Horizontal Curves, Signs, and Safety

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Although the safety of horizontal curves has been researched, data availability and quality have been the Achilles' heel of many studies. Furthermore, safety at horizontal curves has become more significant in view of the changes in the latest *Manual on Uniform Traffic Control Devices* with respect to traffic control devices at horizontal curves. The objective of this research was to evaluate the safety of horizontal curves through the use of curve geometric characteristics and sign data. The focus was on collecting a good-quality large data set to develop models and explore the relationship between safety at horizontal curves and sign types, specifically curve and turn signs. The data set included curves on different types of roads to determine the difference in safety characteristics that had not been examined in the literature. The crash prediction models displayed highly significant variables, which showed a positive relationship with annual average daily traffic, posted speed, and curve length, and a negative relationship with curve radius. The results show that sharper curves (Classes B–F) on two-lane roads are less safe than curves on freeways and multilane and urban roads. However, further investigation is required into the safety characteristics of Class A curves on freeways and multilane roads, compared with two-lane roads. Moreover, sign usage was not found to be a significant factor for sharper curves, which suggests that, regardless of the presence of the curve or turn sign, other influencing factors take over. The crash prediction model results provided greater detail and identified variables with large significance.

Horizontal curves are a necessary and important element of highways because the curves provide a gradual change in direction. However, the curves are also likely to cause safety hazards to road users because of the changes in driver expectancy and vehicle handling. Approximately 25% of all fatal crashes in the United States in 2002 occurred on horizontal curves (*1, 2*). The average crash rate for horizontal curves is about three times the average crash rate for highway tangents (*2*). Schneider et al. provided two explanations from a driver awareness perspective: the driver may be unaware of the approaching horizontal curve, or the driver may underestimate the radius or sharpness of the curve (*3*). In another study, Schneider et al. stated that horizontal curves may reduce the driver's available sight distance and vehicle-handling capabilities (*4*). Persaud et al. categorized the exposure to crashes into two categories: road departure to the outside of the curve and cross-median crashes into the opposite lane (*5*). Research also indicates that there is a greater propensity for severe crashes at horizontal curves, as stated in the Texas Transportation Institute's horizontal curve signing handbook (*6*). Persaud et al. stated that motor vehicle crashes happen more frequently and are more severe on horizontal curves (*5*). Therefore, improving safety at horizontal curves is an essential part of an overall safety management plan.

Although there has been considerable research in the past into safety at horizontal curves, data availability and quality have been the Achilles' heel of many studies. Furthermore, there is added significance to the subject of safety at horizontal curves in view of the changes in the latest *Manual on Uniform Traffic Control Devices* with respect to traffic control devices at horizontal curves. There is a need for renewed research into the safety of horizontal curves with respect to geometric features and traffic control devices, specifically curve warning signs, to gain more insight and understanding into this critical safety problem.

OBJECTIVE

The objective of this research was to evaluate the safety of horizontal curves through crash prediction models pertaining to a number of geometric characteristics. There were two main focus areas. The first focus was on the collection of a good-quality, large data set to enable an accurate and detailed investigation. The emphasis was on the quality and comprehensiveness of the data, which would allow the exploration of the safety impacts of a number of individual geometric features and give the results added significance. The use of a large data set would provide a better chance that accurate models would be developed to predict safety at horizontal curves.

The second focus area was to evaluate the safety performance of horizontal curves with respect to a number of geometric features and sign data, specifically curve and turn signs. The aim was to use the most relevant variables to develop crash prediction models and gain an understanding into the specific contributions of the individual variables, which would provide crucial information on safety and design guidelines for horizontal curves.

LITERATURE REVIEW

Past literature shows that safety at horizontal curves has been studied from a number of perspectives. However, certain crash statistics have influenced the nature of the research undertaken. For example, the primary focus has been on two-lane rural roads; about 75% of all curve-related fatal crashes occur in rural areas, and more than 70% are on two-lane secondary highways, which are mostly local roads (*7, 8*). The use of only rural or two-lane road data can reduce the data set by excluding other types of roads that may provide crucial information on the interactions between crashes and curve geometric features, regardless of the severity of the crashes. Therefore, there is an opportunity in this research to expand the analysis to different types of roads.

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Literature shows that run-off-the-road and head-on crashes accounted for 87% of all fatal crashes at horizontal curves (*2*). Another report states that 76% of the curve-related fatal crashes involve single vehicles leaving the roadway and striking roadside objects, such as trees, utility poles, or rocks (*7*). The effect of geometric features, such as shoulder width, may contribute significantly to safety at horizontal curves—an area that has not seen much research in the literature.

