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WHAT LEADS TO SEVERE MOUNTAINOUS FREEWAY CRASHES IN SOUTHEAST OF CHINA?

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Original scientific paper
This paper adopted chi-square test and binary logistic regression to analyse factors about mountainous freeway crash severity level in the southeast of China and to determine the factor impact on crash severity level to make corresponding measures to improve road safety. Results of this paper indicated that younger and older drivers, female drivers, weekends and driving early in morning all make contribution to severe mountainous freeway crashes. Besides, it is more likely to occur in severe crash in spring, summer and autumn compared to that in winter. The importance of study results to audience is that road users can understand the specific characteristics of mountainous freeway crashes in southeast of China and corresponding measurements could be made to improve the safety level. Therefore, this paper proposed some suggestions to improve mountainous freeway safety: younger and older drivers should be told the driving weakness by means of variable message sign or propaganda; female drivers are not encouraged to drive in some special mountainous freeway sections; traffic designs about careful driving at night are supposed to be set especially between 0 am and 5:59 am.

Keywords: *binary logistic regression; chi-square test; crash severity level; mountainous freeway; road safety*

Zbog čega dolazi do teških sudara na brdskim cestama u jugoistočnoj Kini?

Izvorni znanstveni članak
U radu je primijenjen hi-kvadrat test i binarna logistička regresija u analizi faktora koji dovode do teških sudara na brdskim cestama na jugoistoku Kine i određivanju njihova utjecaja na stupanj težine sudara u svrhu poduzimanja odgovarajućih mjera za poboljšanje sigurnosti na cesti. Rezultati su pokazali da mlađi i stariji vozači, žene, vožnja vikendom i rano ujutro, doprinose težini sudara. Uz to, vjerojatnije je da će se teški sudari dogoditi u proljeće, ljeto i jesen, nego zimi. Važnost dobivenih rezultata je u tome što vozači mogu razumjeti specifične karakteristike sudara na brdskoj autocesti na jugoistoku Kine te se mogu poduzeti odgovarajuće mjere da se stupanj sigurnosti poveća. Stoga se u radu daju sugestije za povećanje sigurnosti; mlađe i starije vozače treba upozoriti postavljanjem raznih prometnih znakova ili propagandom; vozačicama se savjetuje da ne voze na nekim dijelovima te ceste; upozorenja bi trebalo postaviti o pažljivoj vožnji noću naročito između 0 i 5:59 ujutro.

Ključne riječi: *binarna logistička regresija; brdska autocesta; hi-kvadrat test; sigurnost na cesti; stupanj težine sudara*

1 Introduction

Road safety is an important issue in recent years and lots of crashes occur each year, which leads to death, injury and economic damage. Human, vehicle, roadway and environment factors all contribute to crashes [1].

Of human factors, driver race [2], age, gender, alcohol use [3, 4], seat belt use [5, 6], visibility [7] and work characteristics [8] mainly affect crash severity. Of environment factors, weather conditions, sun glare [9] and speed limit [10] significantly influence crash consequence. Besides, impact speed [11], violating the traffic rules [12], driving time, day of week and season of year [13] also relates to crashes.

