Predicting Drivers' Injury Occurrence in Vehicle Crashes Occurring at Horizontal Curve and Grade Combination Segments

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Injury and death rates from vehicle crashes are high for most parts of the world, with major influences including driver, vehicle, roadway, and environmental characteristics.[1] For road characteristics, recent research reported that fatality index-ratio is higher for curved and at-grade segments (rolling terrain roads) than non-rolling terrain roads.[2] Furthermore, Federal Highway Administration (FHWA) reports, that more than a quarter of all crashes occur at horizontal curves where vehicles depart from the roadway and hit trees, utility poles, rocks, or other permanent features.[3] Constrained topography and complex road geometries are among major issues in designing and constructing roads that meet appropriate standards. Substandard cross-section elements and dangerous roadside environments plus human driver's errors in these areas present a risky road traffic situation for drivers.

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HSIS First Place Safety Data Award

This is the first-place winning paper of the Federal Highway Administration's (FHWA) 2022 Excellence in Highway Safety Data Award, which is designed to encourage university students to use Highway Safety Information System (HSIS) data to investigate a topic that advances highway safety and to develop a paper to document the original research. The HSIS Highway Safety Data Awards Program is jointly administered by FHWA and ITE. This paper has been edited for length from the original version.

Previous research shows that most crashes on horizontal curves occur when drivers are speeding or distracted.[4] Also, the magnitudes of radius of adjacent horizontal curves and tangent lengths between curve were associated with departure crashes.[6] Hummer et al., identified these crashes as associated with presence of fixed objects, such as trees and poles; influence of alcohol on drivers; and lighting and roadway surface conditions.[7] Other studies show a higher number of crashes occur at curved segments than tangent segments, and more crashes occur at two-lane than multilane roads.[4] Severity of injuries caused by these crashes varies with radius and length of the curves, where curve radius is negatively correlated with occurrence of crashes.[10] Authors identified 2,500 feet (762 meters) as threshold curve radius below which rate of crash occurrence increases.[10] Rusli et al., reported that steep gradients and sharp curves along rolling terrain roads induce different driving behavior than curved roads in flatter areas.[2]

In light of this review, there remain significant gaps where research is warranted. Most studies in the literature either look at curved or grade alignments; few studies have analyzed safety factors of segments with a combination of the two. Moreover, most of these studies used traditional statistical models which are limited by overfitting and poor performance on non-linear relationship of variables. In addressing these limitations, current study investigates effects of curve and grade combination segments, with other traffic characteristics, in predicting drivers' injury severity. This is achieved by a comparative assessment of robust predictive machine learning models (Random Forest and XGBoost). This study addresses an important road safety issue of crashes along curved and at-grade segments. Road engineers often face challenges in designing and ensuring adequate cross-sectional elements due to constrained road reserves along curved and at-grade roads. A proper understanding of these risk factors in predicting severity of a driver's injury is needed for this reason. Development of an accurate driver's injury severity prediction model along curved and at-grade highways using crash data from Highway Safety Information System (HSIS) for Ohio is therefore of essence.

Data Description

This study utilized Ohio HSIS data. HSIS is a system that provides high-quality traffic data (i.e., crashes, road characteristics). Dataset consist of multiple filegroups, such as accident, curve, grade, roadway inventory, and vehicle files. These files were merged by caseno to create one file of accident, roadway, and traffic characteristics. Data cleaning was performed, and a total of 20,402 observations were used in analysis. Observations were filtered to only include crashes that occurred on curves at grade. Descriptive statistics are presented in Table 1. A conceptual framework of merged variables is presented in Figure 1. This study categorized driver injury as uninjured or injured.

