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Crash Data-Based Investigation into How Injury Severity Is Affected by Driver Errors

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Abstract

Unsafe driving behaviors, driver limitations, and conditions that lead to a crash are usually referred to as driver errors. Even though driver errors are widely cited as a critical reason for crash occurrence in crash reports and safety literature, the discussion on their consequences is limited. This study aims to quantify the effect of driver errors on crash injury severity. To assist this investigation, driver errors were categorized as sequential events in a driving task. Possible combinations of driver error categories were created and ranked based on statistical dependences between error combinations and injury severity levels. Binary logit models were then developed to show that typical variables used to model injury severity such as driver characteristics, roadway characteristics, environmental factors, and crash characteristics are inadequate to explain driver errors, especially the complicated ones. Next, ordinal probit models were applied to quantify the effect of driver errors on injury severity for rural crashes. Superior model performance is observed when driver error combinations were modeled along with typical crash variables to predict the injury outcome. Modeling results also illustrate that more severe crashes tend to occur when the driver makes multiple mistakes. Therefore, incorporating driver errors in crash injury severity prediction not only improves prediction accuracy but also enhances our understanding of what error(s) may lead to more severe injuries so that safety interventions can be recommended accordingly.

According to NHTSA, 37,461 people were killed on U.S. roads in 2016, resulting in more than 100 deaths per day (*1*). The roadway fatality counts in the U.S. increased by 5.6% from 2015. Moreover, non-fatal injury crashes on U.S. roads increased by 4.1% from 2014 to 2015 (*2*). In 2010, the total cost of roadway crashes in the U.S.A. was tagged as $871 billion in economic loss and societal harm (*3*). Because of this economic and societal impact of traffic crashes, researchers have devoted decades of effort to improve traffic safety by implementing safety countermeasures to reduce the occurrence as well as the degree of injury sustained by those involved in crashes.

A significant amount of safety research has examined crash injury outcomes to gain a comprehensive understanding of the factors contributing to crash injury severity. Research has shown that driver injury severities resulting from a crash event are influenced by roadway, traffic, driver demography, and vehicle and environmental characteristics (*4–12*). Discrete response models, both unordered (e.g., multinomial logit, multinomial probit, etc.) and ordered (e.g., ordered logit, ordered probit, etc.) have been used extensively by researchers to explore the relationship between covariates and driver injury severity. The role of driver behaviors has also been widely recognized in a safety-critical system such as the roadway transportation system (*11*, *13–17*). The research on the effect of driver errors on crash injury outcome, however, is limited.

Driver errors specifically refer to unsafe driving behaviors, driver limitations, and conditions that lead to a crash. They belong to a specific category within a broader subject of human factors in roadway safety, and mainly refer to human ability, needs, limitations, and other human characteristics that can influence driving tasks. A significant amount of research has been conducted on human factors, resulting in prolific guidance to highway designers and traffic engineers on handling safety issues in highway design and traffic operations (*18*, *19*). As a result, broader acceptance has been observed towards a

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safety system that means higher safety standards in relation to being more proactive in crash prevention and being more forgiving for driver errors.

Driver errors in a crash can be obtained by reviewing a crash report, including police officers' judgments and witness accounts. Then, a structured approach is usually taken to explore the underlying mechanism of error-prone situations. Representative theories have been proposed along with established taxonomies from the physiological, cognitive, and information processing perspectives regarding human errors in fields such as aviation and railways (*20*, *21*). A comprehensive review of human error categorization including driver error can be found in the study conducted by Stanton and Salmon (*22*). Four human error classification schemes are popular among existing literature: Norman's error categorization based on schema activation (*23*), Rasmussen's skill, rule, and knowledge error classification (*24*), Reason's slips, lapses, mistakes, and violations classification (*25*), and Treat et al.'s recognition, decision, performance, and non-performance errors based on the stages of information processing during a driving task (*26*). Several safety studies have used these different taxonomies to categorize driver errors and explore their effect on crash occurrence (*27*, *28*).

This study attempted to explore the effect of driver errors on crash injury severity levels for segment-related crashes, categorizing driver error information from crash records, following the error taxonomy based on sequential events in a driving task. Possible combinations of driver error categories were generated to explore the effect of different combinations of driver errors on the crash outcome. An exploratory analysis was then conducted to check the dependency between driver error categories and injury severity levels. Injury severity models were subsequently developed to understand the effect of driver error combinations on crash injury severity. Considering the effect of driver errors, injury severity modeling results may provide specific insights into explanatory variables and help researchers and safety professionals to develop cost-effective countermeasures.

