

7th International Symposium on Naturalistic Driving Research

A Framework to Enhance the Transferability of the SHRP2 NDS by Considering Heterogeneity of Driver Behavior Using Spatial-Temporal Factors in a Trajectory Level

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 UNIVERSITY OF WYOMING

Introduction

Spatial and temporal features of roadway environment can impact driver performance and behavior



Introduction

Advanced technologies have enabled researchers to provide an in-depth analysis of driver-behavioral factors for a specific driver across time and space.

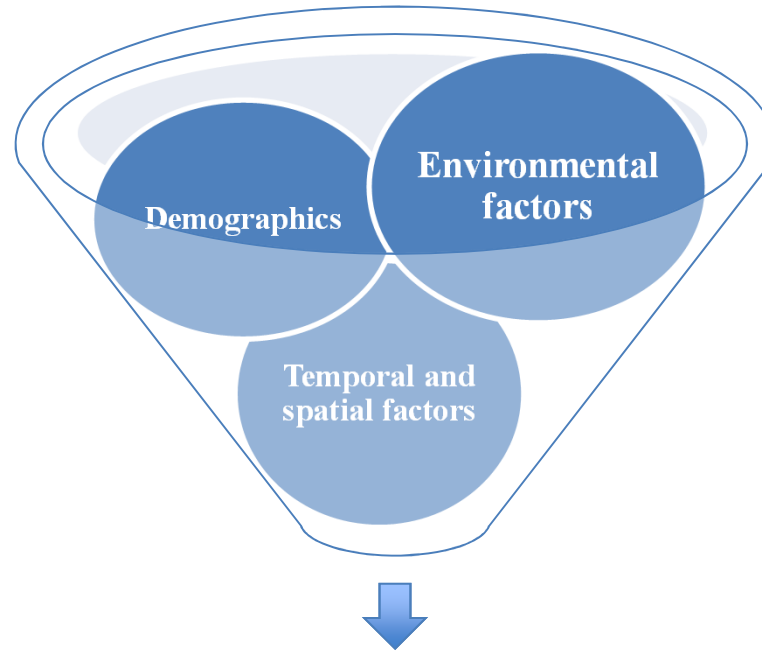
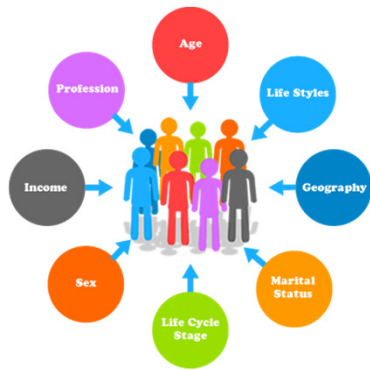


Introduction

- Why is it important to analyze driver behavior?



Introduction



Driver performance and behavior



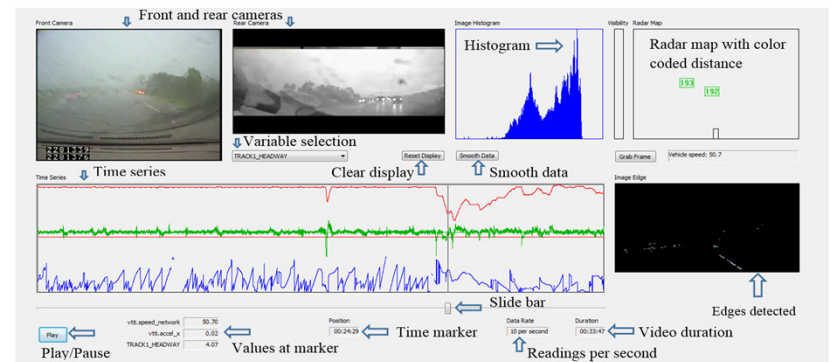
Introduction

- Utilizing naturalistic driving data to evaluate intelligent active safety systems are increasingly being used in recent years.
- Naturalistic driver behavior can be defined as an unobtrusive observation of driver behavior taking place in its natural setting.
- Naturalistic driving data is proven superior.



