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Modeling the effects of drive error and impairment on crash injury severity

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Abstract: Under the safe system approach, drivers will inevitably make mistakes and errors that can contribute to crashes. Driver errors are widely cited as one of the critical reasons for crash occurrence in safety literature. Despite universal acceptance, the discussion of their effects on crash injury outcomes is limited. The primary objective of this study is to quantify the effects of driver errors in the crash injury severity model at urban intersections. To obtain research objectives, driver errors were categorized as sequential events in a driving task. Combinations of driver error categories were created and ranked based on their odds-ratios with injury severity levels. Furthermore, driver impairment was considered in combination with the driver error categories to explore the compounding effects on crash consequences. Multiple ordered logit models were estimated to quantify the effect of driver errors and their interactions with driver impairment on the crash injury levels at uncontrolled, sign-controlled, and signal-controlled intersections. Improved model performance was observed when driver error combinations were modeled along with traditional crash variables. The exploration of multiple model formulations indicated that including driver impairment as an error category can yield informative inferences from both theoretical and modeling perspectives. Appropriate countermeasures were recommended for major contributing factors to improve intersection safety based on modeling results. It is expected that this study can offer specific insights into explanatory variables and help safety professionals to develop effective countermeasures.

Keywords: compounding effect, driver errors, error categorization, impairment, injury severity model

1 Background

Improving traffic safety in the roadway network is, and will continue to be, one of the pivotal tasks on the national transportation agenda due to the significant social and financial implications of motor vehicle crashes. National Transportation Research Nonprofit (TRIP) estimated that fatal and serious traffic crashes in the US in 2022 caused a total of \$1.9 trillion in the value of societal harm, which includes \$465 billion in economic costs and \$1.4 trillion in quality-of-life costs (TRIP, 2023). Compared with 2014, there was a 30% increase in roadway fatality in the US in 2022 (NHTSA, 2024). Crashes resulting in major injury and property damage also significantly increased during the last decade. Therefore, it is paramount for transportation agencies to identify contributing factors related to crash injury severity and implement effective safety countermeasures to minimize crash consequences.

To improve roadway safety conditions for all road users, transportation agencies are now adopting the Safe System approach. The principles of safe system approach dictate that drivers will inevitably make mistakes and errors that will contribute to crashes and a proactive approach is needed to identify and address safety issues. Contemporary crash injury severity research has noted ample appropriate highlights on contributing factors related to crash injury severity; albeit some concerns and limitations regarding the influence of driver behavior related factors remain unaddressed. The role of human behaviors has been widely recognized in a safety-critical system such as a roadway transportation network (NHTSA, 2008; Shaon, 2019; Rumar, 1985). Driver errors refer to unsafe driving behaviors, driver limitations, and physical conditions of the driver that lead to a crash. Human ability, needs, limitations, and other human characteristics can actively or passively influence drivers' decision-making capabilities and ability to perform driving tasks. However, research on the impact of driver errors on crash occurrences is limited. As indicated by police records, driver errors can range from a traffic infraction in which the driver is not paying attention, to an intentional traffic violation such as failure to yield or significantly exceeding the speed limit (Shaon et al., 2018; Wang & Qin, 2015). The National Motor Vehicle Crash Causation Survey (NMVCCS) sponsored by NHTSA found that almost 94% of crashes are caused by driver errors (NHTSA, 2008). Using the same dataset, NHTSA published another report noted that driver errors can be attributed to about 96% of intersection-related crashes (Choi, 2010).

The major obstacle regarding exploring the effect of driver errors on crash events is the unavailability of driver behavior related information. Conventional roadway safety databases only cover a small fraction of a large number of elements that define human behavior while driving (Mannering et al., 2016). Standard procedures for collecting driver behavior data also do not exist, as highway agencies are not obligated to gather such information for safety management systems. As defined in Econometrics, the unavailability of relevant contributing factors including driver errors were considered as the source of unobserved heterogeneity in previous safety research and usually modeled as a random error in crash modeling (Mannering et al., 2016). Information of driver errors during a crash event can be obtained by reviewing a crash report, including police officers' judgments and witness accounts. However, a structured approach is needed 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 (CAA, 1998; Baysari et al., 2009). A comprehensive review of human error categorization including driver error can be found in the study conducted by Stanton & Salmon (2009). Several safety studies used the driver error taxonomy developed by Treat et al. (1979) where driver errors were categorized into recognition, decision, performance, and non-performance errors to errors to help understand when, where, and why drivers make mistakes and how we can prevent them (NHTSA, 2008; Shaon et al., 2018; Wang & Qin, 2015). For example, Wang & Qin (2015) noted that there is a potential correlation due to observed and unobserved factors between driver errors, crash type, vehicle damage, and injury severity. But these studies did not consider the concurrence of multiple errors. Shaon & Qin (2020) developed 16 driver error combinations considering the concurrence of multiple driver errors and explored the effect of different driver error combinations on crash injury outcomes in rural segment-related crashes. The authors noted that complex driver error combinations with the concurrence of multiple driver errors tend to be involved in more severe injury crashes. The authors also pointed out that the incorporation of driver error combination can significantly improve model performance indicating driver errors as a major contributor to crash severity outcomes. However, there has been only a handful of studies that investigated the effect of driver errors on crash occurrences and resulting injury severities. Further investigation was recommended to better understand the concurrence of driver errors and their impact on crash events.

The growing aspiration to understand the influence of driver errors can be perceived from the amount of research effort devoted to analyzing the effect of driver impairment on crash events. Impaired driving has been identified as one of the major traffic safety problems in existing safety literature (Ye & Lord, 2014; Moskowitz & Florentino, 2000; Behnood & Mannering, 2017). Alcohol and drug tend to influence driver's vision, drowsiness, perception-reaction time, and drivers' performance which significantly increases the probability of getting involved in a more severe crash event (Moskowitz & Florentino, 2000; Behnood & Mannering, 2017). Previous safety studies mostly investigated the impact of driver impairment as a surrogate measure in crash injury severity modeling by interpreting the inference of impairment variable as a probability to be involved in risk-taking driving behavior such as exceeding posted speed limit, drowsy driving, ability to control vehicle, etc. However, it is not always true that only drivers that are alcohol or drug impaired will make mistakes while driving. Investigating the interactions between driver impairment and driver error may provide valuable insight to understand the effect of driver impairment on crashes as well as driver errors.

Driving behaviors are a critical component in intersection-related crashes due to traffic rules in effect, intersection control types, and interacting traffic movements at the intersection. More than 50% of the combined total roadway fatalities and injury crashes occurred at intersections in the US (NHTSA, 2023). Intersections typically have an increased risk of more severe crashes due to a larger number of traffic conflict points that exist as two or more roadways intersect. Intersections are also the areas where streams of both motorized and non-motorized road users interact. As a result, research efforts have been devoted to intersection areas examining contributing factors related to crashes and injury outcomes. Devlin et al. (2011) explored the effect of driver errors in serious causality crashes that occurred on intersections in Western Australia. Authors noted that the effect of driver errors is different for different intersection control types. The common driver errors at signalized intersections include higher driving speed, selecting an inappropriate gap, running a red light, and choice in the dilemma zone whereas failing to yield the right-of-way and inaccurate approximation of the speed of approaching vehicles during a turn are predominant at uncontrolled intersections include (Devlin et al., 2011). Research has shown that crash injury outcomes are influenced by intersection control types, driver demography, vehicle, roadway, and environmental characteristics (Morgan & Mannering, 2011; Yasmin et al., 2014; Qin et al., 2013).

