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Research Paper

Attitude to Speeding in Iran: Identifying Drivers Characteristics

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Abstract

Exceeding the posted speed limit is a contributing factor in rural crashes, and speed violations have a significant effect on road safety. The current study aims to identify at-fault driver features in speeding violations occurring at all rural roads of Iran using 11,636 drivers involved in two-vehicle speeding crashes. For this purpose, the quasi-induced exposure concept, Classification and regression tree, and logistic regression methods were employed. Drivers' gender had a significant effect on being at-fault, and women's risk was approximately two times higher than men. The risk of drivers in the ">58" age group was the highest and nearly twice the "18-27" group. In the vehicle type, the pickup had a risk of nearly 26 times higher than the bus. The finding showed that females have more risky behavior than male counterparts in speeding. Totally, the at-fault risk will grow more with increasing drivers' age. Type 1 driving license in speeding crashes has a significant effect on the risk of drivers' being at-fault. Moreover, among statistically significant vehicle types, the pickup had the highest risk. The results emphasize more attention to female and old drivers, their license type, pickup vehicles, and prepare practical countermeasures to reduce these crashes.

Keywords: Speeding crashes, CART, Quasi-induced exposure, Datamining

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1. Introduction

Speeding is a major roadway safety problem due to increased economic and technological development, which has led to higher motorized activity [Nordfjærn et al. 2014]. Moreover, the advancements in vehicle performance and improvement in road standards caused even higher speeds [Haglund and Åberg 2000]. It has been recognized that speed violations have a tremendous effect on road safety, probably more prominent than any other known risk factor, and it is a risk factor for all accident types [Elvik et al. 2004] [Ziolkowski 2019]. According to NHTSA, in 2017, speeding was a contributing factor in 26% of all traffic fatalities [NHTSA 2019]. In Iran, the highest percentage of human risk factors (69.9%) was allotted to neglecting rules and legislation [Bakhtiyari et al. 2014]. These numbers confirm the need to identify influential factors in drivers' speed choice to develop more effective ways to prevent speed-related violations. Roads are either urban or rural. The latest roadway statistics published by the Road Maintenance and Transportation Organization in 2018 shows there are 88,873 kilometers of rural roads in Iran ["Roads Network" 2018]. The present study aims to identify the characteristics of drivers involved in speeding crashes in rural roads of Iran, which are among the highest traffic crash rates in the world.

Speeding has been considered in several factors that could be categorized into three main groups. (1) human-related factors: studies like [Romano et al. 2021] [Hu et al. 2020], [Yu et al. 2019], [Yazdani and Rassafi 2019], [Harootunian et al. 2014], [Tavakoli Kashani et al. 2016] claimed that gender and age have a significant effect on observing speed compliance. [Perez et al. 2021] claimed that age and gender significantly affect speeding and speeding odds for 16-24 years was 1.5 times of drivers with more than 80 years old and females have fewer speeding odds than males. Also, males' lower speed compliance was confirmed by [Yadav and Velaga 2021]. [Yadav and Velaga 2021] found that drivers with prior crash experience tend to comply speed limits more than others. [Chee et al. 2021] interestingly examined drivers' mobile phones on speed compliance in four conditions: without the phone, phone in the holder, phone off, phone on in pocket. Studies also considered the effect of drivers' license type [Peer and Rosenbloom 2013], [Tavakoli Kashani et al. 2016], valid driving license [Balasubramanian and Sivasankaran 2021], drivers' education level, passenger presence [Tavakoli Kashani et al. 2016], and drivers' familiarity with the route [Harootunian et al. 2014], [Ryeng 2012] in speeding studies. (2) road and environment factors: road speed limit was analyzed by [Chee et al. 2021] and concluded that speeding behavior in roads with 10-20 miles per hour was about ten times more than roads with greater than 60 miles per hour speed limit. Roads' lane numbers, controlling type of junction roads, road dividers, light condition [Balasubramanian and Sivasankaran 2021], climate ([Harootunian et al. 2014], [Bolderdijk et al. 2011], [Stradling 2007]), land use ([Elvik et al. 2004], [Horswill and Coster 2002]), and presence of speed camera warnings [Stradling 2007] were also analyzed in speed-related studies. (3) Vehicle type was also considered, which demonstrated that the newer the vehicle, the more risk for speeding [Javid et al. 2020] [Fildes et al. 1991b]. [Balasubramanian and Sivasankaran 2021] indicated that light motor vehicles and motorcycles are more involved in speeding crashes than other vehicle types.

