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Driving Risk Assessment Using Near-miss Events Based on Panel Poisson Regression and Panel Negative Binomial Regression

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ORIGINAL ARTICLE

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This study proposes a method to identify and evaluate driving risk as the primary step to calculate premiums in the newly emerging context of usage-based insurance. Telematics data obtained from the Internet of vehicles contains a large number of near-miss events, which can be regarded as an alternative to modeling claims or accidents, to estimate a driving risk score for each vehicle. Poisson regression and Negative binomial regression are applied to a summary data set with one record per vehicle and to a panel data set of daily vehicle data containing near-miss events; i.e. counts of excess speed, high speed brake, harsh acceleration or deceleration, and additional driving behavior parameters not including accidents. Negative binomial regression performs better than Poisson regression. Vehicles are classified with a driving risk score computed from individual effects of the panel model. This study provides a research basis for actuarial insurance premium calculations even if no accident information is available and enables precise supervision of dangerous driving behaviors based on driving risk scores.

KEYWORDS
driving risk assessment; usage-based insurance (UBI); driving risk

Abbreviations: UBI, usage-based insurance; IoV, Internet of vehicles; PAYD, pay as you drive; PHYD, pay how you drive; MHYD, manage how you drive; POS, Poisson; ZIP, Zero-inflated Poisson; NB, Negative binomial; ZINB, Zero-inflated Negative binomial; XTPOS, Panel Poisson; XTNB, Panel Negative binomial; AIC, Akaike information criterion; BIC, Bayesian information criterion.

score; telematics; near-miss event; driving behavior; panel data analysis

1 | INTRODUCTION

Near-miss events are incidents that denote the existence of danger, even if no accident occurs. Reporting of near-miss event is an established error reduction technique that has been used by many industries to manage risk and reduce accidents. In the auto insurance industry, insurers traditionally calculate premiums by analyzing the claims the insured policy holders reported in the past and reward with discounts those drivers that do not report accidents. However, this may be a rather incorrect approach to assess accident risk, when the insured has suffered accidents but has not claimed to avoid loosing a discount. Fortunately, the advent of internet of vehicles (IoV) has given an improved solution to this problem, using near-miss events to identify driving risk. Near-miss events ultimately provide information that can lead to actuarial premium calculations in the auto insurance industry[1].

This study purposes to explore how to evaluate driving risks and score drivers in the short term without claims and accidents, but based on information on near-miss counts in a short period of time. Dealing with the absence of claims combined with a short period of observation of the drivers using telematics sensors is one of the main novelties of our approach. The model obtained in this study has important significance for driving risk identification. Not only can the model reflect risk factors that influence each near-miss event, but the coefficients can also help us evaluate drivers' risks and fixed-effects panel count data models can be used to rank drivers according to their individual effects. The modeling method and results are valuable for insurance companies to develop usage-based insurance (UBI) to personalize premiums. In addition, they are also interesting for traffic regulatory authorities to promote safe driving and prevent accidents.

Near-miss events are incidents that need to be defined and extracted from the original raw data files for further processing and analysis. Because the original telematics data in this study does not contain claims or accidents, the extraction of near-miss events that are highly relevant to identify driving patterns is critical. This study was carried out both on a per driver summary data set and on a panel data set where each driver has a daily summary. Our data contain counts of the four near-miss events in our study. Here, over speed, high speed braking, harsh acceleration and harsh deceleration, have been defined based on actual driving conditions and local laws and regulations. Since the extracted frequency of near-miss events is an unbounded non-negative integer, Poisson regression and Negative binomial regression are suitable for modelization.

Poisson regression, Negative binomial regression, Zero-inflated Poisson regression and Zero-inflated Negative binomial regression were respectively applied to the summary data set. Average speed, brake times, accelerator pedal position, engine fuel rate etc., were selected as independent variables. In particular, either mileage or fuel consumption could be chosen as exposure variable to offset the model. In order to have a clear understanding of risky factors of different near-miss events, each near-miss event was individually used as a dependent variable. However, no matter which one was selected as the dependent variable, Negative binomial regression provide the best fit in the summary data in this study.

Negative binomial regression also performed better than Poisson regression on the panel data sets. Individual effects and time effects were estimated using panel Poisson regression and panel Negative binomial regression on our short panel data set of 6 days in length. The regression results not only confirmed the existence of individual effects and time effects but allowed the driving risk of each vehicle to be ranked. Then, according to the individual effects converted into scores, the driving risk level of vehicles could be classified, providing an important reference for further accurate calculation of premiums.

The rest of this article is organized as follows. The development of UBI and previous efforts on driving risk assessment are summarized in Section 2. Section 3 describes the data and introduces the key parameters used in modeling. Section 4 presents the model expression of Poisson regression and Negative binomial regression in this study. Negative binomial regression results on summary data set and panel data set are reported and analysed in Section 5. The results are discussed and the conclusions are presented in Section 6.

2 | LITERATURE REVIEW

The auto insurance industry has never stopped pursuing new ways to calculate more accurate actuarial premiums. However, traditional auto insurance business has been limited by the difficulty of obtaining information on policy holders, so classical ratemaking uses simple information of drivers (age and gender), vehicles (type of car, model and brand) and driving sections[2]. With the continuous progress of information technology, a new type of insurance business, UBI, based on multi-source data and personalized premium calculation is becoming the mainstream. Pay-as-you-drive (PAYD) mode of charging premiums depends on the driving mileage or fuel consumption and is based on the premise that mileage or fuel consumption correlatives with the probability of suffering an accident[3]. Then, PAYD has evolved into a newer scheme, called the pay-how-you-drive (PHYD) ratemaking mode, which is based on multiple sources of data including driving behavior data[4]. After the development of 5G communication technology, it may be possible to implement an even more sophisticated monitoring and pricing strategy known as the manage-how-you-drive (MHYD) principle, i.e. real-time calculation of premiums based on multi-source data and providing real-time information to drivers to restrain bad driving behavior[2, 5]. However, due to various reasons such as technological, regulatory and other issues regarding privacy[6], there is still no mature PHYD product on the market at present[7, 8]. In terms of MHYD, driving risk needs to be further studied to produce products that are more suitable for meeting the demand[9].

Traffic accidents all over the world cause a large number of casualties every year, and high risk driving is one of the main factors that cause traffic accidents[2]. Therefore, the research on driving risk has been a hot topic in recent decades. Fundamentally, simulation experiments have beeb designed in the laboratory setting to identify driving risk factors[10, 11, 12, 13]. Further,real vehicle experiments on real road environments have been conducted to evaluate driving risk[14, 15, 16, 17, 18]. In addition, questionnaire surveys for driving risk assessment have also been studied [19, 20]. In fact, the naturalistic type of driving data collected by the Internet of vehicles or smart phones, telematics data, can effectively reduce the influence of subjective factors and unreasonable assumptions in producing effective risk mitigating actions[21, 22, 23, 24, 25].

In the research of driving risk assessment in the auto insurance industry, machine learning and generalized linear models coexist. With its strong ability to process big data efficiently, machine learning is increasingly entering explored the auto insurance business. Logistic regression[26], cluster analysis[27], decision tree[4], support vector machine[28], neural network[29] and other machine learning models[30, 31, 32] have been widely studied in the field of driving risk assessment, and the results also show that machine learning is a powerful tool [33]. However, since most machine learning procedures as black box algorithms do not have good interpretability, they cannot completely replace the conventional generalized linear models implemented for decades in the auto insurance industry[7].

Conventional generalized linear models pay attention to the correlation between influencing factors and claims or accidents in frequency and severty models[34, 23, 24, 8]. But the study of near-miss events even when there is a lack of information on claims and accidents should not be ignored[14, 1], on the contrary, since near-misses are more frequent than accidents and they are positively associated with them, near-misses can be considered good alternatives for risk modeling for driving risk assessment.

3 | DATA DESCRIPTION

The telematics data used in this study is collected from an IoV information service provider in China. The original data set contains 182 data files representing sensor data for 182 vehicles observed from July 3, 2018 to July 8, 2018[9]. Each data file contains 62 different measurements, but after data processing[35], less than one-third of them could be retained due to recording errors and inconsistencies. The original data were transformed for modeling into summary data set, with information on each driver (see details in Table 1).

TABLE 1 Descriptive statistics of the summary data set for 182 drivers observed from July 3 to July 8 2018..

Variable	Mean	Standard Deviation	Minimum	Maximum	Definition
overspeed	19.19	45.37	0	330	Frequency of driving speed greater than 90km/h
highspeedbrake	44.23	108.3	0	942	Frequency of braking when the driving speed is greater than 60km/h
harshacceleration	139.0	134.7	0	899	Frequency of cases when the acceleration is greater than $6m/s^2$
harshdeceleration	141.9	137.8	1	913	Frequency of cases when the acceleration is less than $-6m/s^2$
kilo	2,223	1,674	3.73	7,164	Total driving distance (km)
fuel	621.7	470.9	10.25	2,018	Total fuel consumption (L)
brakes	1,588	1,426	6	9,243	Total number of brakes
range	5.201	5.021	0.027	26.78	Range of driving (geographical units)
speed	36.88	16.37	0.297	67.84	Mean of speed (km/h)
rpm	1,028	188.3	233.1	1,620	Mean of revolutions per minute (r/min)
acceleratorpedalposition	21.05	7.110	0.187	39.29	Mean of acceleration pedal position (%)
enginefuelrate	11.52	4.464	1.868	22.01	Mean of engine fuel rate (%)

The number of observation is 182.

