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Impact Analysis of Road Infrastructure and Traffic Control on Injury Severity of Single- and Multi-vehicle Crashes

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Impact Analysis of Road Infrastructure and Traffic Control on Injury Severity of Single- and Multi-vehicle Crashes

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Abstract: Single and multi-vehicle crashes are a significant issue that causes economic and social costs and has therefore gained attention. This study explored the factors associated with injury severity for both single- and multi-vehicle crashes using over 550,000 crash data points in Japan between 2019 and 2021. We identified the determinants of road infrastructure and traffic control while controlling for driver, vehicle, environmental, and accident characteristics by applying ordered logit and bias-reduced binomial regression models. Our findings are as follows. 1) Traffic control variables did not affect single-vehicle crashes. 2) Guardrails had a higher severity in both single-vehicle crashes and multi-vehicle crashes at intersections. 3) The impact of the centerline differed between intersections and non-intersections for multi-vehicle crashes. These results of this study provide transportation agencies with important guidance as to the road infrastructure and transport control.

Keywords: injury severity; road infrastructure; traffic control; singe- and multi-vehicle crash; population density

1. Introduction

The effective treatment of road accidents and the enhancement of road safety are major concerns for societies owing to the loss of human lives, economic costs, and social impact. Accident severity has gained the attention of many researchers, and transportation practitioners have made tremendous efforts to improve road safety [1].

While advancements owing in airbags, sensing technology, road structures, and traffic signal control have contributed to reducing the number of driver and passenger fatalities in traffic accidents in the United States, Europe, and Japan, the ratio of driver and passenger fatalities to the total number of traffic fatalities remains high at over 50%. In this study, we analysed the factors associated with the severity of both single- and multi-vehicle crashes.

Numerous studies have recently analysed the factors that impact injury severity under limited conditions (see **Table 1**). Wu et al. (2014) highlighted significant differences in the causal attributes determining driver injury severity between single- and multi-vehicle crashes [2]. They analysed accident type and weather conditions (visibility) for both types of crashes. In analysing multi-vehicle crashes, it is essential to differentiate between intersections and non-intersections [3]. Furthermore, a comparative analysis was performed on single-vehicle crashes in urban and rural areas. Additionally, a multi-vehicle accident analysis that includes motorcycles, which have a relatively high risk, was conducted.

Table 1. Previous studies [2, 4-28].

Conditions	Single-vehicle	Multi(Two)-vehicle
Intersection		Sharafeldin et al. (2022a) [4]

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		Yuan et al. (2022) [5]
Accident type	Zhou and Chin (2019) [6] Khan and Vachal (2020) [7]	Wang and Abdel-Aty (2008) [8] Liu and Fan (2020) [9] Zhang et al. (2021) [10] Yaman et al. (2022) [11] Sharafeldin et al. (2022b) [12]
Weather (Visibility)	Naik et al. (2016) [13] Li et al. (2018) [14] Li et al. (2019) [15] Cai et al. (2021) [16]	Mphekgwana (2022) [17]
Vehicle type		Zou et al (2017) [18] Agrawal et al. (2019) [19] Wahab and Jiang (2019) [20] Yang et al.(2019) [21] Champahom et al. (2022) [22]
Region (Urban/rural)	Wu et al. (2016) [23]	
Comparison	Wu et al. (2014) [2], Rezapour et al. (2018) [24], Ma et al. (2023) [25]	
Road barrier	Li et al. (2018) [26], Russo & Savolainen (2018) [27], Molan et al. (2020) [28]	

The following six factors have been identified as potential influential factors [29].

- Driver: age, sex, drug/alcohol impairment, seat belt use.
- Vehicle type
- Environment: weather, time of day, day of the week, region (urban/rural), land use
- Accident status: rollover, collision mark of crashed vehicle, airbag activation
- Road structure: centreline, boundary between sidewalk and roadway, road alignment (curve and slope), number of lanes, etc.
- Traffic control: speed limit, traffic signals, stop signs, zone 30 etc.

Out of these six factors, policymakers cannot control the first four. In this study, we focused on the road structure and traffic control.

This section discusses the impact of road structures on the injury severity in single-vehicle crashes. Wu et al. (2016) analysed driver injury severity in single-vehicle crashes on rural and urban roads [23]. Using 2010–11 accident data from New Mexico, USA, they found that curved, multi-lane roads in urban areas, in addition to alcohol impairment, female and senior drivers, rain conditions, no-passing zones in rural areas, and drug-impaired drivers in urban areas, increased severity. Li et al. (2018) and Moran et al. (2020) analysed the injury severity of the boundary between sidewalks and roadways including various road barriers and found different impacts based on barrier and vehicle types [26, 27].