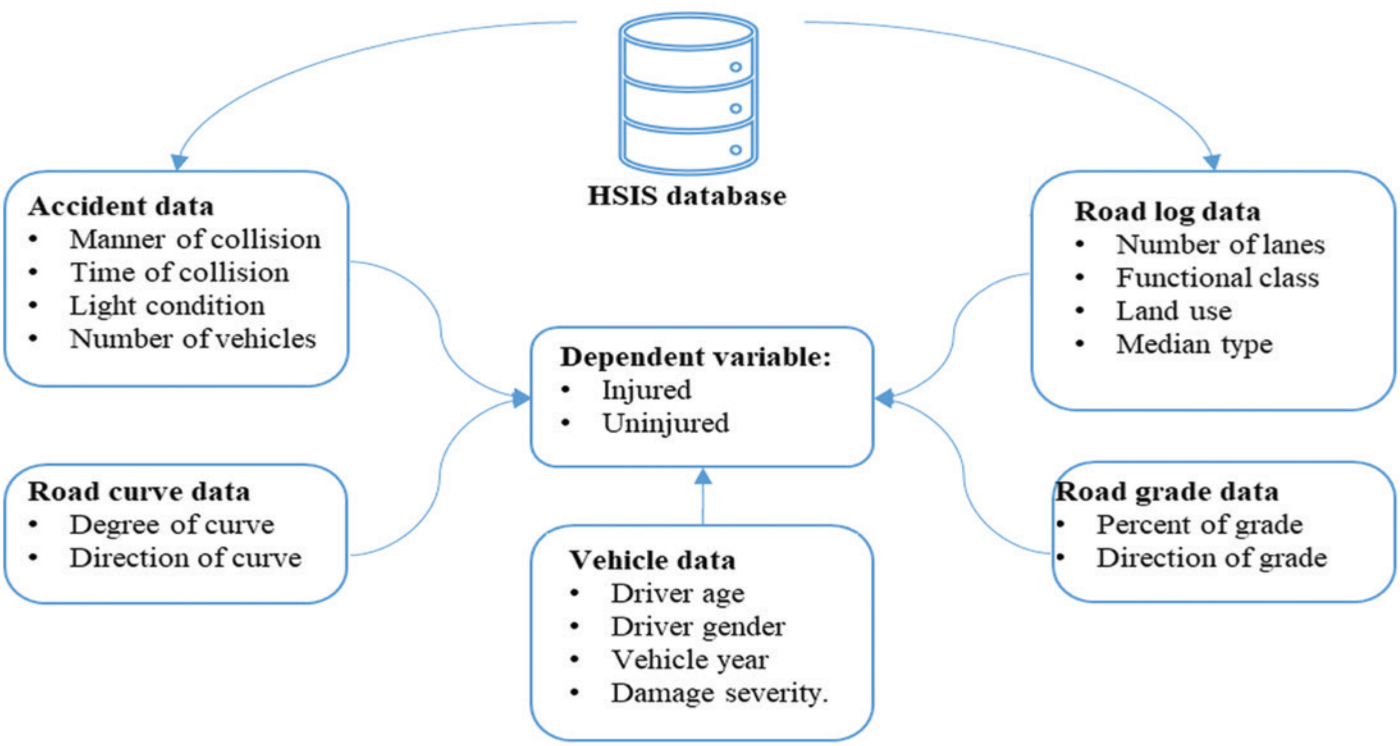


Figure 1. Variable conceptual framework.

Table 1. Categorical variables distribution.

Uninjured		Injured		
Count	**Percent**	**Count**	**Percent**	**Variable**
Weekday				
Weekend	3991	26.92%	1784	31.99%
Weekday	10834	73.08%	3792	68.01%
Collision Manner				
Head-on	86	0.58%	138	2.47%
Rear-end	2673	18.03%	449	8.05%
Side crashes	2788	18.81%	715	12.82%
Other crashes	9278	62.58%	4274	76.65%
Peak Hour				
Off-peak hour	7623	51.42%	3130	56.13%
Peak hour	7202	48.58%	2446	43.87%
Light Condition				
Light	9295	62.70%	3570	64.02%
Dark	5530	37.30%	2006	35.98%
Location Type				
Intersection	2790	18.82%	667	11.96%
Not Intersection	12035	81.18%	4909	88.04%
Number Vehicles				
Less than three vehicles	14753	99.51%	5557	99.66%
More than three vehicles	72	0.49%	19	0.34%
Driver Age				
Young (<20 years)	1809	12.20%	693	12.43%
Adult (20–64 years)	12058	81.34%	4470	80.16%
Senior (>65 years)	958	6.46%	413	7.41%
Driver Restraint				
None	332	2.24%	904	16.21%
Restraint on	14493	97.76%	4672	83.79%
Driver Gender				
Female	5572	37.59%	2254	40.42%
Male	9253	62.41%	3322	59.58%
Hazard Material				
No	14792	99.78%	5561	99.73%
Yes	33	0.22%	15	0.27%
Traffic Control				
Not present	2200	14.84%	655	11.75%
Present	12625	85.16%	4921	88.25%