In particular, $overspeed$, $highspeedbrake$, $harshacceleration$ and $harshdeceleration$ are individually filtered by combining the rules of traffic law and driving code. Firstly, previous studies have confirmed that over speed is a dangerous driving behavior that is likely to cause traffic accidents[2]. And China's traffic safety regulations stipulate a maximum speed for the each type of vehicles on all types of roads. Secondly, if the emergency braking of a car running at a high speed is operated improperly or subjected to lateral force, it is prone to side-slip or even cartwheel, thus high-speed braking is a risky near-miss event worthy of study. Thirdly, both harsh acceleration and harsh deceleration are near-miss events that need to be avoided in terms of driving safety and fuel economy. Previous studies have already defined a threshold value of harsh acceleration and harsh deceleration[36, 1]. It can be seen from Figure 1 that near-miss events are all non-negative integers. Combined with the relationship between expectation and variance shown in Table 1, the four near-miss events are suitable as dependent variables of a Poisson regression or a Negative binomial regression.

The panel data set has one summary per day for each driver. The statistics of panel data set are shown in the Table 2.

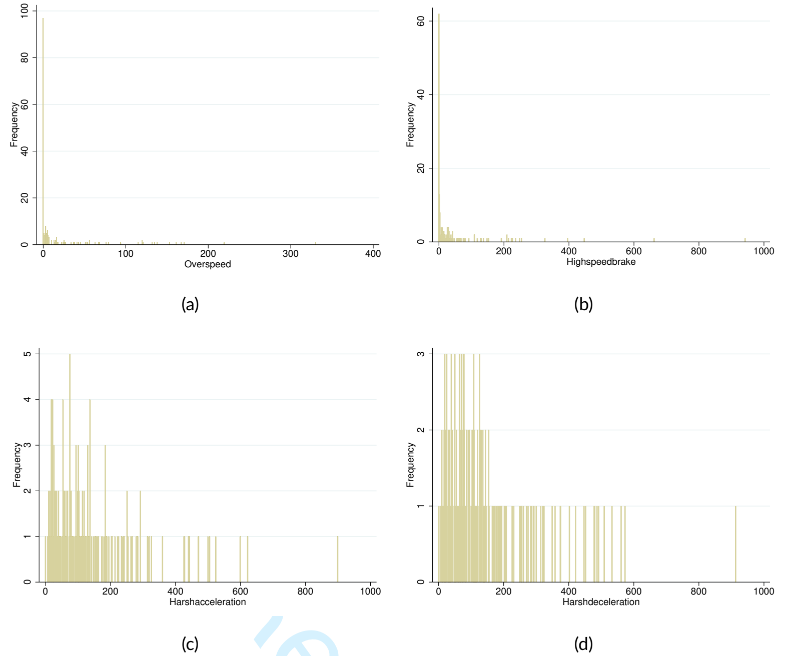


FIGURE 1 Histogram of frequency distribution of four near-miss events: (a)Over speed;(b)High speed brake;(c)Harsh acceleration;(d)Harsh deceleration.

TABLE 2 Descriptive statistics of a panel data set for 182 drivers observed over six days (total cases 1092).

Variable	N	Mean	Standard Deviation	Minimum	Maximum
overspeed	1,092	3.199	14.37	0	315
highspeedbrake	1,092	7.435	21.74	0	215
harshacceleration	1,092	23.37	29.78	0	223
harshdeceleration	1,092	23.86	30.16	0	233
kilo	1,092	372.6	373.2	0	1,739
fuel	1,092	104.1	105.7	0	565.8
brakes	1,092	264.7	291.0	0	1,940
range	1,092	2.406	2.963	0	14.07
speed	1,092	31.96	21.58	0	77.74
rpm	1,092	894.3	346.9	0	1,731
acceleratorpedalposition	1,092	17.51	10.19	0	45.74
enginefuelrate	1,092	9.794	5.835	0	26.18

4 | METHODS

Poisson regression is a generalized linear model. Generally speaking, Negative binomial regression can be considered as a generalization of Poisson regression with over-dispersion of the dependent variable Y_i where sub-index i refers to the i-th observation in the data set. The probability density function of the Poisson distribution is:

$$Pr(Y_i = y_i \mid x_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \tag{1}$$

where λ_i is the Poisson arrival rate and is determined by explanatory variable x_i in Poisson regression to represent the average number of events, which is equal to the expectation and variance of the explained variable $E(Y_i \mid x_i) = V(Y_i \mid x_i) = \lambda_i$.

The Negative binomial distribution is a mixture of a Poisson(λ) and a Gamma(a,b) distributions. The probability density function of the Negative binomial distribution is:

$$Pr(y \mid a, b) = \int_0^\infty f(y \mid \lambda) g(\lambda \mid a, b) d\lambda = \frac{\Gamma(y+a)}{\Gamma(y+1)\Gamma(a)} \left(\frac{b}{1+b}\right)^a \left(\frac{1}{1+b}\right)^y \tag{2}$$

where $\mathrm{E}(y) = \frac{a}{b} = \bar{\lambda}$ and $\mathrm{V}(y) = \frac{a}{b}\left(1+\frac{1}{b}\right) = \bar{\lambda}\left(1+\frac{\bar{\lambda}}{a}\right)$.

The zero-inflated model is applicable when the counting data contains a large number of zero values. Theoretically, it is a two-stage decision. First, it decides whether to choose zero or a positive integer, and then it determines which positive integer to choose. Therefore, the probability distribution of Y_i is a mixed distribution:

$$Pr\,(Y_i = y_i \mid x_i) = \begin{cases} \theta + (1-\theta)\,\mathrm{P}\,(K_i = y_i \mid x_i) & y_i = 0 \\ (1-\theta)\,\mathrm{P}\,(K_i = y_i \mid x_i) & y_i > 0 \end{cases} \tag{3}$$

where θ is the probability of an extra zero value, K_i can follow a Poisson distribution or a Negative binomial distribution depending on the characteristics of the dependent variable.

The conditional expectation function of a Negative binomial regression model depends on a vector of explanatory variables x_i and similar to Poisson, is usually defined by a log-link as:

$$E(y_i \mid x_i) = \lambda_i = t_i \times \exp(\alpha + \beta_1 x_{1i} + \cdots + \beta_k x_{ki}) \tag{4}$$

where i is the number of the observation, k depends on the number of independent variables, T_i denotes the offset varables (so in our application it is $kilo_i$ or $fuel_i$ as the exposure variable), $x_{1i} \dots x_{ki}$ represent the independent variables such as $brakes_i$, $range_i$, $speed_i$, rpm_i, $acceleratorpedalposition_i$ and $enginefuelrate_i$, α and $\beta_1 \dots \beta_k$ are unknown parameters that need to be estimated.

The two-way fixed effect model of panel Poisson regression and panel Negative binomial regression is specified as:

$$E(y_{it} \mid x_{it}) = \lambda_{it} = t_{it} \times \exp(\alpha + \beta_1 x_{1it} + \cdots + \beta_k x_{kit} + d_i + p_t) \tag{5}$$

where i is the number of the observation, t is of time reference, k depends on the number of independent variables, T_{it} denotes the offset variables (so in our application it is $kilo_{it}$ or $fuel_{it}$ as the exposure variable), $x_{1it} \dots x_{kit}$ represent the independent variables such as $brakes_{it}$, $range_{it}$, $speed_{it}$, rpm_{it}, $acceleratorpedalposition_{it}$ and $enginefuelrate_{it}$, α and $\beta_1 \ldots \beta_k$ are unknown parameters that need to be estimated, t_{it} is the offset and it equals $kilo_{it}$ or $fuel_{it}$ as the exposure variable in our application, d_i represent the individual effect and p_t represent the time effect. To avoid identification problems in the model specification, $d_1 = p_1 = 0$.

This study has gone through data preparation, modeling, risk scoring of driving risk, etc. The whole technical process is shown in the Figure 2. As the basic research of application, the result of this study has a good application prospect. Data processing in the preparation and Poisson regression and Negative binomial regression on different data set in the modeling can be implemented with Stata and Python.

