TRB Annual Meeting

Comparison of Crash Characteristics Among Electric Vehicles and Internal Combustion Engine Vehicles

--Manuscript Draft--

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ABSTRACT

With an increasing market penetration of electric vehicles (EVs) in the traffic mix, it become necessary to examine crashes involving EVs. In addition, there is a need to identify differences compared with traditional internal combustion engine vehicles (ICEVs), as EVs are heavier and have different performance characteristics than ICEVs. To date, there is limited research comparing crash characteristics among EVs and ICEVs and further, differentiating among different types of EVs: battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs). To fill this research gap, this paper estimates crash injury frequency and crash severity outcomes through statistical regression analyses. The statistical models and hypothesis testing results suggest both similarities and differences in crash characteristics among BEVs, PHEVs, HEVs, and ICEVs. The similarity lies in human-related factors and traffic-related factors, and the differences come from four types of factors including vehicle, roadway, crash, and environment. The potential reasons (in terms of vehicles' engine type, software, and hardware) that could contribute to the differences in crash characteristics among four types of vehicles are discussed. The findings of this paper can provide insights into devising safety regulations for EVs. For example, EVs equipped with advanced driving assistant technologies can help relieve crash injury counts. However, the high acceleration rate of electric motors could positively contribute to the crash severity, and the front of BEVs needs more protection since head-on crashes of BEVs cause more severe crashes.

Keywords: Crash Analysis, Electric Vehicles, Negative binomial regression model, Multinomial logit regression model

INTRODUCTION

Electric vehicles are automobiles that are completely or partially powered by electricity and are divided into three categories: battery electric or all-electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs) (*1*). The power source of BEVs, as the name implies, is electricity from batteries. Both PHEVs and HEVs are partially powered by batteries but several differences exist between them. To be specific, compared with HEVs, PHEVs can be charged through external plugs and have larger batteries (*2*). In other words, PHEVs are similar to BEVs with gas engines, and HEVs are similar to internal combustion engine vehicles (ICEVs) with batteries.

According to the statistics from 2016 to 2020 provided by the U.S. Department of Energy (US DOE), the number of BEV, PHEV, and HEV registration increased by 110 %, 75%, and 24% respectively (*3*). Such a significant increase in the number of EVs on the road brings attention to their safety issues. There is still no widely accepted conclusion on whether EVs are safer or not than ICEVs. Meanwhile, plenty of analyses and experiments are performed on EVs to demonstrate whether EVs are different from ICEVs in terms of vehicle crashes. For instance, the Highway Loss Data Institute (HLDI) states the insurance claim frequency of EVs is lower than ICEVs (*4*). Researchers also conducted crash experiments on both EVs and ICEVs and concluded that EVs are less vulnerable to crashes compared with ICEVs (*5*). However, there are still concerns about the safety issues of EVs brought by large batteries (*6*).

Previous work attempted to analyze the EV crash data to figure out factors that influence the severity levels of EV crashes. However, previous research did not analyze the crash severity of different types of EVs separately, which makes it hard to figure out the internal difference in factors that influence the crash severity among different types of EVs. Moreover, no previous research investigates the factors that influence injury counts in EV-involved crashes. Using the 2014-2022 vehicle crash data provided by the Iowa Department of Transportation (Iowa DOT), this study compares crash characteristics between EVs and ICEVs and further, differentiates among different types of EVs. Moreover, this study further investigates what factors could influence the injury number of EV-involved crashes.

The rest of the paper is organized as follows. First, we conduct a literature review on previous EV safety analyses. Then, we describe the data and statistical models used in this study. After that, we present the results and findings from statistical regression analyses. The last section concludes with research implications, research limitations, and future research directions.

LITERATURE REVIEW

Numerous studies have examined motor vehicle crashes, which include two main research questions: crash probability and crash severity (*7*). For crash severity studies, both statistical methods and machine learning models are used for parameter estimation. According to Savolainen et al., the frequently used statistical methods are binary outcome models, ordered discrete outcome models, and unordered multinomial discrete outcome models (*8*). In comparison, machine learning methods like support vector machines, neural networks, classification, regression trees, and clustering are also commonly used for crash severity studies (*9*).

With the increasing number of EVs on the road, some studies have shed light on the statistical analysis of EV crashes. Liu et al. applied Pearson's chi-squared test to confirm that the distribution of severity levels for EV (mixing of BEVs and PHEVs) crashes is different from that of ICEV crashes. They used the logistic regression model to identify essential factors influencing crash severity. For EVs' crash data, the presence of medians has a negative effect on crash severity, and collisions with motorcycles have a positive effect on crash severity (*10*). However, this study did not include any explanatory variables on humans and vehicles involved in crashes, which could lead to omitted-variables bias. Moreover, several published government reports compared HEVs' crash data with ICEVs' crash data. Chen et al. directly compared the crash statistics between HEVs and ICEVs and noted that occupants of HEVs tended to be older than occupants of ICEVs, fire incidents were not common in both HEV and ICEVs, and occupants of HEVs were more likely to experience arm, wrist, and hand injuries but less likely to experience leg, ankle, and foot injuries when being compared with that of ICEVs (*11*). However, that study did not account for roadway conditions and environmental factors into consideration and simply employed descriptive analysis instead of using statistical methods or tests.