Uninjured		Injured		
Count	**Percent**	**Count**	**Percent**	**Variable**
Curve Direction				
Left	6238	42.08%	2379	42.66%
Right	8587	57.92%	3197	57.34%
Grade Direction				
Downgrade	9283	62.62%	3455	61.96%
Upgrade	5542	37.38%	2121	38.04%
Functional Classification				
Local	39	0.26%	14	0.25%
Collector	4800	32.38%	2299	41.23%
Arterial	9986	67.36%	3263	58.52%
Land Use				
Rural	8992	60.65%	2925	52.46%
Urban	5833	39.35%	2651	47.54%
Median Type				
No median or unprotected area less than 4 feet wide	9529	64.28%	4138	74.21%
Median exists with a width of 4 feet or more	5296	35.72%	1438	25.79%
Number of Lanes				
2 lanes	8378	56.51%	3730	66.89%
3 lanes and above	6447	43.49%	1846	33.11%
Speed Limit (mph)				
0-25mph.	402	2.71%	185	3.32%
30-50 mph	5482	36.98%	2175	39.01%
55-70 mph	8941	60.31%	3216	57.68%
Surface Type				
Flexible pavement	14154	95.47%	5273	94.57%
Rigid pavement	521	3.51%	242	4.34%
Combination rigid and flexible pavement	150	1.01%	61	1.09%
Vehicle Damage Severity				
None	388	3%	23	0.2%
Minor damage	9142	62%	1416	25%
Severe damage	5295	36%	4137	74%

Methodology

This section introduces relevant concepts of models employed.

Feature variables correlation analysis. To improve prediction performance of any prediction model, feature selection using correlation analysis was used. A variable can have a high redundancy impact if it is correlated with other variables. Criteria threshold for filtering correlating variables is 0.5.[11] Median types, number of lanes and surface width have high correlation values.

Synthetic Minority Oversampling Technique (SMOTE). Most machine learning classification models assume an even distribution of observations among different classes. Like other crash datasets, our data have unequal class samples. Dealing with an imbalanced dataset in model training causes bias towards the majority class.[12] One approach to address this is the SMOTE technique. SMOTE generates synthetic data for minority class samples while maintaining the original data's correlation to balance the class distribution. New synthetic example introduced in the minority class causes the classifier to create a larger decision surface, thus increasing reliability of prediction estimates.[13]

Machine learning algorithms

Random Forest (RF) Model

RF model is made up of a collection of decision trees. This supervised machine algorithm randomly generates and combines the output of multiple decision trees and aggregates them to give a single forecast. Model prediction is based on the confidence vote strategy from multiple decision trees[14]. Traditional classification tree methods are prone to considerable risk of overfitting, due to presence of anomalies from data.[15] Random Forest combat overfitting problems by pruning uncorrelated trees while limiting increase of unbiased error.[16]

XGBoost Model

XGBoost model is a tree-based ensemble technique that dominates both regression and classification modeling problems. Trees are created sequentially during the training process while minimizing errors of former trees. The final model prediction is obtained by summing up all the newly developed trees.[17] This parallel processing algorithm can handle a complex nonlinear relationship between features with reliable prediction accuracy and high-performance speed.[18]

Bayesian Hyperparameter Optimization

During model training, machine learning algorithms need to optimize their hyper-parameters to correctly map input variables into class of interest. Traditionally, hyper-parameter tuning for learning algorithms can be done using either grid search or randomized search. Recently, Bayesian Optimization has been adopted as a powerful and flexible tool that gives better model settings in fewer iterations.[20] Cross-validation was used in measuring the stability of the model.10-fold cross-validation is employed, where the model is trained using nine subsets and the remaining is used as a validation set.

Receiver Operating Characteristic curve and statistical performance metrics

ROC is a graphical plot illustrating ability of the model to classify target variables. [22] The area under the curve (AUROC) is a metric that summarizes the overall prediction performance from the AUROC curve. An AUROC value near 1 represents a more reliable model, while the AUC closer to 0 highlights a weaker prediction capability for a specific model. The AUROC at 0.5 indicates a valueless prediction was set as minimum limiting threshold value.

Sensitivity analysis using partial dependence (PD) plots

Complex models like RF and XGBoost are not immediately interpretable. To understand the association of the important predictor variables on the injury prediction of the driver, the partial dependencies were calculated using the validating dataset (30 percent of the whole dataset). And PD plots were used to display the relationships. PD plots of categorical variables were centered at a particular point to present a clear comparison between two or more categories of the same variable. as shown in equation 1. The centering was achieved by computing the difference in average probability of prediction of each group from a base group. [24]

$$\text{Marginal effect} = \left(\frac{P_{X1} - P_{X0}}{P_{X0}}\right) * 100\% \qquad \text{equation 1}$$

The marginal effect is the average impact of the categorical explanatory variable *x* on probability of driver injury occurrence, and is set as base condition. For a predictor variable with more than two groups, for example, damage severity, marginal effect was computed for each of its groups, where one of its class probability values was set as base condition.

