Drivers' Lane-Keeping Ability in Heavy Rain

Preliminary Investigation Using SHRP 2 Naturalistic Driving Study Data

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There is a lack of studies that have examined the impact of weather conditions on drivers' lane-keeping performance. Many driver behavior studies have been conducted in simulated environments. However, no studies have examined the impact of heavy rain on lane-keeping ability in naturalistic settings. A study used data from the SHRP 2 Naturalistic Driving Study to provide better insights into driver behavior and performance in clear and rainy weather conditions. In particular, a lane-keeping model was developed using logistic regression to better understand factors affecting drivers' lane-keeping ability in different weather conditions. One interesting finding of this research is that heavy rain can significantly increase the standard deviation of lane position, which is a widely used method for analyzing lane-keeping ability. More specifically, drivers in heavy rain are 3.8 times more likely to show a higher standard deviation of lane position than in clear weather condition. An additional interesting finding is that drivers have better lane-keeping abilities in roadways with higher posted speed. Results from this study could provide a better understanding of the complex effects of weather conditions on drivers' lane-keeping ability and how drivers perceive and react in different weather conditions. Results from this study may also provide insights into automating the activation and deactivation of lane departure warning systems.

According to FHWA, 90% of crashes are related to driver behavior, and human error is identified as the primary factor contributing to over 60% of crashes (*1*).

Many studies in the literature have analyzed drivers' lane-keeping ability from distraction perspective (*2–5*). While these studies are important to understand how different forms of distracted driving affect lane-keeping ability, the impact of heavy rain on lane-keeping ability has not been researched in naturalistic settings before. Adverse weather conditions such as fog, snow, ground blizzard, slush, rain, and strong wind have been recognized to have significant effects on traffic flow dynamic, drivers' performance and severity of crashes (*6, 7*). Previous studies showed that the probability of rear-end crashes increases during adverse weather conditions (*8, 9*). According to FHWA, weather contributed to over 24% of the total crashes between 1995 and 2008. In Canada and the United Kingdom, such crashes account for approximately 30% and 20%, respectively (*10, 11*).

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Several studies concluded that crashes increase due to vision obstruction during rainfall by 100% or more (*12, 13*), while others found more moderate (but still statistically significant) increases (*14, 15*). Sudden reduction in visibility was found to increase the severity level of crashes and tend to involve more vehicles. While these studies provided insights into the impacts of adverse weather conditions on traffic safety, they failed to provide comprehensive understanding of the underlying causes of weather-related crashes owing to lack of driver behavior data.

Drivers' lane-keeping performance is one of the vital factors that can affect run-off-road events. Deterioration of lane-keeping ability might be exacerbated by adverse weather conditions due to reduction in visibility and slippery surface conditions (*15, 16*).

Understanding drivers' responses, when the visibility falls below a certain threshold, might be helpful not only in reducing the lane departure–related crashes in heavy rain but also in finding a new efficient threshold for lane departure warning (LDW) systems in adverse weather conditions (*17*). Although many studies have been conducted on analyzing driver behavior, not many research studies have focused on the effects of heavy rain on driver performance on a microscopic scale (*18, 19*). In the last few years, naturalistic driving studies (NDS) have made it possible to obtain more information about driver behavior and performance in different conditions. The NDS data will allow for better understanding of how drivers adjust their behaviors to compensate for increased risk resulting from reduction in visibility.

The main goal of this study was to investigate the feasibility of using the second SHRP (SHRP 2) NDS data to analyze drivers' lane-keeping ability in heavy rain and slippery road conditions. This was conducted by compiling a sample data set from the SHRP 2 NDS data and then extracting and reducing data for heavy rain trips and their matching clear weather condition trips on freeways to address the following research questions. Can inclement weather trips be identified effectively using the NDS and Roadway Information Database (RID) data? Can driver responses (i.e., lane-keeping) during inclement weather (i.e., reduction in visibility and slippery surface condition because of heavy rain in this study) be characterized and analyzed efficiently from the NDS data?

DATA SOURCE

SHRP 2 collected more than 4 petabytes worth of naturalistic driving data over 3 years (2010 to 2013), approximately 35 million vehicle mi with more than 3,500 drivers having participated from six U.S. states: Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington State. Data were collected using the

SHRP 2 NDS onboard data acquisition system installed in participants' vehicles. The collected NDS data included vehicle network information, vehicle kinematics recorded at 10-Hz frequency (e.g., speed, acceleration, steering wheel position), and video views (forward and rear views and driver's face and hands view), in addition to information obtained from a variety of sensors such as forward radar, alcohol sensor, and accelerometers (*20*). Driver vehicle use was recorded continuously during the SHRP 2 NDS project, making this project the biggest NDS with collision prevention as the primary focus in the United States (*21*).

