The Pennsylvania State University

The Graduate School

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MODELING SAFETY EFFECTS OF GEOMETRIC DESIGN CONSISTENCY ON TWO-LANE RURAL ROADWAYS USING MIXED EFFECTS NEGATIVE BINOMIAL REGRESSION

A Thesis in

Civil Engineering

by

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Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Master of Science

May 2014

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ABSTRACT

Previous research has examined the relationship between roadway safety and design consistency using measures such as the difference between design and operating speeds and the difference in operating speeds on successive elements. While such measures have proven effective in identifying inconsistencies in the roadway, they do not directly identify the conditions associated with safety performance. The purpose of this research was to directly quantify the effects of geometric design consistency on roadway safety using measures that can be linked to specific geometric elements. To do so, five years of crash data and roughly 5,000 miles of alignment data from the state of Washington were utilized to model crash experience on 2.5 mile segments.

Using mixed effects negative binomial modeling, three safety performance functions (SPFs) were developed. The first contained typical roadway parameters that were suggested for use by several contemporary safety management tools, while the second contained various geometric design consistency measures developed from the dataset. The final SPF contained both typical and design consistency parameters. After Empirical Bayes adjustments were applied using the conditional overdispersion parameters from the mixed effects negative binomial models, sites with potential (SWiPs) for safety improvements were ranked for each model using the scaled differences in frequencies between the predicted and adjusted number of crashes.

A comparison was then made based on differences in SWiP rankings between the typical parameter model and the final model containing additional design consistency parameters. Ultimately, 40 unique segments were identified by each SPF out of the top 220 segments ranked; this constitutes a 19 percent change in the top 10 percent of

segments identified as SWiPs. Additionally, there was marked variation in the order in which SWiPs were ranked. This disparity may lend credence to the incorporation of geometric design consistency parameters in the development of predictive safety models. Ultimately, by directly modeling the inconsistencies in geometric roadway design, practitioners may be able to better identify and categorize unsafe roadways both in the design stage and post-construction. However, it is important to note that the use of design consistency parameters does not ameliorate the modeling process solely based on a difference in SWiP identification; rather, it should encourage further avenues of research into the use of such measures in predictive safety modeling. Although this investigation is only preliminary, the results may help to burgeon the ever-expanding body of literature regarding the relationship between geometric design consistency and roadway safety.

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ACKNOWLEDGEMENTS

First and foremost, I would like to thank my thesis advisor, Dr. Paul P. Jovanis, for providing the encouragement and inspiration to undertake this research. His constant support and guidance has been essential from the outset of my career in transportation engineering. I would also like to thank the other members of my thesis committee, Dr. Eric T. Donnell and Dr. Vikash V. Gayah. Their wisdom and insightful comments over the past several years have not only vastly improved this work, but they have played a key role in my development as an engineer. I also owe a great deal of gratitude to doctoral candidate, Jonathan Wood, whose constant willingness to impart statistical knowledge made the completion of this research possible in my lifetime.

Additionally, I would like to thank the Federal Highway Administration's Universities and Grants Program, the Pennsylvania State University's Graduate Fellowship Program, and the College of Engineering at the Pennsylvania State University, whose financial support helped fund this research and my graduate studies.

Finally, I would like to thank my parents, without whom, I would not be at this point in my career. Their constant support and encouragement helped instill the requisite motivation for undertaking and completing my graduate work.

Chapter 1. INTRODUCTION

1.1. General Background

One of the foremost aspirations of transportation professionals, regardless of realm of expertise, is to maintain the highest levels of safety throughout the roadway network. Over the past decade, there has been a marked decrease in the number of fatal automobile crashes, even with a steadily increasing number of vehicle-miles-traveled (VMT) by motorists. It remains to be seen whether this trend comes by dint of the recent economic downturn or through the efforts of programs like AASHTO's *Towards Zero Deaths* and the methodologies established in the Highway Safety Manual (HSM). However, one fact remains evident. Current levels of safety, both those perceived by the roadway user and analytically derived through crash statistics, should leave transportation professionals far from complacent. It is imperative that innovative and more proficient methods for evaluating roadway safety are continuously being developed through research efforts at all levels of the profession.

Although novel in terms of the overall history of transportation safety, the currently-established method for evaluating roadway safety utilizes statistical regression modeling to estimate crash frequency. These safety performance functions (SPFs) utilize historical crash data to estimate the predicted number of crashes for a roadway segment based on a set of baseline conditions. The disparity between the actual number of crashes experienced on a segment and the number predicted by the SPF may be an indication of a roadway that would benefit from investments in safety improvements. Though the parameters included in these models vary significantly, they typically include measures of exposure, such as Annual Average Daily Traffic (AADT) and roadway segment length. The HSM provides recommendations for several other general roadway parameters to help predict crashes; however, the means and procedures utilized for the development of safety performance functions are far from being perfected. Therefore, considerable research has been directed towards developing more proficient and efficacious means to help estimate levels of safety.

One such method, which has warranted significant study over the past decade, utilizes inconsistencies in roadway design to help identify potentially unsafe sections of roadway. Since these inconsistencies may take various different forms, the recent literature is rather diffuse; the full breadth of these current evaluation practices is evaluated in the subsequent section. It is important to note, however, that some of these methods developed for assessing design consistency, such as measuring the disparity between 85^{th} percentile speeds on successive elements, may require extensive financial and development efforts on the behalf of practitioners. Although the development of speed profile equations have allowed for the estimation of 85^{th} percentile speeds, these equations require field validation to ensure circumstantial applicability. Furthermore, such measures of consistency may only become efficacious in the evaluation of existing roadway systems. If, for example, a practitioner was attempting to evaluate the potential safety performance of several design alternatives, they would have to place their faith in the pertinence of speed profile equations to estimate 85^{th} percentile speeds; the practitioner has no method for verifying the applicability of the selected speed models to their potential designs.

1.2. Purpose of Research

Therefore, it is the objective of this study to develop a methodology for assessing potential levels of roadway safety that do not require surrogate measures of design consistency. This is achieved through the direct use of geometric design inconsistencies, such as changes to intra-segmental horizontal curve radii and the number of changes in vertical grade within a segment. By incorporating these parameters into safety performance functions, levels of design consistency can be evaluated in a more direct manner.

One advantage of using actual geometric alignment parameters to measure consistency stems from their general accessibility; most public agencies possess records of the geometric layout of their roadway network. Although the precision and diligence by which these files are maintained vary from agency to agency, geometric alignment parameters are much more readily available for utilization in safety performance functions (SPFs) than the values for 85^{th} percentile speed or driver workload for each particular segment of roadway under the agency's control. By directly modeling inconsistencies in the geometric alignment, practitioners will also be afforded the ability to estimate the safety performance of existing roadways, as well as the performance between several alternatives in the design stage. The geometric data required to utilize the safety performance functions should be available to safety professionals conducting safety analysis on a single roadway or an entire network of roadways. Therefore, the incorporation of changes to geometric elements into current safety evaluation methods may serve practical applications with a trivial amount of effort. Before this analysis is performed, however, it is imperative to first gain an understanding of the current state of practice of design consistency in the field of roadway safety.

Chapter 2. BACKGROUND AND LITERATURE REVIEW

2.1. Design Consistency

The notion of using design consistency as a means of assessing roadway safety is not a novel one. Transportation professionals have long recognized the need to design roadways in a consistent manner; however, the manner in which they define "design consistency" has been subject to substantial discrepancy. Alexander & Lunenfeld (1986) suggest that design consistency implies that the roadway does not violate the expectancy of the driver or impede their ability to guide and control their vehicle in a safe manner. It makes sense intuitively that drivers will make more errors at geometric features that violate expectations than those that conform to their expectations. In order for a design to be considered inconsistent, however, it must possess a geometric feature or a combination of adjacent features, that violates driver expectations; which in turn, may surprise drivers and possibly make them drive in an unsafe manner (Messer, 1980).

Others have taken a more specific approach. Wu et al. (2013) defined design consistency as the difference between operating speed and inferred design speed on successive elements. Similarly, Castro et al. (2011) describe an inconsistent design as one that violates driver expectancies solely through differences in operating and design speeds. However, using definitions such as these ultimately limit the scope of research on the relationship between design consistency and roadway safety.

A survey conducted by Wooldridge et al. (2003) confirms the multiplicity of accepted definitions in practice. In a mail-back survey comprised of over thirty state agencies, practitioners were asked to provide their putative definition of design consistency. Despite being given five prepared definitions, nearly 40% of the respondents offered their own definitions with particular emphasis on the selected phrasing. Many called for the inclusion of a spatial limit to design consistency over a given section of roadway. As discussed by Wooldridge et al. (2003), however, the term highway "section" is readily hard to define. A driver's expectancy is not merely limited to their experiences on the preceding segment of road; expectancy can be developed over a driver's career, or at the very least, their career within a certain region. Therefore, Wooldridge et al. (2003) developed a multifaceted definition of design consistency as the "conformance of a highway's geometric and operational features with driver expectancy."

The more generalized definitions provided by Messer (1980) and Wooldridge et al. (2003) are used in this study, as they allow for a wide range of design consistency measures to be explored. The purpose of this study is to directly quantify the effect of design consistency measures in a way that relates it to specific geometric elements. Since the exact measures of design consistency that are used in this study have not yet been illuminated, it would not be prudent to assume a definition of consistency that limited potential results. Although many studies have followed similar approaches to modeling design consistency, it is important to recognize the unique contributions of each. Some of the most common measures used to develop a relationship between roadway safety and geometric design consistency are discussed in the subsequent sections.

2.2. Speed Differences

One of the most prevalent methods for evaluating design consistency has been the use of speed-profiles. It has been hypothesized that significant variations in speeds are an indication of inconsistent design features, while more consistent designs will produce a more uniform speed profile (Nicholson, 1994; Fitzpatrick et al., 2000). This is perhaps best demonstrated by Figure 2-1, which illustrates a more pronounced drop in speed due to a horizontal curve with a small radius.

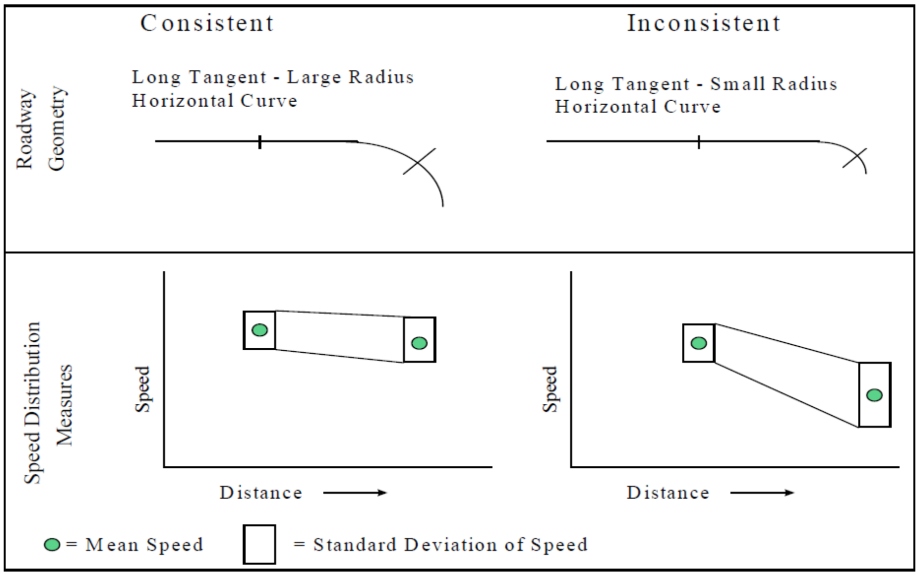

Figure 2-1. Relationship of roadway geometry and standard deviation of speed (Fitzpatrick et al., 2000)

Significant changes in operating speeds, such as this, may be a good indicator of a geometric design inconsistency. By modeling either the difference between design speeds (V_d) and operating speeds (V_{85}) or the difference in operating speeds on successive roadway elements, researchers have attempted to identify sites where inconsistencies are present. Perhaps the most proverbial method for classifying design inconsistencies due to speed differences was proposed by Lamm et al. (1999). The criteria, which can be seen in Table 2-1, identify segments as either “good,” “fair,” or “poor” based on the magnitude of speed differential.

Table 2-1. Design consistency criteria (Lamm et al., 1999)

Consistency Rating	Criterion I (km/h)	Criterion II (km/h)
Good	$\lvert V_{85} - V_d \rvert \leq 10$	$\lvert V_{85i} - V_{85(i+1)} \rvert \leq 10$
Fair	$10 < \lvert V_{85} - V_d \rvert \leq 20$	$10 < \lvert V_{85i} - V_{85(i+1)} \rvert \leq 20$
Poor	$\lvert V_{85} - V_d \rvert > 20$	$\lvert V_{85i} - V_{85(i+1)} \rvert > 20$

The use of these broad categories of "good, fair, and poor," however, may not be the most effective manner in which to quantify design inconsistencies. For instance, if two successive elements experienced an operating speed differential of 20 kilometers per hour, the roadway's consistency would be rated "fair" by Criterion II. However, if two successive elements along the same corridor experienced a speed differential of 20.1 kilometers per hour, they would be experiencing "poor" design consistency. In reality, both situations are subject to nearly the same level of speed consistency, but the first set of successive segments may go unnoticed using the criteria established by Lamm et al. (1999). The three categories provide for an absolute statement about a particular segment's consistency; rather, consistency would be more accurately identified through gradation.