The safe system approach emphasizes incorporating driver-related factors in developing proactive roadway safety analysis procedure. Based on the above discussion, it is evident that driver error and impairment has been unanimously considered as primary contributors to crash occurrences and resulting injury outcomes in previous safety literature. Despite the ubiquitous influence of driver error, researchers have started incorporating driver errors in crash data modeling in recent years. Moreover, the exploration of the compounding effect of driver errors and impairment on intersection-related crash outcomes is limited. The unavailability of standardized method of collecting and processing driver error information resulted in limited studies evaluating the effect of driver errors. Additionally, due to the interaction between road users, traffic rules, and control types, intersections are prone to driver errors. Thus, it will be beneficial to explore the compounding effect of driver errors and driver impairment on crash injury severities occurred at intersection to fill the existing knowledge gap.

This study attempts to explore the effect of driver errors on crash injury severity levels for urban intersection-related crashes by categorizing driver error information collected from crash records. Combinations of driver error categories were generated to explore their effect on the crash outcome. The driver error combinations were further expanded by including their interactions with driver impairment to understand the influence of impairment on both driver errors and injury severity outcomes. Considering the effect of driver errors and impairment, injury severity modeling results may provide specific insights into explanatory variables and help researchers and safety professionals to develop cost-effective countermeasures.

2 Data collection and processing

Intersection-related crashes that occurred in Wisconsin between 2011 and 2015 were collected from the WisTransportal data hub maintained by TOPSLAB (Parker & Tao, 2006). Deer-related and hit-and-run crashes were removed from the crash dataset as the driver-related information for these crashes were not available. To quantify the impact of driver errors, crashes were further categorized in uncontrolled, sign-controlled, and signal-controlled intersections (Wang & Qin, 2015; Devlin et al., 2011). Specific driver actions in each crash event were extracted from the MV4000 database (Wisconsin DoT, 1998). There is a list of 14 driver actions from which the reporting police officer identifies the driver action(s) associated with a crash in MV4000 crash report as indicated in Table 1. As each crash can be associated with multiple driver actions from multiple drivers, there can be a large number of combinations of driver actions available in the study dataset which can be difficult to incorporate in a quantitative injury severity model. Moreover, a structured approach by categorizing driver actions can be beneficial in quantifying the impact of driver errors on crash injury severity. The taxonomy used to categorize driver errors is presented in Table 1. Please refer to the study conducted by Shaon & Qin (2020) for a detailed overview of the driver errors related factors collected from Wisconsin crash reports.

Based on the error categorization taxonomy developed by Treat et al. (1979), driver actions during a crash event were grouped into recognition, decision, performance, and non-performance errors. However, non-performance errors cannot be directly considered as a driver error category as the driver condition (disability, driver's health condition) cannot be controlled. Thus, the non-performance error category was excluded in this study. The categorization of driver errors follows a sequence of information processing during driving. While driving, a driver needs to detect and identify a hazard, decide what to do, and execute driving task accordingly. 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 leads to decision error, whether it is a decision after detecting a hazard or a decision while driving. A reckless decision such as 'exceeding the speed limit' may result in a crash without an imminent hazard. In the same sequence, if a decided maneuver is not properly performed, are categorized as performance error.

As drivers may make several sequential errors that resulted in a crash, one crash event may involve multiple driver error categories. It is also possible that none of the driver errors are involved in a crash event. Based on the three driver error categories used in this study, there can be 8 possible combinations of driver errors (${}^3C_0 + {}^3C_1 + {}^3C_2 + {}^3C_3 = 8$, where C represents combination). Although previous studies considered driver impairment as a surrogate for drivers making mistakes, it was not considered as a driver error in the error categorization taxonomy developed by Treat et al. (1979). To understand the effect of driver impairment, driver impairment was considered as a driver error category to understand the compound effect of driver impairment and other driver error categories in this study. Incorporating driver impairment within driver error combinations can lead to another additional 8-levels of driver error combination which represents the occurrence and/or concurrence of driver errors under impairment. Each error combination (EC_i) was designated using an initial letter coding system (recognition [R], decision [D], performance [P], and impairment [I]. The no driver error category was represented using the letter 'O'. For example, a driver failed to yield to another driver while driving over the speed limit. This case represents a combination of recognition and performance errors, denoted as 'RP'. An example of interaction with the impairment category can be a driver who was under the influence of alcohol while driving, talking on the phone, and failed to keep the vehicle under control on a horizontal curve, coded as 'RPI'. The occurrence of impairment without any driver errors was coded as 'OI'.

To develop injury severity models, The KABCO scale of injury severity was further categorized 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 crash (Shaon, 2019; Shaon & Qin, 2020). Four categories of explanatory variables were considered: driver characteristics, roadway, environmental factor, and crash characteristics. A study conducted by NHTSA using NMVCCS data found that turning left and right, and crossing over are the most common pre-crash events at an intersection, which were also included in the study data (Choi, 2010). Table 2 provides the summary statistics of explanatory variables.

3 Exploratory analysis

An exploratory analysis was conducted to understand the dependence between driver error combinations and crash injury severity levels. In a previous study, Shaon & Qin (2020) proposed an odds-ratio estimate to explore the correlation between driver error categories and crash injury severity. Following the methodology proposed by Shaon & Qin (2020), the odds of major injury with specific driver error combinations were estimated to explore the effect of driver error combinations on injury severity levels. Table 3 presents the association between driver error combinations and injury severities. In Table 3, the odds of major injury with EC_i indicate the probability of major injury crashes compared with non-major injury (minor+no injury) crashes when EC_i driver error occurs. The odds of injury crashes with driver errors are

Table 1 Taxonomy used to categorize driver errors (Shaon & Qin, 2020)

Error category	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 errors	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
Impairment	Alcohol-impaired; drug-impaired	Involve alcohol; involve drug

estimated using the following equations:

$$OR\ of\ EC_i = \frac{O^{Mj\ Inj}\ (EC_i)}{\underset{(for\ all\ j\neq i)}{O^{Mj\ Inj}\ (EC_j)}} \tag{1}$$

$$O^{Mj\ Inj}\ (EC_i) = \frac{N^{Mj\ Inj\ C}\ (EC_i)}{N^{(Mn+PDO)\ C}\ (EC_i)} \tag{2}$$

$$\underset{(for\ j\neq i)}{O^{Mj\ Inj}(EC_j)} = \frac{\sum^{Mj\ inj\ C} - \sum^{Mj\ Inj\ C}(EC_i)}{\sum^{(Mn+PDO)} - \sum^{(Mn+PDO)}(EC_i)} \tag{3}$$

Where:

OR = odds ratio;

$O^{MjInj}(EC_i)$ = odds of major injury with EC_i;

$N^{MjInjC}(EC_i)$ = number of major injury crashes with EC_i;

$N^{(Mn+PDO)C}(EC_i)$ = number of (minor + PDO) crashes with EC_i;

$\sum^{Mj\ Inj\ C}$ = total of major injury crashes;

$\sum^{(Mn+PDO)}$ = total of (minor + PDO) crashes.