The NDS data used in this paper were a subset of data reduced from the SHRP 2 NDS data for Florida and Washington freeways. Florida has the highest rainfall precipitation among all states in the SHRP 2 project (*22*).

In addition to the NDS data used in this study, the SHRP 2 Roadway Information Database was used. The RID contains a comprehensive description of roadway characteristics for the six NDS states (*23*). The RID also provides additional data on crashes, aggregate traffic, work zones information, and so on. The NDS and RID data were linked to associate driving behavior with roadway characteristics. To demonstrate proof of concept of how the SHRP 2 data can be used in different safety studies, several projects, including the work described in this paper, were commissioned. Therefore, some constraints exist, including sample size, lack of drivers' demographics, and events of interest.

DATA REDUCTION

Data extraction and reduction are crucial steps in this study. As mentioned earlier, a subset of data reduced from the SHRP 2 NDS was requested to examine driver response in rain and heavy rain in the states of Florida and Washington. In particular, 50 NDS trips during rain and heavy rain on freeway segments were targeted. The provided NDS data included forward-facing and rear-facing videos, basic trip characteristics, and selected vehicle time-series variables. The RID as well as visual inspection of aerial and street view images from Google maps were also used. To address the first research question of identifying appropriate trips in rainy conditions, a preliminary criterion for data extraction was developed.

Identifying and extracting requested data was a challenging task in this study. Unlike many NDS in the literature, the criterion for extracting NDS trips in rain and heavy rain is unique. Although wiper settings could give an indication about rain intensity, wiper settings are not consistent across different vehicles. Wiper settings in the NDS data indicate the position of the wipers switch rather than the swipe rate of the wipers. Moreover, different drivers have different tolerances to rain and visibility. Splashes from other vehicles may affect driver choice of the appropriate wiper speed. A unique extraction process was developed to effectively identify NDS trips in rain and heavy rain without introducing bias to the sample data. The NDS extraction steps for trips in rain and heavy rain were as follows:

1. Only trips with multiple wiper settings were targeted; vehicles that did not include the full spectrum of values for the wipers status (0, 1, 2, and 3) were filtered out. Vehicles with on and off wipers settings only would not provide an indication of rain intensity. Minimum duration for high wipers settings (Level 2 and Level 3) were considered as 5 min.
2. Months with high rain precipitation in the states of Washington and Florida were targeted.
3. Only NDS daytime trips in rain on freeways were considered. Nighttime trips were eliminated in this study because of the low resolution of the provided sample video data.
4. Honda Civics were eliminated from the data set because of the lack of wiper blade coverage of the windshield surface in front of the camera.
5. Potential events were tagged with the duration of the trip that different wipers settings of 0, 1, 2, and 3 were active to facilitate data reduction for light and heavy rain conditions.
6. Each identified trip in rain was matched with two trips in clear weather conditions for the same route, subject, and day of the week and month of the year as much as possible.

Matching criteria may not always be achieved. For example, a driver could be matched on the same route but not the same day of the week or month of the year. While the time of the day and day of the week and month are good surrogates for traffic conditions, driver population, and traffic composition, the exact time and date of trips are considered personally identifiable information (PII) and so were not provided. PII refers to any information that has the potential to identify a specific individual. Therefore, matched trips (same driver, same time of day, and the same route) were requested from the Virginia Tech Transportation Institute (VTTI) data warehouse to address the PII issue. In fact, even though exact time of the trips and drivers' information are considered as PII data, VTTI provided matching trips in clear weather without revealing the information related to the driver and exact time of the trip. All trips were visually inspected to ensure proper matching for traffic conditions.

An additional 100 matching NDS trips during clear weather on the same segments and subjects in the states of Florida and Washington were extracted. A total of 147 valid trips with requested characteristics in rain/heavy rain and their matching clear weather trips were considered in this study. Although most of the trips in heavy rain were matched with two trips in clear weather conditions, only a matching rate of 1:1 was achieved in this study owing to data limitation; some of the provided trips in rain did not have matching trips in clear weather and thus were excluded from the analysis. Matching is important to control for sundry factors such as driver population, roadway geometry, and so on.

During the manual verification of the trips, some trips were found to be driven in both free-flow and heavy traffic conditions. These trips were considered as mixed traffic.