From the methods perspective, many researchers have used statistical methods. for example, Yazdani and Rassafi used Tukey and Bonferroni test to evaluate influential factors in drivers' speed choice [Yazdani and Rassafi 2019]. [Balasubramanian and Sivasankaran 2021] Used contingency table and logistic regression model to evaluate risk factors associated with speed violation. Fitzpatrick et al. applied logistic regression in investigating the speeding-related crash designation factors [Fitzpatrick et al. 2017].[Perez et al. 2021] used a beta-binomial regression model to compare the likelihood of drivers' speeding with naturalistic driving data. A latent class analysis was used by [Peterson et al. 2021] to consider the factors affecting speed behavior. [Tavakoli Kashani et al. 2016] used chi-square test to identify factors affecting the drivers' speeding.

Non-parametric models have also been used more in recent years. For instance, Yu and Bao used Random Forest (RF) algorithm to establish a model for predicting speeding drivers for warning systems [Yu et al. 2019]. A non-parametric classification tree and classification and regression tree (CART) approaches were used for identifying injury severity factors and motorcycle involved responsibility factors respectively in [Rovšek et al. 2017] and [Magazzù et al. 2006] studies. Tang and Donnell applied model-based recursive partitioning (MOB) for crash frequency prediction and found that the posted speed limit is one of the influential factors affecting crash frequency [Tang and Donnell 2019]. Castillo et al. examined the relationships among speed limits and traffic fatalities by the fixed effects model and random effects model in the meta-analysis method [Castillo-Manzano et al. 2019].

The contribution of the literature review shows that due to the widespread effect of speeding on road safety, numerous researches have been proceeding studying in this field. These studies analyzed vehicular, human, road, and environmental variables using separated statistical and non-parametric methods. However, this study applied both types of statistical and-non parametric (i.e., Classification and regression tree (CART) and logistic regression methods) using the whole country crash database as a big data to identify at-fault driver features in speeding violations occurring at rural roads of Iran. Therefore, this study fills the gap through the vastness of the study area and combined methodologies used.

2. Methods

To achieve this purpose (i.e., identify at-fault drivers' features), first, the CART method was utilized for screening; next, the logistic regression model was used to identify the primary influential factors.

2.1. Quasi-induced Exposure

Methods have been developed to achieve crash exposure from data instead of some estimates like miles driven. This methods, were first developed by Haight (1970) as quasi-induced exposure, which was applied in several studies in traffic safety [Zhang et al. 2018], [José et al. 2016] to estimate road crashes risk among various groups. The quasi-induced exposure concept has two underlying assumptions: (1) in two-vehicle crashes; one driver is at-fault and the other is not-at-fault, which requires using two-vehicle crash data with one at-fault and one not-at-fault driver; (2) not-at-fault drivers are randomly selected in two vehicle crashes which implies not-at-fault drivers are a sample of drivers population and an exposure measure. Therefore, two elements of quasi-induced exposure are: first, initial raw crash data screening; second, crash responsibility assignment for two-vehicle crashes [Jiang et al. 2014]. A remarkable benefit of the quasi-induced exposure method is that it can estimate the exposure for driver and vehicle groups from the distribution of non-responsible drivers/vehicles in two-vehicle crashes. As mentioned, the basic assumption of this concept is that the distribution of non-responsible drivers or vehicles is a random sample of the driving population at the crash occurrence [Kirk and Stamatiadis 2001]. The broad validity and usage of quasi-induced exposure in crash data evaluation are due to the shortage of disaggregate exposure data in specific situations and the ability of this method in deriving the exposure directly from crash data [Jiang et al. 2014].

2.2. Classification and Regression Tree (CART)

CART is among the well-known machine-learning methods for developing predicting models. It is a non-parametric model, does not need to make assumptions about the nature of the data, and can easily identify and explain the complex patterns associated with the crash risk. In Classification, there is a need for the categorical dependent variables, independent variables, a dataset for learning the tree, and finally, a test dataset for accurate prediction. A root node containing all the data is split into two binary child nodes based on the best variable to split, the child nodes split again, and the process continues recursively. The best splitting variables are identified through Gini index calculating as follows:

$$p(j|m) = \frac{p(j,m)}{p(m)},\ p(j,m) = \frac{\pi(j)N_j(m)}{N_j},$$

$$p(m) = \sum_{j=1}^{j} p(j,m) \tag{1}$$

$$\mathrm{Gini}(m) = 1 - \sum_{j=1}^{j} p^2\,(j|m) \tag{2}$$

Where j is the number of dependent variable classes, $\pi(j)$ is the prior probability for class j, $p(j|m)$ is the probability of a record being in class j while exists in node m, and Gini(m) is an indication of impurity in node m. A node with all classes in the same type will have G=0, an equal split of classes for binary classification problems will have G=0.5.

