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The impacts of heavy rain on speed and headway Behaviors: An investigation using the SHRP2 naturalistic driving study data

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ABSTRACT

Adverse weather conditions can significantly impact roadways by influencing roadway conditions, vehicle performance and driver behavior. Vehicle user characteristics and behavior can be considered as the most important factors affecting the driving task. The ability to see objects in motion, so called "dynamic visual acuity", and the proper reaction process, such as headway and speed selection, are imperative factors for safe driving. In this study, data from the SHRP2 naturalistic driving study (NDS) are used to provide better understanding of driver speed and headway selection behaviors in clear and rainy weather conditions. A unique procedure to identify rain-related trips from the massive SHRP2 database was introduced in this study. In addition, roadway information database (RID) and NDS were utilized to compare driver behavior in clear and heavy rain conditions using matching trips. Matching trips were defined as trips with same driver, same vehicle, and same traversed routes. Preliminary descriptive statistics, partial proportional odds model, as well as geographical information system analyses showed significant differences between driver behavior and performance in clear and rainy weather conditions. One interesting finding of this research is that drivers were less likely to drive above the speed limits on road segments with higher posted speed limits. In addition, it was found that the probability of reducing speed more than 5 kph below the speed limits were 23% and 29% higher in light rain and heavy rain, respectively. Not only will the findings of the study help in providing better insights on drivers' behavior and performance in rainy weather conditions, but it will also serve as a foundation for further studies to investigate driver behavioral factors in other weather conditions using naturalistic driving data.

1. Introduction

Human error has been identified as one of the main causes of traffic crashes. A previous study showed that 45% to 75% of crashes were human error-related (Hankey et al., 1999). The taxonomy of driver errors has been investigated in previous studies (Treat et al., 1977; Hankey et al., 1999; Stanton and Salmon, 2009). As an example, Treat et al. (1979) have taxonomized driver errors into three main groups including "*errors of recognition*", "*errors of decision*", and "*errors of performance*". Despite the previous efforts into human error role in car crashes, the types of these errors that drivers make need to be more investigated, specifically in different traffic and environmental conditions. Driving in adverse weather conditions might be challenging due to the slippery roadways and reduced visibility. In addition, it might introduce complexities for drivers in selecting appropriate speeds and headways, which may have a significant impact on the safety and operation of freeways. Identifying factors affecting driver speed and headway selection behavior are important for policymakers and traffic engineers. This will help in overcoming the gap of the unpredictability of driver behavior

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and will help to set appropriate speeds in Variable Speed Limit (VSL) systems during various weather conditions.

2. Literature review

Inclement weather events such as fog, snow, ground blizzard, slush, rain, and strong wind, affect roadways by impacting pavement conditions, vehicle performances, visibility, and drivers' behavior (Donnell and Mason, 2004; Peterson et al., 2008; Ahmed et al., 2015). Adverse weather conditions can result in a sudden reduction in visibility on roadways leading to an increased risk of crashes. According to the Fatality Analysis Reporting System (FARS), inclement weather of rain, snow and fog/smoke resulted in 5897 fatal crashes between 2005 and 2014. The National Highway Traffic Safety Administration (NHTSA) reported that weather contributed to over 22% of the total crashes between 2005 and 2014 (Hamilton, 2015). In Canada and the UK, such crashes account for approximately 30% and 20% respectively (Hambly et al., 2013; Vogt and Bared, 1998). The financial burden of weather-related crashes in the US is approximately $42 billion US dollars (Strong et al., 2010).

The impact of vision obstruction caused by adverse weather conditions on traffic safety and operation has been investigated in previous studies. Brodsky and Hakkert, 1988 investigated the risk of traffic crashes in rainy weather conditions. The study found that the risk of injury crashes in rainy weather conditions could be significantly 2–3 times greater than in clear weather conditions. Two main risk factors were associated with the added risk caused by adverse weather conditions in their study, including the slippery road surface and reduction in visibility. More specifically, they found that the longer stopping sight distance needed due to a reduction in friction between the tiers and the wet road surface might be more challenging on curves. In addition, the reduction in visibility during adverse weather increases the risk of crashes, which might be exacerbated at night due to glare and distraction provided by shining surface conditions. A study by Andrey et al. (2003) investigated the impact of adverse weather on crashes severity in several Canadian cities. They found a 75% increase in total crashes and a 45% increase in injury crashes in comparison with clear weather conditions. Another study by Ahmed et al. (2012) reported that an additional one-inch increase in precipitation elevated the risk of a crash by 169%. They mentioned that the added risk of crashes could be doubled in snowy seasons due to the interaction between steep grades and surface conditions. The literature shows a variation of crash risk estimates; however, a general trend can be concluded that adverse weather and road conditions can easily elevate the risk of crashes.

Rahman and Lownes, 2012 found that drivers might reduce their speed, maintain a larger headway and drive more carefully in adverse weather to compensate for reduced visibility and slippery road conditions. Drivers make decisions based on their risk perception. Drivers' decisions to adjust the crash risk can be investigated at three hierarchical levels including strategic, tactical, and operational (Fuller, 2005). The strategic level can be defined as those decisions that usually are made off-road and called "off-road decisions". Decisions at this level can be travel mode alternation, route change, trip timing change, etc. Tactical and operational decisions are made on the road. Particularly, these decisions are made in high-risk circumstances, including but not limited to speed adaptation, lane changing, headway increments, and evasive maneuvers (Afrin, 2013). Each of the mentioned decision stages might be affected by adverse weather conditions. More specifically, driver attentiveness and control behavior are two important factors that might be negatively affected by adverse weather conditions (Andrey and Olley, 1990).

As mentioned earlier, effects of adverse weather conditions on the operations and safety of transportation are considerably researched; however, the primary elements of driver behavior and performance are not well researched or understood. Few recent studies utilized vehicle kinematics to better understand driver deviation from normal driving under inclement weather conditions (Ahmed et al., 2017; Azizi et al., 2018; Ghasemzadeh et al., 2018a, 2018b; Ghasemzadeh and Ahmed, 2018, 2017; Kamrani et al., 2018). Road-user characteristics and behavior are among the most important elements influencing the driving task. Aggregate traffic and weather parameters e.g., average speed, headways, and global weather information were used in previous studies. These studies utilized traffic and weather data collected from inductive Loop Detectors (ILD), Automatic Vehicle Identification (AVI) systems, and Roadway Weather Information System (RWIS) to separate 'crash prone' conditions from 'normal' conditions (Barrett and Pigman, 2001; El-tawab and Olariu, 2010; Xu et al., 2013). Although the approach is novel, the aggregation level of traffic and weather information might have some limitations. Drivers' performance and behavior are absent in safety modeling due to lack of driver data. The second Strategic Highway Research Program (SHRP2) has collected the most comprehensive Naturalistic Driving Study (NDS) data. This study will help in gaining insights into driver's dynamics of adapting speeds and selecting headways, and what cues are the most effective in providing drivers with a more realistic variable speed limit system. It will also provide valuable information about how drivers interact with roadway and weather, which can be used for effective countermeasures. The unique NDS data will enable researchers to understand the role of driver performance and behavior in various highway research. The NDS data will allow for better understanding of how drivers adjust their behaviors to compensate for increased risk due to a reduction in visibility.

The research approach includes; (1) development of data queries of the NDS and RID data, (2) reducing and extracting relevant information for the study from the NDS video data, (3) conducting a preliminary analysis to better understand drivers' performance and behavior in different weather conditions, and (4) developing a speed and headway selection models to identify contributing factors affecting speed and headway behavior in different weather conditions.