Furthermore, a driver's desired operating speed (V_{85}) is dependent on several factors, including weather, roadway condition, and geometric alignment (Fitzpatrick et al., 2000). As a result, desired operating speeds cannot be measured directly. In order to use them as a design consistency tool, they must be estimated assuming a relationship with roadway characteristics (see Table 2-2). There has been a multitude of studies (Lamm et al., 1999; Morrall & Talarico, 1994; TAC, 1994; Ottesen & Krammes, 2000; Voigt, 1996; Islam & Seneviratne, 1994) that have attempted to model this relationship with reasonable success using measures such as horizontal curve radii, degree of curvature, and length of horizontal curve. Perhaps the most extensive study into developing speed prediction equations was put forth by Fitzpatrick & Collins (2000). By utilizing alignment data from over six states, the researchers were able to derive a series of equations to account for a wide variety of alignment conditions. These equations are shown in Table 2-2.

Table 2-2. Speed prediction equations (Fitzpatrick & Collins, 2000)

Equation No.	Alignment Condition	Speed Equation
0	Tangent on grade	Desired speed
1	Horizontal curve on grade, $-9 < G < -4\%$	$V_{85} = 102.10 - 3077.13/R$
2	Horizontal curve on grade, $-4 < G < 0\%$	$V_{85} = 105.98 - 3709.90/R$
3	Horizontal curve on grade, $0 < G < 4\%$	$V_{85} = 104.82 - 3574.51/R$
4	Horizontal curve on grade, $4 < G < 9\%$	$V_{85} = 96.61 -2752.19/R$
5	Horizontal Curve combined with a sag vertical curve	$V_{85} = 105.32 -3438.19/R$
6	Horizontal Curve combined with a non-limited sight distance crest vertical curve	Smallest values from eqns. [1]-[4]
7	Horizontal Curve combined with a limited sight distance crest vertical curve	$V_{85} = 103.24 -3576.51/R$; also check eqn. [6]
8	Sag vertical curve on a tangent	Desired speed
9	Non-limited sight distance crest vertical curve on a tangent	Desired speed
10	Limited sight distance crest vertical curve on a tangent	$V_{85} = 105.08 -149.69/K$
Where R is the horizontal curve radii, G is the grade of the vertical curve, and K is rate of vertical curvature		

As evidenced by the sheer multitude of speed-profile equations developed in the aforementioned studies and the numerically-explicit formulas seen in Table 2-2, one might expect there to be variations in the classification of design consistency using methods like those in Table 2-1 depending on the speed-profile equations selected. Richl & Sayed (2005) attempted to demonstrate this fact by applying some of the most prevalent speed-profile equations to the same roadway and evaluating the design consistency achieved by each using the criteria developed by Lamm et al. (1999). Using an existing 36-segment roadway alignment proven to have substandard horizontal and vertical curve features (using British Columbia highway standards established in BC MoTH, 1994), the researchers developed a summary of the design consistency evaluation, shown in Table 2-3.

Table 2-3. Design consistency evaluation summary (Richl & Sayed, 2005)

	Safety Criteria I (as in Table 2-1)			Safety Criteria II (as in Table 2-1)		
Speed Model	Good	Fair	Poor	Good	Fair	Poor
Lamm et al., 1988	34	1	1	27	8	1
Lamm et al., 1999 (lane width)	30	6	0	29	6	1
Lamm and Choueiri, 1987	31	5	0	31	5	0
TAC, 1999	12	9	15	16	7	13
Kanellaidus et al., 1990	15	9	12	22	5	9
Morrall and Talarico, 1994	32	4	0	29	6	1
Lamm et al., 1999	31	5	0	31	5	0
Ottesen and Krammes, 2000 (model 1)	20	16	0	26	9	1
Ottesen and Krammes, 2000 (model 2)	19	16	1	23	8	5
Islam and Seneviratne, 1990	25	11	0	24	9	3
Voigt, 1996	24	12	0	24	10	2
FHWA, 2000	23	13	0	23	12	1

As shown in the table, the speed-profile equations developed by TAC (1999) and Kanellaidus et al. (1990) generate operating speeds that are vastly different from the design speed of the roadway. The 15- and 12- "poor" roadway segments identified by these studies in Criteria I, respectively, would lead one to believe that there are significant design inconsistencies within the study corridor. However, several other studies show little design inconsistency. Even if the equations developed in these two studies (TAC and Kanellaidus et al.) were disregarded as outdated or inconsequential, other speed models exhibit similar differences. The discrepancy in the number of "good" and "fair" ratings generated from equations in the Lamm et al. (1999) and FHWA (2000) studies are significant; these are arguably two of the most prominent studies regarding operating speed estimation. This level of disparity between models may lead to significantly different safety regression models to be developed. This is not to say that speed variations within roadway elements cannot be viable indicators of design consistency; in fact, many studies suggest a strong correlation. Rather, it establishes that any attempts to develop a relationship between design consistency and roadway safety using speed variations is only as strong as the speed-profile equations utilized.

One of the first studies to actually model speed consistency as a measure of safety was put forth by Anderson et al. (1999). Using the speed prediction models developed by Fitzpatrick & Collins (2000) (using an earlier draft from 1998, but identical equations), the researchers were able to generate a speed-profile for over 290 highway segments (~3,000 miles) of two-lane rural roadways in the state of Washington. Due to the shape of the accident distribution, Anderson et al. applied count regression models to the data to generate the relationship shown in the equation below:

$$Y = e^{-7.1977} AADT^{0.9224} CL^{0.8419} e^{0.0622*SR}$$

Where:

Y = the number of accidents that occurred over the three year study period,

CL = the length of the horizontal curve in feet, and

SR = the speed reduction between adjacent segments [i.e., $V_{85i} - V_{85(i+1)}$] in miles-per-hour.

The positive relationship between speed reduction and accident experience indicates that any increase in the speed discrepancy between two adjacent segments would increase the expected accident frequency experienced at those segments. With a high level of significance for all parameters (>95% confidence level), the results of this model substantiate previous conjectures that changes in operating speeds can be a useful indicator of design inconsistencies. One measure that may lend more credence to this study would be to identify the hazardous sites (i.e., SWiPs) using the regression model and compare them to the hazardous or “poor” sites identified using the safety levels developed by Lamm et al. in Table 2-1. If similar sites were identified across both methods, it would further validate the use of speed reduction as an identifying factor of design consistency, and ultimately, roadway safety.

Ng & Sayed (2004) took a similar approach towards modeling the relationship between speed reductions and safety. Using the speed prediction models developed by Morrall & Talarico (1994), the researchers again generated a negative binomial model relating accident experience as function of exposure and changes to operating speeds. These regression models can be seen below:

$$Accidents\ per\ 5\ years = \ e^{-3.380}L^{0.8920} * AADT^{0.5913}e^{0.00909(V_{85}-V_d)}$$

$$Accidents\ per\ 5\ years = \ e^{-3.796}L^{0.8874} * AADT^{0.5847}e^{0.04828(\Delta V_{85})}$$

Where:

L = the length of the segment.

The positive coefficient of the speed reduction term in the first equation (V_{85}-V_d) indicates that differences in operating speeds are a good indicator of inconsistencies within a segment; while the positive coefficient of the speed reduction term in the second equation (ΔV_{85}) validates that a speed drop between two successive segments is expected to increase accidents. With a high level of significance for each parameter and the accident prediction models failing to reject the null hypothesis of the Pearson χ^2-test, Ng

& Sayed further substantiate the use of speed reductions as an indicator of roadway safety.

Anderson & Krammes (1999) and Awatta & Hassan (2002) both took markedly different approaches towards modeling operating speed changes as a measure of safety. While both studies still utilized the criteria established by Lamm et al. (1999) in Table 2-1, they attempted to model crash rates, rather than frequency, along horizontal curves. Since crash rates are a function of exposure, the researchers were able to take a more simplistic statistical approach towards modeling. Anderson & Krammes utilized a linear model of mean crash rates against the mean speed differentials within a segment:

$$\overline{CR} = 0.54 + 0.27(\overline{\Delta V_{85}})$$

Where

CR = the mean crash rate in crashes per million vehicles, and

ΔV_{85} = the mean estimated speed drop experienced between successive segments in miles-per-hour.

The regression equation indicates that crash rates should rise when a greater speed drop is experienced. The model yielded an R^2-value of 0.93. This may appear as though ΔV_{85} explains an extremely high percentage of the variation in crash rates; however, this high coefficient of determination was only achieved because sites were grouped into speed-reduction intervals. By using these intervals in the regression equation, the scatter in the data became more limited.

Awatta & Hassan modeled crash rates by developing a quadratic relationship with operating speed based measures. It is important to note, however, that the alignment used in the study was artificial. As a result, the crash rates used in regression were only predicted rates using the methods developed by the Federal Highway Administration in Report 99-207. The alignment also only consisted of eight horizontal curves, leading to a relatively small sample size. Nevertheless, the safety models obtained are shown below:

$$CR = 0.0041(V_{85} - V_d)^2 + 0.2118(V_{85} - V_d) + 3.4325$$

$$CR = 0.0292(\Delta V_{85})^2 - 0.2465(\Delta V_{85}) + 1.8499$$

With all other factors being held constant, the lack of change in speed within an element or between successive elements should indicate the average crash rate for a roadway element that has a consistent design. However, the parabolic nature of these equations would suggest that operating speeds below the design speed of the roadway would also lead to higher crash rates. This is illustrated in Figure 2-2.

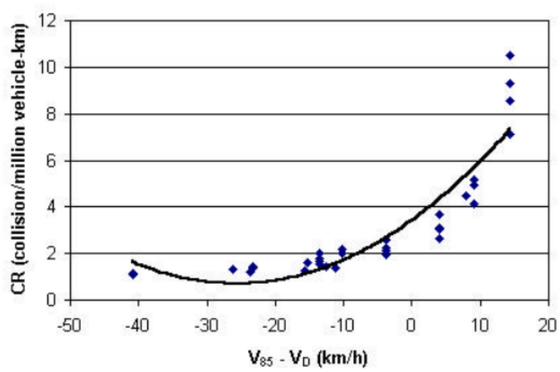

Figure 2-2. Relationship between (estimated operating speed-design speed) and crash rates (Awatta & Hassan, 2002)

As evidenced by the figure, the relationship developed between crash rates and the predicted speed drop between successive elements contains increasing crash rates at both ends of the quadratic function. If all other factors affecting crashes are held constant, it may be difficult to explain why crash rates increase as operating speeds drop below the design speed of the roadway. Despite this limitation, the relationships developed by Awatta and Hassan reaffirm the use of operating speed changes as an indicator of roadway safety.

One of the apparent weaknesses of these previous studies is the lack of validation of the expected operating speeds when using the prediction models similar to that of Table 2-2. As evidenced by Richl & Sayed (2005), the application of any particular speed prediction model may result in a unique consistency and safety evaluation. If the actual operating speeds on the roadway cannot be accurately predicted by the speed-profile models, the safety analysis will not hold much merit. In order to overcome this, Wu et al. (2013) conducted a field study to measure the actual operating speeds on two Pennsylvania highways. They then validated the field results with the operating speeds predicted using the Design Consistency Module of the Interactive Highway Safety Design Model (IHSDM). However, rather than just evaluating the difference between speeds in successive elements, Wu et al. developed a measure of design consistency termed the "design consistency density." In essence, this term measures changes between the operating speed and the inferred design speed (i.e., the design speed of road using the actual dimensions, rather than the limiting-criterion dimensions) while accounting for the effects of elements upstream and downstream of the study element (Wu et al., 2013). Donnell et al. (2009) established the inferred speed as a suitable measure of design consistency for operating speed measures.

After evaluating multiple regression alternatives, Wu et al. determined that a mixed-effects negative binomial regression model would be the most appropriate given the repeated crash observations at identical locations over the seven years of data.

Utilizing both the continuous and categorical form of design consistency density (δ), the researchers were able to develop a set of models for both forms. The relationship developed between observed crash frequency and the continuous-form of design consistency density is shown in Table 2-4.

Table 2-4. Crash frequency as a function of exposure and continuous design density (Wu et al., 2013)

Variable	A1	A2	A3
Presence of a Horizontal Curve	0.272	0.278	0.366**
log(AADT)	0.816**	1.000	0.701**
log(Element Length)	0.829***	0.873***	1.000
δ	0.029	0.0136***	0.008
Constant	-3.314***	-1.574***	-1.733
Model Statistics			
Number of groups	560.000	560.000	560.000
AIC	754.700	755.600	755.000
BIC	780.700	777.200	776.600
Log-likelihood	-371.400	-372.800	-372.490
** Significant at 5% level, ***Significant at 1% level			

It is important to first note the differences between the models within this set. Model A1 features no constraints on the parameter coefficients; Model A2 constrains the coefficient of the AADT term to 1.0; and Model A3 constrains the coefficient of the element length to 1.0. The positive coefficient of the consistency term in each model indicates that there is a significant relationship at the 95% level between roadway safety performance and changes in speed within an element. As δ increases, so too does the expected crash frequency on the element. After applying statistically-thorough methodology to real-world data, the results of this work appear to further validate the notion of a significant link between speed changes and roadway safety performance.