Using data from four US states, Li et al. (2019) investigated driver injury severity in rural single-vehicle crashes under rainy conditions [15]. They demonstrated that *curved*, *on-grade*, *multi-lane* roads significantly increased the probability of incapacitating injuries, controlling for driver, vehicle, and environmental factors. Additionally, signal control was found to be an influencing factor. Zhou and Chin (2019) analysed the factors influencing single-loss-of-control single-vehicle crashes for two- and four-wheeled vehicles in Singapore [6]. They showed that the type of median lane and high-speed limit roads had different influences on riders and drivers in terms of injury severity.

Some recent studies have investigated the impact of speed limits on injury severity in traffic accidents. For instance, Khan and Vachal (2020) examined the factors influencing the severity of single-vehicle rollover crashes, including variables such as environment, driver, vehicle type, and accident location [7]. They found that higher speed limits were associated with more severe injuries. Similarly, Zhang et al. (2021) focused on left-turn accidents and found that high-speed limits and

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protected left-turn signals were related to increased injury severity [10]. Gong et al. (2022) identified several risk factors for injury severity, including speed limit, driver age and gender, seatbelt use, speeding, and vehicle type [30].

Additionally, Sharafeldin et al., (2022a) analysed the factors affecting the severity of two-vehicle crashes and found that urban and signalized intersections were associated with reduced severity levels and higher pavement friction was associated with less severe crashes [4].

Several studies have compared single and multi-vehicle crashes, such as those by Wu et al. (2014) and Rezapour et al. (2018) [2, 24]. Ma et al. (2023) found that time, road, speed, lighting, and weather correlate positively with single-vehicle crash injury severity but negatively with multi-vehicle crash injury severity [25]. Factors such as area, location, and angle are significant only for single-vehicle crashes, whereas the day, interference, and wind are significant only for multi-vehicle crashes. However, it is assumed that the parameters are the same at intersections and non-intersections, except for the intercept. Thus, there is a need for further studies that compare single-vehicle crashes, which mostly occur at non-intersections.

However, there are limited analyses that focus on road structures and traffic control, as well as differences between single- and multi-vehicle crashes at non-intersections and intersections.

Hence, this study aims to identify the factors that influence road structures and traffic control in single and multi-vehicle crashes. It also compares the common and different factors in single- and multi-vehicle crashes at non-intersections and investigates the differences in influencing factors between intersections and non-intersections for multi-vehicle crashes. There are three novelties in this research. First, the road structure and traffic regulation are analyzed using the eight variables described later. More than 550,000 single- and multi-vehicle crashes in Japan are analyzed. And, we compared the factors affecting the severity between single- and multi-vehicle crashes and between intersections and non-intersection sections for multi-vehicle crashes.

2. Materials and Methods

2.1. Materials

This study utilizes crash data obtained from the National Police Agency (NPA) of Japan. The dataset consists of 995,611 traffic crashes that occurred between 2019 and 2021, which includes 8,500 fatalities. These data provide information on the severity of the crashes, as well as variables related to road infrastructure, and traffic control at crash locations. These variables were first published in 2020. For the purposes of this study, 11,882 single-vehicle and 554,365 multi-vehicle crashes were identified.

Regarding single-vehicle crashes, driver injuries were categorised as fatality (788 cases), injury (6,719 cases), and no injury (4,375 cases). The fatality rate for drivers in single-vehicle crashes was high, with 6.6% of all single-vehicle crashes resulting in driver fatalities compared to 0.9% for all crashes. In this study, only single-vehicle crashes that occurred at non-intersections were analysed since the number of single-vehicle accidents at intersections is relatively low.

In multi-vehicle crashes, injury levels were separated into fatality (1,468 cases), injury (410,510 cases), and no injury (142,387 cases). Because the number of fatalities was quite low in this study, injury severity was defined as either fatality or not.

Table 2 presents the descriptive statistics for the 18 categorical variables selected for this dataset and for the population within 500 m of the crash location. The variables common to both kinds of accidents were: (1) centreline, (2) boundary between sidewalk and roadway, (3) road alignment curve, (4) road alignment slope, (5) speed limit, (6) zone-30-policy, (7) traffic signal, (8) stop sign, (9) land use, (10) population density (population within 500-m radius), (11) weather, (12) time period, (13) day type, (14) collision marks of a crashed vehicle, (15) airbag activation.

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Table 2. Variables and their distributions.