Motivation

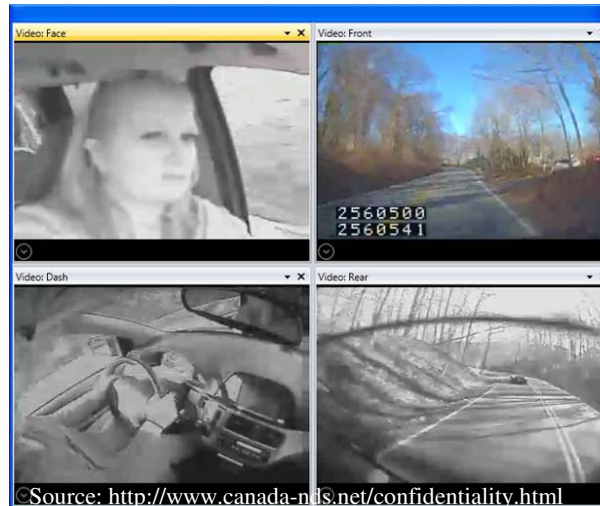
- The important role of spatial-temporal characteristics
- Heterogeneity
- Connected/autonomous vehicle (CAV) data



Motivation

- Is it possible to do NDS in all states?

logistical|yspeaking



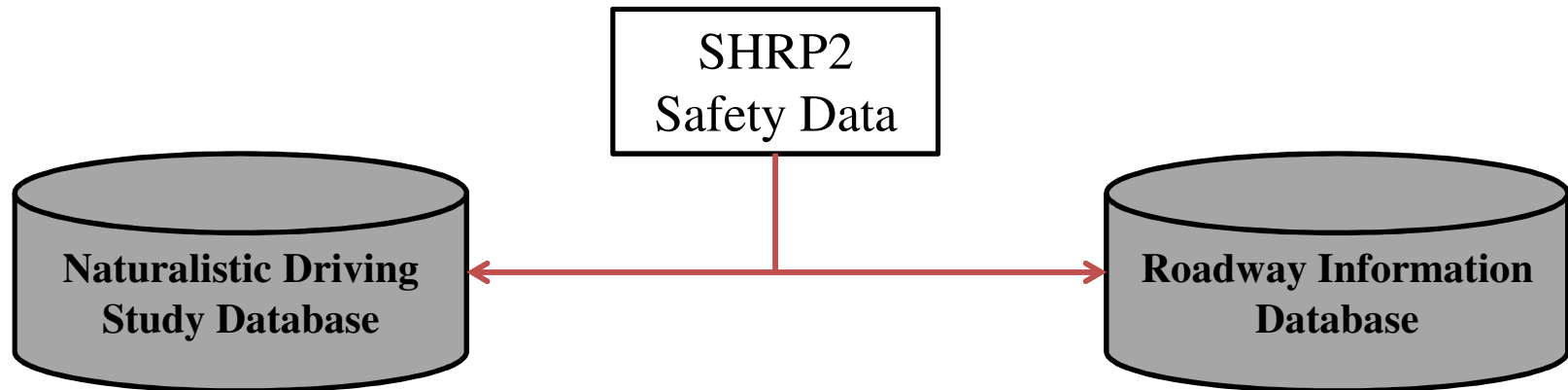
Contributions

- Defining an index called spatial and temporal characteristics index (STCI).
- Three main drivers' behavioral factors including speed selection, acceleration/deceleration, and lane keeping behaviors were analyzed.
- Identifying factors affecting the differences between behavioral factors for the most frequent observed road environments.



SHRP2 Safety Data

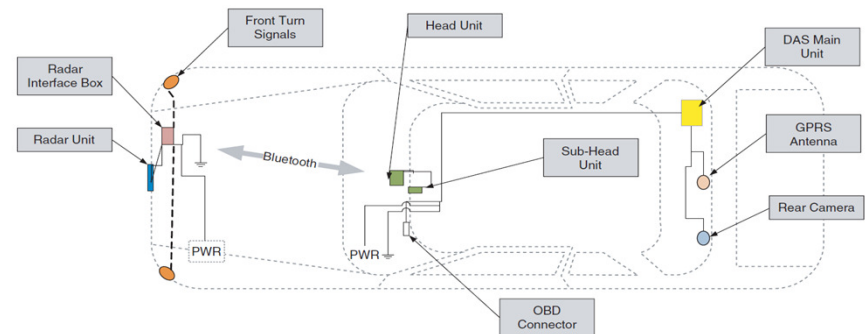
SHRP2 was created to find strategic solutions to three national transportation challenges: improving highway safety, reducing congestion, and improving methods for renewing roads and bridges.