The main goal of this study is to examine the feasibility of using the SHRP2 NDS data to enhance the understanding of how drivers respond to rainy weather and road conditions in case of speed and headway behaviors. This will be conducted by compiling a sample dataset from the NDS data, then extracting and reducing the data for heavy rain and their matching clear weather events on freeways to address the following research questions:

1. Can inclement weather trips be identified effectively using NDS and RID data?
2. Can driver responses (i.e., speed and headway adaptation) during a reduction in visibility due to heavy rain be characterized and

analyzed efficiently from the NDS data?

3. Data source

The Naturalistic Driving Study (NDS) data used in this study were a subset of data reduced from the Second Strategic Highway Research Program (SHRP2). The NDS data is collected and maintained by the Virginia Tech Transportation Institute (VTTI). The main goal of the SHRP2 is to investigate the latent causes of highway crashes and congestion in a timely manner program of focused research. Identifying and implementing countermeasures that have significant safety benefits through a comprehensive understanding of drivers' performance and behavior. More than 3400 drivers in six states (Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington) were recruited in this project. Driver vehicle use was recorded continuously during the SHRP2 NDS project, which has made this project the biggest naturalistic driving study with collision prevention concentration in the US. Since crashes are one of the main causes of non-recurring congestion, collision prevention policies have added advantages not only for safety applications but also regarding fuel consumption and delay mitigation strategies. The Roadway Information Database (RID) was also utilized in this study, RID was created in parallel with the NDS data. The RID contains inventory data related to the six NDS states and also includes additional data on crash histories, general weather information, work zones, and ongoing safety campaigns. The NDS and RID data can be linked to provide a rich data source associating driving behavior with roadway and environmental characteristics (McLaughlin and Hankey, 2015).

4. Data acquisition and preparation

The initial acquisition of data is crucial to the success of this study and it presented a unique challenge for researchers to develop a creative and unique method for leveraging the full extent of the provided NDS and RID data. Dealing with the NDS data could be challenging for various reasons; the size and complexity of the data, the continuous nature of the data, the difficulty of identifying events of interests, processing and reducing video data, linking NDS data with RID data, identifying surrogates for increased traffic safety risks, and defining baselines in normal driving conditions.

Unlike many previous NDSs, identifying weather-related trips from the massive SHRP2 database is unique. In this study, a novel extraction process was developed to identify rain-related trips from the SHRP2 database. The process relied on the time series wiper status variable to identify cases where wipers were active at high speed for an extended length of time along freeway segments. Minimum duration for high wipers settings (level 2 and level 3) was considered as 5 min. Using wiper status only may not be appropriate to identify other adverse weather conditions such as slippery surface and foggy conditions. While the research team is working on other methodologies to identify other adverse weather conditions in the SHRP2 NDS data, the main focus of this study was to identify the effect of rainy weather conditions on driver behavior and performance. To address the first research question of identifying appropriate trips in rainy conditions, a preliminary criterion for data extraction was identified. A total of 80 NDS trips during rain/heavy rain and additional 160 NDS matching trips (same driver, same vehicle, same route) in clear weather conditions on freeway segments from Florida and Washington States were targeted in this study. The data extraction procedure can be summarized as shown in Fig. 1:

As mentioned earlier, extracting rain-related trips is a challenging task because of various reasons. Even though wiper setting can be considered as an indication for rain-related trips and rain intensity, preliminary investigation of the received sample trips showed that wiper settings are not consistent across different vehicles. In addition, wiper settings in the NDS data indicate the position of the wipers switch rather than swipe rate of the wipers. Moreover, drivers' tolerances towards the rain/visibility are different. Finally, driver choice of the appropriate wiper speed might be affected by splashes from other vehicles. Therefore, a unique procedure as shown in Fig. 1 was developed to extract rain-related trips without introducing bias to the sample data.

Before acquiring the full NDS trips in rainy weather conditions, 5 sample trips were investigated to identify possible issues with the NDS data. There was an issue encountered during the preliminary investigation on the five sample trips to fine tune the extraction process: the wiper blades of Honda Civic vehicles did not cover the whole windshield in front of the camera. Moreover, only vehicles with multiple wiper settings were targeted; vehicles that did not include the full spectrum of values for the wiper status (0, 1, 2, and 3) were filtered out – as vehicles with only on/off wiper settings would not provide an indication of rain intensity. Preliminary investigation of precipitation rate in SHRP2 States showed that Florida and Washington could be good candidates for identifying and extracting possible rain-related trips. Hence, months with high rain precipitation in the states of Washington and Florida were targeted for this study. In addition, preliminary investigation of the received sample trips revealed that trips not occurring during daylight on freeways should be filtered out; freeways were considered due to the project scope and nighttime trips were eliminated because of the low video resolution, specifically in adverse weather conditions. Potential events were tagged with the duration of the trip that different wiper settings of 0, 1, 2, and 3 were active to facilitate data extraction for light/heavy rain conditions. Finally, each identified trip in rain was matched with two trips in clear weather conditions for the same driver, route and vehicle.

In order to reduce the NDS time series and video data, a semi-automated methodology was developed, which has the ability to reduce the dimensionality of the data by considering variables that are relevant to characterize driver behavior in rainy weather conditions. After considering variables of interests (e.g., speed and headway), each trip was divided into one-minute segments. In fact, a previous study revealed high variability in weather conditions within single trips (Ghasemzadeh et al., 2018a, 2018b). Hence, dividing each trip into 1-min chunks can help researchers to create more homogeneous segments considering the similar traffic and environmental conditions. Next, manual video observation was conducted to extract and verify additional information including roadway type, weather conditions, surface conditions, visibility and traffic conditions from the forward view camera. Wyoming's

