Journal of Safety Research 88 (2024) 344–353

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Investigating the severity of single-vehicle truck crashes under different crash types using mixed logit models

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ARTICLE INFO

Keywords:
Crash severity
Truck crashes
Single-vehicle crashes
Mixed logit model
Road safety

ABSTRACT

Introduction: Almost 90% of fatal road crashes occur in developing countries. Among these countries, Iran has a noticeable fatal crash rate of 21.47 deaths per 100,000 persons. Improving the safety of trucks is of particular importance in Iran where road freight is used to transport almost 90% of the commodities. Researchers have suggested dichotomizing crashes into single- and multi-vehicle categories and found that when this is performed vast differences can be identified between the mechanisms behind these categories of crashes, particularly when investigating truck crashes. *Method:* This study investigated single-vehicle truck crashes in Khorasan Razavi province in Iran from 2013 to 2021. Likelihood ratio tests were employed to show that separate models are statistically valid for different crash types. Subsequently, three mixed logit crash-type models were developed to investigate 5,703 single-vehicle truck crashes. *Results:* Four significant variables were exclusive to collisions with an object (brake failure, ABS, primary roads, and rainy or snowy weather), five significant variables were associated with run-off-road crashes (driving a loaded truck, speed limit (>60 km/h), paved shoulders, driving uphill, and inability to control the truck), and three significant variables were associated with overturn crashes (overloaded truck, curved roads, and changing direction suddenly). In all crash types, both fastening the seatbelt and speeding were found to be significant factors. *Conclusion*: The research highlights the need to analyze single-vehicle truck crashes using distinct crash type models and highlights the unique contributing factors of three common single-vehicle crash types. *Practical applications*: The study presents recommendations for policy to address key crash risks for trucks in Iran, including education and training to improve driver experience, compliance with seat belt usage, enforcement of speeding, and vehicle technologies to monitor drivers.

1. Introduction

Road traffic deaths are a global public health issue and mitigating them has become a priority (United Nations, 2023). According to the World Health Organization (WHO), almost 90% of fatal road crashes occur in developing countries (WHO, 2018). Among these countries, Iran has a noticeable fatal crash rate of 21.47 deaths per 100,000 persons (WHO, 2020). These high crash rates necessitate analysis of crash statistics to develop effective countermeasures to reduce road trauma.

Among road crashes, truck-involved crashes are not only concerned with the safety of drivers and passengers, but they also can have a significant economic impact due to the importance of providing a safe and reliable movement for commodities (Zou, Wang, & Zhang, 2017). Improving the safety of trucks is of particular importance in a developing country like Iran where road freight is used to transport almost 90% of the commodities by ton-km (Samimi, Rahimi, Amini, & Jamshidi, 2019).

Numerous previous studies have investigated the severity of road crashes (Abdi, Seyedabrishami, Llorca, & Moreno, 2022; Abdi, Seyedabrishami, & O'Hern, 2023; Azimi, Rahimi, Asgari, & Jin, 2020; Behnood & Mannering, 2019; Hosseinzadeh, Moeinaddini, & Ghasemzadeh, 2021; Uddin & Huynh, 2018; Yu, Ma, Zheng, Chen, & Yang, 2022; Yuan & Abdel-Aty, 2018). In addition, researchers have suggested dichotomizing crashes into single- and multi-vehicle categories and found that when this is performed vast differences can be identified between the mechanisms behind these two categories of crashes (Chen & Chen, 2011; Dong, Ma, Chen, & Chen, 2018; Geedipally & Lord, 2010; Wu et al., 2014). Regarding truck-involved crashes, this dichotomy gains more importance as the severity of multi-vehicle truck-involved crashes is mainly controlled by the injury severity of the personal vehicle(s)

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https://doi.org/10.1016/j.jsr.2023.12.001
Received 8 May 2023; Received in revised form 26 September 2023; Accepted 1 December 2023
Available online 11 December 2023

involved in the crash. However, the severity of single-vehicle truck crashes solely depends on the truck driver and passengers. Despite this point, the number of instances that explicitly focused on the severity of single-vehicle truck crashes is few (Rahimi, Shamshiripour, Samimi, & Mohammadian, 2020). Furthermore, only a limited number of studies on single-vehicle truck crashes utilize data sourced from low- and middle-income countries (Hosseinzadeh et al., 2021; Rahimi et al., 2020). This paper addresses these gaps in the literature by focusing on single-vehicle truck crashes that occurred in Iran.

Additionally, previous studies have found that crash-type variables play a significant role in the severity of truck-involved crashes (Al-Bdairi & Hernandez, 2017; Behnood & Mannering, 2019; Rahimi et al., 2020; Uddin & Huynh, 2017, 2020). However, these studies have not analyzed the impact of crash type using distinct models. To address this limitation, we determined if each crash type should be considered in separate models for single-vehicle truck crashes. In this respect, a model separation test was deployed to test this hypothesis. Then, separate mixed logit models were utilized to shed light on the effects of different statistically significant factors under each crash type. In this study, factors affecting the injury severity are identified and safety countermeasures are proposed to help policymakers and practitioners mitigate the severity of single-vehicle truck-involved crashes.

The remainder of this paper is organized as follows: Section 2 is a literature review on recent truck-involved crash severity studies and discusses the gaps in the literature. Section 3 introduces and provides detailed information on the data used in this research. Section 4 explains the methodological approach used in the study. Section 5 presents the results of the estimation models. Section 6 discusses the statistically significant variables shown by the models. Section 7 summarizes the major findings and explains the limitations of this study. Finally, section 8, proposes safety countermeasures as practical applications of this study.

2. Literature review

Truck-involved crashes contribute to fatal and injury outcomes disproportionately in part due to the weight and size of trucks. Furthermore, truck crashes can also impose significant economic losses, even in property damage only (PDO) crashes, due to the damage imposed on cargo and disruptions to the supply chain. To reduce road trauma and alleviate these losses, various studies have investigated truck crashes over the past decades to understand the contributing factors and interaction between factors (Savolainen, Mannering, Lord, & Quddus, 2011). Table 1 summarizes recent studies conducted on the severity of truck-involved crashes in terms of the study area, modeling method, severity levels, significant factors, and main objectives.