Real-time traffic data are not available in the NDS data. To isolate the impact of heavy rain on driver behavior, trips in free-flow traffic were identified. Traffic conditions were characterized and categorized into two groups: heavy traffic and free-flow conditions. Traffic density was determined based on the number of vehicles present in the NDS driver's travel lane, ability of selecting speed, and ability of maneuvering between lanes. A trip was considered as a free-flow speed when the NDS driver has no leading traffic in any lanes or when a leading vehicle is present at least in one lane, but the NDS driver is still not affected by other vehicles. Other conditions where NDS drivers were affected by other vehicles were considered as other traffic conditions. All the NDS trips were manually checked to identify the accurate traffic conditions. Travel times were also used to identify trips in free-flow and light traffic. More clearly, if a trip was traveled within the speed limit range, trip was considered as a free-flow condition; otherwise, the trip was considered as other traffic conditions (mixed and heavy traffic). As mentioned earlier, roadway characteristics including speed limit information are provided in the RID.

For automatic identification of trips in rain, other basic trip characteristics such as number of brake activations, high variability in headway times and distances, electronic stability control, roadway departures, number of antilock braking system (ABS) activations, and number of traction control activations were examined in this study. A preliminary analysis on trips in rain and heavy rain indicated that there were no ABS, traction control, or electronic stability control activations in any of the trips. This could be explained because the activation of these safety features is not common in rain on freeway segments; moreover, these variables are not available in the NDS data for all vehicles. As mentioned earlier, 147 NDS total trips were acquired, but only 56 were considered for the preliminary analysis when matching was needed. The total of 147 acquired trips was used in developing the lane-keeping logistic regression model.

DESCRIPTIVE STATISTICS

The NDS video data were manually analyzed to verify and validate results. Classifying the NDS data into two traffic states (free-flow and mixed traffic) resulted in a total of 56 trips that were considered for the preliminary analysis. Table 1 shows a summary of the statistics for the number of trips, length of routes, total travel times, and percentages of wiper use at different settings along with their matching clear weather trips. All corresponding RID data were identified and linked to the provided NDS data. The 56 NDS trips constituted a total of about 1,775 Interstate km traveled over 21.94 h on six Interstate routes in the states of Florida and Washington. These trips occurred mostly on I-4, I-75, and I-275 in Florida; and on I-5, I-90, and I-405 in Washington State.

Analysis of wipers status as well as visual inspections of all NDS videos were used to identify heavy and light rain and clear weather condition trips. Table 1 provides a breakdown of the percentage of the time that the wipers were engaged at each level.

If the wipers were engaged at Level 3 for greater than 75% of the whole trip duration, the trip will be considered as a heavy rain trip. Heavy rain trips in free-flow traffic had about 94% active wipers at Setting 3. Similarly, if the wipers were active at Level 1 or Level 2 for greater than 75%, the trip would be considered as a light rain trip (light rain trips in free-flow conditions had 82% active wipers at Settings 2 and 3). A trip with inactive wipers (Level 0) for more than 91% of the time would be marked as a clear weather trip (0% for Settings 2 and 3). This classification was used to provide a consensus of the impact of heavy and light rain only on drivers' lane-keeping ability as well as other driving behaviors for the free-flow conditions only.

PRELIMINARY ANALYSES

Tables 2 through 6 show preliminary analyses and various statistical tests for the main time-series variables of interest for heavy rain and clear weather in free-flow conditions. In addition, descriptive statistics are shown for trips that included heavy rain and clear weather conditions within the same trips. Cohen's *d*-effect size, which is an indication of the magnitude of the difference between heavy rain and clear weather, is also provided in Tables 2 through 6. Cohen's *d*-effect size can be interpreted as $d = 0.2$ small size effect; $d = 0.50$ medium size effect; and $d = 0.80$ large size effect (*24*).

As can be seen in Table 2, a *t*-test indicated that the average speed in heavy rain under the free-flow traffic conditions was significantly (16.32 km/h) lower than in clear weather and free-flow traffic conditions. Speed in free-flow conditions is important for variable speed limit application because the speed choice here is not affected by the interaction with traffic. It was also found that speeds have higher variability during heavy rain in comparison with clear conditions under free-flow traffic, which could be an indication of increased safety risk (*25*).

The acceleration–deceleration variable was examined (Table 3), and ±0.3 *g* acceleration–deceleration rates were set as a threshold to identify aggressive braking–acceleration events (*26*). The preliminary analysis showed that while heavy rain has a wider range of acceleration and statistically has a higher average, the average deceleration was found to be statistically higher in the matching clear weather

