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Investigating the Impact of Fog on Freeway Speed Selection using the SHRP2 Naturalistic Driving Study Data

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Md Nasim Khan[1], Ali Ghasemzadeh[1], and Mohamed M. Ahmed[1]

Abstract

The negative effect of reduced visibility on driver performance has been recognized as one of the main causes of motor vehicle crashes in fog. Although many studies have concentrated on driver behavior during foggy weather in a simulated environment, there is a lack of studies that have addressed the impact of fog on driver behavior and performance in naturalistic settings. This paper utilized the data from the SHRP2 Naturalistic Driving Study (NDS) database to understand driver behavior in general and speed selection in particular during clear and foggy weather conditions. In this study, a comparative preliminary analysis and an ordered logit model were developed to evaluate driver speed behavior in fog and clear weather conditions. Results from the preliminary analysis showed 10% and 3% reduction in speed because of near fog and distant fog, respectively. In addition, results from the speed selection model showed that the odds of reducing speed were 1.31 and 1.28 times higher for drivers traveling in near fog and distant fog, respectively, compared with drivers who were driving in clear weather conditions. However, there is an over-representation of young drivers in the SHRP2 NDS database, which was reflected in the dataset used in this study. Therefore, a more representative sample of age groups might provide different results. The results from this study could provide a better insight into driver speed selection during foggy weather conditions, which can be utilized to improve various safety strategies including variable speed limits.

According to the Federal Highway Administration, roughly 15% of fatal crashes, 19% of injury crashes, and 23% of property-damage-only (PDO) crashes occur in the presence of adverse weather, which results in approximately 5,100 fatal crashes, 304,800 injury crashes, and 922,200 PDO crashes every year (*1*). Many studies have explored the impact of adverse weather on crashes and found that crash rate increases during inclement weather (*2–4*).

Driving in foggy weather is challenging because of reduced visibility, limited contrast, and distorted perception, which causes many accidents every year. From a visual perspective, fog can be described as a reduction in contrast in the visual field (*5*). In fog, drivers face difficulty in perceiving speed and headway, as well as road signs and markings, which are crucial for safe driving (*6*). Fog-related crashes tend to involve multiple vehicles and usually have more fatalities compared with crashes under clear weather conditions (*7*). A previous study showed that foggy conditions may increase crashes specifically in lack of road lighting (*8*). Moore and Cooper found that drivers usually considered the leading vehicle as a means of guidance and drove at a speed similar to the leading vehicle while driving in foggy weather. They stated this tendency to be the main cause of rear-end crashes in foggy weather (*9*).

Yan et al. investigated the effect of foggy weather conditions on driver speed control at different risk levels and found that at the high-risk level, driver speed compensation because of fog did not reduce their crash-involvement risk, though it effectively lowered the crash severity (*10*). A study conducted in a driving simulator environment investigated driver speed perception in foggy weather conditions. They found that drivers perceived their speed as slower than the actual speed in foggy weather conditions (*11*). However, several studies using more sophisticated driving simulators contradict these results. For instance, Owens et al. showed that drivers tended to overestimate their speed and drove at a speed lower than instructed (*12*). In another study, based on 566 surveyed drivers in Florida, Hassan et al. concluded that drivers usually take shorter headways from lead vehicles during limited visibility conditions caused by near fog. The study also mentioned that the variable speed limit (VSL) signs during fog cannot reflect the accurate safe speed limit because of the frequent fluctuation of fog thickness (*13*).

[1]Department of Civil & Architectural Engineering, University of Wyoming, Laramie, WY

Corresponding Author:
Address correspondence to Ali Ghasemzadeh: aghasemz@uwyo.edu

As mentioned in the previous section, the majority of the studies were mainly performed in a simulated environment or utilizing survey questionnaires (*10–15*). However, utilizing real-world data is becoming more and more accessible and popular (*16 –20*).

There is a lack of studies that have examined the impact of fog on driver behavior and performance under naturalistic settings. The data used in this study were collected from the second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS), which is the largest study on naturalistic driving behavior to date in the U.S. In addition, the Roadway Information Database (RID) was also utilized. The RID was developed mainly to link roadway information to the NDS database.

This study will help in gaining insights into driver dynamics of adapting speed. It will also provide valuable information about how drivers interact with roadway and foggy weather conditions, which can be used for effective countermeasures.

The SHRP2 NDS data have several advantages over studies that are conducted in a simulator or controlled experimental environment. For instance, driver behavior in a simulator or in a controlled environment may not properly represent actual behavior in normal driving conditions. More specifically, driver behavior and performance might be biased, and drivers may not behave naturally, as they do in real life. Naturalistic driving studies can overcome these problems and provide an opportunity to investigate the safety impacts of driver behavior during different weather and roadway conditions.

The overall objective of this study is to assess driver behavior and performance during clear and fog weather conditions by utilizing the NDS and RID database. This will be attained by developing an appropriate NDS and RID data acquisition technique, then conducting a preliminary analysis between clear and foggy weather conditions, and finally developing a speed selection model to identify the major contributing factors that might influence driver speed selection under foggy weather conditions.

