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Examination of the Factors Influencing the Electric Vehicle Accident Size in Norway (2020–2021)

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Abstract: With the great increase of electric vehicles (EVs) in the past decade, EV-involved traffic accidents have also been increasing quickly in many countries, bringing many new traffic safety challenges. Norway has the largest EV penetration rate in the world. Using the EV accident data from Norway in 2020 and 2021, this study aims to investigate the features of EV safety comprehensively. Firstly, a descriptive analysis is conducted. It has been found that rear-end collisions are the major collision type of EVs, and EVs are very likely to collide with pedestrians/cyclists. In addition, in terms of roadway type, EV accidents mainly occur on medium- and low-speed roads; in terms of environment, they mainly occur in good visibility conditions and dry road surface conditions. Then, a regression analysis is conducted to identify the key factors affecting the accident size, which is the number of traffic units involved in an accident and taken as the accident severity surrogate here. Since EV accidents are divided into four categories in order of accident size, the ordered logit model is adopted. It divides a multi-categorical dependent variable into multiple binary data points in order and calculates the probability of the dependent variable falling into each category with the logit model, respectively. The estimation results indicate that time of day, speed limit, and presence of medians have statistically significant impacts on the EV accident size. Finally, some countermeasures to prevent EV accidents are proposed based on the research results.

Keywords: traffic safety; electric vehicles; traffic accidents; accident size; ordered logit model

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1. Introduction

Transportation is a major source of fossil energy consumption and carbon emissions, with motor vehicles being the primary contributor. According to the International Energy Agency [1], roadway transportation accounted for 32% of global energy consumption in 2017. Therefore, automotive electrification is essential for transportation decarbonization, and in recent years, many countries have made significant efforts to promote electric vehicle (EV) adoption. However, with the increase of EVs, EV-involved traffic accidents have also been increasing rapidly in many countries [2–5]. In addition, the traffic accident data from 2018 to 2020 in China, the largest EV auto market in the world, reveals that both crashes and deaths per 10,000 vehicles of EVs are significantly higher than those of ICEVs [6]. Compared to traditional internal combustion engine vehicles (ICEVs), the unique technical features of EVs bring many new traffic safety challenges.

Firstly, EVs pose great threats to the surrounding road users due to their silent engines, especially in low-speed scenarios. Compared with ICEVs, the absence of ICEs greatly improves the comfort level of driving EVs but also brings greater danger to pedestrians and cyclists [7,8]. As early as 2009, researchers have pointed out this issue [9]. According to data from the U.S. National Highway Traffic Safety Administration on pedestrian/bicycle accidents, hybrid electric vehicles (HEVs) were found to be 22% more likely to be involved than ICEVs. Recently, based on crash data from Norway between 2011 and 2018, Liu et al. verified that EV crashes were more likely to involve pedestrians/cyclists than ICEV ones [2]. A recent study analyzed the EV crashes in Changsha, China, from 1 January 2020 to 27 June 2022, and found that nearly one-fourth of them were hit-pedestrian ones [3]. Compared to vehicle occupants, pedestrians/cyclists lack protection from vehicles. Once they collide with EVs, serious consequences might occur. Literature [3] found that nearly half of hit-pedestrian EV crashes caused deaths. Aiming at this issue, many countries have enacted laws requiring EVs to produce alert sounds with warning systems. For example, the EU has required all EVs to be equipped with an Acoustic Vehicle Alerting System (AVAS) as of 1 July 2021 [10]. However, whether these policies are helpful for preventing such crashes still needs to be validated in the future.

Secondly, the lithium-ion batteries of EVs are prone to suffering from thermal runaway under overcharging, mechanical collisions, or overheating conditions, leading to fires or explosions [11]. Visvikis et al. compared the accidents of EVs and ICEVs and found that EVs were more likely to have chemical reactions and short circuits, posing a great threat to accidents [12]. Based on the EV injury and fatality data from the Fatality Analysis Reporting System of the U.S., Alter et al. found that fire was one of the primary factors directly related to the EV fatality [5]. After analyzing some serious EV fire incidents globally between 2014 and 2019, literature [13] discovered that collision was one of the major causes of battery fire. Furthermore, quiet engines and chemical materials also make the emergency response to EV crashes high-risk. Emergency responders need to face the dangers of electric shock, poisoning, burns, etc. [14]. In addition, many other technical features of EVs, including the one-pedal driving mode, the fast acceleration function, etc., also raise new safety concerns.