As shown in Table 1, mixed logit models and various forms of random parameter models have been among the most widely used methods. The main merit of these techniques over other traditional methods such as multinomial logit is that they relax the assumption of independence of irrelevant alternatives and can consider unobserved heterogeneity (Abay, Paleti, & Bhat, 2013). Incorporating heterogeneity not only improves the performance of models but also helps identify factors that do not have a fixed effect on injury severity (Behnood & Mannering, 2019).

Table 1 also highlights key findings with respect to explanatory variables. First, various factors have been found to have the same direction of effect on injury severity. For instance, driving under the influence (DUI) has been shown by numerous studies to increase the probability of severe outcomes (Al-Bdairi & Hernandez, 2017; Behnood & Mannering, 2019; Naik, Tung, Zhao, & Khattak, 2016). However, some other factors have been found to vary between studies. For instance, adverse weather was found to increase the probability of severe outcomes in the study by Uddin and Huynh (2017), while others found the opposite (Naik et al., 2016; Osman, Paleti, Mishra, & Golias, 2016; Wang & Prato, 2019). These contradictions may stem from several reasons including spatial and temporal instability of the datasets, inadequate number of observations, incompleteness of the dataset in terms of available explanatory variables, differences in methodologies used by researchers, and unobserved heterogeneity.

Some research gaps in the existing literature are as follows:

- As shown in Table 1, most studies focused on truck-involved crashes considering both single-vehicle and multi-vehicle crashes simultaneously. However, one study found that there were substantial differences between significant factors for the two crash types (Zou et al., 2017). Our study aims to narrow the existing gap by focusing on single-vehicle truck crashes explicitly.
- The number of studies that considered low-and-middle-income countries is few. Most studies presented in the literature review were conducted in the United States (Table 1). Our research aims to broaden the existing knowledge of contributing factors of single-vehicle truck crashes in low- and middle-income countries, through analysis of single-vehicle truck crashes in Iran.
- When examining crash-type indicator variables, run-off-road, overturning, and collision with an object crashes have been shown to represent a significant proportion of truck-involved crashes (Al-Bdairi & Hernandez, 2017; Behnood & Mannering, 2019; Rahimi et al., 2020; Uddin & Huynh, 2017, 2020). Nonetheless, previous studies have not modeled these different crash types separately for truck-involved crashes. As a further novelty of this study, we employed separate severity models for each crash type to explore the difference between factors affecting each crash type.

3. Data

This study investigated truck crashes that occurred in the Khorasan Razavi province of Iran from 2013 to 2021. Crash data were provided by the Road Maintenance and Transportation Organization (RMTO). The dataset contains crash-specific factors such as crash time, geographical coordinates of the crash location, crash type, crash severity, roadway characteristics, vehicle information, driver and occupants' information, and driver violations and actions. To complement the crash data, weather data from 20 synoptic weather stations throughout the province were used to extract the weather conditions at the crash time from the nearest weather station.

Crash data are filtered to include only single-vehicle truck crashes based on vehicle information. In this study, a k-nearest neighbors imputation algorithm is used to deal with missing values (Zhang, 2012). The final dataset utilized for model development comprises 5,703 single-vehicle truck crash records classified into three crash types: Collision with an object (843 or 14.78%), run-off-road crash (1436 or 25.18%), and overturn crash (3424 or 60.04%). Furthermore, each crash record defines severity level by the maximum level of injury sustained by the driver with regard to three levels: PDO (3227 or 56.58%), injury (2068 or 36.26%), and fatal (408 or 7.15%). Table 2 provides descriptions of the included variables along with summary statistics with respect to the three crash types. The explanatory variables are introduced in five categories: Human factors, weather and lighting conditions, driver characteristics, truck characteristics, and roadway characteristics.

4. Methodology

Mixed logit models have various capabilities such as exploring unobserved heterogeneity and being able to better detect the interactions between contributing factors. Owing to these merits, mixed logit models have been among the frequently used tools in crash severity studies (Islam et al., 2022; Uddin & Huynh, 2017, 2020). In the following subsections the mixed logit models equations are introduced, including the process used to test and validate the hypothesis that crash models should be separated.

Table 1
Summary of truck-involved crash severity studies.