Crash type	Single		Two			Single		Two	
Variable and category	N	%	N	%	Variable and category	N	%	N	%
Road infrastructure					**Environment**				
Centerline					***Weather***				
No	3,356	29.9	140,462	25.3	Clear	7,401	62.3	361,933	65.3
Paint	6,435	54.2	294,000	53.0	Cloudy	2,634	22.2	113,893	20.5
Median	1,699	16.2	112,458	20.3	Bad	1,847	15.5	78,539	14.2
Other (a)	192	1.4	7,445	1.3	***Time period***				
Boundary between sidewalk and roadway					After dawn	447	2.5	19,431	3.5
Curb	5,735	48.3	370,920	66.9	Daytime	6,774	54.2	361,971	65.3
Guard rail	1,311	11.0	46,302	8.4	Before dusk	561	40.5	36,643	6.6
White line	2,438	20.5	79,742	14.4	**After dusk**	592	7.5	41,678	7.5
No	2,398	20.2	57,401	10.4	Nighttime	3,206	40.5	87,912	15.9
Road alignment- Curve					Before dawn	302	2.8	6,730	1.2
Straight	8,725	73.5	531,416	95.9	***Day type***				
Inside	1,845	15.5	10,611	1.9	Weekday	3,901	32.8	151,176	27.3
Outside	1,312	11.0	12,338	2.2	Holiday, weekend	7,981	67.2	403,189	72.7
Road alignment- Slope					**Vehicle and driver**				
Flat	9,254	77.9	507,036	91.5	***Vehicle type***				
Up	1,022	8.6	20,102	3.6	Cars	4,107	34.6	-	-
Down	1,606	13.5	27,227	4.9	Kei cars	2,341	19.7	-	-
Traffic control					Large truck	337	2.8	-	-
Stop sign					Small/Medium truck	1,035	8.7	-	-
Yes			57,874	10.4	Motorcycle 126+cc	1,383	11.6	-	-
No			150,386	27.1	Motorcycle –125cc	2,679	22.5	-	-
Not applicable (b)			346,105	62.4	***Driver age***				
Speed limit (km/h)					16–24	2,284	19.2	-	-
20,30	1,683	14.2	43,656	7.9	25–34	1,376	11.6	-	-
40	3,349	28.2	170,695	30.8	35–44	1,401	11.8	-	-
50	2,587	21.8	153,493	27.7	45–54	1,862	15.7	-	-
60	4,263	35.9	186,521	33.6	55–64	1,768	14.9	-	-
Traffic signal					65–74	1,884	15.9	-	-
Three-light	760	6.4	145,607	26.3	75–	1,307	11.0	-	-
Pedestrian-controlled (c)	41	0.3	6,525	1.2	**Accident type**				
Pedestrian-vehicle separated	20	0.2	2,711	0.5	***Airbag***				
Flashing	9	0.1	4,582	0.8	Activated	2,740	23.1	154,396	27.9
None	11,052	93.0	394,940	71.2	Non-activated/Unsupported	9,142	76.9	399,969	72.1
Zone-30-policy					***Collision marks of a crashed car***				
Yes	97	0.8	4,381	0.8	Front	4,596	38.7	246,896	44.5
No	11,785	99.2	549,984	99.2	Right	1,245	10.5	29,366	5.3
Environment					Rear	437	3.7	107,615	19.4
Land uses					Left	1,467	12.3	37,839	6.8

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Urban- DID	4,780	40.2	251,700	45.4	diagonally right front	841	7.1	66,243	11.9
Urban- nonDID	2,669	22.5	177,870	32.1	diagonally left front	1,887	15.9	58,712	10.6
Rural	4,433	37.3	124,795	22.5	No	1,409	11.9	7,694	1.4
					Crash location				
Population density	Mean	s.d,	Mean	s.d.	Non-intersections	11,882	100.0	346,105	62.4
Population within 500-meter radius	3,929	5,698	4,050	3,829	Intersections	0	0	208,260	37.6

(a) Particular processing such as "High-brightness paints," "Postcones," and "Chatter bars."
(b) This refers to cases where the crash occurred at a location other than within intersections, or where the vehicle type is unknown.
(c) A traffic signal where the pedestrian signal turns green only when a button is pressed. In the UK, pedestrian crossings with this type of signal are called "pelican crossings".

Variables related to road infrastructure (variables (1)–(4)) and traffic control (variables (5)–(8)) were categorised in detail. This study considers these nine variables.

For (3) road alignment curve, "Inside" refers to driving on the inside of the curve, and "Outside" refers to driving on the outside of the curve, as vehicles in Japan drive on the left side of the road. In multi-vehicle crashes, data recorded the direction of the curve as seen from the perspective of the at-fault driver. The same applies to road alignment slopes.