Results Discussion

Model performance comparison. Figure 2 shows resulting training prediction accuracy plots against density of distribution for respective model. 5000 iterations of Bayesian hyper-parameter tuning process through a cross-validation approach were run to obtain balanced accuracy. RF model portrays highest training prediction accuracy (0.828), followed by XGBoost model (0.821). Almost comparable good accuracies of these models portray accuracy in data preparation and training.

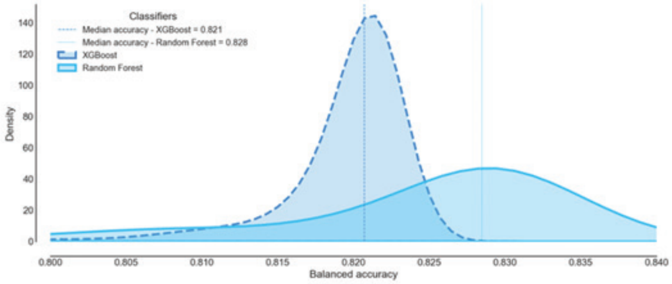


Figure 2. Balanced accuracy of optimized models.

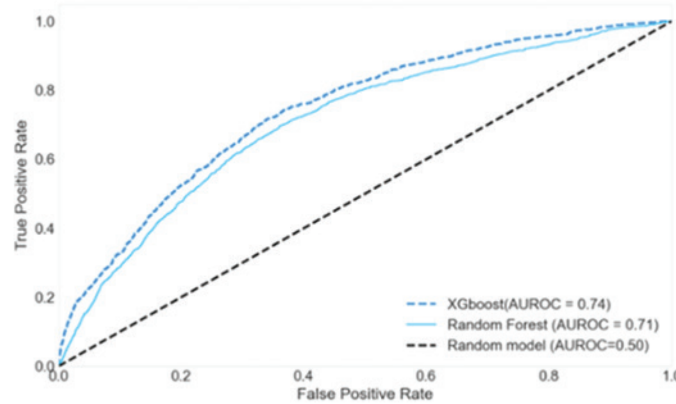


Figure 3. ROC (XGBoost and RF).

Figure 3 shows the AUROC for the XGBoost classifier (AUROC= 0.74) is higher than that of RF Classifier (AUROC= 0.71) on test dataset. Meaning, the XGBoost classifier showed ability to classify the driver's injury from uninjured with higher precision than RF classifier. Based on this, XGBoost classifier was adopted for feature importance analysis and sensitivity analysis of predictor variables.

Feature importance analysis. This study used mean-decrease-accuracy based on permutation importance algorithm on validating data set then ranked variables in order of influencing injury prediction. Permutation importance algorithm permutes values of each feature and measures how much the permutation negatively impacts the scoring metric.[25] Feature importance from the XGBoost classifier is presented in Figure 4. Higher score value of relative importance implies an influential predictor variable on the likelihood of the driver sustaining an injury.[26] In order of their importance top predictors are vehicle's damage severity, driver's restraint, manner of collision, speed limit, and number of occupant's present.

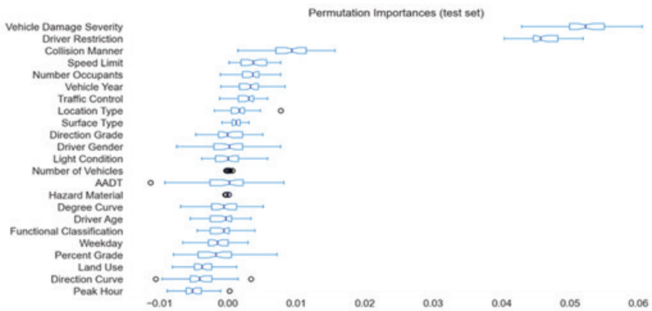
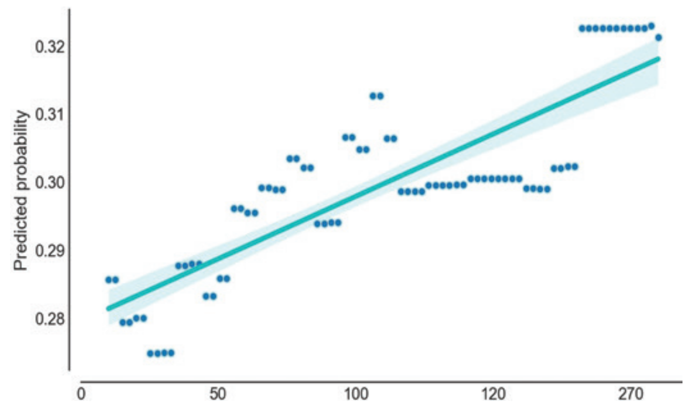


Figure 4. Relative importance of variables (XGBoost).