With the results of the aforementioned studies, it would be difficult to argue the lack of correlation between operating speed variations and roadway safety. Most, if not all, of the empirical evidence demonstrates that as speed differentials increase, so does crash experience. However, this does not necessarily imply that operating speed changes are a suitable design consistency measure to be used by practitioners. These changes in speed are only surrogate measures of the true inconsistencies; they do not identify the reasons or conditions associated with the drop in speed. This is easily seen in equations used to estimate speed, as many of the speed-profile equations developed in Table 2-2 are direct functions of other geometric elements. Furthermore, the design speeds used in many of the studies are used to determine the values of various geometric roadway features, including superelevation rates, curve radii, and sight distances. In order to quantify the true, underlying effects of design consistency on roadway safety, investigations must be made into the effects of changes to individual roadway characteristics. Although the research in this area has been rather limited, several studies have attempted model design consistency using alternative measures.

2.3. Alignment Indices

One means to measure the quantitative effects of design consistency on safety is to use alignment indices. The purpose of indices is to quantitatively represent the general characteristics of the roadway segment's alignment through the use of averages or ratios of geometric elements. After careful analysis of indices for both the horizontal and vertical alignment, Fitzpatrick et al. (2000) recommends several indices that have a high potential to draw out inconsistencies in the roadway. These include the average radius of a segment, the ratio of the maximum and minimum radius experienced within a segment, the average tangent length, and the average rate of vertical curvature. A high rate of change or significant jump in one of these measures should indicate design inconsistencies.

There are several benefits to using alignment indices in consistency analysis over traditional measures. First, they are relatively easy to understand and calculate for use by practitioners (Fitzpatrick et al., 2000). This is essential when attempting to establish methods that can be implemented in real world scenarios. Additionally, the indices are direct functions of the horizontal and vertical alignments, which would allow for "quantitative analysis of successive segments from a system-wide perspective" (Fitzpatrick et al., 2000). Ultimately, this is the main motive for even conducting design consistency analysis.

Despite the benefits of alignment indices, their use in safety analysis has been limited. Anderson et al. (1999) has been one of the only studies to apply indices in safety regression models. The researchers investigated many of the same indices recommended by Fitzpatrick et al., including average radius, the ratio of maximum to minimum radius, and the average rate of vertical curvature. Anderson et al. also developed a rather unique alignment index using the ratio of a specific horizontal curve radius to the average radius of the entire segment. It is intuitive that encountering a radius that is significantly different than the average for the segment would violate driver expectancy. This index, dubbed the Curve Radius Ratio (CRR), is shown in the subsequent equation:

$$CRR_i = \frac{(Individual\ Radius)_i}{Average\ radius\ for\ sement}$$

After applying lognormal regression to crash frequencies using exposure and the individual alignment indices as parameters, several significant relationships were developed. These regression equations can be seen in Table 2-5.

Table 2-5. Lognormal regression results of alignment indices applied to entire roadway sections (Anderson et al., 2000)

Model No.	Parameter	Coefficient	Significant at 95% level?	Additional R^2 gained after adding design consistency criterion
1	Intercept	-7.845	Yes	1.40%
	AADT (logscale)	0.995	Yes	
	Section Length (km) (logscale)	1.108	Yes	
	Average Radius (m)	-0.000137	Yes	
2	Intercept	-7.859	Yes	0.66%
	AADT (logscale)	0.988	Yes	
	Section Length (km) (logscale)	1.058	Yes	
	(Max Radius) / (Min Radius)	0.0043	Yes	
3	Intercept	-8.297	Yes	3.29%
	AADT (logscale)	1.052	Yes	
	Section Length (km) (logscale)	1.167	Yes	
	Average Vertical Curvature Rate (m / % grade)	-0.0028	Yes	
				Freeman-Tukey R^2
4*	Intercept	-5.932	Yes	17.80%
	AADT (logscale)	0.8265	Yes	
	Curve Length (km) (logscale)	0.7727	Yes	
	CRR	-0.3873	Yes	
*Poisson Regression utilized				

Each of the coefficients of the design consistency parameters represents the anticipated relationship between crash occurrence and the respective alignment index. As the average radius within a segment increases, one would expect the number of crashes related to design consistency to decrease since larger radii are usually more easily-traversed by the driver. Correspondingly, as the average length of vertical curves are increased (thereby increasing the average VCR in model 3), fewer crashes would be expected. The ratio-based indices in models 2 and 4, however, require more careful analysis. The positive relationship between the ratio of maximum radius to minimum radius and crash frequency indicates that a larger disparity between extreme radii increases the number of expected crashes. Innately, any substantial variation of radii within the same segment would most likely result in higher crash frequencies. The negative relationship between CRR and crash experience signifies as an individual radius reaches or exceeds the segment average, the higher the reduction in expected crashes. The high level of significance and notable increase in the amount of variability explained in the crash data by adding the alignment indices to each model would indicate that these measures are appropriate for assessing design consistency.

The only other notable study to include the use of alignment indices as measures of design consistency was conducted by Awatta & Hassan (2002). Their analysis, however, was only limited to a single index: CRR (as established by Anderson et al.). While their efforts in confirming previous work are well-founded, there lies an inherent problem with their use of any alignment indices relating to horizontal radii. As mentioned in the previous subheading, "*Speed differences*", Awatta & Hassan developed their study using an artificial alignment with only the predicted number of crashes as a means of safety evaluation. The accident modification factors (AMFs) used to predict crashes along the alignment are a direct function of the horizontal curve radii present in each section. Since the alignment index of CRR is also a direct function of curve radii, any regression attempts would suffer from significant autocorrelation.

Although there is an abundance of literature to help conjecture at the plausibility of alignment indices as a measure of design consistency (Polus & Dagan, 1987; Krammes et al., 1995a; Fitzpatrick et al., 2000; Castro et al., 2005), there is a considerable lack of applied safety analysis. Therefore, there is great potential to expand on the results of Anderson et al. (1999) with further study into the relationship between alignment indices and roadway safety.

2.4. Vehicle Stability

Another important measure of design consistency is vehicle stability while traversing the roadway, particularly over horizontal curvature. If insufficient side friction is provided through the roadway alignment, vehicles may begin to skid and slide off the roadway or into opposing travel lanes. A lack of consistency in side friction may inhibit drivers' ability to guide and control their vehicle in a safe manner, violating driver expectancy (Ng & Sayed, 2004).

There have been several studies (McLean, 1974; Dunlap et al., 1978; Lamm et al, 1991; Morrall & Talarico, 1994; Lamm et al., 1999) that have attempted to model vehicle stability using the disparities between supplied and demanded side friction. The most prolific, however, has been the Highway Design and Traffic Safety Engineering Handbook established by Lamm et al. (1999). Similar to the speed consistency criteria presented in Table 2-1, Lamm et al. developed a criterion for evaluating the consistency of side friction; this is shown in Table 2-6.

Table 2-6. Design consistency criterion for side friction (Lamm et al., 1999)

Evaluation	Criterion
Good	$\Delta f_R \geq 0.01$
Fair	$0.01 > \Delta f_R \geq -0.04$
Poor	$\Delta f_R < -0.04$
$\Delta f_R = f_R - f_{RD}$	

Where Δf_R is the difference between the side friction assumed (f_R) and the side friction demanded by the vehicle (f_{RD}). It can be seen that as the demanded side friction exceeds that provided by the roadway alignment, the consistency rating and potentially safety of the roadway segment decreases. To estimate the available side friction, Lamm et al. also developed an empirical equation based on the roadway's design speed:

$$f_R = 0.22 - 1.79x10^{-3}V_d + 0.56x10^{-5}V_d^2$$

As previously mentioned, the design speed is a surrogate measure of geometric elements, including horizontal curve radii. With regards to the side friction demanded by the vehicle, analysis of a simple free body diagram of a cornering vehicle will lead to the development of the following equation:

$$f_{RD} = \frac{V_{85}^2}{127R} - \mathrm{e}$$

Ng & Sayed (2004) applied this method for evaluating consistency to the five years of crash data and over 319 horizontal curves they obtained from the Ministry of Transportation of British Columbia. Using negative binomial regression, they were able to develop a meaningful relationship between crashes and Δf_R:

$$Accidents\ per\ 5\ Years = e^{-3.303}L^{.8733}AADT^{.5680}e^{(-2.194)\Delta f_R}$$

With all parameters statistically significant at the 95% level, this model helps verify the assumptions made about vehicle stability as an indicator of design consistency. The negative coefficient indicates a decrease in the number of expected crashes as the available side friction further exceeds the side friction demanded by the vehicle.

Awatta & Hassan (2002) also applied the measures established by Lamm et al. to their artificial alignment and crash data. With the dependent variable (crash rates) already accounting for exposure, the model only includes Δf_R as an independent parameter. This relationship is shown below:

$$CR = 153.34(\Delta f_R)^2 - 21.549\Delta f_R + 1.9921$$

The coefficient of correlation for this model was 0.978. This abnormally high value of the variation in crash rates is most likely due to the small sample size and the use of predicted crash rates, rather than actual crash rates in the study. The strong positive coefficient of the squared term in the model validates previous conjectures about the relationship between safety and vehicle stability. As the side friction demanded by the vehicle begins to exceed the assumed side friction provided by the roadway, the crash rates will begin to increase significantly. This is best illustrated by Figure 2-3.

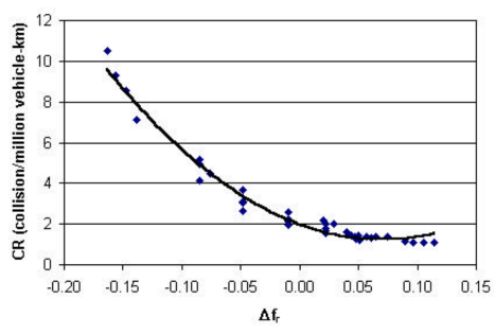

Figure 2-3. Relationship between crash rates and Δf_R (Awatta & Hassan, 2002)

Despite the limited number of studies evaluating the direct relationship between vehicle stability as a design consistency measure and roadway safety, the current literature demonstrates that disparity between the assumed and demanded side friction values serves as a good indicator of inconsistences in the roadway alignment. It is intuitive that a sudden deficiency in available side friction would violate driver expectancy and should warrant further research.

2.5. Driver Workload

Save for the development of speed-profiles, one of the most heavily investigated design consistency measures has been driver workload. As a result of the extensive work on the topic, a multitude of definitions have arisen. Senders (1970) defines driver workload as a measure of the "effort expended by a human operator while performing a task, independently of the performance task itself." While Messer (1980) relates driver workload to the time rate at which drivers must perform the driving task. Regardless of the specific phrasing used, however, driver workload has generally been attributed to two parameters: available sight distance and visual demand on the driver. Shorter sight distances restrict the visual information that drivers can perceive, requiring them to update their predictions more often (i.e., increasing their mental workload). This mental effort is exacerbated when drivers are less familiar with the roadway (Fitzpatrick et al., 2000). As a driver becomes more experienced with a particular road, they may come to expect many of the complex features that would require higher concentration from less familiar drivers. This relationship, however, has not been subject to any quantitative efforts in the literature. Rather, a preponderance of the research efforts have been focused on developing a relationship between visual demand and the geometric elements of the roadway.

One of the primary means of modeling visual demand is the use of visual occlusion. In essence, test subjects are placed on a test track or in a simulator with a device that blocks a portion of their vision. Subjects are able to request a glimpse of the roadway using a switch or button, but they are instructed to only take enough glimpses to stay on the roadway. By measuring the amount of “glimpses” needed at each point in the roadway, researchers can determine which geometric elements require more visual demand from drivers. Krammes et al. (1995b) and Fitzpatrick et al. (2000) performed visual occlusion studies, where visual demand was defined as the percentage of time spent looking at the roadway (i.e., un-occluded). Both studies found that visual demand was highly related to the radius of horizontal curves.

Messer (1980) and Messer et al. (1981) modeled visual demand by focusing on the roadway’s effect on driver performance. Typically, very little visual processing capacity is required to perform driving tasks; it has been regarded as almost a subconscious act (Fitzpatrick et al., 2000; Wooldridge et al., 2003). However, when complex alignments and terrains are introduced, more frequent driver visual evaluations are required, which may violate driver expectancy. Consistent roadway geometry allows the driver to accurately predict the roadway’s path with little cognitive effort, in turn, leaving much of the driver’s mental capacity to be devoted to obstacle avoidance or navigation (Wooldridge et al., 2003). Using this principle, Messer and Messer et al. collected empirical data regarding driver expectations of roadway features and relating violations of those expectancies to driver workload. The result was a series of equations that relates visual demand to roadway geometry (i.e., horizontal curve radius):

$$VD_{LU} = 0.173 + \frac{43.0}{R}$$

$$VD_{LF} = 0.198 + \frac{29.2}{R}$$

The first equation represents the visual demand for drivers that are unfamiliar with the roadway, while the second represents the visual demand of familiar drivers. It can be seen that the relationships developed are highly dependent on horizontal curve radii, similar to the results of the visual occlusion studies by Krammes et al. (1995b) and Fitzpatrick et al. (2000). Further validating these relationships, Easa & He (2006) developed nearly identical equations for visual demand in their research.