Interesting results can be observed for driver error combination with the impairment. The estimated odds ratios for driver errors-impairment combinations occupied the rank from 1^{st} to 6^{th} across all intersection control types despite their low frequency in occurrence. For example, DP, a combination of decision and performance error ranked 8^{th} in uncontrolled intersections. When a driver makes a DP error while impaired, the odds ratio jumped from 8^{th} position to 2^{nd} position. It is possible that drivers can make the same mistake with a larger magnitude while impaired. A chi-square test was conducted to test the statistical dependence between the driver error combinations and injury severity levels. The critical chi-square value with 15 degrees of freedom at a 5% level of significance is 43.77. The estimated chi-square values for urban crash severities among 16 driver error combinations are 506.22, 482.79, and 638.62 for uncontrolled, sign-controlled, and signal-controlled intersections, respectively. The chi-square test results indicate that the driver error combinations and crash injury severities are not statistically independent across intersection control types. These results show the evident influence of driver error on crash injury severity. Therefore, the influence of driver error needs to be considered while developing crash severity models.

Table 2 Summary statistics of explanatory variables

Variable	Description	Count		
		Uncontrolled	Sign-controlled	Signal-controlled
'K+A'	Major injury crashes	2.08%	2.14%	1.9%
'B+C'	Minor injury crashes	29.15%	32.49%	34.82%
O	No injury crashes	68.77%	65.37%	63.28%
Driver characteristics				
Gender	Female	15 691 (44.9%)	15 492 (48.83%)	27 441 (45.7%)
	Male	19 219 (55.1%)	16 233 (51.17%)	32 591 (54.3%)
Age	Young driver (< 25 years)	10,668 (30.6%)	8 966 (28.26%)	17 071 (28.4%)
	Middle age (25–65 years)	20 862 (59.7%)	18 268 (57 58%)	36 887 (61.5%)
	Old driver (> 65 years)	3 380 (9.7%)	4 491 (14.16%)	6 074 (10.1%)
Vehicle type	Passenger car	29 257 (83.8%)	27 290 (86.02%)	50 593 (84.3%)
	Motorcycle	630 (1.8%)	224 (0.71%)	445 (0.7%)
	Light truck	3 744 (10.7%)	3 217 (10.14%)	6 248 (10.4%)
	Heavy truck	1 279 (3.7%)	994 (3.13%)	2 746 (4.6%)
Safety-restrained	No	3 072 (8.8%)	2 874 (9.06%)	4 689 (7.8%)
	Yes	31 838 (91.2%)	28 851 (90.94%)	55 343 (92.2%)
Roadway Factors				
Horizontal curve	No	29 359 (84.1%)	30 481 (96.08%)	57 885 (96.4%)
	Yes	5 551 (15.9%)	1 244 (3.92%)	2 147 (3.6%)
Vertical curve	No	31 318 (89.7%)	28 625 (90.23%)	55 998 (93.3%)
	Yes	3 592 (10.3%)	3 100 (9.77%)	4 034 (6.7%)
Posted speed	Low speed (≤ 25 mph)	16 038 (45.9%)	22 046 (69.49%)	15 163 (25.3%)
	Med. speed (26–50 mph)	17 205 (49.3%)	9 209 (29.03%)	43 720 (72.8%)
	High speed (> 50 mph)	1 667 (4.8%)	470 (1.48%)	1 149 (1.9%)
Construction zone	No	34 401 (98.5%)	31 519 (99.35%)	59 163 (98.6%)
	Yes	509 (1.5%)	206 (0.65%)	869 (1.5%)
Visibility	No	34 397 (98.5%)	30 941 (97.53%)	59 650 (99.4%)
	Yes	513 (1.5%)	784 (2.47%)	382 (0.6%)
Contextual factors				
Weather condition	Clear	18 621 (53.3%)	16 698 (52.63%)	31 207 (52%)
	Cloudy	10 827 (31%)	10 266 (32.36%)	18 742 (31.2%)
	Rain	2 700 (7.7%)	2 468 (7.78%)	5 528 (9.2%)
	Snow	2 762 (7.9%)	2 293 (7.23%)	4 555 (7.6%)
Pavement condition	Dry	24 649 (70.6%)	22 588 (71.20%)	43 011 (71.7%)
	Wet	2 004 (5.7%)	4 712 (14.85%)	10 311 (17.2%)
	Snow	4 269 (12.2%)	3 638 (11.47%)	5 740 (9.6%)
	Ice	988 (2.8%)	787 (2.48%)	970 (1.6%)
Lighting condition	Day	27 033 (77.4%)	26 107 (82.29%)	45 295 (75.5%)
	Nighttime without lighting	6 190 (17.7%)	1 249 (3.94%)	1 760 (2.9%)
	Nighttime with lighting	1 687 (4.8%)	4 369 (13.77%)	12 977 (21.6%)
Crash characteristics				
TOD	AM peak (6:00–9:59)	5 269 (15.1%)	5 620 (17.71%)	8 957 (14.9%)
	Mid-day (10:00–15:59)	14 453 (41.4%)	14 282 (45.02%)	25 072 (41.8%)
	PM peak (16:00–18:59)	9 077 (26%)	7 543 (23.78%)	14 382 (24%)
	Night (19:00–5:59)	6 111 (17.5%)	4 280 (13.49%)	11 621 (19.4%)
Manner of collision	SVC	6 203 (17.8%)	2 110 (6.65%)	5 074 (8.5%)
	Rear-end	11 526 (33%)	3 546 (11.18%)	21 050 (35.1%)
	Head-on	528 (1.5%)	268 (0.84%)	993 (1.7%)
	Sideswipe	6 272 (17.9%)	2 552 (8.04%)	7 651 (12.7%)
	Angle	10 381 (29.7%)	23 249 (73.28%)	25 264 (42.1%)
Turning movement	No	20 072 (57.5%)	20 117 (63.41%)	31 851 (53.1%)
	Yes	14 838 (42.5%)	11 608 (36.59%)	27 181 (45.3%)
Merging/lane-changing	No	32 442 (92.9%)	31 560 (99.48%)	58 506 (97.5%)
	Yes	2 468 (7.1%)	165 (0.52%)	1 526 (2.5%)
Presence of bike/ped	No	33 914 (97.2%)	30 397 (95.81%)	57 951 (96.5%)
	Yes	996 (2.8%)	1 328 (4.19%)	2 081 (3.5%)
Rollover	No	34 758 (99.6%)	31 704 (99.93%)	59 985 (99.9%)
	Yes	152 (0.4%)	21 (0.07%)	47 (0.1%)

