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What are the characteristics and trends in electric vehicle crashes in Sweden?

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Executive Summary

This study analyses real-world crash data from Sweden (2022–2023) to examine crash patterns in electric vehicle (EV) collisions. The study identified EV crash trends and developed models to identify key factors that influence crash severity. This research supports Sweden's commitment to safe, sustainable, and zero-emission transport while aiding stakeholders in promoting safer mobility solutions globally.

Keywords: Electric Vehicles, Health and Safety Considerations, Sustainable Energy.

1 Introduction

In a world struggling with the urgent challenges of climate change and decreasing fossil fuel resources, electrification has become a key technology for transitioning to fossil-free road transport for both light and heavy vehicles. Many countries plan timelines for phasing out fossil-fuel-powered internal combustion engine vehicles (ICEVs) from the automotive market such as Norway in 2025, Netherlands and Denmark in 2030, UK, France and China in 2040 [1]. In Sweden, projections suggest that by 2030 all new passenger car sales could be electric [2].

Amidst the surge in on-road electric vehicles (EVs), concerns regarding their safety have gained prominence [3]. The transition to vehicle electrification presents novel challenges to traffic safety, distinct from those posed by internal combustion engine vehicles (ICEVs). Despite their global adoption, limited research exists on EV safety, particularly studies leveraging real-world crash data, which constrains the development of effective traffic safety measures.

The perception of vehicle safety plays a pivotal role in influencing potential buyers' decisions [5]. This perception encompasses various safety metrics, including accident rates, which are crucial when evaluating safety aspects of vehicles. Safety also includes meeting rigorous safety standards that need to be met by both traditional ICEV and EVs [6]. Given that some members of the public may have reservations regarding the safety of EVs, it is imperative to understand their safety impact. It's worth noting that EVs represent a relatively new technology, and thus, concerns about their safety are natural. However, these concerns should be weighed against the potential safety risks associated with ICEVs.

As EVs sales continue to rise, it is essential to assess their safety. Safety, in this context, is assessed based on injury and fatality rates, with safety indicators encompassing factors such as risk factors and the number of EV-related crashes, including incidents resulting in minor injuries, severe injuries, and fatalities. These assessments consider both internal risks, affecting drivers and passengers, and external risks, impacting other road users, pedestrians, and cyclists.

Despite the growth of EVs in the world, their impact on injuries and fatalities remains an area that warrants further study and investigation. Few studies have been conducted to understand crash frequency, and crash and injury risk of EVs. One US study analysed data from the Fatality Analysis Reporting System (FARS) for electric vehicles sold in the US from 2014 to 2020 [4]. It found no significant increase in EV fatality per capita (FPC) during this period, though the total number of EV fatalities did increase. Other studies [6] analysed hybrid electric vehicle crashes involving pedestrians and bicyclist in the US, for crashes occurring before 2009, and found that hybrid electric vehicles had higher incident rate in pedestrian or cyclist crashes than ICEVs. Chen et al. [7] examined hybrid and electric vehicle crashes using U.S. crash data from 2009 to 2013; however, the dataset included only 20 EVs, making it insufficient for drawing robust conclusions.

Recent studies [8] on data from Crash Report Sampling System (CRSS) for crashes in 2020 and 2021 crash year, reported that in the event of a crash, occupants of EVs were at a higher risk of sustaining severe injuries compared to those in ICEVs. In [9], the authors analysed crash data from Chicago from 2015 to 2022, for EV (including EV and PHEV) and ICEV involved crashes with vulnerable road users (VRUs). The study indicates that there is insufficient evidence to conclude that EVs are more likely to collide with VRUs compared to ICEVs. However, notable differences were observed between EV and ICEV crashes in the distribution of factors such as VRU type, hit-and-run occurrences, damage severity, crash time, weather and road surface conditions. In [10], the crash conditions for EVs were found to be comparable to those of ICEVs. Additionally, the occurrence of run-off-road crashes was similar between EVs and ICEVs, for crashes occurring in crash years 2017 to 2021 from eight states departments of transportation.

