduction Percentage Based on NLS Regression Model

Site	Speed Reduction Percentage*					Length of Off-Ramp	
	Taper	Deceleration Lane		Off-Ramp			
				Merge to WB (Left)	Merge to EB (Right)	Left	Right
Location 1-735ft	10.19%	15.20%		74.61%		1370ft	
Location 2-755ft	6.15%	15.47%		78.38%		975ft	
Location3-1380ft		18.74%	24.96%	81.26%	75.04%	5800ft	3010ft
Location3-1860ft		18.60%	23.12%	81.40%	76.88%		
Location3-2265ft		38.88%	47.49%	61.12%	52.51%		
*Note: Speed reduction percentage=speed reduction/total speed reduction from deceleration lane start point to the off-ramp end point							

Brake pedal usage further emphasizes that the effective deceleration segment was on the off-ramp rather than the deceleration lane (as presented in Figure 28). When compared with the off-ramp, the average braking pedal usage for all drivers is higher than the deceleration lane in general (73.19% for off-ramps and 38.99% for deceleration lanes).

The average and 85th percentile deceleration rates were acquired and compared with the Green Book criteria. It was found that the deceleration rates on the deceleration lane were the smallest among diverging areas (taper section, deceleration lane, and off-ramp). Most of the deceleration rates on the deceleration lane and the off-ramp were lower than those assumed by the Green Book, which indicates that the Green Book may need an update on setting up the minimum length of freeway deceleration lanes.

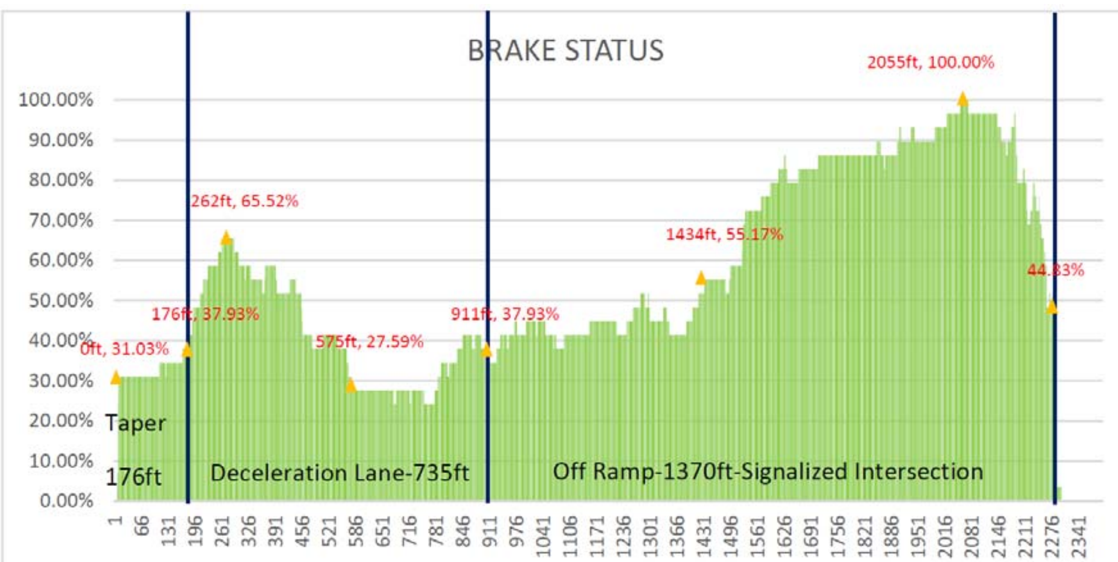

FIGURE 28 Brake status distribution of Location 1.

LESSONS LEARNED

The integration issue of data in terms of discontinuous speed data and blank brake pedal status caused a lot of inconveniences. Most of the time series reports have the speed data at the 0.1-s interval, but some of them contain the speed data at 0.5-s to the 2-s interval. Thus, regression analysis can be used to interpolate the missing speed values. Brake pedal status was unavailable in many time series reports. Only 29 trips in Location 1 and 11 trips in Location 2 have certain information.

The relationship between speed data and acceleration rate in column X was unclear. Speed may decrease with a positive deceleration rate, and the deceleration rate may not be zero when the vehicle remained stopped. This can be solved by taking the derivative of speed data to determine the acceleration rates.