Table 3 Exploratory analysis results

<table>
<tr><th>Error combinations</th><th colspan="3">Uncontrolled (34 910)</th><th colspan="3">Sign-controlled (31 725)</th><th colspan="3">Signal-controlled (60 032)</th></tr>
<tr><th></th><th>Total crashes</th><th>% injury, major | minor | PDO</th><th>OR (rank), major injury</th><th>Total crashes</th><th>% injury, major | minor | PDO</th><th>OR (rank), major injury</th><th>Total crashes</th><th>% injury, major | minor | PDO</th><th>OR (rank), major injury</th></tr>
<tr><td>One driver error</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>O</td><td>5 566</td><td>1.9 | 26.3 | 71.8</td><td>0.90 (12)</td><td>3 391</td><td>1.7 | 30.4 | 67.9</td><td>0.76 (13)</td><td>8 700</td><td>1.3 | 30.3 | 68.4</td><td>0.67 (15)</td></tr>
<tr><td>R</td><td>5 701</td><td>1.4 | 31.6 | 66.9</td><td>0.64 (13)</td><td>2 503</td><td>1.4 | 29.0 | 69.5</td><td>0.65 (16)</td><td>8 956</td><td>0.8 | 34.5 | 64.6</td><td>0.39 (16)</td></tr>
<tr><td>D</td><td>6 206</td><td>1.1 | 25.9 | 73.0</td><td>0.48 (14)</td><td>4 031</td><td>1.6 | 32.1 | 66.3</td><td>0.74 (14)</td><td>17 029</td><td>1.7 | 35.5 | 62.8</td><td>0.89 (12)</td></tr>
<tr><td>P</td><td>12 335</td><td>2.2 | 29.8 | 68.1</td><td>1.06 (11)</td><td>17 594</td><td>1.7 | 32.7 | 65.5</td><td>0.66 (15)</td><td>16 417</td><td>2.2 | 4.8 | 62.9</td><td>1.25 (10)</td></tr>
<tr><td>Multiple driver errors</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>RD</td><td>881</td><td>0.8 | 36.0 | 63.2</td><td>0.37 (15)</td><td>476</td><td>3.2 | 31.5 | 65.3</td><td>1.50 (11)</td><td>2 209</td><td>1.4 | 41.2 | 57.4</td><td>0.75 (14)</td></tr>
<tr><td>RP</td><td>1 075</td><td>2.7 | 32.0 | 65.3</td><td>1.31 (10)</td><td>1 573</td><td>3.8 | 34.3 | 62.0</td><td>1.86 (10)</td><td>1 338</td><td>3.3 | 38.0 | 58.7</td><td>1.79 (9)</td></tr>
<tr><td>DP</td><td>1 565</td><td>3.5 | 27.7 | 68.8</td><td>1.73 (8)</td><td>1 132</td><td>4.1 | 36.2 | 59.7</td><td>2.00 (9)</td><td>3 021</td><td>2.2 | 35.1 | 62.7</td><td>1.18 (11)</td></tr>
<tr><td>RDP</td><td>247</td><td>3.2 | 41.3 | 55.5</td><td>1.58 (9)</td><td>267</td><td>5.6 | 48.3 | 46.1</td><td>2.76 (8)</td><td>597</td><td>3.7|47.1|49.3</td><td>2.00 (8)</td></tr>
<tr><td>Interaction with impairment</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>OI</td><td>373</td><td>5.6 | 29.0 | 65.4</td><td>2.85 (6)</td><td>146</td><td>6.2 | 32.9 | 61.0</td><td>3.03 (7)</td><td>420</td><td>6.7 | 31.9 | 61.4</td><td>3.76 (5)</td></tr>
<tr><td>RI</td><td>144</td><td>9.0 | 35.4 | 55.6</td><td>4.73 (3)</td><td>58</td><td>1.7 | 34.5 | 63.8</td><td>0.80 (12)</td><td>251</td><td>1.6 | 33.5 | 64.9</td><td>0.84 (13)</td></tr>
<tr><td>DI</td><td>170</td><td>8.2 | 29.4 | 62.4</td><td>4.28 (4)</td><td>137</td><td>9.5 | 43.1 | 47.4</td><td>4.87 (6)</td><td>367</td><td>9 | 39.0 | 52</td><td>5.24 (2)</td></tr>
<tr><td>PI</td><td>336</td><td>8.0 | 33.0 | 58.9</td><td>4.22 (5)</td><td>233</td><td>11.6 | 33.5 | 54.9</td><td>6.20 (3)</td><td>403</td><td>7.2 | 38.5 | 54.3</td><td>4.09 (3)</td></tr>
<tr><td>RDI</td><td>32</td><td>0 | 37.5 | 62.5</td><td>NA (NA)</td><td>27</td><td>18.5 | 33.3 | 48.1</td><td>10.46 (1)</td><td>71</td><td>4.2 | 46.5 | 49.3</td><td>2.29 (7)</td></tr>
<tr><td>RPI</td><td>66</td><td>4.5 | 37.9 | 57.6</td><td>2.24 (7)</td><td>31</td><td>9.7 | 35.5 | 54.8</td><td>4.92 (5)</td><td>71</td><td>7 | 45.1 | 47.9</td><td>3.93 (4)</td></tr>
<tr><td>DPI</td><td>176</td><td>12.5 | 36.4 | 51.1</td><td>6.89 (2)</td><td>99</td><td>17.2 | 37.4 | 45.5</td><td>9.70 (2)</td><td>138</td><td>13 | 37.7 | 49.3</td><td>7.87 (1)</td></tr>
<tr><td>RDPI</td><td>37</td><td>18.9 | 27.0 | 54.1</td><td>11.05 (1)</td><td>27</td><td>11.1 | 33.3 | 55.6</td><td>5.74 (4)</td><td>44</td><td>4.5 | 50.0 | 45.5</td><td>2.47 (6)</td></tr>
</table>

OR = Odds ratio
NA = Not applicable

4 Model development

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

$$U = \beta' X + \varepsilon \tag{4}$$

where X is a vector of independent variables defining the discrete ordering for each observation, β is a vector of estimable model coefficients, and ε is an error term accounting for the unobservable effects assumed to follow a standard logistic distribution across observations. Using this structure, the observed ordinal dependent variable, or the crash injury severity for each observation can be defined as:

$$\begin{Bmatrix} y = 1 & if\ U \leq \mu_1 \\ y = 2 & if\ \mu_1 \leq U \leq \mu_2 \\ \ldots & \\ y = I & if\ U \geq \mu_{I-1} \end{Bmatrix} \tag{5}$$

where the μ's are estimable thresholds that define y corresponding to integer ordering of injury severity levels with I as the highest integer level of injury severity.