Factors That Influence Horizontal Curve Safety

Intensive research has been conducted to investigate the correlation between crash frequency and severity and the geometric parameters of curves. Some key factors and research findings are summarized in Table 1.

Horizontal Curve Crash Prediction Models

Several studies have focused on the development of crash prediction models for horizontal curves, predominantly through the use of generalized linear models. Caliendo et al. developed a crash prediction model based on four-lane, median-divided roads in Italy using the average daily traffic (ADT), the curve length, the intersection presence, and the radius as factors (*15*). Schneider et al. developed a model for truck crashes on horizontal curves through the use of length, the truck ADT, the passenger vehicle ADT, and the degree of curvature (*3*). Persaud et al. developed a model that included the annual average daily traffic (AADT), the length of the curve, and the curve radius as parameters (*5*). The results of the abovementioned studies indicated a positive relationship between crashes, ADT, and curve length and a negative relationship between crashes and curve radius.

A different set of studies have focused on the development of crash modification factors for horizontal curves. Bonneson et al. and Bonneson and Pratt developed horizontal curve crash modification factors for multilane highways through the use of radius and speed limit data (*16, 17*). Fitzpatrick et al. developed a crash modification factor for freeways by using only the degree of curvature as an independent variable and assuming zero degrees as the base condition (*18*). The *Highway Safety Manual* also provides a crash modification factor for horizontal curves; however, the standard error values are unknown, which makes the results unreliable (*19*).

The literature review results, with regards to crash prediction models and factors, showed the use of a limited number of variables to gain an understanding of safety at horizontal curves. Therefore, there is a need to conduct research that includes additional factors (posted speed, road types, signs, etc.) and a larger data set.

Horizontal Curve Warning Signs

The previous version of the *Manual on Uniform Traffic Control Devices* (2003) provided guidelines on the usage of turn and curve signs based on engineering judgment at horizontal curve locations (*20*). The latest version (2009) provides standards on the placement of such signs based on speed differentials and directs states to comply with the standards in the coming years (*21*). In view of these changes, and the limited research on sign usage at horizontal curves, there is a need to explore past usage of warning signs to understand the effects of the changes in the standards on the future safety of horizontal curves.

DATA COLLECTION AND PROCESSING

This research emphasized putting together a thorough and high-quality data set. Data were collected and merged from a number of sources at the Wisconsin Department of Transportation (DOT), details of which are described in the following sections.

Horizontal Curve Data

The Wisconsin DOT maintains horizontal curve information collected from the Wisconsin DOT photo log data set that detects changes in the horizontal alignment through the use of automated

TABLE 1 Summary of Literature Review: Factors That Influence Horizontal Curve Safety

Author	Factor	Summary
Zegeer et al. (*9*)	Curve radius and degree of curvature	A 500-ft radius curve is 200% more likely to produce a crash than an equivalent tangent section, and a 1,000-ft radius curve is 50% more likely to produce a crash than an equivalent tangent section.
Schneider et al. (*3, 4*)		When curves become sharper, the model predicts an increase in truck crashes on horizontal curves. The radius and degree of curvature significantly influence motorcycle crashes on horizontal curves.
Transportation Research Circular E-C033 (*10*)		The degree of curvature and radius are significant variables influencing crash rate on horizontal curves.
Council (*11*)		Crash rates increase as the degree of curvature increases.
Miaou and Lum (*12*)		Truck crash involvement increases as horizontal curvature (degree of curvature) increases.
Schneider et al. (*4*), Zegeer et al. (*13*)	Curve length	Curve length is a significant factor for truck crash involvement. A horizontal curve with a length of 31 m (100 ft) and a radius of 31 m (100 ft) on a roadway segment would be expected to have an accident rate of more than 28 times as high as a tangent section on the same roadway.
Schneider et al. (*3, 4*)	Traffic volume	The increase in passenger vehicle average daily traffic (ADT) is associated with an increase in truck crashes on curves. The total ADT also affects motorcycle crashes on curves.
Schneider et al. (*4*), Zegeer et al. (*13*)	Shoulder width	Shoulder width is a significant variable that affects crashes on curves.
Hallmark et al. (*14*)	Tangent length before curve	Crash rates on curves with long preceding tangent lengths will be more dangerous when the curve is located on a downgrade of 5% or more, and if the tangent lengths are more than 200 m.

algorithms. The Wisconsin DOT photo log data set contains data points with accurate mile marker position data at 50-ft intervals on the Wisconsin state trunk network (STN) roads. The horizontal curve data included attribute information, such as radius, degree of curvature, length, route, county, and the mile marker for the start and end point of each curve. The data were mapped with the photo log lane mile routes, which were created to enable the integration of photo log–based data with other Wisconsin DOT geographic information system (GIS) databases (*22*).

