ANALYSIS OF THE MAGNITUDE AND PREDICTABILITY OF MEDIAN CROSSOVER CRASHES UTILIZING LOGISTIC REGRESSION

By

George X (xiaozhao). Lu
(Corresponding Author)*
Graduate Research Assistant
University of Wisconsin-Madison
Department of Civil and Environmental Engineering
B239 Engineering Hall
1415 Engineering Drive
Madison, WI 53706-1691
Email: xlu@cae.wisc.edu
Phone: 608-265-8583

David A. Noyce, Ph.D., P.E.
Assistant Professor
University of Wisconsin-Madison
Department of Civil and Environmental Engineering
1210 Engineering Hall
1415 Engineering Drive
Madison, WI 53706-1691
Email: noyce@engr.wisc.edu
Phone: (608) 265-1882; Fax: (608) 262-5199

Regan J. McKendry
Graduate Research Fellow
University of Wisconsin-Madison
Department of Civil and Environmental Engineering
B239 Engineering Hall
1415 Engineering Drive
Madison, WI 53706-1691
Email: rjmckendry@wisc.edu
Phone: 608-265-8583

Prepared for the 85th Annual meeting of the
Transportation Research Board, Washington, D.C.
January, 2006

Length of Paper:
5205 words, 7 tables and 3 figures @ 250 words each
7705 equivalent words

ABSTRACT

A median crossover crash (MCC) is defined as an accident in which a vehicle traverses the median area and penetrates the opposing travel lane. Crashes vary from vehicles coming to rest in the opposing lane, to vehicles passing through the opposing lane without hitting an opposing vehicle, to head-on or sideswipe impacts with opposing vehicles. Until recently, the magnitude, characteristics, and causes of MCCs were not widely investigated.

The objective of this research was to determine the magnitude, severity, and predictability of MCCs in Wisconsin state. A total of 15,194 crash reports from Wisconsin's median divided freeways and expressways were analyzed for the period of 2001-2003. The results of this analysis identified 631 reported MCCs over this three-year period. The magnitude of MCCs indicated that this crash type is a considerable issue in Wisconsin and required additional investigation to determine the causes of these crashes and to develop appropriate countermeasures.

To identify the significant attributes of MCCs, ordinal logistic regression models were developed to predict MCC severity based on a number of predictors, including: roadway and driver characteristics, traffic operations, incident management, temporal elements, and environmental factors. Crash severity was selected as the response variable so that the significant variables identified and associated countermeasures developed focused initially on improving safety, although reducing the frequency was also of critical interest.

Statistically, the initial statistical analysis found no predictors to have significant effects on the severity of the 631 MCCs, although the time of year (Quarter predictor) was found to have a relatively low p-value. Additionally, further analysis showed that driver age and time of year affected crash severity on high volume roadways. Road condition was found to affect severity when traffic volume was low. Moreover, weather condition and emergency response time were found to be significant if median width is inadequate. If the median is wider, no significant explanatory variable is responsible for aggravating the median crossover crash severity.

The results indicate that modeling MCC severity as an ordinal response is statistically appropriate, and resultant findings could be used by traffic authorities to determine the probability of crash severity based on a set of predictors and facilitate the decision-making process regarding roadway safety enhancements.

Keywords: Median crossover crash, logistic regression, freeway operations, medians, crash severity

BACKGROUND

Over the four year period from 2000 to 2003, totally 169,789 persons lost their lives on America's roadways [1]. In 2003 alone, 42,643 motorists in the United States died in roadway crashes; this number of fatalities has remained nearly unchanged for more than a decade. Of the 42,643 fatalities in 2003, over 25,000 were a result of vehicles leaving the travel lane. Lane departures, or run-off-road (ROR) crashes, are associated with vehicles that leave the travel lane and enter the shoulder, ditch area, or other roadside environment. Often times, these crash types also involve collisions with one or more of any number of objects including opposing vehicles, bridge rail, utility poles, embankments, guardrails, parked vehicles, or trees [2]. In recent years, approximately 55 percent of traffic fatalities were a result of ROR type crashes [3]. Roughly 40 percent of fatal crashes were single-vehicle ROR crashes.

Over that same four-year period, 3,206 people were killed in crashes on Wisconsin's roadways, representing nearly 1.9 percent of the nation's gross [4]. In 2003 alone, Wisconsin experienced 836 fatalities in 748 fatal crashes. An average of 757 motorists was killed annually in Wisconsin from 1993 to 2003 [5]. Wisconsin is also no exception to the high number of ROR crashes experienced nationally. A recent study found that approximately 54 percent of all non-intersection crashes on undivided roadways in Wisconsin were ROR type crashes [6]. This number may be even higher on the divided roadway system.

Separation of opposing traffic volumes can be important and effective in the attempt to prevent head-on collisions, one of the most potentially serious types of crashes resulting from lane departures. Median areas to separate opposing traffic flows have long been an important design consideration related to roadway safety. The American Association of State Highway Transportation Officials (AASHTO) defines a median as the "portion of a highway separating directions of the traveled way" (7). AASHTO's *A Policy on Geometric Design of Highways and Streets* states that "medians are highly desirable on arterials carrying four or more lanes" of traffic [7]. Even with the implementation of AASHTO's policy and wide median widths of 60 feet or more, crashes involving vehicles traveling through the median and entering the opposing traffic stream are increasing in frequency across the United States, and Wisconsin is believed to be no exception to this trend.

A median crossover crash (MCC) is defined as a vehicle traversing the median area and penetrating the opposing travel lane. Crashes vary from vehicles coming to rest in the opposing lane, to vehicles passing through the opposing lane without hitting an opposing vehicle, to head-on or sideswipe impacts with opposing vehicles. The primary causes of MCCs are not well understood. Accordingly, a detailed analysis of MCC magnitude and severity was necessary to improve safety on Wisconsin highways. Moreover, crash severity modeling could be used to facilitate the decision-making process with regard to identifying common attributes of MCC and associated roadway safety enhancements.

This paper describes the evaluation of MCCs and the statistical methodology used to develop crash severity models. Logistic regression procedures are used to investigate potential associations among the response and various predictors and to compute the probability of crash severity given a set of roadway attributes. Specifically, this research tests an ordinal response for crash severity prediction and determines which explanatory variables best explains the severity of MCCs.

LITERATURE REVIEW

Statistical approaches have been applied to model crash severity as a function of geometric, operational, temporal, environmental, and other explanatory variables. Modeling crash severity as a discrete outcome involves estimating the probability (*conditional probability* in nature) that a vehicular crash has a certain severity by determining the likelihood of outcomes *given* that a crash (i.e., a median crossover crash) has occurred.

By using the nested logit model, Lee et al [8] estimated the severity of run-off-road crashes in Washington State. Environmental, temporal, driver, roadway, and roadside factors were involved to estimate property damage and possible injury probability for rural run-off-road crashes conditioned on no evident injury. It was found that wet pavement surfaces resulted in possible injury, motorists younger than 25 had higher likelihood of being involved in injury crashes, intoxicated motorists were more likely to be involved in injury crashes, and crashes in the presence of a horizontal curve had more likelihood of incurring an injury.

In a study of using log-linear models by Abdel-Aty et al [9], the results indicated that significant relationships exist between driver age, average daily traffic (ADT), injury severity, collision manner, vehicle speed, alcohol involvement, and roadway characteristics. Another study identified the behavioral and personal predictors of automobile crash and injury severity in Hawaii. In this study, Kim et al [10] used log-linear models to predict automobile crash and injury severity. It was found that certain driver behaviors, which were alcohol/drug involvement and lack of seat belt use, significantly enhance the likelihood of more severe crashes and injuries. Driver errors were found to have a small influence, while personal characteristics such as age and gender were generally insignificant. Importantly, log-linear models were useful for study of the association among categorical variables; however, logistic regression model were more appropriate when a response variable is used to measure the direct effects of a set of independent variables.

