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Research Article

Understanding the Factors Affecting Urban Vehicle-to-Vehicle Crash Severity with Focus on Drivers' Route Familiarity

Mahyar Vahedi Saheli*

Department of Civil Engineering, Faculty of Engineering, University of Guilan, Rasht, Iran

Keywords

Urban crash severity, Vehicle-to-vehicle accidents, Unfamiliar drivers, Familiar drivers, Route familiarity.

Abstract

Human factors are usually of paramount importance when it comes to traffic crashes. Drivers' route familiarity or unfamiliarity is a critical human-related factor that has less been considered in the literature. This factor can lead to inattention, distraction, and dangerous behaviors due to familiar drivers' over-confidence or unfamiliar drivers' insufficient knowledge of road geometry and environment. The main objective of this study is to discover the factors affecting the severity of vehicle-to-vehicle crashes in Rasht city (in northern Iran) involving unfamiliar and familiar drivers using a logistic regression model. The results indicate the significant effect of human factors such as driver's familiarity and age, collision type, angle and reason, temporal factors (season and time of day), vehicles involved in the crash, and environmental conditions on the injury severity of vehicle-to-vehicle crashes in urban roads. The results of this study can be used by policymakers and implementers to take appropriate measures to reduce the severity of vehicle-to-vehicle crashes in urban areas.

1. Introduction

Traffic crashes are a leading cause of injury and death in many countries worldwide. Iran is one of the developing countries with high rates of traffic-related injuries and deaths. The proportion of traffic injuries in Iran is higher than in most other parts of the middle-east and the rest of the world. Road traffic crashes are also one of the country's most serious problems and among the top five leading causes of death in Iran [1].

The five categories of contributing factors to traffic collisions are human, vehicle, road, environment, and traffic [2, 3]. Research has shown that human factors play a significant role in about 90% of crashes [4]. Among all human-related crash variables, one of the most frequent driver-related critical errors is driver distraction [4-7]. The issue of driver distraction can be closely linked to the drivers' route familiarity, which however is less considered in the literature.

A route familiar driver travels on a route well-known from long or close association, and traveling on that specific route made up of various road features has been the stimulus frequently encountered [8]. Both familiarity and unfamiliarity with roads may have adverse effects on driving tasks. High route familiarity can cause driving distraction and overconfident driving behaviors like overspeed driving to reduce the travel time [9]. On the other hand, high route unfamiliarity may lead to driving errors due to unfamiliar road features [10]. At first glance, unfamiliar drivers may seem safer than familiars since their attentional capacity is strongly focused on collecting information related to the road environment. Therefore, because the road is not well-known, they should be less likely to be distracted and less prone to speeding and risk-taking behaviors [9]. Yet, this good

* Corresponding Author: Mahyar Vahedi Saheli
E-mail address: mahyarvahedi@msc.guilan.ac.ir

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practice concept is often followed in road design guidelines: road design should be considered for users who are driving on a roadway for the first time and are unfamiliar with its characteristics [11].

It is unexpected and, of course, unsafe for all drivers to encounter a sudden sharp curve after a long stretch of straight road because the reality (the unexpected curve) differs from the expectations formed during the previous long section of the straight road [9]. However, the curve is not, in fact, unexpected for all drivers. It is just unexpected for drivers who never/rarely traveled on that road (unfamiliar drivers), and it could lead to errors in speed and steering [9]. The justification mentioned above might easily explain the reason unfamiliar drivers are likely to exhibit road safety weaknesses.

Furthermore, driver route familiarity indicates the driver's awareness of the overall driving environment, road traffic congestion, the best rescue route after a crash, and the direction of invisible objectives that are all closely linked to the severity of the crash injury [10, 12, 13].

This research aims to identify contributory factors (including the familiarity and unfamiliarity of at-fault and not-at-fault drivers) that significantly influence the injury severity of vehicle-to-vehicle crashes in Rasht, the biggest city and the capital of Guilan Province of Iran, by employing a logistic regression model. Guilan Province is located in northern Iran, host to many tourists (unfamiliar drivers) who annually travel to the north of Iran on holidays [14-16].