SHRP 2 Safety Data

Naturalistic Driving Study

- Virginia Technical Transportation Institution (VTTI)
- 3,500 drivers
- 6 data collection sites
- Driver participation for a 12-24 month period
- 5 M trip files
- 32 M vehicle miles



SHRP 2 Safety Data

Roadway Information Database

- 25,076 total miles of roadway data collected as part of Mobile Data Collection Project (Iowa State)
- Speed limits
- Roadway curvature
- Intersection design
- Archived weather data
- Aerial images
- State DOT provided crash histories
- Traffic laws
- Safety campaigns
- Construction schedules



Methodology

- **Data Acquisition**
- **Data Reduction**
- **Data preparation**



1. A. Ghasemzadeh and M. M. Ahmed, “Utilizing naturalistic driving data for in-depth analysis of driver lane-keeping behavior in rain: Non-parametric MARS and parametric logistic regression modeling approaches,” *Transp. Res. Part C*, vol. In press, 2018.
2. M. M. Ahmed *et al.*, “Implementation of SHRP2 results within the Wyoming connected vehicle variable speed limit system: Phase 2 early findings report and phase 3 proposal,” 2017.
3. A. Ghasemzadeh, B. Hammit, M. M. Ahmed, and H. Eldeeb, “Complementary Methodologies to Identify Weather Conditions in Naturalistic Driving Study Trips: Lessons Learned from the SHRP2 Naturalistic Driving Study & Roadway Information Database. 97th Transportation Research Board Annual Meeting. Washington, D.C.,” in *Accepted for Presentation at 97th Transportation Research Board Annual Meeting*, 2018.



Methodology

TABLE 1 Spatial and temporal factors considered for developing Spatial-Temporal Characteristics Indices

Spatial/ Temporal	Variable	Type	Categories	Assigned Code	Description
Temporal	Time Bin	Categorical	Morning (6-9)	M	Computed Time of Day
			Day (9-15)	D	
			Afternoon (15-21)	A	
Temporal	Day	Categorical	Weekend	W	Computed Day of week
			Weekday	R	
Spatial	Speed Limit	Categorical	< 55 mph	55	Predominant posted speed limit in 1-min video observation
			55-60 mph	60	
			> 65 mph	65	
Spatial	Presence of Curve	Binary	Tangent	T	Whether the majority of 1-min driving was driven on tangent or curve
			Curve	C	
Spatial	Number of Lanes	Categorical	≤2	L1	Number of lanes that the majority of the 1-min driving was travelled in one direction
			>2	L2	
Spatial	Ramp	Binary	Ramp	Y	Presence of Ramp within 1-min driving
			No Ramp	N	
Spatial	Tollway	Binary	Non- Toll-way	1	Whether the majority of 1-min driving was driven on toll-way or not
			Toll-way	2	
Spatial	Tunnel	Binary	No Tunnel	1	Only 20 observations in tunnel were identified; therefore eliminated from the Spatial-Temporal Characteristics Indices
			Tunnel	3	
Spatial	Bridge	Binary	Bridge	BR	Presence of bridge within 1-min driving
			No bridge	NB	
Spatial	Weather Conditions	Categorical	Clear	1	the majority of weather conditions on 1-min driving
			Rain	2	
			Heavy Rain	3	
			Snow	4	
			Fog	5	
			Heavy Fog	6	