Author(s)	Study area	Modelling method	Severity levels	Single-vehicle truck crashes are analyzed separately	Main objective	Explanatory variables with a positive direction of effect on the severity	Explanatory variables with a negative direction of effect on the severity
(Naik et al., 2016)	Nebraska, U. S.	MNL and RPORL	PDO, possible injury, visible injury, severe injury	✓	Combining detailed 15-min climatic data with the crash and roadway geometry data to analyze the relationship between the severity of single-vehicle truck crashes and weather factors	Curved road, number of lanes, weather, temperature, wind speed, driving under the influence (DUI)	Icy road surface, concrete pavement, dark conditions, fix-object collision, collision with animals, urban areas
(Osman et al., 2016)	Minnesota, U.S.	GOL, MNL, NL, and OL	PDO, injury, severe injury	×	Exploring the significant factors affecting injury severity of large truck crashes at work zones	Urban principal arterial, urban minor arterial, Rural principal arterial, curved road, two-lane road, No access control, speed limit (65–70 mph), adverse weather, daytime (6:00 a. m. – 6:00p.m.), crash on a bridge, large truck	Wet pavement condition, peak hours, single-vehicle crash
(Zou et al., 2017)	New York City, U.S.	Spatial GORP, RPORP	PDO, non-capacitating injury, capacitating injury, fatal	✓	Investigating the differences between determinants affecting single-vehicle and multi-vehicle truck crashes	*Single-vehicle crash model*: Truck weight, the presence of cyclist or pedestrian, road geometry (curve and grade), high-occupancy traffic flow *Multi-vehicle crash model:* weight difference, road geometry (curve and hill crest), business establishment density (Industrial and entertainment)	*Single-vehicle crash model:* - *Multi-vehicle crash model:* road geometry (curve and grade), high-occupancy traffic flow, taxi, business establishment density (office)
(Al-Bdairi & Hernandez, 2017)	Oregon, U.S.	RPORP	PDO, minor injury, severe injury	×	Shedding light on factors contributing to the severity of run-of-road truck crashes	Curved road, dry surface condition, single-vehicle crash, overturn crash, straight maneuver before the impending crash, lost control of the vehicle, speeding, DUI, fatigue	Existence of raised median, crash month between January and April, seatbelt fastened
(Uddin & Huynh, 2017)	Ohio, U.S.	ML	PDO, minor injury, major injury	×	Investigating determinants of severity of truck-involved crashes for separate lighting conditions on rural and urban roads	Curved road, collision with a fixed object, temporal condition (early morning and late night), single-unit truck, higher speed limits *Note:* As this research employed six separate models based on lighting conditions (daylight, dark, and dark-lighted) and area type (rural and urban), the abovementioned variables showed different magnitudes of impact on the severity of truck-involved crashes.	Seating condition, Average Annual Daily Traffic (AADT), adverse weather, gender (male), weekday
(Uddin & Huynh, 2018)	California, U.S.	RPORP, ORP	PDO, minor injury, major injury	×	Identifying factors explaining the severity of crashes involving hazardous materials (HAZMAT)	Rural location, speed limit (greater than 65 mph), weekday, dark-unlighted condition, dark-lighted condition, occupant gender (male)	Non-interstate highway, flat terrain, rear-end crash, collision with an object, truck turning, age (over 60 years old), the presence of passenger(s)
(Wang & Prato, 2019)	Jiangxi and Shaanxi, China	Partial proportional odds model	PDO, injury, fatal	×	Analyzing influential factors of injury severity for truck crashes on mountainous expressways	Curved road, wet pavement, weather condition (rainy, snowy, or foggy), season (fall and winter), time of day (24:00–06:00), rear-end crash, brake failure, overloaded truck	Season (summer), commercial transport (type of truck)
(Behnood & Mannering, 2019)	Los Angeles, U.S.	RPORL	PDO, minor injury, severe injury	×	Analyzing instability of the influential factors contributing to large-truck crash severities across temporal periods	*Considering both morning and afternoon models:* Ethnicity, gender (male), DUI, dark – street light, dry surface, intersection-related crash, old truck (the truck is above 15 years old)	*Considering both morning and afternoon models:* Ethnicity, young-age driver (younger than 31 years), movement preceding the crash (stopped, proceeding straight, and backing),

(*continued on next page*)

Table 1 (*continued*)

Author(s)	Study area	Modelling method	Severity levels	Single-vehicle truck crashes are analyzed separately	Main objective	Explanatory variables with a positive direction of effect on the severity	Explanatory variables with a negative direction of effect on the severity
							type of crash (sideswipe, hit an object, rear end, and head-on), parked motor vehicle, fixed object, violation category (improper passing and unsafe lane change), daylight, wet surface
						Variables with different directions of effect between afternoon and morning models: middle-aged driver, movement preceding the crash (making U-turn, left turn, or passing another vehicle), violation category (traffic signals and signs), pedestrian, weekday, rainy, new truck (less than 6 years old)	
(Azimi et al., 2020)	Florida, U.S.	RPORL	PDO, injury, fatal	×	Uncovering significant factors related to large truck rollover crashes	Dry surface, unpaved shoulder, downhill, curve right, the existence of traffic control device, hazardous materials released, vehicle defect (tires), front airbag deployed, driver action (ran red light), driver condition (asleep or fatigued, ill or fainted), lack of restrain system, crash month (June and July)	Local road
(Rahimi et al., 2020)	Iran	Random threshold random parameters HOPIT	PDO, injury, fatal	✓	Exploring significant factors of injury severities sustained by truck drivers in single-vehicle truck crashes in a developing country	Speed limit (greater than 90 km/h), more than 2 lanes in each direction, horizontal and vertical curve, minor urban road, truck malfunction, younger driver (less than 30 years old)	Straight segment, wet and icy surface, major urban road, highway, deployed ABS, heavy truck, crash type (run-off-road, fixed object, animals), driver with a college degree or higher
(Uddin & Huynh, 2020)	Ohio, U.S.	ML	NO injury, minor injury, major injury	×	Determining statistically significant variables affecting injury severity under three different weather conditions (normal, rainy, snowy)	Results of model for normal weather: dark-lighted, temporal variable (between 7 a.m. – 9:59 a.m.), sideswipe collisionResults of model for rainy weather: speed limit (greater than 65 mph) , rural area, daylightResults of model for snowy weather: curved road, temporal variable (between 4p.m. – 6:59 a.m.), urban area, rear-end collision	Results of model for normal weather: male, collision type (rear-end fixed object), speed limit (45–60 mph)Results of model for rainy weather: maleResults of model for snowy weather: single-unit truck, collision with a fixed object
(Hosseinzadeh et al., 2021)	Eight provinces of Iran	RPBL	Non-fatal, fatal	✓	Investigating determinants of severity of large truck-involved crashes through three separate models (multi-vehicle truck crashes when non-truck driver is at fault, multi-vehicle truck crashes when non-truck driver is at fault, and single-vehicle truck crashes)	*Single-vehicle crash model:* deviation to the left *Multi-vehicle crash model when the truck driver is at fault:* vehicle defect, deviation to the left, fatigue *Multi-vehicle crash model when the non-truck driver is at fault:* motorcycle, fatigue, deviation to the left	*Single-vehicle crash model:* unsafe lane-changing, failure to yield the right of way, dawn *Multi-vehicle crash model when the truck driver is at fault:* unsafe lane-changing, failure to yield the right of way, daylight *Multi-vehicle crash model when the non-truck driver is at fault:* Sedan vehicle, unsafe lane-changing, distracted driving, tailgating
(Islam, Hosseini, & Jalayer, 2022)	North Carolina, U.S.	ML	No injury, minor injury, severe injury	✓	Identifying the significant factors associated with injury severity of single-vehicle truck crashes on curved	*Model for straight segments:* traffic volume (AADT below 5,000 veh/day), driver age (50–65 years old), driver characteristics (exceeded safe speed or	*Model for straight segments:* undivided roadway, bituminous surface, segment length (less than 0.25 mile), physically normal