RESPONSES TO AUDIENCE QUESTIONS

Questions centered on driver behavior (some drivers accelerate) and the need for information on the ramp and deceleration lane alignments.

REFERENCE

Torbic, D. J., J. M. Hutton, C. D. Bokenkroger, D. W. Harwood, D. K. Gilmore, M. M. Knoshaug, and J. J. Ronchetto (MRIGlobal); and M. A. Brewer, K. Fitzpatrick, S. T. Chrysler, and J. Stanley (Texas A&M Transportation Institute). Design Guidance for Freeway Mainline Ramp Terminals. NCHRP Project 730, 2012.

Closing Remarks

JAMES P. HALL
University of Illinois Springfield, rapporteur

Hall reviewed the symposium's initial goals, which were to:

- Identify what has been done with safety data;
- Explore what have we learned from the research;
- Bring together researchers and practitioners;
- Provide insights to future applications of the data; and
- Provide a forum for the exchange of ideas.

He believed all of these goals had been met particularly through the presentations, the question–answer periods and the opportunities to network.

The presentations successfully covered a wide variety of safety-related investigations using the SHRP 2 Safety Program Data ranging across vehicle types (e.g. cars, motorcycles), roadway features/infrastructure (e.g., ramps, rail-highway crossings), situations (e.g., work zones, congested traffic) and driver behavior (e.g., speed, teen drivers, distracted driving).

The presentations also covered a wide variation of data integration and analysis approaches and interpretation of results. In particular, driver behavioral analysis, using NDS data, was complex but results are useful for future policy and standard development. The exploration of a variety of data analysis and interpretative techniques are beneficial to the entire community. It is important to be accurate to avoid misapplication of the data. A key focus area for researchers is to properly understand the data in order to attempt to understand the behavior.

Especially evident at the symposium and throughout the research project presentations, was the broad collaboration among researchers and also the SHRP 2 Safety Data Program personnel. Researchers often spoke on advancing their research through data sharing and building on previous data interpretation and analysis approaches.

There are ongoing challenges to the SHRP 2 safety data community. Already, given advances in-vehicle and mobile technologies, driver behaviors are changing from the original NDS data collection. Research should continue to integrate SHRP 2 Safety Program Data with other data sources such as roadway asset data, traffic flow information and meteorological data. Data analysis techniques and tools continue to evolve and there is a need for more rapid analysis in order to impact decision making and change.

The SHRP 2 Safety Data Program provides multiple opportunities to continue to advance the noble cause of transportation safety. Hall encouraged the participants to adapt research results into products that would bring about policy change. The growing fatality and crash rates emphasize the need for solutions. There is a primary need to communicate results and quantify benefits to practitioners and stakeholders. The ultimate goal should be to advance improvements in safety and safety decision making at the local, state, and national levels.

APPENDIX A

List of Acronyms

AASHTO	American Association of State Highway and Transportation Officials
AFE	automated feature extraction
AIM	automated identity masking
CDS	Crashworthiness Data System
CMF	crash modification factor
CR	critical reason
CTRE	Iowa State University Center for Transportation Research and Education
DOT	department of transportation
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
FRA	Federal Railroad Administration
GPS	Global Positioning System
HOS	hours-of-service
HSM	*Highway Safety Manual*
LHS	left-hand side
LME	linear mixed effects
LOS	level of service
LRS	linear referencing system
LVM	lead vehicle moving
LVS	lead vehicle stopped
MAIS	maximum abbreviated injury scale
MBA	Market Basket Analysis
MPH	miles per hour
MVMT	million vehicle miles traveled
NASS	National Automotive Sampling System
NCHRP	National Cooperative Highway Research Program
ND	naturalistic driving
NDS	Naturalistic Driving Study
NHTSA	National Highway Traffic Safety Administration
NLS	nonlinear least squares
NMVCCS	National Motor Vehicle Crash Causation Survey
NEST	Naturalistic Engagement in Secondary Tasks
NTSB	National Transportation Safety Board
OR	odds ratio
ORNL	Oak Ridge National Laboratory
PC	principal components
PCA	principal components analysis
PDA	personal digital assistant
PDO	property damage-only

POV	principle other vehicle
PSL	posted speed limit
RHS	right hand side
RID	Roadway Information Databases
SCE	Safety Critical Event
SHRP 2	Strategic Highway Research Program 2
STAC	Safety Training and Analysis Center
TFFC	too fast for conditions
TRB	Transportation Research Board
TCD	traffic control device
TTC	time-to-collision
USDOT	United States Department of Transportation
VMS	variable message sign
VRU	vulnerable road user
VTTI	Virginia Tech Transportation Institute