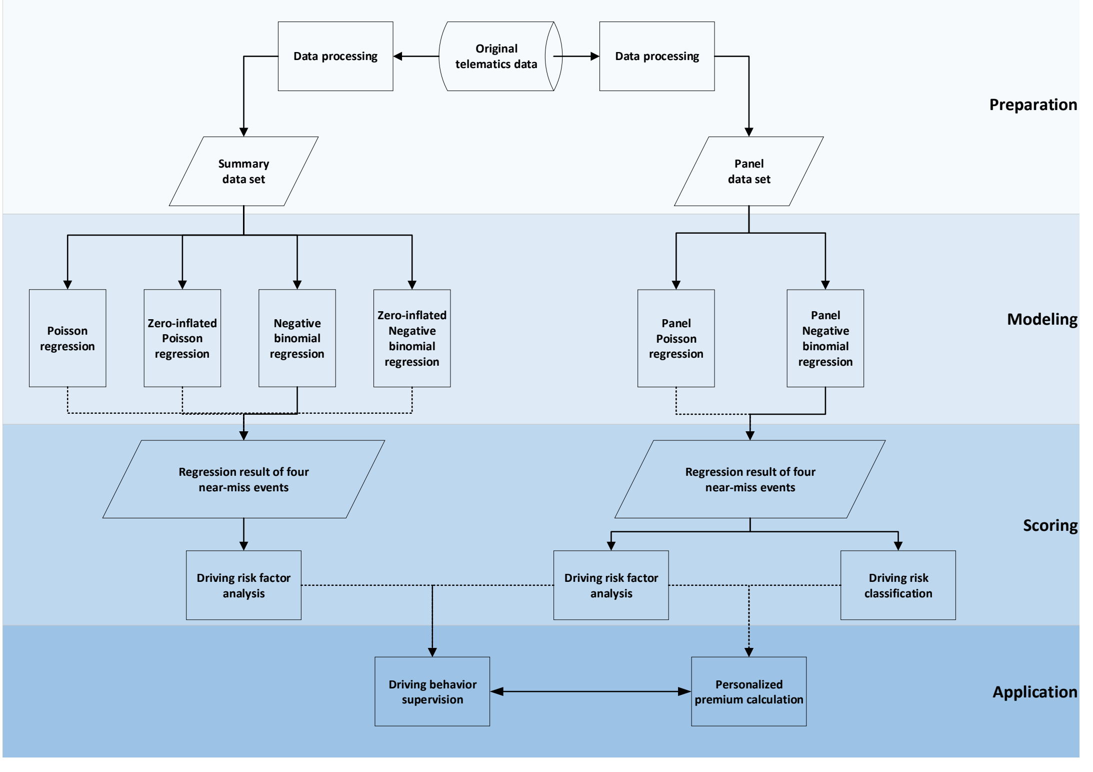


FIGURE 2 Technique flow chart.

5 | RESULTS

Both Poisson regression and Negative binomial regression were applicable to this study, and the Zero-inflated model was taken as a consideration for the large number of zero values of dependent variables. In order to determine the most suitable model for this study, the performance of models on different dependent variables was compared.

5.1 | Results of summary data set

In summary data set, four near-miss events were respectively treated as dependent variables. The independent variables were *brakes*, *speed*, *rpm*, *acceleratorpedalposition* and *enginefuelrate*, where *kilo* was chosen as the exposure variable or offset. Poisson regression, Zero-inflated Poisson regression, Negative binomial regression and Zero-inflated Negative binomial regression were estimated (see Table 3). No matter which near-miss event is the dependent variable, Negative binomial regression has maximum log-likelihood value, and minimum AIC value and BIC value. That is, Negative binomial regression has the best performance in this data set.

TABLE 3 Model performances of Poisson, Zero-inflated Poisson, Negative binomial and Zero-inflated Negative binomial in summary data set.

Variable	Model	N	log-likelihood	df	AIC	BIC
overspeed	POS	182	-3518.92	7	7051.846	7074.274
	ZIP	182	-2369.82	8	4755.64	4781.272
	NB	182	-490.517	8	997.0338	1022.666
	ZINB	182	-490.516	9	999.0315	1027.868
highspeedbrake	POS	182	-2830.75	7	5675.498	5697.926
	ZIP	182	-2667.02	8	5350.034	5375.666
	NB	182	-627.422	8	1270.843	1296.476
	ZINB	182	-627.422	9	1272.843	1301.68
harshacceleration	POS	182	-5857.26	7	11728.51	11750.94
	ZIP	182	-5857.26	8	11730.51	11756.14
	NB	182	-1032.81	8	2081.623	2107.255
	ZINB	182	-1032.81	9	2083.623	2112.459
harshdeceleration	POS	182	-6269.47	7	12552.93	12575.36
	ZIP	182	-6269.47	8	12554.93	12580.56
	NB	182	-1037.14	8	2090.285	2115.917
	ZINB	182	-1037.14	9	2092.285	2121.121

According to the results of Negative binomial regression in different dependent variables (see Table 4 and Figure 3(a)), different near-miss events are affected by different driving risk factors with different influences. Relatively speaking, the number of braking has the most obvious influence on near-miss events, it has a significant positive effect on high speed braking(0.000191), harsh acceleration(0.000133) and harsh deceleration(0.000126). The impact of average speed on near-miss events is also significant. The higher the average driving speed, the less rapid acceleration(-0.0474) and rapid deceleration(-0.0402) occur. In addition, average RPM is positively correlated with harsh acceleration(0.000947), and average accelerator pedal position is positively correlated with harsh acceleration(0.0214) and harsh deceleration(0.0330). Interestingly, some influencing factors have opposite effects on different dependent variables. Range of driving has positive effect on high speed brake(0.0541) but negative effect on harsh deceleration(-0.0305). And average engine fuel rate has a significant positive effect on high speed braking(0.158) but a negative effect on sharp deceleration(-0.0351). What's more, the significance of the constant term indicates that in addition to the factors considered in this study, there are other factors that also influence near-miss events.

TABLE 4 Negative binomial regression results for four near-miss events in the summary data set of drivers..

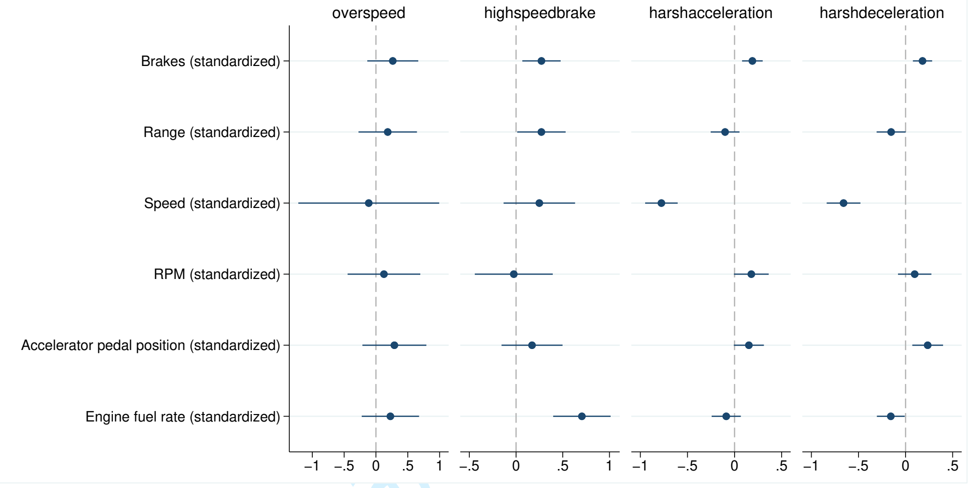
Variable	overspeed	highspeedbrake	harshacceleration	harshdeceleration
Constant	-7.536***	-8.456***	-2.101***	-1.903***
	(-3.363)	(-7.526)	(-4.006)	(-3.933)
brakes	0.000185	0.000191***	0.000133***	0.000126***
	(1.293)	(2.601)	(3.384)	(3.450)
range	0.0369	0.0541**	-0.0200	-0.0305*
	(0.791)	(2.052)	(-1.287)	(-1.942)
speed	-0.00690	0.0152	-0.0474***	-0.0402***
	(-0.200)	(1.277)	(-8.810)	(-7.201)
rpm	0.000666	-0.000128	0.000947*	0.000515
	(0.431)	(-0.113)	(1.896)	(1.072)
acceleratorpedalposition	0.0407	0.0241	0.0214*	0.0330***
	(1.130)	(1.028)	(1.872)	(2.815)
enginefuelrate	0.0508	0.158***	-0.0198	-0.0351**
	(0.987)	(4.493)	(-1.116)	(-2.073)
log-likelihood	-490.5169	-627.4217	-1032.811	-1037.142
AIC	997.0338	1270.843	2081.623	2090.285
BIC	1022.666	1296.476	2107.255	2115.917
Observations	182	182	182	182

Robust z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1

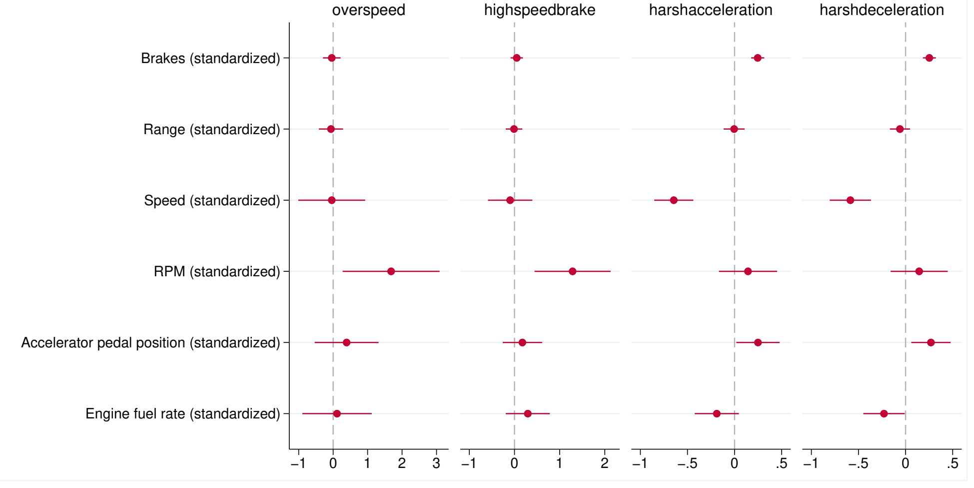
5.2 | Results of panel data set

As shown in Table 5, the evaluation index(log-likelihood, AIC and BIC) of Negative binomial regression is lower than that of Poisson regression under each dependent variable. Therefore, Negative binomial regression is better than Poisson regression on panel data.