For data analysis, the horizontal curve location was selected as the spatial unit of analysis for which other data elements and attributes would be collected and assembled. However, as a result of the large number of horizontal curves on STN roads in Wisconsin, the data set was trimmed with reasonable assumptions. There were two options available in this respect. The first option was to select horizontal curves based on a reasonable value of radius, because curves with a very large radius (e.g., greater than 10,000 ft) would probably not have significant impacts on horizontal curve safety because of their geometry. Moreover, such horizontal curves did not experience any curve-related crashes because of their very large radii.

The second criterion was based on the degree of curvature, which was used to classify curves into the following classes (*23*):

1. Class A (0.0° to 3.45°),
2. Class B (3.45° to 5.45°),
3. Class C (5.45° to 8.45°),
4. Class D (8.45° to 13.95°),
5. Class E (13.95° to 27.95°), and
6. Class F (27.95° to infinity).

The idea was to use only Class B–F curves (the maximum radius of Class B curves was approximately 1,660 ft) because they captured a large enough data set and excluded the less sharp, and potentially less critical, larger-radius Class A curves.

In this research, both criteria were used so that the results from the two data sets could be compared and contrasted. The two data sets were named Data Set 1 and Data Set 2. Figure 1 shows a flowchart that describes the two data sets, and Table 2 presents the descriptive statistics of the relevant parameters in the two data sets (continuous variables only). Once the two data sets had been assembled, data from additional sources were associated with each horizontal curve record to obtain information on additional variables, which are described in Figure 1 and the paper's subsequent sections.

Data Sets 1 and 2 were further subdivided into Data Sets 1B and 2B, as shown in Figure 1, based on the presence of a turn or curve sign. In other words, Data Sets 1B and 2B were subsets of Data Sets 1 and 2, respectively, based on the presence of a turn or curve sign.

Crash Data

Crash data were obtained for 5 years, between 2005 and 2009, on Wisconsin STN roads. A 300-ft buffer around the horizontal curves was specified to capture the crashes that may have ended outside the proximity of the curves. The resulting data set was further filtered to remove deer- or other animal-related crashes, crashes at ramps and gore, and intersection crashes. The final data set consisted of 11,224 crashes, which were mapped in GIS to locate the crashes on individual horizontal curves. The crash location, as documented by the reporting officer, was identified from the Wisconsin DOT MV4000 crash reporting form, with an intended accuracy of 0.01 mi.

Geometric Data

The geometric characteristics of the horizontal curve locations were obtained from the MetaManager road data set, which contains a large number of attributes related to safety, mobility, traffic forecasts, and so forth. The most relevant variables were selected to analyze horizontal curve safety, and data were checked for errors and missing elements. MetaManager also contains traffic volume data in the form of AADT. The MetaManager data were available in GIS, enabling seamless integration with the other data set.

Sign Data

The Wisconsin DOT maintains a database of all signs on STN roads in its Sign View database. The database contains information on several types of signs and their locations. However, the data are not readily integrated with the Wisconsin DOT STN database. Therefore, the Sign View data were mapped with the photo log lane mile routes to enable integration with the other data set (*22*). For the purpose of this research, the focus was only on turn (W1-1) and curve (W1-2) signs to explore the relationship between the use of the two signs and safety at horizontal curves.