(*continued on next page*)

Table 1 (*continued*)

Author(s)	Study area	Modelling method	Severity levels	Single-vehicle truck crashes are analyzed separately	Main objective	Explanatory variables with a positive direction of effect on the severity	Explanatory variables with a negative direction of effect on the severity
					and straight rural segments	overcorrected in maneuver) *Model for curved segments: speed limit (55–65 mph),* traffic volume (AADT below 5,000 veh/day), graded surface, right shoulder between 4 and 8 feet, driver characteristics (exceeded safe speed, overcorrected in maneuver or careless driving), non-restraint usage	condition of driver, restraint usage *Model for curved segments:* undivided roadway, segment length (less than 0.25 mile), physically normal condition of driver, restraint usage
(Azimi, Rahimi, Asgari, & Jin, 2022)	Florida, U.S.	RPORL	PDO, injury, fatal	×	Analyzing the crash injury severity of large truck-involved crashes when the driver was at fault.	Brake or tire failure, driver action (running a red light, wrong-way driving, and failing to yield the right of way), not using restraint systems, dark conditions	Y-intersection, straight road, driver action (improper passing, improper backing, and not staying in the correct lane), single unit trucks with weights more than 10,000 lbs

Notes: MNL: multinomial logit model, GOL: generalized ordered logit model, OL: ordered logit model, NL: nested logit model, ML: Mixed logit model, ORP: Ordered probit model, RPORP: Random parameter ordered probit model, RPORL: Random parameter ordered logit model, GORP: Generalized ordered probit model, HOPIT: Hierarchical ordered probit model, RPBL: Random parameter binary logit model.

4.1. Mixed logit model

The relationship between the dependent variable and independent variables in a logit model is shown in Eq. (1) (Washington, Karlaftis, Mannering, & Anastasopoulos, 2020).

$$Y_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{1}$$

When developing a crash severity model, Y_{in} is severity category i for crash case n where $i \in I$ (I is a set consisting of all severity levels), X_{in} represents a vector of independent variables, β_i are the parameters of the model for each level i, and ε_{in} denotes an error term explaining the effects of unobserved factors. If it is assumed that error terms have a generalized extreme value distribution and are independently and identically distributed, the resulting model is a multinomial logit model with the outcome probabilities shown in Eq. (2) (Washington et al., 2020).

$$P_n(i) = \frac{\exp[\beta_i X_{in}]}{\sum_{i \in I} \exp[\beta_i X_{in}]} \tag{2}$$

$P_n(i)$ is the probability of severity level i for case n. Eq. (2) requires some extensions to show unobserved heterogeneity due to randomness. The outcome probability for mixed logit is defined as Eq. (3) (Train, 2001).

$$P_n(i/\phi) = \frac{\exp[\beta_i X_{in}]}{\sum_{i \in I} \exp[\beta_i X_{in}]} f(\beta_i/\phi) d\beta_i \tag{3}$$

$P_n(i/\phi)$ is the conditional probability on $f(\beta_i/\phi)$ which is the density function of the parameters with ϕ representing the parameter vector with a specified density function. Eq. (3) enables mixed logit to explain observation-specific variations in the effects of independent variables as β_i is calculated based on a density function $f(\beta_i/\phi)$. The probabilities in Eq. (3) are a weighted average for different values of β_i across observations in which some elements are fixed and some have a random distribution. For randomly-distributed parameters, weights are calculated based on the density function $f(\beta_i/\phi)$ (Washington et al., 2020).

In this study, a simulation-based approach has been employed using maximum likelihood estimation to account for the computational complexity due to the desired numerical integration over the parameters β_i of the mixed logit model. The simulation-based maximum likelihood estimation employs Halton draws to achieve a proper distribution of draws for numerical integration (Halton, 1960).

The pseudo-R-squared value is computed to evaluate the overall fit of the models. The higher this value, the better the proposed model predicts the outcome. Eq. (4) defines pseudo R-squared (ρ^2).

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{4}$$

where $LL(0)$ is the log-likelihood of the null model and $LL(\beta)$ is the log-likelihood of the converged model.

4.2. Marginal effects

Marginal effects explain how a change in an independent variable affects the probability of a specific outcome (severity category). As this study employs indicator variables, the marginal effect for an indicator variable is defined as the change in the estimated probabilities when the indicator variable shifts from 0 to 1. Eq. (5) shows the equation for calculating the marginal effect of an indicator variable in a mixed logit model.

$$M_{X_{ink}}^{P_{in}} = P_{in}[when X_{ink} = 1] - P_{in}[when X_{ink} = 0] \tag{5}$$

P_{in} is the probability of severity category i for crash case n and X_{ink} is the k –th dependent variable given severity category i and case n.

4.3. Model separation

The log-likelihood ratio (LR) test was conducted to show that three separate crash-type models are required. The equation of this test is given in Eq. (6) (Washington et al., 2020).

$$LR_{full} = -2[LL(\beta^{full}) - LL(\beta^{collisionwithanobject}) - LL(\beta^{run-off-roadcrash}) - LL(\beta^{over-turncrash})] \tag{6}$$

where $LL\left(\beta^{full}\right)$, $LL\left(\beta^{collision\ with\ an\ object}\right)$, $LL(\beta^{run-off-road\ crash})$, and $LL(\beta^{over-turn\ crash})$ represent the log-likelihood at convergence for the full

Table 2
Descriptive statistics of variables used in the models.