Data Source

The SHRP2 NDS data used in this study were requested from the Virginia Tech Transportation Institute (VTTI). The SHRP2 is the largest study on naturalistic driving behavior to date in the U.S. Data were collected from six sites around the United States, including Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington. Participant vehicles were instrumented with a data acquisition system (DAS). The DAS includes forward radar; four video cameras, including one forward-facing color wide-angle camera; accelerometers; vehicle network information; geographic positioning system; onboard computer vision lane tracking, plus other computer vision algorithms; and data storage capability. In addition to the NDS data, the SHRP2 RID was also utilized in this study. The RID database was developed by the Iowa State University Center for Transportation Research and Education. The primary objective of this database is to provide high-quality roadway data that can be linked to the NDS database. The RID contains a comprehensive description of roadway characteristics including curve radius, grade, superelevation, number of lanes, shoulder information, and so forth (*21*).

To effectively identify the NDS trips occurring in fog, weather data from the National Climate Data Center (NCDC) was used. Previous studies have utilized NCDC weather data to identify road weather conditions (*22*, *23*). The NCDC archives weather data from various weather stations nationwide, including radar, satellites, airport weather stations, and military weather stations. Among these data sources, the airport weather stations proved to be the most beneficial to identifying adverse weather events.

Data Reduction

Acquisition and preparation of the NDS data were challenging for various reasons. For instance, identifying the event of interest, processing and reducing video data, and linking the NDS data with the RID and questionnaire data were difficult, labor-intensive, and time-consuming tasks.

To efficiently extract the fog-related trips, a unique method was developed. This method used weather data from the NCDC. In order to identify the spatial-temporal segments of freeways as a potential location for trips occurring in fog, a buffer zone of influence needed to be specified. In this study, a buffer zone of 5 nautical miles (n.m.) was used as a zone of influence. This method was utilized in a previous study and found that the accuracy of identifying fog-related crashes is over 60% (*22*). NDS trips were requested based on the daily weather information to identify all trips affected by adverse weather conditions. By using this process, the research team received data for weather-related trips and matched trips in clear weather conditions. The provided NDS data included video views of forward and backward roadways, basic trip characteristics, and time series data. The received data were then processed and observed manually to filter out the trips that were not related to fog.

To effectively reduce time series and video data an extensive data reduction procedure was conducted. As weather conditions were not consistent throughout the whole trip, each trip was divided into 1-minute segments to ensure consistent weather and traffic conditions within each segment. In addition, video reviewers were provided with observation templates. They extracted environmental and traffic-related data including visibility, surface conditions, freeway segment type, and traffic conditions for each 1-minute segment by observing the videos manually.

Although visibility information could be obtained from the NCDC, the weather station reporting frequency is relatively long, usually 1 hour, and the fluctuation of visibility within 1 hour is common. Moreover, weather stations are mostly mounted at a higher elevation and do not necessarily represent roadway surface visibility. It is worth mentioning that identifying near fog and distant fog based on visibility range from weather stations would not provide real-time visibility conditions. To overcome these limitations, each NDS trip was observed manually and the visibility level was identified for each 1-minute segment.

Considering visibility conditions, foggy weather was classified into two levels including near fog and distant fog. The fog that was close to the NDS vehicle and was more likely to affect driver speed choice and performance was considered as near fog; whereas, fog that was not immediately near to the NDS vehicle but covered the surroundings of the roadway was considered as distant fog. To maintain consistency in reducing video data, video observers were provided with comprehensive training. Video observers reported a weather condition as distant fog if the horizon could not be seen properly but the roadside surroundings (delineators, guardrail, and so forth) can be recognized to some extent, and the information on the road signs and markings can be recognized properly. On the other hand, a weather condition was categorized as near fog if roadside surroundings (delineators, guardrail, and so forth), road markings, and the horizon could not be seen clearly, and the information on road signs is not readable.

The speed limit data, as well as other roadway characteristics such as curve length, radius, superelevation, and so forth, provided in the RID database, were then merged with each 1-minute segment. Finally, driver demographics such as age, income, gender, mileage last year, and so on, collated from the questionnaire survey, were added to each 1-minute segment to create the summary files. These summary files then served as the foundation for modeling and representing driver behavior in foggy weather conditions. It is worth mentioning that online questionnaires were filled out by the NDS participants before involving them in the project. These questionnaires collected information about driver demographics as well as other data about driver sleep, health, and risk-taking behavior (*24*).

Previous studies by the authors using sample trips indicated that the resolution/quality of the forward-facing camera videos during nighttime was very low, especially in adverse weather conditions. Therefore, considering the fact that several variables, including traffic conditions and weather and surface conditions, needed to be reduced from the forward-facing video cameras, nighttime trips were eliminated from the final dataset (*25–27*).

A total of 124 trips in fog and 248 matched trips in clear weather conditions have been fully processed using the described data reduction procedure, which resulted in a total of 7,147 1-minute segments (2,549 in fog, 4,598 in clear weather). As mentioned earlier, this study is trying to provide better insights into driver speed selection under foggy weather conditions, which can lead to providing more realistic speed limits for the VSLs on freeways. Therefore, data were requested for freeways only. However, preliminary analysis showed that some trips have some non-freeway segments at the beginning and at the end of the trips (entering and exiting freeways). Therefore, non-freeway segments were removed from the start and end of these trips. Once the non-freeway segments were removed, the number of 1-minute segments was reduced to 5,587 (i.e., 1,912 in fog and 3,675 in clear weather). A total of 62 drivers between 16 to 79 years of age participated in the selected NDS trips, with more than 80% of drivers aged below 34 years. The number of male and female drivers was almost equal, with a marginally higher percentage (56%) of male drivers. Figure 1 shows the details of the data reduction procedure.