Other researches have been completed that modeled crash severity by using logistic regression. For example, logistic models were employed in two studies to explore the injury severity of head-on highway crashes and that of young-driver crashes. In the case of modeling young-driver crash severity, Dissanayake et al [11] utilized a sequential binary logistic approach to compare response variable with two levels. As the result, independent variables proved to be most influential in predicting the young-driver crash severity encompassed the following: alcohol/drugs involvement; occupant ejection; impact point; crash location; existence of horizontal curve or vertical grades at the crash site; vehicle speed; and safety restraint usage. Donnell et al [12], by using both ordinal and nominal responses, employed logistic regression to model median-related crash severity, based on the data from roadway inventory and crash records for Pennsylvania Interstate highways. Explanatory variables such as cross-section, traffic volume, and environmental predictors were included in resultant logistic models, and the results indicates that modeling crash severity as an ordinal response rendered appropriate results for cross-median crashes, whereas a nominal response was proved to be more appropriate for median barrier crashes. Explanatory variables such as pavement surface conditions, use of drugs or alcohol, presence of an interchange entrance ramp, horizontal alignment, crash type, and average daily traffic volumes significantly affected the MCC severity.

Summarily, past studies show that logistic regression model has been frequently harnessed to model crash severity. A number of explanatory variables, such as traffic operational measures, environmental conditions, geometric configurations and safety restraint use, have been frequently used to estimate the odds of crash severity. It is worth noting that past research efforts mainly concentrated on two distinct structures: the binary response and a nested model. Only quite a few predictive models have been developed to model crash severity by treating the response in an ordinal or multinomial way.

DATA AND METHODOLOGY

Statistical Model

Linear regression is a common way of studying association between a dependent variable and independent variables in crash data. Unfortunately, the relationship between crash severity and the explanatory factors in this study are not linear. A more appropriate method is *logistic regression*, a widespread method for predicting the probability of the outcome of a dichotomous dependent variable based on a set of explanatory predictors [13]. Conceptually, logistic regression is defined as a model whose dependent variables are discrete or categorical, and it describes the relationship between a categorical response variable and a set of explanatory predictors no matter whether these predictors are continuous or not. Logistic regression is similar to linear regression but is used to estimate the probability that the event of interest will occur. The regression coefficients provide estimates of the impact of each independent variable on the odds of the event of interest occurring. Used prevalently to assess risk factors for various diseases, the logistic regression has also been exploited widely in transportation research.

For a logistic regression model, the categorical response variable can be a binary variable, an ordinal variable, or a nominal variable. Importantly, each type of categorical variables requires different techniques to model its relationship with all predictors involved in a resultant logistic model. For a binary response variable y, the linear logistic regression model has the form as follows [14]:

$$Logit(p_i) = \ln[p_i / (1 - p_i)] = \alpha + \beta' X_i \qquad (1)$$

Where,

$p_i = \Pr ob.(y_i = y_1 \mid X_i)$ is the response probability to be modeled, and y_1 is the first ordered level of y;

α = Intercept parameter;

β' = Vector of slope parameters;

X_i = Vector of explanatory variables.

This logistic regression equation models the logit transformation of the *i* th observation probability, p_i, as a linear function of the explanatory variables in the vector, X_i. In addition, a dependent variable is regarded as ordinal when the absolute distance between its categories is not identified and there is an evident ordering of all categories, and a proportional odds model should be fitted to an ordinal response variable such as low, medium and high. The proportional odds model has its mathematical form as follows:

$$\log it(\theta_i) = \alpha_i + \beta X \qquad (2)$$

Where

θ_i = the i th cumulative probabilities;
α_i = Intercept parameter for the i th cumulative logit;
β = Vector of slope parameters;
X = Vector of explanatory variables.

Accordingly, the intercept may be different for different cumulative logit functions, but the effect of the explanatory variables will be the same across different logit functions. This 'rule' is the proportional assumption and leads to the name "proportional odds model". The proportional odds model is also referred as the logit version of an ordinal regression model, and it extends binary logistic regression further to handle ordinal response variables. Methodologically, several selected independent variables were used in such a modeling technique to predict the probability that the dependent variable is of an ordinal scale, and all parameters are estimated by maximum likelihood methods.

In this study, a logistic regression model for MCC severity was developed for some Wisconsin *divided* highways. The response categories are assumed to be of three ordered levels of severity: PDO (Property-Damage-Only), Injury, and Fatality. Severity was selected as the response variable so that the significant variables identified and associated countermeasures developed focused initially on enhancing roadway safety, although reducing the frequency was also of critical interest. The proportional odds model was employed to determine the probability of fatal, injury or PDO crashes given certain traffic operational, geometric, and environmental conditions. The LOGISTIC procedure in SAS-9.1 was used to estimate the model parameters and assess the model goodness-of-fit [17]. After the ordinal logistic model was utilized to fit the data set, if the proportional odds assumption was not violated, the ordinal logit model was appropriate for the data set. Otherwise, by using appropriate SAS procedures, the models were reestimated with another model which is potentially more appropriate than its ordinal counterpart.

The premise behind this research was to build a model to describe the association between the ordinal response (MCC severity) and some explanatory variables (such as weather condition, geometric configuration, driver demographics, and reaction time after crash occurrence). The first step in the modeling process was to establish probabilities:

π_1 = Probability of "Property Damage Only";
π_2 = Probability of "Injury";
π_3 = Probability of "Fatality";
$\theta_1 = \pi_1$: Probability of "Property Damage Only";
$\theta_2 = \pi_1 + \pi_2$: Probability of "Property Damage" or "Injury" (or: "not Fatality").

Then the cumulative logits can be developed:

$$\operatorname{logit}(\theta_1) = \ln\frac{\theta_1}{1-\theta_1} = \ln\frac{\pi_1}{\pi_2+\pi_3} = \alpha_1 + \beta X \quad (3)$$

$$\operatorname{logit}(\theta_2) = \ln\frac{\theta_2}{1-\theta_2} = \ln\frac{\pi_1+\pi_2}{\pi_3} = \alpha_2 + \beta X \quad (4)$$

Although this model is in terms of cumulative odds, it is not difficult to recover the probabilities of each response category:

$$\pi_1 = \theta_1 = \frac{e^{\alpha_1 + \beta X}}{1 + e^{\alpha_1 + \beta X}} \tag{5}$$

$$\pi_2 = \theta_2 - \theta_1 = \frac{e^{\alpha_2 + \beta X}}{1 + e^{\alpha_2 + \beta X}} - \frac{e^{\alpha_1 + \beta X}}{1 + e^{\alpha_1 + \beta X}} \tag{6}$$

$$\pi_3 = 1 - \theta_2 = \frac{1}{1 + e^{\alpha_2 + \beta X}} \tag{7}$$

Data Sources and Collection

The domain of this research was restricted to MCCs on freeways and expressways in Wisconsin from 2001 to 2003. A three year period was chosen to get comprehensive, normalized results of the three most recent years of available data. Nearly all divided highway sections without median barriers in Wisconsin were considered. With the assistance of the Wisconsin Department of Transportation (WisDOT) traffic engineering staff, Interstate, expressway, and freeway segments with a divided median were selected as examination sites from the state's roadway database. The highways selected are presented in section I of Table 1.

Only crash data available through the Wisconsin crash records system were considered. Crashes in Wisconsin are documented by law enforcement personnel on the Wisconsin Motor Vehicle Accident Report (WMVAR) which is a Scantron sheet designed to record crash information into a computer database. A form contains various data from each crash that is scanned and then archived into searchable databases, including location and time of day, drivers and vehicles information, weather and road conditions, presence of alcohol, manner of collision, first and most harmful event, and supporting narrative and drawing. Unfortunately, the accident form has no entry space to directly identify MCCs. Therefore, all crashes that involved lane departures on median divided roadways were identified as *potential* crossover crashes and were selected for possible inclusion in this analysis.

Over 15,000 potential crossover crashes were identified and the associated WMVAR report obtained to review the narratives and crash diagrams. Each of the crash reports were individually reviewed by researchers to determine if the crash was indeed a MCC. Crashes not considered to be a MCC were discarded from the analysis.

Selected crashes were classified by location (county and roadway) and severity. Crashes were grouped into three categories: Fatal (At least one person was killed in the crash), Personal Injury (At least one person sustained bodily injuries during the crash), and Property Damage Only (No person was hurt in the crash). Median widths and ADTs for the crash sites were added to each crash report's data summary. Median widths were obtained from the Wisconsin State Trunk Highway Log. ADTs were obtained from the 2003 Wisconsin Highway Traffic Volume Data Book. To obtain the correct median width and ADT, each selected crash was located either through its WisDOT Reference Point (RP) number or crossroads reference. Several roadways and crash locations were verified through field visits.