As Hassan et al. (2001) notes, however, the dependence of visual demand estimation models on curve radii may unfairly bias low-speed roadways. The selection of radii is often dependent on the design speed of the roadway; therefore, low-speed roads may contain smaller radii, which raise the visual demand. Although, if similar roadway classifications are utilized in a study (as two-lane rural roadways are used almost exclusively in consistency studies), then variations in radii will be limited between roadways.

Despite the extensive research in modeling driver workload, there are limited applications to evaluate its effect on roadway safety. Krammes & Glascock (1992) and Ng & Sayed (2004) both applied the methodology developed by Messer et al. to determine a relationship between crash frequency and visual demand. Using negative binomial regression with real world crash data, it was found that both models for predicting visual demand are good indicators of crash experience on two-lane rural roads. The regression models developed by Ng & Sayed are shown below:

$$Accidents\ per\ 5\ Years = e^{-4.297} L^{0.8866} AADT^{0.5831} e^{3.076 VD_{LU}}$$

$$Accidents\ per\ 5\ Years = e^{-4.679} L^{0.8873} AADT^{0.5841} e^{4.566 VD_{LF}}$$

The positive coefficients of both VD_{LU} and VD_{LF} indicate that as the expected visual demand placed on the driver by the roadway increases, so too does the expected crash frequency. This confirms the intuitive assumptions of many researchers.

Awatta & Hassan (2002) also attempted to model workload as a measure of safety. However, by using an artificial alignment, they depended on using predicted crashes to develop crash rates. As previously mentioned, the predicted crash rates are directly related to horizontal curve radii by means of AMF equations. One also notices that the visual demand models used (those of Messer et al.) are highly dependent on curve radii. Therefore, it is no surprise when high coefficients of correlation (R^2 = 0.977) are obtained between predicted crash rates and estimated visual demand.

Nevertheless, most of the literature coincides in its assessment of driver workload as a design consistency measure to model roadway safety. Although many of the relationships developed to model visual demand are reliant on subjective measures, increasing the workload of the driver does not have a positive effect on safety. Driver workload certainly merits further investigation; however, it may be a surrogate measure for other alignment indices which may better reflect changes to geometric elements.

2.6. Perceived Radius

One aspect that remains missing from many analyses on design consistency is the exploration of the combined effects of horizontal and vertical alignments on driver perception. Current practices commonly result in the development of horizontal and vertical alignments at separate stages of design; they are then combined with only cursory consideration of consistency. AASHTO design standards only suggest the avoidance of several combinations of horizontal and vertical curves, such as refraining from introducing sharp horizontal curvature at or near the top of a pronounced crest vertical curve (AASHTO, 2004). These standards do not take into account the effect of combined horizontal and vertical curvature on driver perception, notably when entering horizontal curves. Several studies (Hassan & Easa, 2003; Taiganidis & Kanellaidis, 1999; Lipar. 1997; Smith & Lamm, 1994; Appelt, 2000) have illustrated that drivers may experience an optical illusion when approaching horizontal curves that are combined with vertical curves. As Lamm et al. (1999) illustrate in Figure 2-4, horizontal curves may appear sharper when overlain with a crest vertical curve and less sharp when overlain with a sag vertical curve. (Note the lines are equally spaced, but the curves are perceived as “more” or “less” sharp when combined with vertical curvature.)

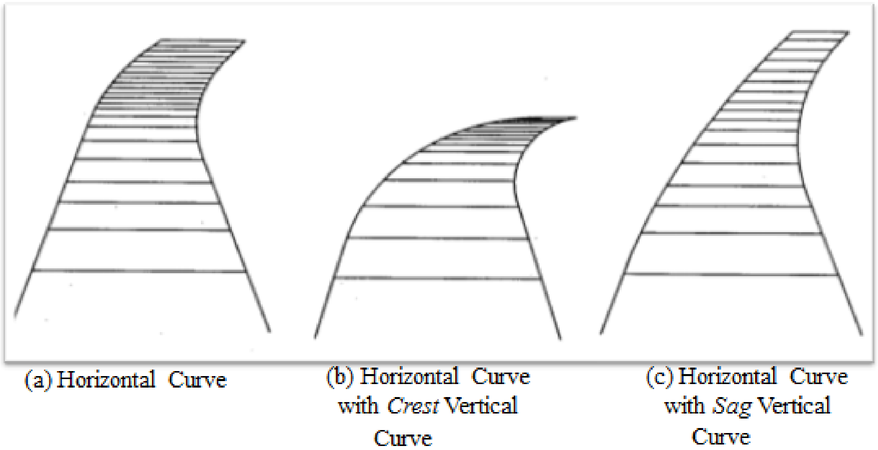

Figure 2-4. Effect of vertical curvature on horizontal curve perception (Lamm et al., 1999)

This optical illusion may have an important effect on a driver's selection of speed when entering a horizontal curve, and thereby, may affect the safety of the curve. This is particularly true for horizontal curves overlain with sag vertical curves. As the third curve (c) in Figure 4 illustrates, the driver may underestimate the radius of combined sag and horizontal curves, causing the driver to select a speed higher than the actual curve may permit. Smith & Lamm validated this effect using crash rate statistics on several roadways, where it was also found that excessive speed was the most common cause of crashes on horizontal curves overlain with sag vertical curves.

While many researchers have recognized the need for further investigation into the effects of combined horizontal and vertical curvature, most have avoided efforts to develop a quantitative relationship for the so-called "perceived" radii. It was not until a series of endeavoring papers by Bidulka et al. (2002) and Hassan et al. (2002) that a relationship was developed.

In order to quantify the influence of vertical alignment on horizontal curve perception, Bidulka et al. and Hassan et al. created a three-dimensional model of 40 horizontal curve segments with varying alignment parameters. These included numerous radii (R), superelevation rates (e), differences in vertical grades (A), turning directions, rates of change in vertical curvature (K), sight distances, and different visual backgrounds. By placing each test curve next to three reference curves, as seen in Figure 2-5, the researchers were able to test whether drivers could determine differences between actual radii and perceived radii. Of the three curves, one was constructed with the same radius as the test curve, and the other two were designed with either a 100 meter increase or decrease in radius.

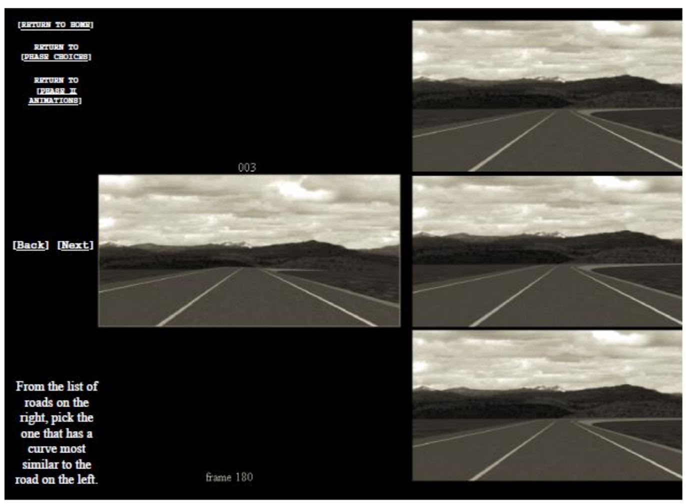

Figure 2-5. Test curve and three reference curves shown to study participants (Hassan et al., 2002)

The researchers presented the still images (40 curves in all) to 90 study participants, asking them to select which of the three curves was most similar to the test curve presented on the left side of the screen. A Chi-Squared test showed that a significant difference (α = 5%) existed between the actual radius and the perceived. The analysis also verified the original hypothesis about the effect of sag and crest curves overlain with the horizontal curve. The mean perceived radius on crest vertical curves was markedly lower than the actual radius for all 20 sag curves, while the mean perceived radius for sag curves was considerably higher than the actual radius. This would indicate that drivers may end up selecting a speed that is too great for the actual radius present when sag vertical curves are overlain with horizontal curvature. A t-test verified the statistically significant difference between the actual and perceived radii at the 95% confidence level.

Hassan et al. also investigated the effect of the different alignment parameters, aforementioned, and several driver characteristics (driver population, gender, age, eyeglass use, education, experience, rural driving, and trip duration) on the perception of curve radii. Using one-way ANOVA tests, significant parameters included the actual radius used in testing, the type of overlapping curve (sag curves more pronounced), turning direction, and sight distance. The researchers were unable to find any effects at the 95% significance level in superelevation rates, rates of vertical curvature, algebraic differences in grade, and each of the driver characteristics. In order to quantify the relationship between actual and perceived radii, linear regression was conducted using the significant alignment parameters. Several models evidenced that the use of turning direction and sight distance did not increase the coefficient of correlation. The final model is shown below:

$$R_p = -51.28 + 0.953R_a + 132.11V + 0.125R_aV$$

Where:

R_p = the perceived radius,

R_a = the actual radius, and

V is a dummy variable for vertical curvature (0 for crest curves; 1 for sag curves).

The high R^2-value of 0.996 can mainly be attributed to the small sample size utilized. Although additional studies are warranted, the relationship developed by Bidulka et al. and Hassan et al. represents a substantial step towards quantifiably linking the effects of combined horizontal and vertical alignments; thereby providing a more suitable means for evaluating design consistency of collective geometric parameters.

Richl & Sayed (2005) attempted to measure the effects of using actual versus perceived radii on design consistency. Using the model developed for estimating perceived radius by Hassan et al., they constructed a table identical to Table 2-3. The use of perceived radius had an evident effect on calculated operating speeds, which in turn, changed the number of horizontal curve segments that received a “good” rating under Criteria I and II. Richl & Sayed found that the use of perceived radii resulted in a higher disparity between operating speeds on their alignment, causing markedly more design inconsistencies to be identified. Although they did not measure the effects of using perceived versus actual radii on crash frequencies, their study evidences the potential for using perceived radii as a more effective measure of design consistency.

With the noticeable absence of studies that use perceived radii or any other measure that quantifies the relationship between horizontal and vertical curvature, there is a definite need to analyze the effects of such design consistency measures on roadway safety. Given the findings of this literature review, perhaps the best means to account for these measures would be through the use of alignment indices and other direct measures where actual radii are replaced with perceived radii. Alignment indices could also be developed to measure the differences between actual and perceived radii (e.g., the maximum difference between R_p and R_a). The use of such parameters would make a significant contribution to the literature; although, it would only serve as a preliminary study in a widely vacant corner of the literature.

2.7. Summary

Although safety professionals and practitioners have long acknowledged the need to develop consistent roadway designs, a putative definition of design consistency has yet to be established. The resulting eclectic nature of design consistency has led researchers to investigate a wide range of potential measures of consistency. Although measures, such as differences in speeds on successive elements, vehicle stability, and driver workload have been shown to effectively predict crash frequency, they act as surrogate measures of the true geometric inconsistencies in the roadway. Some of the more neoteric measures of consistency, such as alignment indices and perceived radius, hold more potential for evaluating the effects of design consistency on crash frequency since they directly measure changes to the geometric alignment. As a result, there is significant room to expand on these concepts, and they are thusly included in this investigation.

Chapter 3. METHODOLOGY

3.1. Development of Safety Performance Functions

To evaluate the relationship between roadway safety and the consistency of geometric elements, regression models were developed to test the significance between crash frequency and the geometric parameters provided in the dataset. By forming roadway segments and utilizing multiple years of crash data, these relationships represent safety performance functions (SPFs) for the roadway classification(s) used in the study. The Highway Safety Manual (HSM) offers methods to calibrate generic SPFs to a particular location; however, given the extensive data set obtained, the development of jurisdiction-specific (Washington) safety performance functions may lead to a more effective method for modeling the subject at hand. Jovanis & Chang (1986) and Shankar et al. (1995) established the appropriateness of using count regression methods to model crash frequency; and hence, these methods have become a standard technique for the creation of most safety performance functions. Count regression was, therefore, investigated in this study. Given the typically overdispersed nature of crash data, negative binomial models may be the most appropriate distribution, as Poisson distributions constrain the mean and variance to be equal. Both count distributions are investigated; however, the overdispersion parameters in the preliminary models indicate that the crash frequency data are indeed overdispersed.

Since the crash data also contains observations from the same segments over multiple years, it is important to account for the heterogeneity of each individual segment. One method to account for this would be to develop cross-sectional time-series or longitudinal data (i.e., panel data). Panel data groups individual observations from the same location across time, which helps correct for the omitted time series variables that influence the behavior at each location (Kennedy, 2011). It also alleviates multicollinearity problems by combining variation across locations over time. This ultimately leads to more efficient estimation (Kennedy, 2011).