When the relationship between these factors and crash is analysed, corresponding measures about changing the relationship can be made to improve road safety. Many researchers have done much work to figure out the relationship. Based on 6-year crash data of a freeway in Colorado, Ahmed et al. [14] used Poisson models and Bayesian to obtain significant factors associated with crash risk and results indicated that roadway geometry significantly affects crash risk, segments with steep downgrades drastically increase the crash risk, and compared to dry season, crash risk could be increased significantly during snow season. Kononov et al. [15] examined the relationship of traffic flow with safety via the data collected from existing automatic traffic recording stations around the Denver, Colorado, metropolitan area for four-lane freeways and a segment of Interstate 70 and found that as the flow increases, the crash rate initially remains constant until a certain critical threshold combination speed and density is reached and once the threshold is exceeded, the crash rate rapidly rises. Li et al. [16] divided the overall traffic state into free flow (FF), congested traffic (CT), back of queue (BQ), and front of queue (FQ) according to the speed at up- and downstream detector locations, used the logistic regression model to analyse the impacts of average speed (AS), standard deviation of speed (SD) and coefficient of speed variation (CSV) based on 448 crashes from a freeway stretch in California, and found that speed variation impacts on collision likelihood are different in different traffic states, the SD and CSV are effective surrogate safety measures for collisions in CT and BQ but may not in FF and FQ, and the AS is a crash determinant in FF and BQ but not in other states. Mergia et al. [17] applied a generalized ordinal logit model to identify factors significantly increasing the likelihood of one of the five KABCO scale of injury severity (no injuries, possible/invisible injuries, non-incapacitating injuries, incapacitating injuries, or fatal injuries) at freeway merging and diverging locations in Ohio and results showed that at freeway merging locations semi-truck related crashes, higher number of lanes on ramps, higher number of lanes on freeways, alcohol related crashes, and speed related crashes tend to increase the likelihood of sustaining severe injuries, and at diverging areas speeding related crashes, alcohol related crashes, angle-type collisions and lane-ramp configuration type D increase the likelihood of severe injury crashes significantly. Chu [18] used an ordered logit and latent class models to examine significant factors causing severe injuries in crashes of high-deck buses in long-distance driving on freeways in Taiwan and results indicated that drivers or passengers not wearing a seat belt, driver fatigue, drunk driving, reckless driving, crashes occurred at interchange ramps, and crashes occurred between midnight and dawn were found significantly affect injury severity involving high-deck buses. Choi et al. [19] applied a binary logistic regression to identify causal factors affecting truck crash severity on Korean freeways and results showed that speed-related variables such as speed enforcement, variable speed limit and lane restriction representing prevailing traffic conditions before crash occurrences are the most significant factors affecting truck crash severity compared to volume-related variables such as the volume-to-capacity ratio.

In China, over 50000 people per year were dead because of traffic crashes, which is much higher than in developed countries such as USA and Japan. Though traffic crash number is less than India (over 100000 people per year were dead because of traffic crashes), much attention should be paid to Chinese traffic crashes. Although many researchers have done much work about the road safety to analyse impact of factors, few researchers detected factors of crash severity about freeway in the southeast of China, in which human behaviours, environment factors and freeway conditions are very different from other places, so it is inevitable to analyse the factors about freeway crashes in these places, especially for mountainous freeway.

This paper analysed crash data of one mountainous freeway-Taigan Freeway, on which pedestrians and bicycles are not allowed, to find factors that lead to severe crashes to make corresponding measures to protect occupants. The research of this paper can make some contribution to better understanding the crash characteristics in China.

2 Methodology

2.1 Data collection

Taigan Freeway, which is one typical mountainous freeway in the southeast of China from Taihe to Ganzhou in Jiangxi Province as shown in Fig. 1 and is characterized by numerous tunnels and bridges, long-steep sections, small radius curves, bad roadside conditions and so on, is a section of Daguang Freeway. Taigan Freeway is one important freeway and can reflect the overall characteristics of mountainous freeways in southeast of China and that is why Taigan Freeway is studied here. The length of Taigan Freeway is 128km with two-way four lanes and the design speed is 100km/h. The AADT (Average Annual Daily Traffic) of Taigan Freeway is about 30000 vehicles and the level of service (LOS) most time is LOS A or LOS B. Data of 2737 crashes from January, 2007 to July, 2012 including 1273 injury crashes and 1464 crashes of poverty damage only (PDO) of Taigan Freeway were provided by the Department of Transport in Jiangxi Province. The data information includes year, month, day of week, daytime and weather condition of crashes, driver age, gender and year of driving experience. Crash numbers on Taigan Freeway from 2007 to 2012 per year is shown in Fig. 2.