The importance of variable (VIM) is one of the main outputs of the CART model, which is calculated from the following equation and determines variables orderly based on their importance.

$$\mathrm{VIM}(X) = \sum_{i=1}^{m} \frac{mx_i}{n}\left(\mathrm{Gini}(C|X = x_i) - (c)\right) \tag{3}$$

For a variable X with different conditions (x_1,x_2,…c), C is class variable (at-fault /not-at-fault), mx_i is the number of cases with X=x_i, m is the total number of cases [Breiman et al. 1998].

2.3. Logistic Regression

Logistic regression is a mathematical modeling approach that can be used to describe the relationship between independent variables to a dichotomous variable [Wooff 2004]. The general form of logistic regression is:

$$\mathrm{logit}\ P(X) = \mathrm{LN}\left(\frac{P_i}{1 - P_i}\right) = \alpha + \sum \beta_i X_i \tag{4}$$

Where:

$$P(X) = \frac{1}{1 + e^{-(\alpha + \sum \beta_i X_i)}} \tag{5}$$

The terms α and β_i represent unknown parameters that are estimated using the maximum likelihood (ML) method. In logistic regression, the odds ratio (OR) measures association between an exposure and an outcome. The OR represents the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of that exposure. The odds ratio can also be used to determine whether a particular exposure is a risk factor for a particular outcome and compare the magnitude of various risk factors for that outcome. The odds ratio equal to one means exposure does not affect odds of outcome, the odds ratio greater than one means exposure is associated with higher odds of outcome, and the odds ratio less than one means that exposure is associated with lower odds of the outcome [Cramer 2003]. Also, the p-value for each variable tests the null hypothesis if the coefficient equals zero (no effect). A low p-value (less than 0.05 at 5% significance level) indicates that the null hypothesis could be rejected. In other words, a predictor with a low p-value is likely to be a meaningful addition to the model because changes in the predictor's value are related to changes in the response variable [Wooff 2004].

3. Crash Data

The study was conducted using the 2012 to 2016 crash database containing information about the driver, vehicle, crash scene, and passenger characteristics. The data was obtained from the police crash report database completed by trained police officers. As this study examined driver characteristics, only related variables were extracted from the database. After preprocessing the rural speeding crash data, which included: filtering only two-vehicle crashes with one at-fault and one not-at-fault driver, selecting acceptable driver ages between 18 to 85 years, and cleaning missing data, finally 11,636 drivers involved in 5,818 two-vehicle crashes remained. Descriptive statistics of the crash database have been summarized in Table1.

Table 1. Variable decription

Variables	Description	Frequency	Percentage
Fault status	1.At-fault	5,818	50%
	2.Not-at-fault	5,818	50%
Gender	1.Male	11,119	95.6%
	2.Female	517	4.4%
License type	1.Type1	2,029	17.4%
	2.Type2	3,976	34.2
	3.Type3	5,519	47.4
	4.Special	112	0.96%
Education	1.Under diploma	2,543	21.9%
	2.High school Diploma	6,956	59.8%
	3.University Education	9,093	18.4%
Vehicle type	1.Bus	8,127	69.8%
	2.Mini-bus	1,203	10.3%
	3.Truck	1,549	13.3
	4.Mini-truck	23	0.2%
	5.Passenger car	280	2.4%
	6.Taxi	177	1.5%
	7.Pickup	38	0.3%
	8.Emergency vehicle	150	1.3%
	9.Military	89	0.8%
Age	18-27	2,375	20.4%
	28-37	4,611	39.6%
	38-47	2,624	22.6%
	48-57	1,402	12.0%
	>58	624	5.4%

Driving licenses in Iran are categorized into five types, namely first-grade license (Type1), second-grade license (Type2), third-grade license (Type3), Motorcycle license and special license type (Special). Each of these licenses has restrictions, and requirements. It should be mentioned that Motorcycles were not considered in this study. The special license type is allocated to the operators of the agricultural and construction instruments. Emergency vehicle types are ambulance, fire trucks, and police cars.

4. Results

The results of the first and second models are presented in two sections.