TABLE 1 Specifics of Median Crossover Crash Data

Section I: WI HIGHWAYS REVIEWED FOR CROSSOVER CRASHES		
Interstates	I-39, I-43, I-90, I-94	
U.S. Highways (USH)	10, 12, 14, 18, 41, 51, 53, 141, 151	
WI State Highways (STH)	23, 29, 30, 35, 54, 57, 172, 441	
Section II: SUMMARY OF CROSSOVER CRASH TOTAL CALCULATIONS		
Initial Selected Crossover Crashes	**732**	
Object Crossover Crashes	-64	
Tire Crossover Crashes	*(-52)*	
Other Object Crossover Crashes	*(-12)*	
Median Barrier Crossover Crashes (vehicle jumped existing barrier)	-32	
Intentional Crossover Crashes (median u-turns or police evasion)	-5	
Final Selected Crossover Crashes	**631**	
Vehicle Crossover Crashes	624	
Trailer Crossover Crashes	7	
Section III: MEDIAN CROSSOVER CRASHES BY YEAR		
Year	**MCCs**	
2001	197	
2002	229	
2003	205	
Total	**631**	
Section IV: MEDIAN CROSSOVER CRASHES BY SEVERITY		
	Frequency Distribution of Crashes	
MCC Severity Level	Number of Crashes	Percent
Property Damage only	254	40.3
Injury	336	53.2
Fatal	41	6.5
Total	**631**	**100.0**
Section V: MEDIAN CROSSOVER CRASHES AND MEDIAN WIDTH		
Median Width (ft)	**MCCs**	
< 30	13 (2.1%)	
30 – 39	33 (5.2%)	
40 – 49	34 (5.4%)	
50 – 59	135 (21.4%)	
60 – 69	348 (55.1%)	
70 – 79	10 (1.6%)	
80 +	58 (9.2%)	

Wisconsin Median Crossover Crashes

As a result of the aforementioned procedure, a total of 15,194 WMVCR reports were obtained from the WisDOT crash data archives for the period of 2001 to 2003, and reviewed/analyzed between May and September of 2004. After completing the review and analysis, 732 crossover crashes were initially identified. Each selected MCC was re-examined to both determine the first action (potential cause) and to also confirm that each was by definition a median crossover crash. A total of 101 crashes were disqualified from the crossover crash data set since they involved objects crossing over the median such as tires, animal carcasses, crash debris, people, or other variables that median design would likely not have hindered. Tire crossovers compromised 52 of the 64 total object crossovers. Thirty two crashes involved vehicles vaulting a median barrier already in place. Five MCCs were intentionally committed. The remaining 12 crashes were made up of a variety of object crosses (debris, deer, etc). This re-examination reduced the total number of crashes for evaluation to 631. The breakdown of the reductions taken to achieve the final total is given in section II of Table 1. Figure 1 illustrates all 631 MCCs on the Wisconsin divided highway network from 2001 to 2003, which clearly provides a visual impression of widespread MCCs in this state.

Median Crossover Crashes, Median Width, and ADT

Wisconsin guidelines for installation of median barriers use median width and ADT to determine if a median barrier is warranted. To evaluate this relationship, the median width of each selected crossover median crash was plotted against the ADT of the crash.

Section III of Table 1 shows the distribution of each of the three years evaluated, while Table 2 shows the breakdown of crashes selected for each roadway reviewed. According to Table 2, it can be seen that MCCs occurred prevalently at various highway classes (Interstates, US Highways, and WI State Highways). In instances where two, or even three, highways run concurrently, the commonly referenced/coded highway was selected. The length of the highway is the total mileage of the divided highway without median barrier that was reviewed. A ratio of ‘MCCs selected’ to ‘crashes reviewed’ was not possible due to the fact that not all reviewed crashes were MCCs, i.e., some crashes occurred on highway ramps, and some involved vehicles at an at-grade intersection with a highway. Section V of Table 1 lists the total number of crossover median crashes by median width.

Figure 2 displays the median width of each selected crash plotted against the ADT of the crash, with the Wisconsin median barrier standard inserted. Of the 631 selected crashes, 514 crossover median crashes (81.5%) occurred at locations at which the Wisconsin FDM states that a median barrier was not warranted.

In an attempt to derive a median crossover crash rate, crashes were grouped together based on their roadway and county location. Crossover crashes for each segment were normalized by VMT to obtain a crossover median crash rate. The rates were plotted against the average median width for each segment. Figure 3 displays the 66 highway segment points and their average median width. Note that several highway segments exhibit noticeably high crossover crash rates in spite of large median widths. Thus, very little linear correlation was found between MCC rate and median width.

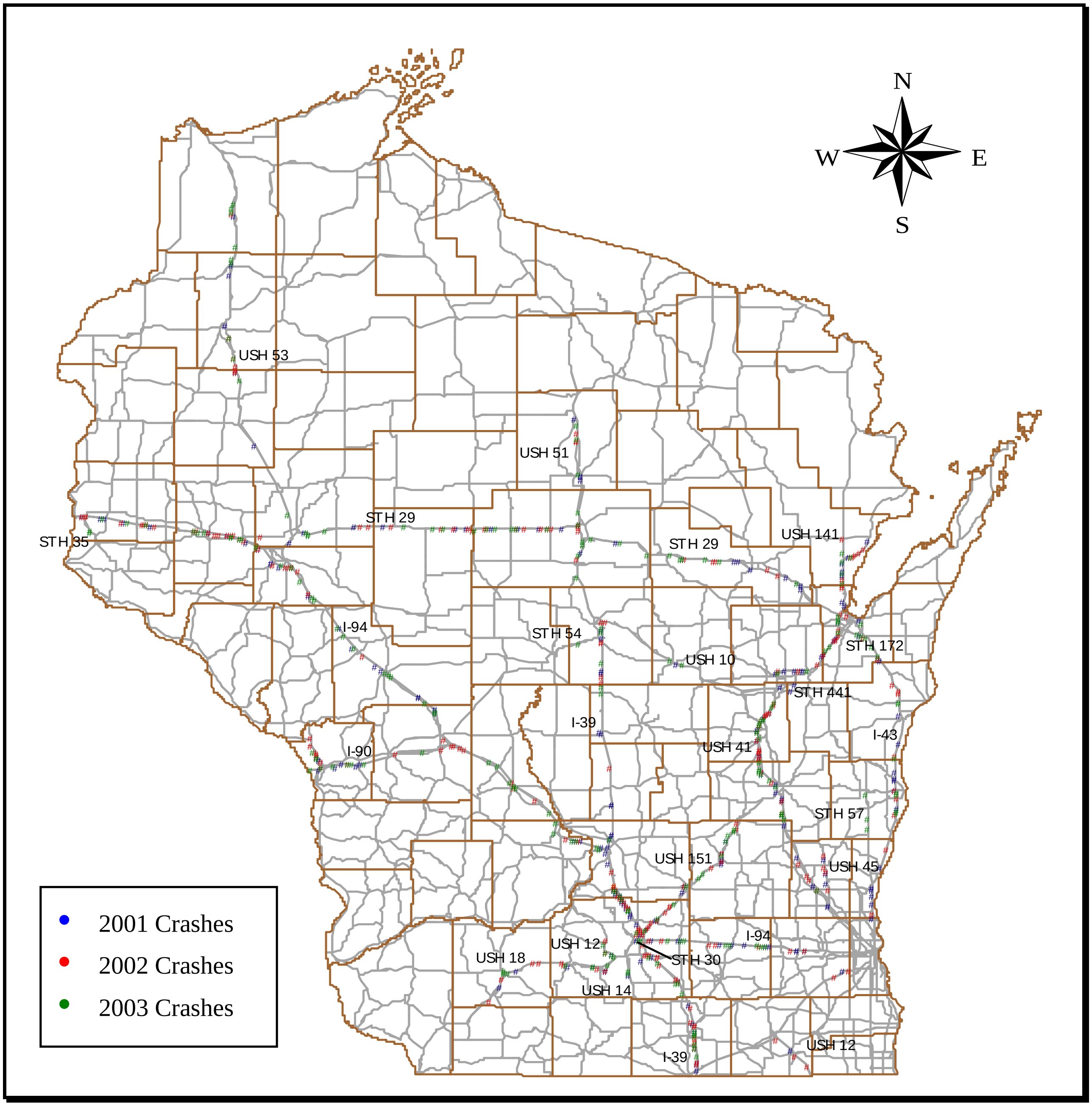

FIGURE 1 Median crossover crashes in Wisconsin (2001 – 2003).