Literature Review

The taxonomy of human errors has been widely used in most safety-critical systems to analyze the effects of human errors (*22*). Such taxonomy is required to classify and categorize a wide range of improper driving behaviors that compromise safety situation. Norman categorized human errors based on a psychological theory of schema activation (*23*). He noted that human action sequences are triggered by knowledge structures that are organized as memory units called schemas. As the action is directed by schemas, faulty schemas or faulty activations of schemas will lead to erroneous performance. Rasmussen proposed skill, rule, and knowledge-based human error classification in his classic paper (*24*) and stressed that "errors cannot be studied as a separate category of behavior fragments" but must be viewed within "cognitive control of behavior." Human errors can be affected by skill, experience, and familiarity with the situation encountered. Experienced drivers do not tend to commit the same kinds of errors as novice drivers. For the categorization of driver errors, the study conducted by Reason et al. has been popular (*29–32*). The authors categorized human errors of vehicular drivers into slips, lapses, mistakes, and violations (*25*). They defined attentional and memory failures as slips and lapses, respectively. Both slips and lapses represent human errors in which the action is unintended, whereas mistakes are associated with the intended action. Violations are more complex, categorized as behaviors that deviate from accepted procedures, standards, and rules, either deliberate or unintentional.

Based on driver behaviors collected from crash and incidents, Treat et al. categorized driver errors into recognition, decision, performance, and non-performance errors which are broadly based on the stages of information processing during the driving task (*26*). The error categorization developed by Treat et al. was used by several other researchers (*13*, *28*, *33*). Najm et al. classified driver errors in recognition, decision and erratic error (*33*). The National Motor Vehicle Crash Causation Survey study used error categorization taxonomy developed by Treat et al. and found that 94% of total crashes are caused by driver error (*13*).

Many driver errors such as speeding, reckless driving, overtaking, improper gap acceptance, adherence to traffic controls, and so forth, have been identified as a contributor of crash occurrence and injury outcome in safety literature (*13*, *27*, *28*). Multiple safety countermeasures ranging from roadway reengineering, improved vehicle safety features, and strategies to influence driver behavior have been developed to reduce crash occurrences and injury severities. It is also noted that crash countermeasures achieve the best results when they influence driver behavior (*34*). Adanu and Jones noted that driving behaviors such as speeding, DUI, and distracted driving significantly contribute to the occurrence of crashes with higher injury severities (*35*). They suggested designing targeted outreach and education campaigns to address these specific behaviors.

Based on statistical evidence provided in previous research, it is worth exploring the effect of driver errors on the injury outcome. Categorizing driver errors based on driver factors observed from crash reports seems a reasonable choice because of the availability of data and error categorization taxonomy.

Methodology

The ordered-probit (OP) model is used to account for the ordinal nature of the crash injury severity levels. The structure of an OP model is derived by defining an unobserved latent propensity U, which can be described as a linear function:

$$U = \boldsymbol{\beta}' \boldsymbol{X} + \varepsilon \quad (1)$$

where **X** is a vector of independent variables defining the discrete ordering for each observation, $\boldsymbol{\beta}$ is a vector of estimable model coefficients, and ε is an error term accounting for the unobservable effects. Using this structure, the observed ordinal dependent variable, or the crash injury severity for each observation can be defined as (*36*):

$$\left.\begin{array}{ll} y = 1 & if\ U \leqslant \mu_1 \\ y = 2 & if\ \mu_1 \leqslant U \leqslant \mu_2 \\ \bullet\bullet & \bullet\bullet \\ y = I & if\ U \geqslant \mu_{I-1} \end{array}\right\} \quad (2)$$

where the μ values are estimable thresholds that define y corresponding to integer ordering of injury severity levels, and I is the highest integer level of injury severity. If the random error term ε is assumed to follow a standard normal distribution, the model is derived to be an OP model. The probability of each category can be calculated as follows:

$$\text{prob}(y = i) = \boldsymbol{\Phi}(\mu_i - \boldsymbol{\beta}' \boldsymbol{X}) - \boldsymbol{\Phi}(\mu_{i-1} - \boldsymbol{\beta}' \boldsymbol{X}) \quad (3)$$

where i corresponds to the injury severity level to be analyzed, and $\boldsymbol{\Phi}$ (•) is the cumulative standard normal distribution.

Data Description and Exploratory Analysis

Segment-related crashes that occurred on the Wisconsin state trunk network system between 2011 and 2015 were collected from WisTransportal data hub maintained by TOPSLAB (*37*). Deer-related and hit-and-run crashes were removed from the crash dataset as driver-related information for these crashes are not available. After cleaning crashes for missing attributes, 56,564 rural crashes were extracted from the crash database. The severity for each crash is listed in the "KABCO" scale in Wisconsin Motor Vehicle Accident Reporting Form (MV4000) crash database. The "KABCO" scale of crash injury severity is defined as fatality (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C), and no injury (O). It is a common practice to consolidate KABCO into three levels—major injury (K + A), minor injury (B + C), and no injury (O) to ensure that a sufficient number of observations is available in each injury severity level (*10*, *14*, *38*). Specific driver errors were extracted from the MV4000 database, in which the investigating police officers documented detailed accident information (*37*). There is a list of 14 driver-related factors from which the reporting police officer identifies the driver-related factor(s) associated with a crash.

Based on similarities in driver-related factors and error categorization taxonomy developed by Treat et al., driver-related factors were then grouped into recognition, decision, performance, and non-performance errors (*26*). Note that driver impairment is not considered as a driver error in the error categorization taxonomy developed by Treat et al. (*26*). However, driver impairment influences drivers' decision-making ability which may affect all error categories. Table 1 shows the taxonomy used to categorize driver errors in the study.