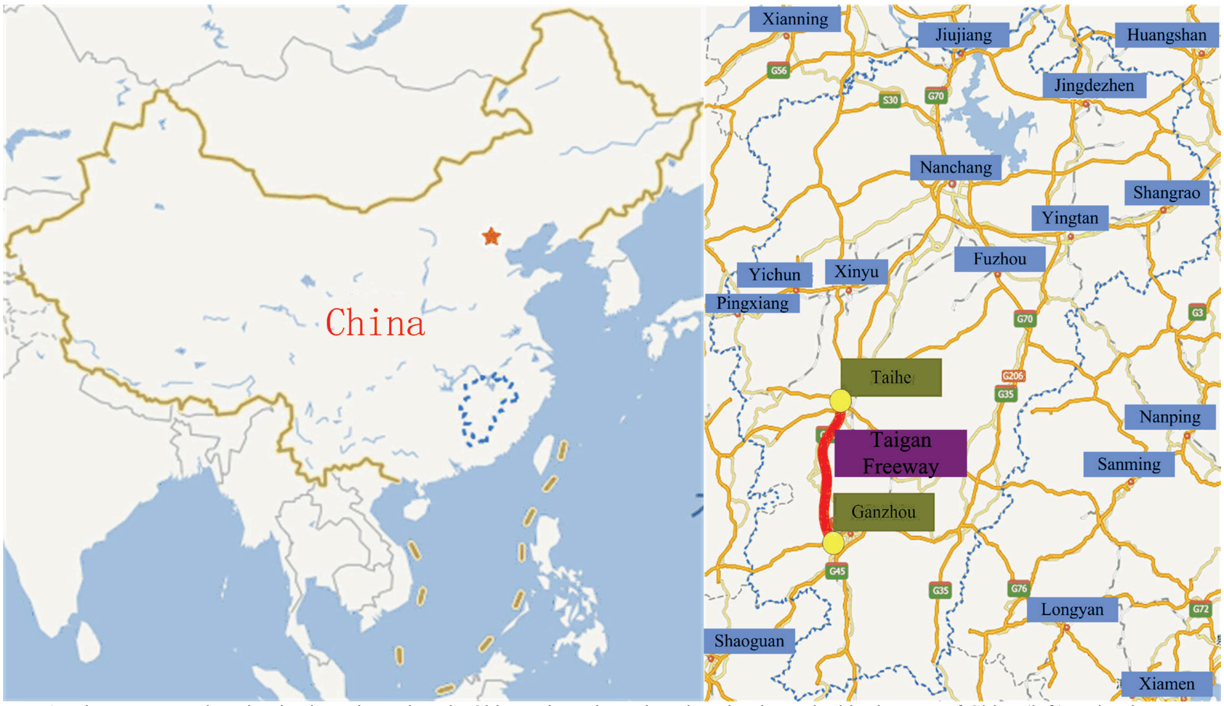

Figure 1 Taigan Freeway location in Jiangxi province in China - Jiangxi province location is marked in the map of China (left) and Taigan Freeway location is marked in the map of Jiangxi province (right)

2.2 Chi-square test

In order to analyse whether these variables affect the crash severity level, chi-square test [20, 21] was adopted. Chi-square test is very common and useful to analyse transportation questions such as the number of crashes by crash type, number of people who fall into different age and gender categories, number of vehicles purchased per year by household type and that is why it is selected to do the following analysis [22]. Chi-square statistics are calculated as shown in Eqs. (1) and (2), degrees of freedom (d_f) is calculated in Eq. (3) and the application assumption of chi-square test is that expected frequencies are not less than 5 for each category [22, 23],

$$\chi^2 = \sum_i^r \sum_j^c \frac{(O_{ij} - E_{ij})^2}{E_{ij}}, \quad (1)$$

$$E_{ij} = \frac{R_i C_j}{n}, \quad (2)$$

$$d_\mathrm{f} = (r-1)(c-1). \quad (3)$$

where, χ^2 denotes chi-square statistic, i denotes variable classification number, j denotes crash severity level number, r denotes total number of variable classification, c denotes total number of crash severity levels and equals 2 in this paper, O_{ij} denotes the observed crash number of each classification and crash severity level, E_{ij} denotes the expected crash number of each classification and crash severity level, R_i and C_j denote the sum of crash number of all crash severity levels for classification i and the sum of all classifications for crash severity level j respectively, n denotes the total crash number, and d_f denotes the degrees of freedom.