TABLE 2 Selected Crossover Median Crashes by Highway

Highway	Counties	Crossover Median Crashes	Highway Length (miles)	Crashes/ Year/ Mile
I-39	Rock, Dane, Columbia, Marquette, Waushara, Portage, Marathon	107	182.38	0.196
I-43	Waukesha, Milwaukee, Ozaukee, Sheboygan, Manitowoc, Brown	44	148.86	0.0985
I-90	La Crosse, Monroe[1], Juneau[1], Sauk[1], Columbia[1,2], Dane[2], Rock[2]	19	45.27	0.140
I-94	St. Croix, Dunn, Eau Claire, Jackson, Monroe, Juneau, Sauk, Columbia[2], Dane[2], Jefferson, Waukesha	127	269.46	0.157
USH 10	Portage, Waupaca, Calumet	6	31.35	0.0638
USH 12	Dane, Walworth	16	40.54	0.132
USH 14	Dane[3]	3	7.17	0.140
USH 18	Iowa, Dane[3]	15	26.67	0.187
USH 41	Washington, Fond Du Lac, Winnebago, Outagamie, Brown, Oconto	112	136.54	0.273
USH 45	Washington[4]	7	26.11	0.0894
USH 51	Dane, Columbia[2], Marquette[2], Waushara[2], Portage[2], Marathon[2], Lincoln	19	61.59	0.103
USH 53	La Crosse, Chippewa, Barron, Washburn, Douglas	35	149.37	0.0781
USH 141	Oconto	2	8.40	0.0794
USH 151	Grant, Iowa[5], Dane[5], Columbia, Dodge	41	99.75	0.137
STH 23	Sheboygan	1	12.73	0.0262
STH 29	Chippewa, Clark, Marathon, Shawano, Brown	64	183.46	0.116
STH 30	Dane	4	3.28	0.407
STH 35	St. Croix	2	8.36	0.0797
STH 54	Portage, Brown	1	16.77	0.0199
STH 57	Sheboygan	3	15.36	0.0651
STH 172	Brown	1	9.29	0.0359
	Total	**631**	**1,482.71**	**0.142**

[1]*Crashes on concurrent sections of I-90/I-94 were counted as part of I-94.*
[2]*Crashes on concurrent sections of I-39/I-90, I-39/I-90/I-94, and I-39/USH 151 were counted as part of I-39.*
[3]*Crashes on concurrent sections of USH 12/USH 14 and USH 12/USH 18 were counted as part of USH 12.*
[4]*Crashes on concurrent sections of USH 41/USH 45 were counted as part of USH 41.*
[5]*Crashes on concurrent sections of USH 18/USH 151 were counted as part of USH 18.*

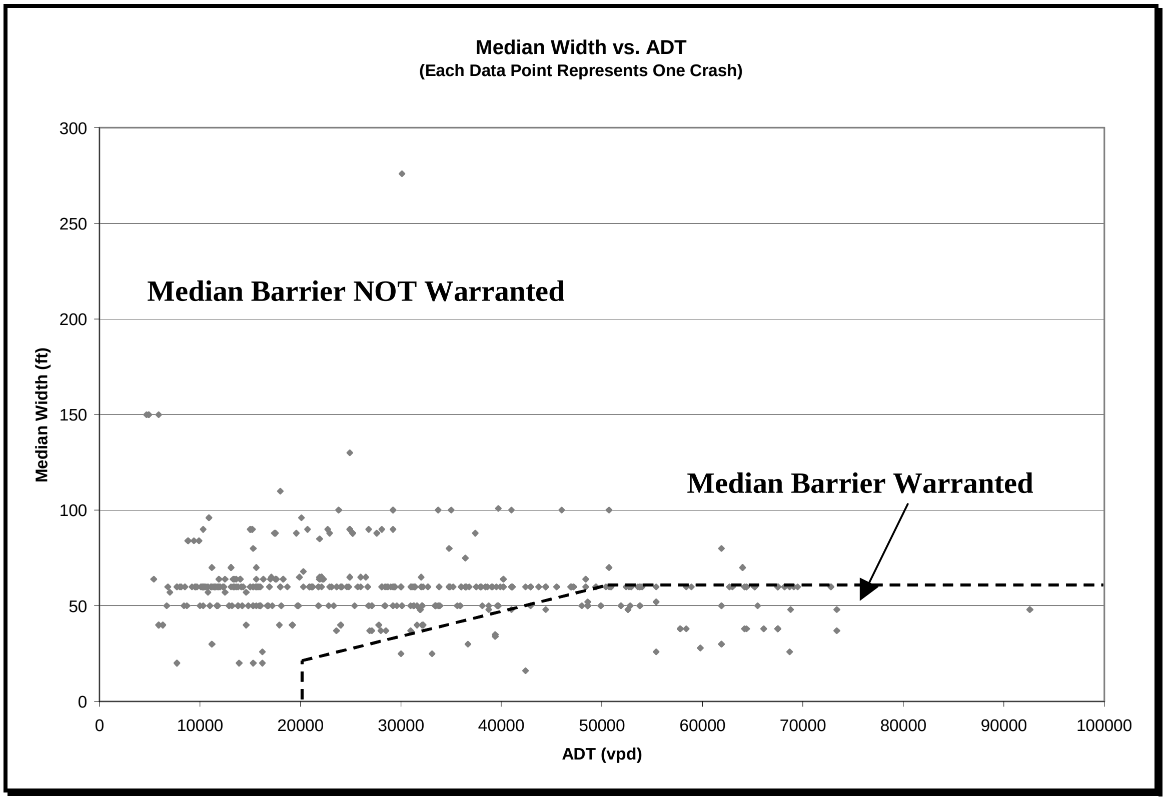

FIGURE 2 Crossover median crashes with the Wisconsin median barrier standard.

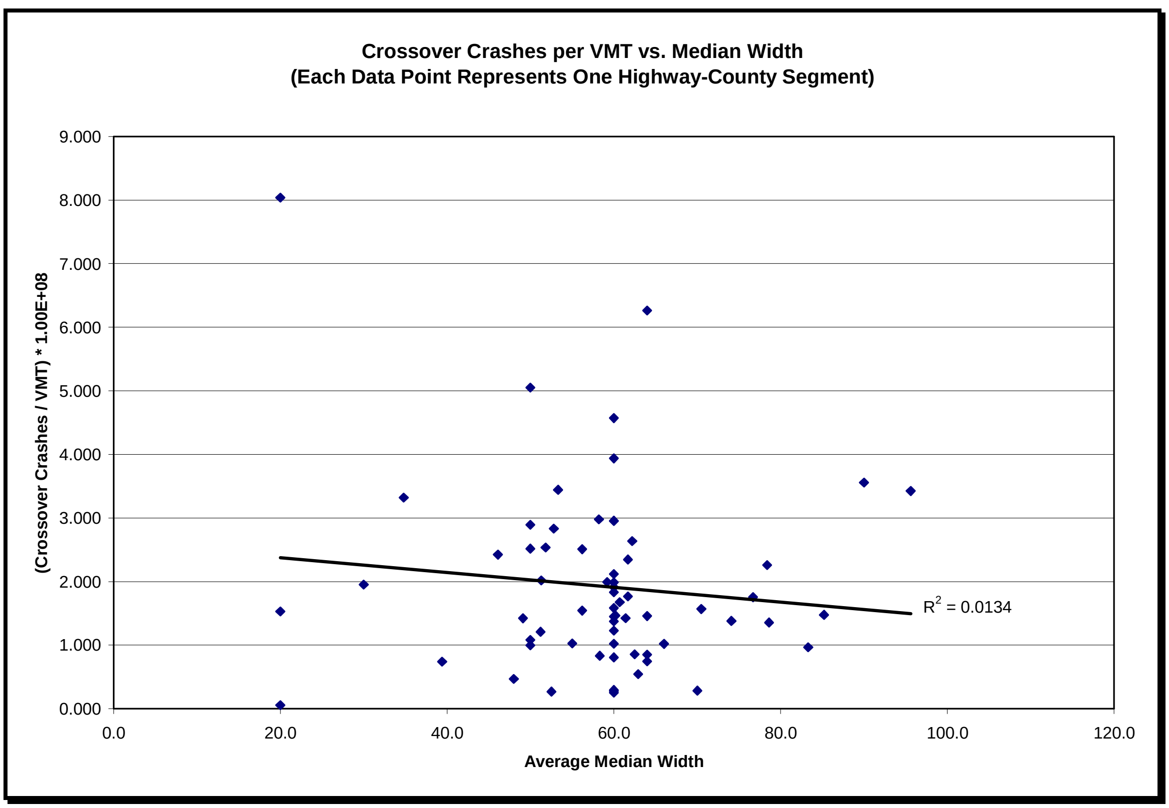

FIGURE 3 Crossover median crash rates vs. average median width.

