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A Nested Logit analysis of the influence of distraction on types of vehicle crashes

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Abstract

Purpose: This work aims to study factors, such as driver characteristics, environmental conditions, and vehicle characteristics, that affect different crash types with a special focus on distraction parameters. For this purpose, distraction factors are divided into five groups: cellphone usage, cognitive distractions, passengers distracting the driver, outside events attracting the driver's attention, and in-vehicle activities.

Methods: Taking the crashes that occurred in the USA into account, the crash types are divided into two main groups, single-vehicle crashes and two-vehicle crashes. Since there were different crash types (alternatives) in the dataset and the probable correlation in the unobserved error term, the Nested Logit model is developed.

Results: The results of model illustrate that all of the aforementioned distraction-related factors increase the probability of run-off-road crashes, collision with a fixed object, and rear-end crashes. Cognitive distraction increases the probability of collision with a pedestrian. Distractions caused by passengers or out-of-vehicle events increase the probability of sideswipe crashes.

Conclusion: By examining how a factor affects multiple crash type outcomes, it is possible to devise countermeasures, improvements to roadway geometry, and traffic control strategies, while minimizing unintended consequences. The results should be of value in the design of educational programs and propose road safety improvement techniques.

Keywords: Crash types, Distraction, Single-vehicle crashes, Two-vehicle crashes, Nested logit model

1 Introduction

Safety is one of the most important characteristics of transportation networks. It can be simply defined as arriving at the destination with no injuries and functional loss. A plethora of factors affect crashes and make them intricate, e.g. traffic conditions, road geometry, vehicle specifications, pavement specifications, and drivers' characteristics. Damages caused by crashes have different economic, cultural, environmental, sanitary and psychological aspects. According to the WHO reports in 2012, 24% of deaths among the world are caused by road traffic injuries. For people of ages 5 to 49, road crashes are among the four most widespread causes of death in the world, and road traffic injuries are the leading cause of death worldwide among those aged 15–29 years [1].

A work by "Traffic Safety Culture Survey" in 2008 showed that 35% of drivers feel unsafe while driving in roads, and 31% of them introduce distraction as the most important cause of crashes [2]. Based on a report by National Highway Traffic Safety Administration, 0.04% of drivers in 2002 allocated their driving time to electronic devices (e.g. texting), while this share increased to 1% in 2008 [2]. It is also worth noting that driver distraction is not just defined as the usage of electronic devices and new technologies during driving, but it is defined as any activity that influences drivers' vision, hearing capabilities, reflection speed and decision making.

Generally, many scholars have widely discussed the subject of driver distraction. They have investigated the relations between crashes and driver distraction through many different methods, such as watching driver's behavior while driving, trying driving simulators, analyzing the statistics of crashes, and personally talking to drivers [3–5]. However, the effects of distraction on the crash types have been seldom studied.

Crash type is one of the important features of a collision. Zaloshnja et al. estimated the total cost per crash for

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different types of crashes by considering different aspects like property damage or lost productivity [6]. It is also worth noting that based on Highway Safety Improvement Program (HSIP), analyzing the crash types is put into action to measure the safety of a road [7].

Most of the researchers usually investigate the relations between distraction factors and the occurrence of crashes [8–10], while this work mainly focuses on the influences of driver distraction on crash types. For this purpose, it defines a hypothesis at first and then tests it by the aid of police reports about various crashes. Few works have been performed to study driver distraction, but this one, though in a limited scope, significantly magnifies and investigates it. Effects of driver distraction on crashes are perused in the presence of other different factors, too. Factors related to drivers' characteristics (e.g. age, gender, physical abilities or health), and other factors such as time of crash, lighting, and weather conditions are discussed. Other important factors are road and vehicle specifications, such as number of lanes, super elevation, slope, curves, vehicle type, and age.

2 Literature review

There are a few studies that analyze different types of crashes by modeling techniques. One of the primary studies in this area was conducted by Khattak et al. [11]. They examined the factors affecting single-vehicle and two-vehicle crashes. They also compared the rear-end crashes with sideswipe crashes in their work. Driving over the speed limit, urban areas, daily traffic volume, peak hours, wet surfaces, and straight roads with grade were the factors that increase the probability of rear-end crashes when compared with sideswipe crashes. On the contrary, male drivers, increase of driver's age, trucks, short age of vehicles, increase of number of lanes, increase of allowed speed limit, frozen surface, and driving on the road with curvature increase the probability of sideswipe crashes [11].

Kim et al. [12] investigated crashes which occurred at rural intersections. The results showed that clear weather increases the probability of angular and sideswipe crashes in the same direction, and decreases the probability of rear-end and sideswipe crashes in the opposite direction. Wet surface conditions increase the probability of sideswipe crashes in the same direction, while the dry surface conditions increase the probability of angular, rear-end, and sideswipe crashes in the opposite direction [12].

In terms of modeling, Bham et al. [13] analyzed single-vehicle and multivehicle crashes by developing the Multinomial Logit model. They examined various factors affecting the crashes, e.g. light conditions, surface conditions, road's curvature, sloped roads, and time of crashes [13]. Yu et al. conducted a study in 2013 to investigate the effect of weather conditions and road characteristics on three types of crashes that occurred on a mountainous freeway. The crashes included rear-end, sideswipe and single-vehicle crashes. The developed mixed Logit model revealed that single-vehicle crashes are more probable at snow season [14]. Romo et al. developed mixed Logit models in order to explore the factors that lead into three types of crashes. Based on General Estimates System database (GES) collected from 2005 to 2008, they found effective vehicular factors and factors related to driving quality among cars and trucks [15].