In Norway, another study examined crash data from 2011 to 2018, revealing that the proportion of EV crashes in total traffic crashes increased from zero to 3.11% during this time [11]. Despite this increase, the severity of EV crashes did not show statistically significant differences compared to ICEV crashes. Regarding crash patterns, EV crashes were more likely to occur on weekday peak hours, urban areas, roadway junctions, low-speed roadways, and in good visibility scenarios, reflecting their predominant use for urban commuting in Norway [11].

A recent study, [12], investigated traffic crashes in China, the country with the largest electric vehicle (EV) market globally. Using crash data from a major Chinese city in 2023, the researchers found a rise in EV-related crashes. The analysis revealed that crashes involving EVs were more likely to result in fatalities compared to those involving ICEVs. Additionally, EV crashes were more frequently associated with pedestrian collisions, and EV crashes occurred more often during the vehicle's starting phase than ICEV crashes [12]. An analysis of one year of crash data from freeways in Guangdong Province, China (crash year 2021), revealed that factors such as time of day, type of vehicle involved, EV color, and average travel times during morning and evening peak hours significantly influence the severity of injuries in EV crashes [13].

Although these above studies have analysed the injury and fatality trends of EVs, there is no consensus regarding the crash patterns of EVs versus ICEVs, and further research is necessary to gain a comprehensive understanding of these trends in various countries and the underlying causes of crashes involving EVs, in light of the growing prevalence of EVs. For example, all these studies lack crash data from recent years in Europe, and also it is not known which of these findings are applying to other countries such as Sweden.

This study aims to address this knowledge gap by analysing recent Swedish traffic crash data (2022-2023) from region of ‘Västra Götalands’ in Sweden. The primary objective is to gain an understanding of the distinctive characteristics and emerging trends associated with EV-related crashes and their severity. By providing insights into EV crash characteristics, the findings aim to inform safety strategies in Sweden and contribute to broader efforts within the European community to enhance EV safety.

2 Method

2.1 Dataset

This study analysed EV and ICEV crashes using real-world crash data from Swedish Traffic Accident Data Acquisition (STRADA) database [14]. STRADA is Sweden’s national information system for road traffic crashes, including data from police-reported incidents. By law (SFS 1965:561, most recently updated in SFS 2021:319), Swedish police are required to report all road crashes resulting in at least one personal injury. These reports are based on observations made by police officers at the crash scene. The types of police reported crashes submitted to STRADA are strictly regulated and align with Sweden’s official definition of a road crash, which specifies that: the crash must occur on a road in traffic; involve at least one moving vehicle; and result in at least one personal injury.

The objective of this study was to investigate crash frequency, crash scenarios, and injury and fatality outcomes for crashes involving at least one motor vehicle that occurred between 2022 and 2023 in Västra Götalands region in Sweden. Specifically, an EV-crash was considered when at least one EV is involved in the crash. To ensure comparability between ICEVs and EVs, the analysis was restricted to vehicles with a model year of 2006 or later, as safety features in earlier vehicles were not documented in the database. Hybrid vehicles were excluded to focus solely on fully electric vehicles.

2.2 Analysis

Descriptive statistics are provided for crashes with the focus on specific factors. A distribution is provided of EV-related crashes and ICEV-related crashes and associated crash severity across identified scenarios. Additionally, a Pearson’s chi-squared test [15, 16] is employed to assess whether there is a statistically significant difference in the severity distributions between EV and ICEV crashes (α = 0.05). A double-tailed *t*-test was used to test whether the distributions of vehicle weight between EV and ICEV were different; the threshold for statistical significance was set to α = 0.05.

2.2.1 Models for regression analysis on crash severity

Identifying key factors influencing crash severity is critical for developing effective countermeasures. Accordingly, two Bayesian regression models were constructed to examine factors influencing the crash severity (i.e., slight versus severe crash) for ICEVs and EVs, respectively. For the modelling part and considering that there is unbalanced distribution by crash severity, crashes are encoded in two categories: (1) severe, which combines killed and severe crashes; and (2) slight, which refers to slightly injured.