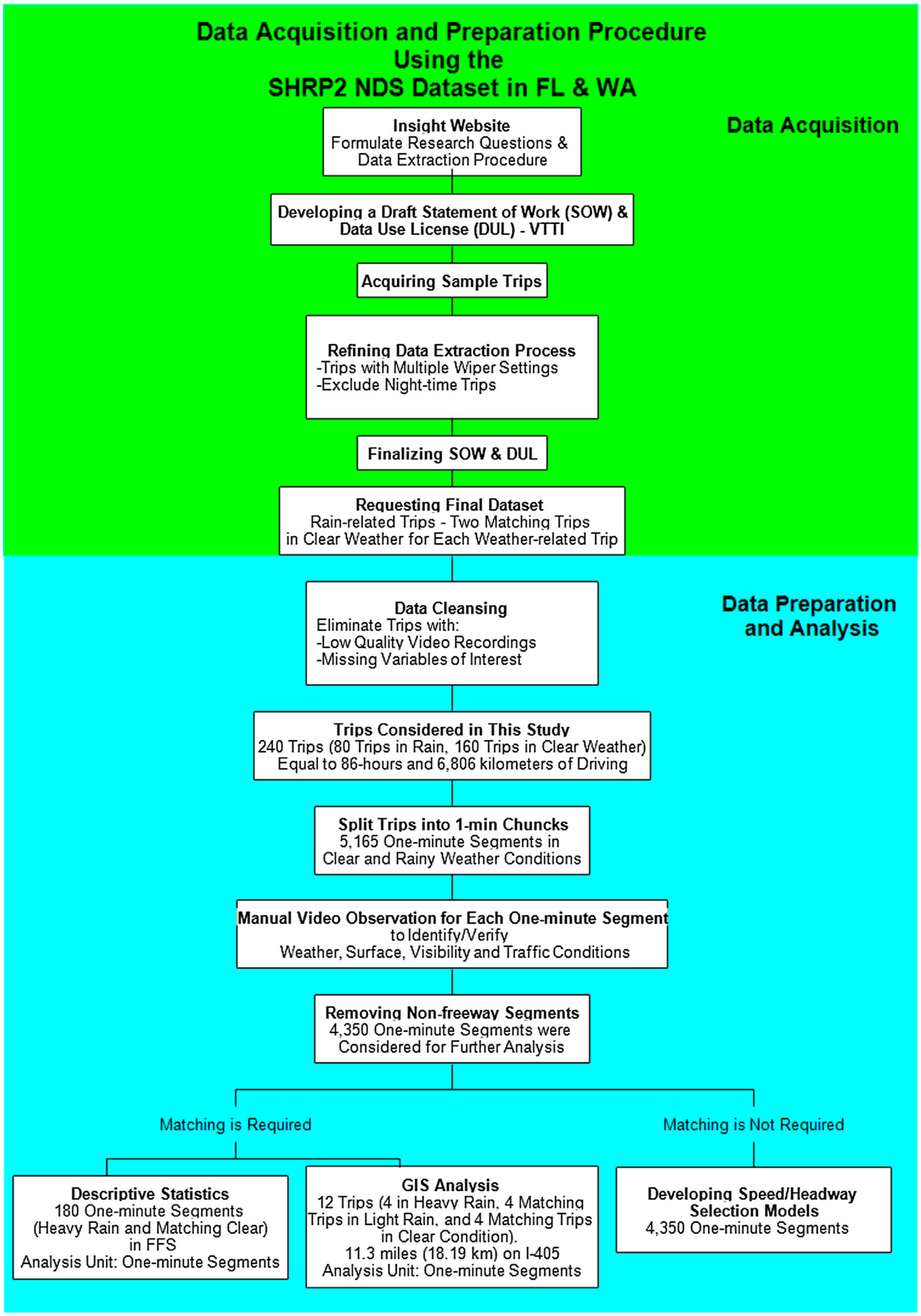


Fig. 1. Data acquisition and preparation procedure using the SHRP2 NDS dataset.

Visualization and Visibility Identification Tool (Fig. 4) was utilized by video observers to report traffic and environmental conditions for each 1-min segment, effectively.

It is worth mentioning that real-time traffic data are not available in the NDS data. Therefore, to isolate the impact of rainy weather conditions on driver behavior, trips in free-flow traffic were identified using the manual observation of the forward facing videos. Traffic conditions were categorized into two groups including mixed traffic and free flow speed conditions. More specifically, traffic density was characterized based on the driver ability of selecting speed and maneuvering between lanes considering number of vehicles present in the NDS driver's travel lane. A free flow speed conditions is considered in absence of leading traffic in any lanes or when leading vehicle is present in one lane, but NDS driver is still not affected by other vehicles. Other conditions where NDS drivers were affected by other vehicles were considered as congested traffic. It is worth mentioning that travel times can also be used to identify traffic conditions. More specifically, travelling within the speed limit can be an indication of a free flow conditions. All NDS trips were manually checked to extract traffic information and verify weather conditions.

As mentioned earlier, in order to verify rain-related trips and differentiate between light rain and heavy rain conditions visual inspections of all NDS videos as well as analysis of wipers status for each one-minute segment were utilized. More specifically, if the wipers were used at level 3 that segment is considered as a heavy rain. In addition, if the wipers were used at level 1 or 2, that segment is considered as a light rain trip. Finally, a trip with inactive wipers (level 0) is marked as a clear weather trip.

It is worth noting that other basic trip characteristics including number of brake activation, Electronic Stability Control (ESC), roadway departures, number of Anti-Lock Braking System (ABS) activations, and number of traction control activations were also considered in this study for automatic identification of rain-related trips. However, a preliminary investigation on rain-related trips revealed that there were no ABS, traction control, or electronic stability control activations in any of the trips, which might be due to the fact that the activation of mentioned safety features is not common in rain on freeways. Moreover, mentioned variables are not available for all the NDS vehicles.

As shown in Fig. 1, a total of 240 trips were acquired and used in this study (80 in rain and 160 in clear). Among the acquired NDS trips, few trips were removed and were not considered in this study due to the low quality of the recorded video from the forward-facing camera (caused by dirty windshield in front of the camera) or the missing variables representing driver performance (speed, acceleration/deceleration and headway) probably caused by errors in the DAS recording.

5. Trips used in this study

As mentioned earlier, a total of 240 trips including 80 trips in rain and additional 160 trips in clear weather conditions from the state of Florida and Washington were considered in this study (Fig. 1). Mentioned trips involve 55 drivers between 19 and 84 years old. In total, 5165 one-minute segments, which is equivalent to nearly 86 h and 6806 km of driving, were processed in this study. The speed limit data provided in the RID as well as age and gender of each specific driver, provided in the driver demographic questionnaires, were combined with each one-minute segment. After removing non-freeway related segments, 4350 one-minute segments were considered to model speed and headway selection models.

In order to compare driver behavior in clear and heavy rain weather conditions under free-flow speed (FFS), where speed is not affected by traffic conditions, a total of 180 one-minute segments in heavy rain as well as their matching trips in clear weather

Table 1
Descriptive Statistics for the NDS Instrumented Vehicles.

	Statistical tests	Free-flow traffic (matching trips)			
		Heavy rain		Matched clear	
Speed (kph)	Average	92.12		105.53	
	SD	10.19		11.99	
	Min.	56.92		62.66	
	Max.	119.80		134.59	
	Median	93.96		104.22	
	Mann-Whitney *U* test	Driver speed in heavy rain is statistically significantly lower than driver speed in clear weather conditions. U = 134340, p-value < 2.2e − 16; 95 percent confidence interval:[10.53038, 14.10869]			
Acceleration/Deceleration (m/s^2) (Positive columns = Acceleration)		Acc.	Dec.	Acc.	Dec.
	Average	0.0955	−0.0836	0.1193	−0.1630
	SD	0.0790	0.0772	0.0990	0.3685
	Min.	0.0021	−0.3812	0.0001	−2.5304
	Max.	0.4492	−0.0013	0.5858	−0.0002
	Median	0.0821	−0.0691	0.1009	−0.0956
	Mann-Whitney *U* test	Driver acceleration in heavy rain is statistically significantly lower than driver acceleration in clear weather conditions.U = 36496, p-value = 0.02419; 95 percent confidence interval: [0.00211, 0.02914]Driver deceleration in heavy rain is statistically significantly lower than driver deceleration in clear weather conditions (negative sign just represent deceleration).U = 7634, p-value = 0.03159; 95 percent confidence interval: [−0.04711, −0.00187]			
85th Percentile Headway (sec)	Average	3.61		2.2	
	SD	1.96		1.23	
	Min	0.35		0.98	
	Max	8.00		6.22	
	Median	3.19		1.88	
	Mann-Whitney *U* test	Driver 85th percentile headway in heavy rain is statistically significantly higher than driver 85th percentile headway in clear weather conditions.U = 6624, p-value = 6.979e − 05; 95 percent confidence interval: [0.59289, 1.97922]			