At the time of this research, Chu conducted the most recent study on this subject in 2015. Based on the GES crash database for the crashes, which occurred between 2011 and 2013 in the USA, a mixed random parameter Multinomial Logit model was developed to measure the probability of different crashes. The study analyzes single light vehicle collisions and collisions between two light vehicles. The results show that all of crash types are less likely to occur in inclement weather and between midnight and 7 AM. Among the roadway characteristics, angular and rear-end crashes are less likely to occur on curved roads. Among driver behaviors, reckless drivers are more likely to experience head-on, angular, and rear-end crashes [16].

It is important to note that this paper focuses on analyzing factors instead of frequency of different crash types. The frequencies of different crash types can be used to predict the number of crashes [17–21]; however, this study wants to assess the importance of factors. The factors are chosen based on driver's characteristics, conditional and environmental properties, vehicles and road characteristics.

Previous studies show that both single-vehicle and multivehicle crashes have not been well investigated yet. The studies usually consider all types of single-vehicle crashes as one type of crash, and start to develop models. However, in order to have a broader view, each type of crash should be treated separately in the model for investigating the effect of driver distraction. Afterwards, the effect of driver distraction factor between different kind of crashes can be analyzed. It is also worth noting that all of the studies have been performed considering the independence of irrelevant alternatives (IIA) as an assumption, which is not always true, particularly for both types of sideswipe crashes and different single vehicle crash types. This study then aims to overcome the weakness of previous studies by using developed Nested Logit model and considering eight different crash types.

There have been a few studies about the effect of driver distraction on different crash types as well. Khattak et al. [11] considered reckless driving as a variable in their study. This factor increases the probability of single-vehicle crashes compared with two-vehicle crashes, and also sideswipe crashes compared with rear-end crashes. In a descriptive study conducted in the Unites States for crashes that occurred from 1997 to 2000, driver distraction was reported as one of the main causes of rear-end and run-off-road crashes.

Cognitive distraction has the major share of crash reasons among the distraction factors [22].

By the authors' knowledge, there are only three studies focusing on the effect of driver distraction-related factors on different crash types [23–25]. Neyens and Boyle [23] as pioneers in this topic, studied the effect of distraction-related factors on the crash types of teenage drivers [23]. They utilized three main collision types of angular, rear-end, and collision with fixed objects as dependent variables for developing the models. They also considered four main distraction-related factors: distractions due to the presence of passengers, distractions due to the usage of cellphones, cognitive distractions, and distractions due to in-vehicle activities. They developed a Multinomial Logit model to anticipate the probability of each of the three mentioned crash types. The results showed that the probability of rear-end crashes increases when the driver is distracted due to the presence of passengers or usage of cell phone. In-vehicle activities increase the probability of collision with fixed objects in comparison with angular crashes. Cognitive distraction increases angular and rear-end crashes compared with collision with fixed objects [23]. They also utilized the same data to investigate the effect of distraction-related factors on the crash severity [24].

Ghazizadeh and Boyle [26] explored the effects of distraction-related factors on the probability of crash types happening in Missouri, considering all drivers' ages. They analyzed the three collision types of angular, rear-end, and single-vehicle crashes. Distraction-related factors are classified into three groups: distractions related to cell phones, distractions related to electronic devices, and passenger-related distractions. The results showed that distractions caused by passengers increase the probability of rear-end and angular crashes compared with single-vehicle crashes, while distractions caused by electronic devices increase the single-vehicle crashes compared with rear-end and angular crashes. Distraction caused by cell phone usage also increases the probability of angular crashes [26].

As we see, the effect of distraction was studied on a few types of crashes. The implications of considering more types of crashes and more distraction factors help the authorities to have a broader overview on this topic. Therefore, this study tries to fill this gap by considering more type of crashes. In addition, more distraction factors are considered for the study. In the following sections, the paper describes methodology, used data, modeling techniques and finally, results and conclusion.

3 Methodology

According to Gumbel distribution for errors in the Nested Logit model, the observation probability function of nest "i" is defined as:

$$p_{ni} = \frac{e^{\beta_i x_{ni} + \phi_i LS_{ni}}}{\sum_{\forall I} e^{\beta_I x_{nI} + \phi_I LS_{nI}}} \tag{1}$$

Where,

P_{ni} = Unconditional probability of crashes for driver "n" in alternative "i"

x_{ni} = Vector of measurable characteristics

β_i = Vector of estimable coefficients

LS_{ni} = Inclusive Value (IV) or logSum which is calculated from the alternatives "i" in (3).

It should be mentioned that β coefficients for alternative "I," is calculated by Logit model, based on (1).

$p_n(j|\, i)$= The probability of crash types "j" for the driver "n" in a situation that the alternative places in nest "i." Equation (2) defines how it is calculated.

$$p_n(j|i) = \frac{e^{\beta_{j|i} x_{nj}}}{\sum_{\forall J} \beta_{J|i} x_{nJ}} \tag{2}$$

$$LS_{ni} = Ln\left[\sum_{\forall J} e^{\beta_{J|i} x_{nJ}}\right] \tag{3}$$

McFadden interpreted an inclusive value (IV) (the coefficient of logsum = ϕ) as the following:

1. If ϕ is greater than one, the compatibility with utility maximization is violated.
2. If it stands between zero and one, it means that increase of utility increases the probability of choosing the nest and the alternatives inside the nest. It shows that there is an unobserved correlation between the alternatives placed in a nest.
3. If the coefficient of logsum is equal to one, the Nested Logit model turns into Multinomial Logit model. It should be mentioned that both of these models are from generalized extreme value model (GEV) [27].