The former studies did not take heterogeneity into consideration, which may introduce biased estimation and incorrect inferences. Taking heterogeneity and heteroskedasticity into consideration, Huang et al. evaluated HEV crashes' severity through a hierarchical mixed logit model and concluded that higher occupant vehicles and older occupants were associated with higher injury counts, but crashes happen on the wet road surface and regional artery roads (not expressway) result in fewer injury counts (*12*). Also, Huang et al. pointed out that the statistical analysis results could support strong heterogeneity effects in crash data (*12*). Based on this conclusion, Seraneeprakarn et al. further validated the influence of unobserved heterogeneity by comparing estimation from the mixed logit model, mixed logit model with heterogeneity in means, and mixed logit models with heterogeneity in means and variance (*13*). These studies identify the importance of taking heterogeneity effects into consideration when analyzing EVs' crash data. Still, these studies only analyzed crash data involving HEVs instead of other types of EVs.

Other than focusing on driver injuries in EV-involved crashes, some studies focused on vulnerable road users (i.e., pedestrians or cyclists). Hanna studied pedestrian or cyclist crashes with HEVs and ICEVs. Based on hypothesis testing results, Hanna concluded that motor vehicle crashes involving pedestrians and cyclists usually happened on roads with low-speed limits under good lighting (daytime) and weather (great visibility) conditions. More importantly, HEVs were more likely to collide with pedestrians and cyclists compared with ICEVs (*14*). Focusing on speed limits, vehicle actions, and crash locations, Wu et al. further verified this conclusion through statistical methods including a case-control approach, relative risk, and odds ratio (*15*). These studies suggest collision counterparts like pedestrians and bicycles are worth taking into consideration when analyzing EV crash data. However, a limited number of variables are explored in these studies. Such limitation makes it hard to identify potential differences and effects of various factors in crash data between EVs and ICEVs.

In addition to studies that use statistical modeling methods to analyze real crash data, Karaaslan et al. used agent-based modeling to conduct traffic simulation and showed EVs have a greater potential of posing a threat to pedestrians than ICEVs by performing sensitivity analysis on the simulated crash data (*16*). Furthermore, Karaaslan et al. confirmed the simulation results by analyzing the crash data from the Fatal Analysis Reporting System (FARS) through a chi-squared test (*16*). This study further confirms the idea proposed in earlier studies that EVs have a higher possibility to hit pedestrians or bicyclists than ICEVs.

Table 1 summarizes the factors and objects (types of vehicles) in previous studies on EV crashes. Compared with previous studies, this study compares both crash severity and the number of injuries between EVs and ICEVs and further, differentiates among different types of EVs.

Table 1. Summary of studies involving EV crash data.

Study	Statistical Models	Explanatory Variables						Research Objects
		Human	***Vehicle***	***Crash***	***Roadway***	***Environment***	***Traffic***	
Hanna (2009)	Hypothesis Testing	-	Vehicle action	Collision counterpart, Crash location	-	Light, Weather	Speed limit	*HEV*, *ICEV*, *Non-motorist*
Wu et al. (2011)	Case-control Approach, Relative Risk, Odds Ratio	-	Vehicle action	Collision counterpart, Crash location	-	Light, Weather	Speed limit	*HEV*, *ICEV*
Chen et al. (2015)	-	Age, Gender, Risk of injury	Restraint, Velocity change	Collision type, Fire incidence	-	-	-	*HEV*, *ICEV*
Huang et al. (2016)	Hierarchical Mixed Logit	Age	Years, Width, Weight, Occupant number	Number of vehicles, Collision type, Crash location	Functional class, Surface	-	-	*HEV*
Seraneeprakarn et al. (2017)	Mixed Logit	Age	Years, Weight, Driver age, Occupant number	Number of vehicles, Collision type, Crash location, Crash reason, Ratio: non-hybrid to hybrid	Functional class, Surface	-	-	*HEV*
Karaaslan et al. (2018)	Agent-based modeling (simulation), Chi-square test	-	-	-	-	-	-	*HEV*, *ICEV*, *Non-motorist*
Liu et al. (2022)	Logistic Regression	-	-	Collision counterparts, Crash area, Crash location	Median presence, Surface	Day of Week, Time of day, Visibility	Speed limit	*BEV*, *PHEV*, *ICEV*

DATA PROCESSING AND ANALYSIS METHODS

The analyses in this study include two consecutive parts: data processing and statistical modeling. For data wrangling, the crash data for EVs is identified based on vehicles' makes and models. Besides, ICEV crashes within the 50-meter-geological-buffer of EV crashes are selected. For regression analyses, correlation analysis and Forward Stepwise Selection based on AIC are performed to select the optimal variable combinations (*17*).