Methodology

Spatial-Temporal Characteristic Index

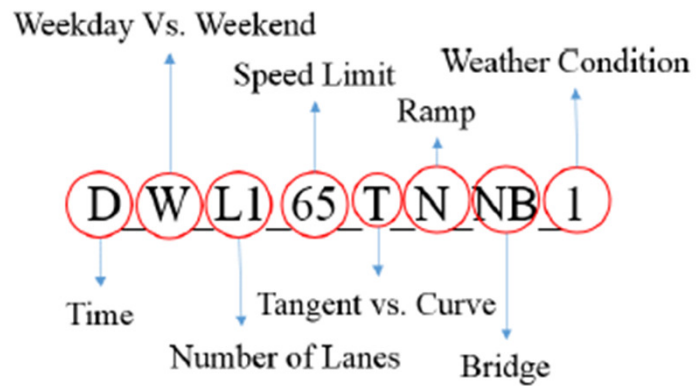
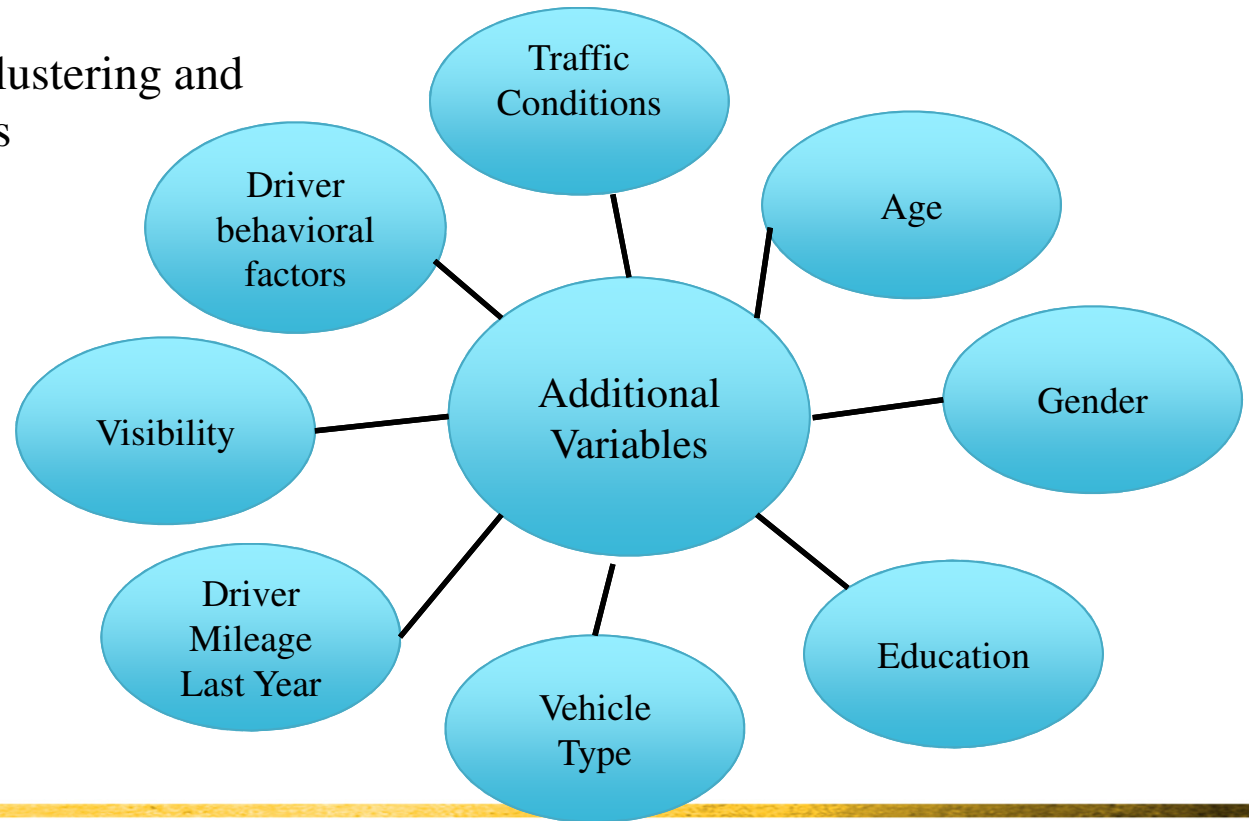


FIGURE 1 Sample STCI Representing Different Spatial-Temporal Characteristics of a Segment



Methodology

Additional Variables used for Clustering and Subsequent Regression Analysis



Methodology

After data reduction and developing a STCI for each one-minute segment:

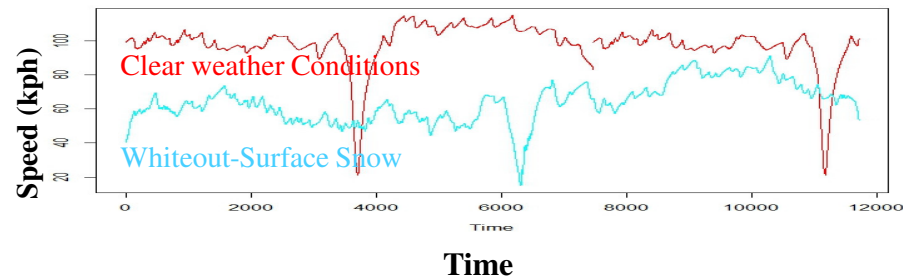
- 312 unique STCIs across all drivers in New York.
- The most frequent STCI, “M_R_L1_65_T_N_NB_1” represents 683 minutes (one-minute segments).
- 42 STCIs were observed only once; therefore, excluded.
- Excluding trips with less than 20 observations resulted in 81 STCIs representing 10,718 minutes of driving.