The speed limit variable (5) in this study pertains to non-highway roads in Japan, with speed limits ranging from 20 to 60 km/h. Expressways with speeds exceeding 60 km/h were not included in the data. The (6) zone-30-policy is a traffic safety measure implemented in residential areas surrounded by arterial roads, with a speed limit of 30 km/h to ensure the safety of pedestrians and cyclists. For non-intersection accidents, (7) traffic signal data were recorded only for accidents within 30 m of a pedestrian crossing at an intersection, where traffic signals were used in combination with other safety measures to restrict vehicle speed. The variable (9) land uses in this study used population density within a 500-m radius, with "DID" standing for "Densely Inhabited District," referring to census tracts with a population density of 4,000 or more people per square kilometre and a population of 5,000 or more people. Table 2 provides details on the categories for each variable.

Additionally, to study driver characteristics in single-vehicle crashes, we considered vehicle type (16) and driver age (17) as variables. For multi-vehicle crashes, we used (18) vehicle type combination (hit and being hit) and (19) driver age combination (hit and being hit) as additional variables. For multi-vehicle crashes, we built a separate model based on the crash location (intersection and non-intersection).

Table 3 shows the descriptive statistics for the variables used in this study. Age groups were classified as (0–24, 25–64, and 65–), and vehicle types were classified as passenger cars (cars and kei cars), large trucks, small/medium trucks, and motorcycles. For each category, the attribute before the "×" represents the perpetrator, and the attribute after the "×" represents the victim.

Table 3. Driver age and vehicle type combination of multi-vehicle crash.

Variable and category	N	%	Variable and Category	N	%
Driver age combination			***Vehicle type combination***		
16–24 × 16–24	9,716	1.8	(C-C) Passenger car × Passenger car	304,732	55.0
16–24 × 25–64	57,532	10.4	(C-M) Passenger car × Motorcycle	86,652	15.6
16-24 × 65–	2,727	0.5	(C-ST) Passenger car × Small/Medium truck	78,516	14.2
25–64 × 16–24	63,005	11.4	(LT-C) Large truck × Passenger car	30,426	5.5
25–64 × 25–64	362,344	65.4	(ST-M) Small/Medium truck × Motorcycle	14,700	2.7
25–64 × 65–	24,420	4.4	(ST-C) Small/Medium truck × Passenger car	11,428	2.1

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65– × 16–24	3,864	0.7	(ST-ST) Small/Medium truck × Small/Medium truck	8,680	1.6
65– × 25–64	28,470	5.1	(LT-ST) Large truck × Small/Medium truck	6,308	1.1
65– × 65–	2,287	0.4	(LT-M) Large truck × Motorcycle	5,386	1.0
			(M-M) Motorcycle × Motorcycle	4,913	0.9
			(LT-LT) Large truck × Large truck	2,624	0.5

We did not observe accidents in which the vehicle type combination of the perpetrator and victim was motorcycle × (large truck, small/medium truck, passenger car), or small/medium truck × large truck. The number of passenger car × large truck combinations was also very low at 130. Therefore, we included vehicle-type combinations as variables in 11 categories, excluding the above five categories.

2.2. Methods

In this study, we utilized ordered logit and bias-reduced binomial regression models to analyse the severity of injuries for single- and multi-vehicle crashes. We employed ordered logit models to assess the connections between the dependent variables, which were categorical and ordered, such as "fatalities," "injuries," and "no injuries," and a range of independent variables. This entry specifically pertains to models in which the outcomes can be ordered. An ordered logit model estimates the underlying score by a linear function of the independent variables and a set of cutoff points.

The probability of observing outcome i corresponds to the probability that the estimated linear function, plus random error, is within the range of the cutoff points estimated for the outcome. Its equation can be given as follows:

$\Pr(\text{outcome}_j = i) = \Pr(\kappa_{i-1} < \beta_1 x_{1j} + \beta_2 x_{2j} + \cdots + \beta_k x_{kj} + u_j \leq \kappa_i)$

where uj is assumed to be logistically distributed in ordered logit. In either case, we estimate the coefficients $\beta_1, \beta_2, \ldots, \beta_k$ along with the cutoff points $\kappa_1, \kappa_2, \ldots, \kappa_{k-1}$, where k is the number of possible outcomes. κ_0 is taken as $-\infty$, and κ_k is taken as $+\infty$. This is a direct generalisation of the ordinary two-outcome logit model **[30].**