The paper starts with an overview of the literature on the impact of familiar and unfamiliar drivers on severity, frequency, and risk of crashes. The data and methodology are then described, followed by a discussion of the model estimation. At last, a summary of findings is presented.

2. Literature Review

Previous studies on the effect of familiar and unfamiliar drivers on road crashes have reported both positive and negative outcomes [10].

Ref. [17] discovered that 49 percent of international drivers and motorcyclists involved in road crashes in Australia that resulted in at least one fatality (single and multi-vehicle) died, and 20 percent were hospitalized, while the percentages for all drivers were 44 percent and 11 percent, respectively. They also speculated that the disparity could be due to the unfamiliar driver's higher involvement in single-vehicle collisions or differences in safety belt use compared to Australians.

Ref. [18] found that drivers involved in collisions with trucks are less likely to experience severe injuries on a roadway they are unfamiliar with. According to Ref. [19], drivers traveling on familiar roadways are more likely to be involved in run-off-road collisions (64% of single-vehicle crashes involving familiar drivers were run-off-road, compared to the 54% of the unfamiliar ones).

Ref. [20] examined out-of-state drivers in three different states of the US and found that their probabilities of being involved in an at-fault single-vehicle collision were much greater than those of in-state drivers. Ref. [21] investigated the effect of distance between the crash location and the driver's residence on crash fault determination, predicting that drivers traveling more than 50 miles from their residence have a roughly 50%–200% increased likelihood of being at-fault compared to familiar drivers.

Ref. [22] resulted that foreign drivers of heavy trucks in Norway were more likely to cause fatal crashes, which was explained as a consequence of the drivers' unfamiliarity with the roads, as well as their lack of experience with Norway's narrow roads with snow, ice, and high gradients. Ref. [23] revealed that unfamiliar drivers from diverse cultural backgrounds had considerably different injury-severity predictions than their Saudi counterparts. Non-Saudi drivers, for example, are more prone to be involved in fatal single-vehicle crashes in Riyadh, Saudi Arabia. Additionally, it was shown that unfamiliar drivers from countries that drive on the opposite side of the road had a greater possibility of both no injuries and fatalities.

The research above demonstrates conclusively that unfamiliar drivers may have various crash risks and resulting injury severities compared to familiars. The purpose of this study is to examine this issue with Iranian urban crash data, focusing on resulting injury severities of vehicle-to-vehicle crashes involving familiar and unfamiliar drivers.

3. Data and Method

3.1. Study Area, Database, and Variables Definition

Guilan is the 28th biggest province in Iran, while it is the 12th province by population [16, 24, 25]. Rasht (Figure 1) is its capital and one of the most congested cities in Iran, and the most populous city in the north of Iran, with high traffic volume most days during the year [26]. According to the 2016 official census, the city's population is 680,000. The urban population of Rasht has increased almost 1.5 times during the past three decades and experienced an average annual growth of 3.3 percent [27]. The result of such rapid population growth is the uncontrolled growth and traffic congestion in the city. On average, 250,000 vehicles cross the city every day [28].

The crash data is consisted of six-year records of crashes occurring from March 21, 2015, through March 20, 2021, and was obtained from the traffic center of the Guilan urban police department. The database contains 15000 crash records, including 7500 vehicle-to-vehicle crashes. After eliminating the unknown records, 6189 records of vehicle-to-vehicle crashes remained for modeling purposes (motorcycle-involved, multi-vehicle crashes, and work zone-related crashes [29] are removed from the database as they are inherently different from vehicle-to-vehicle crashes). The crash data include various factors, including time and location of the crash, driver attributes (such as age and gender), vehicle characteristics (such as company, model, type, and number), road-related and environmental factors (such as weather and lighting condition) and crash attributes (such as reason, type, angle, and severity of crash).