When modeling time-variant variables, it is also important to consider the use of the random effects model. Random effects models are able to provide more efficient estimates of coefficients over fixed effects by reducing the degrees of freedom. Therefore, as long as the explanatory variables are not correlated with the composite error, the random effects models provide for a more accurate estimation of time-variant parameters (Kennedy, 2011). However, it is important to note that when using the random effects negative binomial model, the overdispersion parameter varies randomly from group to group, such that the inverse of one plus the dispersion follows a Beta(r, s) distribution (Stata, 2013):

$$\frac{1}{1+\ \delta_i} \sim \beta(r, s)$$

Where:

δ_i = the dispersion parameter, and

r and *s* = parameters for beta distributed random effect.

In other words, each segment of roadway would experience a different α-value; this drastically increases the complexity of calculations necessary to generate a weighting factor for the Empirical Bayes adjustments (which is addressed subsequently). This precipitously-augmented statistical complexity is best evidenced by the joint probability for the counts of group *i* under a random effects negative binomial distribution, which is specified as (Stata, 2013):

$$\Pr\left(Y_{i1} = y_{i1}, \dots, Y_{in_i} = y_{in_i} \middle| X_i\right) = \int_0^{\infty} \prod_{t=1}^{n_i} Pr\,(Y_{it} = y_{it} | x_{it}, \delta_i) f(\delta_i) d\delta_i$$

$$= \frac{\Gamma(\mathrm{r}+\mathrm{s})\Gamma(\mathrm{r}+\sum_{t=1}^{n_t}\lambda_{it})\,\Gamma(s+\sum_{t=1}^{n_t} y_{it})}{\Gamma(r)\Gamma(s)\Gamma(r+s+\sum_{t=1}^{n_t}\lambda_{it}+\sum_{t=1}^{n_t} y_{it})} \prod_{t=1}^{n_i} \frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)}$$

Where:

y_{it} = the outcome for road segment *i* at time *t*,

x_{it} = the vector of variables x for individual *i* at time *t*, and

f is the probability density function for δ_i.

Therefore, it would be prudent to investigate a method of regression that maintains the improved estimation of time-variant parameters achieved with random effects negative binomial modeling, but still allows for a reasonably direct manner, by which, to calculate an overdispersion parameter. One option would be to use a random effects Poisson distribution to model crash frequency, as established in Shin & Washington (2013). Shin & Washington (2013) and Wood (2013) demonstrate that a random effects Poisson model can provide nearly the same level of estimation efficiency as a random effects negative binomial model, as both types of count regression account for variance in parameters over time. However, the procedure for estimating an overdispersion parameter that can be used in EB adjustments is rather statistically involved. That is not to say the procedure is infeasible, but one of the primary goals of this research is to recommend a practical methodology for including geometric design consistency parameters in real-world safety evaluations. If the procedure for doing so becomes so complex statistically, it may face significant opposition from practitioners and be relegated only to the realm of research.

As a result, the most efficient method for developing a relationship between crash frequency and geometric roadway parameters would be through mixed effects negative binomial regression. Mixed effects negative binomial regression, in essence, combines both fixed effects and random effects into negative binomial regression. Although the overdispersion parameter of mixed effects NB regression is conditional upon the variance component corresponding to the random intercept (σ^2), it inherently maintains the benefits of random effects modeling. In order to establish an overdispersion parameter that can be directly utilized in EB adjustments, a simple calculation can be made using the output of the statistical model. This equation can easily be derived by observing the disparity between the variance functions of the standard and mixed effects negative binomial models:

Standard NB Regression: $Var\ (y_{it}) = \mu_{it} + \alpha(\mu_{it})^2$

M.E. NB Regression: $Var\ (y_{it}) = \mu_{it} + \{\exp(\sigma^2)(1-\alpha)-1\}(\mu_{it})^2$

Where:

μ_{it} is the predicted outcome (i.e., the predicted crash frequency for individual *i* at time *t*).

It can be seen that the only difference between these two variance functions is the scaling factor of the squared predictor. Therefore, the following conversion equation can be established to calculate an overdispersion parameter (α') based on the conditional overdispersion parameter (α) generated from the mixed effects negative binomial regression:

$$\alpha' = \{e^{\sigma^2}(1-\alpha)-1\}$$

Note: This α' can be used directly in the calculations of a weighting factor for Empirical Bayes adjustments.

Using mixed effects negative binomial regression, three safety performance functions were developed. The first contained typical roadway parameters (e.g., roadway width, shoulder width) that may be found in SPFs developed using the methods established in the HSM. The second contained geometric design consistency parameters (e.g., changes to intra-segmental horizontal curve radii and the number of changes in vertical grade within a segment), while the third combined parameters from the aforementioned models. By evaluating the disparity between the sites with potential (SWiPs) for safety improvements between the SPFs, an assessment can be made about the value of directly incorporating geometric design consistency parameters in safety performance evaluations.

3.2. Empirical Bayes Adjustments

Before the sites with promise for safety improvement can be identified, however, Empirical Bayes adjustments must be performed on the data. As explained by Hauer et al. (2002), these adjustments increase the precision of estimates beyond a potentially limited number of years of data and help account for regression-to-mean bias. These adjustments are critical when accident history is related to the reason behind conducting a safety analysis (Hauer et al., 2002). Although the use of Empirical Bayes adjustments have become commonplace in the safety arena due to inclusion in safety management tools, such as the Interactive Highway Safety Design Model (IHSDM), it is still important to understand the connection between the output of the mixed effects negative binomial models (i.e., the SPFs) and the adjusted crash frequency. Figure 3-1 illustrates the overall concept of the EB adjustments.

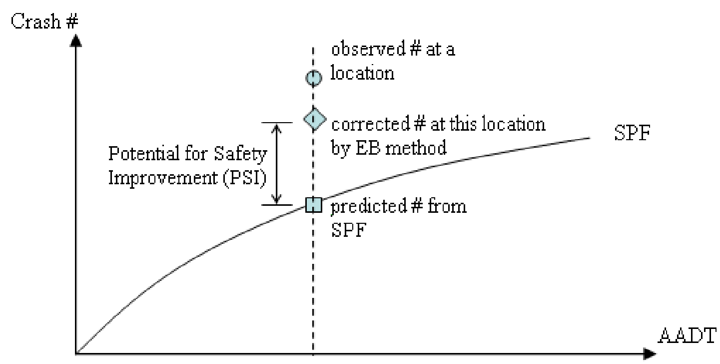

Figure 3-1. Potential for safety improvement after Empirical Bayes adjustments (FHWA, 2014).

In order to get the “corrected” (‘adjusted’ may be a more suitable term) number of crashes at a particular location (the diamond in Figure 3-1), a weighting factor must be used to help balance the influence of the predicted crash frequency from the SPF and the number of years contained in the data set. This weighting factor is defined as (Hauer et al., 2002):

$$weight = \frac{1}{1 + (\mu_i * Y_i)/\alpha}$$

Where:

μ = the number of crashes predicted for location *i* by the SPF,

Y = the number of years of crash data for location *i* utilized in the SPF, and

α = the overdispersion parameter from the SPF (α' from the equation derived above).

Since the dataset obtained is unbalanced (i.e., not every roadway segment contains data for the full five years), the weight factor cannot be universally scaled against the overdispersion parameter and μ. For example, a segment where only two years of crash data were obtained would experience an adjustment more heavily weighted on the crash frequency predicted by the SPF, when compared to a similar segment with five years of data. The adjusted number of crashes can be calculated using the weighting factor in the following manner (Hauer et al., 2002):

$$\begin{aligned} &Expected\ \#\ of\ crashes\ for\ an\ entity \\ &\qquad = (weight * crash\ frequency\ predicted\ by\ SPF) + [(1 - weight) \\ &\qquad * actual\ crash\ frequency] \end{aligned}$$

3.3. Identification of Sites with Potential for Safety Improvements

After a unique EB adjustment is performed on each roadway segment (a different adjustment is made for each SPF), the next step in the analysis is to identify the sites with promise (SWiPs) for safety improvements using both the general roadway SPF and SPF with additional design consistency parameters. However, as Hauer (1996) points out, there are a multitude of methodologies for identifying sites with promise for safety improvements, and each one may identify a unique set of sites. For instance, the use of observed crash frequencies will most likely identify the most heavily traveled roads as SWiPs, as increasing exposure generally results in higher expected crash frequencies. Meanwhile, the use of crash rates as an identifying factor will indicate sites of high risk to particular road users, particularly those on roads with low exposure rates. The criteria used to identify unsafe sites are highly dependent on the motive for the individual study. If practitioners are focused on achieving economic efficiency, the use of observed crash frequencies (F) or the largest jump in frequency may provide for the most effective use of funds. To achieve fairness to all users, the use of crash rates (R) or the scaled difference in crash rates ($\Delta R/\sigma_R$) would identify sites that expose users to an unacceptable level of risk (Hauer, 1996). Given the motivation for this study, however, it would be appropriate to utilize an identifying factor that recognizes sites that are deficient due to their initial geometric design. Therefore, sites are identified using the scaled difference between expected and observed crash frequencies ($\Delta F/\sigma_F$); this allows for the comparison of SWiPs identified by each model (i.e., those identified by general parameter model vs. design consistency model).

Chapter 4. DATA ACQUISITION AND PREPARATION

4.1. Database Acquisition

In order to conduct this research, roadway and crash data were acquired from the Highway Safety Information System (HSIS), which is maintained by the University of North Carolina Highway Safety Research Center (HSRC) through contracts with the Federal Highway Administration. The HSRC has made the data readily available for research purposes. While HSIS collects and maintains data from nine different states in the U.S., only Washington State and Illinois contain the necessary information regarding crashes, roadway inventory, and horizontal/vertical alignment to conduct the analyses described in the preceding section. When comparing the roadways within these two states, the diversity of Washington's topography and spatial interactions may provide for greater variability in road design compared to the relatively uniform landscape of Illinois. For this reason, five years (2006-2010) of the most recent HSIS data from Washington State were selected to conduct analyses.

Within each individual year of the dataset, there is a plethora of pertinent information. The roadway inventory documents important roadway elements, including: Annual Average Daily Traffic (AADT), roadway and lane widths, median type, shoulder width and type, roadway lighting information, terrain, and roadway classification. A separate file contains horizontal curve information with curve radii, curve angles, and degree of curvature. Similarly, another file contains the vertical alignment information with direction and percentage of grade for each roadway in the inventory. Perhaps the most important data, however, is contained in the HSIS accident files. Each year contains accident locations to the nearest $1/100^{th}$ of a mile, the type of accident (e.g., run off the road), the severity, the number of vehicles involved, and the apparent contributing factors.

4.2. Preparation of Fixed-Length Segments

Given the disjointed nature of the data files obtained through HSIS, a significant amount of work was done to prepare the data for analysis. In its original state, the database contained four separate data files, including: the roadway inventory, horizontal alignment, vertical alignment, and the accident files. To conduct the proposed safety analysis using safety performance functions, the data were integrated into a single file of roadway segments. Many previous studies regarding design consistency have utilized homogeneous segments in their regression analysis (Anderson et al., 2012; Richl & Sayed, 2005; and Ng, 2004). Since this method calls for segments to be generated with homogeneous geometric elements (Miaou et al., 1991), researchers have been left with segments of varied length. These unequal segment lengths can lead to greater heteroskedacity problems and a loss of estimation efficiency when conducting regression analysis (Shankar et al., 1995). For this reason, fixed-length segments of 2.5 miles were utilized for this research. Although 2.5 miles may seem arbitrary, it was selected to allow for sizeable variance of geometric elements within each segment. The primary goal of this research was to establish the relationship between safety and design consistency. If segment lengths are designed short enough to only contain minute changes in geometric characteristics, it may prove extremely difficult to capture the inconsistencies within the intra-segmental design. However, the procedure for segment creation utilized in this research would allow for different segment lengths to be generated with relative ease, including the 1-mile segment that has pragmatically been used in traditional safety analysis. This procedure is described subsequently.

Comprised of over 7,200 miles of Washington State roadways, the database contains a substantial amount of data in its raw form. In order to create a more focused analysis, only two-lane rural roadways were utilized in this study. This eliminates many of the more uniformly-designed roadways, such as urban freeways, which may contain limited design variation between adjacent segments. Although utilizing only two-lane rural roadways limits the scope of the research, it still leaves over 4,900 miles (per year) of roadway for analysis. After careful scrutiny and examination of the remaining data, several sections of roadway were further eliminated due to erroneous or missing data points, such as a negative curve length or missing grade information. Due to the high quality of data collection demanded by the HRSC for its HSIS database, these instances were limited, and approximately 4,800 miles of two-lane rural roadways remain for final analysis.

To combine the four data files into a single dataset comprised of 2.5-mile segments, a computer program was developed using Visual Basic for Applications (VBA). Several different macros were written to gather information from each file on a line-by-line basis to calculate the proper roadway measurements and design consistency measures. Careful attention was paid to ensure that accurate statistics are produced when generating roadway segments; in particular, certain attention must be given to horizontal curvature that overlaps two adjacent segments. To account for this, a criterion has been established to exclude the double counting of any horizontal curves and to place the curve in the segment in which the Point of Intersection (PI) occurs.

For example, if a segment contained multiple horizontal curves, the average weighted (by curve length) radius, the average un-weighted radius, the maximum and minimum radii, the average change in radius, and the maximum change in radius would be calculated. These same measures would also be calculated using the perceived radius, as established in Bidulka et al. (2002) and Hassan et al. (2005). Altogether, over eighty statistics were calculated for each segment. This allowed for a comprehensive analysis of the relationship between safety and both traditional and design consistency parameters. A summary of the most important segment statistics is shown in Table 4-1; it is important to note that these values are calculated using all segments.