STATISTICAL METHODOLOGY

Poisson Model Form

The basic form of the Poisson regression model is

$$\log(\mu_i) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{1}$$

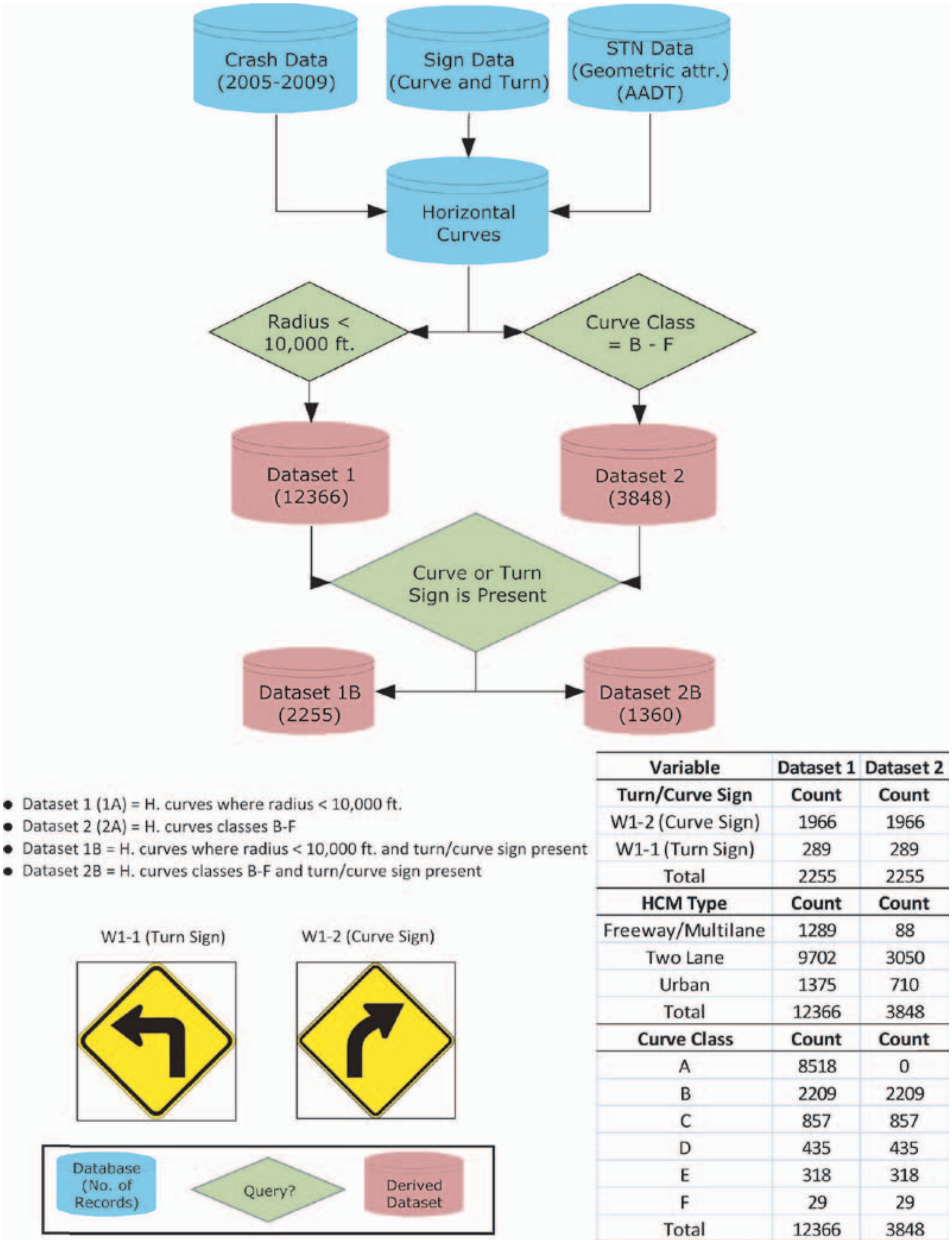
where

μ_i = expected number of crashes on the *i*th horizontal curve,
β_0 = constant,
$\beta_1, \ldots, \beta_n$ = estimated parameters, and
$x_1, \ldots, x_n$ = explanatory variables that influence crashes on the *i*th horizontal curve.

Poisson regression is traditionally used because of its simplicity, but the constraint on the equality of the mean and the variance has driven many researchers to consider negative binomial regression instead. In practice, the Poisson model is often useful for describing the mean but underestimates the variance in the data, rendering all model-based tests liberal.

Quasi-Poisson Model

One way of dealing with the traditional restrictions of the Poisson model is to use the same estimating functions for the mean but to base the inference on the more robust quasi-Poisson regression. Quasi-Poisson uses the mean regression function and the variance function from the Poisson generalized linear model but leaves the dispersion parameter unrestricted. Thus, the dispersion parameter is not assumed to be fixed at one but is estimated from the data.



Variable	Dataset 1	Dataset 2
Turn/Curve Sign	**Count**	**Count**
W1-2 (Curve Sign)	1966	1966
W1-1 (Turn Sign)	289	289
Total	2255	2255
HCM Type	**Count**	**Count**
Freeway/Multilane	1289	88
Two Lane	9702	3050
Urban	1375	710
Total	12366	3848
Curve Class	**Count**	**Count**
A	8518	0
B	2209	2209
C	857	857
D	435	435
E	318	318
F	29	29
Total	12366	3848

FIGURE 1 Development process and description of horizontal curve (H. curve) data set for crash prediction models (HCM = *Highway Capacity Manual*).