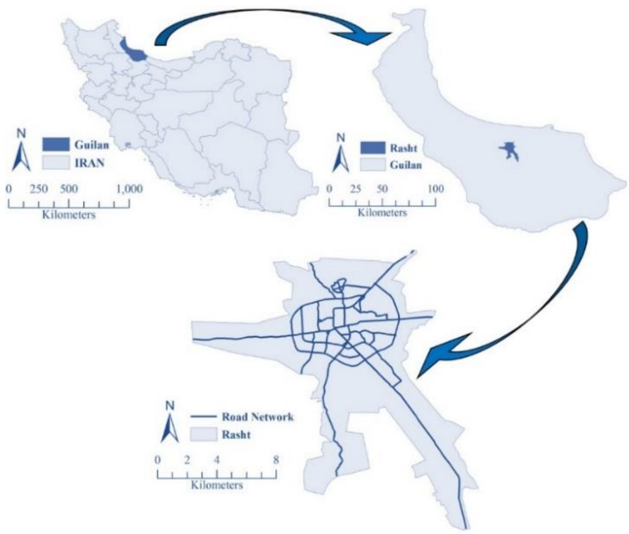

Figure 1. Study area

In this paper, a driver was presumed familiar if their vehicle number was for Guilan province; otherwise, they were supposed to be unfamiliar (travelers from other provinces of Iran). The percentages of familiar and unfamiliar drivers in data were 78.86% and 21.14%, respectively.

As it remained only 15 fatal crashes after eliminating unknown records, fatal and injury crashes were integrated. Therefore, the dependent variable is a binary variable with the value of 1 if the crash severity is fatal or injury; and 0 if the crash severity is no injury [3]. The dataset includes 1403 injury/fatal and 4786 no injury vehicle-to-vehicle crashes.

Table 1 represents a summary of the variables used for modeling in this study. This summary includes a description of each variable as well as its maximum, minimum, mean, and standard deviation values.