TABLE 1 Summary Statistics of NDS Trips Considered in This Study

	Weather Condition				
	Heavy Rain	Matched Clear	Light Rain	Matched Clear	Total
Free-flow traffic					
Number of trips	7	7	9	9	32
Total duration (h)	3.26	2.80	1.42	1.37	8.85
Total length (km)	308.67	308.67	172.76	172.76	962.86
% wiper setting					
0	6.1	99.5	0.0	96.6	
1	0.0	0.0	60	3.4	
2	0.0	0.0	22	0.0	
3	93.9	0.5	18	0.0	
Heavy/mixed traffic					
Number of trips	3	3	9	9	24
Total duration (h)	1.34	1.64	5.44	4.67	13.09
Total length (km)	95.3	95.3	309.64	312.05	812.29
% wiper setting					
0	0.0	99.9	6	91.2	
1	10	0.0	50	8.8	
2	14	0.0	26	0.0	
3	75.2	0.1	18	0.0	
Total number of trips	10	10	18	18	56

TABLE 2 Preliminary Analysis for NDS Instrumented Vehicles: Speed

	Free-Flow Traffic (matched trips)		Comparison Within Trips	
Statistical Test	Heavy Rain	Matched Clear	Heavy Rain	Clear Weather
Average	85.07	101.39	91.8	106.36
SD	14.69	11.25	14.65	6.53
Minimum	17.4	70.4	35.09	53
Maximum	109.4	133.5	125.5	125.9
Median	87.5	101	94.19	106
t-test	Average speed is significantly lower in heavy rain. $t(21{,}021) = -303$, $P < .05$ Effect size (Cohen's d) = −1.24		Average speed is significantly lower in heavy rain. $t(3{,}713) = -164.6$, $P < .05$ Effect size (Cohen's d) = −1.28	
F-test	Speed variability is higher in heavy rain. $F_{1,9969,12454} = 0.990$, $P < .05$		Speed variability is higher in heavy rain. $F_{1,30006,46129} = 5.5$, $P < .05$	
Z-test	Proportion of violation ≥ 10 km/h above the speed limit is significantly higher in clear weather. $Z = 206.6731$, $P < .05$		Proportion of violation ≥ 10 km/h above the speed limit is significantly higher in clear weather. $Z = 50.47$, $P < .05$	

NOTE: Analysis was performed for 1-min aggregation level and 95% confidence interval. Matched data have equal trip distance; different travel times are due to lower speed because of weather. Speed is measured in kilometers per hour.

TABLE 3 Preliminary Analysis for NDS Instrumented Vehicles: Acc./Dec.

	Free-Flow Traffic (matched trips)				Comparison Within Trips			
	Heavy Rain		Matched Clear		Heavy Rain		Matched Clear	
Statistical Test	Acc. (g)	Dec. (g)	Acc. (g)	Dec. (g)	Acc. (g)	Dec. (g)	Acc. (g)	Dec. (g)
Average	0.0263	−0.0266	0.0253	−0.0276	0.0213	−0.0282	0.0158	−0.0162
SD	0.0181	0.0214	0.0184	0.0225	0.0157	0.0245	0.0160	0.0185
Minimum	0.0029	−0.3132	0.0015	−0.4321	0.0015	−0.2842	0.0029	−0.2610
Maximum	0.2059	−0.0029	0.1769	−0.0015	0.1769	−0.0015	0.1624	−0.0029
Median	0.0232	−0.0232	0.0203	−0.0232	0.0174	−0.0218	0.0116	−0.0087
t-test	Average acc. is significantly higher in heavy rain and average dec. is higher in clear weather. Acc.: $t(11{,}232) = 8.64$, $P < .05$ Effect size (Cohen's d) = 0.05 Dec.: $t(8{,}199) = 6.49$, $P < .05$ Effect size (Cohen's d) = 0.04				Average acc./dec. is significantly higher in heavy rain. Acc.: $t(3{,}223) = 33.68$, $P < .05$ Effect size (Cohen's d) = 0.37 Dec.: $t(2{,}199) = -45.51$, $P < .05$ Effect size (Cohen's d) = −0.61			
F-test	Acc./dec. variability is higher in clear weather. Acc.: $F_{1,7251,5258} = 0.97$, $P < .05$ Dec.: $F_{1,4256,4031} = 0.90$, $P < .05$				Acc./dec. variability is higher in clear weather. Acc.: $F_{1,1507,2520} = 0.95$, $P < .05$ Dec.: $F_{1,1228,1633} = 1.75$, $P < .05$			
Z-test	Proportion of dec. lower than −0.3 g is significantly greater in clear weather. No acc. was found higher than +0.3 g. Dec.: $Z = -4.2732$, $P < .05$				No acc./dec. was found higher or lower than ±0.3 g.			

NOTE: Analysis was performed for 1-min aggregation level and 95% confidence interval. Matched data have equal trip distance; different travel times are due to lower speed because of weather. Acc. = acceleration; dec. = deceleration.