This strategy leads to the same coefficient estimates as the standard Poisson model, but the inference is adjusted for overdispersion. Consequently, quasi-Poisson does not correspond to models with fully specified likelihoods and its Akaike's information criterion (AIC) does not have the traditional meaning.

Negative Binomial Model

Another way to model overdispersed count data is to assume negative binomial distribution for which there can be a gamma mixture of Poisson distributions. One parameterization of its probability density function is

$$f(y;\mu,\theta)=\frac{\Gamma(y+\theta)}{\Gamma(\theta)y!}\cdot\frac{\mu^{y}\theta^{\theta}}{(\mu+\theta)^{y+\theta}} \tag{2}$$

with mean μ and shape parameter θ; $\Gamma(\ )$ is the gamma function. It has variance $V(\mu)=\mu+\mu^2/\theta$. When θ goes to infinity, the negative binomial approaches a Poisson distribution.

TABLE 2 Descriptive Statistics of Parameters

Variable	Mean	Median	SD
Descriptive Statistics of Relevant Parameters (Data Set 1)			
Curve length (ft)	974.3	770.4	678.6
Curve radius (ft)	2,908.0	2,330.2	1,983.8
AADT (vpd)	6,652.1	3,200.0	12,780.3
Posted speed (mph)	52.8	55.0	8.2
Left shoulder width (ft)	5.6	6.0	3.2
Right shoulder width (ft)	6.1	6.0	3.5
Number of crashes	0.9	0.0	1.9
Descriptive Statistics of Relevant Parameters (Data Set 2)			
Curve length (ft)	828.9	691.4	462.1
Curve radius (ft)	1,082.6	1,166.9	414.6
AADT (vpd)	4,368.2	1,860.0	7,683.1
Posted speed (mph)	50.2	55.0	10.0
Left shoulder width (ft)	4.2	4.0	3.1
Right shoulder width (ft)	4.4	4.0	3.2
Number of crashes	1.3	1.0	2.1

NOTE: vpd = vehicles per day; SD = standard deviation.

Akaike's Information Criterion

The AIC is a measure of the relative goodness of fit of a statistical model, which loosely describes the trade-off between the accuracy and the complexity of the model. In the general case, the AIC is

$$\text{AIC} = 2k - 2\ln(L)$$

where k is the number of parameters in the statistical model, and L is the maximized value of the likelihood function for the estimated model.

Cross Validation

Cross validation is a method to estimate how accurately a predictive model will perform in practice. One round of cross validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (the training set), and validating the analysis on the other subset (the testing set). To reduce variability, multiple rounds of cross validation are performed with different partitions, and the validation results are averaged over all the replications.

Variance Inflation Factor

The variance inflation factor (VIF) quantifies the severity of multicollinearity in regression analysis by calculating a factor by which variance in the regression coefficient is inflated as a result of multicollinearity (*24*). Generally, a VIF value of greater than four requires a further review of the coefficients, and a value greater than 10 is considered to be an indication of serious multicollinearity (*24*).

MODEL DEVELOPMENT, RESULTS, AND DISCUSSIONS

The availability of a large and rich data set enabled horizontal curve safety to be analyzed using four data sets, as described in Figure 1. The objective was to develop crash prediction models to explore and analyze geometric features and turn and curve sign data through statistical analysis. Poisson and negative binomial models were both fitted with the R generalized linear model framework (*25*).

The process of model development started with the specification of a base model, and the final crash prediction models were generated based on the results of stepwise regression that used AIC as the model selection criteria. The models were updated at every step by adding or removing variables and checking for the smallest AIC values. The final Poisson model was refitted with the quasi-Poisson method to get the adjusted standard errors and significance levels. The quasi-Poisson and negative binomial models were compared with each other with fivefold cross validation. Based on the cross validation score and the ease of interpretation, the negative binomial models were selected as the best models to be used in the final results. Finally, the VIF test was performed for each of the models to check for multicollinearity in the regression coefficients, and the models were modified accordingly to remove the correlated variables.