Table 1. Data summary and descriptive statistics of explanatory variables

Variable	Mean	S.D.	Min.	Max.	Description
Temporal factors					
ERMRN	0.083	0.275	0	1	1 if the crash is occurred on early morning; 0 if otherwise
MORN	0.197	0.397	0	1	1 if the crash is occurred on morning; 0 if otherwise
AFTRN	0.408	0.492	0	1	1 if the crash is occurred on afternoon; 0 if otherwise
NIGHT	0.312	0.463	0	1	1 if the crash is occurred on night; 0 if otherwise
WKND	0.274	0.446	0	1	1 if the crash is occurred on weekend; 0 if otherwise
SPRNG	0.228	0.420	0	1	1 if the crash is occurred on spring; 0 if otherwise
SUM	0.257	0.437	0	1	1 if the crash is occurred on summer; 0 if otherwise
AUTMN	0.235	0.424	0	1	1 if the crash is occurred on autumn; 0 if otherwise
WINTR	0.280	0.449	0	1	1 if the crash is occurred on winter; 0 if otherwise
Human factors					
AFUNF	0.213	0.410	0	1	1 if the at-fault driver is unfamiliar; 0 if otherwise
AFYNG	0.322	0.467	0	1	1 if the at-fault driver is younger than 31 years old; 0 if otherwise
AFOLD	0.101	0.302	0	1	1 if the at-fault driver is older than 55 years old; 0 if otherwise
AFFMAL	0.129	0.336	0	1	1 if the at-fault driver is female; 0 if otherwise
NAFUNF	0.210	0.407	0	1	1 if the not-at-fault driver is unfamiliar; 0 if otherwise
NAFYNG	0.286	0.452	0	1	1 if the not-at-fault driver is younger than 31 years old; 0 if otherwise
NAFOLD	0.096	0.294	0	1	1 if the not-at-fault driver is older than 55 years old; 0 if otherwise
NAFFMAL	0.140	0.347	0	1	1 if the not-at-fault driver is female; 0 if otherwise
Vehicle-related factors					
AFAUTO	0.661	0.473	0	1	1 if the at-fault vehicle is an Iranian company made passenger car; 0 if otherwise
AFFOAUTO	0.205	0.405	0	1	1 if the at-fault vehicle is a foreign company made passenger car; 0 if otherwise
AFPKP	0.056	0.231	0	1	1 if the at-fault vehicle is a pickup; 0 if otherwise
AFHVY	0.073	0.260	0	1	1 if the at-fault vehicle is a heavy vehicle; 0 if otherwise
NAFAUTO	0.662	0.473	0	1	1 if the not-at-fault vehicle is an Iranian company made passenger car; 0 if otherwise
NAFFOAUTO	0.252	0.434	0	1	1 if the not-at-fault vehicle is a foreign company made passenger car; 0 if otherwise
NAFPKP	0.047	0.212	0	1	1 if the not-at-fault vehicle is a pickup; 0 if otherwise
NAFHVY	0.038	0.191	0	1	1 if the not-at-fault vehicle is a heavy vehicle; 0 if otherwise
Road and environmental factors					
WET	0.132	0.339	0	1	1 if the surface is wet while the crash occurred; 0 if otherwise
ADVRSWTHR	0.112	0.316	0	1	1 if the weather is rainy, snowy, or foggy while the crash occurred; 0 if otherwise
DRKNIT	0.015	0.122	0	1	1 if the crash occurred on night in a road without enough lighting; 0 if otherwise
LITNIT	0.272	0.445	0	1	1 if the crash occurred on night in a road with enough lighting; 0 if otherwise
Crash-related factors					
HDON	0.103	0.304	0	1	1 if the crash was head-on; 0 if otherwise
RREND	0.394	0.489	0	1	1 if the crash was rear-end; 0 if otherwise
SDIMP	0.375	0.484	0	1	1 if the crash was side-impact; 0 if otherwise
SDSWP	0.128	0.335	0	1	1 if the crash was side-swipe; 0 if otherwise
SDNCHNG	0.095	0.294	0	1	1 if the crash occurred as a result of a sudden change in a vehicle's direction; 0 if otherwise
IGNROW	0.245	0.430	0	1	1 if the crash occurred as a result of ignoring the ride of way; 0 if otherwise
WRNGWAY	0.007	0.083	0	1	1 if the crash occurred as a result of wrong-way driving; 0 if otherwise
RVRS	0.0364	0.187	0	1	1 if the crash occurred as a result of reversing; 0 if otherwise
REDLIT	0.028	0.165	0	1	1 if the crash occurred as a result of red-light running; 0 if otherwise
DOROPN	0.011	0.103	0	1	1 if the crash occurred as a result of sudden opening the vehicle's door; 0 if otherwise

3.2. Modeling and Validation

Of all the regression models, logistic regression is often the most appropriate method when the intent is to model binary outcomes as a function of predictor variables [30]. In the logistic regression model, a latent variable is formulated by the following expression [31]:

$$g(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_j x_j + \cdots + \beta_p x_p \tag{1}$$

where x_j is the value of the jth independent variable, with j as the corresponding coefficient, for $j = 1, 2, 3, \ldots, p$, and p is the number of independent variables. With this latent variable, the conditional probability of a positive outcome is determined by:

$$\pi(x) = \frac{exp\big(g(x)\big)}{1 + exp\big(g(x)\big)} \tag{2}$$

The maximum likelihood method is then employed to measure the associations by constructing the likelihood function as follows:

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i} \big(1 - \pi(x_i)\big)^{1-y_i} \tag{3}$$

where y_i denotes the i^{th} observed outcome, with the value of either 0 or 1 only, and $i = 1, 2, 3, \ldots, n$ where n is the number of observations. By maximizing the log-likelihood expression as,

$$LL(\beta) = \ln\big(l(\beta)\big) = \sum_{i=1}^{n} \{y_i \ln\big(\pi(x_i)\big) + (1 - y_i) \ln\big(1 - \pi(x_i)\big)\} \tag{4}$$

the best estimate of β could be obtained accordingly [15].