The broad categorization of driver errors follows a sequence of information processing during driving. When driving, a driver needs to detect and identify a hazard, decide what to do, and react accordingly. A driver's recognition efficiency can be affected by an internal or external distraction or by any form of inattention. Recognition error refers to all the driver factors that may lead to a lack of awareness or failure in the recognition of hazardous situations. A driver's decision on what to do directly leads to what happens next, whether it is a decision after detecting a hazard or a decision while driving. A bad maneuver decision after recognizing a hazardous situation may cause a crash. A reckless decision such as "exceeding the speed limit" may go wrong even without an imminent hazard. In the same sequence, if a maneuver is not properly performed, a crash may happen. Poorly performed driving tasks are categorized as performance error, which is dependent on the driver's experience and skills. Although non-performance error is not related to driver behavior, it represents a driver's health conditions, fatigue, level of impairment, or other non-performance issues.

One crash event may involve one or multiple driver error categories, as drivers may make several sequential errors that resulted in a crash. Based on the driver error categorization used in this study, there can be 16 possible combinations of driver errors (${}^4C_0 + {}^4C_1 + {}^4C_2 + {}^4C_3 + {}^4C_4 = 16$, where C represents combination) out of four different driver error categories. These combinations include no driver error, any one of the driver error categories, any two driver error categories, any three driver error categories, and all driver error categories. Each error combination ($\boldsymbol{EC_i}$) was designated using an initial letter coding system where the sequence of letters follows the error categorization sequence (recognition [R] → decision [D] → performance [P] → non-performance [N]). The no driver error category was represented using the letter "O." For example, a driver

Table 1. Categorization and Distribution of Driver Error

Error category	Error examples	Wisconsin criteria
Recognition error	• Inadequate surveillance • Internal distraction • External distraction • Inattention	• Inattentive driving
Decision error	• Too fast for conditions • Too fast for curve • False assumption of other's action • Illegal maneuver • Misjudgment of gap or other's action • Following too closely • Aggressive driving behaviors	• Too fast for condition • Exceed speed limit • Disregard traffic control • Following too close
Performance error	• Overcompensation • Poor directional control • Panic/freezing • Other performance error	• Improper overtake • Improper turn • Failure to keep vehicle under control • Left of center • Unsafe backing • Failure to yield
Non-performance error	• Sleep • Heart attack • Other non-performance errors	• Disability • Driver condition • Others

failed to yield to another driver while driving over the speed limit. This case represents a combination of decision and performance errors, denoted as "DP." Another example can be a driver was talking on the phone while driving and failed to keep the vehicle under control on a horizontal curve. This case represents a combination of recognition and performance error, coded as "RP."

The odds of major injury with and without a specific driver error combination was estimated to explore the effect of driver error combinations on injury severity levels. Table 2 presents the association between all 16 combinations of driver errors and injury severities. In Table 2, the odds of major injury with EC_i indicate the probability of major injury crashes compared with non-major injury crashes when EC_i driver error occurs. Similarly, the odds of major injury with EC_j (for all $j \neq i$) indicate the probability of major injury crashes compared with non-major injury crashes for all driver error combinations except for the occurrence of $\boldsymbol{EC_i}$ error. The odds of injury crashes with driver errors are estimated using the following equations:

$$\text{Odds of Major Injury with } EC_i = \frac{\text{Number of major injury crashes with } EC_i}{\text{Number of minor injury crashes with } EC_i} \times 100\% \tag{4}$$

$$\text{Odds of Major Injury with } EC_j \text{ (for all } j \neq i) = \frac{\text{Total number of major injury crashes} - \text{Number of Major injury crashes with } EC_i}{\text{Total number of minor injury crashes} - \text{Number of minor injury crashes with } EC_i} \times 100\% \tag{5}$$

$$\text{Odds ratio of } EC_i = \frac{\text{Odds of Major injury with } EC_i}{\text{Odds of Major Injury with } EC_j \text{ (for all } j \neq i)} \tag{6}$$

Table 2 also presents the odds of major injury with EC_i, the odds of major injury without EC_i, the resultant odds ratio and the ranking. Twelve out of 16 error combinations exceed 6.16%, the average odds of major injury crashes. Performance error only (P) has the maximum frequency of both major and non-major injury severity in rural crashes. Despite its dominance in the major injury severity, P's odds ratio is ranked 10th. DPN, a combination of decision, performance, and non-performance errors, stays atop with an odds ratio of 4.09, meaning its odds of major injury crashes is 4.09 times higher than any other error combinations. RDPN includes all error types but has the second highest odds ratio. This indicates the participating driver errors in each driver error category may have different effects. The rank of the estimated odds ratio is the lowest for "O" representing no driver error, which is expected.