Variables	Collision with an object (n = 843)	Run-off-road crash (n = 1436)	Overturn crash (n = 3424)
	Percentage (Frequency)	Percentage (Frequency)	Percentage (Frequency)
Response variable	PDO: 75.09% (633) Injury: 20.64% (174) Fatal: 4.27% (36)	PDO: 62.81% (902) Injury: 32.94% (473) Fatal: 4.25% (61)	PDO: 49.42% (1692) Injury: 41.50% (1421) Fatal: 9.08% (311)
Explanatory variables			
Driver characteristics			
Experienced driver (1 if the driver had more than 10 years of driving experience)	0: 37.49% (316) 1: 62.51% (527)	0: 32.66% (469) 1: 67.34% (967)	0: 35.13% (1203) 1: 64.87% (2221)
Seatbelt fastened (1 if seatbelt was used)	0: 30.13% (254) 1: 69.87% (589)	0: 29.39% (422) 1: 70.61% (1014)	0: 29.70% (1017) 1: 70.30% (2407)
Truck characteristics			
Brake failure (1 if brake system malfunctioned)	0: 95.14% (802) 1: 4.86% (41)	0: 94.01% (1350) 1: 5.99% (86)	0: 94.71% (3243) 1: 5.29% (181)
ABS (1 if the truck had ABS equipped)	0: 65.95% (55) 1: 34.05% (287)	0: 61.56% (884) 1: 38.44% (552)	0: 63.61% (2178) 1: 36.39% (1246)
Loaded truck (1 if truck carried cargo)	0: 13.52% (114) 1: 86.48% (729)	0: 16.78% (241) 1: 83.22% (1195)	0: 12.09% (414) 1: 87.91% (3010)
Overloaded truck (1 if the truck was overloaded)	0: 96.56% (814) 1: 3.44% (29)	0: 98.33% (1412) 1: 1.67% (24)	0: 94.80% (3246) 1: 5.20% (178)
Roadway characteristics			
Speed limit (1 if the roadway has a speed limit greater than 60 km/h)	0: 24.67% (208) 1: 75.33% (635)	0: 22.21% (319) 1: 77.79% (1117)	0: 27.92% (956) 1: 72.08% (2468)
Paved shoulder (1 if the roadway has a paved shoulder)	0: 61.21% (516) 1: 38.79% (327)	0: 58.64% (842) 1: 41.36% (594)	0: 61.13% (2093) 1: 38.87% (1331)
Uphill (1 if the crash occurred on an uphill segment)	0: 84.46% (712) 1: 15.54% (131)	0: 83.57% (1200) 1: 16.43% (236)	0: 83.27% (2851) 1: 16.73% (573)
Primary road (1 if the crash occurred on a primary road including national highways and freeways)	0: 28.11% (237) 1: 71.89% (606)	0: 25.28% (363) 1: 74.72% (1073)	0: 35.34% (1210) 1: 64.66% (2214)
Curved road (1 if the crash occurred on a curved road segment)	0: 74.85% (631) 1: 25.15% (212)	0: 70.26% (1009) 1: 29.74% (427)	0: 65.51% (2243) 1: 34.49% (1181)
Human factors			
Speeding (1 if the driver violated the speed limit)	0: 73.43% (619) 1: 26.57% (224)	0: 75.07% (1078) 1: 24.93% (358)	0: 71.87% (2461) 1: 28.13% (963)
Inability to control (1 if the driver lost control of the truck)	0: 95.73% (807) 1: 4.27% (36)	0: 97.08% (1394) 1: 2.92% (42)	0: 94.10% (3222) 1: 5.90% (202)
Fatigue (1 if the driver was fatigued)	0: 91.70% (773) 1: 8.30% (70)	0: 91.85% (1319) 1: 8.15% (117)	0: 91.12% (3120) 1: 8.88% (304)
Changing direction suddenly (1 if the driver changed t direction suddenly)	0: 94.19% (794) 1: 5.81% (49)	0: 96.24% (1382) 1: 3.76% (54)	0: 92.03% (3151) 1: 7.97% (273)
Weather and lighting conditions			
Rainy or snowy weather (1 if weather condition was snowy or rainy)	0: 84.82% (715) 1: 15.18% (128)	0: 85.17% (1223) 1: 14.83% (213)	0: 86.65% (2967) 1: 13.35% (457)
Dark-unlit (1 if the crash occurred in a dark and unlit condition)	0: 92.65% (781) 1: 7.35% (62)	0: 95.75% (1375) 1: 4.25% (61)	0: 90.57% (3101) 1: 9.43% (323)

model, collisions with an object model, run-off-road model, and overturn model, respectively. The statistic calculated by Eq. (6) is χ^2 distributed with the degrees of freedom calculated by subtracting the total number of estimated parameters in separated models (crash-type models) from the number of estimated parameters in the full model.

NLOGIT version 6 was the statistical software that was employed for performing the model separation test and estimating mixed logit models (Econometric Software Inc, 2023).

5. Results

The overall calculated statistic for the log-likelihood ratio test was 762.95, which denotes that crash types should be modeled individually with over 99% confidence level. As a result, separate models were estimated based on the three crash types (collision with an object, overturn crash, and run-off-road crash). The predicted variable in each model has three levels for crash severity, as such two constant terms were required in the models' specifications.

As mixed logit models include random parameters through specified distributions, we examined the Normal, Lognormal, Uniform, and Triangular distributions to find the best fit for random parameters. In this study, results indicate that the Normal distribution was the preferred distribution for random parameters. This finding is consistent with previous studies where similarly the Normal distribution was utilized (Azimi et al., 2022; Islam et al., 2022; Uddin & Huynh, 2020). During modeling, variables were added to the specification of models, and those which showed t-statistics corresponding to a 90% confidence level or higher on a two-tailed *t*-test were retained in the specification. Also, random parameters with significant standard deviations indicating a 90% confidence level or higher were retained.