TABLE 4 Preliminary Analysis for NDS Instrumented Vehicles: Yaw Rate

	Free-Flow Traffic (matched trips)				Comparison Within Trips			
	Heavy Rain		Matched Clear		Heavy Rain		Matched Clear	
Statistical Test	Acc.	Dec.	Acc.	Dec.	Acc.	Dec.	Acc.	Dec.
Average	0.84	–0.97	0.89	–0.8	1.01	–0.97	0.64	–0.61
SD	0.73	0.65	0.71	0.59	0.88	0.86	0.41	0.46
Minimum	0.33	–8.78	0.33	–3.9	0.16	–8.78	0.16	–4.55
Maximum	6.83	–0.33	5.85	–0.33	10.08	–0.16	3.25	–0.16
Median	0.65	–0.65	0.65	–0.65	0.65	–0.65	0.49	–0.33
t-test	Yaw rate (right rotation) is significantly higher in clear weather—no significant difference in left rotation. Right rotation: $t(2{,}515) = -6.4$, $P < .05$ Effect size (Cohen's d) = –0.08 Left rotation: $t(3{,}022) = 0.3$, $P > .05$ Effect size (Cohen's d) = 0.003				Yaw rate is significantly higher in heavy rain. Right rotation: $t(1{,}010) = 34.62$, $P < .05$ Effect size (Cohen's d) = 0.69 Left rotation: $t(1{,}793) = -41.62$, $P < .05$ Effect size (Cohen's d) = –0.62			
F-test	Yaw rate variability is higher in heavy rain. Right rotation: $F_{1,2704,1258} = 1.05$, $P < .05$ Left rotation: $F_{1,4504,1586} = 1.2$, $P < .05$				Yaw rate variability is higher in heavy rain. Right rotation: $F_{1,755,958} = 4.64$, $P < .05$ Left rotation: $F_{1,1229,1505} = 3.48$, $P < .05$			

NOTE: Analysis was performed for 1-min aggregation level and 95% confidence interval. Matched data have equal trip distance; different travel times are due to lower speed because of weather. Negative signs = left rotation. Yaw rate is measured in degrees per second.

TABLE 5 Preliminary Analysis for NDS Instrumented Vehicles: Lane Offset

	Free-Flow Traffic (matched trips)				Comparison Within Trips			
	Heavy Rain		Matched Clear		Heavy Rain		Matched Clear	
Statistical Test	Acc.	Dec.	Acc.	Dec.	Acc.	Dec.	Acc.	Dec.
Average	24.4	–23.04	62.26	–71.92	39.55	–45.99	34.56	–43.39
SD	22.55	26.87	130.79	135.39	76.44	83.33	65.58	75.06
Maximum	964.95	0	999.86	–0.01	838.83	–0.01	955.04	–999.59
Minimum	0	–590.8	0.05	–999.12	0.05	–998.61	0.05	–0.04
Median	20.32	–17.02	18.66	–29.08	16.85	–26.94	15.54	–26.88
t-test	Average lane offset to the right and left from the lane center is significantly higher in clear weather. Right: $t(1{,}450) = -34.23$, $P < .05$ Effect size (Cohen's d) = –0.57 Left: $t(4{,}113) = 66.80$, $P < .05$ Effect size (Cohen's d) = 0.66				Average lane offset to the right and left from the lane center is significantly higher in heavy rain. Right: $t(1{,}493) = 4.91$, $P < .05$ Effect size (Cohen's d) = 0.08 Left: $t(4{,}200) = -3.78$, $P < .05$ Effect size (Cohen's d) = –0.03			
F-test	Lane offset to the right and left variability is higher in clear weather. Right: $F_{1,3424,1415} = 0.02$, $P < .05$ Left: $F_{1,2494,3649} = 0.03$, $P < .05$				Lane offset variability is higher in heavy rain. Right: $F_{1,810,1392} = 1.36$, $P < .05$ Left: $F_{1,2174,3650} = 1.23$, $P < .05$			

NOTE: Analysis was performed for 1-min aggregation level and 95% confidence interval. Matched data have equal trip distance; different travel times are due to lower speed because of weather. Lane offset is measured in centimeters.

TABLE 6 Preliminary Analysis for NDS Instrumented Vehicles: Headway

	Free-Flow Traffic (matched trips)		Comparison Within Trips	
Statistical Test	Heavy Rain	Matched Clear	Heavy Rain	Clear Weather
Average	2.17	2.01	1.98	2.02
SD	1.00	1.12	1.16	1.14
Minimum	7.84	6.65	7.58	6.68
Maximum	0.16	0.08	0.12	0.15
Median	2.10	1.99	1.83	1.81
t-test	Headway is significantly higher in heavy rain. $t(8{,}268) = -21.93$, $P < .05$ Effect size (Cohen's d) = −0.15		No significant difference	
F-test	Headway variability is higher in clear weather. $F_{1,4030,4303} = 1.04$, $P < .05$		No significant difference	

NOTE: Analysis was performed for 1-min aggregation level and 95% confidence interval. Matched data have equal trip distance; different travel times are due to lower speed because of weather. Headway is measured in seconds.

conditions. The variability of acceleration and deceleration and the proportions of deceleration that were lower than −0.3 *g* were found to be greater in clear weather conditions. These findings coupled with the observed reduction in speed during heavy rain indicate that drivers compensate for the slippery surface conditions by not decelerating by rates greater than −0.3 *g*.