Development of Crash Prediction Models with Geometric Data

Data Set 1 and Data Set 2 were assembled with the aim of analyzing geometric parameters related to safety on horizontal curves. The data set consisted of more than 12,000 curves on the Wisconsin STN associated with continuous and categorical variables, as shown in Figure 1 (categorical variables) and Table 2 (continuous variables). The crash prediction models developed for horizontal curves showed the curve radius, the curve length, and the natural log of the AADT to be significant variables ($p < .0001$) in all models, along with other variables. The results showed that crashes increased with a decrease in radius, an increase in curve length, and an increase in AADT, which was in line with the findings in the literature. However, the strength of the model and the parameters was what made the model findings interesting, as described in a later section. The coefficients were in the correct direction and reasonable in magnitude.

Modeling Crash Counts with Geometric Data for Horizontal Curves (Data Set 1)

The results of the negative binomial crash prediction models, which used Data Set 1 (Class A–F curves), are shown in Table 3 (Equation 3) and Table 4 (Equation 4), where R is the radius of the curve; L is the length of the curve; PS is the posted speed; F, M, and U denote freeway, multilane, and urban, respectively; RSW is the right shoulder width; and LSW is the left shoulder width. The difference between the two models is the use of the *Highway Capacity Manual* (HCM)–type variable, which is present in the model in Table 3 and is replaced with the posted speed variable in the model in Table 4 (*26*). The reason for developing separate models based on the HCM type and posted speed variables was the multicollinearity in the two variables, which was confirmed with a VIF test (HCM-type VIF = 8.5; posted speed VIF = 3.5). However, because both of the

TABLE 3 Negative Binomial Regression Results for Data Set 1 with HCM Type

Variable	Estimate	SE	z-Value	Pr(>|z|)
Constant	−3.872	0.135	−28.674	0.000
Curve radius (ft)	−4.222 E–04	0.000	−40.130	0.000
Curve length (ft)	4.677 E–04	0.000	24.573	0.000
Log of AADT	0.556	0.019	29.032	0.000
HCM type: freeway and multilane	0.507	0.054	9.350	0.000
HCM type: urban	−0.812	0.066	−12.289	0.000
Right shoulder width (ft)	−0.049	0.006	−8.303	0.000

NOTE: SE = standard error.

TABLE 5 Negative Binomial Regression Results for Data Set 2 with HCM Type

Variable	Estimate	SE	z-Value	Pr(>|z|)
Constant	−3.722	0.203	−18.331	0.000
Curve radius (ft)	−5.619 E–04	0.000	−9.513	0.000
Curve length (ft)	5.610 E–04	0.000	10.922	0.000
Log of AADT	0.569	0.029	19.821	0.000
HCM type: freeway and multilane	−0.359	0.140	−2.569	0.010
HCM type: urban	−0.954	0.094	−10.158	0.000
Right shoulder width (ft)	−0.052	0.009	−5.596	0.000

variables were important, they were included in separate models because one of the contributions of this research was the inclusion of different types of roadway (HCM type) instead of restricting the data set to only rural or two-lane roads. Freeways and multilane roads were combined as one level in the HCM-type variable (representing rural locations) because of the relatively small sample size, as shown in Figure 1.

$$\mu_i = \exp\left[-3.872 - 0.000422 * R + 0.000467 * L + 0.556 * \ln(\text{AADT}) + 0.507 * FM - 0.812 * U - 0.049 * \text{RSW}\right] \quad (3)$$

$$\mu_i = \exp\left[-5.670 - 0.000425 * R + 0.000459 * L + 0.558 * \ln(\text{AADT}) + 0.032 * \text{PS} - 0.037\text{LSW}\right] \quad (4)$$

The results of the models are presented in Table 3 (Equation 3) and Table 4 (Equation 4) and show that the HCM type and posted speed variables are significant. More crashes are expected on freeway and multilane roads (rural), and fewer crashes are expected on urban roads, compared with the base condition of two-lane roads; this finding was very interesting because the expectation was that freeways, which generally have higher speed limits, are safer than two-lane roads. A possible explanation could be that the safety characteristics of Class A curves (many of which are on freeway and multilane roads) included in Data Set 1 are more closely related to straight segments of road on which other factors take over, rather than horizontal curvature. The results of Data Set 2 could provide some insight in this regard. The right shoulder width is replaced by the left shoulder width between the two models, which warrants further investigation into the relationship and interaction between the two variables. The coefficients of the common variables between the models in Table 3 and Table 4 are similar, signifying the stability of the model. Therefore, both the models are useful in an estimation of crashes on horizontal curves that uses different sets of variables.