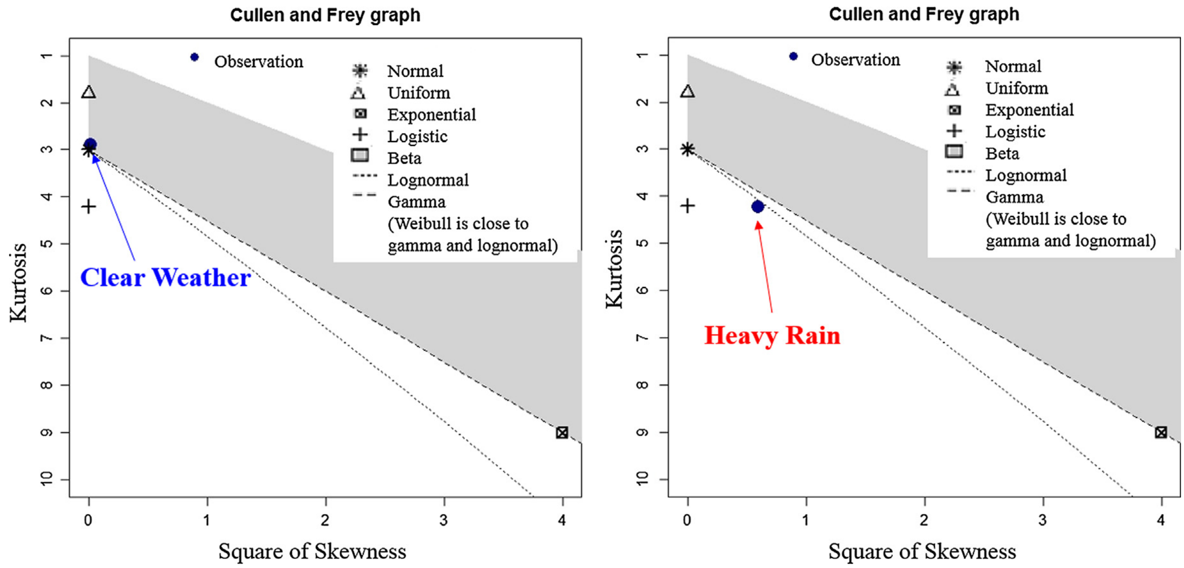


Fig. 2. Cullen frey graphs for clear weather and heavy rain observations.

conditions were considered for developing the descriptive statistics table (Table 1). Moreover, 12 matching trips (4 in heavy rain, 4 in rain, and 4 in clear conditions) were considered for the GIS trajectory-level analysis (Fig. 5), where matching trips in FFS for all three weather conditions (clear, light rain, and heavy rain) were needed. Matching is important to control for sundry factors such as driver population, roadway geometry, etc. The total 4350 one-minute segments were used for developing the speed/headway models.

6. Data analysis

6.1. Descriptive analysis

This study investigated the distribution and variation of speeds between clear and heavy rain in free-flow speed conditions. Characterization of traffic flow became very important for various reasons: realistic traffic conditions and the appropriate distributions are needed for the calibration of the simulation models, and predictability of traffic state in various weather conditions is needed for an effective and realistic VSL system (Carlson et al., 2011, 2010; Papamichail et al., 2008; Lin et al., 2004). Characterization of traffic state and speed in different weather conditions, moreover, will help in applications such as connected vehicle (CV) technology. If unusual traffic patterns are detected, these geospatial locations could be flagged for a possible and timely mitigation strategy.

After analyzing NDS one-minute segments, it was found that 180 one-minute segments during heavy rain were traversed on free flow conditions and considered for the preliminary analysis with their matching segments in clear weather conditions. The Cullen Frey graph was utilized to identify the distribution of vehicle speed in clear and heavy rain weather conditions (Fig. 2). As can be seen the kurtosis and squared skewness of the speed observations for clear and rainy weather conditions is shown as a blue point in Fig. 2. From the NDS sample data, it was concluded that speeds might have possible distributions include Weibull and lognormal distribution in heavy rain under free-flow condition. However, the AIC of the Weibull fit is lower compared to the lognormal fit for rainy weather conditions (AIC equal to 1338 and 1370 for Weibull and lognormal distributions, respectively); therefore, it was concluded that speeds have a Weibull distribution in heavy rain under free-flow condition while the speeds were normally distributed in clear weather for the matching data set as shown in Fig. 3.

Speed in free-flow condition is important for VSL application because the speed choice here is not affected by the interaction with traffic. Descriptive statistics provided in Table 1 indicated that the average speed in heavy rain under free-flow traffic condition was (13.41 kph) lower than in clear weather and free-flow traffic conditions. It was also found that speeds have higher variability in clear weather compared to heavy rain under free-flow traffic conditions. Other speed distributions for other scenarios were examined, but their graphs were not included in this paper for brevity.

Examining drivers' selection of speed during traffic congestion is also important. This could help to determine whether drivers take higher risks during heavy rain weather conditions to make up for delays encountered because of congestion. Speed distribution during heavy rain in congestion (mixed/heavy traffic) did not fit a specific distribution, which may indicate higher speed variability. The speeds during clear weather conditions in mixed/heavy traffic volumes on the same routes and subjects fitted bimodal distribution, which is common during congestion on freeways. Although matching technique may control for sundry factors (among them roadway geometry, traffic condition, and driver population) supplementary traffic-flow parameters may be needed to fully isolate driver behavior of speed selection due to the environment.

As mentioned earlier, trips in rainy conditions were identified by extracting trips with a high number of minutes of wipers used at

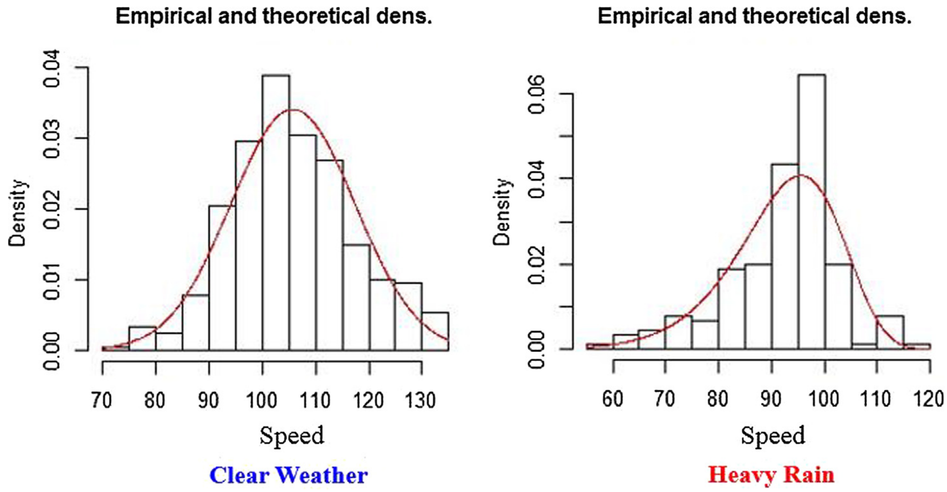


Fig. 3. Observed and fitted distributions for speeds during heavy rain and clear weather under free-flow traffic.

different speed settings. NDS video data were manually analyzed for all one-minute segments to verify and validate the results. In addition, traffic conditions were characterized and categorized into two groups including heavy traffic and free flow condition using presence and distance to other vehicles, as well as average headway times.

Table 1 shows descriptive statistics for the main time-series variable of interest for heavy rain/clear weather in free-flow speed conditions. The acceleration/deceleration variable was examined, and ± 0.3 g acceleration/deceleration rates were set as a threshold to identify aggressive braking/acceleration events (Bagdadi, 2013). The preliminary analysis showed that acceleration and deceleration have higher average and variability in clear weather conditions, which could be due to drivers' higher maneuverability in clear weather and free flow speed conditions.

Average and variability of 85th percentile headways were found to be higher in heavy rain compared to clear weather condition under free-flow traffic. This could be explained by the fact that drivers tend to compensate for the increased risk due to the limitation in visibility by maintaining longer headway times.