As noted earlier, driver impairment was not explored as driver error in previous literature. However, driver impairment may have significant influence of driver errors and resulting crash outcomes. Driver impairment can be considered either as an independent variable or under the driver error category. To understand the effect of driver errors, impairment, and their concurrence, two models are proposed as follows:

Model with Partial Error Combinations: Using driver impairment as independent variable and interaction between impairment and driver errors (8 levels) in association with other explanatory variables.

Model with All Error Combinations: Using driver impairment as an error category resulting in 16 driver combinations in association with other explanatory variables.

In the *Model with Partial Error Combinations*, driver impairment was considered as an independent variable outside driver error categories. An interaction term between driver impairment and 8-levels of driver errors was defined in *Model with Partial Error Combinations*. *Model with All Error Combinations* considers driver impairment as an error category which resulted in 8 driver errors without impairment and 8 driver errors with impairment. A comparison between alternative model specifications can help to understand the proper way to consider driver impairment when both driver impairment and driver errors are available to the analyst.

The OL model was estimated for urban intersection-related crashes by control types. The coefficient estimates from the OL model 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 OL models for *Model with Partial and All Error Combinations* are presented in Table 4 and Table 5, respectively.

To compare model performance, a Base Model was estimated without driver error combinations. The Akaike Information Criterion (AIC) and Log-Likelihood of the estimated Base Model were 43414, 42033.58, 80276.28, and -21677, -20998.79, -40111.14, respectively for uncontrolled, sign-controlled and signal-controlled intersections. A comparison between the model performance comparison indicates that both AIC and log-likelihood significantly improved with the incorporation of driver error combinations into injury severity modeling for all intersection control types. A likelihood-ratio (L-R) test was conducted to determine the statistical significance of the model performance after incorporating driver error combinations into injury severity models. The L-R test results indicate that statistically significant improvement in model performance can be achieved with both *Model with Partial* and *All Error Combinations* compared with the Base Model. Thus, it can be noted that the incorporation of driver errors can significantly improve model performance in predicting crash injury outcomes.

Comparing model performance between partial and all error combinations, it can be noted that both models yielded almost similar AIC and log-likelihood estimates. This result indicated that the OL model can yield similar model performance regardless of how the impairment variable is considered in the model formulation. One possible reason for obtaining similar model performance can be a low sample size of impairment-related crashes. There were 3.82%, 2.39%, and 2.94% impairment-related crashes at uncontrolled, sign-controlled, and signal-controlled intersections,

Table 4 Model estimation result for Model with Partial Error Combinations

Variable	Value	Uncontrolled		Sign-controlled		Signal-controlled	
		Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Driver characteristics							
Gender (female)	Male	-0.11	0.03	-0.09	0.03	-0.11	0.02
Age (young)	Mid-age (25–65 yrs)	0.05	0.03	0.05	0.03	0.04	0.02
	Old (> 65 yrs)	0.08	0.05	*0*	*0.04*	0.08	0.03
Vehicle type (passenger car)	Motorcycle	2.57	0.1	2.39	0.15	2.32	0.11
	Light truck	-0.03	0.04	-0.15	0.04	*-0.05*	*0.03*
	Heavy truck	-0.34	0.08	-0.23	0.08	-0.48	0.05
Safety-restrained (no)	Yes	-0.84	0.04	-0.79	0.04	-0.68	0.03
Roadway factors							
Horizonal curve (no)	Yes	-0.39	0.04			-0.24	0.05
Posted speed (< 25 mph)	Medium (26–50 mph)	0.34	0.03	0.29	0.03	0.33	0.02
	High (> 50 mph)	0.23	0.06	0.54	0.1	0.25	0.07
Construction zone (no)	Yes	-0.29	0.11	NA	NA	NA	NA
Visibility (no)	Yes	0.23	0.1	NA	NA	NA	NA
Environmental factors							
TOD (midday)	AM peak	*-0.05*	*0.04*	*-0.03*	*0.04*	-0.08	0.03
	PM peak	-0.05	0.03	-0.08	0.03	-0.13	0.02
	Night	-0.12	0.04	*0.05*	*0.05*	-0.12	0.03
Pavement condition (dry)	Wet	-0.1	0.04	-0.11	0.04	-0.08	0.02
	Snow	-0.63	0.04	-0.65	0.04	-0.69	0.03
	Ice	-0.68	0.09	-0.83	0.1	-0.81	0.09
Lighting condition (day)	Night w/o lighting	NA	NA	*-0.09*	*0.07*	NA	NA
	Night with lighting	NA	NA	-0.1	0.05	NA	NA
Crash characteristics							
Crash type (SVC)	Rear-end	0.4	0.05	*-0.09*	*0.07*	0.55	0.04
	Head-on	1.26	0.1	0.61	0.14	1.54	0.08
	Sideswipe	-0.43	0.05	-0.44	0.08	*0.06*	*0.05*
	Angle	0.55	0.05	0.38	0.06	0.96	0.04
Turning movement (no)	Yes	-0.09	0.03	-0.35	0.03	-0.22	0.02
Merging/lane-changing (no)	Yes	-0.21	0.06	-0.45	0.2	-0.92	0.08
Presence of bike/ped (no)	Yes	3.01	0.08	2.67	0.07	2.99	0.06
Overturn (no)	Yes	1.2	0.17	0.96	0.44	1.18	0.32
Driver errors (O)	R	0.22	0.05	0.14	0.06	0.22	0.04
	D	0.11	0.05	0.4	0.05	0.25	0.03
	P	0.2	0.04	0.22	0.04	0.2	0.03
	RD	0.36	0.08	0.35	0.11	0.41	0.05
	RP	0.36	0.08	0.35	0.07	0.39	0.06
	DP	0.41	0.07	0.65	0.08	0.35	0.05
	RDP	0.85	0.14	1.02	0.13	0.72	0.09
Impairment (no)	Yes	*0.2*	*0.13*	0.53	0.18	0.46	0.11
Interactions	R-Impair:Y	0.53	0.21	*-0.57*	*0.35*	-0.44	0.18
	D-Impair:Y	0.47	0.21	*0.26*	*0.26*	*0.07*	*0.16*
	P-Impair:Y	*0.19*	*0.17*	*-0.04*	*0.23*	*-0.05*	*0.15*
	RD-Impair:Y	*0.02*	*0.4*	*0.39*	*0.46*	*-0.13*	0.27
	RP-Impair:Y	*0.1*	*0.29*	*-0.21*	*0.42*	*0.09*	*0.28*
	DP-Impair:Y	0.62	0.21	*0.13*	*0.29*	0.48	0.22
	RDP-Impair:Y	*0.31*	*0.39*	*-0.55*	*0.47*	*0.12*	*0.34*
Intercept	m_1	0.53	0.07	0.36	0.08	0.84	0.06
	m_2	4.13	0.08	4	0.09	4.67	0.07
Model performance							
AIC			43 316.3		41 896.2		80 116.43
Log-likelihood			-21 615.15		-20 906.1		-40 017.21

Parameter estimates presented in italic font are not statistically significant at a 10% significance level