Preliminary Analysis

Summary Statistics

Traffic conditions were categorized into free-flow (Level of service A and B) and mixed traffic condition (Level of service C to F). According to the *Highway Capacity Manual*, free-flow is defined as low-volume roadway conditions, where drivers are free to drive at desired speed and are not constrained by the presence of other vehicles (*28*). In this study, 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 in which NDS drivers were affected by other vehicles were considered as mixed traffic conditions.

Each trip in fog was matched with two trips in clear weather considering the same driver, same vehicle, and same location. Matched trips were requested from the VTTI. As mentioned in a previous study, weather conditions may not be consistent within a trip (*26*). Therefore, considering the possible variations in weather conditions, exact match of the 1-minute segments in fog and clear weather was conducted by importing the longitude and latitude of the trips and eliminating non-matching segments in the ArcGIS software.

Removing the non-matching segments resulted in 5,398 1-minute matching segments (1,867 in fog, 3,531 in clear weather), which was equivalent to nearly 90 hours of driving time and 8,335 kilometers of mileage. The summary statistics of these 5,398 1-minute segments are provided in Table 1.

Speed Distribution

This study investigated the distribution of speeds between clear and foggy weather conditions in various traffic states. From the NDS sample data, it was concluded that the speeds have a Weibull distribution in near fog under free-flow conditions, whereas the speeds were normally distributed in clear weather for the matching dataset. A similar trend was

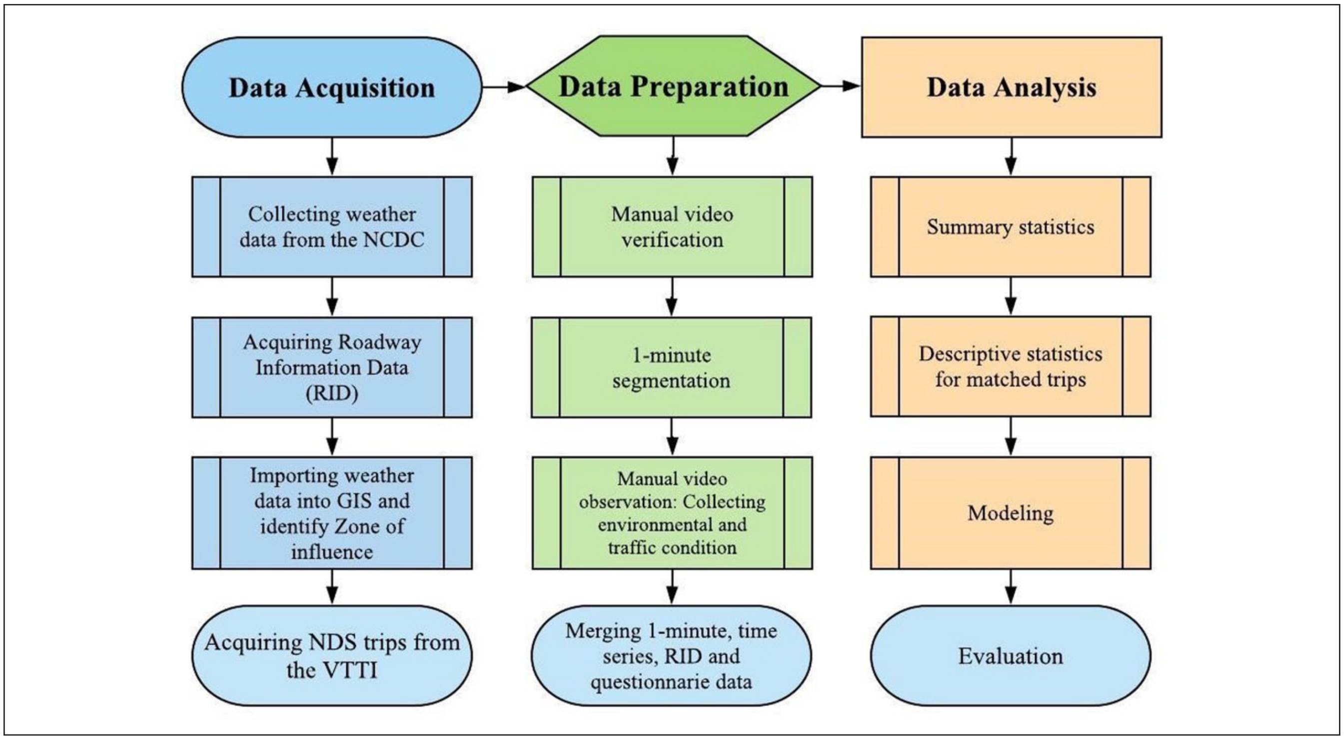

Figure 1. Flow chart summarizing the data reduction and analysis procedure.