The panel Negative binomial regression was used to estimate the two-way fixed effect model considering both individual effect and time effect on four dependent variables. The influencing factors reflected by it (seeing Table 6



(a)



(b)

FIGURE 3 Partial coefficient estimation results of (a) Negative binomial regression; (b) Panel Negative binomial regression.

TABLE 5 Model performances of Poisson and Negative binomial in the panel data set of drivers with six observations per driver.

Variable	Model	N	log-likelihood	df	AIC	BIC
overspeed	XTPOS	1092	-1926.78	188	4229.559	5168.763
	XTNB	1092	-957.497	189	2292.993	3237.193
highspeedbrake	XTPOS	1092	-2594.37	188	5564.733	6503.937
	XTNB	1092	-1527.05	189	3432.105	4376.305
harshacceleration	XTPOS	1092	-6117.44	188	12610.89	13550.09
	XTNB	1092	-3526.09	189	7430.186	8374.386
harshdeceleration	XTPOS	1092	-6042.02	188	12460.03	13399.24
	XTNB	1092	-3547.66	189	7473.311	8417.51

and Figure 3(b)) are not all the same as the results of summary data. What remains is that rapid acceleration and rapid deceleration are positively affected by the number of brakes (0.000845 & 0.000869) and average accelerator pedal position (0.0244 & 0.0265) but negatively affected by the average speed (-0.0299 & -0.0272) and average engine fuel rate (-0.0323 & -0.0392). However, RPM which is not significant in the summary data is significantly positive for over speed (0.00485) and high speed braking (0.00371). The brakes (0.000191) and engine fuel rate (0.158), which had a significant positive effect on the summary data, become insignificant.

The advantage of panel data over summary data is that fixed effects can be estimated and thus individual effects and time effects can be interpreted. The time effect are significant in most cases for high speed braking, rapid acceleration and rapid deceleration, which indicates that these three near-miss events are greatly influenced by time. The time effect of the over speed event is significant for only one day, suggesting that it is less influenced by time. Most importantly, the individual effects of the four near-miss events can be used to score each observation. It should be noted that the first individual has been omitted in the regression to avoid complete multicollinearity, and its coefficient value is expected to be zero used in the subsequent driving risk classification.

6 | DISCUSSIONS AND CONCLUSIONS

In this study, the results obtained by panel regression were more reliable than those obtained by pooled regression. Table 4, Table 6 and Figure 3 show that some coefficient are not significant in the pooled Negative binomial regression become significant in the panel Negative binomial regression, while some significant parameters in the pooled Negative binomial regression become not significant in the panel Negative binomial regression. It means that the dependent variables are affected by individual effects and time effects. Most of the individual and time coefficients in the panel Negative binomial regression are significant, which indicates the effectiveness of the panel negative binomial regression.

Driving risks can be evaluated by the regression coefficients of Negative binomial models on panel data. The value of the individual coefficients within a regression indicates the individual's deviance from the level the expected number of such a near-miss event, given the information on all the other explanatory variables. Four near-miss events have been used as dependent variables to obtain four sets of regression coefficients. Given the influencing factors and generating mechanisms of different near-miss events are different, it is not recommended to combine the four groups of regression coefficients into one group.

In order to transform individual effect estimates of near-miss models into a driving risk grading, several steps need to be done. Firstly, winsorization avoids the influence of possibly spurious outliers (the double tail was winsorized with the threshold 0.01 in this study). Secondly, the regression coefficient can be compressed to the interval of [0,1] through normalization. Then, each group of coefficients is mapped into an interval of [0,5] (see Table 7), each observation then gets a driving risk level from 1 to 5, i.e. excellent, good, medium, bad and terrible (see Figure 4). To be clear, the values of exactly 0 and 5 are because the corresponding observations are the minimum and the maximum values in their group and are Min-Max scaled. In $overspeed$ and $highspeedbrake$ groups, two types of observations with high risk or low risk can be clearly seen. It indicates that these two near-miss events are more sensitive to driving behavior than $harshacceleration$ and $harshdeceleration$ and can be considered with higher priority and weight in subsequent studies. Note that the same observation (id125) has different risk levels for different near-miss events, which also explains why multiple near-miss events cannot be analyzed together. Ultimately, the premium will be charged individually according to the driving risk level of the insured one.

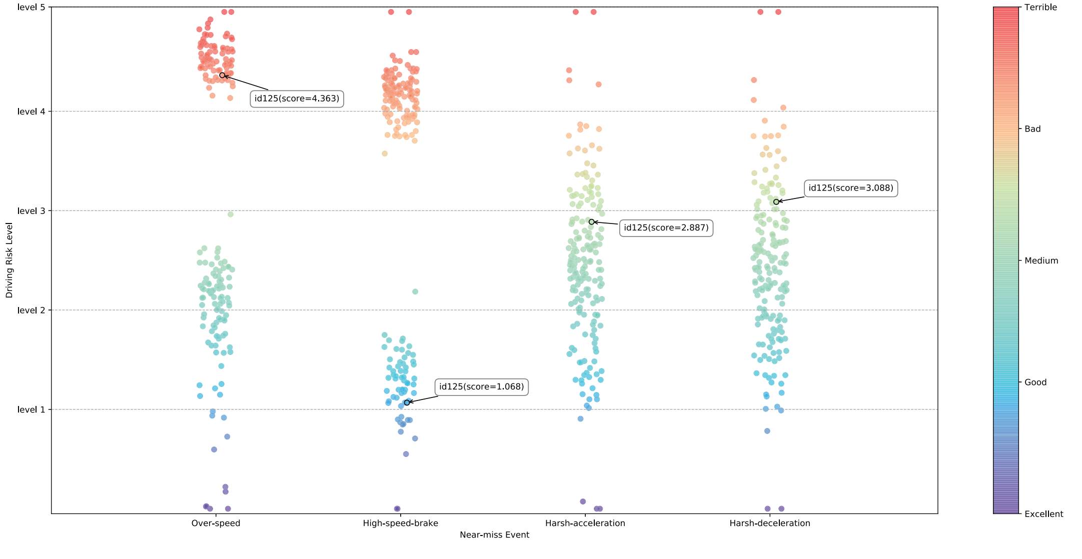


FIGURE 4 Driving risk rank of four near-miss events.

The number and type of dependent variables and independent variables selected in this study are limited by the size and quality of the original data. With the promotion and innovation of IoV and of new energy vehicles, the amount and dimension of data will be greatly increased. Therefore, near-miss events as dependent variables could be increased or decreased flexibly according to needs. For example, it is recommended to include sharp turn as a near-miss event if possible, because sharp turn is highly studied and accident-proven patterns of high driving risk. For the same reason, more driving behavior indicators such as steering wheel angle speed, brake pedal position and so on could be used as independent variables in the regression model. In addition, traditional auto insurance factors such as driver information, vehicle information, road information, environment information and the health status of batteries (of new energy vehicles) should be considered to provide more optional independent variables for the model.

In practical applications, near-miss events can be combined with claims and accidents to accurately evaluate driving risks. This study proves that near-miss events can be used as driving risk scores when there is no claims and accidents. However, when claims or accidents exist, it is recommended to adopt the driving risk evaluation strategy as follows. The driving risk score obtained from claims or accidents can be used as the basis for premium calculation, while the driving risk rating obtained from near-miss events can be used to remind and warn drivers to reduce the corresponding dangerous driving habits.

In general, near-miss events can provide insurers with effective risk information in the absence of claims and accident data. Negative binomial regression is the most suitable modeling method for near-miss events as dependent variables in our real case study. This study provides a technical reference for the promotion and development of PHYD ratemaking schemes.

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conflict of interest

The authors declare no conflict of interest.

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A | APPENDIX

TABLE 6 Panel Negative binomial regression results for four near-miss events.