APPENDIX B

Symposium Agenda

10th SHRP 2 Safety Data Symposium: From Analysis to Results

October 6, 2017

7:30 Registration and light breakfast

8:30 **Welcoming Remarks**
Neil Pedersen, TRB

8:45 **Symposium Objectives and SHRP 2 Safety Data Program Update**
Ann Brach, TRB

9:00 **Session 1: Driver Distraction**
Moderator: Bruce Simons-Morton, National Institutes of Health
The NEST Dataset: Description and Preliminary Results
Huei-Yen Winnie Chen, Birsen Donmez, and Martina Risteska, University of Toronto
A Study on the Dynamics of Driver Vision Transitions and Its Impacts on Vehicle Safety
Sehyun Tak, Hwasoo Yeo, Yeeun Kim, and Seongjin Choi, Korea Advanced Institute of Science and Technology
Does an Interaction Between Last Glance Duration and Closure Rate Cause Rear-End Crashes?
Richard Young, Driving Safety Consulting, LLC

10:15 Coffee break

10:30 **Session 2: Speed**
Moderator: Joanne Harbluk, Transport Canada
A Framework for Identifying Speed-Related Crashes in the SHRP 2 NDS Driving Event Dataset
Christian Richard, Randolph Atkins, Joonbum Lee, and James Brown, Battelle, National Highway Traffic Safety Administration
Effect of Speed Variance on Crash Frequency on Freeways Using SHPR 2 Safety Database
Jianqing Wu and Hao Xu, University of Nevada, Reno
Speed Prediction in Work Zones Using the SHRP 2 Naturalistic Driving Study Data
Shauna Hallmark, Amrita Goswamy, Omar Smadi, and Sue Chrysler, Institute for Transportation at Iowa State University, Texas Transportation Institute

11:45 Lunch
More room available in Keck 101, 103, 105, 106

12:45 **Session 3: Special Topics**
Moderator: Charles Fay, Federal Highway Administration
Motorcycle Crash Patterns in Florida
Wei Zhang, Lin Xiao, FHWA, National Research Council
The Association Between Secondary Task Engagement and Crash Risk by Age Group
Pnina Gershon, Johnathon P. Ehsani, Sheila G. Klauer, Tom Dingus, Bruce Simons-Morton, National Institutes of Health, Johns Hopkins Bloomberg School of Public Health, Virginia Tech Transportation Institute
Computer Vision Tools for Automated Feature Extraction in Naturalistic Driving Studies
Thomas Karnowski, Oak Ridge National Laboratory

2:00 **Session 4: Data Analysis & Methodologies**
Moderator: Reginald Souleyrette, University of Kentucky
Using Principal Components Analysis to Characterize Safety in Work Zones
Carol Flannagan, Andrew Leslie, Selpi Selpi, University of Michigan, Chalmers University of Technology
Extracting Association Rules from the SHRP 2 Naturalistic Driving Data: A Market Basket Analysis
Saleh Mousa, Sherif Ishak, Osama Osman, Louisiana State University
Development & Validation of Post-Processing Methods for the SHRP 2 MASK Head Pose Data
Aaron Dean, David Nelson, Pasi Lautala, Myounghoon Jeon, Michigan Technological University
Toward Naturalistic Driving Crash Representativeness
Ronald Knipling, Safety for the Long Haul, Inc.

3:35 Coffee break

3:45 **Session 5: Roadway Features**
Moderator: Nicole Oneyear, Iowa State University
Driver Behavior Near Urban Interchanges with Closely Spaced Ramps
Jeffrey Taylor, Juan Medina, R. J. Porter, University of Utah, VHB
Using NDS data to evaluate driver behavior at highway-rail grade crossings
Pasi Lautala, David Nelson, Myounghoon Jeon, Modeste Muhire, Michigan Technological University
Impact of Deceleration Lane Length on Vehicles' Speed and Deceleration Rates Based on NDS Data
Huaguo Zhou, Dan Xu, Auburn University

5:00 **Closing Remarks**
James P. Hall

5:15 **Networking Reception**
Keck Atrium, 3rd Floor

7:00 **Close**

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