Table 1. Summary Statistics of NDS Trips Considered in This Study

	Weather condition	Near fog	Matched clear	Distant fog	Matched clear	Total
Free-flow condition LOS A & B	Number of 1-minute segments	241	539	717	1467	2964
	Total duration (hour)	4.02	8.98	11.95	24.45	49.40
	Total length (km)	418.59	973.72	1260.29	2637.26	5289.86
Congested traffic condition LOS C to F	Number of 1-minute segments	271	405	638	1120	2434
	Total duration (hour)	4.52	6.75	10.63	18.67	40.57
	Total length (km)	340.35	542.85	750.54	1411.11	3044.85
Total number of 1-minute segments		512	944	1355	2587	5398
Total duration (hour)		8.53	15.73	22.58	43.12	89.97
Total length (km)		758.94	1516.57	2010.83	4048.37	8334.71

also found for distant fog, as shown in Figure 2. Speed in free-flow conditions is important for VSL application, as speed selection here is not affected by the interaction with traffic (*25*). Other speed distributions for other scenarios were also examined. Speed distribution during near fog in mixed traffic conditions did not fit a specific distribution. However, speeds during distant fog as well as their matched clear weather conditions in mixed traffic fitted a bimodal distribution, which is common during congestion on freeways (*29*). Figure 2 shows the speed distribution for trips in near fog, distant fog, and matched trips in clear weather under free-flow and congested (i.e., mixed/near traffic) traffic conditions.

Descriptive Analysis

Driver speed behavior, including selection of speeds and accelerations under free-flow conditions, was investigated in clear and foggy weather in order to have a better understanding of driver behavior in different weather conditions. Various statistical tests, including *t*-test, *F*-test, and *Z*-test, were used to compare driver behavior between foggy and clear weather, as shown in Table 2. A *t*-test indicated that the average speed in near fog, as well as in distant fog, was significantly lower than in clear conditions under free-flow traffic. However, speed reduction was greater in near fog compared with distant fog. Speed in near fog and distant

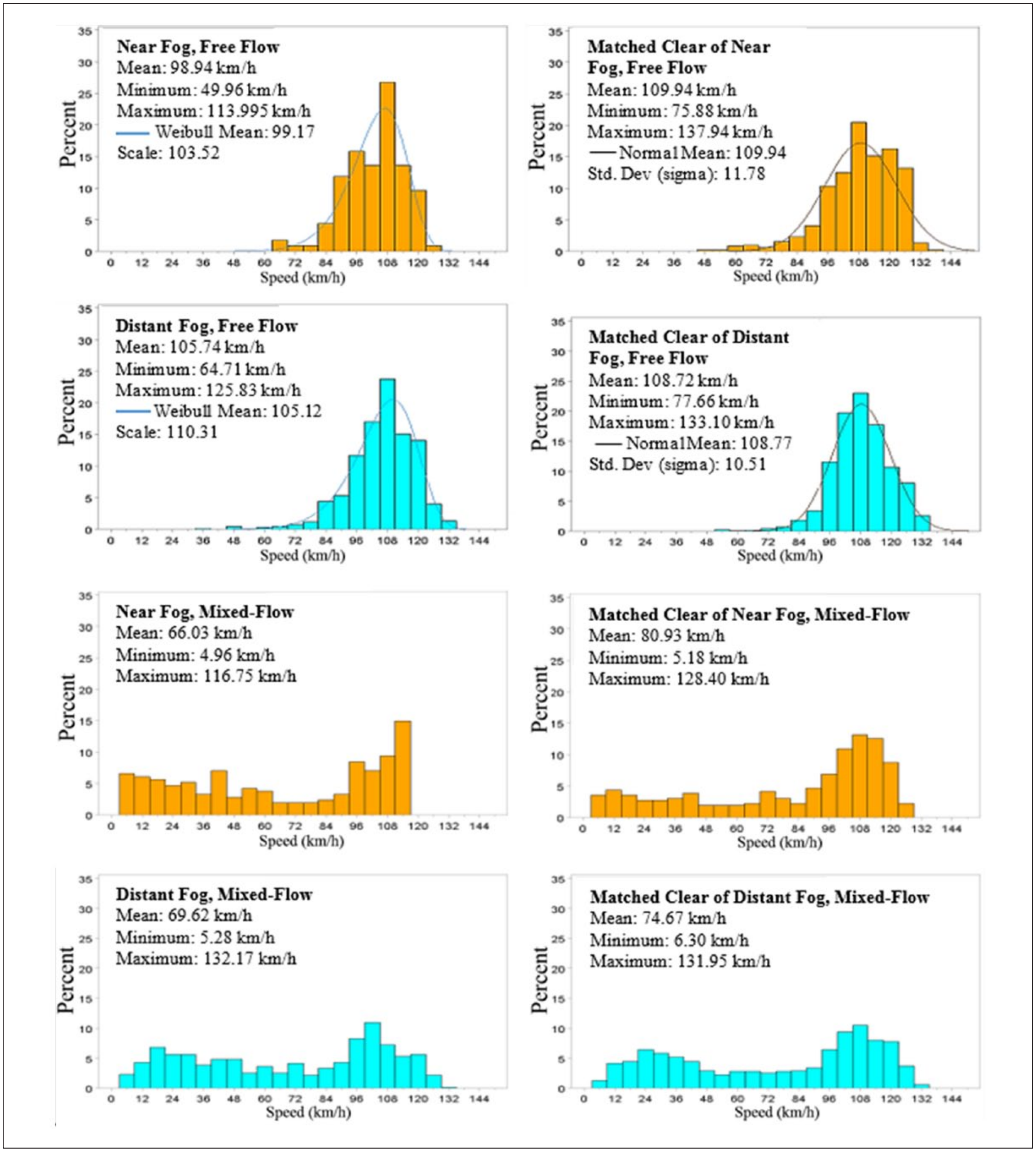

Figure 2. Observed and fitted distributions for speeds during fog and clear weather under free-flow and mixed traffic conditions.