For the multi-vehicle crash analysis, we applied a bias-reduced logistic regression [31]. Conventional logistic regression analysis causes a first-order term in the asymptotic bias of the maximum likelihood (ML)coefficient estimates. The logistic regression model $\mathrm{P}(y_i = 1|x_i) = (1 + \exp(-x_i\beta))^{-1}$ with i = 1, . . . , N associates a binary outcome $y_i \in \{0, 1\}$ with a vector of covariate values $x_i = (1, x_{i1}, \ldots, x_{ip})$ using a (p + 1)-dimensional vector of regression parameters $\beta = (\beta_0, \beta_1, \ldots, \beta_p)'$. The ML estimate $\hat{\beta}_{ML}$ is given by the parameter vector maximising the log-likelihood function $l(\beta)$ and is usually derived by solving the score equations $\partial l/\partial \beta r = 0$ with r = 0, . . . , p. For ML estimates, the proportion of observed events is equal to the average predicted probability. This can be observed in the explicit form of the ML score function $\partial l/\partial \beta r = \sum_i (y_i - \pi_i)x_{ir}$ where $\pi_i = (1 + \exp(-x_i\beta))^{-1}$ denotes the predicted probability for the i^{th} observation.

Firth (1993) showed that penalising the likelihood function using the Jeffreys invariant prior removes the first-order term from the asymptotic bias of the ML coefficient estimates [32]. Jeffreys invariant prior is given by $|I(\beta)|^{1/2} = |X'WX|^{1/2}$, where $I(\beta)$ is the Fisher information matrix, X is the design matrix, and W is the diagonal matrix $\mathrm{diag}(\pi_i(1-\pi_i))$. Estimates of coefficients $\hat{\beta}_{FL}$ for Firth-type penalised logistic regression (FL) can be found by solving the corresponding modified score equations:

$$\partial l/\partial \beta r = \sum_{i=1}^{N} \left(y_i - \pi_i + h_i\left(\tfrac{1}{2} - \pi_i\right)\right) x_{ir} = 0, \ r = 0, \ldots p,$$

where h_i is the i^{th} diagonal element of the hat matrix $W^{1/2} X|X'WX|^{1/2}X'W^{1/2}$.

Moreover, we incorporated the Bayesian information criterion (BIC) for selecting the most appropriate model. We also included an interaction term to account for potential variations in the impact of a factor, based on the surrounding environment.

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3. Results

3.1. Single-vehicle crash

Table 4 illustrates the findings from the ordered logistic regression analysis of the single-vehicle crashes. Our analysis revealed that road alignment curve, boundary between sidewalk and roadway, time period, vehicle type, driver age, airbags, primary collision marks, and population density were significant variables impacting fatality risk. Most single-vehicle crashes are attributable to driver error or violations of laws and regulations. ¸Conversely, the risk of death is lower for "Daytime," "Before dusk," and "Populated areas." Surprisingly, night-time does not increase the risk of mortality. Furthermore, the interaction term analysis suggests that the fatality risk from single motorcycle crashes is higher in populated areas.

Table 4. Estimation results of single vehicle crashes (ordered logistic regression).

Variable	Category	Coef.	t value	Fatality	n
Road alignment-Curve	(ref) Straight			418	8,725
	Inside	0.23***	3.70	209	1,845
	Outside	**0.29*****	4.12	161	1,312
Boundary between sidewalk and roadway	(ref) Curb			353	5,735
	Guardrail	0.18**	2.58	97	1,311
	White line	**0.23*****	4.06	184	2,438
	No	0.15**	2.69	154	2,398
Time period	(ref) After dawn			37	447
	Daytime	−0.32**	−2.91	384	6,774
	Before dusk	**−0.44****	**−**3.06	25	561
	After dusk	*−0.25*	−1.78	29	592
	Nighttime	*0.06*	0.50	287	3,206
	Before dawn	*−0.06*	−0.34	26	302
Population density	In logarithm	−0.14***	−10.31	-	-
Airbag	(ref) Activated			313	2,740
	Daytime	−0.99***	−17.32	475	9,142
Primary collision mark	(ref) Front			472	4,596
	Right	−0.17*	−2.22	52	1,245
	Rear	−1.01***	−8.08	21	437
	Left	−0.26***	−3.58	85	1,467
	Diagonally right front	−0.17*	−1.99	72	841
	Diagonally left front	−0.71***	−11.17	75	1,887
	No	−1.39***	−15.82	11	1,409
Vehicle type	(ref) Cars			158	4,107
	Kei cars	1.01***	16.73	183	2,341
	Large truck	0.73***	5.67	41	337
	Small/Medium truck	1.10***	13.67	108	1,035
	Motorcycle 126+cc	**2.59*****	15.11	168	1,383
	Motorcycle –125cc	2.30***	12.85	130	2,679
Driver age	(ref) 16–24			114	2,284
	25–34	0.52***	6.70	76	1,376
	35–44	0.62***	7.86	85	1,401
	45–54	0.67***	9.07	126	1,862
	55–64	0.60***	7.99	115	1,768
	65–74	0.72***	9.73	113	1,884
	75–	**1.22*****	14.55	159	1,307