IDENTIFICATION OF VARIABLES RELATED TO CRASH SEVERITY

Table 3 shows the roadway, environmental, driver behavior, personal characteristics, temporal, incident managerial, and traffic operational data that were available for modeling the MCC severity in Wisconsin and the detailed description of all these variables and construction of their corresponding indicator variables. As indicated, 12 explanatory variables were encompassed for estimating crash severity model parameters. Four variables (total ADT, median width, driver age, and reaction time spent after crash) were continuous and the remaining eight explanatory variables were categorical or discrete, while the response variable (MCC severity) was initially considered ordered with three levels: Property Damage, Injury and Fatality. Section III of Table 1 shows the distribution of each of the three years evaluated and the frequency distribution of MCC severity for the three year analysis period.

A bivariate logistic regression of each individual variable was performed to investigate the effect of each independent variable on MCC severity which acted as the ordinal response variable. For this purpose, point estimates and odds ratios were reviewed to identify unfavorable logistic regression variables [16].

Section I of Table 4 demonstrates the results of the bivariate logistic regression analysis, including the name of each explanatory variable, likelihood ratio chi-square (χ^2) test with k-1 degrees of freedom (k is the number of levels of independent variable), and p-values for each level independent variable. Furthermore, the individual odds ratios are also computed based on the estimated coefficients for the logistic model.

Scrutiny of each individual independent variable and its effect on crash severity indicates that ‘Quarter’ (crash date), ‘Weather’, ‘Road Condition’, ‘Road Cause’ (Initial cause of crash), and ‘Reaction’ (EMS response time) predictors have the greatest influences on crash severity. Moreover, it was important that all potential interaction terms were also included in the modeling. The interaction terms included the ‘Weather’ predictor as well as the ‘Reaction’ predictor. The SAS PROC LOGISTIC statement was employed with a significant level of 0.10 to maintain variables in the model during selection, and the STEPWISE model selection procedure was also used. The resultant multivariate ordinal logistic regression is displayed in section II of Table 4.

Interpretation of the final MCC severity model in Table 4 indicates that the score test for the proportional odds assumption has a p-value of 0.8944 ($\chi^2 =$ 0.6089, DF=3), which verifies that the proportional odds model is adequately valid for fitting the data because the null hypothesis that the regression lines for cumulative logits are parallel is retained. The p-value of the likelihood ratio chi-square test is 0.0310 ($\chi^2 =$8.8720, DF=3) which means that the global null hypothesis for the whole model is rejected. Statistically, this result indicates that the predictor variables given in the model affect MCC severity.

TABLE 3 Wisconsin Median Crossover Crash Severity Data

Raw Data Name	Data Explanation	Data Type	Variable Names used in SAS 9.1	Categories/Ranges
ACCDSVR	Median crossover crash severity	Categorical	SVRLEVEL (Response)	1= Property Damage 2= Injury 3= Fatal
DAYNMBR	Day of a week in which the median crossover crash occurred	Categorical	WEEKDAY (predictor)	1= Mon 2= Tue 3= Wed 4= Thu 5= Fri 6= Sat 7= Sun
ALCFLAG	Flag on data to indicate whether a driver was listed on the police report as drinking alcohol before the recorded median crossover accident	Categorical	LIQUOR (predictor)	1= No 2= Yes
ROADCOND	Pavement surface of the road at the point of median crossover crash site	Categorical	RDCOND (predictor)	1= Dry 2= Wet 3= Snow 4= Ice
WTHRCOND	Weather condition under which the recorded median crossover crash occurred	Categorical	WEATHER (predictor)	1= Clear 2= Wind/Cross wind 3= Cloudy 4= Foggy 5= Rainy 6= Sleety 7= Snowy
LGTCOND	Code which describes the light condition at the time of the accident	Categorical	LIGHT (predictor)	1= Clear 2= Dawn 3= Dusk 4= Dark
RDCAUSE	Roadway-based initial cause of crash	Categorical	ROADCOZ (predictor)	1= Other 2= Wind 3= Lost Control 4= Barrier 5= Vehicle Collision 6= Wet road 7= Snowy surface 8= Icy surface
GEOMETRY	Geometric condition of median crossover crash site	Categorical	GEO (predictor)	1= Straight 2= Curve or Near Intersection
ACCDDATE	Date of a month on which the recorded median crossover crash occurred	Categorical	QUARTER (predictor)	1: Jan to Mar 2: Apr to Jun 3: Jul to Sep 4: Oct to Dec
REACTION	The hour spent for the enforcement agency's being notified of the recorded median crossover crash and reaction to rescue actions	Continuous	REACTION (predictor)	Range: 0-23 hours
AGE	The age of a customer at the time of the recorded median crossover crash, generated from birthdate	Continuous	AGE (predictor)	Range: 15 -91 years
MDNWDTH	Highway median width where the recorded median crossover crash occurred	Continuous	MDNWDTH (predictor)	Range: 16-276 feet
TOTALADT	Total ADT	Continuous	TOTALADT (predictor)	Range: 4,700-92,600 vehicles per day

TABLE 4 Bivariate and Multivariate Logistic Regression Analysis for MCC

Section I: MCC BIVARIATE LOGISTIC REGRESSION ANALYSIS RESULTS

#	Predictor	DF	Likelihood Ratio (Chi-square)	p-value	Odds Ratio Estimates: Effect	Estimate	95% Wald Confidence Limit
1	QUARTER (Quarter)	3	8.872	0.031	Quarter 1 vs. 4	0.7711	(0.517, 1.150)
					Quarter 2 vs. 4	1.3271	(0.834, 2.111)
					Quarter 3 vs. 4	1.3099	(0.824, 2.083)
2	GEO (Geometric condition)	1	0.167	0.683	Geo 1 vs. 2	1.1829	(0.542, 2.586)
3	LIGHT (Light condition)	3	0.172	0.982	Light 1 vs. 4	0.9990	(0.724, 1.380)
					Light 1 vs. 4	0.8437	(0.366, 1.946)
					Light 1 vs. 4	0.9685	(0.397, 2.363)
4	LIQUOR (Liquor involvement)	1	0.641	0.423	Liquor 1 vs. 2	0.8163	(0.499, 1.335)
5	WEATHER (Weather condition)	6	12.513	0.051	Weather 1 vs. 7	1.2815	(0.833, 1.974)
					Weather 2 vs. 7	3.2252	(0.674, 15.410)
					Weather 3 vs. 7	0.8130	(0.511, 1.294)
					Weather 4 vs. 7	0.6313	(0.089, 4.491)
					Weather 5 vs. 7	1.1196	(0.549, 2.284)
					Weather 6 vs. 7	0.5210	(0.251, 1.080)
6	ROADCOZ (Causes by road)	7	12.971	0.073	Roadcoz 1 vs. 8	0.3362	(0.063, 1.806)
					Roadcoz 2 vs. 8	4.0633	(0.072, 229.293)
					Roadcoz 3 vs. 8	1.7246	(1.124, 2.646)
					Roadcoz 4 vs. 8	1.1877	(0.387, 3.640)
					Roadcoz 5 vs. 8	1.1735	(0.658, 2.092)
					Roadcoz 6 vs. 8	1.1770	(0.653, 2.121)
					Roadcoz 7 vs. 8	0.9930	(0.584, 1.689)
7	RDCOND (pavement surface condition)	3	6.864	0.076	Rdcond 1 vs. 4	1.5023	(0.995, 2.268)
					Rdcond 2 vs. 4	1.1140	(0.619, 2.008)
					Rdcond 3 vs. 4	0.9343	(0.547, 1.597)
8	WEEKDAY (Weekday)	6	3.698	0.717	Weekday 1 vs. 7	0.6084	(0.346, 1.071)
					Weekday 2 vs. 7	0.7211	(0.392, 1.327)
					Weekday 3 vs. 7	0.6991	(0.360, 1.361)
					Weekday 4 vs. 7	0.8155	(0.452, 1.471)
					Weekday 5 vs. 7	0.8496	(0.485, 1.489)
					Weekday 6 vs. 7	0.7276	(0.427,1.239)
9	AGE (Driver age)	1	0.188	0.665	Coefficient = 0.002165	SE= 0.005035	
10	MDNWDTH (Median width)	1	0.390	0.532	Coefficient = 0.002705	SE= 0.004353	
11	TOTALADT (Median width)	1	0.009	0.924	Coefficient = 4.159E-7	SE= 4.3217E-6	
12	REACTION (Reaction time)	1	2.414	0.120	Coefficient = 0.01910	SE= 0.0123055	