fog was found to be 11 km/h (10% reduction) and 3 km/h (2.8% reduction) lower than the speeds in their matching clear weather conditions, respectively. Previous studies have also concluded similar results of speed reduction. For instance, Liang and Kyte found 6–10 km/h speed reduction as a result of the poor visibility caused by fog (*30*). It was also found that speeds had a higher variability during distant fog compared with clear weather under free-flow traffic, which could be an indication of increased safety risk (*31*, *32*). However, an opposite trend was found for near

Table 2. Descriptive Statistics for NDS Instrumented Vehicles in Fog

		Free-flow traffic							
		Near fog		Matched clear		Distant fog		Matched clear	
	Statistical test	Speed (km/h)	% Speed difference from speed limit	Speed (km/h)	% Speed difference from speed limit	Speed (km/h)	% Speed difference from speed limit	Speed (km/h)	% Speed difference from speed limit
Speed (km/h)	Average	98.944	−1.556	109.944	−8.420	105.739	−4.213	108.722	−7.803
	SD	10.436	10.141	11.785	9.831	11.087	10.070	10.511	8.558
	Min.	49.957	−21.360	75.877	−42.627	64.707	−33.525	77.660	−42.104
	Max.	113.995	43.548	137.942	27.530	125.832	33.385	133.097	26.683
	Median	100.313	−2.754	110.195	−8.100	107.018	−5.005	108.887	−7.847
	t-test	Average speed is significantly lower in near fog. $t(317) = -11.15$, $p < 0.05$ Effect size (Cohen's d) = −0.92				Average speed is significantly lower in distant fog. $t(2009) = -5.84$, $p < 0.05$ Effect size (Cohen's d) = − 0.29			
	F-test	Speed variability is significantly lower in near fog. $F_{523,201} = 1.32$, $p < 0.05$				Speed variability is significantly higher in distant fog. $F_{648,1361} = 1.11$, $p < 0.05$			
	Z-test	Proportion of violation ≥10 km/h above the speed limit is significantly lower in near fog. $Z = -5.73$, $p < 0.05$				No significant difference between the proportion of speeding ≥10 km/h in distant fog and clear weather. $Z = 0.69$, $p > 0.05$.			
Acceleration/ deceleration (g)		Acc. (g)	Dec. (g)	Acc. (g)	Dec. (g)	Acc. (g)	Dec. (g)	Acc. (g)	Dec. (g)
	Average	0.017	−0.013	0.016	−0.012	0.016	−0.019	0.017	−0.016
	SD	0.017	0.014	0.017	0.0140	0.014	0.016	0.013	0.015
	Min.	0.000	−0.061	0.000	−0.067	0.000	−0.070	0.000	−0.067
	Max.	0.082	0.000	0.079	−0.000	0.065	0.000	0.072	0.000
	Median	0.011	−0.009	0.011	−0.006	0.011	−0.012	0.013	−0.011
	t-test	Average acceleration is significantly lower in near fog. $t(453) = 0.13$, $p < 0.05$ Effect size (Cohen's d) = −0.02 No significant difference between the average deceleration in near fog and clear weather. $t(218) = -0.80$, $p > 0.05$ Effect size (Cohen's d) = −0.12				No significant difference between the average acceleration in distant fog and clear weather. $t(1191) = -1.14$, $p > 0.05$ Effect size (Cohen's d) = −0.10 No significant difference between the average deceleration in distant fog and clear weather. $t(816) = -1.60$, $p > 0.05$ Effect size (Cohen's d) = −0.12			
	F-test	No significant difference between the acceleration variability in near fog and clear weather. $F_{1011,362} = 1.09$, $p > 0.05$ No significant difference between the deceleration variability in near fog and clear weather. $F_{86,144} = 1.03$, $p > 0.05$				No significant difference between the acceleration variability in distant fog and clear weather. $F_{384,807} = 1.06$, $p > 0.05$ No significant difference between the deceleration variability in distant fog and clear weather. $F_{263,553} = 1.14$, $p > 0.05$			
	Z-test	No acceleration/ deceleration were found higher/lower than ±0.3 g				No acceleration/ deceleration were found higher/lower than ±0.3 g			

Table 3. Odds Ratio for Speed Behavior

Weather condition	Driving below speed limit	Driving above speed limit	Odds ratio	Confidence interval	Significance level
Near fog	77 (33.7 %)	151 (66.3%)	2.42	1.69 to 3.45	$p < 0.0001$
Matched clear of near fog	386 (17.4%)	1525 (82.6%)			
Distant fog	196 (29%)	480 (71%)	1.90	1.54 to 2.36	$p < 0.0001$
Matched clear of distant fog	253 (17.7%)	1180 (82.3%)			

fog, where speeds in clear weather conditions had more variability.

In addition, the acceleration/deceleration variability was examined, and ±0.3 *g* acceleration/deceleration rates were set as a threshold to identify aggressive braking/acceleration events (*33*). However, no acceleration and deceleration events were found to be higher or lower than ±0.3 *g*, indicating the occurrence of zero aggressive events, as shown in Table 2.