Tables 3 through 5 show parameter estimation results together with calculated marginal effects for each crash type. The ρ^2 values of these models are between 0.63 and 0.72 indicating a very good overall model fit. As mentioned before, a mixed logit model is made up of fixed parameters and random parameters accounting for unobserved heterogeneity. To interpret a fixed parameter, the sign of the coefficient indicates its direction of effect on the severity level in which the variable is used. In other words, a positive (negative) value of a coefficient in a defined severity level means that the probability of the severity level will increase (decrease) if that variable increases. However, interpreting the results of a random variable (mean and standard deviation) is not that straightforward. Considering the distribution introduced for a random

Table 3
Estimated parameters and marginal effects for single-vehicle truck crashes (crash type: collision with an object).

Variable	Coefficient	t-statistics	Marginal effects		
			PDO	Injury	Fatal
Defined for PDO					
Speed limit (≤60 km/h)	1.04**	2.33	0.028	−0.016	−0.012
Experienced driver (standard deviation of parameter distribution)	−0.92*** (2.26***)	−6.73 (4.23)	0.019	−0.003	−0.016
Rainy or snowy weather	0.97***	3.11	0.024	−0.022	−0.002
ABS	1.32***	2.89	0.039	−0.008	−0.031
Defined for Injury					
Constant	−1.37*	−1.90			
Dark-unlit	0.72**	2.12	−0.016	0.018	−0.002
Primary road (standard deviation of parameter distribution)	0.67** (1.93**)	2.41 (2.00)	−0.002	0.007	−0.005
Brake failure	2.61***	2.74	−0.048	0.054	−0.006
Defined for Fatal					
Constant	−3.05*	−1.77			
Speeding	1.48***	4.01	−0.031	0.000	0.031
Seatbelt fastened	−1.75***	−3.47	0.044	0.000	−0.044
Model statistics					
Number of observations	843				
LL at the null,$\boldsymbol{LL}(0)$	−1105,72				
LL at the model,$\boldsymbol{LL}(\boldsymbol{\beta})$	−396,23				
ρ^2	0.64				

***, ** and * indicate 99%, 95%, and 90% confidence level, respectively.

Table 4
Estimated parameters and marginal effects for single-vehicle truck crashes (crash type: run-off-road).

Variable	Coefficient	t-statistics	Marginal effects		
			PDO	Injury	Fatal
Defined for PDO					
Paved shoulder	1.33***	4.18	0.021	−0.012	−0.009
Uphill	0.42**	2.22	0.008	−0.008	0.000
Loaded truck (standard deviation of parameter distribution)	−1.27** (2.74***)	−2.48 (2.72)	0.041	−0.034	−0.007
Seatbelt fastened	0.81***	3.43	0.015	−0.014	−0.001
Defined for Injury					
Constant	−2.13*	−1.88			
Speed limit (> 60 km/h)	0.39**	2.30	−0.006	0.006	0.000
Inability to control (standard deviation of parameter distribution)	−1.03** (2.44***)	−2.31 (4.05)	−0.023	0.024	−0.001
Fatigue	1.38***	3.26	−0.014	0.015	−0.001
Defined for Fatal					
Constant	−3.79**	−2.30			
Speeding	0.25***	6.54	−0.007	−0.002	0.009
Model statistics					
Number of observations	1436				
LL at the null,$\boldsymbol{LL}(0)$	−1,724,38				
LL at the model,$\boldsymbol{LL}(\boldsymbol{\beta})$	−576.40				
ρ^2	0.67				

***, ** and * indicate 99%, 95%, and 90% confidence level, respectively.

Table 5
Estimated parameters and marginal effects for single-vehicle truck crashes (crash type: overturn).

Variable	Coefficient	t-statistics	Marginal effects		
			PDO	Injury	Fatal
Defined for PDO					
Experienced driver (standard deviation of parameter distribution)	−1.23*** (1.76***)	−5.24 (5.83)	0.048	−0.017	−0.031
Speed limit (≤ 60 km/h)	0.66**	2.44	0.010	−0.003	−0.007
Defined for Injury					
Constant	−1.83*	−1.69			
Overloaded truck	2.84***	5.57	−0.048	0.054	−0.006
Changing direction suddenly	1.37***	7.26	−0.015	0.018	−0.003
Curved road (standard deviation of parameter distribution)	0.79** (1.02**)	2.36 (2.10)	−0.007	0.008	−0.001
Fatigue	1.44**	2.14	−0.018	0.020	−0.002
Dark-unlit	0.76**	2.13	−0.009	0.011	−0.002
Defined for Fatal					
Constant	−1.62*	−1.87			
Speeding	2.09***	4.69	−0.027	−0.003	0.030
Seatbelt fastened	0.88***	3.19	0.017	0.000	−0.017
Model statistics					
Number of observations	3424				
LL at the null,$\boldsymbol{LL}(0)$	−4,186.95				
LL at the model,$\boldsymbol{LL}(\boldsymbol{\beta})$	−1,535.08				
ρ^2	0.63				

***, ** and * indicate 99%, 95%, and 90% confidence level, respectively.

parameter, it indicates that one segment of the observations may have a higher probability of a severity level while the others have a lower probability.

Table 3 presents the results of the model considering trucks colliding with a fixed object. In this model, the experienced driver parameter (specific to PDO) is a random variable with a mean of −0.92 and a standard deviation of 2.26. Based on the Normal distribution curve and these values, it can be deduced that 65.80% of single-vehicle truck collisions with an object involving experienced drivers had a higher probability of resulting in a PDO severity level. The remaining 34.20% of collisions were more likely to result in injuries or fatalities. Another significant random parameter in Table 3 is the indicator variable representing the primary road (specific to injury level), with a mean of 0.67 and a standard deviation of 1.93. The distribution for this variable indicates that 36.43% of truck collisions with objects on primary roads had a higher probability of resulting in an injury level, while the remaining 63.57% of these crashes were more likely to result in one of the other severity levels (PDO or Fatal).