A chi-square test was conducted to test whether the driver error combinations and injury severity levels are independent or not. The critical chi-square value with 15 degrees of freedom at a 5% level of significance is 24.99. The estimated chi-square value for rural crash severities

Table 2. Cross-Classification Table for Driver Error Combinations and Injury Severity

Error combination	Recognition error	Decision error	Performance error	Non-performance error	No error	Major injuries (K + A)	Non-major injuries	Total	Odds of major injury with EC_i	Odds of major injury with EC_j (for all $j \neq i$)	Odds ratio (rank)
O					✓	309	10,610	10,919	2.91%	6.97%	0.42 (16)
R	✓					350	6,538	6,888	5.35%	6.27%	0.85 (13)
D		✓				380	11,640	12,020	3.26%	6.97%	0.47 (15)
P			✓			732	8,102	8,834	9.03%	5.64%	1.60 (10)
N				✓		222	2,380	2,602	9.33%	6.01%	1.55 (11)
RD	✓	✓				77	1,508	1,585	5.11%	6.19%	0.82 (14)
RP	✓		✓			186	1,540	1,726	12.08%	5.98%	2.02 (8)
RN	✓			✓		51	398	449	12.81%	6.11%	2.10 (7)
DP		✓	✓			414	7,268	7,682	5.70%	6.23%	0.91 (12)
DN		✓		✓		56	435	491	12.87%	6.10%	2.11 (6)
PN			✓	✓		149	719	868	20.72%	5.96%	3.48 (3)
RDP	✓	✓	✓			89	872	961	10.21%	6.09%	1.68 (9)
RDN	✓	✓		✓		17	111	128	15.32%	6.14%	2.49 (5)
RPN	✓		✓	✓		67	388	455	17.27%	6.08%	2.84 (4)
DPN		✓	✓	✓		135	553	688	24.41%	5.97%	4.09 (1)
RDPN	✓	✓	✓	✓		48	220	268	21.82%	6.09%	3.58 (2)
Total						3282	53282	56564	6.16%		

Note: D = decision error; DN = decision+non-performance error; DP = decision+performance error; DPN = decision + performance+non-performance error; EC = error combination; N = non-performance error; O = no error; P = performance error; PN = performance+non-performance error; R = recognition error; RD = recognition+decision error; RDN = recognition+decision/non-performance error; RDP = recognition+decision+performance error; RDPN = recognition+decision+performance/non-performance error; RN = recognition/non-performance error; RP = recognition+performance error; RPN = recognition+performance+non-performance error.

among 16 driver error combination is 1226.09, indicating that the driver error combinations and crash injury severities are not statistically independent. These exploratory analyses show the evident influence of driver error on crash injury severity. Therefore, the influence of driver error needs to be controlled in crash severity modeling.

Model Development

To quantify the effect of different driver error combinations on crash injury severity, explanatory variables from four broad categories along with driver error combinations were considered for model development: driver characteristics (including driver gender, age, vehicle type, safety restraint use, and impairment), roadway characteristics (including existence of horizontal and vertical curve, roadway type, and posted speed limit), environmental factors (including lighting condition, roadway pavement condition, and weather condition), and crash characteristics (including manner of collision, rollover, roadside element, and existence of pedestrian or bike). Attributes for the above-mentioned variables for each crash were collected from the crash report. Table 3 provides the summary statistics of explanatory variables.

Driver error has been modeled in previous roadway safety literature to help understand when, where, and why drivers make mistakes and how we can prevent them (*16*, *27*, *39*). Modeling results show that driver errors are highly correlated with factors that also influence crash occurrence and injury severity. But these studies did not consider the concurrence of multiple errors (*16*, *27*, *39*). Modeling all error categories and their combinations will provide a detailed view of variables possibly contributing to the errors. Rather than developing complicated models, binary logit models have been run for each of the 15 error combinations with all 21 variables (in Table 3) as the explanatory variables. For brevity, Table 4 shows the count of statistically significant variables for predicting error combination.

According to Table 4, the average number of statistically significant variables is 15.5 for one error, 10.67 for two error combinations, 7.75 for three error combinations, and 4 for four error combinations. Although variations exist among driver, roadway, and environmental factors, the general trend of decreasing number of statistically significant variables with the increasing error complexity remains the same. It is understood that these variables can only partially explain the reasons for making a mistake. But the explanation power appears to dwindle when errors become more complicated. Thus, these variables may not be adequate to explain driver errors, especially the complicated ones which are strongly associated with more severe injuries. Another possible reason for the decreasing trend in the number of statistically significant variables could be the smaller sample size for driver error combinations with multiple driver errors. Although the sample size for driver error combinations (except for EC1101) exceeds the rule-of-thumb