4.1. CART Model

Figure1 illustrates the classification tree diagram for the speeding violation tree model, which includes six terminal nodes. The model produces the following rules of classification for drivers involved in the speeding violation:

- About 54% of drivers with type 3 driving licenses would be at-fault in speeding crashes.
- Drivers with 1, 2, and special license types and drive bus, mini-bus, special vehicles, taxi, or truck would be more likely (66.9%) to be not-at-fault in these crashes.
- Drivers who drive an emergency vehicle, mini-truck, passenger car, or pickup and are older than 50 years old are more likely to be not-at-fault.
- Drivers with the age of 28.5 years old and younger are more expected to have speeding behavior.
- An interesting result is that among drivers who are older than 28.5 years old, women are more prone to be violator while about 55% of men are non-violator.

The relative variable importance (VIM) is computed for the four independent variables and is presented in Table 2. According to this table, the decision tree identified "license type" as the most critical variable influencing speeding crashes.

Table 2. Variable importance

Variable	VIM
License type	0.373
Gender	0.297
Driver age	0.186
Vehicle type	0.144

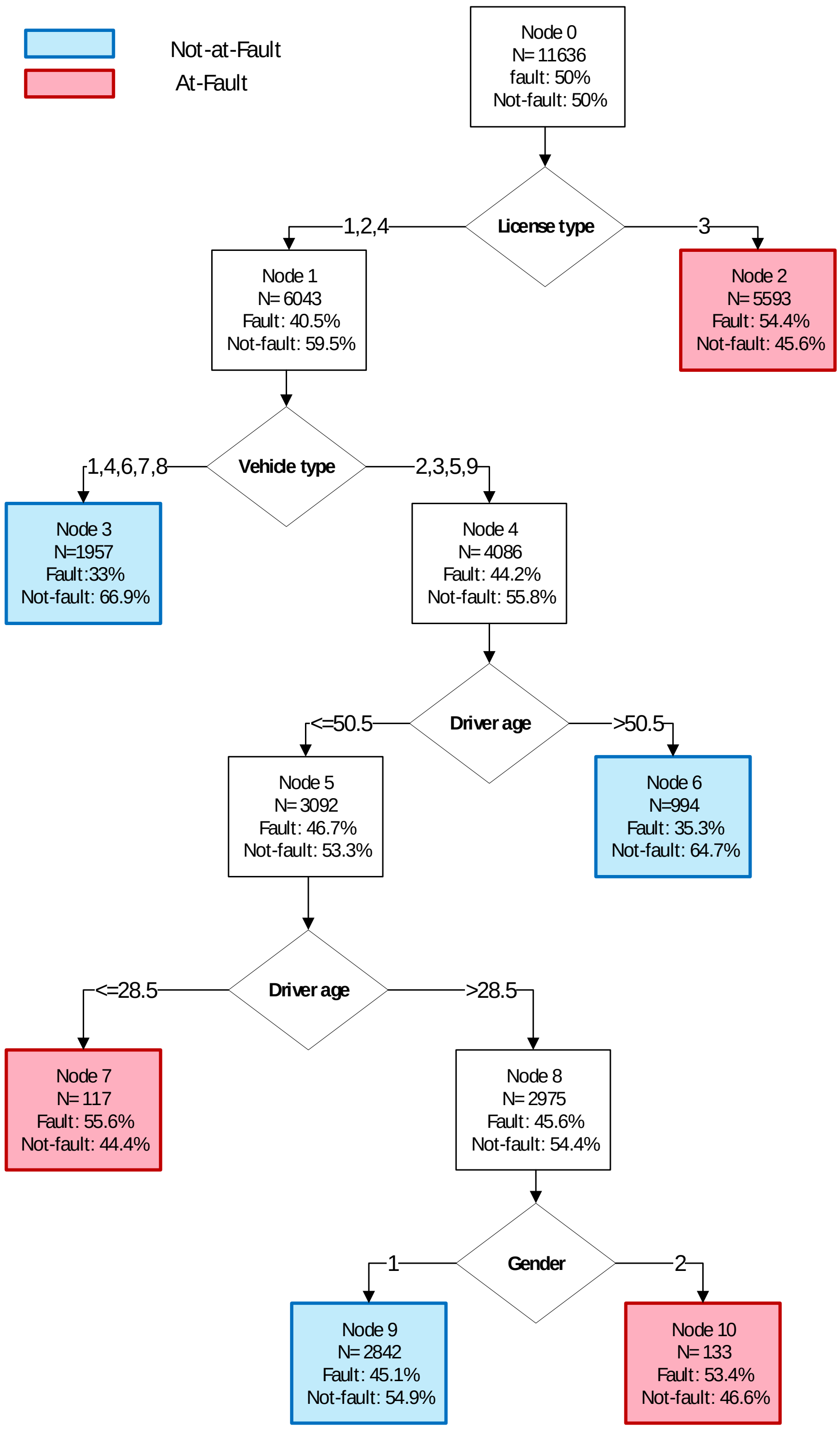

Figure 1. Decision tree model

4.2. Logistic Regression Model

According to the CART model, gender, age, license type, and vehicle type were selected as the influential variables. Table 3 demonstrates the logistic regression model in the final step. In this table, β is the coefficient of variables, S.E. is the standard error, and Wald is a test using standard errors for each variable. By increasing the amount of the Wald test, the variable's significance will be more effective. The intercept is the probability of drivers' being at-fault in the absence of the dependent variables. The reference category is being at-fault. Odds ratio (OR) means the proportion of drivers' being at-fault to being not-at-fault in a crash under specific conditions. In addition, for each variable, one of the categories was used as the reference group to compare with other categories.

As shown in table 3, ">58" age group in speeding crashes has a significant effect on the risk of drivers' being at-fault with the Wald of 44.987. However, type 2 and special license, mini-bus, mini-truck, and passenger cars had no significant effect on drivers' being at-fault (P>0.05). The female drivers have a significant effect on being at-fault, and women's risk was approximately 1.7 times higher than men. The risk of drivers older than 58 years