In order to estimate the Nested Logit model, the Full Information Maximum Likelihood (FIML) approach is used.

$$L(\beta) = \prod_{n=1}^{N} \prod_{j} \left(P_{nj}\right)^{y_{nj}} \tag{4}$$

Where L(β) is the likelihood function. Whenever the crash type "j" is observed for the driver "n", y_{nj} is equal to one. Calculating the logarithm of (4), the log-likelihood function (5) is maximized.

$$LL(\beta) = \sum_{n=1}^{N} \sum_{J} y_{nj} \ \ln P_{nj} \tag{5}$$

3.1 Data

This section describes how to extract data to investigate how distraction factors affect crash types. The data for the study is obtained from the General Estimates System database (GES) that is related to crashes occurred annually in the USA in 2010, as a subset of National Automotive Sampling System from more than 5 million police-reported crashes. The fatal crashes, crashes with injury, or with major property damages are included in this dataset. Many scholars have used this data to conduct their research in the field of safety modeling, showing the reasonably reliability of this data [25, 28–31]. Each GES record has a weight that is applied to permit projection to the national crash frequencies. The data includes characteristics of drivers and vehicles, crashes and roads, and environmental properties.

The crash type is defined by the “First Harmful Event” (first damaging producing event) variable at the accident. Crashes generally are categorized into two divisions: single-vehicle and two-vehicle. A single-vehicle crash can be subcategorized into three divisions; run-off-road, collision with fixed objects (e.g. parked vehicles), and collision with a pedestrian (or animal). A two-vehicle crash is also subcategorized into five divisions of rear-end crashes, head-on crashes, angular crashes, sideswipe crashes in an opposite direction, and sideswipe crashes in the same direction. The remaining types of crashes are expunged from this study, since they are either unrecognized or scarce. The omitted data is almost 2% of the whole dataset. Thus, eight types of crashes are investigated in this study. It is also worth noting that to elaborate on the distraction factors, in-vehicle activity and cognitive distraction should be discussed. The distractions engendered by the following items are considered as in-vehicle activities: a moving object in the vehicle, adjusting audio or climate controls, using other component/controls integral to vehicle, using or reaching for device/object brought into vehicle, eating or drinking, and smoking related activities. The distraction caused by looking but not seeing accurately, being inattentive and being lost in thought are considered as cognitive distractions. To elaborate on that, The NHTSA report mentions that identification of some driver-related tasks which affect distraction has been challenging, within the NHTSA dataset and in dataset that have been reported by police. So, the crashes that are reported to involve distraction without listing a specific driver behavior are listed as having the source “other distraction”. Based on the NHTSA, a person can assume that some portion of the crashes involves electronic devices [32]. The police officers were reporting distraction by investigating the observers and the people who were in the vehicle. The author clarifies that this might engender some bias into the study; for instance, police-reported distraction might not be 100% accurate. Due to the widespread use of this dataset, the author decided to implement it in this study; however, collecting a 100% reliable data related to distraction might not be possible.

According to the exploited variables, the observations that have missing values are excluded from the study. Subsequently, in order to develop a model, a random sample of the weighted data, having no missing value with the approximate sample size of 14,500 (27% of the data), is selected. In the final sample, run-off-road crashes are 11% of the crashes, collisions with fixed objects are 2.3% of the crashes, collision with individuals are 5.1% of the crashes, rear-end crashes are 37.4% of the crashes, head-on crashes are 3.1% of the crashes, angular crashes are 31.4% of the crashes, sideswipe crashes in an opposite direction are 1.2% of the crashes, and the last type of crashes, sideswipe crashes in the same direction are 8.5% of the total crashes. The methodology for selecting a random sample with the lower number of data without the changes in the distribution of the variable has been previously reported in the GES data studies [33]. According to the randomization of data, the results of this study can be broadened and applied to society [34, 35]. Table 1 demonstrates the analytical characteristics of the samples.

3.2 Modeling of crash type

In this section, the modeling technique is discussed. According to General Estimates System (GES) data, the crash data are classified into eight different types which were previously illustrated.

In addition to 5 types of distraction-related factors, the independent variables that are employed in the model include driver’s characteristics, environmental conditions, and vehicle’s characteristics. Regarding the available alternatives, the methodological approach, and the peculiarities of crash’s data, Multinomial Logit has been selected. In order to find the effective variables and the order of adding variables in the model, two Multinomial Logit models have been developed. The first model contains four different crash types; run-off-road crashes, collision with a pedestrian, collision with an object and two-vehicle crashes. The second models contain six different crash types; rear-end crashes, head-on crashes, angular crashes, sideswipe crashes in the opposite directions, sideswipe crashes in the same direction and single-vehicle crashes.

The modeling starts with entering all of the variables and studying each one in different ways. For example, the age variable has been divided into eight intervals, 16 to 19, 20 to 24, 25 to 34, 35 to 45, 46 to54, 55 to 64, 65 to 74, and 75 and higher. The significance of dummy variables corresponding each interval has been determined using a

Table 1 Data Descriptive

Variable	Percentage	Standard Deviation
Characteristics of the driver		
Driver's gender		
Female	47.1	0.499
Driver's age		
16–24	24.6	0.431
25–60	62.4	0.484
60 above	13.0	0.336
Driver's Impairment		
Under the Influence of Alcohol, Drugs	2.1	0.144
Asleep or Fatigue	0.9	0.093
Safety Equipment		
Not Using Seatbelts	3.2	0.176
Wrong Use of Equipment	0.3	0.053
Driver's Distraction		
No Distraction	92.4	0.264
Cognitive	4.9	0.215
Passenger Related	0.3	0.058
In-Vehicle Tasks	1.1	0.103
Out-Vehicle	0.6	0.079
Cellphone	0.7	0.081
Speeding		
Driving Over the Speed Limit	10.8	0.311
Conditional and Environmental Properties		
Passenger		
Presence of Passengers	28.2	0.450
Driver and Passengers Age: 16–24	4.0	0.196
Vision condition		
Vision Obscured	2.7	0.163
Light condition		
Daylight	77.0	0.423
Dark – Not Lighted	6.2	0.240
Dark – Lighted	13.5	0.342
Dawn or Dusk	3.3	0.178
Weather condition		
Fair/Cloudy Weather	87.1	0.35
Rainy	8.8	0.283
Snowy	3.8	0.191
Sleety or Foggy	0.3	0.054
Crash Day		
Weekend	22.7	0.419
Time of Day		
Regular Hour (after morning peak hour and before afternoon peal hour)	52.8	0.499
Morning Peak Hour	11.7	0.322

t-test. By considering the goodness of fit and t-test results, we determined the best way to enter the age variable was the interval mode. In the final model, based on the coefficients, all the variables that had no statistical difference with zero have been eliminated in a significant level of 5%. The t values of all the coefficients are greater than 1.96, which means that coefficients of all of the variables are at the 5% significant level.