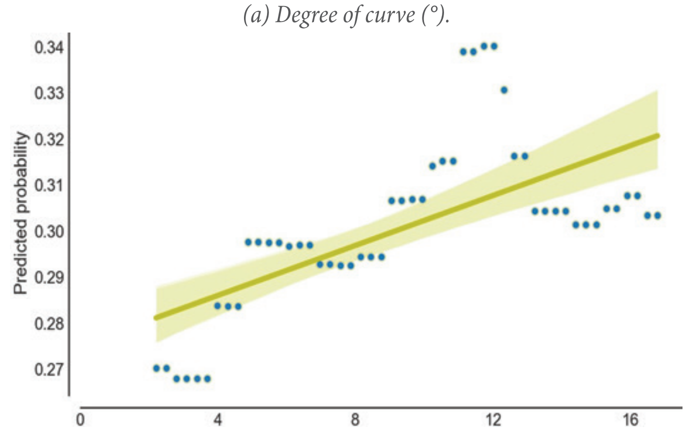
Sensitivity analysis of roadway horizontal and vertical curvature impacts. Figure 5 presents sensitivity analysis of roadway horizontal and vertical curvature predictor variables. Generally, it can be inferred that increase in the degree of curve (Figure 5(a)) is associated with a higher probability of driver's injury. Curved road alignments are also found to be associated with higher crash frequency and the typical road runoff type of crash due to a driver failing to effectively traverse the curve.[27] A similar pattern was found in the percent of grade (Figure 5(b)) where the higher percentage of the grade was associated with an increased risk of driver's injury severity. Moomen et al., also found that a percent increase in grade poses a threat to driver's safety.[29] Rusli et al., argue that grades more than 8 percent increase vehicle crashes by as much as 19 percent compared to level segments.[30] Consequently, this finding implies that areas with a combination of a curved alignment at grade such as rural mountainous areas are more injury prone.

In Figure 5(c) the marginal effect of the direction of the curve predictor shows drivers traversing a right-turn curve are more likely (5.25 percent) to be associated with injury than those turning left. Furthermore, Figure 5(d) shows that drivers executing a curve on a positive grade (upgrade) are more likely (2.9 percent) to sustain an injury than a negative grade (downgrade).[31] A downgrade movement is naturally accelerated by the force of gravity hence drivers' inattention to braking renders them susceptible to head-on collisions in these situations.

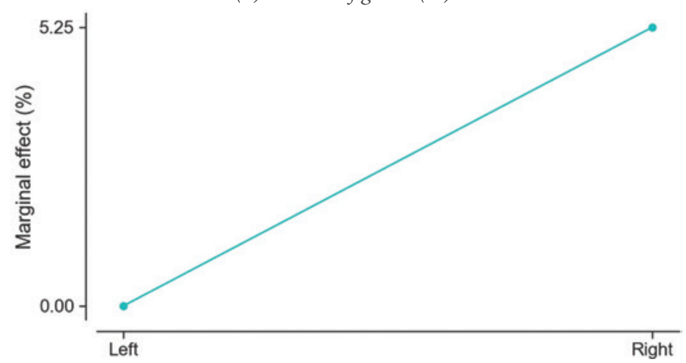
Roadway characteristic variables. Figure 6 presents a sensitivity analysis of roadway characteristic variables. In Figure 6(a) presence of traffic control devices is associated with driver's injury occurrence compared to no traffic control device. Figure 6(b) shows that a driver is 10.58 percent less likely to be injured in areas with higher speed limits (55-70 mph) than with low-speed limits (0-25 mph). Furthermore, a driver is 5.31 percent more likely to sustain a severe injury in crashes occurring on rigid pavements than on flexible pavement Figure 6(c). arterials are associated with a higher likelihood (0.32 percent) of driver injury occurrence than local and collector roads while collector roads are associated with 0.3 percent less likelihood for diver injury than local roads Figure 6(d).