Methodology

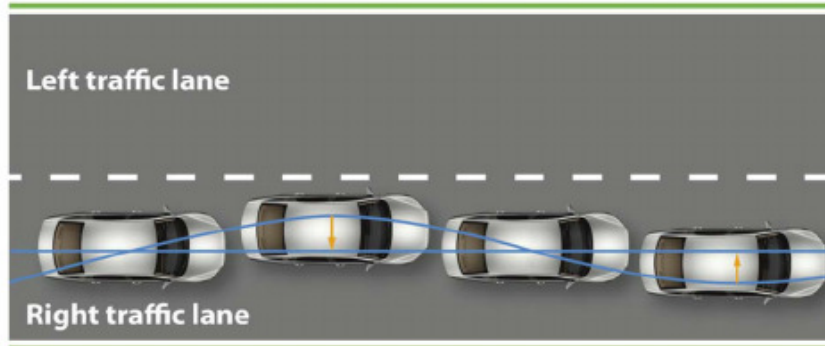
Speed Reduction Percentage

1. Speed reduction greater than 10%,
2. Speed reduction between 0 and 10%,
3. Speed increase between 0 and 10%, and
4. Speed increase greater than 10%.



Methodology

SDLP
SDLP < 20 cm
SDLP > 20 cm



Acc./Dec.

four categories based on the median acceleration/deceleration as below (negative sign represents deceleration):

1. Acceleration greater than 0.012g;
2. Acceleration between 0 and 0.012g;
3. Deceleration between -0.012g and 0; and
4. Deceleration greater than -0.012g.



Methodology

TABLE 3 First Five Most Frequent STCIs

Model	TSCI	Definition	Freq.	%	Cumulative Frequency	Cumulative Percent
1	M_R_L1_65_T_N_NB_1	Morning, Weekday, Less than 2 Lanes, Speed limit 65 mph, Tangent, Non-ramp, Non-bridge, Clear weather	683	5.68	683	5.68
2	D_R_L1_65_T_N_NB_1	Day, Weekday, Less than 2 Lanes, Speed limit 65 mph, Tangent, Non-ramp, Non-bridge, Clear weather	673	5.60	1356	11.29
3	M_R_L2_55_T_N_NB_1	Morning, Weekday, More than 2 Lanes, Speed limit 65 mph, Tangent, Non-ramp, Non-bridge, Clear weather	554	4.61	1910	15.90
4	D_R_L1_65_C_N_NB_1	Day, Weekday, Less than 2 Lanes, Speed limit 65 mph, Curve, Non-ramp, Non-bridge, Clear weather	459	3.82	2369	19.72
5	A_R_L1_65_T_N_NB_1	Afternoon, Weekday, Less than 2 Lanes, Speed limit 65 mph, Curve, Non-ramp, Non-bridge, Clear weather	436	3.63	2805	23.35



Methodology

Three different scenarios were assessed to measure volatility of aggregate safety behavioral factors:

- (1) Road segments that were travelled by the same driver (all STCIs that were traversed by the same driver);
- (2) Road segments with the same spatial-temporal indices that were travelled by all drivers; and
- (3) Road segments with the same spatial-temporal indices that were travelled by the same driver.



Results

TABLE 4 Longitudinal Versus Cross-Sectional Variability by STCI

Speed Red %			ACC/Dec			Lane Keeping		
Thresholds	Longitudinal Variability (%)	Cross sectional variability (%)	Threshold	Longitudinal Variability (%)	Cross sectional variability (%)	Threshold	Longitudinal Variability (%)	Cross sectional variability (%)
<-0.1	60.38	39.62	Number of events where acceleration is >0.012	53.42	46.57	SDLP ≤ 20	19.74	80.26
Between -0.1 and 0	60.87	39.13	0 < Acc. ≤ 0.012	51.02	48.98	SDLP >20	46.74	53.26
Between 0 and 0.1	45.69	54.31	-0.012 < Dec < 0	47.96	52.04	-	-	-
Above 0.1	44.44	55.56	Dec < 0.012	48.24	51.76	-	-	-



Results

- The average of the difference between the COV for a specific spatial-temporal index (scenario 2) and the COV for each driver in the same spatial-temporal index (scenario 3).
- More reduction in speed increases the longitudinal variability. Conversely, in higher speeds individual drivers showed less variability in comparison with overall sample behavior.
- Lane keeping behavior=> 100% of STCIs have more cross-sectional variability than longitudinal variability.