Modeling Crash Counts with Geometric Data for Horizontal Curves (Data Set 2)

The results of the negative binomial crash prediction models that used Data Set 2 (Class B–F curves) are shown in Table 5 (Equation 5) and Table 6 (Equation 6). The difference between the two models is the use of the HCM type variable, which is present in the model in Table 5 and is replaced with posted speed in the model in Table 6.

$$\mu_i = \exp\left[-3.722 - 0.000561 * R + 0.000561 * L + 0.569 * \ln(\text{AADT}) - 0.359 * FM - 0.954 * U - 0.052 * \text{RSW}\right] \quad (5)$$

$$\mu_i = \exp\left[-4.137 - 0.000520 * R + 0.000560 \times L + 0.448 * \ln(\text{AADT}) + 0.02 * \text{PS} - 0.024\ \text{RSW}\right] \quad (6)$$

The results of the models in Table 5 (Equation 5) and Table 6 (Equation 6) show that the HCM type and posted speed variables are both significant. However, compared with the model results

TABLE 4 Negative Binomial Regression Results for Data Set 1 with Posted Speed

Variable	Estimate	SE	z-Value	Pr(>|z|)
Constant	−5.670	0.153	−37.009	0.000
Curve radius (ft)	−4.253 E–04	0.000	−40.478	0.000
Curve length (ft)	4.591 E–04	0.000	24.096	0.000
Log of AADT	0.558	0.013	42.780	0.000
Posted speed (mph)	0.032	0.002	15.900	0.000
Left shoulder width (ft)	−0.037	0.005	−7.385	0.000

TABLE 6 Negative Binomial Regression Results for Data Set 2 with Posted Speed

Variable	Estimate	SE	z-Value	Pr(>|z|)
Constant	−4.137	0.280	−14.754	0.000
Curve radius (ft)	−5.205 E–04	0.000	−8.806	0.000
Curve length (ft)	5.604 E–04	0.000	10.819	0.000
Log of AADT	0.448	0.023	19.183	0.000
Posted speed (mph)	0.020	0.003	6.663	0.000
Right shoulder width (ft)	−0.024	0.008	−2.955	0.003

from Data Set 1, the results show a decrease in crashes on freeway and multilane roads (rural) and urban roads compared with the base condition of two-lane roads. This result is possibly because of higher design standards (larger radii curves) on freeway, multilane, and urban roads than on two-lane roads. The results were in line with the expectation and suggested differences in safety characteristics of Class A curves; however, more investigation is required to deduce reliable conclusions. Furthermore, as curves become sharper (Data Set 2, Class B–F curves), the coefficients of the curve radius and the right shoulder width become larger, showing an increased effect of the variables. Also, higher posted speeds result in more crashes on sharper curves. Right shoulder width is significant in both models, indicating its importance in predicting crashes on horizontal curves in Data Set 2. The coefficients of the common variables between the models in Table 5 and Table 6 are similar, signifying the stability of the model.

Development of Crash Prediction Models with Sign Data

Data Set 1B and Data Set 2B were created as subsets of Data Set 1 and Data Set 2, respectively, to study the effects of turn and curve signs on horizontal curves. The reason for creating the subsets was because only a limited number of horizontal curves contained curve or turn signs within the larger Data Sets 1 and 2. Figure 1 and Table 2 show the characteristics and variables of Data Sets 1B and 2B. A new variable that represented the type of sign was introduced with two levels: W1-1 (turn sign) and W1-2 (curve sign). The HCM-type variable was not used in the crash prediction models developed with sign data because almost all the curves within the data set were located on two-lane roads, which would skew the results.

The crash prediction models developed with sign data to predict crashes on horizontal curves showed similar results in terms of curve radius, length, and AADT having a strong significance level. However, the effect of shoulder width was markedly decreased. The use of sign data was a unique aspect of this research, aimed at investigating the relationship between turn and curve signs and horizontal curve safety.

Modeling Crash Counts with Sign Data for Horizontal Curves (Data Set 1B)

The results of the negative binomial crash prediction models that used Data Set 1B (Class A–F curves) are shown in Table 7 (Equation 7), where W1-2 is a curve sign. The initial model contained left and right shoulder width variables with very high VIF values, showing a high correlation (right shoulder width VIF = 8.6; left shoulder width VIF = 7.9). Therefore, the left shoulder width variable was removed from the model. The VIF values did not show any correlation between the radius and the curve or turn sign (radius VIF = 1.3; turn or curve sign VIF = 1.3). The crash prediction model shows the sign type as a significant variable, with fewer crashes expected at horizontal curve locations with a curve sign compared with a turn sign. One logical interpretation of the results is that the engineer's judgment to place a curve versus a turn sign was correct in terms of horizontal curves and their propensity for crashes; however, further investigation is required. The crash prediction model in Table 7 shows the right shoulder width as less significant compared with previous models.