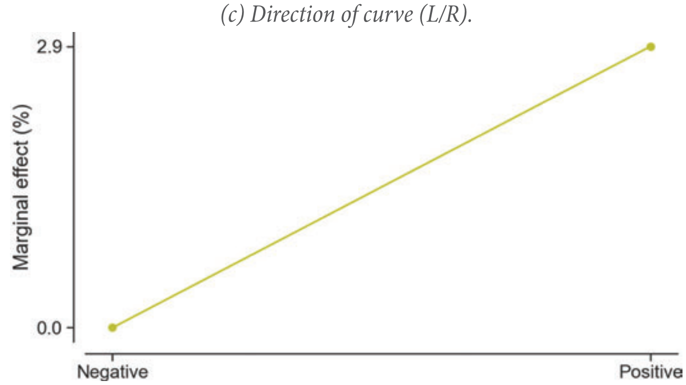
(a) Degree of curve (°).



(b) Percent of grade (%).

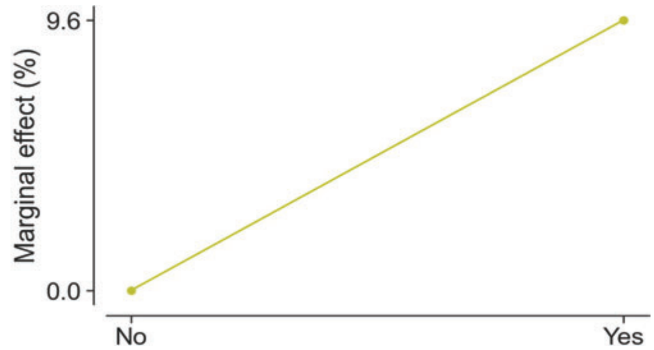


(c) Direction of curve (L/R).

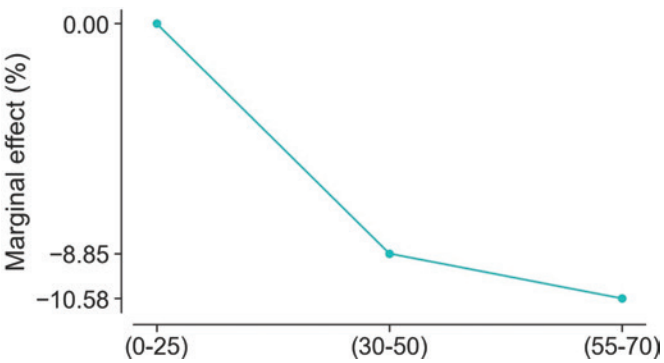


(d) Direction of grade (-/+).

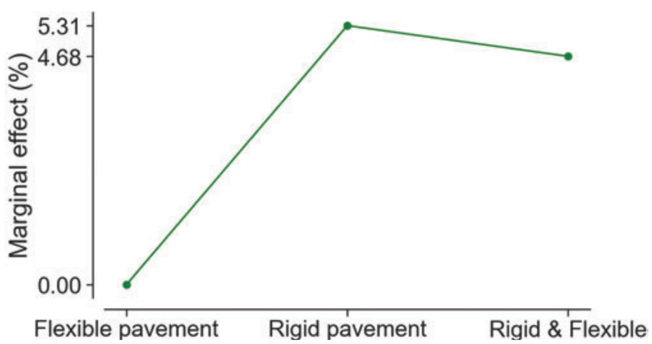
Figure 5. PD-plots (curve and grade characteristics).



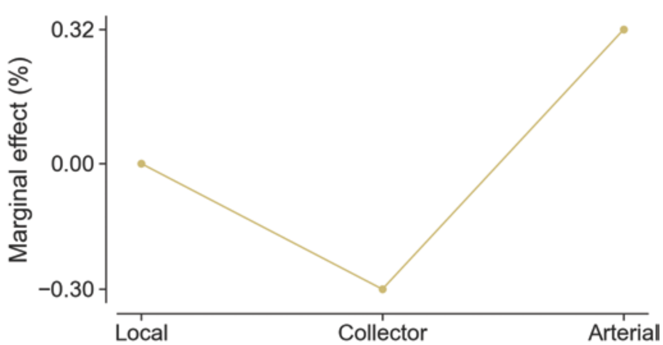
(a) Traffic control devices.



(b) Speed limit (mph).



(c) Roadway surface.



(d) Functional classification.

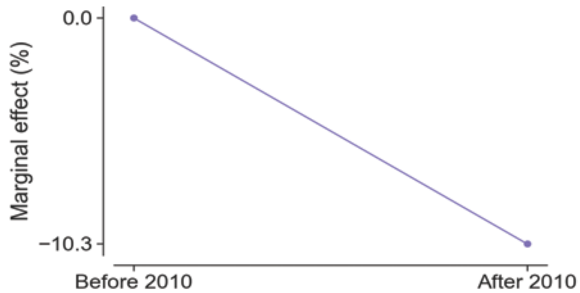
Figure 6. PD-plots (curve and grade characteristics).