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Interaction term	Vehicle type: "Motorcycle" × Population density (in logarithm)	0.10***	4.44
Intercept	Fatality ∣ Injury	−0.96***	−5.90
	Injury ∣ No injury	3.23***	19.19
BIC			15,989
BIC (null)			20,698
Number of observations			11,882

3.2. Multi-vehicle crash

Table 5 presents the outcomes of the bias-reduced logistic regression analysis of multi-vehicle crashes. Our analysis revealed that in both intersection and non-intersection models, the centerline, speed limit, time period, airbag, primary collision mark, driver age combination, vehicle type combination, and population density were significant variables impacting fatality risk. In the intersection crash model, only the boundary between sidewalk and roadway, stop signs, and day types were identified as factors influencing the risk of fatalities. In contrast, only the road alignment curve was identified as a significant variable in the non-intersection crash model. Moreover, several road infrastructure and traffic control variables substantially affected the risk of fatalities compared to single-vehicle crashes.

Table 5. Estimation results of multi-vehicle crashes (bias-reduced logistic regression).

Crash location (fatality rate)		Intersections (0.4%)				Non-intersections (0.2%)			
Variable	**Category**	**Coef.**	**Z value**	**fatality**	**n**	**Coef.**	**Z value**	**fatality**	**n**
Centreline	(ref) No			426	96,560			50	43,902
	Paint	−0.57***	−7.06	272	88,239	1.17***	7.62	640	205,761
	Median	**−1.05*****	−7.46	62	21,751	0.78***	4.38	113	90,707
	Other	−0.96*	−2.03	4	1,710	**1.35*****	5.07	23	5,735
Road alignment-curve	(ref) Straight	-	-	-	-			533	328,059
	Inside	-	-	-	-	0.54***	3.88	68	8,019
	Outside	-	-	-	-	**1.04*****	9.11	225	10,027
Boundary between sidewalk and roadway	(ref) Curb			456	125,566	-	-	-	-
	Guardrail	**1.07*****	11.04	154	14,075	-	-	-	-
	White line	−0.50***	−4.13	88	38,578	-	-	-	-
	No	**−0.86*****	−6.19	66	30,041	-	-	-	-
Stop sign	(ref) Yes			103	57,874	-	-	-	-
	No	0.51***	4.55	661	150,386	-	-	-	-
Speed limit (km/h)	(ref) 20,30			37	27,306			13	16,350
	40	0.44*	2.41	192	61,068	0.59*	2.09	190	109,627
	50	0.78***	4.25	205	37,583	0.92**	3.26	328	115,910
	60	**0.85*****	4.84	330	82,303	**1.02*****	3.61	295	104,218
Time period	(ref) After dawn			39	7,817			43	11,614
	Daytime	**−0.62*****	3.63	396	135,390	**−0.42***	−2.50	477	226,581
	Before dusk	−0.51*	−2.19	34	13,868	*−0.29*	−1.24	37	22,775
	After dusk	*−0.43*	−1.95	42	14,174	*−0.35*	−1.50	35	27,504
	Night-time	**0.37***	2.10	227	34,171	0.51**	2.83	198	53,741
	Before dawn	*0.30*	1.16	26	2,840	**0.73****	3.07	36	3,890
Day type	(ref) Weekday			527	150,614	-	-	-	-
	Weekends/Holiday	0.26**	3.23	237	57,646	-	-	-	-
Population density	in logarithm	−0.38***	−16.75	-	-	−0.28***	−14.86	-	-
Airbag	(ref) Activated			670	87,255			692	67,141
	Non-activated/Unsupported	−1.73***	−12.59	94	121,005	−2.34***	−21.06	134	278,964
Primary collision mark	(ref) Front	-	-	-	-			482	105,635
	Right	-	-	-	-	−0.56***	−4.04	67	18,213
	Rear	-	-	-	-	**−1.49*****	−10.43	60	178,370
	Left	-	-	-	-	−0.38*	−2.03	33	11,433
	Diagonally right front	-	-	-	-	*0.20*	1.86	158	18,313
	Diagonally left front	-	-	-	-	−0.77**	−3.07	17	11,587
	No	-	-	-	-	*−0.28*	−0.85	9	2,554
	(ref) (C-C)			89	104,980			154	199,752