Data Processing

This study uses the crash data from 2014 to 2022 provided by the Iowa Department of Transportation. Since the given data does not contain the Vehicle Identification Number (VIN) or any variables to distinguish EVs from ICEVs, the vehicle makes (brand of the vehicle), vehicle models, and vehicle years are used to identify the fuel type of a given vehicle through fuel economy information provided by U.S Department of Energy (*18*).

In addition, previous studies on motor vehicle crash analyses state that geographic variations cannot be ignored and suggest using buffer analysis to control the spatial heterogeneity (*7*, *19*). Thus, a 50-meter-buffer is used to select ICEV crashes around the EV (including BEV, PHEV, and HEV) crashes. In the end, there are 189 crashes for BEVs (Figure 1-b), 132 crashes for PHEVs (Figure 1-c), 3120 crashes for HEVs, and 129733 crashes for ICEVs respectively (Figure 1-d). Observing the spatial distributions of crash locations, BEV and PHEV crashes mainly happen in urban areas while HEV crashes cover all main roads in Iowa, which may be due to the limited mileage of BEVs and PHEVs compared with HEVs.

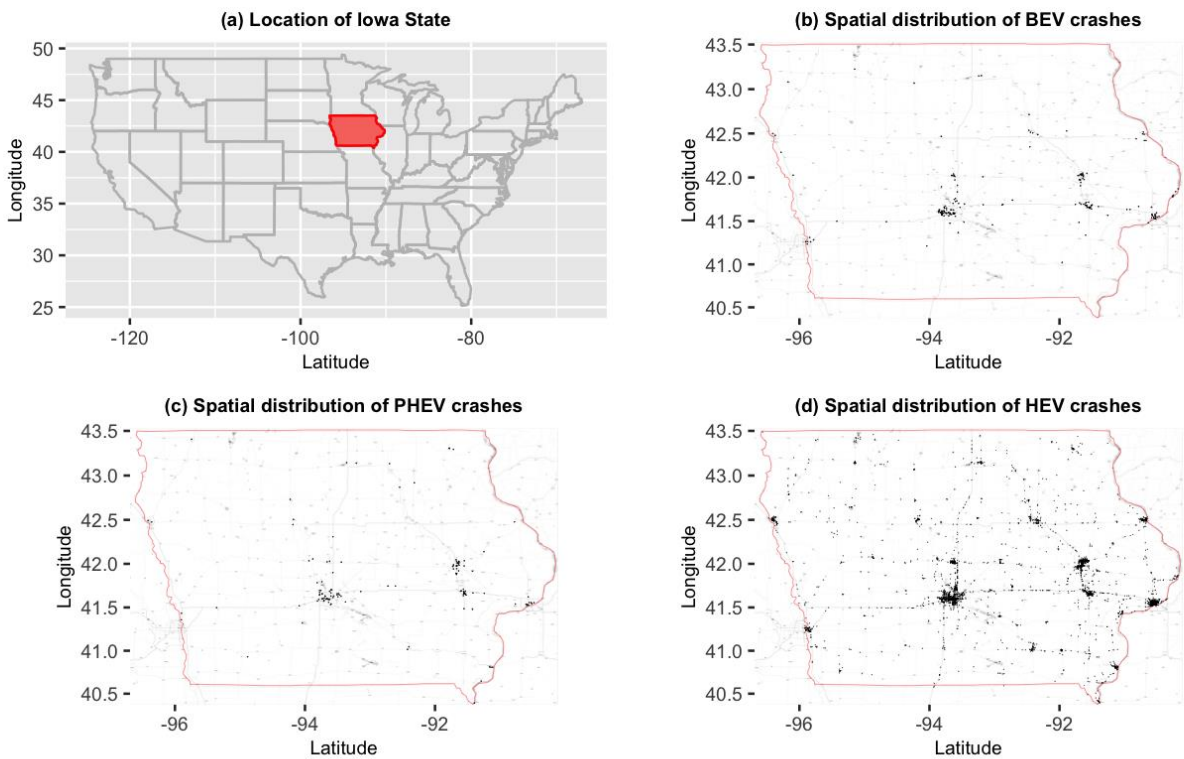

Figure 1. The spatial distribution of crashes by vehicle types.

Statistical Analysis

Hypothesis Testing

Pearson's chi-squared test is applied to test whether the distribution of injury counts of BEV, PHEV, HEV, and ICEV crashes have different statistical distributions (*20*).