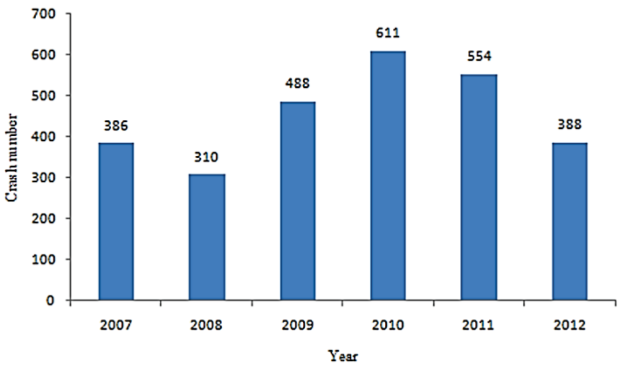

Figure 2 Crash numbers of Taigan Freeway from 2007 to 2012
Note: for year 2012, the crash number is from January, 2012 to July, 2012

2.3 Binary logistic regression

Although ordered logistic regression [17], multinomial logit model [24] and other methods were used in many past researches, the binary logistic regression was selected to determine the factor impact on crash severity level because the fatal crash percentage is much less about 13,1 % (358 fatal crashed out of 2737 total crashes) and it is not reasonable to divide crashes into three parts instead of two parts including injury crashes and PDO crashes. That is why the binary logistic regression is selected and not others. Then, binary logistic regression, which is a frequently used regression model for data analysis and of which the outcome variable is discrete, taking on two possible values, was adopted to detect the specific variable impact on crash severity level. The binary logistic regression is shown in Eq. (4) and Eq. (5), and the likelihood function can be calculated in Eq. (6) [25].

$$\pi(x) = \frac{\mathrm{e}^{g(x)}}{1 + \mathrm{e}^{g(x)}}, \quad (4)$$

$$g(x) = \ln\left(\frac{\pi(x)}{1 - \pi(x)}\right) = \beta_0 + \beta_1 x, \quad (5)$$

$$l(\beta) = \prod_{k=1}^n \pi(x_k)^{y_k} \left[1 - \pi(x_k)\right]^{1-y_k}. \quad (6)$$

where, β_0 denotes the constant, β_1 denotes the coefficient of crash affection variable x such as driver's age, driver's gender and so on, n denotes the total number of crashes, y_k denotes the k^{th} outcome of crash severity level, which is coded as 0 or 1. In order to obtain β values, the log-likelihood is shown in Eq. (7), and the β_0 and β_1 could be obtained by differentiating $L(\beta)$ respectively and setting the resulting equations equal zero as shown in Eq. (8) and Eq. (9) [25].

$$L(\beta) = \ln\left[l(\beta)\right] = \\ = \sum_{k=1}^n \left\{y_k \cdot \ln\left[\pi(x_k)\right] + (1 - y_k) \cdot \ln\left[1 - \pi(x_k)\right]\right\}, \quad (7)$$

$$\sum_{k=1}^n \left[y_k - \pi(x_k) = 0\right], \quad (8)$$

$$\sum_{k=1}^n x_k \left[y_k - \pi(x_k) = 0\right]. \quad (9)$$

However, the relationship between the continuous variable x (driver's age) and g(x) in Eq. (5) may not be linearity and LOWESS (Locally Weighted Scatter Smoothing) [26] method was used to determine the relationship. The smoothed value for variable x for the i^{th} observed value is computed as shown in Eq. (10) and Eq. (11) [25].

$$\bar{y}_{\text{smoothed } i} = \frac{\sum_{j=i_\text{low}}^{i_\text{up}} w(x_i, x_j) y_i}{\sum_{j=i_\text{low}}^{i_\text{up}} w(x_i, x_j)}, \quad (10)$$

$$w(x_i, x_j) = \left[1 - \left(\frac{|x_i - x_j|^3}{\Delta}\right)\right]^3. \quad (11)$$

where, Δ is defined so that the maximum $w(x_i, x_j)$ is not over one, i_low and i_up denote the smoothed range, which can be determined by the bandwidth k in STATA 12.0. Then the $\bar{l}_{\text{smoothed } i}$ in Eq. (12) versus x_i is plotted using the STATA 12.0's *lowess* command to find the possible relationship between the continuous variable x and $g(x)$ in Eq. (5).

$$\bar{l}_{\text{smoothed } i} = \ln \frac{y_{\text{smoothed } i}}{1 - y_{\text{smoothed } i}}. \quad (12)$$

3 Results and discussion

From the following results, the characteristics of higher traffic crashes in China than in developed countries can be understood. The Taigan Freeway crash distribution of different variables and chi-square test results are shown in Tab. 1 and from Tab. 1, it is known that season, time of day, day of week, weather condition, driver's age, gender and years of driving experience significantly affected (all P-values were less than 0,001 except the P-value of weather, which was 0,002) the crash severity level.