Driver-Vehicle characteristic variables. The marginal effects in Figure 9(a) indicate that driver's injury severity decreases with newly manufactured vehicles (after 2010) with better safety features such as airbags etc. Figure 7(b) reveals that a driver is 56.03 percent less likely to sustain an injury when a safety restraint (i.e., seat belts) is on compared to when it is not. Figure 7(c) portrays that female drivers are 12.1 percent more likely to sustain an injury than male drivers. And Figure 7(d) shows that drivers aged 20-64 years are 6.67 percent likely to be involved in an injury resulting crash than drivers 19 years or younger. Even worse observation for older drivers 65 years and above 26.94 percent more likely to sustain an injury compared to drivers 19 years or younger. Further, in Figure 7(e) when the damage is minor the injury likelihood is up by 29 percent compared to no damage and when the damage is severe, injury severity likelihood is up by 205.8 percent.

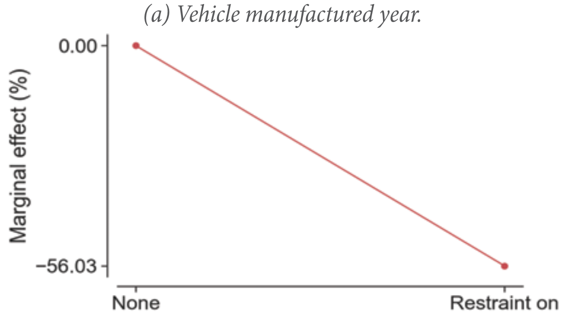
Crash characteristic variables. Figure 8(a) presents that the head-on collision is associated with a higher likelihood of driver injury severity compared to other types of collision. While rear-end collision is observed to be the least manner of collision to lead to drivers' injury severity among others, drivers in this type of crash are found to be 43.77 percent less likely to sustain a severe injury compared to head-on collisions. Drivers are also found to be 31 percent less likely to suffer an injury when involved in a crash from the side of the vehicle compared to head-on crashes. Figure 8(b) shows that drivers are 9.63 percent less likely to sustain an injury during night than during day. Figure 8(c) indicates that drivers are 4.38 percent less likely to suffer an injury in morning or evening peak hours compared to free-flowing conditions. Else, in Figure 8(d) a driver is less likely to have severe injuries when involved in a crash on a weekday compared to a weekend.

Conclusion

This study applied a comparative machine learning approach to examine factors contributing to driver injury occurrence in vehicle crashes along curved and grade combination roadway alignments. The study utilized 5 yearlong (2012–2017) data provided by HSIS for crashes and roadway characteristics in Ohio. First, we used mean-decrease-accuracy permutation feature importance technique to assess relative importance of predictor variables in predicting injury severity in crashes occurring at curved alignments at grade using XGBoost model. Second, based on partial dependency and marginal effect, we visualized relationships between independent variables and dependent variables (curved and grade characteristics geometric, vehicle, driver, and crash characteristics). Then discussed the influence thresholds across which their effects can vary. Among other findings, the partial dependency analysis revealed that the increase in the degree of roadway curvature is associated with a higher risk of the injured driver in a crash. Similarly, the risk is seen to be higher with an increase in grade (positive or negative) while traversing the curve.

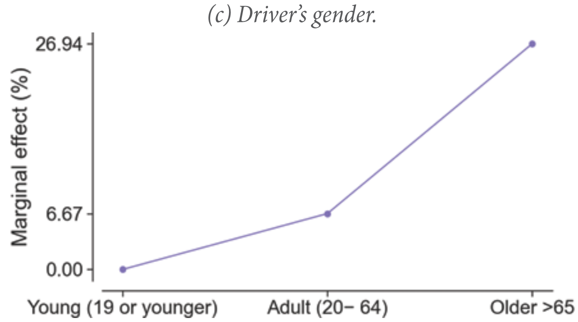


(a) Vehicle manufactured year.

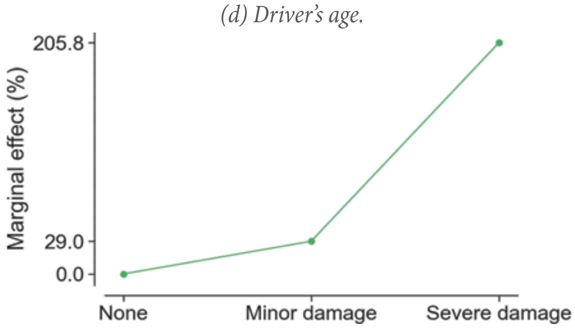


(b) Driver safety restraint.

(c) Driver's gender.