Variable	overspeed	highspeedbrake	harshacceleration	harshdeceleration
Constant	-8.820***	-8.364***	-2.029***	-2.035***
brakes	-0.000138	0.000174	0.000845***	0.000869***
range	-0.0215	-0.00365	-0.00139	-0.0201
speed	-0.00188	-0.00447	-0.0299***	-0.0272***
rpm	0.00485**	0.00371***	0.000412	0.000417
acceleratorpedalposition	0.0384	0.0172	0.0244**	0.0265**
enginefuelrate	0.0193	0.0505	-0.0323	-0.0392**
2018-07-04	0.273	0.216*	-0.111**	-0.216***
2018-07-05	-0.168	-0.0572	-0.206***	-0.317***
2018-07-06	-0.00718	-0.228**	-0.257***	-0.370***
2018-07-07	-0.477**	-0.200*	-0.485***	-0.600***
2018-07-08	0.206	0.117	-0.694***	-0.784***
id2	-29.70***	-2.001**	1.266***	1.342***
id3	-19.47***	-17.47***	2.004**	1.740***
id4	-18.62***	-16.69***	1.891***	1.960***

id5	-30.60***	-4.956***	-1.193***	-1.072***
id6	-1.478**	-0.554*	1.067***	0.935***
id7	-3.237***	-0.645	0.656***	0.835***
id8	-21.39***	-2.368***	-0.190	0.124
id9	-1.156	-0.0679	-0.251	-0.109
id10	-3.110***	-1.527***	-0.345**	-0.256
id11	-2.026**	-1.163***	-0.162	-0.272
id12	-1.342**	-0.772**	0.0781	0.0981
id13	-2.344***	-0.808**	-0.138	-0.129
id14	-3.178***	0.442	-0.629***	-0.365**
id15	-1.254**	0.167	-0.0894	0.0270
id16	-23.00***	-20.31***	0.271	0.439**
id17	-22.41***	-2.102***	-0.200	0.0983
id18	-21.61***	-0.805	-1.124***	-1.267***
id19	-0.998	0.380	0.587***	0.586***
id20	-24.78***	-3.749***	0.292	0.0926
id21	-22.39***	-2.577***	0.322	0.458***
id22	-2.642***	-0.229	0.496***	0.538***
id23	-0.792	0.00111	-0.474	-0.409*
id24	-24.05***	-21.10***	-0.329	-0.103
id25	-21.70***	-19.47***	-0.882***	-0.731**
id26	-2.739***	-1.000***	-0.440*	-0.667***
id27	-23.77***	-20.99***	-0.0464	0.0656
id28	-18.27***	-17.04***	0.0432	0.309
id29	-1.137	-0.872**	0.591***	0.625***
id30	-21.14***	-18.81***	-0.223	-0.102
id31	-0.407	-0.632**	-1.148***	-0.949***
id32	-3.255***	-2.923**	-0.110	0.143
id33	-19.47***	-18.27***	-0.177	-0.153
id34	-2.431***	-1.547***	-0.00573	-0.0439
id35	-3.832***	-1.041**	-0.607***	-0.552***
id36	-4.135***	-2.411***	-0.285	-0.343*
id37	-39.82***	-1.232*	-0.480	-0.218
id38	-20.79***	-1.364**	-1.484***	-1.121***
id39	-39.80***	10.89***	11.65***	11.77***
id40	-1.325	-0.416	-0.278	0.0791
id41	-2.443***	-1.020**	0.180	0.155
id42	-0.467	0.442	0.607	0.398
id43	-2.164**	0.219	-0.0359	0.0900
id44	-2.465***	-0.156	0.336	0.468*
id45	-2.110***	-1.315***	0.105	0.282
id46	0.132	-0.480	-0.312***	-0.235*
id47	-2.957***	-0.975	-0.853***	-0.656***

id48	0.486	1.381***	0.829***	0.787***
id49	-26.13***	-1.575***	-0.568***	-0.353*
id50	-2.556***	-1.907***	-0.413**	-0.331*
id51	-21.19***	-19.04***	1.123***	1.140***
id52	-21.82***	-20.71***	-0.354	-0.952***
id53	-21.26***	-19.27***	-0.133	0.200
id54	-4.881***	-1.082***	-0.686***	-0.639***
id55	-4.290***	-1.731***	0.472*	0.476
id56	-2.462***	-0.0866	0.119	0.377
id57	-21.86***	-0.700	0.110	0.719**
id58	-1.877*	-0.692	-0.344	0.0660
id59	-40.00***	-0.0709	-0.726**	-0.587*
id60	-3.117***	-3.813***	-0.711**	-0.565*
id61	0.821	1.078*	-1.288***	-1.076**
id62	-0.465	0.546	-0.670	-0.473
id63	-22.05***	-19.52***	1.393***	1.513***
id64	-2.529	-1.707	1.334***	1.339***
id65	-22.00***	-19.36***	-1.923***	-1.288***
id66	-1.389	-1.510***	0.504***	0.971***
id67	-26.39***	-3.400***	-0.371**	-0.304*
id68	-19.61***	-17.60***	-1.286***	-1.660***
id69	-25.19***	-20.76***	-0.589***	-0.625**
id70	-21.81***	-3.693***	-1.489***	-1.501***
id71	-32.23***	-28.28***	0.587***	1.212***
id72	-5.534***	-1.058*	-0.516	-0.643*
id73	-4.323***	-2.863***	-1.527***	-1.523***
id74	-31.88***	-27.94***	0.299	0.765***
id75	-2.868***	-1.677***	-0.267	-0.0911
id76	-21.77***	-22.16***	-1.646***	-1.903***
id77	-20.38***	-18.72***	0.835***	0.729***
id78	-24.70***	-3.260***	-2.855***	-2.759***
id79	-3.449***	-0.618	-0.232	-0.110
id80	-22.34***	-20.24***	-0.0149	0.0509
id81	-35.06***	-1.132**	-0.341**	-0.336**
id82	-1.391	-0.541	-0.312	-0.326
id83	-1.516***	0.157	-0.123	-0.242
id84	-24.88***	-1.866**	-0.750***	-0.855***
id85	-22.91***	-3.843***	-1.430***	-1.318***
id86	-29.96***	-2.036***	-1.272***	-1.111***
id87	-1.851**	1.034***	0.196	0.425**
id88	-20.59***	-18.45***	-0.208	-0.165
id89	-26.39***	-22.35***	1.100**	1.135**
id90	-4.008***	-0.841	-0.972***	-0.982***

id91	-20.05***	-19.02***	0.676***	0.818***
id92	-26.97***	-22.96***	0.848**	0.663**
id93	-24.47***	-21.29***	-0.290	-0.300
id94	-2.684***	-1.034***	-0.157	0.0139
id95	-25.60***	-21.99***	-0.503	-0.670
id96	-23.42***	-20.46***	1.374***	1.343***
id97	-21.44***	-19.45***	-0.464**	-0.282
id98	-19.05***	-17.65***	-1.405***	-0.887**
id99	-18.58***	-17.09***	-1.774***	-1.369***
id100	-4.226***	-20.22***	0.802**	0.824**
id101	-23.30***	-20.24***	0.955**	0.814*
id102	-25.66***	-22.49***	0.0308	-0.0294
id103	-18.28***	-16.93***	0.542**	0.606***
id104	-20.60***	-18.55***	0.131	0.262**
id105	-3.426***	-0.430	-0.464	-0.925**
id106	-25.81***	-22.46***	0.317*	0.252
id107	-21.63***	-19.42***	0.0144	0.147
id108	-24.10***	-2.647***	-0.532**	-0.635***
id109	-21.46***	-19.64***	-0.347***	-0.782***
id110	-21.03***	-20.38***	-1.801***	-1.044***
id111	-3.405***	-1.277***	0.173	0.198
id112	-20.18***	-18.15***	-1.453***	-0.831***
id113	-30.49***	-2.997***	-1.703***	-1.296***
id114	-24.22***	-21.07***	0.637***	0.537***
id115	-22.90***	-20.24***	-0.0179	-0.109
id116	-22.43***	-3.753***	-1.349***	-1.135***
id117	-21.32***	-19.05***	-0.156	-0.273**
id118	-19.53***	-0.705	0.116	0.00337
id119	-20.89***	-18.80***	-0.145	-0.143
id120	-28.10***	-24.40***	-0.0170	0.133
id121	-29.59***	-0.687*	0.239	0.387**
id122	-22.31***	-2.515**	0.623**	0.653**
id123	-23.52***	-3.892***	0.698	0.886**
id124	-4.268**	-2.612**	0.698***	0.361
id125	-3.828**	-21.08***	0.296	0.619*
id126	-2.023	-2.183**	0.576*	0.539*
id127	-22.73***	-19.80***	1.158***	1.010***
id128	-21.55***	-19.82***	0.762***	0.618**
id129	-1.540**	0.777**	0.0280	0.165
id130	-25.56***	-22.20***	-1.578***	-1.635***
id131	-1.659**	-0.403	-0.980***	-0.794***
id132	-19.92***	-17.86***	-0.863***	-0.435*
id133	-27.00***	-2.904***	-0.622***	-0.691***