was the highest, and the risk was nearly 2 times higher than 18-27 group, while 38-47 age group has the lowest risk, and their risk is 1.408 of the reference category. It can be inferred that the risk of being at-fault increases with an increase in drivers' age. In the vehicle type characteristic, except mini-truck, mini-bus, and passenger car, other significance levels were less than 0.05 in this model and pickup has the highest risk of 25.89 times rather than the bus as the reference category.

Table 3. Results of logistic regression

Characteristic	Variable	β	S.E.	Wald	P	OR
Gender	Male[a]					1
	Female	0.534	0.097	30.331	0.000	1.707
Age	18-27[a]					1
	28-37	0.345	0.054	40.514	0.000	1.412
	38-47	0.343	0.062	30.338	0.000	1.408
	48-57	0.496	0.074	44.432	0.000	1.641
	>58	0.660	0.098	44.987	0.000	1.936
License type	Type 1[a]					1
	Type 2	-0.149	0.087	2.964	0.085	0.861
	Type 3	-0.443	0.090	24.373	0.000	0.642
	Special	-1.107	0.719	2.369	0.124	0.331
Vehicle type	Bus[a]					1
	Mini-bus	-0.046	0.063	0.543	0.461	0.955
	Truck	0.401	0.093	18.655	0.000	1.494
	Mini-truck	0.223	0.424	0.276	0.600	1.249
	Passenger car	0.150	0.124	1.457	0.227	1.162
	Taxi	0.555	0.182	9.239	0.002	1.741
	Pickup	3.254	0.859	14.343	0.000	25.895
	Emergency	0.637	0.180	12.558	0.000	1.891
	Military	0.981	0.249	15.532	0.000	2.668
	Intercept	-0.633	0.136	21.698	0.000	0.531

[a] Reference category

5. Discussion

The results analysis showed that among the different variables, the gender of the driver, age, license type, and vehicle type had a significant effect on drivers' being at-fault in speeding crashes at a 5% significance level.

5.1. Gender

The results associated with the drivers' gender demonstrated that unexpectedly, females are more prone to be at-fault. Nowadays, due to the increasing number of women drivers, women's mile driven has also been increased than ever before, that increases their riskier actions and affects their safety level adversely. Therefore, female drivers should be more informed in pre-test classes. However, Bakhtiyari et al. considered the role of human risk factors in the severity of road traffic injuries in Iran and mentioned that the odds ratio of men involving in urban traffic crashes is 24% more than women [Bakhtiyari et al. 2014]. Ryeng claimed that male drivers are more challenging as they drive 10 km/h above the speed limit [Ryeng 2012]. Also, studies like [Yazdani and Rassafi 2019] and [Tavakoli Kashani et al. 2016] claimed that women are more tend to choose lower speed limits; however, some others did not find any significant effect for the gender of the driver [Harootunian et al. 2014].