To test the significant difference in drivers speed, acceleration/deceleration, and headway selections in clear and rainy weather conditions, first, the Kolmogorov-Smirnov test was utilized to evaluate the normality of the data. The results revealed that the speed data were not normally distributed with 95% confidence interval ($D = 0.55174$, p-value $< 2.2e-16$). The same trend was seen for acceleration ($D = 0.15301$, p-value $= 0.01383$) and headway behavior ($D = 0.45356$, p-value $= 1.922e-05$). Hence, utilizing non-parametric test to compare the significant difference between driver behaviors in clear and heavy rain weather conditions is justified. A non-parametric Mann-Whitney *U* test was used and revealed that there is a statistically significant difference in median of driver speed, acceleration/deceleration, and 85th percentile headway in clear and heavy rain weather under free-flow speed conditions, as shown in Table 1.

A visualization software was developed as part of this study with the ability of displaying two video files for the front and rear cameras as well as the time-series data. The software synchronizes all three NDS time series and two video files which allows the user to review trips quickly and efficiently. Fig. 4 shows a continuous speed profile, acceleration, and headway data (red[1], green, and blue continuous profiles, respectively) for one of the trips with both clear and rainy weather conditions in a free-flow condition. The driver reduced the speed by more than 20 kph at the onset of the heavy rain; speed varied significantly afterword. It is worth mentioning that the results from trips that included clear and heavy rain were not consistent with the matching trips for obvious reasons, which shows the importance of developed one-minute segmentation method to provide segments with homogeneous weather and traffic conditions. In addition, the beauty of using matched trips is that the number of accelerations, decelerations, and lane changes due to exit, entry, and weaving maneuvers, among other variables, are controlled for in the matching approach.

6.2. GIS analysis

Fig. 5 shows speed behavior in clear and rainy weather conditions. Twelve NDS trips were linked to the RID via ArcGIS software. The main objectives of linking the NDS continuous data and RID were to: (1) compare the NDS speed to the speed limit along a defined route, and (2) provide a visual representation of speed selection in ArcGIS environment. Three sets of trips in heavy rain, light rain, and clear weather conditions and in free flow traffic (To isolate the impact of rainy weather conditions on driver behavior) were identified on the same 18.19-km route (Interstate 405) in Washington.

A new layer was added in the ArcGIS to indicate the speed selection in both clear and rainy trips along the same route. As can be seen, on the same I-405 route in Washington, 37% of the speeds were under the posted speed limit. This was reduced to more than

[1] For interpretation of color in Figs. 2 and 4, the reader is referred to the web version of this article.

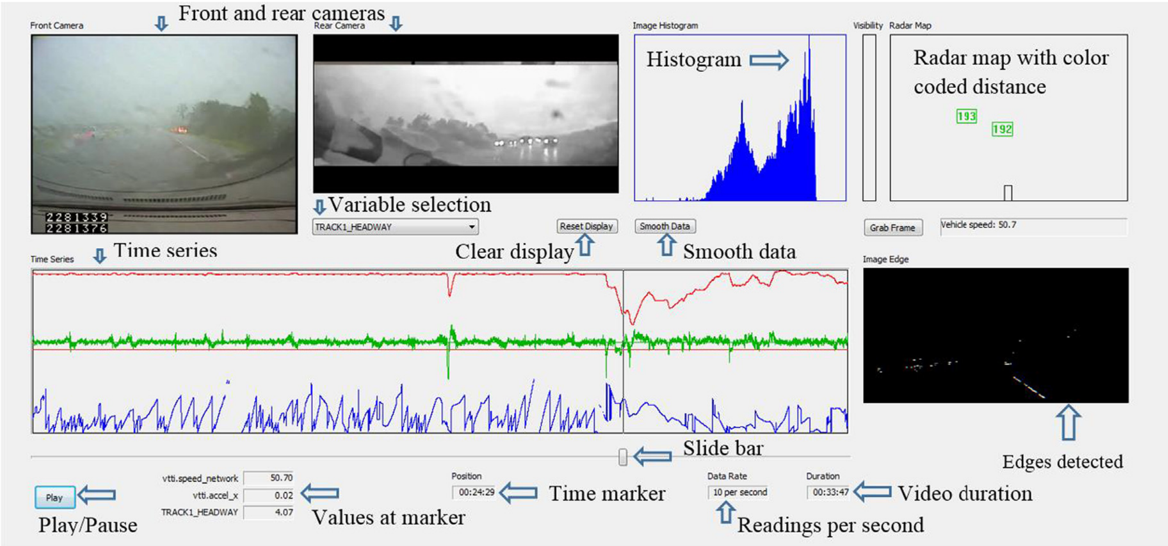


Fig. 4. Illustration of sudden reduction in visibility impact on driver's performance.

85% during heavy rain events.

7. Speed and headway selection models

7.1. Methodology: Partial proportional odds model

To model driver speed and headway selection behaviors the prominent approach of discrete choice models was used. Considering the fact that speed and headway selections are ordered response variables in nature, an ordered logistic regression model (OLM) can be written in terms of probability of speed/headway selection levels as shown in Eq. (1).

$$P(y_i > j) = \frac{\exp(\alpha_j - x_i'\beta)}{1 + \exp(\alpha_j - x_i'\beta)}, \quad \text{j= 1,2,...,k}-1 \tag{1}$$

where the probability of occurrence of speed/headway selection level j associates to a vector of explanatory variables (X_i) for NDS driver i. β is a vector of coefficients that need to be estimated and α_j is a vector of cut points for the ordered model.

Proportional odds assumption, also known as parallel-line assumptions, is an underlying ordered logit regression assumption, which implies that the effect of an explanatory variable should be uniform for different levels of the response variable (Sasidharan and Menéndez, 2014). Considering the fact that this assumption might be violated for several variables in the speed and headway selection models, partial proportional odds (PPO) model also known as generalized ordered logit (GOLOGIT) model, was used in this study. Partial proportional odds model is capable to address some limitations of ordered and unordered logistic/probit regressions (Mergia et al., 2013; Savolainen et al., 2011). This model has been known as a more flexible modeling technique in the literature that has the ability to relax the parallel-line assumptions in the ordered logit model (Williams, 2006). In fact, while the partial proportional odds model is capable to keep the ordinal nature of the data, it can address the limitation of ordered logit model by enabling the parameter β to be varied across outcome levels (Mergia et al., 2013). The Brant test can be used to test the parallel line assumption (Brant, 1990). The probability of speed/headway selection for a given driver can be expressed as:

$$P(y_i > j) = \frac{\exp(\alpha_j - x_i'\beta_j)}{1 + \exp(\alpha_j - x_i'\beta_j)}, \quad \text{j= 1,2,...,k}-1 \tag{2}$$