Results

TABLE 5 Within STCI Versus Between STCI Variability by Driver

Speed Reduction %			Acc./Dec.			Lane Keeping		
Thresholds	Within STCI Variability (%)	Between STCI variability (%)	Threshold	Within STCI Variability	Between STCI variability	Threshold	Within STCI Variability	Between STCI variability
<-0.1	15.69	84.31	Number of events where acceleration is >0.012	28.57	71.43	SDLP ≤ 20	25.58	74.42
Between -0.1 and 0	30.16	69.84	0 < Acc. ≤ 0.012	31.48	68.52	SDLP >20	15.25	84.25
Between 0 and 0.1	39.25	60.75	-0.012 < Dec < 0	14.13	85.87	-	-	-
Above 0.1	29.49	70.51	Dec < -0.012	12.82	87.18	-	-	-



Results

- The procedure mentioned above was implemented for each COV of the individual driver across all STCIs (scenario1) in comparison with the COV for the same driver in the same STCI (scenario 3).
- for all drivers the variability of different behavioral-factors within STCIs is less than the variability between STCIs.
- This finding confirms the consistency of driver behavior considering STCI method and the issue of using aggregate traffic data in driver behavior modelling.



Results

- Road segments were aggregated based on S & T characteristics.
- Next, examine the differences in the behavioral and driver factors related to each spatial-temporal environment.
- Separate models were developed for each STCI (five most frequent).
- Two-step cluster analysis was conducted for each STCI.
- Cluster membership was utilized as a dependent variable in the subsequent logistic regression analysis to determine significant variables in differentiating between membership in the first and second clusters.



Results

- Individual cluster and binary logistic regression were conducted for each STCI.
- From examining the frequency of cluster membership in different methods=> the resulting clusters for each model are very different.
- Therefore, it is justified to create separate model for each STCI=> this reveals nothing about factors associated with cluster membership.
- A binary logistic reg. was run for each STCI with the same variables used for cluster membership.



Results

TABLE 6 Regression Analysis Results

Model1 STCI: M_R_L1_65_T_N_NB_1							
Parameter	Level	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio
Speed	2	1	-1363.5	484.2	7.93	0.005	0
Speed	3	1	-1368	18.463	5489.434	0	0
Age	3	1	-2744.3	8.62	101345.82	0	0
Model2 STCI: D_R_L1_65_T_N_NB_1							
Speed	4	1	2.188	1.053	4.318	0.038	8.917
Acc./Dec.	3	1	-1.851	0.796	5.405	0.02	0.157
Model3 STCI: M_R_L2_55_T_N_NB_1							
Speed	3	1	-2.009	0.561	12.824	0	0.134
Acc./Dec.	2	1	2.01	1.096	3.364	0.067	7.465
Acc./Dec.	4	1	-1.45	0.531	7.452	0.006	0.235
Lane keeping	2	1	-1.092	0.398	7.537	0.006	0.336
Gender	2	1	1.561	0.843	3.431	0.064	4.762
Age	1	1	1.760	1.034	2.895	0.089	5.812
Age	3	1	-4.710	1.917	6.037	0.014	0.009
Education	3	1	-3.961	0.859	21.268	0	0.019
Driver Mileage Last Year	2	1	1.801	0.86	4.388	0.036	6.055
Driver Mileage Last Year	3	1	-4.765	1.283	13.785	0	0.009



Conclusions

- The study proposed a methodology to reduce driver heterogeneity considering spatial and temporal factors.
- The results of this study clearly showed that controlling the spatial, temporal and environmental factors, the longitudinal variability of behavioral factors is less than cross sectional variability.
- The variability of speed behavior is longitudinally higher when speed is affected by other environmental factors such as traffic congestion.
- However, in case of free flow speed condition, the cross-sectional variability is higher than the longitudinal variability.