Table 4-1. Summary statistics of 2.5 mile segments

Variable	Average Value	Maximum	Minimum	Std. Dev.
# of Horizontal Curves	5.7621	46	0	5.426
Average Radius (ft.)	2723.0380	50000	0	3212.347
Average Change in Radius (ft.)	1367.1587	32470	0	2281.233
Average Perceived Radius (ft.)	2736.3786	51990.415	0	3231.520
Average Change in Perceived Radius (ft.)	1393.9941	35009.474	0	2298.438
Average Curve Angle (ft.)	2292.4335	16603.7	0	1546.109
Max Change in Curve Angle (ft.)	4382.1055	21807.2	0	3334.501
# of Intersections	3.4585	48	0	3.887
AADT	2976.3388	25505	16	3089.083
Left Shoulder Width (ft.)	4.5750	10	0	2.279
# of Left Shoulder Changes	2.0660	29	0	2.558
Average Lane Width (ft.)	11.5660	19.23	8.014	0.899
Average Grade (%)	1.7965	8.64	0	1.198
Average Change in Grade (%)	1.9316	11.50	0	1.245
# of Grade Changes	12.9298	90	0	9.275
# of Accidents	3.1921	61	0	4.324

To develop panel data out of the HSIS dataset, segment indicators were developed for each 2.5-mile segment created. In Table 5-1, it can be seen that this resulted in the creation of 2,183 groups (i.e., groups of segments). The maximum number of observations per group is five, intuitively, since there are only five years of data. The average number of observations per group is 4.1, which is indicative of unbalanced data. This comes as a result of missing roadway data for one or more years.

Chapter 5. RESULTS

5.1. Safety Performance Functions

By utilizing all 8,969 segments developed with 5 years of data, the mixed effects negative binomial relationships developed represent safety performance functions for two-lane rural roadways in the state of Washington. Three models are presented in this report. The first is the typical parameters model (shown in Table 5-1), which contains many parameters that would be utilized in an SPF developed using current methods in the HSM. As aforementioned, over 80 statistics were tabulated for each segment. Although these consisted of roughly a 60/40 split of typical vs. design consistency parameters, extensive efforts were placed on testing combinations of typical roadway parameters within the safety performance function developed in Table 5-1. All ~80 segmental statistics can be found in Appendix Table A-1.

Parameters were tested in an iterative manner, as their statistical insignificance in one model did not preclude their inclusion in a subsequent iteration. The significance of each variable was tested "alone" (i.e., only with exposure parameters) in a regression model. If a parameter demonstrated reasonably significant (~80% significance) predictive power alone, it was again tested in a combined model (i.e., more than one predictor beyond exposure parameters). Parameters that were found to be significant by themselves, but that did not provide any predictive power when used in combination, were not immediately thrown out. The iterative process led to constant updating of the variables that were included in the SPF, and parameters that were not significant in one model may hold a great deal of predictive power in another. Ultimately, roughly 50 combined models were produced to generate the SPF in Table 5-1 (not including the testing of individual parameters); the independent variables selected for this model were determined to provide the strongest explanation of crash frequency within a segment when used in combination. These parameters include averages of many geometric elements for each segment. Typically, segment length is also included as an exposure parameter; however, all segments are a uniform 2.5 mile length.

Table 5-1. Safety performance function with typical roadway parameters

	# of Observations	8,969		
	# of Groups	2,183		
Observations per group	Min:	1		
	Average:	4.1		
	Max:	5		
	Initial Log-L	-18,119.1		
	Final Log-L	-16,501.4		
Parameter	Coefficient	Std. Error	z	P>|z|
ln(AADT)	0.9627391	0.0162774	59.15	<0.001
# of intersections	0.0268844	0.0034275	7.84	<0.001
Avg. Radius (un-weighted)	-0.0000163	4.18E-06	-3.89	<0.001
Avg. Curve Angle	0.0000335	8.73E-06	3.84	<0.001
Avg. Left Shoulder Width	-0.0488078	0.0063489	-7.69	<0.001
Avg. Lane Width	-0.0595456	0.0157426	-3.78	<0.001
Average Grade	0.0264751	0.0110543	2.40	0.017
Constant	-3.921031	0.2074754	-28.28	<0.001
ln(α)	-3.352199	0.1506368	-22.25	<0.001
panelID: var(constant)	0.1762309	0.0097513		
Likelihood-ratio test vs. negative binomial regression: chibar2(01) = 1031.00, Prob≥ chibar2 < 0.001				

Where:

ln(AADT) = the natural logarithm of the Annual Average Daily Traffic of the segment,

ln(α) = the natural logarithm of the conditional overdispersion parameter, and

var(constant) = the variance component of the random intercept.

The likelihood-ratio test compares the use of mixed effects negative binomial regression over standard negative binomial regression; the chi-bar squared statistic shows that there is enough variability to validate the use of mixed effects negative binomial regression over standard negative binomial regression. As expected, both exposure parameters are significant at the 99% level. If the natural logarithm of AADT was not an effective predictor of crash frequency, it may indicate an error in the dataset or an anomaly in the data; as intuitively, increasing traffic should lead to a higher number of expected crashes. The coefficients of the typical roadway parameters also correspond with a priori expectations. As horizontal curve radii, left shoulder widths, and lane widths increase within a segment, it would be expected that crash frequency would decrease. Furthermore, it is intuitive that as grades increase within a segment that roadway safety would suffer. The correlation table for this model is shown in Table 5-2.

Table 5-2. Correlation matrix for parameters in the typical parameter SPF

	ln(AADT)	# int.	Avg. Radius	Avg. C.A.	Avg. Left S.W.	Avg. L.W.	Avg. Grade
ln(AADT)	1.00						
# of intersections	0.29	1.00					
Avg. Radius (un-weighted)	0.09	-0.06	1.00				
Avg. Curve Angle	-0.14	0.08	-0.20	1.00			
Avg. Left Shoulder Width	0.37	0.01	0.18	-0.29	1.00		
Avg. Lane Width	0.29	0.41	0.09	-0.11	0.24	1.00	
Average Grade	-0.18	-0.11	-0.13	0.21	-0.19	-0.10	1.00

There is noticeable correlation between the average lane width of a segment and the number of intersections within a segment; this comes as a result of the widening of the roadway at many intersections. Despite this high correlation between explanatory parameters, both variables were left in the model because it was determined that each would provide valuable insights to portions of segments where they do not overlap (e.g., large lane widths at non-intersections).

The next model establishes a safety performance function utilizing geometric design consistency parameters. These parameters include averages of many geometric elements for each segment; the primary purpose of this model is to determine which geometric design consistency parameters are the best candidates for addition into the combined model (Table 5-5), which includes both typical and geometric design consistency parameters. The geometric design consistency parameter model is shown in Table 5-3.

Table 5-3. Safety performance model with geometric design consistency parameters

	# of Observations	8,969		
	# of Groups	2,183		
Observations per group	Min:	1		
	Average:	4.1		
	Max:	5		
	Initial Log-L	-18,211.6		
	Final Log-L	-16,498.0		
Parameter	Coefficient	Std. Error	z	P>|z|
ln(AADT)	0.908171	0.0149916	60.58	<0.001
# of intersections	0.0202198	0.0031904	6.34	<0.001
# of Horizontal Curves	0.0092413	0.0032352	2.86	0.004
Max Change in Radius	-9.01E-06	3.26E-06	-2.77	0.006
Max Change in Curve Angle	0.0000208	5.95E-06	3.49	<0.001
Avg. Change in Degree of Curvature	0.0144231	0.0037762	3.82	<0.001
# of Changes in Left Shoulder Width	0.0087365	0.0049757	1.76	0.079
# of Grade Changes	0.0057835	0.001439	4.02	<0.001
Constant	-6.484452	0.1192542	-54.38	<0.001
ln(α)	-3.346905	0.1493171	-22.41	<0.001
panelID: var(constant)	0.1804132	0.0097767		
Likelihood-ratio test vs. negative binomial regression: chibar2(01) = 1109.02, Prob≥ chibar2 < 0.001				

Most of the coefficient directions coincide with a priori hypotheses, as the increase in the number or magnitude of changes to a particular element would violate driver expectancy, thereby increasing the expected number of crashes. The only coefficient that is counter-intuitive is the sign of the maximum change in radius parameter. The small magnitude of this coefficient (10^{-6}), however, has marginal effects on the expected number of crashes.

It is important to note that variables utilizing the perceived horizontal curve radius, rather than actual curve radius, were also tested in the regression models. Those tested included: average perceived radius, maximum perceived radius, minimum perceived radius, maximum change to perceived radius, ratio of maximum to minimum perceived radius, maximum perceived CRR, as well as other alignment index measures. The full list can be seen in Table A-1. However, it was determined that the use of perceived radii over actual radii added no additional explanatory benefits. In some cases, the perceived radii parameters offered coefficients that were smaller in magnitude and were less significant than their comparable "standard" radii counterparts (e.g., the use of maximum change in radius was consistently more significant than maximum change in perceived radius). That is not to say that the concept of perceived radius is not a significant predictor of crash frequency; it warrants significant research for use in individual safety studies. In its preliminary state, however, it would not be prudent to recommend that practitioners spend resources on estimating perceived radii when it appears to offer little benefit in large-scale safety analysis. Perhaps the development of more accurate or alternative methods for estimated perceived radius will offer more opportunities for inclusion in safety prediction models.

Numerous alignment indices were also tested, but again, crash frequency has proven to be better estimated by the more “straightforward” geometric design consistency parameters shown in the safety performance function above. It was rather interesting that measures, such as the CRR developed by Fitzpatrick et al. (2000), were not significant when combined with measures beyond the exposure parameters. In order words, alignment indices were found to be significant when modeled against crash frequency by themselves; however, their explanatory power was quickly drained when additional parameters were introduced into the model. Therefore, the more versatile geometric design consistency parameters were included in the final model, and they were among the first added to the combined parameter model.

The likelihood-ratio test, again, validates the use of mixed effects negative binomial regression over the standard negative binomial regression. The correlation matrix for the variables included in this model is shown in Table 5-4.

Table 5-4. Correlation matrix for parameters in the geometric design consistency parameter SPF

	ln(AADT)	# int.	# H.C.	Max Δ R	Max Δ C.A.	Avg. Δ D.C.	# Δ L.S.	# Grade Δ
ln(AADT)	1.00							
# of intersections	0.29	1.00						
# of Horizontal Curves	-0.11	-0.04	1.00					
Max Change in Radius	0.03	0.02	0.18	1.00				
Max Change in Curve Angle	-0.12	0.01	0.42	0.17	1.00			
Avg. Change in Degree of Curvature	-0.11	0.14	0.51	0.11	0.51	1.00		
# of Changes in Left Shoulder Width	0.18	0.39	0.08	0.03	0.09	0.18	1.00	
# of Grade Changes	0.02	0.15	0.32	0.04	0.20	0.26	0.18	1.00

There is a noticeable correlation between the maximum change in curve angle within a segment and the average change in the degree of curvature within a segment.

This high correlation most likely results from the relationship between curve angle and degree of curvature in basic horizontal curve equations. However, both variables are highly significant (99% level) in the model developed and add meaningful insights into effects of changes to these geometric parameters in the design of a roadway.

The final model developed establishes a safety performance function using a combination of several typical roadway and geometric design consistency measures as independent parameters. This is shown in Table 5-5.