Speed Selection

Speed above the speed limit in fog and respective matching trips in clear weather were examined to determine driver compliance to the speed limit in different weather conditions. It was found that NDS drivers drove consistently above the speed limit in all conditions, including near fog. For instance, NDS drivers drove with a speed 1.6% above the speed limit in near fog; whereas in clear weather NDS drivers drove with a speed 8.4% above the speed limit. Similar results were also found for distant fog. A *Z*-test as shown in Table 2 indicates that the violation of speed greater than 10 km/h was significantly lower in near fog compared with matching trips in clear weather. However, no significant difference was found between the violation of speed greater than 10 km/h in distant fog and corresponding matched clear trips, indicating no effect of distant fog on speeding behavior.

According to Table 3, the majority of the drivers drove with a speed above the limit. For instance, speeds of about 66% of the trips in near fog and almost 83% of the trips in matching clear weather were above the speed limit. Similarly, about 71% of the trips in distant fog and 82% of the trips in respective clear weather were driven at speeds more than the speed limit. Table 3 also indicates that speed reduction was more likely to occur in foggy weather conditions in comparison with the matched trips in clear weather conditions. The odds ratios of driving below the speed limit, in general, were 2.4 and 1.9 times more likely to be in near fog and distant fog, respectively, than matching trips in clear weather conditions.

Modeling Speed Selection: Ordered Logit Model

To better understand the factors affecting driver speed selection in different weather conditions an ordered logit model was developed. The model was calibrated utilizing a dataset of 5,587 1-minute segments occurring in various weather and traffic conditions. A logit model has various advantages over other models. For instance, predictors in the logit model can be continuous, categorical, or a mixture of both. In addition, independent variables do not have to be normally distributed or have equal variance in each group (*34*). Table 4 shows the summary of different variables used in the speed selection model. The response variable of the model is speed selection, which is classified into four levels, based on the median percent speed reduction above or below the speed limit $\frac{(Speed\ limit - speed)}{Speed\ limit}$. The four-quartile intervals were defined as: (1) More than 10% increase in speed, (2) 0–10% increase in speed, (3) 0–28% reduction in speed, and (4) more than 28% reduction in speed. These intervals were selected based on quartile values in order to ensure sufficient sample size in each category. The remaining variables are explanatory variables including environmental variables, traffic conditions, driver demographics, and roadway factors.

Speed Selection Model Results

The log likelihood ratio (LR) was used to confirm the fitness of the model. The LR test statistic as shown in Table 5 falls into the rejection region with a *p*-value <0.05, which indicates the overall explanatory variables of the model have significant effect on the response at a statically significant level of 95%. To check the possible presence of multicollinearity, the variance inflation factor (VIF) was calculated for each predictor. The VIF measures how much the variance of an estimated regression coefficient increases if predictors are correlated. A VIF between 5 and 10 shows a high correlation between predictors and a VIF greater than 10 indicates that the regression coefficients are poorly estimated as a result of multicollinearity (*35*). However, the VIF value of all the predictors in the speed selection model fell below 2.5, indicating no multicollinearity problem. Only the statistically significant variables were retained in the final model. Table 5 shows the results of the speed selection model.

Discussion of Key Factors

Fourteen variables and three interaction terms were found to be significant in the speed selection model. As expected, fog

Table 4. Data Descriptions for Speed Selection Model

Variable	Description	Type	Levels
Response variable			
Speed selection	Percent speed reduction above or below the speed limit	Ordinal	1 = More than 10% increase in speed 2 = 0–10% increase in speed 3 = 0–28% reduction in speed 4 = More than 28% reduction in speed
Explanatory variables			
Environmental variables			
Weather conditions	Predominant weather conditions in 1-min video observation	Categorical	1 = Clear 2 = Distant fog 3 = Near fog
Visibility	Predominant visibility conditions in 1-min video observation	Categorical	1 = Not affected 2 = Affected
Surface conditions	Predominant surface conditions in 1-min video observation	Binary	1 = Dry 2 = Wet
Traffic variables			
Traffic condition	Predominant traffic conditions in 1-min video observation	Binary	1 = Free flow 2 = Mixed flow
Speed limit	Predominant speed limit conditions in 1-min segment	Categorical	1 =<55 2 = 55–60 3 = 65–70
Driver demographics			
Gender	The gender the participant	Binary	1 = Male 2 = Female
Age	The age group corresponding to the driver's birthdate	Categorical	1 = Less than 40 years 2 = Greater than 40 years
Education	The highest completed level of education of the participant	Categorical	1 = High school diploma or G.E.D. 2 = Some education beyond high school but no degree and college degree 3 = Some graduate or professional school, but no advanced degree (e.g., J.D.S., M.S. or Ph.D.) and advanced degree (e.g., J.D.S., M.S. or Ph.D.)
Marital status	The participant's marital status	Categorical	1 = Single 2 = Married 3 = Other (divorced, widow, unmarried partners)
Driver mileage last year	The approximate number of miles the participant drove last year	Categorical	1 = Less than 10,000 miles 2 = Between 10,000 to 20,000 miles 3 = Greater than 20,000 miles
Driving experience	Number of years of driving experience	Categorical	1 = Less than 10 years 2 = Greater than 10 years
Roadway factors			
Bridge	Presence of bridge	Binary	1 = No bridge 2 = On bridge
Curve	Presence of curve	Binary	1 = No curve 2 = On curve
Superelevation	Average superelevation of the road in 1-min segment	Continuous	–
Curve length	Average length of curve of the road in 1-min segment	Continuous	–

had a significant effect on speed selection. Results showed that drivers were likely to travel at significantly lower speeds during foggy weather conditions; more specifically, the odds of drivers reducing their speeds were 1.31 and 1.28 times higher for drivers traveling in near fog and distant fog, respectively, in comparison with drivers who were driving in