Total Observations: 631; Time period for data: 2001-2003; Software used: SAS system 9.1; DF: degree of freedom.

Section II: MCC FINAL MULTIVARIATE ORDINAL LOGISTIC REGRESSION MODEL

a: Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > Chi Square
Quarter	3	8.7729	0.0325

b: Analysis of Maximum Likelihood Estimates

Parameter	Estimate	Odds Ratio	Estimated SE	Wald Statistic	p-value
Intercept 3	-2.7062	n/a	0.2125	162.1626	<0.0001
Intercept 2	0.3837	n/a	0.1583	5.8738	0.0154
Quarter 1 (Jan-March)	-0.2603	0.771	0.2040	1.6281	0.2020
Quarter 2 (April-June)	0.2829	1.327	0.2367	1.4287	0.2320
Quarter 3 (July-Sept)	0.2704	1.311	0.2366	1.3067	0.2530

Likelihood ratio test: $\chi^2 = 8.8720$ (DF=3); p-value= 0.0310

Score test for Proportional Odds Assumption: $\chi^2 = 0.6089$ (DF=3); p-value=0.8944

Unfortunately, all the indicator or predictor variables which were retained in the model after the stepwise predictor selection procedure were not statistically significant, except for two intercepts. The indicator variable with smallest p-value is Quarter 1 (0.2020). Although none of explanatory variables in the resultant model are significant, their inclusion in the model after model selection procedure implies that seasonal factor seems to be the most important explanatory variable which contributes to the MCC severity, since the time of year are seasonally related winter and wet road events. Albeit all other tests have adequate statistical validity, this failure to find the significance of explanatory variables makes the ordinal regression results statistically invalid. Accordingly, new directions were considered for bettering the logistic regression modeling in order to explore the relationship between crash severity and potentially significant explanatory variables.

Some studies which applied logistic model to crash severity have found that average daily traffic (ADT) volumes affect crash severity significantly [12], and it is also believed by some professionals that a relationship exists between median width and MCC frequency. Although both were found to be insignificant explanatory variables in the logistic model fitted above, it would be informative if some predictors and crash severity are investigated under conditions having different ADT or median width. In Wisconsin, a median width of 60 feet is the standard non-barrier median width for highways with a speed limit greater than 55 mph. For the sampled 631 MCC data, the median width recorded has a mean of 59.23 ft, a median of 60 ft, and a range of 260. In this study, median width was divided into three classes based on equivalently cumulative percentiles (33.3%, 66.6%, and 100%), which was tried as a preliminary test scenario for investigating MCC severity under unusual conditions. Similarly, the ADT was classified into three levels representing three traffic operational conditions based on the same consideration. Table 6 shows the detailed classification of total ADT and median width. The authors were initially interested in exploring the effects given by ADT and median width and two-way interactions, by constructing a 3×3 (ADT versus Median Width) 2-way combination table. However, due to small sample sizes in most cells, the research was reoriented. In order to make the effects of some explanatory variables embodied in a model in a more protrusive way, only untypical and unusual cases were considered for logistic modeling. Subsequently, the logistic regression was used to examine the predictor variables, which have strong effects on the odds of MCC severity, under four different conditions in two pairs: Inadequate vs. Wider median width, and Low vs. High ADT.

Based solely on 211 MCC with median width not wider than 52 feet, a bivariate logistic regression was performed to investigate the effect of each independent variable. Section I of Table 6 displays the results for bivariate logistic models. The review indicates that ‘Weather’, ‘Roadcoz’, ‘Rdcond’, ‘Totaladt’, and ‘Reaction’ predictors have the greatest influences on the MCC severity. The resulting multivariate ordinal logistic models are given in section II of Table 6.

TABLE 5 Classification of ADT and Median Width

Predictor	Class	Range	Observations
MDNWDTH	Inadequate	16-52 ft	211
	Typical	53-60 ft	306
	Wider	61-276 ft	114
TOTALADT	Low	4,700-19,034 vpd	210
	Normal	19,035-35,334 vpd	211
	High	35,335-92,600 vpd	210

TABLE 6 Bivariate/Multivariate Logistic Regressions for MCC in Median Width Case

Section I: BIVARIATE LOGISTIC REGRESSION - "INADEQUATE " @ "WIDER" MEDIAN WIDTH

#	Predictor	DF	Likelihood Ratio Chi-square		p-value		Parallel lines test (p-value)	
			I	W	I	W	I	W
1	QUARTER (Quarter)	3	3.727	2.265	0.293	0.519	0.756	0.737
2	GEO (Geometry)	1	0.046	0.948	0.830	0.330	0.674	0.597
3	LIGHT (Light condition)	3	2.863	1.239	0.413	0.744	0.516	0.625
4	LIQUOR (liquor involvement)	1	0.000	0.570	0.983	0.450	0.393	0.443
5	WEATHER (Weather condition)	6	16.220	2.768	0.013	0.597	0.610	0.762
6	ROADCOZ (Causes by road)	8	11.944	6.851	0.102	0.335	0.809	0.648
7	RDCOND (Road condition)	4	6.783	6.271	0.079	0.099	0.644	0.425
8	WEEKDAY (Weekday)	6	5.042	2.459	0.538	0.873	0.001	0.040
9	AGE (Driver age)	1	1.382	0.873	0.240	0.350	0.054	0.507
10	TOTALADT (Median width)	1	3.585	1.582	0.058	0.209	0.364	0.236
11	REACTION (Reaction time)	1	5.493	0.194	0.019	0.659	0.317	0.617

DF: degree of freedom; I: Inadequate median width; W: Wider median width

Total Observations: I – 211, W – 114; Time period: 2001-2003; Software used: SAS system 9.1

Section II: FINAL ORDINAL LOGISTIC REGRESSION MODEL FOR MEDIAN WIDTH

1-a: Analysis of Effects for "Inadequate" Median Width

Effect	DF	Wald Chi-Square	Pr > Chi Square
Weather	6	14.8664	0.0213
Reaction	1	7.17287	0.0070

1-b: Analysis of Maximum Likelihood Estimates

Parameter	Estimate	Odds Ratio	Estimated SE	Wald Statistic	p-value
Intercept 3	-3.6578	/	0.5366	46.4639	<0.0001
Intercept 2	-0.4945	/	0.4441	1.2401	0.2655
Weather 1 (Clear)	3.0082	20.251	1.4898	4.0771	0.0435
Weather 2 (Windy)	0.4695	1.599	0.3884	1.4612	0.2267
Weather 3 (Cloudy)	-0.1381	0.871	0.4325	0.1020	0.7494
Weather 4 (Foggy)	1.7021	5.486	2.1008	0.6565	0.4178
Weather 5 (Rainy)	0.5235	1.688	0.7161	0.5346	0.4647
Weather 6 (Sleety)	-1.9333	0.145	0.8595	5.0599	0.0245
Reaction	-0.0356	0.965	0.0231	7.17287	0.0070

Likelihood ratio test: $\chi^2 = 23.6519$ (DF=7); p-value= 0.0013

Score test for Proportional Odds Assumption: $\chi^2 = 6.4420$ (DF=7); p-value= 0.4892