Developing two discussed models, lead to development the Multinomial Logit model with eight different crash types. It is also worth noting that one of the major assumptions of Multinomial Logit model is independencies of alternatives, which may be violated when single-vehicle or two-vehicle crashes are considered. One of the tests to investigate this assumption is developing a Nested Logit model. The models in the study are developed by Nlogit 4 software. If the results of developed Nested Logit model reveals that $\varnothing$ is between 0 and 1 and significantly far from them both, then the Multinomial Logit model is found not to be a proper model and coefficients are found inaccurately, concluding that the Nested Logit should be used.

In order to detect the most proper model and test the assumption, the Nested Logit model has been developed. The most challenging issue to develop the mentioned models is to find a suitable structure to place the alternatives in the nests. The nest structure should be logical and also lead into developing the best-fitted model through the data. According to the nature of various crashes, a logical structure is found, which is presented in Fig. 1.

According to Fig. 1a, it is clear that various single-vehicle crashes have been located in one nest due to their similar specifications. Two-vehicle crashes all have the same characteristic of involving two vehicles (drivers) in the accident – have also been located in the other nest. In this structure, the sideswipe crashes are also in the same nest on the third level, due to the similarity of their characteristics.

By considering the suggested structure, the Nested Logit model has been developed. The outcomes demonstrate that the assumption of the Nested Logit model is invalidated ($\varnothing > 1$). Consequently, various Nested Logit models have been developed. By considering the structural parameter and fitting the model through data, the best-fitted Nested Logit model has been developed. Figure 1b unveils how the best-fitted Nested Model is developed for analyzing the data. The proposed structure is similar to the primary structure suggested, except for shifting from two levels to three levels.

The characteristics of final developed model based on Fig. 1b structure, is observed in Table 2. The likelihood ratio index is equal to 0.35, which is acceptable. According to the first hypothesis, to investigate the

Table 1 Data Descriptive *(Continued)*

Variable	Percentage	Standard Deviation
Afternoon Peak Hour	35.5	0.478
Characteristics of the vehicle		
Vehicle Type		
Cars	57.0	0.495
SUVs	19.2	0.394
Vans	7.1	0.256
Pickups	16.8	0.374
Vehicle Age		
Up to 7	44.4	0.497
7–12	37.1	0.483
12 Above	18.5	0.388
Characteristics of the road		
Road alignment		
Steep roads	18.6	0.389
Curves	20.5	0.404
Surface condition		
Dry	77.5	0.417
Junction Type		
Intersections	47.4	0.499
Speed Limit		
Up to 35 mi/hr	22.8	0.419
35–50 mi/hr	57.7	0.494
Above 50 mi/hr	19.6	0.397
Highway Type		
Interstate Highway	7.4	0.262
Zone Type		
Urban Zone	48.5	0.500
Trafficway Description		
One Way	8.9	0.285
Two Way - Not Physically Divided	33.0	0.470
Two Way - Divided Highway	58.1	0.493
Characteristics of the crash		
Collision Type		
Run-off road	11	0.393
Collision with a fixed object	2.3	0.184
Collision with a pedestrian	5.1	0.290
Rear-End	37.4	0.494
Head-On	3.1	0.172
Angle	31.4	0.491
Sideswipe crashes in an opposite direction	1.2	0.121
Sideswipe crashes in the same direction	8.5	0.327

superiority of the Nested Logit model over the Multinomial Logit model in this study, the likelihood ratio tests should be conducted [27]:

$$\chi^2 = -2\left[LL(\beta_{MLM}) - LL(\beta_{NLM})\right] \tag{6}$$

In the aforementioned equation, the $LL(\beta_{MLM})$is the log likelihood at the convergence of the Multinomial Logit model, and $LL(\beta_{NLM})$ is the log likelihood at the convergence of the Nested Logit model. The chi-square index is equal to $-2[-17{,}384 + 17{,}372] = 24$.

The degrees of freedom for chi-square index is equal to 2, which is calculated as a difference between the number of parameters between the Multinomial Logit and Nested Logit models. Finally, the chi-square index determines that the likelihood ratios of the models are not equal and the Nested Logit model is more interesting than Multinomial Logit model (Significant level = 1%). It is also worth noting that the inclusive value for single-vehicle crashes and sideswipe crashes is located in a place between zero and one, which are 0.78 with the standard deviation of 0.047 for the former and 0.61 with the standard deviation of 0.091 for the latter.

The developed Nested Logit model explains that there is a correlation between the mentioned alternatives. It also demonstrates that the developed nesting structure is appropriate. The results reveal that independency hypothesis between alternatives is revoked, leading into incorrect results by Multinomial Logit model.

4 Results and discussions

According to the alternatives, eight different utility functions have been estimated and assigned to the crash type. In the following table (Table 3), the coefficients of the variables for each crash type have been presented. The t statistics of all variables are greater than 1.64 with a significance level of 10%; in other words, the coefficients are statistically significant at the level of 0.1. To investigate the multicollinearity between the variables, the variance inflation factor (VIF) is calculated, which is less than 3 for all variables. Kutner et al. [36] suggested a VIF of 5 as the threshold that indicates a presence of serious multicollinearity. The results of the study showed that there is no multicollinearity between the variables. It is also worth noting that the coefficients of variables in the utility functions are estimated to be the same if there is not any significant difference between them, and the difference is calculated by t statistics. Table 3 demonstrates the outcomes and the coefficients of the developed model. In the following sections, the results regarding each of the crash types will be discussed.