$$\begin{aligned}\mu_i = \exp\big[&-5.466 - 0.000530 * R + 0.000395 * L + 0.589 \\ &* \ln(\text{AADT}) + 0.033 * \text{PS} - 0.191 * (\text{W1-2}) \\ &- 0.019 * \text{RSW}\big]\end{aligned} \tag{7}$$

TABLE 7 Negative Binomial Regression Results for Data Set 1B: Sign and Geometric Data

Variable	Estimate	SE	z-Value	Pr(>|z|)
Constant	–5.466	0.475	–11.513	0.000
Curve radius (ft)	–5.307 E–04	0.000	–11.873	0.000
Curve length (ft)	3.950 E–04	0.000	7.321	0.000
Log of AADT	0.589	0.038	15.518	0.000
Posted speed (mph)	0.033	0.006	5.278	0.000
W1-2 (curve sign)	–0.191	0.093	–2.063	0.039
Right shoulder width (ft)	–0.019	0.013	–1.504	0.133

Modeling Crash Counts with Sign Data for Horizontal Curves (Data Set 2B)

The results of the negative binomial crash prediction model that used Data Set 2B (Class B–F curves) are shown in Table 8 (Equation 8). The model does not show curve and turn signs as a significant variable, which is an interesting observation. One could argue that engineering judgment becomes more difficult in selecting between turn and curve signs and assessing the safety at sharper curves (Class B–F curves) compared with less sharp curves (Class A). However, any interpretation of the results would require further research and analysis specifically taking advisory speed effects into consideration. The coefficient of the curve radius has increased between the models based on Data Sets 1B and 2B, showing that the curve radius has a higher impact on safety at sharper curves (Class B–F curves).

$$\begin{aligned}\mu_i = \exp\big[&-5.407 - 0.0007330 * R + 0.0004717 * L + 0.567 \\ &* \ln(\text{AADT}) + 0.033 * \text{PS}\big]\end{aligned} \tag{8}$$

CONCLUSIONS

Although research on safety at horizontal curves has been conducted in the past, the lack of good-quality data has hindered some analyses. This research aimed to gather an extensive database that could be used to review safety on horizontal curves with respect to geometric features, traffic control devices (specifically curve warning signs),

TABLE 8 Negative Binomial Regression Results for Data Set 2B: Sign and Geometric Data

Variable	Estimate	SE	z-Value	Pr(>|z|)
Constant	–5.407	0.489	–11.056	0.000
Curve radius (ft)	–7.330 E–04	0.000	–7.328	0.000
Curve length (ft)	4.717 E–04	0.000	6.265	0.000
Log of AADT	0.567	0.038	14.754	0.000
Posted speed (mph)	0.033	0.006	5.111	0.000

and crashes to gain further insight and understanding into the critical safety problem, as well as to analyze curve and turn signs. The variables from the crash prediction models have large significance and describe the characteristics of the curves in greater detail than in previous studies (e.g., using different types of roads, shoulder width, and posted speed variables). The crash prediction models can be used in safety performance functions for horizontal curves.

The data set included horizontal curves on different types of roads to determine the difference in the safety characteristics of horizontal curves on different roadways that had not been examined in the literature. The data show that there is a positive relationship with AADT, posted speed, and curve length and that curve radius is negatively correlated. The results also show that sharper curves (Class B–F curves) on two-lane roads are less safe than curves on freeways and multilane and urban roads. However, for Data Set 1 (Class A–F curves), the results show that freeways and multilane roads are less safe than two-lane roads, which requires further investigation into the safety characteristics of Class A curves with large radii.

The comparison between Data Sets 1 and 2 shows that the coefficient for curve radius becomes larger with a data set that contains curves of a higher degree of curvature. The models based on Data Set 1B show fewer crashes at curves with a curve sign compared with a turn sign. However, for sharper curves (Data Set 2B, Class B–F curves), sign usage is not a significant factor, which means that on sharper curves, regardless of the presence of a turn or a curve sign, other influencing factors take over.

Future research needs to examine the effects of other types of signs, as well as factors such as cross slope, pavement friction, advisory speed, date of installation, sign material, and size. This future research could help in the review of current *Manual on Uniform Traffic Control Devices* guidelines and make recommendations for future editions. The substantial database assembled as part of this research provides a good foundation for future improvements and analyses. With regard to modeling, the types of variables need to be further explored, such as whether shoulder width and speed should be categorical variables instead of continuous.

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