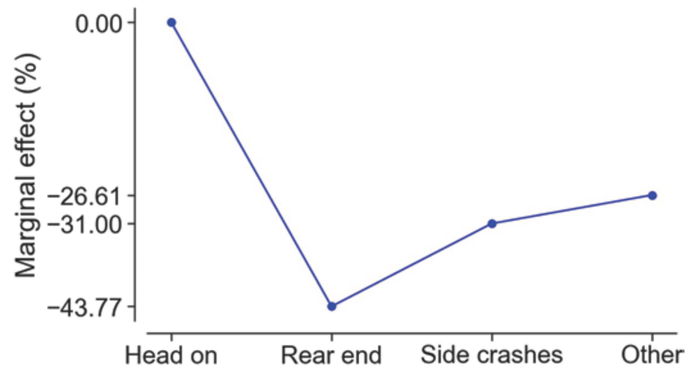


(d) Driver's age.

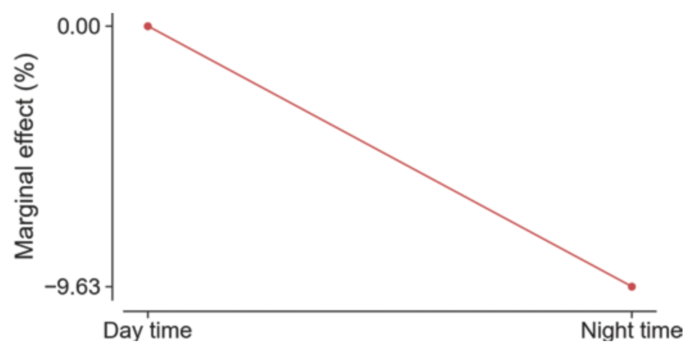


(e) Vehicle damage severity.

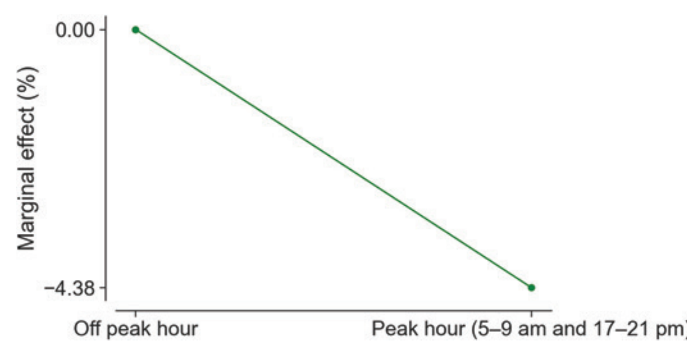
Figure 7. PD-plots (driver and vehicle characteristics).



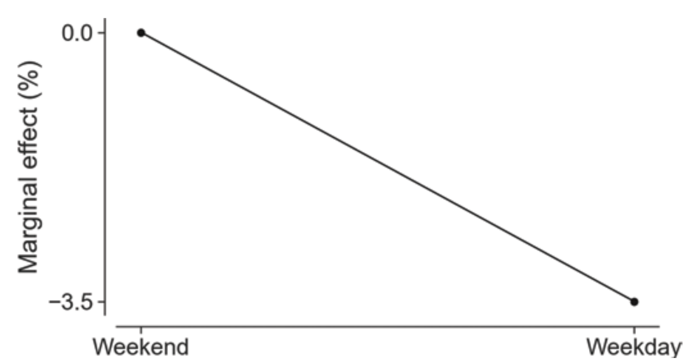
(a) Manner of collision.



(b) Light condition.



(c) Peak hour condition.



(d) Day of week.

Figure 8. PD-plots (crash characteristics).

Moreover, a driver is 5.25 percent more likely to be injured in a right turn curve than a left turn curve while being 2.9 percent more likely to be injured in a downgrade than an upgrade curve.

The findings of this study shed significant light on factors affecting crashes along curved and at-grade segments in Ohio. These findings would be helpful for road engineers, road safety professionals, and relevant authorities to design appropriate countermeasures. The developed model will help to identify high-risk sites in these areas. It will be an opportunity for future work to explore the impact of other safety-threatening scenarios on a driver traversing a curved road at grades such as the presence of a work zone, or other highway incidents. Furthermore, given the imbalanced nature of most crash-related datasets including the one used in this study, while this study used SMOTE up sampling techniques, future studies can use other techniques that can improve the prediction performance of the model. **itej**

Acknowledgments

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Answer to "Where in the World" on page 12: Mons, Belgium. Photo submitted by Jenny Grote, P.E., PTOE, PTP (H).