Table 5-5. Safety performance model with combination of parameters

<table>
<tr><td></td><td># of Observations</td><td>8,969</td><td></td><td></td></tr>
<tr><td></td><td># of Groups</td><td>2,183</td><td></td><td></td></tr>
<tr><td rowspan="3">Observations per group</td><td>Min:</td><td>1</td><td></td><td></td></tr>
<tr><td>Average:</td><td>4.1</td><td></td><td></td></tr>
<tr><td>Max:</td><td>5</td><td></td><td></td></tr>
<tr><td></td><td>Initial Log-L</td><td>-18,179.4</td><td></td><td></td></tr>
<tr><td></td><td>Final Log-L</td><td>-16,470.4</td><td></td><td></td></tr>
<tr><th>Parameter</th><th>Coefficient</th><th>Std. Error</th><th>z</th><th>P>|z|</th></tr>
<tr><td>ln(AADT)</td><td>0.9555412</td><td>0.0162278</td><td>58.88</td><td><0.001</td></tr>
<tr><td># of intersections</td><td>0.0159068</td><td>0.0031686</td><td>5.02</td><td><0.001</td></tr>
<tr><td># of Horizontal Curves</td><td>0.0038799</td><td>0.0032158</td><td>1.21</td><td>0.228</td></tr>
<tr><td>Avg. Radius (un-weighted)</td><td>-0.0000132</td><td>4.14E-06</td><td>-3.18</td><td><0.001</td></tr>
<tr><td>Max. Change in Curve Angle</td><td>0.0000182</td><td>5.82E-06</td><td>3.13</td><td>0.002</td></tr>
<tr><td>Avg. Degree of Curvature</td><td>0.005336</td><td>0.0025353</td><td>2.10</td><td>0.035</td></tr>
<tr><td>Avg. Change in Degree of Curvature</td><td>0.0074592</td><td>0.0042775</td><td>1.74</td><td>0.081</td></tr>
<tr><td>Avg. Left Shoulder Width</td><td>-0.418261</td><td>0.0065761</td><td>-6.36</td><td><0.001</td></tr>
<tr><td>Max. Change in Left Shoulder Width</td><td>0.0075586</td><td>0.0035266</td><td>2.14</td><td>0.032</td></tr>
<tr><td># of Grade Changes</td><td>0.004269</td><td>0.001417</td><td>3.01</td><td>0.003</td></tr>
<tr><td>Constant</td><td>-6.573308</td><td>0.1196526</td><td>-55.22</td><td><0.001</td></tr>
<tr><td>ln(α)</td><td>-3.343782</td><td>0.1496526</td><td>-22.34</td><td><0.001</td></tr>
<tr><td>panelID: var(constant)</td><td>0.1686945</td><td>0.0094311</td><td></td><td></td></tr>
<tr><td colspan="5">Likelihood-ratio test vs. negative binomial regression: chibar2(01) = 986.10, Prob≥ chibar2 < 0.001</td></tr>
</table>

The only new parameter (i.e., not included in one of the previous two models) is the average degree of curvature. This variable was not found to be significant even at moderate levels when incorporated into the previous two models; however, the iterative nature of the model development allowed for its testing in this final model, ultimately leading to the identification of its significance at the 95% level. The positive coefficient of this parameter is innate, as larger degrees of curvature for horizontal curves within a segment would create a more hazardous turning radius for drivers to negotiate. This would in turn increase the likelihood of a crash. The other independent parameters included in the combined model maintain the same sign of their coefficient as in the previous models; however, the significance of several parameters is decreased. This is evidenced by the decrease in coefficient size and z-statistic of average curve radius (un-weighted) and average left shoulder with, which may experience a draining of explanatory power from the inclusion of the geometric design consistency parameters.

To explore which parameters may be affecting one another, a correlation matrix is provided for the final combination model in Table 5-6. For the sake of brevity, the exposure parameters were left out of this correlation matrix; the correlations between these two parameters and the other explanatory variables can be found in Tables 5-2 and 5-4.

Table 5-6. Correlation matrix for combination SPF

	# H.C.	Avg. Radius	Max Δ C.A.	Avg. D.C.	Avg. Δ D.C.	Avg. L.S.	Max Δ L.S.	# Grade Δ
# of Horizontal Curves	1.00							
Avg. Radius (un-weighted)	-0.19	1.00						
Max. Change in Curve Angle	0.42	-0.18	1.00					
Avg. Degree of Curvature	0.52	-0.25	0.46	1.00				
Avg. Change in Degree of Curvature	0.51	-0.18	0.51	0.60	1.00			
Avg. Left Shoulder Width	-0.29	0.21	-0.23	-0.25	-0.24	1.00		
Max. Change in Left Shoulder Width	0.06	-0.02	0.08	0.03	0.09	-0.21	1.00	
# of Grade Changes	0.32	-0.14	0.20	0.20	0.26	-0.21	0.08	1.00

The correlation between average degree of curvature and the average change in degree of curvature is high, intuitively. The inclusion of the average degree of curvature may explain the drop in level of significance of the average change in degree of curvature from 3.82 to 1.74; however, the other typical roadway parameters may also be drawing from its significance as a predictor. The high correlation between average degree of curvature and number of horizontal curves is also interesting, although, not unexpected. By incorporating the number of horizontal curves in a segment into the safety performance function, many of the typical roadway parameters experienced a decreased power to predict crash frequency. However, the inclusion of average degree of curvature and the number of horizontal curves create a more complete model; one where designers and safety practitioners can perceive the effects of geometric design consistency in a more efficacious manner.

With the safety performance functions established, the predicted number of crashes can be calculated for each segment. This process is completed twice (once for the typical SPF and once for the SPF with additional geometric design consistency parameters). An example calculation for a segment along State Route 002 in 2006 is shown below. The statistics for this segment of roadway in 2006 are shown in Table 5-7.

Table 5-7. Parameter values for SR 002, Segment 1 in 2006

Begin MP	End MP	SR	AADT	# of intersections	Avg. Radius (un-weighted) [ft]	Avg. Curve Angle [ft]	Avg. Left Shoulder Width [ft]	Avg. Lane Width [ft]	Avg. Grade (%)
8.65	11.15	002	24850	5	3398.75	1414.75	8	12	1.17778
			# horizontal curves	Max. Δ in Curve Angle [ft]	Avg. Degree of Curvature	Avg. Δ in Degree of Curvature	Max. Δ in Left Shoulder Width [ft]	# Grade Changes	Actual Accident Frequency (5 years)
			4	1522.8	1.9425	1.33333	0	8	10.2

Crash Frequency using Typical Roadway Parameter SPF

$$Crash\ Frequency$$
$$= AADT^{0.9082}e^{0.0269(\#\ int)-0.0001(Avg.R)+0.0003(Avg.C.A.)-0.049(Avg.L.S.)-0.06(Avg.L.W.)+0.026(Avg.Grade)-5.86}$$

$$= 24850^{0.9082}e^{0.0269(5)-0.0001(3398.75)+0.0003(1414.75)-0.049(8)-0.06(12)+0.026(1.1778)-5.86}$$

$$= \mathbf{18.6965}\ \boldsymbol{crashes}$$

Crash Frequency using SPF w/ Additional Geometric Design Consistency Parameters

$$Crash\ Frequency$$
$$= AADT^{0.9556}e^{\substack{0.016(\#\ int)+0.0039(\#H.C.)-0.0001(Avg.R)+0.0001(Max\ \Delta C.A.)+0.005(Avg.D.C.)+0.007(Avg.\Delta D.C.) \\ -0.041(Avg.L.S.Width)+0.0076(Max\Delta\ L.S.\ Width)+0.043(\#\ Grade\ Changes)-6.57}}$$

$$= 24850^{0.9556}e^{\substack{0.016(5)+0.0039(4)-0.0001(3398.75)+0.0001(1522.8)+0.005(1.9425)+0.007(1.333) \\ -0.041(8)+0.0076(0)+0.043(8)-6.57}}$$

$$= \mathbf{18.0857}\ \boldsymbol{crashes}$$

5.2. Empirical Bayes Adjustments

With the number of predicted crashes from each SPF for 2006 generated, the Empirical Bayes adjustments are performed utilizing the conditional overdispersion parameter and variance component of the random intercept from the mixed effects negative binomial model output, shown in Tables 5-4 and 5-6. The first step in this process is to calculate the overdispersion parameter for use in the weighting equation, as explained in the methodology section of this report.

Overdispersion Parameter of Typical Roadway Parameter SPF

$$\alpha' = \left\{e^{\sigma^2}(1-\alpha)-1\right\} = \{e^{0.1762309}(1-e^{-3.352199})-1\} = 0.1509$$

Overdispersion Parameter of SPF w/ Additional Geometric Design Consistency Parameters

$$\alpha' = \{e^{0.1686945}(1-e^{-3.343782})-1\} = 0.14197$$

It is important to note that a different weight is achieved for each safety performance function. This weight is calculated for each SPF based on the five years of data available for this particular segment (SR 002, Segment 1), as described by Hauer (2001):

Weight for Typical Roadway Parameter SPF

$$weight = \frac{1}{1+(\mu_i * Y_i)/\alpha} = \frac{1}{1+(18.6965*5)/0.1509} = 0.001623$$

Weight for SPF w/ Additional Geometric Design Consistency Parameters

$$weight = \frac{1}{1+(18.0857*5)/0.14197} = 0.001581$$

With this weight, the Empirical-Bayes-adjusted number of crashes can be determined, as shown by the diamond in Figure 3-1. The average crash frequencies predicted by the typical SPF and Combined SPF are 18.5650 and 17.9320 crashes per year, respectively, on State Route 002, Segment 1.

<u>Expected # of Crashes using Typical Roadway Parameter SPF</u>

$$\begin{aligned} &\mathit{Expected\ \#\ of\ crashes\ for\ SR}\ 002, \mathit{Segment}\ 1 \\ &\quad = (0.001623 * 18.5650) + [(1 - 0.001623) * 10.2] \\ &\quad = 10.213\ \mathit{crashes\ per\ year} \end{aligned}$$

<u>Expected # of Crashes using SPF w/ Additional Geometric Design Consistency Parameters</u>

$$\begin{aligned} &\mathit{Expected\ \#\ of\ crashes\ for\ SR}\ 002, \mathit{Segment}\ 1 \\ &\quad = (0.001581 * 17.9320) + [(1 - 0.001581) * 10.2] \\ &\quad = 10.212\ \mathit{crashes\ per\ year} \end{aligned}$$

Since this segment of roadway contained all five years of data, the adjusted number of expected crashes (10.213 and 10.212) do not differ significantly from the actual crash frequency (10.2).

5.3. Ranking of Sites with Potential

One final step is necessary to prepare this segment for ranking of SWiPs; the scaled differences in crash frequency (ΔF/σ) must be calculated for both SPFs. This process is shown below:

<u>Scaled Difference in Frequency for Typical Roadway Parameter SPF</u>

$$\frac{\Delta F}{\sigma} = \frac{\mathit{EBAdjusted\ Crash\ Frequency} - \mathit{Predicted\ Crash\ Frequency}}{\mathit{Standard\ Deviation\ of\ Crash\ Frequency}}$$

$$= \frac{10.213 - 18.565}{4.707} = \mathbf{-1.77}$$

<u>Scaled Difference in Frequency for SPF w/ Additional Geometric Design Consistency Parameters</u>

$$\frac{\Delta F}{\sigma} = \frac{10.212 - 17.9320}{4.707} = \mathbf{-1.64}$$

The negative scaled difference in frequencies indicates that this segment experienced fewer crashes than would be expected for a segment of similar characteristics. This process is then repeated for each of the remaining 2,182 segments. The SWiPs were then ranked based on the highest scaled difference in frequencies, as shown in Table 5-8. As it turns out, Segment 1 of SR 002 (the example above) falls in the bottom third in SWiP rankings for both safety performance functions and would not be recommended for safety improvements using both traditional and design consistency evaluation methodologies.

Table 5-8. Top 20 SWiPs identified for each SPF

	Typical Parameter SPF			Combined SPF		
SWiP Rank	State Route (Seg #)	ΔF/σ	Rank by Alternative SPF	State Route (Seg #)	ΔF/σ	Rank by Alternative SPF
1	502 (1)	39.7667	1	502 (1)	39.6058	1
2	532 (4)	17.0199	2	532 (4)	18.9361	2
3	009 (7)	12.5661	3	009 (7)	10.9542	3
4	097 (78)	10.9770	4	097 (78)	10.7164	5
5	539 (2)	8.9003	5	539 (2)	8.6924	4
6	020 (134)	6.9307	6	020 (134)	7.1769	6
7	101 (126)	6.5985	8	097 (228)	5.9918	8
8	097 (228)	5.8141	7	101 (126)	5.9828	7
9	017 (26)	5.6506	9	017 (26)	5.6788	9
10	539 (3)	5.3109	12	009 (10)	5.3193	14
11	009 (17)	5.0044	17	009 (9)	5.2992	13
12	410 (8)	4.9355	15	539 (3)	5.2784	10
13	009 (9)	4.8720	11	410 (2)	5.2136	18
14	009 (10)	4.7261	10	003 (9)	5.0920	16
15	003 (8)	4.5772	19	410 (8)	4.9383	12
16	003 (9)	4.4945	14	101 (119)	4.6637	19
17	507 (9)	4.4536	18	009 (17)	4.4796	11
18	410 (2)	4.4104	13	507 (9)	4.4193	17
19	101 (119)	4.1702	16	003 (8)	4.2849	15
20	101 (143)	3.8932	21	500 (11)	3.9967	30

From the table, it can be seen that there is a not a noticeable amount of disparity between the top 20 sites with potential for safety improvements identified by the two safety performance functions. Save for some swapping of rankings (e.g., SR 410, Segment 2 was identified as the #18 SWiP in the typical parameter SPF and #13 in the combined SPF), most of the roadway segments selected for further investigation and potential safety improvements are similar between the two SPFs. There is only one segment in each of the top 20 sites identified that differs from the alternative SPF; this happens to be the #20 site for both SPFs, which is highlighted in yellow. So, it would appear that the addition of geometric design consistency parameters offer little benefit to safety professionals given the two SPFs identify nearly the same roadway segments.

However, when the evaluation is expanded beyond the top 20 sites, greater disparity becomes readily apparent. Of the top 220 sites (~10% of all segments), there are 40 unique segments that are not identified by the other safety performance function's top 220 ranked sites with potential for safety improvements. In other words, 40 of the top 220 SWiPs identified by the combined model were not identified in the top 220 SWiPs of the traditional model. This indicates that the addition of geometric design consistency parameters to the safety performance function generated roughly a 19 percent change in the sites identified in the top 10 percent of SWiPs in the state of Washington. When tens of millions of dollars are being invested toward safety improvements on an annual basis, this disparity could have a significant impact on potential increases to levels of safety.