Table 5. Estimation of Ordered Logit Model for Speed Selection

Parameter		DF	Estimate	Standard error	Wald chi-square	p-value	Odds ratio	95% confidence interval	
Intercept	4	1	−1.4876	0.2516	34.9552	<.0001	0.226	–	–
Intercept	3	1	0.0017	0.2508	0.0000	0.9945	1.002	–	–
Intercept	2	1	1.4051	0.2509	31.3594	<.0001	4.076	–	–
Weather	Clear	1	–	–	–	–	–	–	–
	Distant fog	1	0.2528	0.0741	11.6346	0.0006	1.288	1.113	1.490
	Near fog	1	0.2726	0.1234	4.8808	0.0272	1.313	1.031	1.673
Visibility	Not affected	1	–	–	–	–	–	–	–
	Affected	1	0.4953	0.1377	12.9452	0.0003	1.641	1.253	2.149
Surface condition	Dry	1	–	–	–	–	–	–	–
	Wet	1	0.7642	0.1878	16.5508	<.0001	2.147	1.486	3.103
Traffic condition	Free flow (A–B)	1	–	–	–	–	–	–	–
	Mixed flow (C–F)	1	1.9217	0.0585	1080.4932	<.0001	6.833	6.093	7.662
Speed limit	<55 mph	1	–	–	–	–	–	–	–
	55–60 mph	1	−1.4557	0.2215	43.1710	<.0001	0.233	0.151	0.360
	65–70 mph	1	−1.8661	0.2238	69.5241	<.0001	0.155	0.100	0.240
Gender	Male	1	–	–	–	–	–	–	–
	Female	1	−0.2529	0.0580	18.9851	<.0001	0.777	0.693	0.87
Age	<40 years	1	–	–	–	–	–	–	–
	>40 years	1	0.1628	0.0801	4.1344	0.0420	1.177	1.006	1.377
Education	High school	1	–	–	–	–	–	–	–
	Beyond high school	1	0.3776	0.1107	11.6391	0.0006	1.459	1.174	1.812
	Advance degree	1	0.9529	0.1267	56.5368	<.0001	2.593	2.023	3.324
Marital status	Single	1	–	–	–	–	–	–	–
	Married	1	0.2804	0.0794	12.4663	0.0004	1.324	1.133	1.547
	Others	1	−0.3879	0.0936	17.1765	<.0001	0.678	0.437	0.741
Driver's mileage last year	<10000 miles	1	–	–	–	–	–	–	–
	10,000 – 20,000 miles	1	−0.5999	0.0731	67.4055	<.0001	0.549	0.475	0.633
	>20,000 miles	1	−0.3879	0.0936	17.1765	<.0001	0.678	0.565	0.815
Driver's experience	<10 years	1	–	–	–	–	–	–	–
	>10 years	1	0.5890	0.0934	39.7381	<.0001	1.802	1.500	2.165
Bridge	No	1	–	–	–	–	–	–	–
	Yes	1	0.7457	0.2241	11.0670	0.0009	2.108	1.358	3.27
Super elevation	–	1	0.0258	0.0113	5.2036	0.0225	1.026	1.004	1.049
Curve length	–	1	− 0.0011	0.0002	21.4193	<.0001	0.999	0.998	1.000
Speed limit × curve length	55–60 mph, curve length	1	0.0010	0.0002	15.8866	<.0001	1.001 at speed limit 55–60 mph	1.000	1.002
	65–70 mph, curve length	1	0.0011	0.0002	20.9590	<.0001	1.001 at speed limit 65–70 mph	1.000	1.002
Driver's experience × visibility	>10 years, affected	1	−0.6644	0.1646	16.2971	<.0001	0.515 at affected visibility	0.373	0.710
Curve × weather	Curve × near fog		0.3835	0.1897	4.0838	0.0433	1.467 at near fog	1.012	2.128

Fit statistics:
Likelihood ratio test: χ^2 = 2284.36, df = 24, p-value <0.0001.
Score test for the proportional odds assumption: χ^2 = 1313.20, df = 48, p-value <0.0001.
Akaike information criterion (AIC) = 13254.61.
–2 log L = 13200.614.

clear weather conditions. Driving over the speed limit could be hazardous especially during inclement weather conditions including fog, because drivers might not have enough time to respond to or mitigate an unexpected event (*36*). This study showed that drivers reduced their speeds to compensate for the negative effect of fog on the primary driving tasks.

Findings related to visibility indicated that the odds of drivers reducing their speeds were 1.64 times greater for drivers who were driving in affected visibility versus those driving in good visibility conditions. A similar result was also found for surface conditions. Wet surface was found to have a significant impact on speed reduction. More clearly, the odds of drivers reducing speeds on wet surfaces were 2.15 times higher compared with dry surfaces.