	(C-M)	1.41***	10.76	355	49,760	0.34*	2.49	168	36,892
	(C-ST)	0.85***	4.61	46	24,664	0.47***	3.18	70	53,852
	(LT-C)	1.91***	11.26	62	8,015	1.86***	15.84	174	22,411
	(ST-M)	1.86***	11.55	88	8,262	0.79***	−4.20	4	6,438
Vehicle type combination	(ST-C)	*0.79*	1.93	6	3,327	*−0.28*	−0.63	5	8,101
	(ST-ST)	1.09*	2.47	5	2,365	*0.54*	1.41	7	6,315
	(LT-ST)	2.73***	10.45	19	1,496	**2.77***	17.73	75	4,812
	(LT-M)	**3.02***	18.09	85	2,276	2.24***	−14.21	97	3,110
	(M-M)	*0.40*	0.99	6	2,712	*−0.09*	−0.23	7	2,201
	(LT-LT)	2.41***	4.30	3	403	2.37***	10.14	25	2,221
	(ref) 16–24 × 16–24			18	3,746			27	5,970
	16–24 × 25–64	*0.23*	0.87	63	19,175	*−0.07*	−0.23	1424	38,357
	16–24 × 65–	**1.75***	4.82	14	1,239	1.68***	4.05	12	1,488
	25–64 × 16–24	*−0.20*	−0.79	104	25,673	*−0.33*	−1.08	91	37,332
Driver's age combination	25–64 × 25–64	*−0.01*	−0.05	388	130,856	*0.08*	0.27	495	231,488
	25–64 × 65–	1.50***	5.77	120	11,103	1.31***	4.26	119	13,317
	65– × 16–24	*0.29*	−0.60	5	2,049	*2.03*	1.42	0	1,815
	65– × 25–64	*0.40*	1.39	41	13,243	0.66*	1.98	29	15,227
	65– × 65–	1.45***	3.77	11	1,176	**1.99***	4.91	20	1,111
Interaction term	Curve: "Outside" × Vehicle type: "Motorcycle"					0.69***	3.82	73	1,642
Intercept		−3.66***	−9.14	-	-	−5.10***	−10.78	-	-
BIC		8,628				8,456			
BIC (null)		10,106				11,637			
Number of observatios		208,260				346,105			

Our study identified several road infrastructure characteristics that impact fatality risk differently. Specifically, "Curved road" (non-intersection), "Guard rail" (intersection), and "No centreline" (intersections) increased the fatality risk, while "Median" (non-intersection) decreased the fatality risk. In terms of intersection crashes, "No stop signs" was identified as a significant factor contributing to higher fatality risk. Additionally, speed limit was found to be a significant variable for both crash locations. Surprisingly, our analysis did not find any effect of traffic signals on fatality risk.

In our study, we also identified other factors associated with a lower or higher fatality risk. The factors that lowered the fatality risk included "Daytime," "Before dusk" (intersections), and "Populated areas." Moreover, factors that raised the fatality risk included "Weekends/Holiday," "Night time," "Before dawn" (non-intersections only), "Airbag Activated," "Perpetrator is Large trucks," "Motorcycle involvement," and "Front collision marks" (non-intersections only). Moreover, motorcyclists were found to be at an even higher risk of death during "Outside curves," which was shown as an interaction term.

Our study found that driver age had a similar impact on the severity of multi-vehicle crashes as in single-vehicle accidents. Specifically, the severity of crash was found to increase as age increases. However, we also found that the impact was not the same between hitting drivers and drivers who were hit. In particular, the risk of death was estimated to be higher in the case of a hit than in the case of a collision.

Furthermore, we found that a higher population density was associated with decreased injury severity in both single- and multi-vehicle crashes. We believe that this may be due to population density acting as a proxy variable for vehicle speed; specifically, the higher the population density, the higher the traffic volume and intersection density, which may result in lower vehicle speeds and, consequently, lower injury severity in the event of a crash.

4. Discussion

4.1. Comparison of single- and multi-vehicle crashes at non-intersection

Our study found that injury severity was higher outside curves, which is consistent with previous research [2, 9]. Excessive speed can make it difficult for drivers to navigate curves, leading to severe accidents. As a result, reducing speed limits and implementing devices to slow down vehicles can be effective measures for preventing serious accidents.