Statistical Models

Due to the limited number of observations for BEV and PHEV crashes, most basic statistical models for count data like Poisson regression and Negative Binomial are first considered in this study. The mean injury counts for BEVs, PHEVs, HEVs, and ICEVs are 0.286, 0.265, 0.352, and 0.171. The corresponding variances are 0.343, 0.425, 0.487, and 0.549. It is obvious that for each type of vehicle crash data, the injury count experiences an over-dispersion issue where the variance is greater than the mean of the injury counts. As a result, in this study, negative binomial regression is used since it has a less complex estimation process and can handle the over-dispersion issue in count data (*24*). Suppose the expected injury count λ_i for the ith vehicle crash is given by Equation 1:

$$\lambda_i = exp(\beta X_i + \epsilon_i) \qquad (1)$$

For Equation 1, β is an unknown coefficient vector, X_i are influencing factors for the injury count, and ϵ_i is the error term. This gives the probability formula in Equation 2 where $P(n_i|\epsilon)$ is the probability of n injuries in the ith vehicle crash over a certain amount of time (*25*). Furthermore, $exp(\epsilon_i)$ is an error term that follows a gamma distribution.

$$P(n_i|\epsilon) = \frac{exp[-\lambda_i exp(\epsilon_i)][\lambda_i exp(\epsilon_i)]^{n_i}}{n_i!} \qquad (2)$$

Other than estimating the injury count of vehicle crashes, this study also models the crash severity of vehicles with different fuel types. Since there are more than two severity levels, and the order of severity levels is not considered, Multinomial Logit Models (MNL), a traditional discrete outcome model, is employed to model the crash severity in this study. Suppose K is the number of severity levels, X means the influencing factors for crash severity levels, and β is the unknown coefficients of the influencing factors, the probability equation for severity level k is given in Equation 3 (*17*).

$$\mathrm{P}(Y = k|X = x) = \frac{\mathrm{e}^{\beta_{k_0} + \beta_{k_1}x_1 + \cdots + \beta_{k_p}x_p}}{1 + \sum_{l=1}^{K-1} \mathrm{e}^{\beta_{l_0} + \beta_{l_1}x_1 + \cdots + \beta_{l_p}x_p}} \qquad (3)$$

Since the probability for all severity levels must sum to one, for $k = 1, \dots, K-1$

$$P(Y = K|X = x) = \frac{1}{1 + \sum_{l=1}^{K-1} e^{\beta l_0 + \beta l_1 x_1 + \cdots + \beta l_p x_p}} \qquad (4)$$

Taking the quotient between Equation 3 and Equation 4 provides Equation 5.

$$\frac{P(Y = k|X = x)}{P(Y = K|X = x)} = e^{\beta_{k_0} + \beta_{k_1 x_1} + \cdots + \beta k_p x_p} \qquad (5)$$

Finally, taking the logarithm on both sides of Equation 5 derives Equation 6.

$$log\left(\frac{P(Y = k|X = x)}{P(Y = K|X = x)}\right) = \beta_{k_0} + \beta_{k_1 x_1} + \cdots + \beta k_p x_p \qquad (6)$$

This gives the log odds function between the selected two severity levels.

DATA DESCRIPTION

Table 2 summarizes the descriptive statistics of numerical variables for crash data of each vehicle type. Table 3 summarizes the count and percentage of different injury levels for each vehicle type.

Personal Variables

Driver age and gender, occupant gender, driver condition, driver action, and personal identity are considered in this study. Driver condition is categorized into five groups based on the National Highway Traffic Safety Administration (NHTSA) definition of risky driving behavior: drug/Alcohol-related, fatigue, normal, other (emotional, illness, etc.), unknown (*26*). The driver's action is a variable that indicates whether the driving is aggressive. Aggressive driving behavior is defined by NHTSA as exceeding authorized speed, driving too fast, reckless driving, erratic lane changing, and road rage (*26*).

Vehicle and Roadway Variables

Vehicle variables including vehicle year, vehicle action, and the number of occupants are studied. Vehicle action is categorized into five groups: changing lanes, moving straight, stopping, turning, and unknown. Besides, roadway factors like surface conditions (dry, wet, icy, unknown) and road type (interchange, intersection, straight, unknown) are also explored in this study.

Crash Variables

The vehicle number, most harmful event, collision type, and safety equipment (safety belt, airbag, other protection) are studied. The most harmful event is categorized into six groups: collision with a fixed object, non-fixed object, non-collision, pre-crash, and miscellaneous. In specific, pre-crash events are events that cause the crash like avoiding animals, and miscellaneous event means events that rarely happen like an explosion, immersion, and others. In addition, the collision type variable is used to indicate whether the crash is a head-on crash.

Environmental and Traffic Variables

There are two environmental factors selected in this study: crash time and light condition. The crash time is categorized into 5 time periods based on a previous study on rush hour period crash analysis (*27*). The five time periods are early morning (1:00 – 5:59), morning rush hour (6:00 – 10:59), noon (11:00 – 14:59), evening rush hour (15:00 – 19:59), and late night (19:00 – 0:59). Besides, Speed limit and traffic control, which are two commonly used traffic-related variables in previous crash analyses, are used in this study. Traffic control is categorized into 3 groups: control present, and unknown. The control present means traffic controls like traffic signals, signs, and directors are available around the crash location.