Table 3. Summary Statistics of Explanatory Variables

Variable	Description	Type	Frequency	Percentage
		Driver characteristics		
Gender	Male	Categorical with 2 levels	34,926	61.75
	Female		21,638	38.25
Age	<25 years	Categorical with 3 levels	16,840	29.77
	25–65 years		35,225	62.27
	>65 years		4,499	7.95
Vehicle type	Motorcycle	Categorical with 4 levels	1,097	1.94
	Passenger car		41,348	73.10
	Light truck		10,172	17.98
	Heavy truck		3,947	6.98
Seatbelt	No	Categorical with 2 levels	4,431	7.83
	Yes		52,133	92.17
Impaired	No	Categorical with 2 levels	53,064	93.81
	Yes		3,500	6.19
		Roadway characteristics		
Horizontal curve	No	Categorical with 2 levels	45,528	80.49
	Yes		11,036	19.51
Vertical curve	No	Categorical with 2 levels	44,815	79.23
	Yes		11,749	20.77
Roadway type	DWB	Categorical with 4 levels	9,549	16.88
	UD		29,069	51.39
	DWOB		16,839	29.77
	1-Way		1,107	1.96
Speed	Mile per hour	Continuous	55.2*	11.03*
		Environmental factors		
Lighting condition	Day	Categorical with 3 levels	35,865	63.41
	Night-unlit		18,749	33.15
	Night-lit		1,950	3.45
Roadway condition	Dry	Categorical with 3 levels	31,056	54.90
	Wet		6,161	10.89
	Snow		19,347	34.20
Weather condition	Clear	Categorical with 4 levels	22,679	40.09
	Cloudy		15,971	28.24
	Rain		3,628	6.41
	Snow		14,286	25.26
		Crash characteristics		
Manner of collision	SVC	Categorical with 5 levels	34,617	61.20
	Angle		2,801	4.95
	Head on		1,025	1.81
	Rear end		11,475	20.29
	Side swipe		6,646	11.75
Rollover	No	Categorical with 2 levels	50,399	89.10
	Yes		6,165	10.90
Roadside element	None	Categorical with 4 levels	31,455	55.61
	Fixed[a]		15,657	27.68
	Moving[b]		2,711	4.79
	Ditch		6,741	11.92
Pedestrian/bike	No	Categorical with 2 levels	56,285	99.51
	Yes		279	0.49

Note: DWB = divided with barrier; DWOB = divided without barrier; SCV = single vehicle crash; UD = undivided.
*The speed variable is continuous, and the descriptive statistics are presented as mean and standard deviation.
[a]Fixed roadside objects represent roadside hardware such as utility pole, traffic sign/signal, guardrail, and so forth, which are meant to guide traveler, prevent fatal injuries, or both.
[b]Moving roadside objects include parked vehicle, small animals, and other moving objects as listed in the crash report.

Table 4. Explanatory Variables for Predicting Driver Error*

	EC	Driver characteristics (8)	Roadway characteristics (6)	Environmental factors (7)	Total (21)	Average
One error	R	8	5	6	19	15.5
	D	4	4	5	13	
	P	8	3	4	15	
	N	8	4	3	15	
Any two errors	RD	5	4	2	11	10.67
	RP	6	5	3	14	
	RN	5	0	5	10	
	DP	7	4	5	16	
	DN	2	0	2	4	
	PN	4	3	2	9	
Any three errors	RDP	6	3	3	12	7.75
	RDN	3	0	1	4	
	RPN	4	2	3	9	
	DPN	3	1	2	6	
All errors	RDPN	2	1	1	4	4

Note: D = decision error; DN = decision+non-performance error; DP = decision+performance error; DPN = decision+performance+non-performance error; EC = error combination; N = non-performance error; O = no error; P = performance error; PN = performance+non-performance error; R = recognition error; RD = recognition+decision error; RDN = recognition+decision+non-performance error; RDP = recognition+decision+performance error; RDPN = recognition+decision+performance+non-performance error; RN = recognition+non-performance error; RP = recognition+performance error; RPN = recognition+performance+non-performance error.
*Value presented in parenthesis indicates the total number of coefficients to estimate within each variable group.

for minimum required sample size (event per variable criterion > 10), caution needs to be exercised while exploring the correlation between driver error combinations and other explanatory variables.

Incorporating driver error as a predictor variable in injury severity modeling may create opportunities to improve model performance as well as our understanding of what the driver error means for the injury severity of a crash. Thus, three models are proposed as follows:

Model 1: Using driver, roadway, environmental, and crash characteristics variables as explanatory variables.
Model 2: Using only driver error combinations as explanatory variables.
Model 3: Using driver error combinations in association with driver, roadway, environmental, and crash characteristics variables as explanatory variables.

In Model 1, all traditional variables including driver characteristics, roadway characteristics, environmental factors, and crash characteristics variables were used as explanatory variables to predict crash injury severity. Model 2 was developed to explore how much deviance in injury severity data can be explained solely by the driver error combination variable. In Model 3, driver error combinations were used along with all explanatory variables used in Model 1. To check estimation bias resulting from multicollinearity, one simple method is to check the variation in the estimated model parameters between Model 1 and 3. The existence of multicollinearity makes the model very sensitive to minor changes, which leads to significant variation in model parameter estimates.

The OP model was estimated to quantify the influence of explanatory variables described above. The "polr" package in R was used to estimate the coefficients of OP models. The coefficient estimates represent the ordered log-odds estimate where a positive coefficient means a possible increase in the latent injury risk propensity and a negative value means a possible decrease in injury risk propensity. The parameter estimates from OP models are presented in Table 5.