To evaluate how accurately the developed model predicts crash severity, testing the model by predicting out-of-sample data is needed. This study aims to utilize a 10-fold cross-validation process for validation. The original input data are randomly partitioned into 10 equally sized subsamples. In each iteration, one subsample is retained as the validation data for testing the models; the remaining subsamples are used as training data. After that, all subsamples are used exactly once as the validation data. The mean absolute deviation (MAD) function is used for the evaluation of the model's prediction performance as follows:

$$MAD = \frac{1}{n} \sum_{t=1}^{n} \left| y_{predicted} - y_{observed} \right| \tag{5}$$

Where $y_{predicted}$ and $y_{observed}$ are the predicted and observed values of crash severity for each record, respectively, and n is the number of crash records.

4. Results and Discussion

After step-wising the preliminary model (a model developed using all the potential explanatory variables), the final model is designed using collinearity and goodness-of-fit measures. In this study, STATA 17 software was used for modeling purposes.

Table 2 shows the results for the developed logistic regression model. Parameter estimates and their standard errors, significance level (p-value), and z-scores are presented for each explanatory variable in Table 2. Most candidate variables are excluded from the final model during the multicollinearity test or backward elimination [14] process, but the remains are primarily significant. The process led to a better model (in terms of variables' significance and lower standard errors).

The final model consists of twenty explanatory variables, which Eighteen of them found to be significant. Positive and negative signs for estimated coefficients of predictor variables across the model results indicate each predictor variable's increasing or decreasing effect on the injury severity of vehicle-to-vehicle crashes, respectively.

Table 2. Parameter estimates for injury severity analysis of vehicle-to-vehicle crashes using the binary logistic regression model

Parameters	Coef.	S.E.	p-value	Z-score
ERMRN	0.764	0.114	0.000***	6.72
MORN	-0.150	0.095	0.114	-1.58
AFTRN	-0.229	0.079	0.004***	-2.90
SPRNG	0.417	0.093	0.000***	4.51
SUM	0.316	0.091	0.001***	3.46
AUTMN	0.240	0.093	0.010**	2.58
HDON	0.266	0.106	0.012**	2.52
RREND	0.143	0.072	0.046**	1.99
AFAUTO	0.652	0.114	0.000***	5.72
AFFOAUTO	-0.229	0.138	0.096*	-1.66
NAFAUTO	0.261	0.121	0.031**	2.16
NAFFOAUTO	-1.139	0.149	0.000***	-7.66
DRKNIT	0.713	0.232	0.002***	3.07
ADVRSWTHR	0.153	0.102	0.134	1.50
AFUNF	-0.687	0.092	0.000***	-7.44
AFYNG	0.120	0.069	0.084*	1.73
NAFUNF	-0.772	0.098	0.000***	-7.87
SDNCHNG	-0.844	0.151	0.000***	-5.60
RVRS	-0.561	0.219	0.011**	-2.56
DOROPN	-1.076	0.483	0.026**	-2.23
Constant	-1.675	0.176	0.000***	-9.53

* Significant at 0. 1 level, ** Significant at 0.05 level, *** Significant at 0.01 level

Significant temporal explanatory variables include early morning and afternoon hours and spring, summer, and autumn seasons. Early morning hours (00:00 to 06:59) are significantly associated with an increase in the severity of vehicle-to-vehicle crashes. The result was expectable because the roads experience very low traffic volumes at this time of the day. This may put drivers at the risk of speeding-related violations as they can easily reach free-flow speed (FFS) when the streets are uncongested. The resulting speeding violations can increase the severity of crashes. Furthermore, drivers are prone to drowsiness during these hours, specifically unfamiliar drivers who traveled many hours prior to the crash. Afternoon hours (12:00 to 18:59) are the next significant temporal variable that negatively affects the severity of crashes. Contrary to early morning hours, traffic flow approaches the road capacity in the afternoon, and the vehicles' speed decreases significantly. Speed reduction can justify the negative effect on crash severity.