id134	-32.40***	-2.618***	0.488**	1.176***
id135	-24.19***	-20.95***	0.930***	1.350***
id136	3.358***	4.212***	2.661***	2.709***
id137	-24.30***	-2.508***	0.0440	0.804***
id138	-19.39***	-17.42***	-0.827***	-0.890***
id139	-4.105***	-1.187**	-0.922***	-0.677
id140	-2.970***	-0.615	-1.276***	-1.035***
id141	-25.41***	-22.20***	-1.071***	-1.100***
id142	-38.18***	-0.873*	0.0500	0.175
id143	-38.58***	-0.397	-0.368	-0.157
id144	-0.585	0.551	0.0261	0.167
id145	-2.485**	-1.273**	-0.750	-0.631
id146	-23.85***	-1.250***	-1.130***	-0.758**
id147	-2.851***	-0.0796	-1.021***	-0.896***
id148	-3.737***	1.617***	-0.0483	-0.0520
id149	-3.202***	-1.184**	-0.554***	-0.343
id150	-3.616***	-0.905**	-1.167***	-0.905***
id151	-0.362	-1.167**	-1.654***	-1.677***
id152	-33.99***	-3.751***	-1.421***	-1.382***
id153	-1.598**	-0.169	-2.936***	-3.067***
id154	-22.42***	-2.716***	-1.703***	-1.483***
id155	-4.238***	-2.441**	-0.759***	-0.814***
id156	-44.40***	-1.456***	-0.590***	-0.429**
id157	-1.868**	0.337	-0.753***	-0.502**
id158	-19.82***	-17.98***	0.678***	0.744***
id159	-19.82***	-18.42***	0.827***	0.715***
id160	-3.790***	0.550	0.148	0.337*
id161	-22.82***	-19.90***	0.608***	0.494***
id162	-20.72***	-18.61***	0.431*	0.176
id163	-23.06***	-20.45***	1.844***	1.656***
id164	-2.923***	-2.557***	-0.245*	-0.301*
id165	-21.48***	-19.51***	1.341***	1.447***
id166	-26.53***	-2.439***	-0.158	-0.0534
id167	-2.696**	-4.124***	1.119***	1.089***
id168	-5.731***	-1.940***	0.0447	0.0115
id169	-26.92***	-23.39***	0.473**	0.422*
id170	-15.44***	-13.89***	-19.55***	-0.684
id171	-3.650***	-1.497***	-0.344	-0.313
id172	-3.659***	-1.951***	-0.427*	-0.367
id173	-3.036***	-3.500***	-0.874***	-0.888***
id174	1.453	0.361	-1.484***	-1.288***
id175	-0.688	1.615***	0.114	0.333
id176	-1.666*	-0.313	0.530	-0.0614

id177	-2.576***	-1.675***	-0.245	0.187
id178	-0.823	0.510	0.213	0.0436
id179	-20.05***	-1.071	-1.386***	-1.021*
id180	-4.457***	-2.934***	-0.402**	-0.277
id181	-1.850**	-0.909**	-0.573*	-0.354
id182	-4.755***	-2.082***	0.387	0.409
log-likelihood	-952.2391	-1519.954	-3479.969	-3488.38
AIC	2292.478	3427.908	7347.937	7364.76
BIC	3261.657	4397.086	8317.116	8333.939
Observations	1,092	1,092	1,092	1,092

*** p<0.01, ** p<0.05, * p<0.1

TABLE 7 Driving risk scores for four near-miss events after winsorizing and Min-Max scaling on regression coefficients.

Variable	overspeed	highspeedbrake	harshacceleration	harshdeceleration
id1	4.824741	4.344986	2.622834	2.52286
id2	1.242371	4.033808	3.753797	3.75
id3	2.476298	1.628204	4.413078	4.113936
id4	2.578824	1.749502	4.312131	4.315106
id5	1.133814	3.574272	1.557084	1.542612
id6	4.646467	4.258833	3.576023	3.377835
id7	4.434299	4.244682	3.208862	3.286394
id8	2.244711	3.976736	2.4531	2.636247
id9	4.685306	4.334427	2.398606	2.423189
id10	4.449618	4.107521	2.314633	2.288771
id11	4.580368	4.164127	2.478113	2.27414
id12	4.662871	4.224932	2.692603	2.612564
id13	4.542011	4.219333	2.499553	2.404901
id14	4.441416	4.413722	2.060925	2.1891
id15	4.673486	4.370957	2.542969	2.547549
id16	2.050515	1.186551	2.864928	2.924287
id17	2.12168	4.018102	2.444167	2.612747
id18	2.218175	4.2198	1.618724	1.364301
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id20	1.835814	3.761974	2.883688	2.607535
id21	2.124092	3.944234	2.910488	2.941661
id22	4.506067	4.309374	3.065928	3.014813
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id24	1.923866	1.063697	2.328926	2.428676
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id26	4.494367	4.189475	2.229766	1.912948

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id33	2.476298	1.503794	2.464713	2.382955
id34	4.531518	4.10441	2.617715	2.482718
id35	4.362531	4.183099	2.080579	2.018105
id36	4.325984	3.970049	2.368233	2.209217
id37	0.021711	4.153396	2.194033	2.323519
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id48	4.883362	4.559747	3.363409	3.242502
id49	1.672979	4.100056	2.115419	2.200073
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id66	4.657202	4.110164	3.073075	3.410753
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id71	0.937206	0	3.147222	3.631127
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id76	2.198876	0.898855	1.152403	0.782736
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id78	1.845464	3.838019	0.07236	0
id79	4.408728	4.24888	2.41558	2.422275
id80	2.130123	1.197437	2.609523	2.569404
id81	0.595856	4.168947	2.318206	2.215618
id82	4.656961	4.260855	2.344113	2.224762
id83	4.641884	4.369402	2.512953	2.301573
id84	1.823752	4.054802	1.952832	1.741039
id85	2.061371	3.747356	1.345364	1.317666
id86	1.21101	4.028365	1.486511	1.50695
id87	4.601476	4.505785	2.797927	2.911485
id88	2.341206	1.475802	2.43702	2.371982
id89	1.641618	0.869308	3.605503	3.560717
id90	4.341302	4.214201	1.754511	1.624909
id91	2.40634	1.387161	3.226729	3.270849
id92	1.571659	0.774446	3.380382	3.129115
id93	1.873206	1.03415	2.363766	2.248537
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id95	1.736907	0.925292	2.173486	1.910205
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id105	4.411502	4.278116	2.208326	1.67703
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id107	2.215762	1.324956	2.635698	2.657279
id108	1.917835	3.933348	2.147579	1.942209
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id121	1.255639	4.23815	2.836341	2.876737
id122	2.133742	3.953875	3.179382	3.119971
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id125	4.363014	1.066808	2.887261	3.088881
id126	4.58073	4.005505	3.137395	3.015728
id127	2.083082	1.265862	3.657316	3.446416
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id134	0.916701	3.937858	3.058781	3.598208
id135	1.906979	1.087024	3.453636	3.757315
id136	5	5	5	5
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id139	4.329602	4.160394	1.799178	1.903804
id140	4.466504	4.249347	1.482937	1.576445
id141	1.759824	0.892635	1.666071	1.517008
id142	0.219526	4.209225	2.6675	2.682882
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id145	4.525004	4.14702	1.952832	1.945867
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id148	4.37399	4.596448	2.579686	2.475311
id149	4.438521	4.160861	2.127926	2.209217
id150	4.388585	4.204249	1.580311	1.695318
id151	4.781077	4.163505	1.145256	0.989393
id152	0.724917	3.761663	1.353404	1.259144
id153	4.631993	4.318705	0	0
id154	2.120474	3.922618	1.101483	1.166789
id155	4.31356	3.965383	1.944792	1.77853

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id167	4.499554	3.703658	3.622476	3.518654
id168	4.133476	4.043294	2.662766	2.533376
id169	1.57769	0.707577	3.045381	2.908742
id170	2.962391	2.184934	0	1.897403
id171	4.384484	4.112186	2.315526	2.23665
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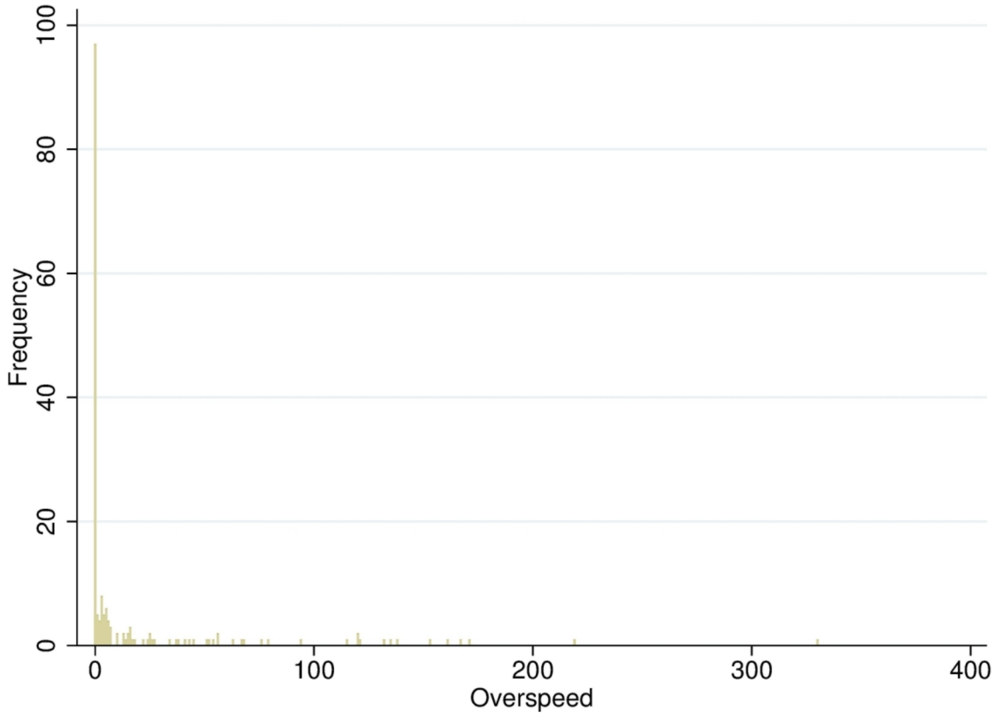