The lane offset variable in the NDS data is estimated using machine vision techniques. Lane offset is an indication of either a lane change or a deviation from the lane. Lane change is defined as an intended and substantial lateral shift of a vehicle (*27*). Lane change could be modeled using multiple variables: turn signal, steering angle, yaw rate, and machine vision lane offset. Although lane change is not the main focus of this study, distinguishing lane change from lane wandering is important to understand driver behavior in heavy rain conditions. Using time series and video data, lane changes were separated from lane wandering.

A criterion for lane offset values within ±0.3 m was set to flag lane-wandering events (Table 5), especially when these events varied to the right and left over a short duration of time. Continuous and steady lane offset within a threshold greater than ±0.3 m to ±9.5 m in one direction was considered as a full lane change. A past NDS study indicated that using a threshold of ±0.1 m resulted in a higher than expected number of lane departures (*28*). Preliminary analysis indicated that the number of lane changes is higher in clear weather conditions while lane wandering was found to be significantly higher in heavy rain.

Analyzing the NDS time series data in conjunction with video data revealed that the estimated NDS machine vision lane offset is noisy but still reliable in heavy rain weather conditions.

The minimum and maximum values for the lane offset also revealed a very interesting finding: drivers tend to change multiple lanes (two to three lanes) during clear weather conditions versus a single lane change in heavy rain conditions. Controlling for entry and exit of the freeway maneuvers, lane changes that occurred in heavy rain were mostly evasive maneuvers to mitigate an increased risk. From video observations, it was found that drivers opted out of speed reduction behind a slower vehicle more often than changing lanes.

Yaw rate and steering angle are additional variables that could be used to analyze lane maintenance. Unfortunately, steering wheel position was only available for a fraction of vehicles (only two trips included steering angle data). Yaw rates were analyzed (Table 4) for events with lane offset within ±0.3 m where there were no lane changes. Yaw rates were significantly higher in heavy rain, which, as mentioned earlier, might indicate frequent evasive maneuvers to mitigate an increased risk. On the one hand, average headways (Table 6) were found to be significantly higher in heavy rain compared with clear weather conditions under free-flow traffic. On the other hand, the variability of headways was found to be significantly higher in clear conditions. This could be explained by the fact that drivers tend to compensate for the increased risk because of the limitation in visibility by maintaining longer headway times.

Additional analyses were conducted on an individual (no matching) seven NDS trips that were identified to have both clear and heavy rain conditions within the same trip. All seven trips were in the free-flow traffic conditions. There was an agreement across the seven trips that speeds were reduced significantly with a higher standard deviation in heavy rain than in clear conditions. Also, the acceleration–deceleration and lane change–maintenance were affected. The number of braking, decelerations, and accelerations were significantly higher in heavy rain than in the clear portion of the trips.

There were 44 and 22 braking events in heavy rain and clear weather conditions, respectively. High variability in yaw rate might indicate either too many lane changes or poor lane maintenance. Although the number of lane changes was very limited in heavy rain compared with clear conditions, the high variability in yaw rate during heavy rain suggested worse lane maintenance capabilities than in the clear condition.

LANE-KEEPING MODEL

Logistic regression has been used to develop the lane-keeping model and investigate the factors that affect drivers' lane-keeping ability in different weather conditions. The dependent variable in the model is the standard deviation of lane position (SDLP), and the explanatory variables are the factors that may have significant influence on the lane-keeping ability. The SDLP is a binary variable defined at two levels: SDLP less than 50 cm and SDLP greater than 50 cm (*29*). If the average SDLP is maintained within 50 cm during the trip, lane-keeping performance can be considered within an acceptable reliability level and vice versa. The 50-cm threshold was selected when considering the LDW system application. Average of the SDLP (30.1 cm during heavy rain) was not used as a threshold in this study, since the driver would still be safe within this range given that it is not caused by distraction. SDLP has been widely used in examining lane-keeping ability. Previous studies used the SDLP for assessing drivers' lane-keeping ability (*30, 31*). The SDLP can be considered as a surrogate for overall driving safety because an increase in the SDLP is associated with an increase in the probability of lane departure events (i.e., when the outside edge of the vehicle tires crosses the lane marking), a precursor of run-off-road crashes (*32*).