Model Performance

All estimated parameters provided in Table 5 are statistically significant at a 5% significance level in predicting crash injury severities. The threshold estimates (both μ_1 & μ_2) presented in Table 5 are found highest in Model 2. This indicates that the estimated injury risk propensity needs to exceed a higher value to be qualified as a minor or a major injury crash in Model 2 compared with Model 1 and 3. A comparison between threshold estimates between Model 1 and 3 indicates that the estimated thresholds are a little higher with Model 3 because of the incorporation of driver error combinations. Considering the higher threshold estimates, it can be noted that the contribution of covariates was overestimated for some

Table 5. Ordered Probit Model Estimation Results

		Model 1		Model 2		Model 3	
Variable	Value	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error
			Driver characteristics				
Gender	Male			Base level			
	Female	0.125	0.012	na	na	0.131	0.012
Age	Young (<25)			Base level			
	Middle-age (25–65)	0.057	0.012	na	na	0.072	0.013
	Old (>65)	0.18	0.022			0.193	0.022
Vehicle type	Motorcycle			Base level			
	Passenger car	−1.081	0.037	na	na	−1.14	0.037
	Light truck	−1.065	0.038	na	na	−1.115	0.039
	Heavy truck	−1.21	0.042	na	na	−1.238	0.042
Seat belt	No			Base level			
	Yes	–0.671	0.019	na	na	–0.643	0.02
Impaired	No			Base level			
	Yes	0.496	0.022	na	na	0.546	0.043
			Roadway characteristics				
Horizontal curve	No			Base level			
	Yes	0.125	0.014	na	na	0.111	0.014
Road type	DWB			Base level			
	UD	0.299	0.018	na	na	0.292	0.018
	DWOB	0.054	0.017	na	na	0.047	0.018
	1-Way	–0.21	0.045	na	na	–0.226	0.045
Speed		0.016	0.001	na	na	0.016	0.001
			Environmental factors				
Lighting condition	Day			Base level			
	Night-unlit	–0.052	0.013	na	na	–0.051	0.013
	Night-lit	–0.089	0.033	na	na	–0.086	0.033
Pavement condition	Dry			Base level			
	Wet	–0.104	0.018	na	na	–0.086	0.018
	Snow	–0.369	0.013	na	na	–0.316	0.015
			Crash characteristics				
Rollover	No			Base level			
	Yes	0.759	0.025	na	na	0.647	0.026
Roadside element	None			Base level			
	Fixed	0.24	0.022	na	na	0.129	0.023
	Moving	–0.312	0.036	na	na	–0.21	0.037
	Ditch	0.377	0.026	na	na	0.265	0.026
Manner of collision	SVC			Base level			
	Angle	0.771	0.03	na	na	0.644	0.031
	Head on	1.655	0.041	na	na	1.523	0.042
	Rear end	0.594	0.023	na	na	0.491	0.025
	Side swipe	0.246	0.026	na	na	0.116	0.027
Ped-bike	No			Base level			
	Yes	2.068	0.073	na	na	1.988	0.073
			Driver error combinations				
Driver errors	O			Base level			
	R	na	na	0.494	0.02	0.346	0.022
	D	na	na	0.229	0.018	0.221	0.02
	P	na	na	0.482	0.019	0.314	0.021
	N	na	na	0.604	0.027	0.382	0.029
	RD	na	na	0.512	0.033	0.324	0.036
	RP	na	na	0.759	0.031	0.523	0.033
	RN	na	na	0.815	0.056	0.514	0.059
	DP	na	na	0.400	0.02	0.371	0.022
	DN	na	na	0.782	0.054	0.45	0.057
	PN	na	na	1.042	0.041	0.62	0.044
	RDP	na	na	0.743	0.04	0.568	0.042
	RDN	na	na	0.996	0.101	0.573	0.104
	RPN	na	na	1.003	0.055	0.6	0.058

(continued)

Table 5. (continued)

Variable	Value	Model 1		Model 2		Model 3	
		Estimate	Standard error	Estimate	Standard error	Estimate	Standard error
	DPN	na	na	1.162	0.045	0.745	0.049
	RDPN	na	na	1.003	0.071	0.608	0.074
Threshold	μ_1	0.294	0.060	0.855	0.013	0.454	0.061
	μ_2	1.597	0.060	2.001	0.015	1.770	0.061
Performance measure	Log-likelihood	–39209.690		–42829.800		–38795.800	
	Residual deviance	78419.38		85659.61		77591.61	
	AIC	78475.380		85693.610		77677.610	

Note: AIC = Akaike Information Criterion; D = decision error; DN = decision+non-performance error; DP = decision+performance error; DPN = decision+ performance+non-performance error; DWB = divided with barrier; DWOB = divided without barrier; N = non-performance error; na = not applicable; O = no error; P = performance error; PN = performance+non-performance error; R = recognition error; RD = recognition+decision error; RDN = recognition+decision+non-performance error; RDP = recognition+decision+performance error; RDPN = recognition+decision+performance+non-performance error; RN = recognition+non-performance error; RP = recognition+performance error; RPN = recognition+performance+non-performance error; SVC = single vehicle crash; UD = undivided.

variables (i.e., existence of pedestrian or bike, roadside object, rollover, crash type, horizontal curve) in Model 1 because of unavailability of driver errors.