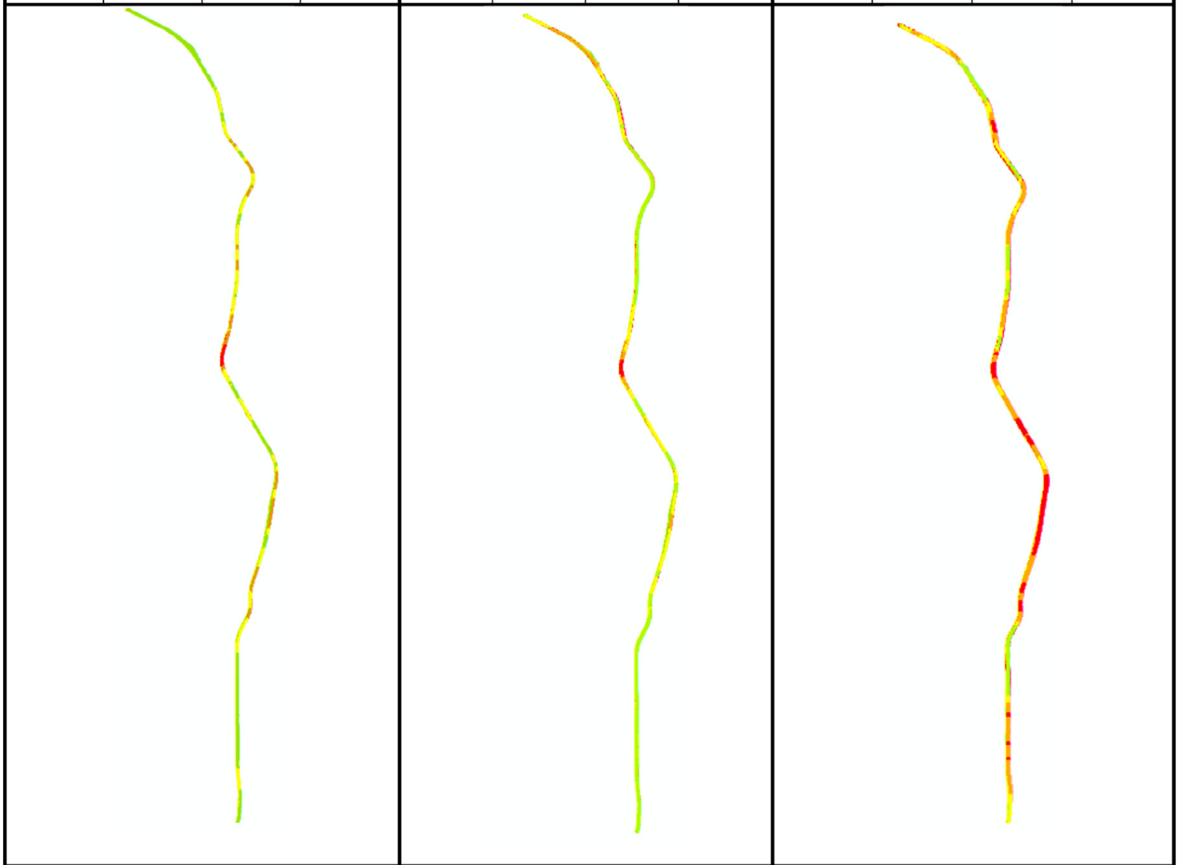
where β_j represents parameters to be estimated including elements that can vary based on the cut points of OLM.

Eq. (3) represents partial proportional odds model (Pour-Rouholamin and Zhou, 2016; Kaplan and Prato, 2012):

$$P(y_i > j) = \frac{e^{(X_{1i}\beta_j + X_{2i}\beta_2 - \eta_j)}}{1 + e^{(X_{1i}\beta_j + X_{2i}\beta_2 - \eta_j)}}, \quad \text{j= 1,2,...,k}-1 \tag{3}$$

In Eq. (3), β_1 and β_2 denote vector of coefficients associated with violated and non-violated parallel line assumption, X_{1i} and X_{2i} are corresponding vector of independent variables that violated and not-violated parallel line assumption, respectively. j represents speed/headway selection groups, η_j is the jth constant coefficient and k is the number of categories of the ordered dependent variable. Maximum likelihood estimation method was used to estimate the coefficients values. The interpretation of the results from the partial proportional odds model is similar to the binary logistic regression (Williams, 2006). Considering a response variable with four outcome levels (k = 4), e.g., speed selection behavior in this study, three comparison groups (k − 1) would be generated. Therefore,

Heavy Rain				Rain				Clear			
Trip ID:643,653,657, and 672				Trip ID: 646,656,660, and 667				Trip ID:642,654,652, and 669			
Total trips duration: 52:36 min				Total trips duration: 46:13 min				Total trips duration: 44:30 min			
Speed Groups				Speed Groups				Speed Groups			
>5 Below SL	(0-5) Below SL	(0-5) Above SL	>5 Above SL	>5 Below SL	(0-5) Below SL	(0-5) Above SL	>5 Above SL	>5 Below SL	(0-5) Below SL	(0-5) Above SL	>5 Above SL
64%	21%	13%	2%	38%	27%	22%	13%	19%	18%	31%	32%



Route: Interstate 405, Washington, Length: 11.3 miles (18.19 km), Start: Mile Marker 27
Speed limit source: Roadway Information Database (RID) and Street View in Google Map

>5 km/hr below the speed limit
0-5 km/hr below the speed limit
0-5 km/hr above the speed limit
>5 km/hr above the speed limit

Fig. 5. Speed behavior in clear, light-rain, and heavy-rain on I-405, washington (mile-marker 27 to mile-marker 38.3).

outcome level 1 would be compared to outcome levels 2, 3, and 4 for $j = 1$. For $j = 2$, outcome levels 1 and 2 would be compared to outcome levels 3 and 4. Finally, outcome levels 1, 2, and 3 would be compared to outcome level 4. Similar to ordinal logistic regression, a positive estimated coefficient indicates that the higher values on the explanatory variable increase the probability/likelihood of selecting higher speed/headway selection levels and a negative coefficient represents that a higher value on the predictor decreases the likelihood of being in the higher levels of speed/headway selection.

Table 2
Data description for speed and headway selection models.

Variable	Description	Type	Levels
Response variables			
Speed Behavior	Average speed of each one-minute segment	Ordinal	1 = More than 5 kph below the speed limit 2 = 0–5 kph below the speed limit 3 = 0–5 kph above the speed limit 4 = More than 5 kph above the speed limit
Headway	85th percentile headway of each one-minute segment	Ordinal	1 = Below 2-s 2 = Between 2 and 3-s 3 = Greater than 3-s
Explanatory variables			
Traffic	Traffic Conditions	Binary	0 = Free-flow 1 = Traffic
Speed Limit	Posted Speed Limit	Categorical	0 = below 90 kph 1 = above 90 kph
Surface Condition	Road surface conditions extracted from the video data	Binary	0 = Dry 1 = Wet
Weather	Weather conditions	Categorical	1 = Heavy Rain 2 = Light Rain 3 = Clear
Gender	The gender the participant identifies with	Binary	1 = Male 0 = Female
Age	The age group corresponding to the driver's birthdate	Categorical	1 = young (< 25) 2 = Middle-aged (25–55) 3 = Older (greater than55)

7.2. Model evaluation and results

To model speed and headway selection, partial proportional odds models were calibrated utilizing all the 4350 one-minute segments occurring in various weather and traffic conditions. The speed model was developed for the dependent variable of four speed intervals: more than 5 kph below the speed limit, 0–5 kph below the speed limit, 0–5 kph above the speed limit, and more than 5 kph above the speed limit. In addition, the headway model was developed for three levels of the independent variable including: average headway below 2-s, between 2 and 3-s and greater than 3-s. Generally, explanatory variables can be considered as driver demographics, roadway factors, and traffic and environmental conditions. Table 2 shows variables for developing the speed and headway selection models in weather conditions. The marginal effects for different speed/headway selection levels are also provided in this section.

As mentioned earlier, considering the four levels of driver speed selection behavior, we have three different panels of results, as shown in Fig. 6.