Table 5 Model estimation result for Model with All Error Combinations

Variable	Value	Uncontrolled		Sign-controlled		Signal-controlled	
		Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Driver characteristics							
Gender (female)	Male	-0.11	0.03	-0.09	0.03	-0.11	0.02
Age (< 25 yrs)	Mid-age (25–65 yrs)	0.05	0.03	0.05	0.03	0.04	0.02
	Old (> 65 yrs)	0.08	0.05	*0*	*0.04*	0.08	0.03
Vehicle type (passenger car)	Motorcycle	2.57	0.1	2.39	0.15	2.32	0.11
	Light truck	*-0.03*	*0.04*	-0.15	0.04	*-0.05*	*0.03*
	Heavy truck	-0.34	0.08	-0.23	0.08	-0.48	0.05
Safety-restrained (no)	Yes	-0.84	0.04	-0.79	0.04	-0.68	0.03
Roadway factors							
Horizonal curve (no)	Yes	-0.39	0.04			-0.24	0.05
Posted speed (≤ 25 mph)	Medium (26–50 mph)	0.34	0.03	0.29	0.03	0.33	0.02
	High (>50 mph)	0.23	0.06	0.54	0.1	0.25	0.07
Construction zone (no)	Yes	-0.29	0.11				
Visibility (no)	Yes	0.23	0.1				
Environmental factors							
TOD (mid-day)	AM peak	*-0.05*	*0.04*	*-0.03*	*0.04*	-0.08	0.03
	PM peak	-0.05	0.03	-0.08	0.03	-0.13	0.02
	Night	-0.12	0.04	*0.05*	*0.05*	-0.12	0.03
Pavement condition (dry)	Wet	-0.1	0.04	-0.11	0.04	-0.08	0.02
	Snow	-0.63	0.04	-0.65	0.04	-0.69	0.03
	Ice	-0.68	0.09	-0.83	0.1	-0.81	0.09
Lighting condition (day)	Night w/o lighting			*-0.09*	*0.07*		
	Night with lighting			-0.1	0.05		
Crash characteristics							
Crash type (SVC)	Rear-end	0.4	0.05	*-0.09*	*0.07*	0.55	0.04
	Head-on	1.26	0.1	0.61	0.14	1.54	0.08
	Sideswipe	-0.43	0.05	-0.44	0.08	*0.06*	*0.05*
	Angle	0.55	0.05	0.38	0.06	0.96	0.04
Turning movement (no)	Yes	-0.09	0.03	-0.35	0.03	-0.22	0.02
Merging/lane-changing (no)	Yes	-0.21	0.06	-0.45	0.2	-0.92	0.08
Presence of bike/ped (no)	Yes	3.01	0.08	2.67	0.07	2.99	0.06
Overturn (no)	Yes	1.2	0.17	0.96	0.44	1.18	0.32
Driver error combinations with interactions							
Driver errors (O)	R	0.22	0.05	0.14	0.06	0.22	0.04
	D	0.11	0.05	0.4	0.05	0.25	0.03
	P	0.2	0.04	0.22	0.04	0.2	0.03
	RD	0.36	0.08	0.35	0.11	0.41	0.05
	RP	0.36	0.08	0.35	0.07	0.39	0.06
	DP	0.41	0.07	0.65	0.08	0.35	0.05
	RDP	0.85	0.14	1.02	0.13	0.72	0.09
	OI	0.2	0.13	0.53	0.18	0.46	0.11
	RI	0.95	0.18	*0.1*	*0.29*	0.23	0.14
	DI	0.78	0.17	1.2	0.18	0.78	0.11
	PI	0.59	0.12	0.71	0.15	0.61	0.11
	RDI	0.58	0.38	1.27	0.42	0.74	0.24
	RPI	0.66	0.26	0.67	0.38	0.93	0.25
	DPI	1.22	0.17	1.31	0.22	1.29	0.18
	RDPI	1.35	0.35	1	0.42	1.3	0.31
Intercept	m_1	0.53	0.07	0.36	0.08	0.84	0.06
	m_2	4.13	0.08	4	0.09	4.67	0.07
Model performance							
AIC			43 316.3		41 812.2		80 116.43
Log-likelihood			-21 615		-20 906.1		-40 017.21

Parameter estimates presented in italic font are not statistically significant at a 10% significance level respectively. However, the driver error interactions with impairment were not statistically significant in predicting crash severity outcomes in the *Model with Partial Error Combinations*. Excluding interaction terms from the partial error combination model resulted in a further reduction in model performance. Thus, *Model with All Error Combinations* has an overall better performance among all developed models across intersection control types.

5 Result and discussion

The OL modeling results presented in Table 4 and Table 5 showed that driver error combinations are statistically significant at a 10% significance level across intersection control types in both models. Comparing estimated log-odds for driver error combinations between partial and all error combination models portrayed that both models can generate almost similar log-odds for driver errors. However, while comparing the estimated log-odds for occurrences of driver errors under impairment, significant changes can be observed. When considering impairment outside the driver error categories in the *Model with Partial Error Combinations*, most of the interaction terms are not statistically significant at a 10% significance level. On the contrary, driver error combination levels generated when considering driver impairment as an error category are statistically significant at a 5% significance level in the *Model with All Error Combinations*.

From the model formulation perspective, log-odds estimates of driver error interactions with impairment in the *Model with Partial Error Combinations* represent the compound effect of the concurrence of driver errors and impairment in addition to their individual effects. But in the *Model with All Error Combinations*, the interactions of driver errors with impairment were estimated considering no driver error as a base level. From a theoretical perspective, it may be beneficial to estimate the effect of driver impairment without any driver errors as specified in the *Model with All Error Combinations* using error combination designation 'OI' rather than estimating the effect regardless of driver errors. The model formulation used in *Model with All Error Combinations* provides a unique approach by considering driver impairment as an error category to understand the influence of each level of driver error combinations, with or without under the influence of impairment on crash outcomes.

A detailed exploration of the estimated log-odds for driver errors both with and without impairment indicated that concurrence of driver errors may have a higher positive impact on injury outcomes compared with driver impairment. This indicates concurrence of multiple driver errors can lead to more severe injury crashes than crashes that occur under driver impairment only. Another notable trend in concurrence of multiple driver errors tends to have a higher log-odds estimate compared with a single error. These results align with the results noted by Shaon & Qin (2020) that more complex errors may lead to severe injury crashes for rural segment-related crashes. The impact of driver errors can be further amplified if they occur under driver impairment.

Regarding the traditional set of variables, similar results can be observed with OL parameter estimates as indicated in previous literature (Wang & Qin, 2015; Morgan & Mannering, 2011; Yasmin et al., 2014). The OL parameter estimate indicates that the latent propensity is higher for motorcycle riders compared with its counterparts. Female drivers and old drivers are more likely to endure higher injury severity in a crash than their counterparts. The negative sign of the use of seatbelt demarcates a decrease in the likelihood of the injury risk propensity. Among roadway factors, a higher speed limit may result in more injury crashes for all control types. The existence of horizontal curves, presence of a construction zone decreases the risk propensity of injury crashes. The positive log-odds for obscured visibility indicate that an intersection without clear signage of the existence of an uncontrolled intersection can increase the risk propensity of injury severity. Among crash characteristics, the presence of a bike or pedestrian in a crash has significantly high log-odds indicating a crash may yield more severe injury if a vulnerable road user is involved. The likelihood of injury risk propensity is also high if a vehicle rolled over in the event of a crash. The estimated log-odds indicate that the turning movement may reduce the risk propensity of severe crashes. Regarding manner-of-collision, angle crash has the highest risk propensity and sideswipe crash has the lowest risk propensity compared with single-vehicle crashes. Consistent but varying in the magnitude of results were observed across intersection control types.