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The analysis found that the speed limit was a significant variable affecting the severity of multi-vehicle crashes, but traffic control measures such as speed limit and Zone 30) were not associated with the severity of single-vehicle crashes. However, this dataset did not include information on the speed at the time of collision; therefore, further investigation is needed to better understand the relationship between speed and crash severity. Additionally, it was found that the severity of single-vehicle crashes cannot be controlled by traffic control measures in Japan. Furthermore, the study revealed that the absence of a curb to separate pedestrians and vehicles increases the severity of crashes, which is often the case on rural roads with few pedestrians or cyclists.

In multi-vehicle crashes, a centerline was found to be a significant factor associated with higher severity, possibly due to the increased impact during collisions or collision with the median strip as a physical barrier. Both single- and multi-vehicle crashes have a high fatality risk at night or before dawn. As reported in previous studies, the elderly and motorcycles are at a higher risk of accidents.

4.2. Comparison of intersection and non-intersection of multi-vehicle crashes

Regardless of whether the crash occurs at an intersection or a non-intersection, the higher the speed limit, the higher the severity of the crash. This finding is similar to that of a previous study.

An intersection with a centreline was found to have a reduced risk of injury severity, while the risk increased for non-intersections. This may be due to the difference in speed between the two vehicles at the time of collision. In a collision at an intersection, one vehicle is likely to stop or move at a lower speed, whereas, on a single road, both vehicles may be moving at high speeds. Interestingly, this result is consistent with the findings of a study on pedestrian-vehicle crashes [33]. The presence of a centreline was also found to decrease injury severity in bicycle-vehicle crashes, both at intersections and non-intersections [34].

The location of a crash was found to be a significant variable for both single- and multi-vehicle crashes. The severity was higher at intersections than at non-intersections, and further investigation is needed to determine the reason for this difference. Additionally, the type of barrier used in the roadway was also found to be a significant variable in determining the severity of a crash. Li et al. (2018) found that hitting a guardrail reduced the probability of fatal and severe injury and that a strong post-W-beam guardrail resulted in significantly more fatal and severe crashes than a low-tension cable system [26]. Russo & Savolainen (2018) showed the severity varies across the different barrier types [27]. Moran et al. (2020) suggested that a rigid barrier might be more effective for reducing truck crash severity than a guardrail barrier. Further investigation is required, including barrier type and crash location [28].

Furthermore, as in previous studies, the risk of death was found to be higher for elderly individuals involved in motorcycle crashes.

5. Conclusions

This study identified the factors contributing to road structure and traffic control in single- and multi-vehicle crashes. This study is the first result of analysis using a dataset of over 550,000 recorded accidents in Japan, applying the ordered logit and bias-reduced logistic regression models and controlling for various driver, vehicle, environment, and accident type characteristics. Then we compared the common and distinct factors of single- and multi-vehicle crashes at non-intersections and investigated the differences in influencing factors between intersections and non-intersections for multi-vehicle crashes. We confirmed that: 1) traffic control variables (such as speed limit and Zone 30) did not affect single-vehicle crashes, 2) guardrails caused high-severity crashes in single- and multi-vehicle crashes at intersections, 3) the impact of the centreline differed between intersections and non-intersections for multi-vehicle crashes, 4) population density had the negative impacts on crash severity.

The results of this study provide transportation agencies with important guidance as to the center line and boundary between sidewalk and roadway and stop signs. Especially, reducing the vehicle speed is crucial in reducing injury severity. However, our study suggests that it may be challenging to lower the severity of single-vehicle crashes through traffic control measures alone. In an attempt to address this issue, a potential solution is to implement optical illusion, as proposed by Pan et al. (2022) [35]. A Computational Illusion Team (2013) has already introduced six optical illusions that can be used, such as: anamorphosis, image bump, changing the interval of repeated patterns, slanted lines inside lane lines, speed-reduction markers, and melody roads [36]. However, it should be noted that using optical illusions may only deceive the observer's eye and may not necessarily result in reduced crash severity. Future studies should investigate the cost-effectiveness of these devices in reducing crash severity.

However, there are several limitations to this study. Firstly, data on driver violations of the law were not included, which has been identified as a significant influencing factor in many previous studies. Because this study focuses solely on road structure and traffic control, if there is a correlation between these variables and driver violations, the obtained parameters may be biased. Secondly, the impact of guardrails on injury severity requires further analysis. Thirdly, machine learning, which does not assume a parametric distribution, has been used as an estimation method in recent years [37]. Finally, Behnood and Mannering (2015) indicate that although data from different years share some common features, the model specifications and estimated parameters are not temporally stable [38]. Therefore, it is challenging to compare the analysis models and verify the stability of the parameters.

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