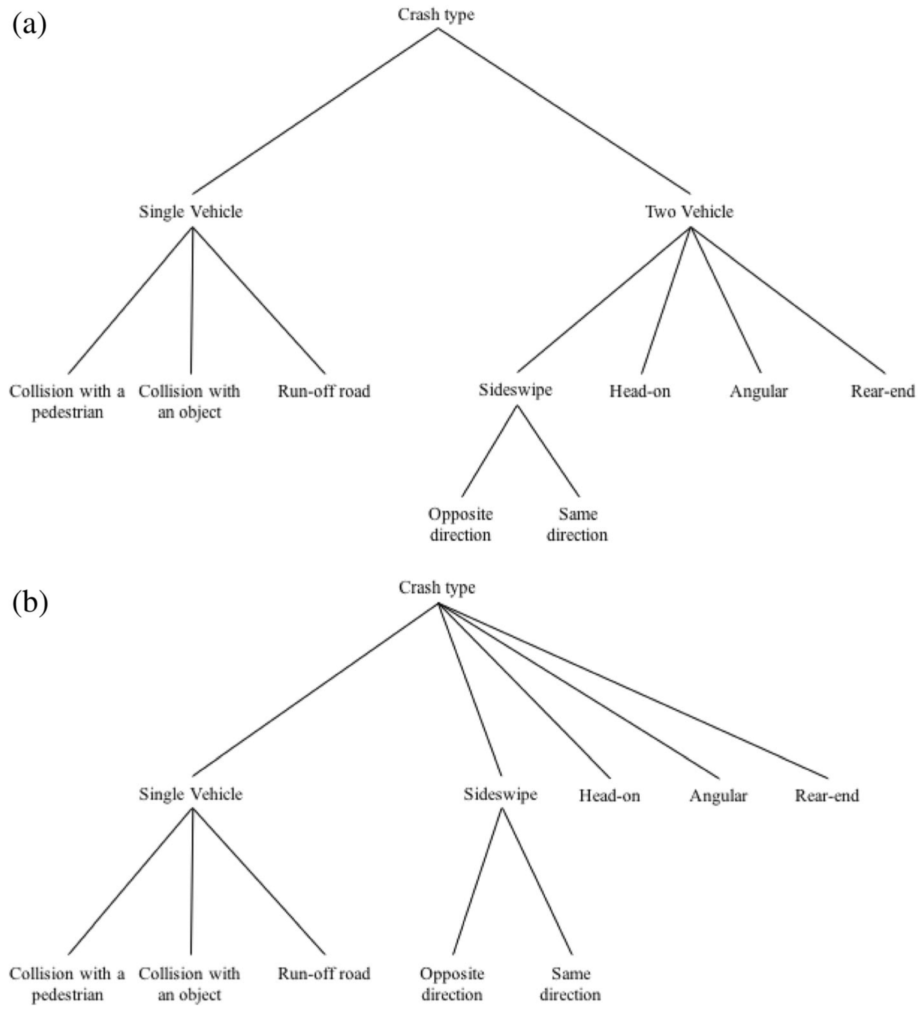

Fig. 1 The primary (**a**) and final (**b**) version of developed nested Logit structure

4.1 Single-vehicle crash

According to the developed Nested Logit model, the significant variables for each of the crash types and the effect of the variables are investigated, which are provided in Table 3. In the following parts, each crash type and significant factors will be discussed.

4.1.1 Run-off-road

According to the data, the most widespread type of single vehicle crash is the run-off-road crashes. As Table 3 shows, all distraction-related factors have significant and positive effects on this type of crash. The positive signs show that distraction-related factors increase the probability of run-off-road crashes. The authors think that the drivers usually become distracted when there is not any interference with other vehicles. In other words, the absence of another vehicle causes drivers to feel safe, and this feeling facilitates distractions causing drivers to crash. To rationalize the sentence, it can be applied in cases where there is not any other vehicle by having any influence on the crash.

The results show that being under the influence of alcohol or drugs increases the probability of this crash type. Difficulties to control the vehicle by drivers who are under the influence of alcohol or drug is highly expected. Thus, they have a higher crash probability in comparison with normal drivers. The drivers who do not fasten the seatbelts are more probable to experience this type of crash. Safety equipment variable can represent the driver's law-breaking risks when not using seatbelts. So, reckless drivers are more probable to experience this type of crash.

Driving over the speed limit has been another reason for run-off-road crashes. It increases the occurrence probability of run-off-road crashes more than all other considered variables. It appears that driving over the speed limit in crowded places heads to collision with another vehicle, though run-off-road crashes happen more often in less crowded areas. It is also worth noting that driving over

Table 2 Crash Types Estimation of Nested Logit Model

Factors	Value
Inclusive value (IV) parameter for single vehicle crash nested (SD)	0.78 (0.047)
Inclusive value (IV) parameter for sideswipe crash nested (SD)	0.61 (0.091)
Observation	14,130
LL(0), Log likelihood with constants only	−26,538.86
LL(β), Log likelihood at convergence	−17,373.34
ρ^2, Likelihood ratio index	0.346

the speed limit will diminish the ability to control the vehicle, i.e., with any little interference on the road, the driver runs-off-road. Moreover, increasing the speed allowance to more than 50 miles per hour has a significant positive effect on the occurrence of this type of crash. The results show that increasing the allowed driving speed increases the tendency of driving over the speed limit, which increases the probability of occurrence of this type of crash.

In the conditional and environmental situations, rainy or snowy weather conditions have a significant positive effect on the probability of the crashes, proving that inclement weather increases the odds of this crash. In rainy or snowy weather, the vehicles will slip over the route which increases the probability of this crash type.