6 Marginal effects and applications

The estimated marginal effects of all driver error combinations are presented in Table 6. The estimated marginal effects indicate that all driver error combinations increase the risk of both minor injury and major injury crashes compared with no driver error crashes. For uncontrolled intersections, RI, DPI, and RDPI are the top factors that have a significant impact on major injury compared with PDO crashes. A similar impact of driver errors with impairment can also be found in sign-controlled and stop-controlled intersections. The highest marginal contribution in sign-controlled and signal-controlled intersections was DPI and RDPI, respectively. Based on results provided in Table 6, it is evident that concurrence of multiple driver errors can lead to more severe injury crashes which can be further largely amplified if the driver is under influence of alcohol or drugs.

Based on the OL modeling results, it is important to identify potential and effective countermeasures that can be implemented to influence and control driver behaviors at the intersection. The recommended countermeasures presented in Table 7 are collected from multiple previous studies (Devlin et al., 2011; FHWA, 2019). These countermeasures focused on mitigating driver errors and minimizing crash consequences for intersections.

Concerning driver errors, law enforcement-related countermeasures can help to identify repeated offenders and enforce driving behaviors allowed by the law. The driver training programs are proposed to educate drivers and improve their capability in driving decision-making. Recent advancements in in-vehicle technologies can also help in reducing the occurrence of certain driver errors such as inattentive driving. Regarding driver impairment, a series of proven and potential countermeasures have been proposed in the literature (Venkatraman et al., 2021). Intersection design-related countermeasures such as installing warning signs, increasing visibility of the stop sign are proposed considering the effect of roadway factors on crash outcomes. Moreover, improved lighting, roadway marking can increase the identification of vulnerable road users at the intersection. The availability of improved vehicle features can be beneficial to protect drivers and occupants in a crash event.

7 Conclusions

This study attempted to understand the effect of driver errors on the crash injury outcome at urban intersections by categorizing driver errors into recognition, decision, and performance based on the stage of information processing during a driving task. Considering the concurrence of driver errors, eight possible combinations were developed. Furthermore, the eight additional combinations were generated by combining driver error with impairment. The statistical dependence between different combinations of driver error categories and injury outcomes shows that more severe crashes tend to occur when the driver makes multiple errors. The compound effect of driver errors and impairment indicates that the impact of driver errors can be amplified while the driver is impaired.

Next, the OL model was applied to quantify the impact of driver errors on the crash injury outcomes at uncontrolled, sign-controlled, and signal-controlled intersections. 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 positive impact on injury crashes compared to crashes with no driver errors. The results also indicate that it might be beneficial from both theoretical and modeling perspectives to consider driver impairment as a driver error category to obtain fine-grained effects of driver impairment while modeling with driver errors. The model performance comparison shows that including driver errors can significantly improve prediction accuracy. Nevertheless, cautions should be used while exploring inter-relationship between driver errors and impairment as statistical modeling results may yield pseudo-relationship. Finally, a list of crash countermeasures was proposed to improve safety conditions at intersections. The proposed countermeasures were further categorized based on the intended application area such as influencing driver behavior, law enforcement, intersection design, vehicle features, and advanced technology.

CRediT contribution statement

Mohammad Razaur Rahman Shaon: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing—original draft, Writing—review & editing. **Xiao Qin:** Conceptualization, Methodology, Writing—review & editing. **Eric Jackson:** Conceptualization, Supervision, Writing—

Table 6 Estimated marginal effects of driver error combinations

Error combinations		Uncontrolled			Sign-controlled			Signal-controlled		
		PDO	Minor injury	Major injury	PDO	Minor injury	Major injury	PDO	Minor injury	Major injury
Driver errors	O	*Base level*								
	R	-0.047	0.045	0.003	-0.033	0.031	0.002	-0.052	0.05	0.003
	D	-0.022	0.021	0.001	-0.094	0.088	0.006	-0.059	0.056	0.003
	P	-0.042	0.039	0.002	-0.049	0.046	0.003	-0.047	0.044	0.002
	I	-0.043	0.041	0.002	-0.126	0.117	0.009	-0.11	0.103	0.007
	RD	-0.08	0.075	0.005	-0.081	0.076	0.005	-0.099	0.093	0.006
	RP	-0.08	0.075	0.005	-0.081	0.076	0.005	-0.093	0.088	0.006
	DP	-0.091	0.085	0.006	-0.156	0.145	0.012	-0.084	0.079	0.005
	RDP	-0.199	0.184	0.015	-0.248	0.226	0.022	-0.177	0.164	0.012
Interactions	RI	-0.224	0.206	0.017	-0.023	0.022	0.001	-0.055	0.052	0.003
	DI	-0.182	0.169	0.013	-0.29	0.261	0.029	-0.19	0.176	0.014
	PI	-0.135	0.126	0.009	-0.171	0.158	0.013	-0.147	0.138	0.01
	RDI	-0.133	0.124	0.009	-0.307	0.275	0.032	-0.18	0.167	0.013
	RPI	-0.152	0.142	0.01	-0.16	0.148	0.012	-0.228	0.211	0.018
	DPI	-0.292	0.266	0.026	-0.317	0.283	0.034	-0.312	0.282	0.03
	RDPI	-0.323	0.292	0.031	-0.242	0.221	0.022	-0.314	0.283	0.031

Table 7 Crash countermeasure recommendations

Contributing factors	Category	Potential countermeasures
Decision errors	Driver behavior	Design and implement driver training programs to develop driver's capability for improved decision-making, e.g. Decision Driving Seminar from insurance agencies
Recognition errors	Law enforcement	Enact and enforce cell-phone use while driving
	Technology	In-vehicle driver warning system to detect and warn driver's when inattentive
Performance error	Roadway design	Increase the visibility of speed limit signs
	Law enforcement	Enact aggressive driving laws such as enhanced penalties for repeated offenders Implement automated enforcement, e.g. red-light camera, speed traps
Impairment	Law enforcement	Enact, publicize, enforce, and adjudicate laws prohibiting alcohol-impaired driving such as high-BAC sanction, providing sobriety checkpoints, zero-tolerance enforcement, etc.
Visibility obscured	Intersection design	Install 'Intersection ahead' warning signs. Increase the visibility of stop signs.
Posted speed limit	Intersection design	Reduce speed limit near intersections and install warning signs for 'Reduced speed ahead'
Age	Driver behavior	Periodically enforced older driver vision and medical review practices. Enforced vehicle control education with license application for specific age groups related to proper vehicle control, traffic rule, and right-of-way compliance.
Overturn	Vehicle feature	Improved vehicle structure with the availability of airbags and warning systems for seat-belt use
Bike/pedestrian	Intersection design	Improved lighting at the intersection for increased pedestrian/bike visibility, leading pedestrian intervals and green painted marking for pedestrian and bike crossing
	Law enforcement	High visibility enforcement for driver yielding to bike/pedestrian

review & editing.