Spring, summer, and autumn seasons are significantly associated with an increase in injury severity of vehicle-to-vehicle crashes. This may arise from the better lighting and weather conditions of these seasons compared to winter, which results in an increase in drivers' movement speed. Yet, it is known that pavement condition (in terms of surface friction) is likely to be worse in winters. This concept can make the seasonal-related effects controversial. Accounting for temporal instability [32, 33] across the crash data is a possible solution to see if the results are yearly or seasonally stable or not.

Human-related significant variables consist of young at-fault drivers as well as at-fault and not-at-fault unfamiliar drivers. Young (less than 31 years old) drivers are found to positively affect the severity of vehicle-to-vehicle crashes when responsible for the crash occurrence (at-fault). This finding is intuitive and is consistent with expectations as young drivers mostly exhibit dangerous behaviors (such as speeding and illegal maneuvers) while driving, more than older drivers. Additionally, young drivers may lack enough experience to do needed maneuvers before collisions (such as distinguishing the best rescue route before a crash) [34]. Unfamiliar drivers are found to be prone to less severe crashes regardless of their percentage of fault. As the literature suggests, it is likely that unfamiliar drivers should be in the road "studying" phase, where the attentional capacity is almost entirely devoted to addressing the unknown situation in the road environment [9]. So, they should be less prone to distraction and less inclined to speeding and risk-taking behaviors since they are not rout-familiar and, of course, confident enough.

On the other hand, familiar drivers are associated with more severe injuries during vehicle-to-vehicle crashes in urban areas. This is because driving on a familiar route is mostly an automatic process in which skill-based tasks are unconscious [35]. Therefore, as previously stated in the literature, a frequent driving condition (route familiarity) can result in distraction and inattention by encouraging mind wandering: the mind is occupied by thoughts not concerning the driving task, and consequentially, responses to external stimuli are potentially slowed down [9]. For the sake of that, inattention can nearly often result in delays in the driver's reaction. Ref. [36] found that route familiar users needed greater reaction times than the unfamiliar drivers in a driving simulator study. Therefore, familiarity can lead drivers to behave in a way that makes them at a higher risk.

Figure 2 reports the ratio of killed/injured to no injury crashes for the studied crash database with regard to drivers' fault and familiarity. As shown in Figure 2, familiar drivers in the database were about two times more prone to severe crashes than unfamiliar counterparts, whether at-fault or not. The descriptive statistics of crash records and modeling results are fairly confirmed by each other.

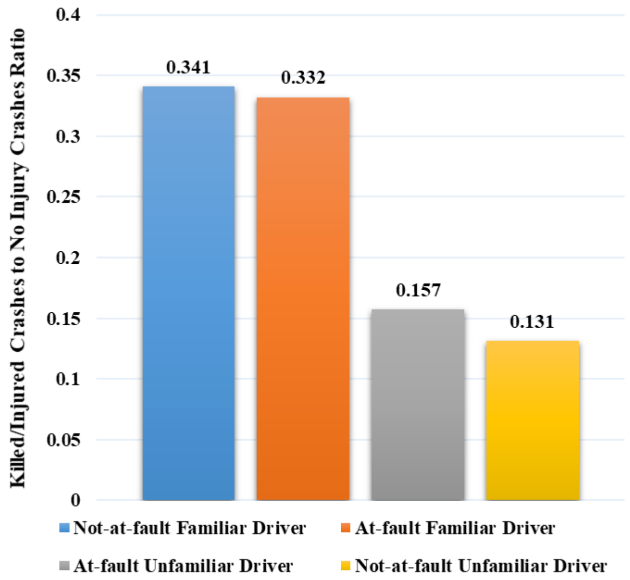

Figure 2. Injury severity level ratio for familiar and unfamiliar drivers by their fault in crashes