Injury Severity Level

The severity level is categorized into 4 groups. Severe injury (including fatality) suggests injuries that prevent victims from moving. Light injury suggests evident injuries but is not serious to victims. No injury suggests the person involved in a crash is not injured. Unknown injury suggests that police officers are unable to fill out the injury level of victims.

Table 2. Descriptive statistics of select variables.

Variables	BEV		PHEV		HEV		ICEV	
	Mean	sd.	Mean	sd.	Mean	sd.	Mean	sd.
Driver Age	40.40	13.65	41.11	13.37	43.25	15.50	40.26	14.18
Victim Age	46.28	17.33	42.5	16.61	43.73	18.01	40.11	17.84
Vehicle Year	5.44	3.72	6.11	3.19	7.83	3.93	9.35	4.61
Number of Vehicles Involved	2.08	0.59	1.98	0.74	1.93	0.64	1.96	0.51
Number of Occupants per Vehicle	1.37	0.60	1.25	0.49	1.34	0.72	1.42	0.76
Number of Total Occupants	2.82	1.42	2.48	1.36	2.57	1.66	2.74	1.63
Month	6.42	3.69	6.73	3.52	6.58	3.58	6.72	3.36
Day of Week (1 – 7)	4.31	1.87	4.15	1.92	4.12	1.89	4.16	1.89
Hour of Day (0:00 – 23:00)	13.87	4.42	13.5	4.93	13.48	5.09	13.45	4.87
Speed Limit	38.46	14.34	37.92	14.54	37.52	13.57	35.84	10.23

Table 3. Distribution of crash severity level by vehicle type.

	BEV		PHEV		HEV		ICEV	
	Count	**Percentage**	**Count**	**Percentage**	**Count**	**Percentage**	**Count**	**Percentage**
Fatality	3	0.5%	0	0.0%	13	0.2%	126	0.03%
Injured	51	7.9%	35	10.7%	1085	12.3%	22,025	6.4%
Unknown	5	0.7%	0	0.0%	65	0.8%	1,721	0.5%

RESULTS AND DISCUSSION

Hypothesis Testing

The injury count measures how many people get injured in one crash. The Chi-squared test results in Table 4 suggest that the distribution of the injury counts of BEVs is statistically different from that of HEVs and ICEVs. Moreover, the injury count distribution of PHEVs is statistically different from that of ICEVs. Finally, the distribution of injury count of HEVs is different from that of ICEVs. In general, differences in injury count distributions among EVs and ICEVs exist. Thus, we further conduct statistical regression analysis on injury count to uncover what factors cause these differences.

Table 4. Chi-squared test results.

	BEV vs. PHEV	BEV vs. HEV	BEV vs. ICEV	PHEV vs. HEV	PHEV vs. ICEV	HEV vs. ICEV
Chi-square	2.4951	12.625	38.024	2.3569	8.2184	539.12
P value	0.4762	0.0055	0.0000	0.5017	0.0417	0.0000

Injury Count Model

Table 5 describes the statistical analysis of crash injury count using the negative binomial model. The influences of different factors are discussed below.

Person Factors

For all types of vehicles, the driver's age shows positive effects on injury count. The reason could be that reaction speed decreases as the driver's age increases (*28*). Besides, aggressive driving behavior tends to have a positive effect on injury count for EVs. One contributing reason could be that the electric motors of EVs have a greater acceleration rate than the engines of ICEVs (*29*). So, when being driven aggressively, EVs are more likely to crash at a relatively high speed compared with ICEVs. This could also explain the gender's influences on injury count. Male drivers are more likely to have risky behavior like aggressive driving than female drivers, and male drivers tend to have a higher injury count than female drivers for both BEVs and PHEVs (*30*).

Vehicle Factors

Some vehicle factors may also impact crash injury counts. For BEVs and PHEVs, moving straight has a higher injury count than other vehicles moving directions. The possible explanation can be that most BEVs and PHEVs are equipped with autopilot or advanced driver-assistant systems (ADAS) which could warn the driver of unobservable risks in the scenarios like turning (*31*, *32*). However, BEVs' and PHEVs' drivers may rely too much on ADAS while driving on straight roads instead of driving carefully. This could make BEVs and PHEVs have a higher injury count for moving straight than other moving statuses. In comparison, for HEVs and ICEVs, turning may be related to a higher injury count than other movements. The possible explanation can be that most HEVs and ICEVs on roads are not equipped with ADAS so drivers may not be able to notice potential risks in the scenario like turning.

Crash Factors

For all types of vehicles, head-to-head (head-on) crashes cause more injuries than non-head-on crashes. Nevertheless, the coefficient of head-on collision for BEVs is statistically significant. The reason could be that the front engine parts of PHEVs, HEVs, and ICEVs absorb a lot of crash forces during head-on collisions. However, most BEVs like Tesla have empty front zones, which have greater deformation during crashes compared with vehicles with engines in front (*33*).