Roads with curvatures increase the probability of crashes, which is so rational. While in curvatures, the driver changes the direction of the vehicle, and controlling the vehicle becomes more challenging. The results also show that in the vicinity of junctions like intersections, squares or ramps, the odds of encountering this type of crash reduces. These places are most likely crowded with heavy traffic which diminishes the odds of experiencing this type of crash. It can be applied to when in the vicinity of junctions as well.

It is also figured that increasing the number of lanes, reduces the odds of experiencing this crash. The routes having fewer lanes, let the driver move off-road easier which reduce his control on the vehicle, so driving on such roads increase the odds of experiencing this crash that seems to be rational.

4.1.2 Collision with an object

Collision with a fixed object or a parked vehicle is included in this type of crash, which has the characteristics of single-vehicle crashes (i.e. only one vehicle involved in the crash). Results were similar to run-off-road crashes. The positive sign of all distraction-related factors demonstrated, that they increase the probability of experiencing this type of crash. It is also concluded that same as collision with an object, weekends and smooth traffic act as distraction-related factors. The magnitude of the variables' coefficients reveals that distractions, caused by passengers and in-vehicle activities, more than all other distractions increase the probability of collision with an object. The results show that many variables affecting this type of crash are similar to those of run-off-road crash.

Conducting a statistical test confirms that the coefficients of passengers' presence variable and an increase in lane number variable, do not have any significant difference in the utility functions of the aforementioned crash-types. As a result, the coefficient of the variables has been considered equal in model development.

The coefficients of speed limit variables show that the relation between them and occurrence of this crash is U-shaped. Limiting the driving allowance speed to below 35 miles per hour and above 50 miles per hour, increases the probability of this crash occurrence. Usually, the auxiliary roads have lower allowed driving speed, and there are many more curbed parked vehicles or fixed objects in these places in contrast with the areas with higher allowed driving speed, thus the probability of the crash increases.

4.1.3 Collision with a pedestrian

Among the distraction-related factors, cognitive distraction is the only significant factor that increases the probability of this type of crash. Comparing the results of this crash type with those of the last two can show that cognitive distraction source became significant in all the single vehicle's crash types. It shows the importance of this distraction source in such crashes. It shows that the probability of engaging in a cognitive distraction can be more in single-vehicle crashes. It can be due to the safe environment that the driver imagines for himself (due to the low traffic), the other thoughts that comes to his mind, etc. [26].

The presence of passengers and young drivers has reduced the probability of this type of crash occurring. It seems that young drivers have more flexibility, faster response, and more powerful maneuverability that let them prevent collisions with pedestrians. It appears that obscuring the driver's vision in bad (lousy) lighting conditions leads to collision with pedestrians. It seems that in this situation, the driver is not able to detect the pedestrians, and hits them.

The shortage of sunlight, e.g., the dark condition without light, dark condition with artificial light, or driving at dawn or dusk, raises the occurring probability of this type of crash. It is evident that in these situations, detecting the pedestrian in the driving path is challenging.

The sign of speed limits higher than 50 miles per hour is also positive. In these zones, pedestrians cannot precisely estimate the vehicle's speed, and drivers also have less control over the vehicle due to their high speed, thus the probability of crashes in high-speed limit zones increases. It is figured that in urban areas, the probability of collision with a pedestrian increases due to the presence

Table 3 Crash Types Estimation Results

Variable	Coefficient							
	Single-Vehicle crash			Two-vehicle crash				
	Run-off-road	Collision with an object	Collision with a pedestrian	Rear-end	Head-on	Angular	Sideswipe opposite direction	Sideswipe same direction
Characteristics of the driver								
Driver's gender								
Female	–	–	–	0.069[a]	–	–	–	–
Driver's age								
16–24	–	0.214[a]	–0.665	– 0.255	–	–	– 0.351[b]	– 0.279
60 above[a]	–	0.356[b]	–	– 0.322	– 0.282[a]	–	–	–
Driver's Impairment								
Under the Influence of Alcohol, Drugs	1.928[b]	1.928	–	1.367[b]	0.588[a]	–	0.670	–
Safety Equipment								
Not Using Seatbelts	1.165	0.951	–	–	1.042	0.416	–	–
Driver's Distraction								
Cognitive	0.447	0.642[b]	0.734	0.335	–	–	–	0.639
Passenger Related	2.069	2.598	–	0.789[a]	–	–	1.278[b]	–
In-Vehicle Tasks	2.062	2.505	–	1.195	–	–	–	–
Out-Vehicle	1.287	2.076	–	1.428	–	–	–	0.928[a]
Cellphone	1.349	1.885	–	0.502[a]	0.818[a]	–	–	–
Speeding								
Driving Over the Speed Limit	2.483	2.082	–	1.968	–	–	0.889	0.446[b]
Conditional and Environmental Properties								
Passenger								
Presence of Passengers	–0.379	–0.379	– 0.379	– 0.128	–	–	–	–
Vision condition								
Vision obscured	–0.759	–	1.072	–0.972	–	–	–	– 0.841
Light condition								
Dark – Not Lighted	0.998	1.597	1.776	–0.231[b]	0.648	–	0.503	–
Dark-Lighted	0.508	1.008	0.755	–0.183	0.258[b]	–	–	–
Down or Dusk	0.387[b]	0.662[b]	0.873	0.228[a]	–	–	–	–0.773
Weather condition								
Rainy	0.599	–	–	0.131[a]	0.273	0.153[a]	0.391[a]	–
Snowy	2.357	1.209[a]	–	1.057[a]	1.920	1.902	1.962	1.356[b]
Crash day								