In order to determine the source of these discrepancies between models, it would be prudent to evaluate the driving force behind the parameters contained within each model. This would typically be done through the use of elasticities; however, there is no direct methodology for obtaining elasticities when using mixed effects negative binomial modeling. Therefore, an ad hoc procedure was utilized to demonstrate the effects of changes to the dependent variable through nominal changes to independent variables. Table 5-9 contains the minimum and maximum values for several of the variables in the combined SPF. Using these values, the expected crash frequencies are predicted using the SPF in Table 5-5, given all other variables are held constant. For example, the maximum value for average radius in the dataset is 50,000 feet; the number of crashes predicted for a segment with this value would be scaled by a factor of 0.517 (again, all other variables held constant). Meanwhile, if the minimum value of average radius were used in the SPF from Table 5-5, the term would take a value of 1. This leads to an overall change of 0.483 in the predicted number of crashes between the maximum and minimum values present in the dataset.

Table 5-9. Changes to crash frequency due to change in independent parameters

	Independent Parameter	Max. Value	Value in SPF [$e^{(value*coefficient)}$]	Min. Value	Value in SPF [$e^{(value*coefficient)}$]	|Change in Crash Frequency|
Typical Parameters	Average Radius	50,000	0.517	0	1	0.483
	# Horizontal Curves	46	1.195	0	1	0.195
Design Consistency Parameters	Max. Change in Curve Angle	21,807.20	1.487	0	1	0.487
	Max. Change in Left Shoulder Width	35	0.001	0	1	0.999
	# Grade Changes	90	1.468	0	1	0.468

Although this methodology is not ideal, it serves as a means to draw out the effects of changes to the independent parameters on crash frequency. It can be seen that changes to the design consistency parameters have a rather substantial effect on the predicted number of crashes. Despite the small magnitude of the coefficients of the design consistency parameters in the combined SPF, Table 5-9 demonstrates that they still have a significant impact on the predicted crash frequency of a segment. This, in turn, may help explain the differences in SWiPs identified between the typical parameter and combined safety performance functions.

Therefore, the results of these analyses illustrate that these direct and arguably more simplistic measures of geometric design consistency can be utilized to help better identify potentially unsafe roadways. Although the use of measures, such as changes to the 85th percentile speeds on successive elements or high driver workloads, may be effective in identifying inconsistencies, they do not directly quantify the effects of geometric design consistency on roadway safety using measures that can be linked to specific geometric elements. Ultimately, practitioners are interested in identifying the conditions present that cause the inconsistencies, rather than just locations where they may be present. By incorporating the geometric consistency parameters developed in this report into safety performance functions, the elements that violate driver expectancy can be more readily identified, and hopefully, levels of design consistency can be evaluated in a more direct and efficacious manner.

Chapter 6. CONCLUSIONS

6.1. Summary

Given the novelty of many current practices regarding roadway safety, considerable research has been directed towards developing new methods for evaluating and predicting levels of roadway safety. Many researchers have focused their efforts on the inclusion of design consistency measures in their evaluation techniques. Although design consistency has long been recognized as an important consideration in the development of roadway networks, researchers and practitioners have yet to agree on a clear-cut definition. This has, in part, resulted in a great deal of ingenuity, as researchers have attempted to directly quantify the effects of unique and innovative consistency parameters, such as changes to 85^{th} percentile speeds on successive elements or driver workload. However, it has also left the body of literature rather diffuse.

In order to focus the efforts to model design consistency, this research proposed the use of direct changes to geometric elements in roadway safety performance functions. Not only would these parameters attempt to directly quantify the effects of design consistency, but they would do so in a manner that could be easily adopted by practitioners. Although they do not replace current practices, the inclusion of parameters, such as the maximum change to horizontal curve radius within a roadway segment, would potential provide for a more efficacious method for evaluating roadway safety.

To test this theory, five years of crash data was obtained for roughly 5,000 miles of two-lane rural roadways in the state of Washington. The roadway was divided into fixed segment lengths of 2.5 miles, and over 80 statistics were tabulated for each segment pertaining to the geometric alignment and consistency of the design. Mixed effects negative binomial modelling was used to develop three safety performance functions. The first contained typical roadway parameters that might be used following the methods developed for the Highway Safety Manual, while the second SPF comprised of only geometric design consistency parameters. The third safety performance function contained typical roadway parameters with additional design consistency measures to potentially help improve the estimation of predicted crashes.

After Empirical Bayes adjustments were performed on the roadway segments to help account for regression to the mean and natural fluctuations in crashes over time, the scaled differences in crash frequencies were calculated. This value, which represents the difference between the predicted crash frequency by the SPF and the adjusted crash frequency scaled by standard deviation of crashes, was then used to rank sites with potential for safety improvements. A larger difference in scaled frequency would, theoretically, indicate a site that would experience greater benefits from investments in safety [provided a safety audit identified the appropriate cause(s) for high crash frequency]. After all 2,183 roadway segments received a ranking based on this value, the rankings were compared between safety performance functions. The idea being that any disparity between SWiPs identified would indicate an improved estimation of the level of safety.

When comparing the SWiP-rankings between the typical parameter SPF and the SPF with additional geometric design consistency parameters, the incongruity becomes evident. Although the top 20 sites with potential identified share similarities, the order of site rankings is evidently varied. When expanding the evaluation to the top 10 percent of SWiPs (a pragmatically-reasonable percentage of segments for practitioners to focus on), 40 of the sites are not contained on the alternative SPF's ranking list. This accounts for roughly 19 percent of the top 10 percent of sites identified for safety improvements. Furthermore, there is a significant jockeying of rankings between these two SPFs at this level; it is much more marked than experienced with the top 20 sites.

6.2. Conclusions

From these outcomes, several conclusions can be made about the direct use of geometric design consistency parameters in safety evaluations of two-lane rural roadways. First, the use of perceived radii does not appear to offer any additional explanatory benefits over standard radii in safety performance functions. This stems from the lack of significance found for many perceived radius variables using mixed effects negative binomial modeling; the parameters tested can be found in Table A-1. Although some of these parameters may have been significant when modeled against crash frequency alone, the standard radius parameters performed more effectively when combined with other geometric design consistency parameters.

A similar conclusion can be made about the use of alignment indices in the development of safety performance functions. Although several indices were found to be significant (e.g., minimum CRR and ratio of maximum to minimum radius) when modeled against crash frequency, they quickly lost any predictive power when combined with other parameters. This may be a result of correlation between these alignment indices and many of the more "direct" consistency measures (e.g., number of grade changes).

As evidenced by the SPFs, there are several geometric design consistency parameters that serve as good predictors of crash experience. These include the maximum changes in radius and curve angles, the average change in degree of curvature, and the number of changes to left shoulder width and vertical grade within a segment. The safety performance function in Table 5-3 demonstrates that these parameters could be utilized to estimate crash frequency; this would allow practitioners to directly model design consistency of geometric elements without using surrogate measures. The SPF in Table 5-5 further establishes the versatility of these geometric consistency measures with their inclusion in a predictive model with standard roadway parameters.

When comparing the sites with potential identified by the typical and combined safety performance functions, it is interesting to note the discrepancies in site rankings. Although this is only a perfunctory analysis, the disparity may be indicative of improved SWiP identification with the inclusion of geometric design consistency parameters in the SPF. However, it would be improper to make any conclusions over which SPF is a more effective means for predicting crash frequency at this time. In order for a conclusion to be made, further analysis would have to be placed on the effectiveness of investments at particular sites and more research would need to be conducted to verify these results. Presently, though, it is important to recognize the ability of geometric design consistency measures to identify alternative sites with potential for safety improvements when combined with traditional roadway parameters.

6.3. Future Work

Based on the novelty of many studies in the current body of literature and the preliminary nature of this work, there are significant opportunities for future exploration into the effects of design consistency on roadway safety. The investigation into the literature exposed the potential of alignment indices to help model crash frequency. The work of Andersen et al. (1999) and Awatta & Hassan (2002) established that certain indices could be used estimate levels of safety; the analysis conducted in this report confirmed these results. However, these indices were only found to be significant when modeled against crash frequency alone. Future work should focus on developing unique and innovative alignment indices that will be effective predictors of crash frequency when combined with other parameters in a safety performance function. The use of alignment indices in SPFs holds enormous potential in future safety evaluations.

Similarly, research efforts should be placed towards gaining a better understanding of the concept of perceived radius. This notion of an optical illusion occurring when horizontal and vertical curvature are superimposed has become generally-accepted in academia; however, there currently exists only one set of papers that attempts to estimate the radius perceived by a driver. If additional inquiries were made into modeling this phenomenon, safety professionals may be inclined to incorporate perceived radii in their evaluation techniques. Although the current equations for estimating perceived radii were extremely beneficial for the purposes of this study, the parameters developed using perceived radii did not provide any additional explanatory benefits over the corresponding standard radii parameters. Perhaps when these equations are validated or alternative equations are developed through future work, a more definitive assessment can be made about the effectiveness of using perceived radii over standard curve radii.

One of the most important assertions of this work has been the advocation for the direct use of geometric design consistency parameters in safety performance functions. However, as previously noted, the major weakness of this study is the inability to substantiate claims that the sites with potential identified by the safety performance function with these additional consistency parameters provides greater insights towards more effective safety improvements. Efforts should be placed into developing a study that utilizes micro-simulation software (e.g., VISSIM or AIMSUN) to test the effectiveness of changes to geometric elements in predicting crash frequency. This could be accomplished by developing several roadway alignments that differ only by the geometric design consistency parameters evaluated in this study (e.g., maximum change to radius within a segment) and observing the differences in crash frequencies experienced. Although the use of micro-simulation to estimate crashes suffers several limitations (notably the ability to accurately represent human behavior and driver error), this type of study could potentially lend credence to the results of this work.

Finally, efforts should be made to help validate the results achieved in this report. This study only included roadways from a single state and a single roadway classification; the results obtained are by no means conclusive. If researchers were to replicate the design of this work using multiple regions and classifications of roadways, achieving similar results would help validate the use of consistency in geometric alignment elements as a primary means for evaluating design consistency. Discrete levels of crash severity should also be modeled to assess the implications of geometric design consistency on various crash outcomes. Consequently, there will consistently be room for development of future work within the field of roadway safety, particularly regarding the conception of new and improved techniques for evaluating safety. Safety professionals and practitioners must persistently strive to establish more proficient methods to improve safety throughout all levels of the roadway network and help prevent crashes wherever possible. Although this study is only a preliminary investigation into the use of geometric design consistency parameters in safety evaluations, it will hopefully aid in the development of an ever-burgeoning body of literature regarding roadway safety.

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Appendix

Table A-1. Variables compiled for each 2.5 mile segment

Variables		
Begin Milepost	Avg. Curve Angle	Avg. Change in Left Shoulder Width
End Milepost	Max. Curve Angle	Max. Change in Left Shoulder Width
Roadway I.D.	Min. Curve Angle	# of Changes in Left Shoulder Width
Median Introduced?	Avg. Change in Curve Angle	Avg. Right Shoulder Width
# Horizontal Curves	Max. Change in Curve Angle	Avg. Change in Right Shoulder Width
Avg. Radius (weighted)	Max. Curve Angle/Min Curve Angle	Max. Change in Right Shoulder Width
Avg. Radius (un-weighted)	(Max. C.A. - Avg. C.A.)/Avg. C.A.	# of Changes in Right Shoulder Width
Max. Radius	Avg. Degree of Curvature	Avg. Lane Width
Min. Radius	Max. Degree of Curvature	Max. Lane Width
Avg. Change in Radius	Min. Degree of Curvature	Min. Lane Width
Max. Change in Radius	Avg. Change in Degree of Curvature	Max. Change in Lane Width
Min. Change in Radius	Max. Change in Degree of Curvature	# Changes in Lane Width
Max. Radius - Min. Radius	Max. D.C. / Min. D.C.	AADT (weighted)
Max. Radius/ Min. Radius	(Max. D.C. - Avg. D.C.)/Avg. D.C.	Avg. Roadway Width
(Max. Radius - Avg. Radius)/Avg. Radius	Access Type	Max. Roadway Width
Min. CRR	# of Intersections	Min. Roadway Width
Max. CRR	# of Intersections w/ Roadway Lighting	Max. Change in Roadway Width
Avg. Perceived Radius (weighted)	Left Shoulder Type	# Changes in Roadway Width
Avg. Perceived Radius (un-weighted)	Left Shoulder Type 2	Avg. Grade
Max. Perceived Radius	Right Shoulder Type	# of Grade Changes
Min. Perceived Radius	Right Shoulder Type 2	Max. Grade
Avg. Change in Perceived Radius	Terrain	Min. Grade
Max. Change in Perceived Radius	Functional Class	Avg. Change in Grade
Max. P. Radius/ Min. P. Radius	Avg. Speed Limit	Max. Change in Grade
(Max. P. Radius - Avg. P. Radius)/Avg. P. Radius	Max. Speed Limit	Accidents
Min. Perceived CRR	Max. Change in Speed Limit	Fatal Crashes
Max. Perceived CRR	Avg. Left Shoulder Width	Injury-Only Crashes
		PDO Crashes