To consider the SDLP as a crash surrogate measure, it was calculated for each NDS trip. Weather conditions were used as explanatory variables in this study. Weather conditions were considered in three levels: clear weather, light rain, and heavy rain. The model also accounted for traffic conditions, posted speed limit, and speed behavior. In case of speed behavior, the 5-km/h interval was considered based on the variable speed limit application (variable speed limits are adjusted at 5 km/h and mph increments). Also, the median of the speed limits was considered as the threshold. Driver demographics and vehicle characteristics (make, model, and year) data were not provided; thus, only environmental and traffic variables were considered. Table 7 summarizes the different variables used in the lane-keeping model.

A lane-keeping model was developed using logistic regression to better understand factors affecting drivers' lane-keeping ability in different weather conditions. Logit models have been used in previous studies (*33, 34*). One of the advantages of logistic regression in comparison with ordinary least squares regressions is that independent variables do not have to be normally distributed, or have equal variance in each group. Also, predictors in the logistic regression can be continuous, categorical, or a mixture of both continuous and categorical. Equation 1 shows a logistic regression model with x as an independent variable, $P(x)$ as a probability of having success for a binary response variable y considering explanatory variable x, α as the probability of response when explanatory variables are the reference level (or when $x = 0$), and β as the regression coefficient (*35*). Also, the conditional probability of positive outcome can be determined by Equation 2.

$$\text{Logit}\left[P(x)\right] = \log\left(\frac{P(x)}{1-P(x)}\right) = \alpha + \beta x \tag{1}$$

$$P(x) = \frac{\exp(\alpha+\beta x)}{1+\exp(\alpha+\beta x)} = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}} \tag{2}$$

The maximum likelihood method was used to measure the associations by constructing the likelihood function as follows. For more discussion about the maximum likelihood method, refer to Agresti (*35*).

$$l(\beta) = \prod_{i=1}^{n} P(x_i)^{y_i}\left(1-P(x_i)\right)^{1-y_i} \tag{3}$$

In Equation 3, y_i represents the ith observed outcome, with the value of either 0 or 1, and $i = 1, 2, 3, \ldots, n$, where n is the number of observations. The best estimate of β could be obtained by maximizing the log likelihood expression as

$$\text{LL}(\beta) = \ln\left(l(\beta)\right) = \sum_{i=1}^{n}\left\{y_i \ln\left(P(x_i)\right) + (1-y_i)\ln\left(1-P(x_i)\right)\right\} \tag{4}$$

Odds ratio (OR) is used in many studies to interpret the logistic regression results (*36*). By exponentiating the coefficient (β), odds ratio could be obtained in a logistic regression model (*35*).

$$\text{OR} = \exp\left(\beta_j\right) \tag{5}$$

DISCUSSION OF RESULTS

To confirm the suitability and fitness of the lane-keeping model, the log likelihood ratio and the pseudo-R^2 were used. Table 8 shows the results of the model; the likelihood ratio test statistic falls into the

TABLE 7 Data Description

Variable	Description	Type	Levels
Response Variable			
SDLP	Standard deviation of lane position	Binary	SDLP ≤50 SDLP >50
Explanatory Variables			
Traffic	Traffic condition	Binary	0 = free flow 1 = traffic
Speed limit	Posted speed limit	Categorical	0 = below 90 km/h 1 = above 90 km/h
Speed behavior	Speed selection in various weather conditions	Categorical	More than 5 km/h below the speed limit 0–5 km/h below the speed limit 0–5 km/h above the speed limit More than 5 km/h above the speed limit
Weather	Type of weather condition	Categorical	Clear Light rain Heavy rain

TABLE 8 Logistic Regression Model for Lane-Keeping Ability in Different Weather Conditions: Analysis of Maximum Likelihood Estimates

Parameter	df	Estimate	Standard Error	Wald Chi Square	Odds Ratio	*P*-Value	95% Confidence Limits	
Intercept	1	−0.4630	0.4621	1.0037	—	0.3164	—	—
Weather								
Clear		—	—	—	—	—	—	—
Light rain	1	−0.7671	0.8352	0.8435	0.464	0.3584	0.090	2.387
Heavy rain	1	1.3389	0.5554	5.8117	3.815	0.0159	1.284	11.331
Speed limit								
Below 90 km/h		—	—	—	—	—	—	—
Above 90 km/h	1	−2.7258	1.1092	6.0395	0.065	0.0140	0.007	0.576
Traffic								
Free flow		—	—	—	—	—	—	—
Traffic congestion	1	−1.5778	0.5387	8.5792	0.206	0.0034	0.072	0.593

NOTE: Dashes represent reference levels for the significant categorical variables.

rejection area (*P*-value < .05), which means that the overall explanatory variables of the model have significant influence on the response at a statistical significance level of 95%. Only statistically significant variables were retained in the final models.