Bayesian modelling was selected due to its flexibility in dealing with different statistical distributions and its ability to quantify uncertainty in model parameters. Unlike traditional frequentist methods, Bayesian methods provide the full posterior distribution of each parameter, enhancing the credibility and interpretability of the results [17,18, 20]. Bayesian regression models with linear predictors were fitted to each the crash severity data using the R package *brms*, version 2.22.0 [17]. A Bernoulli distribution was specified for the response variable, where crash severity was categorized as slight (severity = 0) or severe (severity = 1):

$$\text{severity}_\text{i} \sim \text{Bernoulli}(p_i),$$

where p_i is the predictor of the model, representing the probability that random variable takes the value of 1 (severity = 1). The predictor is modelled by a linear combination of population and group level effects, via a logit transformation:

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1-p_i}\right) = \mathbf{X}_i\boldsymbol{\beta} + \mathbf{Z}_i\mathbf{u},\ \ \mathbf{u} \sim \text{N}(0, \sigma^2\boldsymbol{I}),$$

where **X** is the population-level effect matrix, $\boldsymbol{\beta}$ is the corresponding parameter vector, and **Z** is the group-level effect matrix, with corresponding parameter vector **u**. **u** is sampled from a zero-centered normal distribution with standard deviation σ, constant over all observations [17].

The models were estimated with four Markov chain Monte-Carlo (MCMC) chains, each comprising 2000 iterations. The initial 1000 were used for warm-up and subsequently discarded. The total number of iterations was chosen to ensure convergence of the MCMC chains, as indicated by plots of their traces, and an Rhat value approaching 1 [17]. Weakly informative default priors were employed [17], consistent with the approach of Williams et al. [19] for the ICEV model. Posterior distributions estimated from the ICEV model were then used as priors for the EV model [18]. Model parameters are summarized with their estimated median and a 95% highest-density interval (HDI) [18]. In this study, parameters are considered to have a clear influence if their 95% HDI was strictly positive or strictly negative.

3 Results

The analysis included 158 crashes involving at least one EV and 2783 crashes involving at least one ICEV. For example, crashes between two EVs or two ICEVs are counted twice.

The crash severity distributions of these collisions are detailed in Table 1. It can be observed that larger proportion of the EV crashes are slight in comparison to the ICEVs. Due to this unbalanced distribution by crash severity for both vehicle types, in the following analysis crashes are encoded in two categories: (1) severe, which combines fatal and severe crashes; and (2) slight, which refers to slightly injured.

Furthermore, crashes with known values for the following factors are used in the analysis: time factors (day of the week and time of day), roadway factors (location, speed limit, place type), environmental factors (weather and light), and crash factors (road user type). Out of total 2783 ICEV and 158 EV crashes, 2481 and 137 are kept in the analysis, representing 89.1% and 86.7% of the raw data, respectively.

A Pearson's chi-squared test is employed to assess whether there is a statistically significant difference in the severity distributions between EV and ICEV crashes (see Table 2). The crash severity distributions of EVs and ICEVs do not show statistically significant differences, $\chi^2 = 1.9906$, p = 0.1583.

Figure 1 shows the distribution of the vehicle weights. The average and standard deviation (SD) of the weight of EVs were 1969 (SD = 274) kg, and ICEVs were 1550 (SD = 310) kg. The *t*-test of vehicle weight of EV and ICEV, showed that they are statistically significant different from each other, p<<.001.

Table 1: Crash severity of EV and ICEV-related crashes.

	EV (%), N = 158	ICEV (%), N =2783
Fatal	2.5	1.8
Severe	3.8	7.5
Slight	93.7	90.6
Unknown	0	0.1

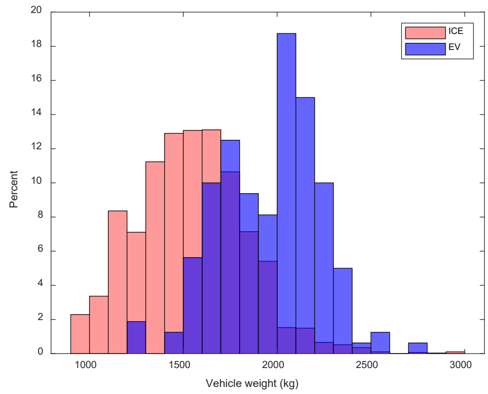

Figure 1: Distribution of vehicle weight in crashes, EVs and ICEVs with other road users.