Table 4 displays the model estimation results for single-truck run-off-road crashes, featuring two significant random parameters. One of these random parameters in this model is the loaded truck indicator (specific to PDO), with a mean of −1.27 and a standard deviation of 2.74. This parameter indicates that 67.85% of run-off-road truck crashes involving loaded trucks had a higher probability of resulting in a PDO severity level, while the remaining 32.15% were more prone to injury or fatality. Additionally, the indicator variable for inability to control (specific to injury level), with a mean of −1.03 and a standard deviation of 2.44, reveals that 66.35% of truck run-off-road crashes in which the driver lost control of the truck had a higher probability of resulting in an injury level, whereas 33.65% of these incidents were more likely to result in PDO or Fatal outcomes.

Table 5 shows the results of the model considering overturning crashes. The variable representing an experienced driver (specific to PDO level) is a significant random parameter variable, with a mean of −1.23 and a standard deviation of 1.76. This parameter signifies that 75.77% of these crashes, in which the driver was experienced, were more likely to result in a PDO severity level, while 24.23% of them were associated with injuries or fatalities. Another significant random parameter is the curved road variable (specific to Injury) with a mean of 0.79 and a standard deviation of 1.02. This parameter indicates that 21.93% of run-off-road single-vehicle truck crashes on curved segments had a higher probability of resulting in an injury level, while 78.07% of them were more likely to result in PDO or Fatal outcomes.

6. Discussion

Separate crash severity models by crash type generate valuable knowledge about influential factors contributing to the severity of single-vehicle truck crashes with respect to each crash type. The results presented in Tables 3 through 5 suggest vast differences in significant factors and the magnitude of their impact on the outcome. For instance, speeding was found to be a significant factor for fatal crashes, but it increases the probability of fatal crashes unequally among different crash types (0.031, 0.009, and 0.030 for collisions with objects, run-off-road crashes, and overturn crashes, respectively). In addition, some factors are found to be statistically significant in one crash type but not in others. For example, the indicator variable for rainy or snowy weather was only significant in truck collisions with an object. Table 6 summarizes and compares the effects of the explored significant factors on severity levels by crash types for single-vehicle truck crashes.

6.1. Driver characteristics

For all crash types, the findings show that truck drivers who fasten their seatbelts lowered the risk of a fatal crash. This result is in line with previous research that emphasized the use of restraints such as seatbelts in trucks (Al-Bdairi & Hernandez, 2017; Islam et al., 2022). Wearing a seatbelt also lowers the risk of injury severity for run-off-road crashes. However, the effect on collisions with an object and overturn crashes were negligible with marginal effects equal to 0.000. Additionally, experienced drivers (with more than 10 years of experience) were found to be less likely to experience fatal and injury crashes for collisions with an object and overturn crashes (Tables 3 and 5). However, the experience factor was not significant for the severity of run-off-road crashes.

Table 6
Summarizing the results.

Variable	Collision with an object			Run-off-road crash			Overturn crash		
	PDO	Injury	Fatal	PDO	Injury	Fatal	PDO	Injury	Fatal
Driver Characteristics									
Experienced driver	↑	↓	↓				↑	↓	↓
Seatbelt fastened	↑		↓	↑	↓	↓	↑		↓
Truck characteristics									
Brake failure	↓	↑	↓						
ABS	↑	↓	↓						
Loaded truck				↑	↓	↓			
Overloaded truck							↓	↑	↓
Roadway characteristics									
Speed limit (≤60 km/h)	↑	↓	↓				↑	↓	↓
Speed limit (>60 km/h)				↓	↑				
Paved shoulder				↑	↓	↓			
Uphill				↑	↓				
Primary road	↓	↑	↓						
Curved road							↓	↑	↓
Human factors									
Speeding	↓		↑	↓	↓	↑	↓	↓	↑
Inability to control				↓	↑	↓			
Fatigue				↓	↑	↓	↓	↑	↓
Changing direction suddenly							↓	↑	↓
Weather and lighting conditions									
Rainy or snowy weather	↑	↓	↓						
Dark-unlit	↓	↑	↓				↓	↑	↓

Notes: (↑): The presence of a condition for an indicator variable increases the probability of associated severity. (↓): The presence of a condition for an indicator variable decreases the probability of associated severity.

6.2. Truck characteristics

When considering truck characteristics, brake malfunctions during collisions with an object were found to increase the chance of injury crashes by 0.054. Similarly, Azimi et al. (2022) found that brake defects have a positive association with higher levels of severity. Furthermore, results show that equipping trucks with ABS reduces the risk of injury and fatal outcomes by 0.008 and 0.031 in crashes with an object, respectively. This finding is consistent with previous research by Rahimi et al. (2020). Regarding run-off-road crashes, the only significant truck-related factor was the loading variable. As shown in Table 4, loaded trucks are more prone to PDO-level in run-off-road crashes. As for overturn crashes in Table 5, the variable representing overloaded trucks was statistically significant with a positive effect on the probability of injury level (0.054 increase in the possibility of an injury outcome). However, when the truck is overloaded the probability of a fatal outcome decreases. This finding was somewhat unexpected; however, it may be a result of overloaded truck drivers being more cautious and warrants further research to understand the direction of the relationship.

6.3. Roadway characteristics

Table 5 shows that overturn crashes that occurred in segments with speed limits equal to or less than 60 km/h have a lower risk of injury and fatal crashes with 0.003 and 0.007 decreases for injury and fatal severities, respectively. The same direction of effect is shown for collision with an object in Table 3 where the injury and fatal probabilities decreased by 0.016 and 0.012, respectively. Additionally, on roads with speed limits higher than 60 km/h drivers were more likely to be involved in higher injury severity crashes when the truck runs off the road. These findings are in line with numerous previous studies that have demonstrated that increased injury severity is associated with driving on higher speed limits roads (Islam et al., 2022; Osman et al., 2016; Rahimi et al., 2020; Uddin & Huynh, 2017, 2018, 2020).