Traffic conditions had a positive coefficient as expected. Controlling for all other variables, drivers were 6.83 times more likely to reduce their speeds in mixed traffic conditions (level of service C to F) compared with free-flow conditions (level of service A and B). It was found that female drivers were less likely to reduce their speed compared with male drivers. More clearly, the odds of female drivers reducing their speeds were 1.29 times less compared with male drivers (OR = 0.777). As expected, older drivers had more speed reduction compared with young drivers. More specifically, the odds of having more speed reduction percentage were 1.18 times higher for drivers older than 40 years compared with drivers of 40 years of age or younger. Education level also came out to be significant in the model. It was found that with the increase of education level, drivers became more compliant to the speed limit. For instance, the odds of a driver with an advanced degree were 2.59 times more likely to reduce speed compared with a driver who is a high school graduate. Marital status was also found to be significant, with a usual trend of married drivers being the safest compared with single drivers (*37*). More clearly, married drivers were 1.32 times more likely to reduce speed compared with single drivers.

Several factors related to the roadway, including the presence of bridge, superelevation, and curve length were found to have a significant effect on driver speed selection. Considering interaction terms, it was found that at an affected visibility condition, experienced drivers (driving experience >10 years) were 48% less likely to reduce speed compared with less experienced drivers (driving experience <10 years), which indicates experienced drivers are usually more confident in reduced visibility compared with less experienced drivers (*38*). Similarly, the interaction between weather condition and curve indicated that the drivers were 1.47 times more likely to reduce their speed on curves compared with their speed on tangents during near fog.

Conclusions

The main focus of this study was to attain better insights into driver behavior in general and speed selection in particular during clear and foggy weather conditions using the SHRP2 NDS dataset. The preliminary analysis showed a Weibull speed distribution in near fog under free-flow conditions, whereas the speeds were normally distributed in clear weather for the matching dataset (i.e., same vehicle, driver, route, and traffic state). Descriptive analysis indicated about 10% reduction in speed during near fog and about 3% reduction in speed during distant fog. The results from the ordered logit model revealed that weather-related factors including the presence of fog, visibility, and surface conditions have a significant impact on driver speed selection behavior. For instance, results showed that drivers were more likely to select significantly lower speeds during foggy weather conditions. More specifically, the odds of drivers reducing their speeds from the posted speed limit were 1.31 and 1.28 times higher for drivers traveling in near fog and distant fog, respectively, compared with drivers who were driving in clear weather conditions. As mentioned before, the majority of the participants in the SHRP2 NDS were young (39% of the NDS drivers were below 25 years old). Considering the fact that the data used in this study represent the age distribution of the actual SHRP2 NDS data, a more representative sample of age groups might provide different results.

Foggy weather conditions can negatively affect driver speed perception and ability to see objects on the roadway, which is one of the main causes of rear-end and lane departure crashes on freeways. Advanced driver assistance systems (ADAS) such as adaptive cruise control (ACC), collision avoidance systems, collison warning system, dynamic brake support, autonomous emergency braking, lane departure warning, and so forth, are currently being used to improve roadway safety in different adverse weather conditions including fog. The main focus of these technologies is to prevent crashes by detecting a conflict, alerting drivers, and aiding in taking appropriate and timely actions. For instance, the ACC can assist drivers to keep a safe distance from a lead vehicle while maintaining a chosen speed (*39*). However, most of the ADAS are based on machine vision techniques, which might be inefficient during adverse weather conditions because of the difficulty of detecting objects in adverse weather. In comparison, sensor-based technologies are usually more effective as they are less susceptible to adverse weather. As the ACC works based on ultrasonic, laser, or LiDAR sensors, it is more effective in adverse weather conditions including fog compared with other machine-based ADAS.

Evaluating driver behavior and performance under the influence of reduced visibility caused by foggy weather conditions is extremely important for developing safe driving strategies, including VSL. Many roadways across the U.S. currently have weather-based VSL systems to ensure safe driving environments during adverse weather. Current VSL systems mainly collect traffic information from external sources, including inductive loop detector, overhead radar, and closed-circuit television. However, human factors, especially driver behavior and performance such as selection of speed and acceleration during adverse weather, are neglected because of the lack of appropriate driver data. The SHRP2 NDS database has huge potential in becoming a good source for driver data. The findings from this study indicated that the NDS data could be effectively utilized to identify trips in foggy weather conditions and to assess the impacts of fog on driver behavior and performance.

The results from this study provided insights into incorporating naturalistic speed selection behavior in VSL systems. While the vast majority of VSL systems are based on road weather iformation system data, previous studies noted many limitations of these systems. Utilization of 1-minute real-time weather and surface conditions and visibility limits may improve VSL logics significantly. With the evolution of connected vehicles, machine vision, and other real-time weather social networks such as WeatherCloud, more accurate real-time data similar to the NDS data will be available in the near future. This study provided early insights into using similar data collected from NDS.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Ali Ghasemzadeh, Mohamed Ahmed; data preparation and reduction: Ali Ghasemzadeh, Nasim Khan; analysis and interpretation of results: Nasim Khan, Ali Ghasemzadeh, Mohamed Ahmed; draft manuscript preparation: Nasim Khan, Ali Ghasemzadeh, Mohamed Ahmed.
All authors reviewed the results and approved the final version of the manuscript.

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