Roadway Factors

For BEVs, HEVs, and ICEVs, wet or icy surfaces post a negative effect on crash injury count. The reason can be that people drive in a very careful manner on icy or wet road surfaces (*10*). Besides, the road type factor has different effects on each type of vehicle. For BEVs and ICEVs, interchanges tend to have a higher injury count than other road types. For PHEVs and HEVs, straight roads tend to have a higher injury count than other road types. However, proper reasons to explain such difference among different vehicle types requires further research studies in other regions.

Environmental Factors

For EVs, evening rush hours (15:00 – 19:59) are associated with a greater injury count than other periods. In contrast, for ICEVs, late night hours (19:00 – 0:59) are associated with a higher injury count than other periods. One possible reason could be EVs are used for commuting purposes (*10*). So, EVs tend to have a greater number of occupants than ICEVs during evening rush hour, and there are more injured people due to greater occupant numbers.

Other than crash time, the light condition also posts different effects on different types of vehicles. For BEVs and PHEVs, a dark environment tends to have a lower injury count compared with a light presence environment. However, for HEVs and ICEVs, a dark environment tends to have a higher injury count than a bright environment. The reason for such difference could be that ADAS on BEVs and PHEVs guides drivers to drive safely in a dark environment (*31*, *34*). Moreover, drivers could be more likely to rely on ADAS in dark situations than in light situations so the ADAS can help EV drivers reduce the driving risks effectively in dark environments.

Traffic Factors

For BEVs, HEVs, and ICEVs, a higher speed limit tends to have more injury counts, since a higher speed limit indicates vehicles are operating at a relatively higher speed, which may cause more injury counts (*35*). Besides, the crash injury counts for all types of vehicles are higher in areas with traffic controls. One possible explanation may be that traffic controls are placed in areas where there are more potential conflicts.

Table 5. Negative binomial model estimation results of injury count by EV type.

	BEV	**PHEV**	**HEV**	**ICEV**
Intercept	-37.58	-62.81	-2.76	-2.21
Driver Age	0.01	0.02	0.003	0.002
Driver Gender				
Male	0.11	0.46	-0.14	-0.13
Unknown	-2.01	1.77	-0.67	-0.18
Driver Condition				
Fatigue	18.09	17.83	0.09	-0.19
Normal	-1.34	20.09	-0.45	-0.35
Other (illness, emotional, etc.)	-33.42	-	-0.02	0.03
Unknown	-0.30	19.05	0.22	0.22
Driver Action				
Aggressive Driver	0.44	0.72	0.09	-0.03
Unknown	1.21	-20.17	0.22	0.06
Vehicle Year	0.05	-0.08	-0.001	0.003
Vehicle Action				
Moving Straight	0.09	0.36	0.75	0.71
Stopped	-0.11	0.36	0.86	0.83
Turning	-0.40	-0.02	0.72	0.60
Unknown	-16.82	-15.79	0.23	0.86
Surface				
Wet	-0.27	1.20	-0.22	-0.01
Icy	-1.10	1.88	-0.59	-0.42
Unknown	-18.65	-17.44	0.77	0.16

Road Type				
Intersection	-1.20	21.20	0.35	0.34
Non-intersection	-1.12	20.29	0.11	-0.01
Unknown	-20.96	9.50	-1.03	0.08
Most Harm Type				
Collision with non-fixed object	18.91	-1.86	0.28	0.19
Miscellaneous events	18.58	-	0.39	0.16
Non-collision events	20.52	-	0.64	0.68
Pre-crash events	-	-20.08	0.10	-0.04
Unknown	18.17	-1.08	-0.31	-0.39
Crash Type				
Head-on Crash	1.93	0.36	0.86	0.52
Unknown	1.15	-18.79	0.35	-0.24
Time Period				
Morning Rush Hour (6:00 – 10:59)	19.502	20.63	-0.03	-0.09
Noon (11:00 – 14:59)	19.501	19.93	-0.09	-0.04
Evening Rush Hour (15:00 – 19:59)	19.504	20.82	0.04	-0.04
Late Night (19:00 – 0:59)	19.474	20.29	-0.12	0.11
Light Condition				
Light Presence	-0.43	-0.40	0.19	0.06
Unknown	16.76	-1.95	-0.03	-0.83
Weather				
Cloudy/Foggy	-0.10	0.87	0.05	0.01
Other (Windy, etc.)	-18.61	-	-0.19	0.09
Rainy	0.05	-0.75	0.08	-0.02
Snowy	0.91	-22.17	0.38	-0.07
Unknown	-	-	-1.52	-0.77
Speed Limit	0.01	-0.001	0.02	0.01
Traffic Control				
True	0.10	0.16	0.15	0.01
Unknown	17.86	15.81	-1.96	-0.93

Crash Severity Model

Table 6 shows the results of the regression analysis on crash severity levels using the multinomial logit model. Findings for different variable groups are discussed separately below.

Person Factors

For crash victims, the likelihood of either light injury or severe injury (including fatality) decreases if the victim is male. This is consistent with the finding from previous studies on gender's influence on injury severity that females are more likely to experience injuries than males (*36*). In addition, compared with victims in vehicles, non-motorists have a greater probability to experience injuries (both light injury and severe injury). One explanation is that non-motorists do not have efficient protection compared to people in vehicles.