In order to detect which variable and how the variable affected crash severity level, the binary logistic regression was used with data of 2710 crashes (1248 injury crashes and 1462 PDO crashes) without 27crashes data with missing driver's age information and the code information was shown in Tab. 2. Besides, the LOWESS smoothing was used through STATA 12.0 with default bandwidth 0,8 [25] to determine the relationship between the continuous variable of driver's age and crash severity level, and the smooth result is shown in Fig. 3. From Fig. 3, the relationship may be quadratic function and quadratic function was used in binary logistic regression. Although years of driving experience significantly affected the crash severity, it was not included in the binary logistic regression because of lots of missing information about years of driving experience, of which 572 crashes were missing.

The binary logistic regression results were shown in Tab. 3. Coefficients of Age 2_10 and Age are 0,177 and −0,143, which are significant with p-value less than 0,001. According to calculation it is not most likely to have severe mountainous freeway crashes when the driver age is about 40 and that is to say both older and younger drivers are more likely to be involved in severe crashes, which is consistent with the study of Yan et al. [27]. That is because younger drivers have less driving experiences and older drivers' bodies are not as strong as those of the middle-aged.

Table 1 Taigan freeway crash distribution and chi-square test results

	Injury crashes (%)	PDO crashes (%)	Chi-square statistics	d_f	P-value
Season					
Spring (Feb, Mar and Apr)	340 (26,7)[1]	399 (27,3)	43,887	3	<0,001
Summer (May, June and July)	284 (22,3)	283 (19,3)			
Autumn (Aug, Sept and Oct)	369 (29,0)	313 (21,4)			
Winter (Nov, Dem and Jan)	280 (22,0)	469 (32,0)			
Time of day[2]					
0 am ÷ 5:59 am	336 (26,4)	266 (18,2)	26,924	2	<0,001
6 am ÷ 7:59 pm	770 (60,5)	990 (67,6)			
8 pm ÷ 11:59 pm	167 (13,1)	208 (14,2)			
Day of week					
Weekday	842 (66,1)	1058 (72,3)	12,032	1	<0,001
Weekend	431 (33,9)	406 (27,7)			
Weather					
Sunny	502 (39,2)	541 (37,0)	12,96	2	0,002
Cloudy	517 (40,6)	546 (37,3)			
Rainy, snowy or foggy	254 (20,0)	377 (25,8)			
Driver's age[3]					
≤25	144 (11,5)	113 (7,7)	31,337	4	<0,001
26 ÷ 35	469 (37,6)	566 (38,7)			
36 ÷ 45	456 (36,5)	571 (39,1)			
46 ÷ 55	128 (10,3)	189 (12,9)			
>55	51 (4,1)	23 (1,6)			
Driver's gender					
Male	1101 (86,5)	1406 (96,0)	80,674	1	<0,001
Female	172 (13,5)	58 (4,0)			
Years of driving experience[4]					
≤5	255 (32,0)	566 (41,4)	24,424	4	<0,001
6 ÷ 10	250 (31,3)	417 (30,5)			
11 ÷ 15	176 (22,1)	221 (16,2)			
16 ÷ 20	77 (9,6)	107 (7,8)			
>20	40 (5,0)	56 (4,1)			

Notes: [1] Numbers in parentheses are percentages. [2] Time of day was categorized as 0 am ÷ 5:59 am, 6 am ÷ 7:59 pm and 8 pm ÷ 11:59 pm to capture the daylight and driver fatigue on crashes, because the driver's energy is very different among these three categories.[3] Age was classified into 5 parts to capture driver's age on crash severity level comprehensively and 27 crashes were excluded because driver's age information was missing or with error.[4] 572 crashes were excluded because the information about years of driving experience was missing.