In the rest of the results, we investigated the different factors that may affect the severity of the crash both for EVs and ICEVs. Table 2 shows a summary of these factors used in the analysis.

3.1 What is the temporal pattern of EV crashes?

Travel behaviour varies by day of the week, with weekdays characterized predominantly by commuting trips and weekends by leisure-related travel. The distribution of the crashes per day of week is shown in Figure 2. There are no obvious pattern differences between ICEV and EV crash travel patterns, but there are slightly larger proportion of EV crashes in the afternoon peak for EVs than ICEVs crashes.

As shown in Figure 2, there are two peaks for both ICEV and EV crashes occurring in morning and afternoon rush hours. In the afternoon peak there are 35.8% for EV and 27.8% of ICEV crashes, while for the nighttime, the EV are 22.6% in comparison to ICEV of 26%, see Table 2.

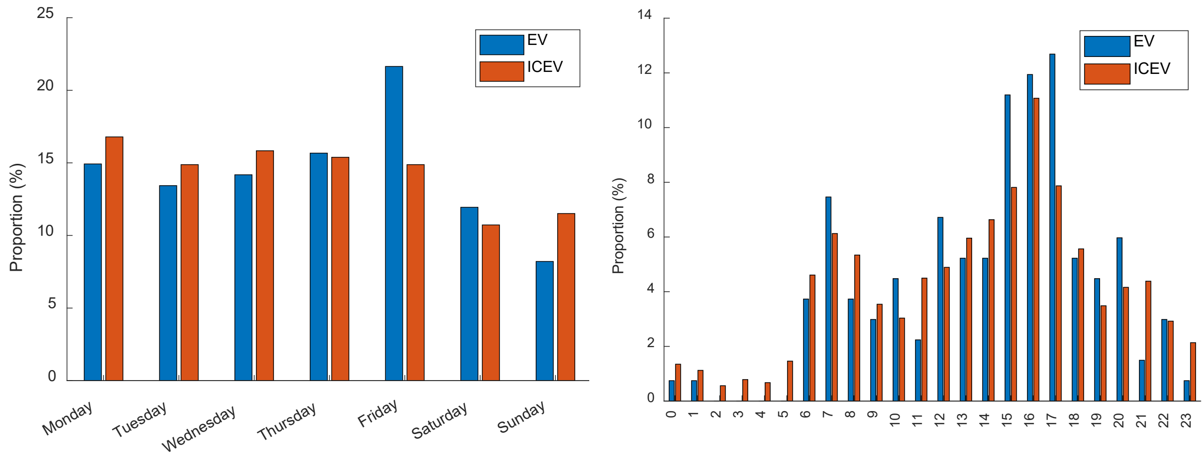

Figure 2: Distribution of crashes by a) day of week and b) time of day.

3.2 In what roadway infrastructure do EV crashes occur?

Regarding location, 48.2% of EV crashes occur in urban areas, and 51.8% in rural areas, and similarly the proportion for ICEV crashes is 48.6% and 51.4% for urban and rural areas, respectively (see Table 2). Furthermore, the speed limit distribution is shown in Table 2, 29.9% of the EV crashes occurred at high-speed limits (>= 80km/h), while the proportion for ICEV crashes was 26.5%. Regarding place type, crashes are divided into two categories: intersections, including crossings and roundabouts, and segments, including roads beyond crossings. The proportion of crashes in intersections and segments for EV crashes is 37.2% and 62.8%, while for ICEV is 35.5% and 64.5%, respectively.

3.3 What are the environment conditions when EV crashes occur?

Regarding weather conditions, 84.7% of the EV crashes occur in fair weather, 13.9% in rainy/snowy weather, while for ICEV crashes, 80% occur in fair and 19.1% in rainy/snowy weather. Table 2, shows the distribution of crashes occurring on snowy and wet road surfaces. When it comes to road surface conditions, a larger proportion of 64.2% occurred in dry conditions for EV crashes and 23.4% in wet road surfaces. For ICEV crashes the proportion was 58.6% in dry roads, and 29.4% in wet road surfaces. This might indicate that the EVs are more frequently driven in fair weather and dry road conditions due to concerns related to battery performance. Furthermore, regarding light conditions, EV crashes occurred with 67.9% during daylight, and 24.1% in dark, and for ICEV the proportion was 65.4% in daylight, and 25.5% in dark.