2-a: Analysis Of Effects for "Wider" Median Width

Effect	DF	Wald Chi-Square	Pr > Chi Square
/	/	/	/

2-b: Analysis of Maximum Likelihood Estimates

Parameter	Estimate	Odds Ratio	Estimated SE	Wald Statistic	p-value
Intercept 3	-2.4567	/	0.3473	50.0315	<0.0001
Intercept 2	0.4643	/	0.1924	5.8244	0.0158

Likelihood ratio test: $\chi^2 = 13.9801$ (DF=3); p-value= 0.0029

Score test for Proportional Odds Assumption: $\chi^2 = 1.1578$ (DF=3); p-value= 0.7631

Interpretation reveals that p-value of the likelihood ratio chi-square test is 0.0013 (χ^2 = 23.6519, DF=7). The global null hypothesis for the whole model is rejected. Accordingly, the inference is that the predictor variables given in the model influence the MCC severity. Additionally, the score test for the parallel lines assumption has a p-value of 0.4892 (χ^2 =6.4420, DF=7), which verifies that the proportional odds model is adequately valid for fitting the data. In addition, two indicator variables ('Weather 1' and 'Weather 6') and one predictor ('Reaction') are statistically significant. Consequently, we can make use of the parameter estimates to quantify the effect of significant independent variables on the response variable, in terms of computing the odds ratio. Mathematically, the odds ratio is simply a parameter estimate and can be used to explain the relative effects of a unit change in predictors on crash severity.

For this model, the relative effects of a driver driving under clear weather conditions versus a driver under snowy weather conditions is exp (3.0082) =20.251. This means that the odds of a PDO crash versus injury or fatality severity are approximately 20 times higher for drivers driving in a clear day than for drivers driving in a snowy day. Interchangeably, the odd of a fatality versus PDO or Injury crash is enhanced when driving under snowy weather conditions. Meanwhile, the relative effects of a driving under sleety condition versus a driver under snowy weather condition is exp (-1.9333) = 0.145. This indicates that odds of a PDO crash versus injury or fatality severity are 0.145 times higher for drivers driving in sleet conditions versus driving in snow conditions. This result also implies that sleet-related crashes have greater severity than snow-related crashes. Moreover, the counterpart effect is 0.965 for Reaction predictor. The odds of a PDO crash versus injury or fatality crash will be 0.965 higher for a crash which has EMS response times greater than one hour. This implies that the speed of EMS response is critical to survivability. On the basis of multivariate ordinal logistic regression results, the ensuing regression equations can be written:

$$\ln \frac{\pi_1}{\pi_2 + \pi_3} = -3.6578 + 3.0082 X_1 - 1.9333 X_2 - 0.0356 X_3 \qquad (8)$$

$$\ln \frac{\pi_1 + \pi_2}{\pi_3} = -0.4945 + 3.0082 X_1 - 1.9333 X_2 - 0.0356 X_3 \qquad (9)$$

Where

$X_1 =$ Clear weather indicator (1 if yes, 0 otherwise);

$X_2 =$ Sleety weather indicator (1 if yes, 0 otherwise);

$X_3 =$ Reaction time predictor.

Accordingly, based on equations (5), (6), and (7), the predicted probabilities can be calculated in the following way:

$$p_{PDO} = \frac{e^{-3.6578+3.0082X_1-1.9333X_2-0.0356X_3}}{1+e^{-3.6578+3.0082X_1-1.9333X_2-0.0356X_3}} \qquad (10)$$

$$p_{Injury} = \frac{e^{-0.4945+3.0082X_1-1.9333X_2-0.0356X_3}}{1+e^{-0.4945+3.0082X_1-1.9333X_2-0.0356X_3}} - \frac{e^{-3.6578+3.0082X_1-1.9333X_2-0.0356X_3}}{1+e^{-3.6578+3.0082X_1-1.9333X_2-0.0356X_3}}$$

$$\left(p_{PDO} + p_{Injury} = \frac{e^{-0.4945+3.0082X_1-1.9333X_2-0.0356X_3}}{1+e^{-0.4945+3.0082X_1-1.9333X_2-0.0356X_3}} \right) \qquad (11)$$

$$p_{Fatality} = 1 - (p_{PDO} + p_{Injury}) \qquad (12)$$

For the wider median width condition, both 'Rdcond' and 'Totaladt' were found to be relatively strong predictor variables in the bivariate logistic model. However, the analysis failed to screen out any significant indicator variables or predictors for the multivariate model. Section II of Table 6 shows the results for ordinal logistic modeling.

High ADT vs. Low ADT

Based on 420 MCCs with high and low ADT, Table 7 displays the results for the bivariate/multivariate logistic regression for two cases. In bivariate logistic model, 'Quarter', 'Age', and 'Mdnwdth' predictors were found to have strong influences under high ADT condition. Meanwhile, 'Weather', 'Roadcoz', 'Rdcond', and 'Mdnwdth' were found to be desirable logistic regression variables for low ADT condition.

For high ADT conditions, a likelihood ratio test ($\chi^2 = 15.2505$, DF =4, p-value=0.0042) shows that the global null hypothesis for the whole model is rejected. Associated score test for proportional odds assumption ($\chi^2 = 3.9580$, DF =4, p-value= 0.4117) retains the null hypothesis. Furthermore, the Wald chi-square test indicates that one indicator ('Quarter 1') and one predictor ('Age') have significant p-values of 0.0106 and 0.0041. The comparative effects of a driver being one year older versus a younger driver is exp (0.0284) =1.029. This means that the odds of a PDO crash versus injury or fatality crash is 1.029 times higher for a driver in each year of age. In other words, a younger driver is more likely to be involved in a more severe MCC.

The relative effects of a time of year in terms of the first quarter versus the fourth quarter is exp (-0.9532) = 0.386. This means that the odds of a crash severity of PDO versus crash severity of injury or fatality are 0.386 times higher for drivers who are driving in a day during the first quarter than for drivers who are driving in a day during the fourth quarter of a year. Implicatively, this means that driving in the first quarter is more hazardous than doing so in the fourth quarter.

For low ADT case, both likelihood ratio test ($\chi^2 = 13.9801$, DF =3, p-value=0.0029 and score test for proportional odds assumption ($\chi^2 = 1.1578$, DF =3, p-value= 0.7631) are good. In addition, the Wald chi-square test indicates that 'Rdcond 1' have significant p-values (0.0036). The odds of a PDO crash versus injury or fatality is exp (0.9974) = 2.711 times higher for drivers driving on a dry pavement surface than for drivers on an icy roadway surface. This also implies that driving on icy roadway will be more likely to be involved in a more severe MCC than on a dry pavement surface.

TABLE 7 Bivariate/Multivariate Logistic Regressions for MCC in Total ADT Case

Section I: MCC BIVARIATE LOGISTIC REGRESSION - "HIGH" AND "LOW" ADT

#	Predictor	DF	Likelihood Ratio Chi-square		p-value		Parallel Lines Test (p-value)	
			H	L	H	L	H	L
1	QUARTER (Quarter)	3	6.425	5.920	0.093	0.116	0.249	0.980
2	GEO (Geometry)	1	0.005	1.043	0.942	0.307	0.468	0.451
3	LIGHT (Light condition)	3	1.341	0.838	0.719	0.840	0.593	0.571
4	LIQUOR (Liquor involvement)	1	0.357	0.510	0.550	0.475	0.749	0.737
5	WEATHER (Weather condition)	5	3.183	19.109	0.672	0.004	0.368	0.318
6	ROADCOZ (Causes by road)	8	8.727	16.188	0.273	0.006	0.176	0.817
7	RDCOND (Road condition)	4	1.946	13.980	0.584	0.003	0.379	0.598
8	WEEKDAY (Weekday)	6	2.205	10.167	0.900	0.118	0.474	0.192
9	AGE (Driver age)	1	7.191	1.220	0.007	0.269	0.587	0.133
10	MDNWDTH (Median width)	1	3.042	4.431	0.081	0.035	0.277	0.101
11	REACTION (Reaction time)	1	0.871	0.001	0.351	0.981	0.638	0.975

DF: degree of freedom; H; High ADT; L: Low ADT
Total Observations: H – 210, L – 210; Time period: 2001-2003; Software used: SAS system 9.1