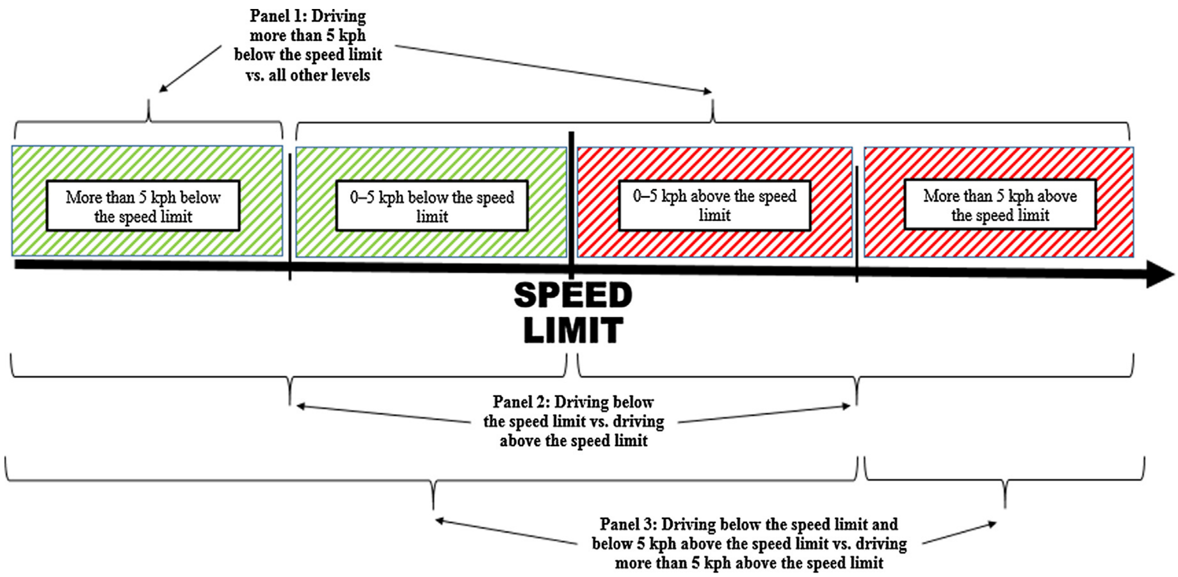


Fig. 6. Graphical representation of different panels - partial proportional odds speed selection model.

Table 3
Partial proportional odds model for speed selection behavior.

	Parameters		Coefficient	Standard error	Z-value	P-value	95% Confidence interval	
							Lower bound	Upper bound
Panel 1	Constant		6.679	0.633	10.55	0.000	5.438	7.92
	Age	Middle-age	−1.304	0.084	−15.4	0.000	−1.47	−1.138
		Old	−0.646	0.1	−6.44	0.000	−0.843	−0.449
	Gender	Male	0.17	0.073	2.32	0.020	0.026	0.314
	Speed limit	Above 90 kph	−0.058	0.006	−9.07	0.000	−0.071	−0.045
	Weather Conditions	Light Rain	−0.932	0.073	−12.6	0.000	−1.077	−0.788
		Heavy Rain	−1.255	0.108	−11.5	0.000	−1.468	−1.041
	Traffic Conditions	Free Flow	0.825	0.0737	11.19	0.000	0.681	0.969
Panel 2	Constant		6.14	0.632	9.7	0.000	4.9	7.381
	Age	Middle-age	−1.304	0.084	−15.4	0.000	−1.47	−1.138
		Old	−0.797	0.098	−8.1	0.000	−0.991	−0.604
	Gender	Male	−0.077	0.074	− −1.03	0.303	−0.223	0.696
	Speed limit	Above 90 kph	−0.054	0.006	−8.55	0.000	−0.067	−0.042
	Weather Conditions	Light Rain	−0.942	0.076	−12.4	0.000	−1.092	−0.793
		Heavy Rain	−1.525	0.127	−12	0.000	−1.774	−1.276
	Traffic Conditions	Free Flow	0.631	0.072	8.68	0.000	0.488	0.773
Panel 3	Constant		4.199	0.653	6.43	0.000	2.918	5.48
	Age	Middle-aged	−1.304	0.084	−15.4	0.000	−1.47	−1.138
		Older	−0.922	0.101	−9.08	0.000	−1.121	−0.723
	Gender	Male	−0.599	0.081	−7.4	0.000	−0.758	−0.44
	Speed limit	Above 90 kph	−0.036	0.006	−5.52	0.000	−0.0495	−0.023
	Weather Conditions	Light Rain	−1.082	0.084	−12.9	0.000	−1.247	−0.917
		Heavy Rain	−2.273	0.213	−10.7	0.000	−2.692	−1.855
	Traffic Conditions	Free Flow	0.465	0.076	6.04	0.000	0.314	0.615
	Number of Observations:			4350				
	Log Likelihood:			−4665.472				
	Pseudo R^2:			0.1057				

Panel 1 is similar to a common binary logistic regression where the response variable is recorded as more than 5 kph speed reduction versus other speed selection levels (0–5 kph speed reduction, 0–5 kph increase in speed, more than 5 kph increase in speed). Panel 2 is analogous to the first one except that the response variable is defined as (more than 5 kph below the speed limit, 0–5 kph below the speed limit) versus (0–5 kph above the speed limit, more than 5 kph above the speed limit). Finally, for panel 3, the dependent variable is recorded as (more than 5 kph below the speed limit, 0–5 kph below the speed limit, 0–5 kph above the speed limit) versus more than 5 kph above the speed limit. For headway selection model, considering the defined three levels of dependent variable, we have two panels. The response in panel 1 is headway below 2-s versus (between 2 and 3-s, Greater than 3-s) and in panel 2 is (headway below 2-s, between 2 and 3-s) versus Greater than 3-s.

It is worth mentioning that for VSL application, speed levels were grouped within 5 kph intervals in this study. The results of the developed speed and headway selection models are shown in Table 3 and Table 4. In addition, the global Wald test for both developed speed and headway selection models revealed that final speed and headway selection models do not violate the parallel line assumption (p-value equal to 0.4494 and 0.1238 for speed and headway selection models, respectively). The Likelihood Ratio (LR) test statistic for both speed and headway selection models falls into the rejection area (p-value < 0.05), which means that the overall explanatory variables of the model have a significant influence on the response at a statistical significance level of 95%.

A previous study showed that the direction of the effect of an explanatory variable is not always represented by the sign of the coefficient for intermediate categories (Sasidharan and Menéndez, 2017). Hence, marginal effects of explanatory variables were calculated for both speed and headway selection models, and the results are provided in Table 5 and Table 6.

7.3. Discussion of key factors

The results showed that drivers were more likely to reduce their speed more than 5 kph in rainy weather conditions. The marginal effects for driving in light rain and heavy rain were positive for level one (reduction more than 5 kph below the speed limits) of driver speed selection behavior indicating that the probability of reducing speed in light rain and heavy rain were 23% and 29% higher when compared to clear weather conditions, respectively. Driving over the speed limit could be risky due to the fact that drivers might lack sufficient time for suitable response to control and handle unexpected situations especially during heavy rain or foggy conditions (Ghasemzadeh and Ahmed, 2016). The results from this study showed that drivers reduced their speeds to compensate for the negative effects of rain on the driving task. This finding is in agreement with a previous study, showing the negative effect of adverse weather on drivers' performance (Brooks et al., 2011).

Traffic conditions were also found to be a significant factor in the developed speed selection model. The results revealed that drivers were more likely to drive above the speed limits in free-flow speed conditions. It is intuitive that lower traffic volumes

Table 4
Partial proportional odds model for headway selection behavior.