3.4 Which road users are involved in EV crashes?

Crashes are divided into categories depending on the road user type involved in the crash: car, moped, VRU (pedestrian, bike, e-scooter), motorcycle, truck/bus or other. Table 2 shows that 62%, 13.9% and 13.9% of EV crashes involve another car, VRU, and truck/bus, respectively. The proportion for ICEVs is 68%, 11.6% and 10.1% for being in a crash with car, VRU and truck/bus. The proportion of colliding with moped was 3.6% and 2.7% for EVs and ICEVs crashes, respectively. While the proportion for colliding with motorcycles was 0.7% which is 2.5 times of the proportion for ICEVs colliding with motorcycles (1.7%).

Table 2: Descriptive statistics for EV and ICEV crashes.

Variable	Definition	EV (%)	ICEV (%)
Crash severity	Severe	6,6	9,8
	Slight	93,4	90,2
Place type	Segment	62,8	64,5
	Intersections	37,2	35,5
Location	Urban	48,2	48,6
	Rural	51,8	51,4
Speed	Middle	60,6	65,8
	Low	9,5	7,7
	High	29,9	26,5
Time of day	Morning: 6-8	15,3	17,2
	Daytime: 9-14	26,3	29,0
	Afternoon: 15-17	35,8	27,8
	Nighttime: 18-5	22,6	26,0
Weekend	Weekend	19,7	22,2
	Weekday	80,3	77,8
Road surface	Dry	64,2	58,6
	Wet	23,4	29,4
	Snow/ice	12,4	12,0
Weather	Fair	84,7	80,0
	Rain/Snow	13,9	19,1
	Fog	1,5	0,9
Light	Day	67,9	65,4
	Dark	24,1	25,5
	Twilight	8,0	9,1
Road user	Car	62,0	68,0
	Moped	3,6	2,7
	VRU	13,9	11,6
	Truck/bus	13,9	10,1
	Motorcycle	0,7	1,7
	Other	5,8	5,9

3.5 Bayesian regression analysis on crash severity

In this section, two Bayesian regression models are created to determine the factors that affect crash severity (i.e., slight vs severe) for EVs and ICEVs, respectively.

Table 3 shows the estimated coefficients of the Bayesian regression analysis for crash severity involving ICEVs. The positive coefficient indicates that compared with the reference state of a variable, the tendency of potential crash severity increases. In general, the findings indicate that while few explanatory factors have a clear influence for ICEV crashes, they have not for EV crashes.

Specifically, for ICEV crashes, rural locations are associated with an increased likelihood of higher crash severity, likely due to higher travel speeds typically observed on rural roads.

Intersection place type shows negative effects, which means that the crashes occurring at intersections are less severe than crashes on segment locations. A possible explanation is that crashes occurring at intersections are happening at lower speeds.

Wet road surface shows positive effects, which indicates that the ICEV crashes on wet roads are more severe than those occurring on dry roads.

Road users involved in crashes with the ICEV such as VRU, truck/bus, and motorcycle show positive effects, while road user-other show negative effects. This shows that crashes between ICEV and pedestrian/bikes, motorcycles, truck/bus are more severe than those between ICEVs and passenger cars. This might be because VRUs and motorcycles are vulnerable road users in crashes. Further, the ICEV with truck/bus is more severe than ICEV crash with another car.

Table 3: Estimated coefficients of Bayesian regression model for crash severity for ICEVs crashes.