Conclusions

- Results clearly showed the vital effect of spatial-temporal factors on driver behavior and the necessity of developing separate model for segments that have similar spatial-temporal characteristics.
- Drivers might behave differently depend on time and location of driving.
- The results of this study can be used to reduce the bias in transferability of findings from different naturalistic driving studies considering spatial-temporal factors.



Publications

1. Ahmed, M.M. and Ghasemzadeh, A. "The impacts of heavy rain on speed and headway Behaviors: An investigation using the SHRP2 naturalistic driving study data." **Transportation Research Part C: Emerging Technologies**. Vol 91. 2018.pp 371-384.
2. Ali Ghasemzadeh*, Mohamed Ahmed. Utilizing naturalistic driving data for in-depth analysis of driver lane-keeping behavior in rain: Non-parametric MARS and parametric logistic regression modeling approaches. **Transportation Research Part C: Emerging Technologies**. Vol 90. 2018. pp 379-392.
3. Ali Ghasemzadeh*, Mohamed Ahmed, Driver's Lane Keeping Ability in Inclement Weather Conditions: Preliminary Investigation using the SHRP2 Naturalistic Driving Study Data, **Transportation Research Record: Journal of the Transportation Research Board**, Volume 2663, pp. 99-108, <https://doi.org/10.3141/2663-13>, 2017.
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5. Khan, M. N., Ghasemzadeh, A., & Ahmed, M. M. (2017). Investigating the Impact of Fog on Freeway Speed Selection using the SHRP2 Naturalistic Driving Study Data. **Transportation Research Record**, 0361198118774748.
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7. Ali Ghasemzadeh*, Britton Hammit*, Mohamed Ahmed, Hesham Eldeeb, Complementary Methodologies to Identify Weather Conditions in Naturalistic Driving Study Trips: Lessons Learned from the SHRP2 Naturalistic Driving Study & Roadway Information Database, Proceedings of the **Transportation Research Board 97th Annual Meeting, 2018**.
8. Ali Ghasemzadeh*, Mohamed Ahmed, Sherif Gaweesh*, Multivariate Adaptive Regression Splines and Logistic Regression Models to Identify the Impact of Rainy Weather on Driver Lane-keeping Performance Considering Driver Demographics and Roadway Characteristics Using SHRP2 Naturalistic Driving Data, Proceedings of the **Transportation Research Board 97th Annual Meeting, 2018**.



Publications

8. Md Nasim Khan, Ali Ghasemzadeh*, Mohamed Ahmed, Investigating the Impact of Fog on Freeway Speed Selection Using the SHRP2 Naturalistic Driving Study Data, Proceedings of the **Transportation Research Board 97th Annual Meeting, 2018**.
9. Anik Das*, Ali Ghasemzadeh*, Mohamed Ahmed, A Comprehensive Analysis of Driver Lane-Keeping Performance in Fog Weather Conditions Using the SHRP2 Naturalistic Driving Study Data, Proceedings of the **Transportation Research Board 97th Annual Meeting, 2018**.
10. Mohamed Ahmed, Ali Ghasemzadeh*, Exploring the Impacts of Adverse Weather Conditions on Speed and Headway Behaviors Using the SHRP2 Naturalistic Driving Study Data. Proceedings of the **96th Transportation Research Board Annual Meeting, 2017**.
11. Ali Ghasemzadeh*, Mohamed Ahmed, A Probit-Decision Tree Approach to Analyze the Effects of Adverse Weather Conditions on Work Zone Crash Severity Using the Second Strategic Highway Research Program Roadway Information Dataset. Proceedings of the **96th Transportation Research Board Annual Meeting, 2017**.
12. Ali Ghasemzadeh*, and Mohamed Ahmed, "Investigating the Feasibility of Using SHRP2 Naturalistic Driving Study to Support Data Requirements of VSL Decision Making Algorithms and its Application in Connected Vehicle". Proceedings of the **23rd Intelligent Transportation Systems World Congress (ITSWC), 2016**.
13. Ali Ghasemzadeh*, and Mohamed Ahmed, "Estimating the Impacts of Adverse Weather Conditions on Work Zone Crash Severity using the SHRP2 Roadway Information Database". Proceedings of the **14th World Congress of Transport Research, 2016**.
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Questions?

A Framework to Enhance the Transferability of the SHRP2 NDS by Considering Heterogeneity of Driver Behavior Using Spatial-Temporal Factors in a Trajectory Level



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