Table 3 Crash Types Estimation Results *(Continued)*

Variable	Coefficient							
	Single-Vehicle crash			Two-vehicle crash				
	Run-off-road	Collision with an object	Collision with a pedestrian	Rear-end	Head-on	Angular	Sideswipe opposite direction	Sideswipe same direction
Weekend	0.218	0.317	–	−0.353	–	−0.144[b]	0.216[a]	–
Time of Day								
Peak Hour (6–9 or 15–19)	−0.242	0.262[b]	–	0.129	–	–	–	–
Characteristics of the road								
Road alignment								
Curves	1.434	–	–	–	1/552[b]	–	–	1.151
Surface condition								
Dry	0.182	2.96	–	0.179	2.95	–	–	–
Junction Type								
Intersections	−4.102	−3.737	−2.719	−1.854	−1.727	–	−3.463[a]	−3.195
Other	−3.584	−4.256	−3.153	−2.441	−1.965	–	− 3.321	− 3.321
Speed Limit								
Up to 35 mi/hr	–	1.543	0.763	−0.728	–	–	–	–
Above 50 mi/hr	0.952	0.566	0.952	–	–	–	0.494	–
Highway type								
Interstate highway	1.411	1.854	–	1.689	–	–	–	1.676
Zone type								
Urban zone	–	–	0.176[b]	0.119[a]	–	–	–	0.177
Traffic way Description								
Two Way	–	–	–	–	1.325	–	1.184[b]	−0.465
Number of lane								
More than one lane in each direction	−0.380	− 0.380	−0.380	–	–	–	− 0.346	0.218
Constant	0.980	−0.568	0.565	1.752	2.368	–	−0.980	0.708

[a]significant at the 10% level, [b]significant at the 5% level, the numbers without any mark are significant at the 1% level, "-"not significant

of many pedestrians in these places. Increasing the number of lanes has reduced the probability of this crash type. It raises the level of services of the roads, leading to the construction of more underpasses and overpasses for pedestrians and reducing the probability of their presence in the driving path.

4.2 Two-vehicle crashes

In order to model two-vehicle crashes, each driver acts as a single observation. In the other words, the developed model investigates the engagement probability of each driver in each crash class. To decrease the collinearity of each crash's observations, the variables related to drivers' different characteristics and similar conditions of area and crash's location have been entered to the model. The supplemented variables can minimize the dependency between two samples. It is also worth noting that the studied sample considers only two-vehicle crashes that do not have the multicollinearity of adding multi-vehicle crashes.

4.2.1 Rear-end crash

Rear-end crashes are the most common type of two-vehicle collisions. According to the data used in this work, 37.4% of all crashes are rear-end, the highest share of crash percentages. All of the distraction-related factors become significant and increase the probability of rear-end collisions. In recent years, many studies have focused on the effects of distraction factors on driving quality, as well as making the driver's reaction time longer [3–5, 37–39]. The authors believe that drivers' distraction prevents them from braking at the right time, making them collide with the front vehicle. It is also worth mentioning that the driver looks at the road less frequently when he is distracted. This means that whenever the driver does not look ahead, he will hit the backside of the front vehicles if they brake unexpectedly. So, it can be said that the probability of rear-end crashes between two vehicles due to drivers' distraction increases. Conversely, if the front driver is distracted and brakes late, the driver behind cannot brake at the right time, and the crash might happen. The magnitude of the distraction-related factors' coefficients show that out-of-vehicle and in-vehicle distractions have the most prominent effects on increasing the probability of rear-end crashes.

The drivers' age has a different effect on this type of crashes in comparison with single-vehicle ones, such that young and old drivers have been less involved in rear-end crashes. Young drivers react and brake faster, diminishing the probability of this crash type. Although old drivers react slower than young drivers, they are less involved in these crashes. The authors believe that It is because they drive more carefully, adequately distant from the front vehicles, and with lower driving speed.

When driving over the speed limit, a longer time is required for braking, and the probability of brakes locking increases. Driving over the speed limit and its effect on the brakes have increased this type of crash probability.

In the realm of environmental factors, darkness decreases the probability of this crash type. Rear end light are visible at night allowing follower drivers to brake on time whenever is needed. Furthermore, drivers drive more carefully at nights and keep a safe distance from the front vehicle. It is also worth noting that the developed model shows the same results for the daylight conditions when the front vehicle is visible more easily. Rainy or snowy weather has increased the probability of this crash. These weather conditions cause the slippage of vehicles on the road surface, preventing drivers from braking on time and making them experience a rear-end collision. The magnitude of the coefficients determines that the snowy weather has a higher impact than rainy weather. Cold air in snowy weather, makes the road surface freeze and increases the probability of rear-end crashes.

At intersections or junctions, the probability of this crash type reduces, which is because of driver's awareness of the conditions and readiness to brake before arriving at these places.

In places with lower speed limits, elapsed time to brake and stop is short, since the vehicle's speed is low. Therefore, it is rational that the probability of rear-end crashes decreases in this situation. The positive sign of interstate highway variable demonstrates that the probability of rear-end crashes increases there, which is because of higher driving speed.

4.2.2 Head-on crash

Only a small share of all crashes are head-on crashes (3.1% of all crashes), but there are many studies focusing on this type of crash. This attention demonstrates the importance of studying the factors that cause this type of crash. The utility function of this crash type contains fewer significant variables than prior utility functions. Among distraction-related factors, only cellphone usage is significant and increases the probability of head-on crashes. The reason for this is the inability of drivers who use cellphones to control the vehicle from deviations to the left. Because the main reason for these crashes is overtaking in two-way paths, it appears that cellphone-using drivers are less able to control the vehicle and more probable to crash.

Older drivers are less probable to experience head-on crashes. It can be deduced that they behave more safely and are less probable to overtake and become involved in a head-on crash. The unfastened seatbelt variable has a positive sign in the utility function, which shows that the drivers who do not fasten the seatbelts are more probable to experience a head-on crash. The signs of these two coefficients demonstrate that drivers who do not wear seatbelts (such as aggressive drivers) are more probable to involve in this crash type.