Safety Equipment

For all types of vehicles in this study, the use of safety belts decreases the likelihood of both light and severe injuries. However, airbag deployment increases the likelihood of light injuries for all types of vehicles. The possible explanation is that airbag deployments are usually associated with an impact of the strong force. Moreover, for PHEVs, HEVs, and ICEVs, airbag deployments also have a higher likelihood of severe injuries, but for BEVs, the deployment of airbags has a lower likelihood of severe injuries. This is supported by previous crash tests which state the force loaded on BEV passengers is lower than that from ICEVs under the protection of airbags (*33*).

Crash Characteristics

The occupant number has a different impact on injury severity for different vehicle types. For BEVs, an increase in occupant number is associated with an increase in the likelihood of severe injuries but a decrease in the likelihood of light injuries. For PHEVs, an increase in occupant number is related to a decrease in the likelihood of both severe and light injuries. For HEVs and ICEVs, an increase in occupant number is associated with an increase in the likelihood of both severe and light injuries, which is consistent with the research result of Seraneeprakarn et al. (*13*).

When the crash force is large, victims may get thrown out of vehicles. Sometimes, a large crash force would cause the deformation of vehicles which can get victims trapped. This could explain when a person is thrown out or trapped in a crash, the person is more likely to get either lightly or severely injured.

For BEVs, PHEVs, and HEVs, an increase in the vehicle number (which may not be the same type) involved in crashes could associate with an increase in the likelihood of light injuries. Moreover, for BEVs, HEVs, and ICEVs, the increase in the likelihood of serious injuries is related to a greater number of vehicles involved. This is not consistent with the research results of Huang et al. who suggest for HEV crashes, more vehicles involved in the crash would increase the likelihood of property damage only (no injury) (*12*).

Roadway and Regulation

At intersections, occupants on BEVs, HEVs, and ICEVs have greater log odds to experience both light and severe injuries. However, at the interchange, occupants on BEVs tend to have higher log odds of both light and severe injuries, which may need further investigation. For PHEVs, occupants have a greater likelihood of light injuries at the intersection and a greater likelihood of severe injuries on straight roads.

The road surface condition will also affect injury levels, but the impacts vary among four types of vehicles. When road surfaces are dry, BEV occupants are more likely to experience severe injuries. HEV occupants are more likely to experience both light and severe injuries. ICEV occupants are more likely to experience light injuries. In comparison, on wet surfaces, BEV occupants have greater log odds to get lightly injured, and ICEV occupants have greater log odds to get severely injured. On icy surfaces, PHEV occupants tend to experience both light and severe injuries compared with other surface conditions. These results suggest that surface conditions could influence the injury severity of both EVs and ICEVs.

For all types of vehicles in this study, an increase in speed limit is associated with an increase in the likelihood of light injuries. However, the decrease in severe injury likelihood is related to an increase in the speed limit for BEVs and PHEVs. One explanation is both BEVs and PHEVs contain heavy batteries that significantly increase the weight of vehicles, and the crash experiment results suggest that heavy vehicles can protect occupants from serious injuries (*37*).

Table 6. Multinomial logit model estimation results of crash severity outcome.