Explanatory variable	Estimate	Est. Error	l-95% HDI	u-95% HDI
(Intercept)	-3.48	0.24	-3.95	-3.03
Weekend	0.11	0.17	-0.23	0.44
Time of day-Morning	-0.35	0.2	-0.80	0.12
Time of day-Afternoon	0.15	0.19	-0.22	0.52
Time of day-Nighttime	0.13	0.19	-0.22	0.50
Place type-Intersection	-0.65	0.18	-1.02	-0.31
Location-Rural	1.35	0.19	0.98	1.73
Speed limit-Low	0.25	0.30	-0.36	0.82
Speed limit-High	0.10	0.17	-0.22	0.43
Road surface-Wet	0.47	0.16	0.16	0.78
Road surface-Snow/ice	0.07	0.23	-0.37	0.50
Road user-Moped	0.43	0.57	-0.80	1.46
Road user-VRU	1.40	0.24	0.93	1.88
Road user-Other	-1.29	0.49	-2.34	-0.42
Road user-Truck/bus	0.71	0.20	0.31	1.09
Road user-Motorcycle	2.43	0.38	1.68	3.17

For the EV related crashes, the estimated coefficients for the model are shown in Table 4. The intersection factor shows negative effect on the severity of the EV crash in comparison to segment places (the whole 95 % HDI is below zero), which is similar as the estimates for the ICEV for the place type factor. The rural location shows positive effect, or more severe crashes occurring on rural roads than on urban roads for EV related crashes, and this is similar as for ICEV model estimates. The estimates for road users involved in EV crashes show positive effects for truck/bus and motorcycles compared to crashes involved with cars. The trend for was similar for ICEV estimates for the same factors (i.e. truck/bus and motorcycles). Furthermore, the 95% HDIs of the estimates for the wet and snow/ice road surface contained neither fully positive nor fully negative values and therefore did not indicate any significant results.

Table 4: Estimated coefficients of Bayesian regression model for crash severity for EVs crashes.

Explanatory variable	Estimate	Est. Error	l-95% HDI	u-95% HDI
(Intercept)	-4.22	0.85	-6.05	-2.74
Place type-Intersection	-0.49	0.24	-0.97	-0.04
Location-Rural	2.05	0.91	0.41	4.01
Road surface-Wet	0.44	0.25	-0.04	0.93
Road surface-Snow/ice	-0.93	1.34	-4.02	1.28
Road user-Moped	0.48	0.25	-0.00	0.97
Road user-VRU	0.45	0.24	-0.02	0.92
Road user-Other	-0.47	0.25	-0.97	0.01
Road user-Truck/bus	0.48	0.24	0.01	0.96
Road user-Motorcycle	0.50	0.24	0.03	0.96

4 Conclusion

This study described the crash patterns of EVs crashes using real-world crash data from Sweden, of the two recent years of crash records occurring in Västra Götalands region.

EV crashes still represent a relatively small proportion compared to ICEV crashes. Moreover, no statistically significant difference in crash severity was observed between EVs and ICEVs. EV crashes were distributed relatively evenly between urban and rural areas, more frequently on segment roads than intersections, in fair weather conditions and dry roads, and more frequently in afternoon peak hours. Of all EV crashes about 14% occurred with VRUs, and about 14% with truck/buses.

Two Bayesian regression models were created to identify factors influencing the severity of the ICEV and EV crashes, respectively. Factors, such as location, place type, road user involved in the crash, show similar effects on ICEV and EV crash severity. Specifically, rural roads, and interaction with truck/bus and motorcycle increase the severity of the crash. However, although the wet road surface and the involvement of VRU increased the severity of ICEV crashes, it was not shown to be a significant factor for the severity of EV crashes. We acknowledge that the small sample size of the EV crashes might affect the regression results. As more data is accumulated, with the proliferation of the EVs on the market, future studies should include also demographics of the drivers, driving styles, attitudes towards safety and sustainability, and socioeconomic status.

The results have potential to promote safety standards for EVs, supporting Sweden's commitment to a safe, sustainable, and zero-emission transportation. By examining the factors contributing to EV crashes, we seek to gain a deeper understanding of these incidents, allowing for the development of appropriate countermeasures and safer road transport systems for all users. These findings have the potential to assist stakeholders, including the road authorities, insurance agencies, automotive industry, research community, and society at large, potentially influencing road users' behaviours by enhancing their awareness of EVs safety.

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Presenter Biography

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