In addition to the speed limit, the presence of paved shoulders was found to decrease injury and fatal outcomes for run-of-road crashes (-0.012 for injury and −0.009 for fatal). Moreover, the vertical geometry of the road and if the section of the road was uphill decreases the injury risk for this crash type by 0.008. Primary roads were found to reduce the chance of fatal crashes by 0.005 when trucks collide with an object. Curved segments were shown to be significant in overturn crashes with a decrease of 0.001 in fatal outcomes. A possible explanation for this finding is that truck drivers are more cautious in curved segments than straight ones and reduce their speed, resulting in a reduced risk of fatal outcomes.

6.4. Human factors

Tables 3 through 5 indicate that speeding is a significant factor in all three crash types and increases the probability of a fatal crash by 0.031, 0.009, and 0.030 for collisions with an object, run-off-road, and overturn crashes, respectively. The findings align with previous research, for example, Al-Bdairi & Hernandez (2017) found that speeding significantly contributes to severe crashes. Driving while fatigued was shown to be significant in both run-off-road and overturn crashes with an increase of 0.015 and 0.020 in the risk of an injury severity level, respectively. Likewise, previous studies have found fatigued drivers are prone to severe crashes (Al-Bdairi & Hernandez, 2017; Azimi et al., 2020; Hosseinzadeh et al., 2021). The indicator variable representing drivers who lost control of the truck was found to increase injury risk for run-off-road crashes by 0.024. This finding is consistent with research by Islam et al. (2022). Also, Table 5 shows that sudden direction changings are associated with injury severities (an increase of 0.018 in injury probability), which was similarly shown in a study by Hosseinzadeh et al. (2021).

6.5. Weather and lighting conditions

Table 3 indicates that collisions with an object that occurred during rainy or snowy conditions decreased the probability of injury and fatal outcomes by −0.022 and −0.002, respectively. This finding is similar to a finding by Uddin and Huynh (2020), which found that drivers are more cautious during inclement weather conditions. Additionally, dark and unlit conditions were shown to increase the probability of injury severities by 0.018 and 0.011 in collisions with an object and overturn crashes, respectively. Similarly, a previous study by Uddin and Huynh (2018) showed that dark condition is related to high probabilities of severe outcomes.

7. Conclusion

This study investigated three single-vehicle truck crash types using crash reports from Khorasan Razavi province in Iran from 2013 to 2021. Likelihood ratio tests were employed to show that separate models are statistically valid for different crash types. Subsequently, three crash-type models were developed to investigate crashes with an object, run-off-road crashes, and overturn crashes. The results denote that a number of statistically significant variables were exclusive to each crash type model, which further highlights the need for analyzing single-vehicle truck crashes in distinct crash types.

It was shown that four significant variables were exclusive to collisions with an object (brake failure, equipped ABS, primary road, and rainy or snowy weather), five significant variables were exclusive to run-off-road crashes (driving a loaded truck, speed limit (>60 km/h), paved shoulder, driving uphill, and inability to control), and three significant variables were exclusive to overturn crashes (overloaded truck, curved road, and changing direction suddenly). Also, across all crash types, the significance of fastening seatbelts and the impact of speeding were consistently observed. In this regard, it was found that speeding increases the probability of a fatal crash, and the use of seatbelts lowers this probability. Moreover, four statistically significant variables were common between the two crash types: (1) Driver experience was shown to be significant in overturn crashes and collisions with an object and the results denote that experienced drivers are less likely to sustain injury crashes in these two crash types. (2) Lower speed limits (below 60 km/h) were significant for overturn crashes and collisions with an object, with the results showing that lower speed limits were associated with lower probabilities of injury and fatal levels. (3) Driving while fatigued was significant for both run-off-road and overturn crashes showing a positive impact on the probability of injury crashes. (4) Driving in dark and unlit conditions at night was found to be significant in both overturn crashes and collisions with objects, resulting in an increased probability of injury outcomes.

There are some limitations to this study. First, the results of this study are limited to a single province and may not be applicable to other regions or countries due to spatial instabilities in factors affecting crashes. As a future avenue, employing crash datasets from diverse regions and comparing the results could provide further insights and confirm the findings from this research. Second, this study analyzed crash severity with three severity levels (PDO, Injury, and fatal), however, these classifications are based on police-reported data and may not represent the actual injury outcomes of the collision. Linking findings with hospital data and patient outcomes could provide further insight. Finally, it has been stated that crash datasets may have temporal instability, which may negatively affect the reliability of the results (Behnood & Mannering, 2019). Incorporating temporal elements into modeling could significantly broaden the existing knowledge. Notwithstanding these limitations, the research has demonstrated the importance of using mixed logit models to investigate single-vehicle truck crashes and highlighted the unique contributing factors of three common single-vehicle crash types.

8. Practical applications

Based on the findings from the research several policy implementations are proposed. The proposed countermeasures are as follows: (1) experienced drivers were shown to be involved in lower-injury crashes. This finding suggests that training and enforcement programs should target inexperienced drivers. (2) Wearing seatbelts by truck drivers was shown to decrease the chance of severe outcomes. In this regard, introducing heavier fines and organizing national seatbelt campaigns are suggested. (3) Our models proposed that equipping trucks with ABS is associated with less severe crashes. Unfortunately, the truck manufacturing industry in Iran is very outdated and the vehicle fleet is typically old compared to other countries. Notwithstanding, efforts should be made to promote purchasing new vehicles that include safety features such as ABS. (4) Overloaded trucks were found to be prone to crashes with higher injury outcomes. This finding suggests enforcement of heavy truck vehicle restrictions regarding weight and volume should be implemented to reduce the severities in overturn crashes. (5) In terms of road design and infrastructures, the results of our models suggest that the installation of paved shoulders and proper illumination will reduce the chance of injury crashes. (6) In terms of human factors, four indicator variables including speeding, inability to control the vehicle, fatigue, and unsafe direction changing were shown to be significant. In this respect, educational programs and enforcing strict laws are suggested. Additionally, the installation of safety features such as electronic stability program (ESP), speed limiters, and sensors that can detect drowsiness could be helpful in reducing crashes associated with these factors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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