In order to explain these other variables related to crash severity, odds ratios were also obtained in Tab. 3. From Tab. 3, the odds ratio of Gender is 0,302 with P-value less than 0,001, and it is to say that driver gender significantly affects mountainous freeway crash severity and female drivers are 3,31 times more likely to occur in severe crashes holding other variables constant and it could be as little as 2,404 with 95 % confidence interval, which is consistent with the study of Hao and Daniel [28]. The interpretation is that female drivers cannot well manipulate vehicles under emergency because of characteristics of women. Odds ratios of Seasondesign1, Seasondesign2 and Seasondesign3 are 1,551; 1,654 and 1,895 with all P-values less than 0,001, and it is to say that season of the year affects mountainous freeway crash severity significantly [13] and it is 1,551 times more to be involved in severe crashes in spring compared to that in winter, 1,654 times in summer and 1,895 times in autumn compared to that in winter holding other variables constant. The reason of these results is that considering temperature impact on vehicle performance, drivers in winter drive carefully so that crash severity could be reduced but not crash number (Tab. 1).

Table 2 Variable code information for binary logistic regression

Variables[1]	Code information
Crash severity level	0-PDO crash, 1-Injury crash
Age2_10	(Driver's age/10)^2
Age	Driver's age
Day of week	0-Weekend, 1-Weekday
Driver's gender	0-Female, 1-Male
Season (Seasondesign1, Seasondesign2, Seasondesign3)	(1,0,0)-Spring, (0,1,0)-Summer, (0,0,1)-Autumn, (0,0,0)-Winter
Time of day (Hourdesign0-5, Hourdesign20-23)	(1,0)-0 am ÷ 5:59am, (0,1)-8 pm ÷ 11:59pm, (0,0)-6 am ÷ 7:59pm
Weather (Weatherdesign2, Weatherdesign3)	(0,0)-Sunny, (1,0)-Cloudy, (0,1)-Rainy, Snowy or Foggy

Note: [1] Though seat-belt use, alcohol consumption and so on are risk factors, this paper did not consider these factors because of no data about these factors.

Table 3 Coefficients and odds ratios of different variables related to crash severity

Variables	Coef.	Std. Err.	[95 % Conf. Interval]		Odds Ratio	Std. Err.	[95 % Conf. Interval]		z	$P>z$
Age2_10***[1]	0,177	0,037	0,104	0,251	-[2]	-	-	-	4,74	0
Age***	−0,143	0,029	−0,2	−0,085	-	-	-	-	−4,87	0
Gender***	−1,196	0,163	−1,515	−0,876	0,302	0,049	0,22	0,416	−7,34	0
Seasondesign1***	0,439	0,11	0,223	0,655	1,551	0,171	1,25	1,924	3,98	0
Seasondesign2***	0,503	0,119	0,27	0,736	1,654	0,196	1,31	2,087	4,24	0
Seasondesign3***	0,639	0,113	0,418	0,86	1,895	0,214	1,518	2,364	5,66	0
Weatherdesign2	0,004	0,097	−0,187	0,195	1,004	0,098	0,83	1,215	0,04	0,967
Weatherdesign3***	−0,344	0,11	−0,559	−0,129	0,709	0,078	0,572	0,879	−3,14	0,002
Weekday***	−0,296	0,087	−0,467	−0,125	0,744	0,065	0,627	0,883	−3,39	0,001
Hourdesign0_5***	0,497	0,103	0,295	0,699	1,643	0,169	1,343	2,011	4,82	0
Hourdesign20_23	0,127	0,122	−0,113	0,366	1,135	0,139	0,893	1,442	1,03	0,301
_cons***	3,426	0,576	2,297	4,555	30,75	17,712	9,944	95,092	5,95	0

Notes: [1] *, ** and *** denote statistically significant at α = 0,1; 0,05 and 0,01. [2] Because the age is continuous variable and the relationship between driver's age and crash severity level is quadratic function, it is meaningless to obtain Odds Ratios of Age and Age 2_10.