A comparison between model performance indicated that Model 3 has significantly better performance than all other models. The residual deviance and log-likelihood estimates indicate that the driver error combination variable solely can account for a significant portion of the variation in the injury severity data in Model 2 although only one variable was used in this model. A likelihood ratio test between Model 1 and 3 resulted in a value of L-R statistics of 798 with a difference in degrees of freedom equal to 15. This result is highly significant, indicating that a significant improvement in model performance can be achieved by incorporating driver error combinations into the model.

Analysis and Discussion

Driver Error Combinations

The modeling results showed that each of the 16 driver error combinations is statistically significant at a 5% significance level in predicting crash injury severity in both Model 2 and 3. Estimated coefficient from the OP models indicates that the occurrence of both single and multiple driver errors increases the probability of a more severe crash compared with no driver error (O). Another notable pattern in the estimated coefficients is that the estimated risk propensities for error combinations with multiple driver errors tend to be higher compared with driver error combinations with only one error. This indicates that the concurrence of multiple driver errors may elevate the injury severity level. However, two exceptions have been noticed: DP and P in Model 2, and RD and R in Model 3. In both cases, parameter estimates with two driver errors were found smaller than one driver error. More research is needed to determine whether the disparity in model parameter estimates is the result of statistical artifacts or because of unobserved underlying relationships.

Between Model 2 and 3 for driver error combinations, all estimated coefficients have the same positive sign indicating a higher increase in the injury crash risk. Estimated coefficients of Model 2 have a slightly higher value than Model 3 because driver error combinations are the only explanatory variables in Model 2. The estimated standard deviation of model coefficients also has a similar value in both Model 2 and 3. This indicates that the estimated model was not sensitive to changes in model formulation.

The estimated marginal effects of driver error combination in Model 3 are presented in Table 6. All driver error combinations increase the risk of both minor injury and major injury crashes compared with no driver error crashes. Recalling the estimated ranks in Table 2, DPN has the highest increase in the crash risk of both minor and major injury crashes among driver error combinations. The estimated marginal effect of DPN means that the probability of minor and major injury crashes will increase by 18.3% and 10.5%, respectively, if decision, performance, and non-performance errors happen in a crash.

Driver Characteristics

Driver demographics such as age and gender have been identified as major contributors to crash injury severity in previous safety research (*9*, *39*). In this study, the OP estimates indicate the driver demographic variables are

Table 6. Estimated Marginal Effects

Variable	No injury	Minor injury	Major injury
O		Base level	
R	–0.128	0.095	0.033
D	–0.08	0.061	0.019
P	–0.115	0.086	0.029
N	–0.143	0.104	0.039
RD	–0.121	0.089	0.032
RP	–0.2	0.139	0.061
RN	–0.197	0.136	0.061
DP	–0.137	0.101	0.036
DN	–0.171	0.121	0.05
PN	–0.239	0.159	0.079
RDP	–0.218	0.148	0.069
RDN	–0.22	0.149	0.071
RPN	–0.231	0.155	0.076
DPN	–0.288	0.183	0.105
RDPN	–0.234	0.156	0.078

Note: D = decision error; DN = decision+non-performance error; DP = decision+performance error; DPN = decision+performance+non-performance error; N = non-performance error; O = no error; P = performance error; PN = performance+non-performance error; R = recognition error; RD = recognition+decision error; RDN = recognition+decision+non-performance error; RDP = recognition+decision+performance error; RDPN = recognition+decision+performance+non-performance error; RN = recognition+non-performance error; RP = recognition+performance error; RPN = recognition+performance+non-performance error.

statistically significant in predicting injury severity. The parameter estimate indicates that a female driver is more likely to endure higher injury severity in a crash than a male driver. For the age variable, parameter estimates suggest that there is a reduction in the likelihood of injury crashes for young drivers (age <25) compared with middle-aged (age 25–65) and old drivers (age >65). The odds of suffering a minor or major injury crash was highest with old drivers compared with young and middle-aged drivers.

For vehicle type, Ordered Probit model results indicate that the latent propensity is higher for motorcycle riders compared with passenger car, light, and heavy trucks. Several previous safety studies noted that motorcycle crashes have considerable potential to produce injury crashes because of natural vulnerability and risk-taking behaviors of their users (*40–43*). The negative sign of the use of seatbelt demarcates a decrease in the likelihood of the injury risk propensity for both models, which is also consistent with results noted in previous safety literature (*9*, *44*). This indicates the unambiguous benefit of employing seatbelt in reducing injury severity in a crash event. As expected, impaired drivers under the influence of alcohol and drugs are likely to have a higher injury risk propensity compared with the sober drivers. The Ordered Probit model parameter estimates for driver characteristics variables are also found almost similar in both Model 1 and 3.

Roadway Characteristics

Regarding roadway characteristics variables, the vertical curve is not statistically significant in predicting latent risk propensity of crash injury severity. With respect to roadway alignment, the existence of horizontal curves increases the risk propensity of injury crashes. The positive value of the model coefficient for the speed variable in both Model 1 and 3 indicates a higher speed limit may result in more injury crashes.