As can be seen in Table 8, heavy rain has a statistically positive effect on SDLP. It means that standard deviation of lane position is more likely to be higher in heavy rain conditions. Particularly, driver lane-keeping ability would be reduced (the SDLP would be increased) by increasing the precipitation intensity. This may be attributed to the shorter sight distance and low visibility of lane marking in heavy rain condition. This finding agrees with other previous studies, showing the negative effect of adverse weather on drivers' performance (*37, 38*). More clearly, drivers in heavy rain condition are 3.8 times more likely than in clear weather to have a higher SDLP (OR = 3.8). It is also shown that driving in light rain conditions does not have any effect on lane-keeping ability.

Interestingly, maximum posted speed limit was found to be significant with a negative coefficient in the developed lane-keeping model. This might stem from the fact that drivers pay more attention to the road ahead considering the higher speed. Road segments with higher speed limits might have better geometry design and sight distance in comparison with segments with lower speed limit. Obtained negative association between lane keeping and posted speed limit could be because of the mentioned advantages of segments with higher speed limits that can compensate for the negative effects of rainy weather condition to some extent. Driving in a segment with higher speed limit does not necessarily mean that the driver has higher speed. More specifically, drivers who are driving in road segments with posted speed limits less than 90 km/h are 15 times more likely to have a higher SDLP in comparison with those who are driving in segments with posted speed limit above 90 km/h (OR = 0.065). It is known that drivers reduce their speed during adverse weather conditions (*39*). Lower speed can enhance drivers' performance, especially at the start of rain as the surfaces are most slippery because of the oil and dust that have not washed away mixing with the moisture. Moreover, lower speed can increase the headway spaces, providing more time to prepare for the appropriate maneuver as driving becomes risky with low visibility.

Traffic conditions were found to be statistically significant as expected. The negative sign depicts the fact that by increasing traffic congestion, drivers have less ability to swerve and change lanes, and generally are forced to have better lane-keeping. More clearly, drivers who drive in a free-flow condition are 4.8 times more likely to have a higher SDLP in comparison with drivers who are driving in traffic congestion conditions (OR = 0.206).

CONCLUSIONS

A unique methodology was introduced in this study to extract weather-related events from the massive SHRP 2 data set. The SHRP 2 NDS data and RID were used to better understand driver behavior in general and lane-keeping performance in particular in clear and heavy rain weather conditions.

Descriptive statistics were used to understand the difference between drivers' behavior in clear and heavy rain weather conditions, and logistic regression was utilized to identify the main contributing factors affecting drivers' lane-keeping ability in different weather conditions.

Based on the obtained results from the performed descriptive analysis, heavy rain had a wider range and a higher average of acceleration; however, average deceleration was found to be higher in matching trips in clear weather conditions. The number of lane changes is higher in clear weather; however, lane wandering is higher in heavy rain conditions. Yaw rates and average headways were found to be statistically higher in heavy rain in comparison with clear weather conditions. Acceleration, deceleration, speed, headway, and lane keeping can be used as indicators of safety. Weather, speed limit, and traffic conditions were found to be significant contributing factors in the developed lane-keeping model.

Analyzing drivers' behavior at a microscopic level has become an important topic for different tasks in transportation engineering. The Naturalistic Driving Study data in particular may help in developing driving models that could be applied to different areas (*40–42*): (*a*) performing safety analyses based on individual driver data; (*b*) calibration of driving behavior models to update microscopic models for traffic simulation, specifically in various traffic and weather conditions; and (*c*) developing control logics for advanced driving assistance systems and connected and automated vehicles. While the results from this paper may improve one's understanding about lane-keeping behavior in heavy rain at a microscopic individual level, the results may also help in developing better LDW systems. The NDS data may address limitations of these systems during adverse weather conditions. Individual drivers' data may provide more insights into drivers' behavior and performance in different traffic and weather conditions than the commonly used macroscopic level of speed, volume, and occupancy. The understanding gained from these data may help in updating microsimulation models.

LIMITATIONS

This study was part of the FHWA SHRP 2 Implementation Assistance Program in Wyoming titled Driver Performance and Behavior in Adverse Weather Conditions: An Investigation Using the SHRP 2 Naturalistic Driving Study Data. The absence of demographics and NDS vehicle information as well as the small sample size used in this study were considered limitations. Wyoming has been awarded a second phase from the FHWA SHRP 2 Implementation Assistance Program to extend the work performed in this study.

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