	Lightly Injured				Seriously Injured / Fatal				Unknown Injury			
	BEV	**PHEV**	**HEV**	**ICEV**	**BEV**	**PHEV**	**HEV**	**ICEV**	**BEV**	**PHEV**	**HEV**	**ICEV**
Intercept	0.69	-1175.06	-2.18	-1.99	-17.11	-228.37	-5.38	-6.19	3.08	-	-20.73	-5.58
Person Gender												
Male	-0.46	-0.58	-0.55	-0.35	-1.14	77.16	-0.18	-0.28	8.58	-	-0.45	0.02
Unknown	-25.56	-788.04	-0.73	-0.57	1.43	316.04	-0.77	-0.34	32.42	-	2.72	2.55
Non-motorist												
True	29.36	1040.32	5.67	5.79	0.93	8.49	7.10	7.11	-14.63	-	-10.84	1.76
Person Protection												
Other	-20.43	490.06	2.58	-2.24	0.84	10.28	-16.04	-2.11	53.29	-	-9.39	-0.73
Safety Belt	-0.11	-1.61	-0.20	-0.48	-2.55	-125.44	-2.68	-2.59	2.97	-	-1.46	-1.94
Unknown	-0.79	-1.26	-0.37	-0.89	-9.29	-318.84	-3.10	-2.57	8.46	-	1.46	1.10
Person Ejected												
True	37.71	-	15.63	3.56	0.38	-	16.37	6.04	0.34	-	-0.01	0.86
Unknown	1.09	-1658.34	-1.81	-2.20	-16.97	-175.60	2.75	1.55	26.78	-	-2.35	-3.06
Airbag Deployed												
True	1.58	1.42	1.77	2.47	-7.60	7.34	2.44	2.85	-0.65	-	1.27	1.26
Unknown	1.44	2.36	1.54	1.52	0.41	196.42	1.83	2.13	17.17	-	3.21	3.19
Person Trapped												
True	37.52	963.52	2.57	2.68	86.78	847.97	5.04	5.34	2.18	-	1.69	0.11
Unknown	1.01	1135.19	0.62	0.62	14.29	-165.39	-3.32	-2.42	-8.24	-	-0.49	0.80
Driver Condition												
Fatigue	-36.06	-452.61	0.67	-0.08	-0.11	10.03	1.51	-0.48	0.36	-	-14.52	0.69
Normal	-2.41	654.51	-0.50	-0.19	3.15	100.12	-1.52	-1.17	10.15	-	-0.70	0.47
Other	-37.87	-	0.44	0.20	-6.88	-	0.47	0.29	2.48	-	-0.58	0.95
Unknown	-36.50	655.29	-0.36	-0.05	17.78	-99.10	0.76	0.18	-11.74	-	1.71	2.34
Vehicle Year	0.12	-0.11	-0.008	0.03	-2.66	8.61	-0.030	0.003	0.19	-	0.10	0.004
Number of Occupants	-0.18	-0.36	0.20	0.04	2.32	-38.10	0.59	0.09	-7.11	-	-0.22	0.05
Surface												
Wet	0.04	0.90	-0.18	-0.23	-8.64	88.07	-0.30	0.09	-6.95	-	-1.35	-0.14
Icy	-1.40	1.44	-0.80	-0.60	-28.02	105.80	-1.35	-1.35	16.55	-	-1.45	-0.22
Unknown	-22.87	-45.65	0.27	-0.42	-1.05	-71.42	-15.29	0.23	0.72	-	-2.10	-0.32
Road Type												
Intersection	-1.78	518.91	0.14	0.44	-4.70	2.17	1.04	0.91	-0.15	-	15.08	0.18
Non-intersection	-1.74	518.57	-0.03	0.01	-9.84	141.36	0.16	0.48	0.85	-	15.48	0.13
Unknown	-	-45.65	-12.91	0.25	-	-71.42	-5.79	-0.15	-	-	15.77	-1.79
Vehicle Number	0.47	0.50	0.22	-0.02	4.23	-8.45	0.10	0.29	-11.18	-	0.08	-0.04
Speed Limit	0.008	0.01	0.009	0.01	-0.19	-4.13	0.05	0.05	-0.67	-	-0.005	-0.009

* The reference class is **No Injury**.
* PHEVs do not have unknown injury.
* The person data for BEV of "unknown" road type is invalid.

CONCLUSIONS

This study fills the research gaps by analyzing the differences in crash injury counts and severity levels among four types of vehicles including BEVs, PHEVs, HEVs, and ICEVs. In detail, the Negative Binomial Model (NB2) is used to estimate factors influencing the injury counts of four types of vehicles, and the Multinomial Logit Model (MNL) is applied to study the severity levels of different types of vehicles. In these statistical regression analyses, this study investigates six main groups of crash factors including human, vehicle, roadway, crash, environment, and traffic. The finding indicates that differences in the distribution of injury counts, crash factors' effect on injury counts, and injury severity among BEVs, PHEVs, HEVs, and ICEVs exist.

Based on the discussion and analyses of the results, vehicles' engine types, software, and hardware could contribute to these differences. For example, EVs (powered by electric motors) have a higher acceleration rate than ICEVs, which makes aggressive driving more likely to result in crash injuries. In addition, many BEVs and PHEVs are equipped with advanced driver-assistant systems (ADAS) which could help drivers avoid potential crashes, especially under low-light conditions or near intersections without clear visions. Finally, due to the presence of large batteries that significantly increase vehicle weights, BEVs and PHEVs are less vulnerable compared to other types of vehicles. The findings from this study can provide suggestions for developing regulations on EVs in terms of traffic safety. For example, there is a need for more education on EV-related driving behaviors, which enables future EV drivers to be aware of EV features and drive safely.

However, this study still has some limitations. Since Iowa is not among the top ten states with the most registered EVs, a limited number of observations could lead to biased estimation for statistical models (*38*, *24*). Moreover, unobserved heterogeneity is not considered in this study due to the limited number of observations, even though addressing unobserved heterogeneity is important for crash analysis (*7*). Future research is recommended to further investigate EV crashes in other states, such as California, to increase the number of EV crash observations and compare the results within various regions. Moreover, a combination of machine learning methods and statistical models can be used to explore the difference between EVs and ICEVs.

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AUTHOR CONTRIBUTIONS

The authors confirm their contributions to the paper as follows: study conception and design: J. Ling, X. Qian, K. Gkritza; data collection: J. Ling, X. Qian; analysis and interpretation of results: J. Ling, X. Qian; draft manuscript preparation: J. Ling, X. Qian, K. Gkritza. All authors reviewed the results and approved the final version of the manuscript.

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