The coefficients of two variables related to brightness show that driving in darkness increases the probability of the crash. The following two reasons can explain this result: First, the high-beam headlight at night bothers the opposite direction driver's vision and makes it difficult for the driver to measure the distance accurately and increases the probability of the crash. Second, driving in darkness causes drowsiness and deviation to the left and increases the probability of a head-on crash.

Driving on road curves increases that probability as well. It can be said that on road's curves –especially in mountainous areas – drivers cannot see the opposite direction well. Also, on road's curves, maintaining the driving route and controlling the vehicle is more difficult for the drivers, and deviation from route causes a head-on crash.

The probability of a crash is reduced when driving on intersections or junctions. The coefficient of two-way roads variable has a positive sign, showing that the probability of a crash increases in these areas. It should be noticed that generally, this type of crash occurs on two-way roads, so the presence of this variable in the model is interesting. Further processing of modeling data clarifies that sometimes drivers who are under the influence of alcohols or drugs, drive in opposite direction on a one-way road. In these situations, the mentioned variable shows the significant effects of two-way roads on head-on crashes rather than one-way roads.

4.2.3 Angular crash

This type of crash is the most widespread crash at the vicinity of intersections. As it was previously mentioned, the probability of other types of crashes occurring at junctions or intersections has reduced, whereas it has increased for this type of crash. The very simple form of the utility function is because of where this type of crash happens; many variables have a very limited interval of changes and are negligibly useful to explain the crash. The positive sign of a coefficient related to the unfastening seatbelt variable shows that drivers who do not fasten the seatbelts have been more probable to experience an angular crash. These drivers are negligent about the laws and pay less attention to signs and traffic lights. Therefore, they are more probable to have an angular crash, which seems thoroughly plausible. Adverse weather condition also increases the probability of this type of crash, while it shows a decrease on weekends. It is because during weekends, the passages are less crowded.

4.2.4 Sideswipe crash in opposite direction

This type of crash account for only 1.2% of all crashes and has the smallest share. Among the distraction-related factors, passengers' distraction has increased the probability of this crash. The positive sign of age variable (for ages between 16 and 24) shows that young drivers are less probable to involve in this type of crashes. Different variables like being under the influence of alcohols or drugs, driving over the speed limits, darkness without light, rainy or snowy weather, weekends, and high allowed driving speed, increase the probability of this crash type.

The increase of the number of lanes also decreases this crash probability. Highways and freeways usually have more lanes; therefore, the vehicles have enough space for maneuver, the direction of the road is divided, and this crash type is less probable to occur. It is also worth noting that the two-way variable coefficient is positive, showing that the probability of this type of crash increases in these ways. The reason for the entrance of this variable into the model is the same as that of head-on crashes.

4.2.5 Sideswipe crash in same direction

Among the distraction-related factors, cognitive and out-of-vehicle factors increase the probability of this type of crash. Driving over the speed limits also has the same effect. One of the principal reasons why sideswipe crashes occur is the driver's inability to prevent the vehicle from deviation. Any small deviation of the steering wheel at high speeds causes transverse displacement of the vehicle, which leads into a sideswipe crash. Obscuring the driver's vision reduces the probability of this type of crash, since it might force the driver to reduce the speed and avoid obstacles. Snowy weather increases the probability of this type of crash too, which is due to the slippery surface of the road that leads into the deviation of vehicles from their paths.

When passing the road curves, the probability of this type of crash increases, since controlling the vehicle in driving path and keeping the line is more challenging at curves and deviation may cause a sideswipe crash. On the other hand, driving at intersections or junctions and the places with lower posted speed limits decreases the probability of the crashes which is expectable. The probability of this crash increases when driving on interstate highways where there are more lanes and drivers drive faster. The positive coefficient of urban places variable also shows that the probability of this crash increases in these areas. According to the negative sign of two-way traffic variable, the probability of this type of crash in one-way traffic ways (which have more lanes) increases.

5 Study limitation and future work

Using a newer version of GES data set might reflect the proliferation of tablet and smartphone usage better in calling, texting, and using social media apps. It should be noted that using a simulator for investigating the relationship between distractions and car crashes could be performed as a future study to increase the quality of the work. Also, considering the use of naturalistic driving data to further explore their hypotheses about the role of different factors in crash occurrences is an interesting topic. It might help scholars to consider other important variables which are missed here, such as drowsiness in explaining the run-off-road crashes.

6 Conclusion

In this study, the effect of distraction-related factors, drivers' characteristics, conditional and environmental properties, and features of cars and roads on the occurrence of eight different crash types (including three kinds of single-vehicle crashes and five kinds of two-vehicle crashes) were investigated. Considering single-vehicle crashes along with two-vehicle crashes made this study unique. To investigate the aforementioned effects, the Nested Logit model, which has rarely been used in previous studies was developed. By examining how a factor affects multiple crash type outcomes, it is possible to devise countermeasures, improvements to roadway geometry, and traffic control strategies, while minimizing unintended consequences. The results should be of value in the design of educational programs; for example, according to the results of run-off-road crashes, drivers' distraction increases the probability of this type of crash. One of the best ways to reduce this type of crash is to highlight the devastating effects of distraction in safety improvement programs even in uncrowned roads and roads with light traffic. Furthermore, results can help in road safety improvement, for example reducing the brightness of roads increases the probability of run-off-road crashes. Therefore, in addition to increasing the brightness, increasing the number of reflecting traffic signs or pieces of reflector paint at the curbs also help drivers detect the path more accurately. Reduction of brightness also increases the probability of collision with a pedestrian. It is recommended that authorities provide an enough lightening equipment at the locations which are used by pedestrians. Also, pedestrians can equip some reflectors stuck to their clothes, letting them be easily detected by drivers at night.

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