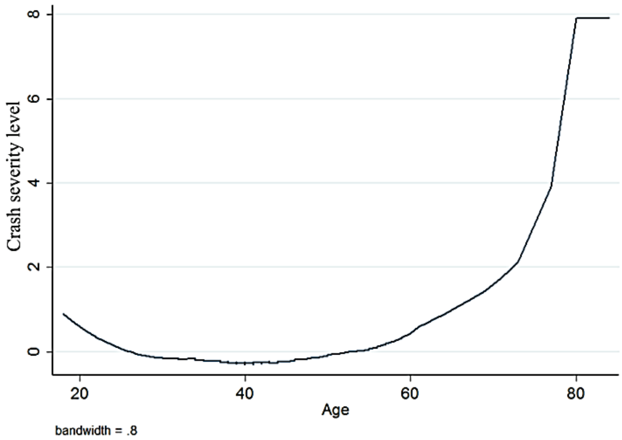

Figure 3 Logit transformed smooth result of driver's age through STATA 12.0

Odds ratios of Weatherdesign2 and Weatherdesign3 are 1,004 and 0,709 with p-values 0,967 and 0,002 and it is to say that there is no significant difference about mountainous freeway crash severity between sunny weather and cloudy weather and there is significant difference about crash severity between adverse weather (rainy, snowy and foggy) and sunny weather. However, severe crashes with adverse weather (rainy, snowy and foggy) are not more likely to occur compared to those with sunny weather (severe crashes in sunny weather are 1,410 times, which could be as little as 1,138 with 95% confidence interval, more likely to occur than those in adverse weather) and that is consistent with "PDO (Property-Damage-Only) crashes that were more affected by adverse 13 weather states compared to severe (injury and fatal) crashes" in study of El-Basyouny et al. [13]. That may be because under adverse weather states, most drivers realize weather impact and may drive much carefully so that relative severe crashes are less.

The odds ratio of Weekday is 0,744 with p-value 0,001 and it is to say that day of the week significantly influences crash severity. Mountainous freeway severe crashes on weekends are 1,344, which could be as little as 1,133 with 95% confidence interval, times more likely to occur than those on weekdays. A possible reason would be that without stress and pressure on weekends, drivers are relaxed and do not attach importance to driving. Therefore, relatively more severe crashes on weekends occurred. Odds ratios of Hourdesin0_5 and Hourdesign20_23 are 1,643 and 1,135 with p-values less than 0,001 and 0,301 and that means there is significant difference about mountainous freeway crash severity between 0 am ÷ 5:59 am and daytime (6 am ÷ 7:59 pm) and there is no significant difference about crash severity between 8 pm ÷ 11:59 pm and daytime (6 am ÷ 7:59 pm). It is 1,643 times, which could be as little as 1,343 times with 95% confidence interval, more likely to occur in severe mountainous freeway crashes between 0 am and 5:59am compared to that between 6 am and 7:59pm, which is consistent with study of Chen and Jovanis [1], and Chen et al. [29]. That is because driving between midnight and dawn, drivers are very fatigued and sleepy and they could not notice driving condition comprehensively, so severe crashes occur.

4 Conclusion

In order to detect factors and to understand characteristics related to mountainous freeway crash severity in the southeast of China, this paper used chi-square test and binary logistic regression to find the relationship between crash severity and driver age, gender, season of the year, weather condition, day of the week, time of day.

Results indicated that both younger and older drivers are more likely to have severe crashes, female drivers are 3,31 times more likely to occur in severe mountainous freeway crashes than male drivers. It is more likely to occur in severe crash in spring, summer and autumn than that in winter. Cloudy weather impact is not significantly different from sunny weather impact, severe crashes are more likely to occur under sunny weather than under adverse weather (rainy, snowy and foggy), and drivers on weekends are easier to be involved in severe mountainous freeway crashes than those on weekdays. Besides, drivers driving between 0am and 5:59am are 1,643 times more likely to have severe crashes than drivers driving in daytime (6 am ÷ 7:59 pm) while drivers driving between 8 pm and 11:59pm are not significantly different from drivers driving in daytime (6 am ÷ 7:59 pm).

The importance of study results to audience is that road users can understand the specific characteristics of mountainous freeway crashes in southeast of China and corresponding measures could be made to improve the safety level. So suggestions are made as follows: younger and older drivers should be told the driving weakness by means of variable message sign or propaganda; female drivers are not encouraged to drive in some special mountainous freeway sections; traffic signs about careful driving at night are supposed to be set especially between 0 am and 5:59 am; education program about road safety should be carried out.

Although the study of this paper would make some contribution to road safety, there are still some limitations of the study. Crashes of more years and crash data of several freeways should be analysed. Besides, some other factors should be considered about mountainous freeway crash severity in the future, such as the drug affection, alcohol consumption, belt use, roadway curve radius, road grade and other roadway elements.

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