Yet, there is a critical issue that unfamiliar drivers may decrease the average speed on roads [37] for the sake of unfamiliarity and less confidence with the route; so, they may choose speeds lower than familiar drivers. In this condition, speed variance increases [9], potentially increasing the crash risk itself. On the other hand, it should be kept in mind that speed-difference-related crashes in urban areas (such as crashes resulting from a sudden change in direction) are not much severe as in rural areas. As a result, unfamiliar drivers may increase the risk or frequency of vehicle-to-vehicle crashes in urban areas, but they decrease the severity of these types of crashes.

Among vehicle-related factors, Iranian-company-made vehicles are determined as a significant predictor variable increasing the severity of vehicle-to-vehicle crashes. The reason for that is the lower safety level of Iranian-company-made vehicles. Many Iranian companies still manufacture vehicles without routine safety-related technologies such as ABS braking systems or airbags. So, regardless of fault and familiarity, Iranian-made cars are more likely to experience severe crashes than foreign-company-made vehicles.

Between all collision angles, head-on and rear-end crashes are found to increase the severity of vehicle-to-vehicle crashes. Considering the previous studies, head-on collisions are the most severe vehicle-to-vehicle crashes types [38]. Rear-end collisions are also considered the most frequently occurring types of crashes worldwide and lead to a significant number of injuries and fatalities. In the USA, for instance, about one-third of all crashes were rear-end crashes [39]. The involvement of heavy vehicles, darkness, higher speed limits, and impaired drivers can significantly increase the severity of rear-end crashes [39].

The only significant road and environmental-related factor is a crash at night without enough lighting. This is clearly because darkness decreases the drivers' sight distance and increases their reaction time. At last, three crash reasons have become significant in the model. Reverse moving, sudden change in vehicle direction, and sudden opening of the vehicle's door are associated with lower severities of vehicle-to-vehicle crashes. However, these are dangerous behaviors; they cannot inherently cause severe crashes in urban areas. Yet, they can significantly increase the risk of crash occurrence.

As previously stated, to evaluate how accurately the developed model can predict crash severity, a 10-fold cross-validation process was used. Table 3 reports the results of MAD for 10 separate validation folds.

Table 3. Results for the 10-fold cross-validation

Validation Fold	MAD
1	0.323
2	0.317
3	0.318
4	0.308
5	0.307
6	0.293
7	0.298
8	0.285
9	0.319
10	0.298

The average of MAD values reported in Table 3 is 0.307. Looking at Table 3, it can be inferred that all the MAD values are fairly close to the average value of MAD (0.307). In addition, considering the target variable values (0-1), the prediction ability of the model seems reasonable but not perfect.

5. Conclusion

Drivers' route familiarity and unfamiliarity can be related to increased crash risk, frequency, and severity. Unfamiliar drivers could be involved in errors due to unexpected road features or interaction situations, while familiar drivers seem prone to inattention and risk-taking behavior. This paper aimed to investigate the factors that significantly affect the severity of urban vehicle-to-vehicle crashes in the presence of familiar and unfamiliar drivers. The crash data of Rasht, the biggest city of Guilan province, in Iran were utilized for this target using a binary logistic regression model.

Results highlighted the decreasing effect of unfamiliar at-fault and not-at-fault drivers, afternoon hours, the foreign-company-made vehicles, reverse moving, sudden change in vehicle direction, and sudden opening of the vehicle's door on injury severity of vehicle-to-vehicle crashes. On the other hand, early morning hours, spring, summer, and autumn seasons, head-on and rear-end collisions, Iranian company-made vehicles, dark roads at night, and young at-fault drivers were found to significantly increase the injury severity of vehicle-to-vehicle crashes in urban areas.

The outcomes of this research can assist transportation engineers and researchers in taking more targeted measures to mitigate the severities of vehicle-to-vehicle crashes in urban areas with a large number of tourists and unfamiliar drivers.

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