Figure 1 Histogram of the frequency distribution of four near-miss events: (a) Over speed

139x101mm (300 x 300 DPI)

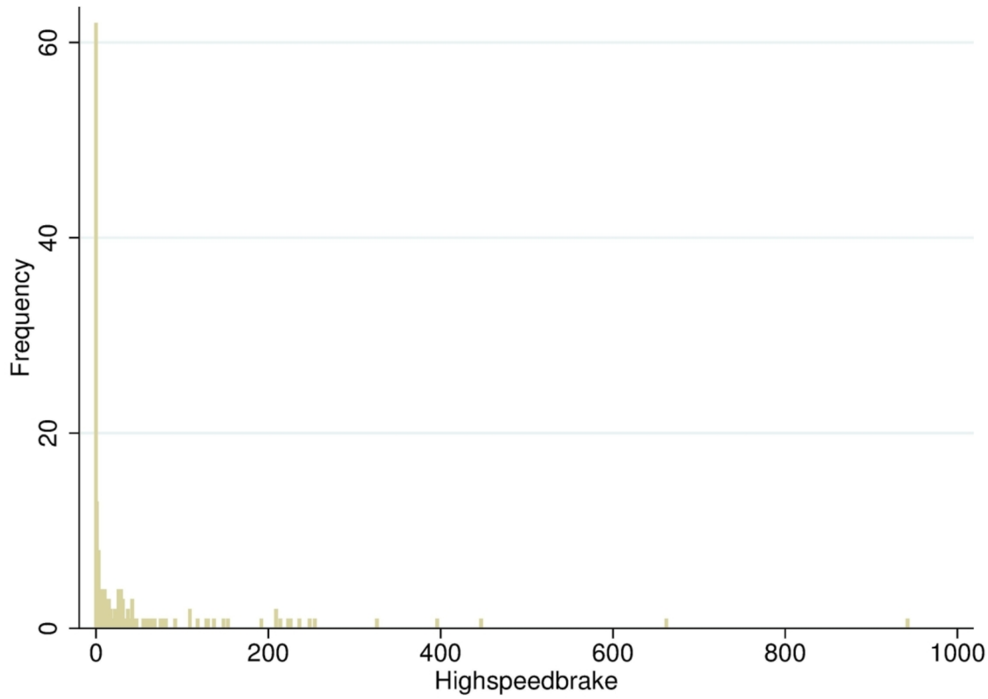


Figure 1 Histogram of the frequency distribution of four near-miss events: (b) High-speed brake

139x101mm (300 x 300 DPI)

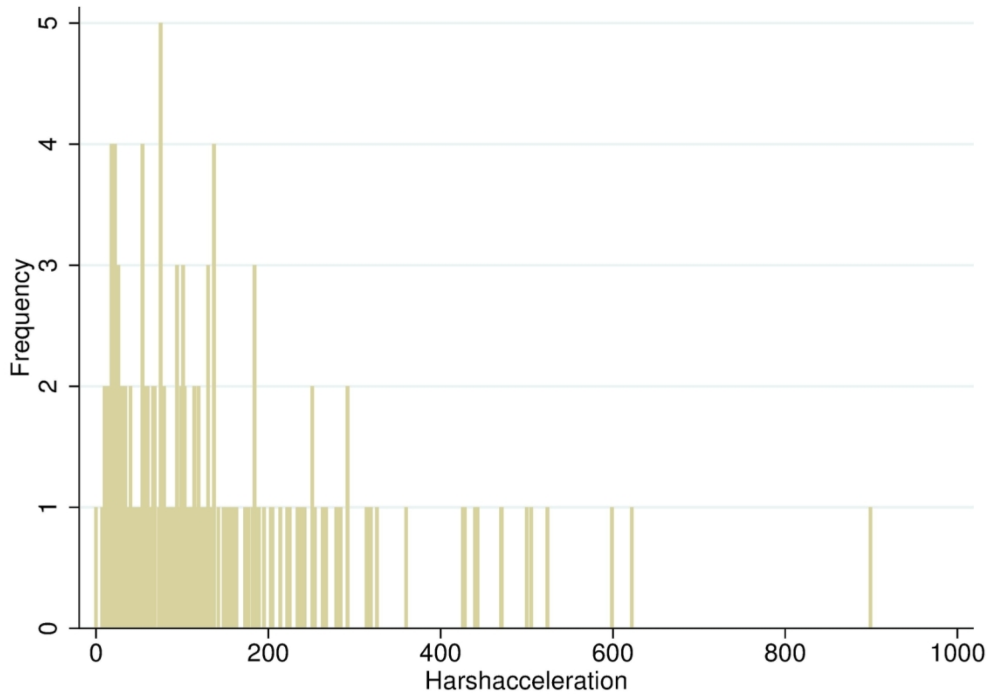


Figure 1 Histogram of the frequency distribution of four near-miss events: (c) Harsh-acceleration

139x101mm (300 x 300 DPI)