With respect to roadway type, divided roadway with barrier was considered as base level in Ordered Probit modeling. Compared with the base level, the Ordered Probit model estimates indicate that the likelihood of injury risk propensity is highest for undivided roadway. On the other hand, one-way roadways tend to have a negative influence on injury risk propensity. The Ordered Probit model estimates were found stable with the same sign and almost similar value in both Model 1 and 3.

Environmental Characteristics

The weather condition variable in environmental characteristics is found insignificant in predicting latent risk propensity, thus left out from the final model. In the case of lighting conditions, the risk propensity is the highest in the daytime compared with the night condition (both with light and unlit). Several past roadway safety studies noted that drivers tend to travel at a higher speed during daylight conditions (*45*, *46*), which can result in a higher impact speed during a crash. Consistent with previous roadway safety studies, roadways without lights were found to have a higher risk propensity compared with roadways with lights for nighttime crashes (*47*, *48*). It is plausible that in the nighttime with roadway lights, a driver may be able to take remedial maneuvers to avoid a more severe impact.

Regarding roadway pavement condition, the Ordered Probit model estimates indicate that dry pavement condition has the highest risk propensity compared with its counterparts. This result indicates that drivers may adopt a higher speed or risker behavior while driving on dry pavement, or drive more cautiously when the pavement is wet or snowy. Comparing wet and snowy pavement conditions, the likelihood of injury risk propensity is higher in wet condition. Similar to the driver and roadway characteristics variable, the Ordered Probit model parameter estimates also have a similar pattern in Model 1 and 3.

Crash Characteristics

All crash characteristics variables used in this study were found to be a significant contributor to injury severity. Higher injury risk propensity was observed when a pedestrian or bike is involved in a crash. The likelihood of injury risk propensity is high if a vehicle rolled over in an event of a crash. These results are consistent with the results noted in safety literature for both variables.

For roadside elements, the existence of a roadside ditch is associated with higher injury propensity, indicating a crash may result in more severe injury if it hits the ditch compared with its counterparts. Hitting a moving object decreases the risk of injury crashes. Among different manners of collision, higher injury risk is associated with head-on crashes among multi-vehicle crashes. On the contrary, single-vehicle crashes tend to result in PDO crashes. Again, the Ordered Probit model parameter estimates were found to have a similar pattern in Model 1 and 3.

Conclusion

This study attempted to understand the effect of driver errors on the crash injury outcome in rural areas. In this process, driver errors were categorized as recognition, decision, performance, and non-performance based on the stage of information processing during a driving task.

Sixteen possible combinations of driver errors were generated because a crash may involve multiple errors. The statistical dependence between different combinations of driver error categories with ordered levels of injury severity was investigated and ranked by the odds ratio of the major injury for a specific error combination. The results show that different combinations of driver error categories and injury severity levels are not statistically independent; the more severe crashes tend to occur when the driver makes multiple errors sequentially.

The OP model was then applied to quantify the impact of driver errors on the crash injury outcomes. Estimated ordered risk propensities were discussed and compared between models with different sets of variables. The model results indicate that all driver error combinations have a statistically significant and higher impact on injury crashes compared with crashes with no driver errors. The results also indicate that the contribution of some variables may be overestimated if important contributors such as driver errors are not used in model development. The model performance comparison shows that including driver errors can significantly improve prediction accuracy.

Typically, driver characteristics, vehicle characteristics, roadway design and operational attributes, and environmental factors are considered as statistically significant contributors to injury severity in safety literature. Although these traditional sets of variables provide valuable information, they only provide partial information on crash injury severity. Several studies also noted the existence of heterogeneity in injury severity data because of the absence of driver behavior (*49–51*). As a result of improved model performance, it is safe to note that driver errors have a substantial influence on the crash occurrence and resultant injury outcome, and should be considered in the model development for better prediction accuracy.

The driver errors used in this study were collected from the crash reports with the assumption that driver errors reported by responding police officers are correct. This study is also limited to exploring the effect of driver errors on crash injury severity for segment-related crashes. A driver may be more prone to errors at an intersection, as the traffic movements at an intersection are more complex in nature than a segment. Different study designs may be needs to address the complex interactions and conflicts between vehicles and between different modes. This study is an attempt to explore whether the proposed method can be helpful to discover meaningful and useful relationships. Based on the knowledge obtained from this study, a future study can be designed to explore the effect of driver errors on intersection-related crashes.

Knowing what errors are associated with more severe crashes, more research is needed to explore why drivers make mistakes and what interventions can help to prevent them. When more information becomes available, the contribution of each driver error also needs to be explored in the future to understand its specific role in causing injuries. The findings along this line of research may help reduce severe crashes by developing specific safety countermeasures and advanced vehicle features targeting specific driver errors.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Shaon and Qin; literature review and data collection: Shaon; Analysis and interpretation of results: Shaon and Qin; draft manuscript preparation: Shaon and Qin. Both authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

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