5.2. Age

Age is one of the important variables considered in speed studies, which is a kind of physical human factor contributing to traffic crashes. As shown in Figure 2, considering 18-27 years as reference, drivers older than 58 years old are more risky than other ages. The reason for this could be that older drivers often have more driving experience, and complying with the speed limits is boring for them, or they may be more involved in daily works and will be more in a hurry and unintentionally forget the area speed limit. However, some studies have reported that the more drivers' age, the lower the speed choice is, as young drivers accept higher risk [Wasielewski 1984]. Quimby et al. found that younger drivers were more likely to drive above the 85th% speed [Quimby et al. 1999]. Besides, research at Monash University showed that older drivers were more likely to slow down their speed limit [Fildes et al. 1991a].

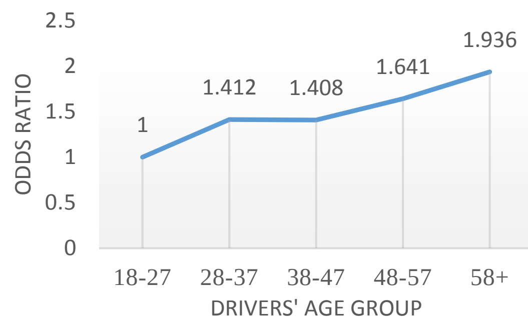

Figure 2. Odds ratio of driver age

5.3. License Type

Few studies considered drivers' license type in crashes. According to the results, drivers with type 1 license, are riskier than others. This finding is not in line with the findings of Mohaymany et al. They claimed that drivers who are younger than 28 years old and have type 2 license are more likely to be responsible for overtaking crashes [Mohaymany et al. 2010]. Pakgohar et al. considered human factors in urban crashes in Iran and concluded that 19% of drivers involved in urban crashes have type 1 license [Pakgohar et al. 2011] Moreover, Magazzu et al. considered only car-motorcycle crashes and found that drivers with car license type are more likely to be at-fault [Magazzù et al. 2006]. This result implies the need for providing obligatory educational classes for type 1 license drivers to inform extensive loss and property damages in speeding crashes.

5.4. Vehicle Type

Among various vehicle types, bus, truck, taxi, pickup, emergency, and military vehicles were statistically significant in drivers' being at-fault, and pickup had the highest risk. Some vehicle characteristics that affect speeding in vehicles like pickup are their engine power, comfort, and vehicles' high wheels [Van Schagen et al. 2018] that distort speed perception and underestimation. Speeding in emergency and military vehicles could be due to their urgency and hurried missions. Providing speed tracking and alert system in such vehicles could control excessive speed and prevent speeding crashes. A study in Hamadan province of Iran concluded that the most important vehicles involved in crashes were cars, trucks, and pickups [Shokouhi and Rezapur-Shahkolai 2018]. Kim et al. determined the features of at-fault drivers in motor-vehicle collisions and concluded 77% of those involved in collisions were cars, 6.8% vans, and 16.2% were pickups [Kim et al. 1998]. Chin and Hauque compared relative crash proneness of different vehicle types for at-fault right-angle collisions and found that light vehicles are more prone to be responsible in these crashes [Chin and Haque 2012]. Vehicle type was also considered in Monash university research which showed vans and light commercial vehicles traveled slower in rural areas [Fildes et al. 1991a].

6. Conclusions

The present study analyzed features of at-fault drivers involved in speed violations in rural roads of Iran using 11,636 crash cases. CART and logistic regression models were developed to achieve this aim.

Using the CART method, license type, vehicle type, driver age, and gender were identified as important factors. Next, by applying the logistic regression method, based on the odds ratio of the variables, the factors that had more significant influence on the risk of drivers' being at-fault were computed. Results showed that females have more risky behavior than males in speeding. In the driver age, the risk of drivers older than 58 years old was about 2 times higher than that of 18-27 years. This could be due to their physical and psychological characteristics, namely the low ability to perceive risk and the escape of risk, which shows the need for serious attention to this category in the safety of traveling [Shokouhi and Rezapur-Shahkolai 2018]. The risk of being at-fault for type 1 license in speeding crashes has a significant effect on the risk of drivers' being at-fault. Moreover, it can be seen that among statistically significant vehicle types, the pickup had the highest risk. The results mentioned above emphasize that road safety policy measures should pay more attention to female and young drivers, their license type as well as pickup vehicles and prepare practical countermeasures to reduce these crashes. The findings of the current research could be beneficial for speed violation policies in developing countries like Iran.

7. Declarations

7.1. Funding and Financial Interests

No funding was received for conducting this study, and the authors have no relevant financial or non-financial interests to disclose.

7.2. Data Availability

The data are not available due to legal restrictions.

8. References

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