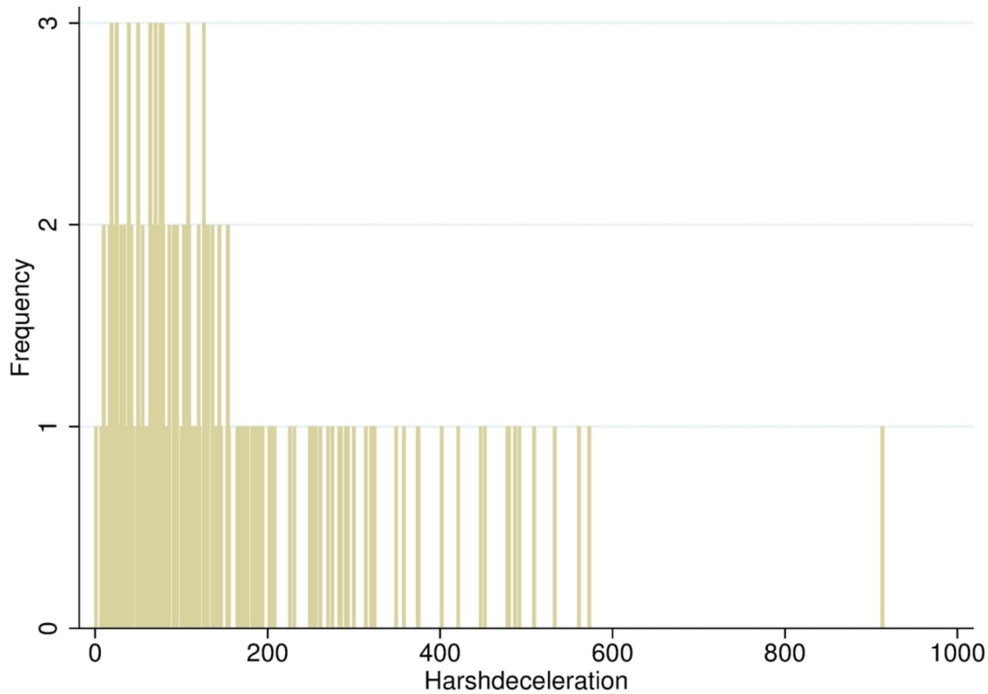
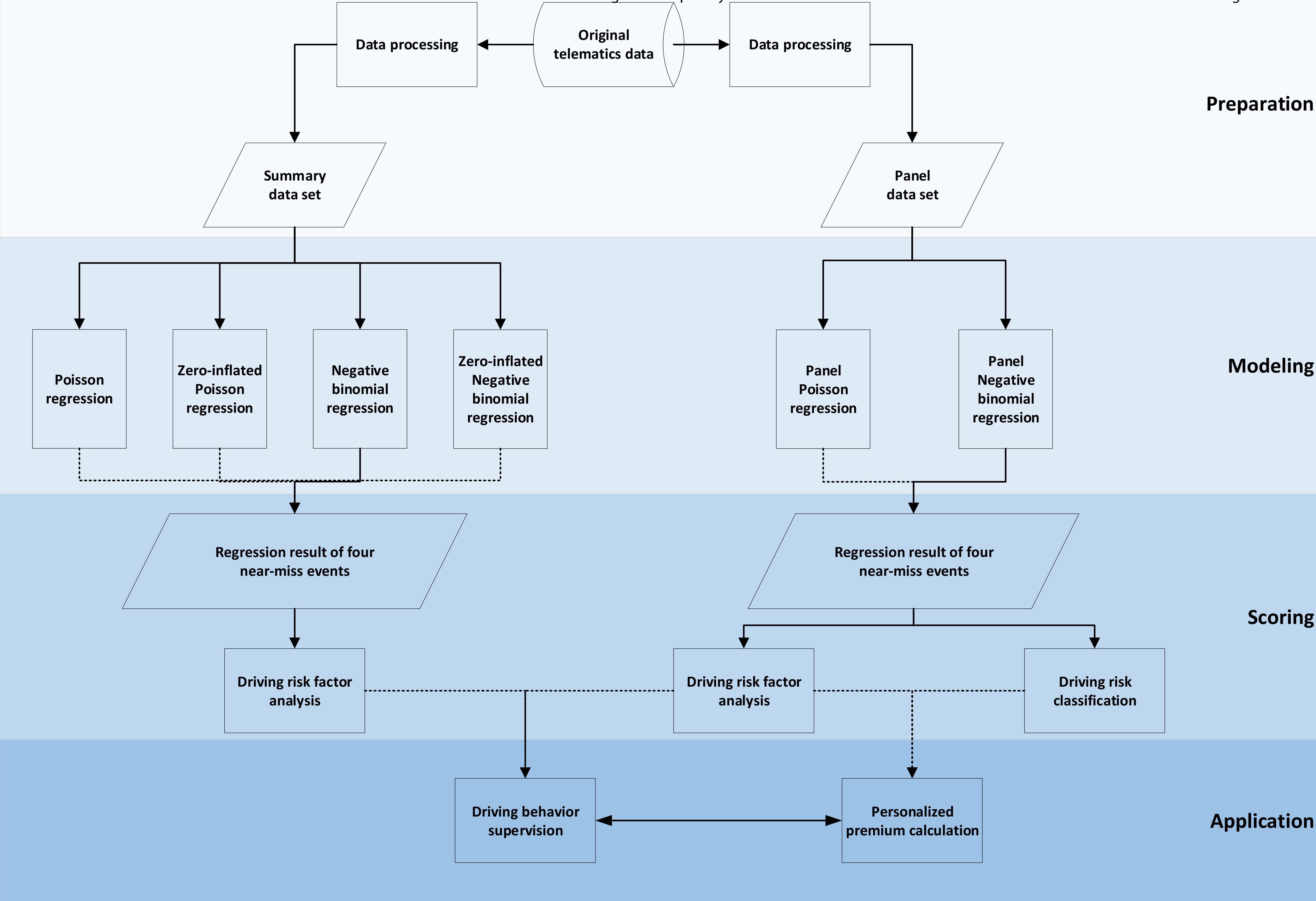


Figure 1 Histogram of the frequency distribution of four near-miss events: (d) Harsh-deceleration

139x101mm (300 x 300 DPI)


Data processing
Original telematics data
Data processing
Preparation
Summary data set
Panel data set
Poisson regression
Zero-inflated Poisson regression
Negative binomial regression
Zero-inflated Negative binomial regression
Panel Poisson regression
Panel Negative binomial regression
Modeling
Regression result of four near-miss events
Regression result of four near-miss events
Scoring
Driving risk factor analysis
Driving risk factor analysis
Driving risk classification
Driving behavior supervision
Personalized premium calculation
Application

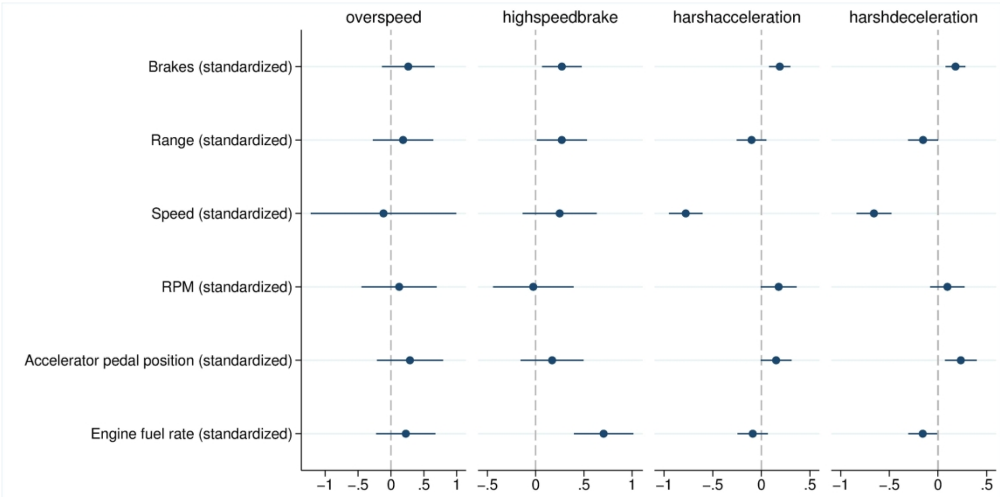


Figure 3 Partial coefficient estimation results of (a) Negative binomial regression

203x101mm (300 x 300 DPI)

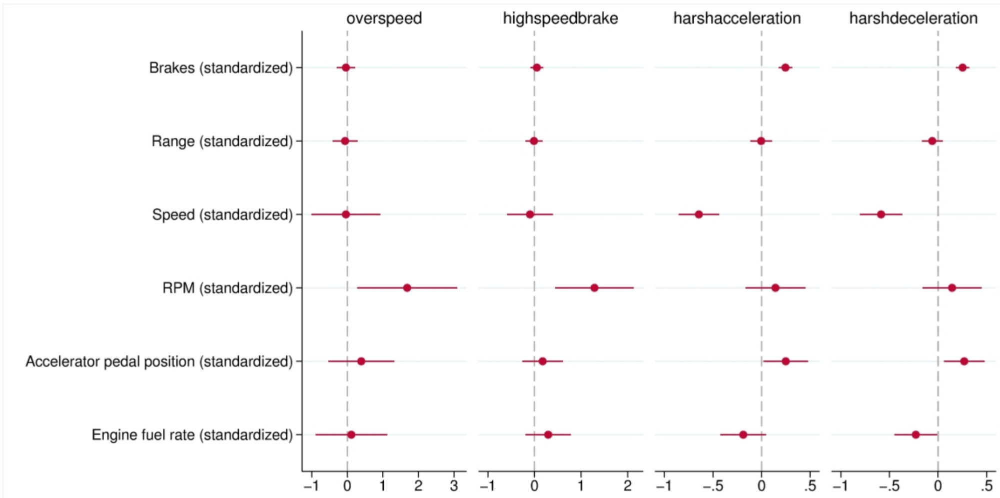


Figure 3 Partial coefficient estimation results of (b) Panel Negative binomial regression.

203x101mm (300 x 300 DPI)

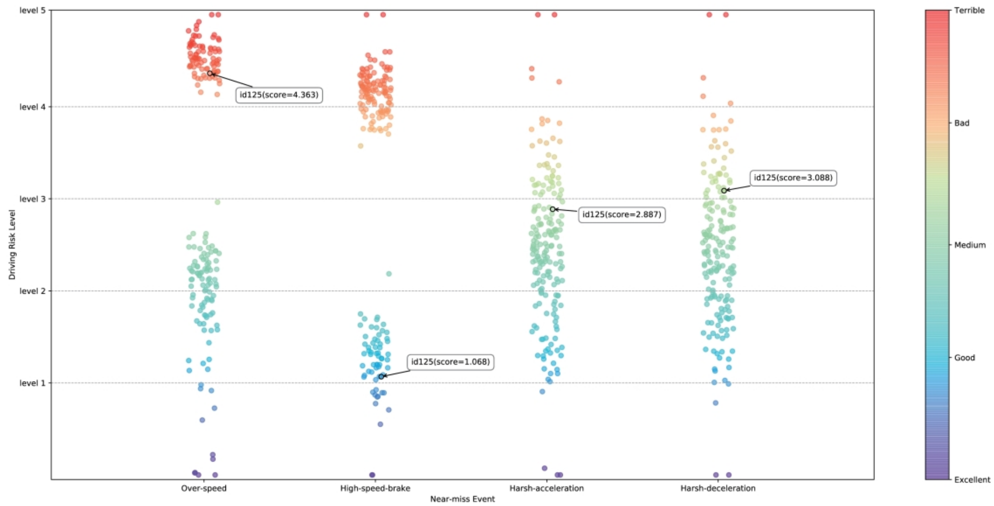


Figure 4 Driving risk rank of four near-miss events

447x230mm (300 x 300 DPI)