Declaration of competing interests

The authors report no competing interests.

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Ethics statement

The study was exempt from requiring ethical approval as the data used this is study is collected from publicly available crash database from Wisconsin DOT.

Declaration of generative AI use in writing

The authors declare that no generative AI was used in this work.

References

Baysari, M. T., C. Caponecchia, A. S. McIntosh, J. R. Wilson (2009), 'Classification of errors contributing to rail incidents and accidents: A comparison of two human error identification techniques', *Safety Science*, 47(7), 948–957, https://doi.org/10.1016/j.ssci.2008.09.012.

Behnood, A., F. L. Mannering (2017), 'The effects of drug and alcohol consumption on driver injury severities in single-vehicle crashes', *Traffic Injury Prevention*, 18(5), 456–462, https://doi.org/10.1080/15389588.2016.1262540.

CAA (1998), 'CAP 681: Global fatal accident review 1980–1996', Civil Aviation Authority, https://www.caa.co.uk/publication/download/12204.

Choi, E. H. (2010), 'Crash factors in intersection-related crashes: An on-scene perspective', NHTSA, DOT HS 811 366, http://www-nrd.nhtsa.dot.gov/Pubs/811366.pdf.

Devlin, A., N. Candappa, B. Corben, D. Logan (2011), 'Designing safer roads to accommodate driver error', Curtin-Monash Accident Research Centre, https://researchmgt.monash.edu/ws/portalfiles/portal/247939697/247939546_oa.pdf.

FHWA (2019), 'Crash modification factors clearinghouse', FHWA, https://cmfclearinghouse.fhwa.dot.gov/about.php.

Mannering, F. L., V. Shankar, C. R. Bhat (2016), 'Unobserved heterogeneity and the statistical analysis of highway accident data', *Analytic Methods in Accident Research*, 11, 1–16, https://doi.org/10.1016/j.amar.2016.04.001.

Morgan, A., F. L. Mannering (2011), 'The effects of road-surface conditions, age, and gender on driver-injury severities', *Accident Analysis & Prevention*, 43(5), 1852–1863, https://doi.org/10.1016/j.aap.2011.04.024.

Moskowitz, H., D. Florentino (2000), 'A review of the literature on the effects of low doses of alcohol on driving-related skills', NHTSA, DOT HS 809 028, https://doi.org/10.21949/1525468.

NHTSA (2008), 'National motor vehicle crash causation survey: Report to congress', NHTSA, Technical Report DOT HS 811 059, https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811059.

NHTSA (2023), 'Intersection safety', NHTSA, Turner-Fairbank Highway Research Center, https://highways.dot.gov/research/research-programs/safety/intersection-safety.

NHTSA (2024), 'Overview of motor vehicle traffic crashes in 2022', NHTSA, Traffic safety facts: Research note, DOT HS 813 560, https://rosap.ntl.bts.gov/view/dot/78044/dot_78044_DS1.pdf.

Parker, S. T., Y. Tao (2006), 'WisTransPortal: A Wisconsin traffic operations data hub', *Applications of Advanced Technology in Transportation*, 611–616, https://doi.org/10.1061/40799(213)97.

Qin, X., K. Wang, C. E. Cutler (2013), 'Logistic regression models of the safety of large trucks', *Transportation Research Record*, 2392(1), 1–10, https://doi.org/10.3141/2392-01.

Rumar, K. (1985), 'The role of perceptual and cognitive filters in observed behavior', in Evans, L., & Schwing, R. C. (eds), *Human Behavior and Traffic Safety* (Boston, USA: Springer), https://doi.org/10.1007/978-1-4613-2173-6_8.

Shaon, M. R. R. (2019), 'Identifying and incorporating driver behavior variables into crash prediction models', PhD thesis, The University of Wisconsin-Milwaukee, US.

Shaon, M. R. R., X. Qin (2020), 'Crash data-based investigation into how injury severity is affected by driver errors', *Transportation Research Record*, 2674(5), 452–464, https://doi.org/10.1177/0361198120916469.

Shaon, M. R. R., X. Qin, Z. Chen, J. Zhang (2018), 'Exploration of contributing factors related to driver errors on highway segments', *Transportation Research Record*, 2672(38), 22–34, https://doi.org/10.1177/0361198118790617.

Stanton, N. A., P. M. Salmon (2009), 'Human error taxonomies applied to driving: A generic driver error taxonomy and its implications for intelligent transport systems', *Safety Science*, 47(2), 227–237, https://doi.org/10.1016/j.ssci.2008.03.006.

Treat, J. R., N. S. Tumbas, S. T. Mcdonald, D. Shinar, R. D. Hume, R. E. Mayer, R. L. Stansifer, N. J. Castellan (1979), 'Tri-level study of the causes of traffic accidents', NHTSA, Final report, DOT HS 805 085, https://rosap.ntl.bts.gov/view/dot/1243/dot_1243_DS1.pdf.

TRIP (2023), 'Addressing America's traffic safety crisis: Examining the causes of increasing U.S. traffic fatalities and identifying solutions to improve road user safety', National Transportation Research Nonprofit, https://tripnet.org/wp-content/uploads/2023/06/TRIP_Addressing_Americas_Traffic_Safety_Crisis_Report_June_2023.pdf.

Venkatraman, V., C. M. Richard, K. Magee, K. Johnson (2021), 'Countermeasures that work: A highway safety countermeasure guide for state highway safety offices', NHTSA, DOT HS 813 097, https://rosap.ntl.bts.gov/view/dot/57466/dot_57466_DS1.pdf.

Wang, K., X. Qin (2015), 'Exploring driver error at intersections: Key contributors and solutions', *Transportation Research Record*, 2514(1), 1–9, https://doi.org/10.3141/2514-01.

Wisconsin DoT (1998), 'Law enforcement officer's instruction manual for completing the wisconsin motor vehicle accident report form (mv4000)', Wisconsin Department of Transportation, https://wisconsindot.gov/Documents/dmv/shared/manual-mv4000.pdf.

Yasmin, S., N. Eluru, A. R. Pinjari, R. Tay (2014), 'Examining driver injury severity in two vehicle crashes—A copula based approach', *Accident Analysis & Prevention*, 66, 120–135, https://doi.org/10.1016/j.aap.2014.01.018.

Ye, F., D. Lord (2014), 'Comparing three commonly used crash severity models on sample size requirements: Multinomial logit, ordered probit and mixed logit models', *Analytic Methods in Accident Research*, 1, 72–85, https://doi.org/10.1016/j.amar.2013.03.001.

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