	Parameters		Coefficient	Standard Error	Z-value	P-value	95% Confidence Interval	
							Lower bound	Upper bound
Panel 1	Constant		9.501	1.613	3.54	0.000	0.205	0.718
	Age	Middle-age	0.462	0.131	3.54	0.000	0.206	0.718
		Old	1.065	0.143	7.42	0.000	0.784	1.346
	Gender	Male	0.574	0.109	5.26	0.000	0.361	0.789
	Speed limit	Above 90 kph	−0.1	0.016	−6.02	0.000	−0.133	−0.067
	Weather Conditions	Light Rain	0.556	0.112	4.93	0.000	0.334	0.777
		Heavy Rain	0.456	0.228	2	0.046	0.008	0.904
	Traffic Conditions	Free Flow	0.333	0.143	2.32	0.020	0.052	0.615
Panel 2	Constant		8.341	1.609	5.18	0.000	5.186	11.496
	Age	Middle-aged	0.462	0.131	3.54	0.000	0.205	0.718
		Older	1.06	0.143	7.42	0.000	0.783	1.346
	Gender	Male	0.574	0.109	5.26	0.000	0.361	0.789
	Speed limit	Above 90 kph	−0.1	0.016	−6.02	0.000	−0.133	−0.067
	Weather Conditions	Light Rain	0.556	0.112	4.93	0.000	0.334	0.777
		Heavy Rain	0.456	0.228	2	0.046	0.008	0.904
	Traffic Conditions	Free Flow	0.584	0.129	4.52	0.000	0.331	0.837
	Number of Observations:			4350				
	Log Likelihood:			−1422.945				
	Pseudo R^2:			0.1036				

Table 5
Marginal effects and standard errors for different speed levels.

Speed selection categories								
	More than 5 kph below the speed limit		0–5 kph below the speed limit		0–5 kph above the speed limit		More than 5 kph above the speed limit	
Variables	Marginal Effect	Standard Error	Marginal Effect	Standard Error	Marginal Effect	Standard Error	Marginal Effect	Standard Error
Middle-age	0.315***	−0.019	−0.0140***	−0.002	−0.065***	−0.005	−0.236***	−0.015
Old	0.160***	−0.024	0.0206	−0.014	−0.028*	−0.014	−0.153***	−0.016
Male	−0.0425**	−0.018	0.0609***	−0.011	0.095***	−0.012	−0.114***	−0.016
Above 90 kph	0.0146***	−0.002	−0.00153	−0.001	−0.006***	−0.001	−0.006***	−0.001
Light Rain	0.228***	−0.017	−0.0182*	−0.010	−0.036***	−0.010	−0.174***	−0.012
Heavy Rain	0.292***	−0.022	−0.000154	−0.015	−0.038***	−0.015	−0.254***	−0.012
Free Flow	−0.202***	−0.017	0.0499***	−0.012	0.064***	−0.012	0.088***	−0.015

Significance levels:
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 6
Marginal effects and standard errors for different headway levels.

	Headway selection categories					
	Below 2-s		Between 2 and 3-s		Greater than 3-s	
Variables	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Middle-age	−0.0920***	−0.025	−0.0227***	−0.008	0.115***	−0.032
Old	−0.200***	−0.024	−0.0605***	−0.011	0.260***	−0.033
Male	−0.118***	−0.023	−0.0231***	−0.005	0.141***	−0.027
Above 90 kph	0.0206***	−0.003	0.00427***	−0.001	−0.0249***	−0.004
Light Rain	−0.109***	−0.021	−0.0287***	−0.008	0.138***	−0.028
Heavy Rain	−0.0852**	−0.038	−0.0284	−0.018	0.114**	−0.056
Free Flow	−0.0666**	−0.028	−0.0783***	−0.025	0.145***	−0.032

Significance levels: *$p < 0.1$.
*** $p < 0.01$.
** $p < 0.05$.

increases the probability of drivers' tendency to drive over the speed limits.

Age groups were found to be significant in all three sets of estimates as shown in Table 3. The marginal effects for middle and older-aged drivers are positive for the first level (reduction of more than 5 kph below the speed limits) of speed selection. This implies that the probabilities of speed reduction more than 5 kph below the speed limit for middle-aged and older drivers were 31% and 16% higher when compared to young drivers, respectively, and when other variables are at their mean values. This could be due to the fact that younger drivers are less experienced and usually take greater risk in comparison with middle-aged and older drivers (Strayer and Drew, 2004). In addition, the marginal effect of gender on drivers' speed selection revealed that male drivers were less likely to reduce their speed more than 5 kph below the speed limits in comparison with their female counterparts, which can be explained considering the psychological differences between males and females (Yan et al., 2016).

Interestingly, speed limit was significant with a positive marginal effect of speed selection level 1 (reduction more than 5 kph below the speed limit), which represents that NDS drivers tend to have a higher speed reduction on freeway segments with higher posted speed limits. This could be not only because of the better design of the high-speed facilities, but also represents the fact that drivers pay more attention and are more cautious of the risk of driving at a higher speed (Ghasemzadeh and Ahmed, 2017; Richard et al., 2016).

Headway was also used as a crash surrogate under various weather and traffic conditions. The results from the headway model were consistent with the preliminary analysis. Analysis results showed that drivers tend to have a longer average headway time in rainy weather conditions, which is consistent with a previous study revealing that drivers maintain a larger headway and drive more carefully in rainy weather to compensate for reduced visibility and slippery road conditions (Rahman and Lownes, 2012). It was also found that drivers tend to have shorter headway time in high-speed facilities and longer average headway time in free-flow speed conditions. The results of the partial proportional odds headway selection model revealed that middle-aged and older drivers were more likely to have longer average headway time (11% and 26%, respectively) compared to young drivers, which is in line with a previous study showing that older-drivers are mostly aware of their limitations such as longer response time in critical situations as well as increased risk of crashes in higher ages (Clark et al., 2017). In addition, it was found that male drivers were more likely to have longer average headway time compared to female drivers.

8. Conclusions

Behavior and road-user characteristics are among the most important elements influencing the driving task. A driver's reaction process to speed and headway choice, along with the dynamic visual acuity, are critically important factors for safe driving. The naturalistic driving study and roadway information datasets utilized in this study revealed that modeling drivers' behavior in rainy weather conditions using vehicle time-series data is realizable. This paper developed an effective automated methodology to identify heavy and light rain trips in the NDS data. The procedure of extracting NDS trips in rainy weather condition will pave the way for other researchers to utilize the NDS data in various studies. The driving variables such as speed selection, acceleration/deceleration, and headway were efficiently characterized. The preliminary analysis showed significant behavior and performance differences between driving in heavy rain and clear weather conditions under free-flow and heavy traffic states. Preliminary analysis and partial proportional odds (generalized ordered logit regression) models were useful to enhance the understanding of driver behavior under various rain and traffic conditions. The results showed that rainy weather conditions have a significant effect on driver speed and headway selection. More specifically, drivers were more likely to reduce their speed and maintain a longer headway time during rainy weather conditions. In addition, it was found that middle-aged and older drivers were more conservative in comparison with younger drivers in speed and headway selection behaviors. To be specific, the results showed that middle-aged and older drivers were more likely to reduce their speed and maintain longer average headway time. While this study is exploratory in nature, it unlocks new horizons of assessing the impacts of rainy weather conditions on driver behavior and performance using one of the most comprehensive Naturalistic Driving Study data that have ever been collected in the US. In addition, the results from this study may help in overcoming the gap of unpredictability of driver behavior and will help setting appropriate speeds in Variable Speed Limit (VSL) systems during adverse weather conditions.

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