Section II: FINAL ORDINAL LOGISTIC REGRESSION MODEL FOR ADT

1-a: Analysis of Effects for High ADT

Effect	DF	Wald Chi-Square	Pr > Chi Square
Quarter	3	7.9083	0.0479
Age	1	8.2534	0.0041

1-b: Analysis of Maximum Likelihood Estimates

Parameter	Estimate	Odds Ratio	Estimated SE	Wald Statistic	p-value
Intercept 3	-3.3581	/	0.4842	48.1042	<0.0001
Intercept 2	-0.1522	/	0.3859	0.1556	0.6933
Quarter 1 (Jan-March)	-0.9532	0.386	0.3728	6.5358	0.0106
Quarter 2 (April-June)	-0.0632	0.939	0.4155	0.0231	0.8792
Quarter 3 (July-Sept)	-0.3119	0.732	0.3872	0.6487	0.4206
Age	0.0284	1.029	0.00990	8.2534	0.0041

Likelihood ratio test: $\chi^2 = 15.2505$ (DF=4); p-value=0.0042

Score test for Proportional Odds Assumption: $\chi^2 = 3.9580$ (DF=4); p-value= 0.4117

2-a: Analysis of Effects for Low ADT

Effect	DF	Wald Chi-Square	Pr > Chi Square
Rdcond	3	13.4946	0.0037

2-b: Analysis of Maximum Likelihood Estimates

Parameter	Estimate	Odds Ratio	Estimated SE	Wald Statistic	p-value
Intercept 3	-3.5051	/	0.4121	72.3522	<0.0001
Intercept 2	-0.0203	/	0.2743	0.0055	0.9411
Rdcond 1 (Dry)	0.9974	2.711	0.3429	8.4616	0.0036
Rdcond 2 (Wet)	0.2844	1.329	0.5511	0.2662	0.6059
Rdcond 3 (Snowy)	-0.2059	0.814	0.4382	0.2208	0.6384

Likelihood ratio test: $\chi^2 = 13.9801$ (DF=3); p-value= 0.0029

Score test for Proportional Odds Assumption: $\chi^2 = 1.1578$ (DF=3); p-value= 0.7631

CONCLUSIONS

Median crossover crash severities were modeled by using ordinal logistic regression using the response (crash severity) levels: PDO, Injury, and Fatality. In the case of the 631 MCCs in Wisconsin between 2001 and 2003, no predictors were found to have significant effects on the MCC severity if significance level is set at 0.05. However, the results showed that seasons or the time of year may play a critical role in determining the MCC severity. This result is likely due to the fact that many of the most severe MCC crashes occur during the winter weather months, correlating road conditions with time of year.

Additional statistical analysis showed that younger drivers had a higher severe crash probability than older drivers when the traffic volume on roadways is relatively high. Reasons for this are unknown, but may be due to inexperience and risky driving maneuvers. The seasonal factor, directly related to weather conditions and pavement conditions, exerts a dramatic effect on the crash severity. When traffic volume is low, the only significant explanatory variable is road condition as driving on an icy pavement surface is more precarious than on a dry roadway. Under the condition of inadequate median width, weather condition has a close relation with crash severity, and EMS reaction time after the crash occurrence is also important for decreasing the rate of fatalities. Therefore, the speed at which emergency vehicles react to a crash occurrence will have a significant impact upon crash consequences. If the median width is sufficient enough, no explanatory variable significantly affects the crash severity.

It is evident that season, weather and road condition variables are causally associated with each other and winter snow or ice in Wisconsin is a prime suspect for increasing the frequency and severity of MCC. Wisconsin's geographical location may play the most significant role in affecting MCC severity. Furthermore, the response time of emergency vehicle units and the age of drivers are also very influential factors in predicting the MCC severity. The results of the MCC severity modeling in this study could be used by traffic management authorities to determine the probability of fatal, injury, and PDO as based on a similar set of environmental or traffic explanatory variables. They may be also helpful to facilitate the decision-making process concerning roadway safety enhancements, such as median barrier protection.

RECOMMENDATIONS FOR FURTHER INVESTIGATION

Though substantial research has been presented here, the authors note that there is still more that can be done to investigate MCC severity and all related explanatory variables and consequently improve the safety of the roadways in Wisconsin. In continuing research, it will be helpful to include additional median geometric data (cross-slope; structure and material) for the locations as well as other data for vehicle types involved and occupant restraint use. Speed is also a desirable attribute in evaluating crash severity but cannot be determined for each crash. Additional years of crash data may also strengthen the results from this study. Furthermore, it is important to continue educate drivers risky driving and crash avoidance related to all crash types, specifically MCCs. This includes improved education of drivers about the potential hazardous of *winter* driving and more effective education of younger drivers in how to anticipate and avoid risky scenarios.

REFERENCES

[1] *Traffic Safety Facts: 2003 Data*. National Center for Statistics and Analysis of the National Highway Traffic Safety Administration, Washington, D.C., 2004.

[2] Neuman, T.R., R. Pfefer, K.L. Slack, K.K. Hardy, F. Council, H. McGee, L. Prothe, K. Eccles. <Guidance for Implementation of the AASHTO Strategic Highway Safety Plan>, Volume 6: A Guide for Addressing Run-Off-Road Collisions. *National Cooperative highway Research Program Report 500*, TRB, National Research Council, Washington, D.C., 2003.

[3] Fatality Analysis Reporting System (FARS) 2001 Annual Report File. National Center for Statistics and Analysis of the National Highway Traffic Safety Administration, Washington, D.C., 2002.

[4] Weekly Fatality Report. Wisconsin Department of Transportation. February 8, 2005. (http://www.dot.state.wi.us/drivers/drivers/traffic/crash/monthfatal.htm).

[5] 1982-2002 (Final) FARS Files and 2003 FARS Annual Report File, FHWA's Highway Statistics Annual Series.

[6] Drakopoulos, A. and E. Ornek. <Systematic Evaluation Run-Off Road Crash Locations in Wisconsin>. State of Wisconsin Department of Transportation, Madison, WI, 2004.

[7] <A Policy on Geometric Design of Highways and Streets>. American Association of State Highway Transportation Officials, Washington, D.C., 2001.

[8] Lee, J., and F. Mannering. <Impact of Roadside Features on the Frequency and Severity of Run-Off-Roadway Crashes: An Empirical Analysis>. Accident Analysis and Prevention, Vol. 34, No. 2, 2002, pp. 149-161.

[9] Abdel-Aty, M. A., C. L. Chen, and J. R. Schott. <An Assessment of Driver Age on Traffic Crash Involvement Using Log-Linear Models>. Accident Analysis and Prevention, Vol.30, No. 6, 1998, pp. 851-861.

[10] Kim, K., L. Nitz, J. Richardson, and L. Li. <Personal and Behavioral Predictors of Automobile Crash and Injury Severity>. Accident Analysis and Prevention, Vol.27, No. 4, pp. 469-481, 1995.

[11] Dissanayake, S., and John Lu. <Analysis of Severity of Young Driver Crashes: Sequential Binary Logistic regression Modeling>. In Transportation Research Record: Journal of the Transportation Research Board, No. 1784, TRB, National Research Council, Washington, D. C., 2002, pp. 108-114.

[12] Eric T. Donnell and John M. Mason. <Predicting the Severity of Median-Related Crashes in Pennsylvania by Using Logistic Regression>. Transportation Research Record, No. 1897, TRB, National Research Council, Washington, D.C., 2004, pp. 55-63.

[13] Simon P. Washington, Matthew G. Karlaftis, and Fred L. Mannering, <Statistical and Econometric Methods for Transportation Data Analysis>. Chapman & Hall/CRC. 2003.

[14] Ben-Akiva, M., and S. R. Lerman. <Discrete Choice Analysis: Theory and Application to travel Demand>. The MIT Press, Massachusetts, 1993.

[15] Agresti, A. <An Introduction to Categorical Data Analysis>. John Wiley and Sons, New York, 1996.

[16] Hosmer, D.W., and S. Lemeshow. <Applied Logistic Regression>. John Wiley and Sons, New York, 1990.

[17] Maura E. Stokes, Charles S. Davis, Gary G. Koch. <Categorical data analysis using the SAS system>, Cary, NC, SAS Institute; Wiley, 2001.