Aiming at the EV safety issue, researchers have conducted some studies. Since crash severity is the primary concern in traffic safety studies, most of the existing studies have explored the crash severity issue from different aspects. Chen et al. analyzed the crash data of the U.S. from 1999 to 2013 and found little difference between HEVs and ICEVs in injury outcome [15]. Recently, Liu et al. analyzed the EV crash data of Norway from 2011 to 2018 and found that EVs did not have significant differences from ICEVs in terms of crash severity [2]. Later, based on the crash data of Spanish cars from 2016 to 2020, Luis et al. conducted a pilot analysis and also found no significant differences between EV crashes and ICEV crashes for belted occupants in terms of the injury risk in frontal impacts [4]. In addition, to develop effective measures to reduce crash severity, some studies also try to quantitatively find the factors influencing crash severity through regression analysis. Liu et al. established a logistic regression model to identify key factors that influence the severity of 278 EV crashes in Norway [2]. The results showed that roads with central dividers could significantly reduce the severity, and accidents involving motorcycles were severer than those involving vehicles. With 309 EV crashes in Changsha, Su et al. built an ordered logit model to analyze crash severity, as those crashes were divided into three categories, i.e., property damage only, injured, and fatal. They found that both collision type and time of day had significant effects [3].

As a summary, although the traffic safety of EVs has attracted more attention over time, there is still a big gap between the fast development of EVs and the existing research due to the short history of the large-scale adoption of EVs in the world. Firstly, compared to ICEVs, only a few researchers have tried to figure out the safety features of EVs by analyzing the real-world crash data. However, crash analysis is the most important tool to figure out traffic safety issues. Secondly, those existing EV crash studies mainly focus on discussing whether EVs have significant differences from ICEVs in terms of crash severity by statistical tests, and only a few of them have tried to conduct in-depth regression analysis to identify the factors influencing their crash severity. However, quantitatively identifying those important influencing factors is essential for agencies to develop effective countermeasures.

Thirdly, since the EV crash data used in these studies is usually very small, only very limited factors are considered, and the results also need to be further verified with bigger crash data. Finally, in crash severity analysis, some researchers have also analyzed the number of vehicles involved in the accident [16–18], i.e., accident size, as it has been proven to have strongly positive correlations with crash severity in many studies [19–22]. It is thought that as more vehicles are involved in the accident, more occupants will be exposed too, which in turn increases the probability of causing injuries or deaths. In addition, many severe crash types, such as head-on and angle crashes, usually involve multiple vehicles. Actually, many factors have also been found to have similar impacts on crash severity and accident size [16,17]. However, none of the existing EV crash studies have analyzed accident size before.

Therefore, with the EV accident data from Norway from 2020 to 2021, this study is designed to figure out the characteristics of EV traffic safety and comprehensively identify the factors influencing the EV accident size from time, roadway, and environment by regression analysis. Although this study adopts Norwegian EV crash data, the findings are expected to be greatly helpful for other countries to prepare for the incoming EV era. The following sections are organized as follows: Section 2 describes the materials used in this study. Section 3 describes the models used in this study. Section 4 conducts a statistical analysis to identify the factors significantly influencing the EV accident size. Section 5 summarizes the research content of this paper and discusses the limitations of this research.

2. Materials

Norway is located in northern Europe, with an area of 385,000 square kilometers and a population of 5.456 million as of October 2022. The number of EVs in Norway has increased rapidly due to the government's efforts to promote EV adoption in the past decade. Currently, Norway has the highest EV penetration rate in the auto market in the world. By 2022, 599,169 EVs had been registered in Norway, accounting for 17.3% of total registrations [23]. The EV traffic accident data for Norway from 2020 to 2021 was collected from the Norwegian Public Roads Administration (NPRA). There were a total of 930 EV-involved crashes. Table 1 shows a summary of some characteristics of these EV accidents.

Table 1. Summary of Some Characteristics of EV Accidents in Norway from 2020 to 2021.

Variable	Definition	Proportion
Accident size	Number of involved units—1	9.6%
	Number of involved units—2	72.8%
	Number of involved units—3	13.1%
	Number of involved units—≥4	4.5%
Collision type	Rear-end	34.6%
	Angle	34.2%
	Head-on	13.5%
	Hit pedestrian	12.3%
	Unknown *	5.4%
Accident category	Car	68.5%
	Pedestrian	11.9%
	Bicycle	16.5%
	Motorcycle	2.8%
	Unknown *	0.3%
Speed limit	Low (<50 km/h)	26.2%
	Medium (50~80 km/h)	49.9%
	High (≥80 km/h)	23.9%
Road location	Junctions	42.0%
	Segments	55.4%
	Unknown *	2.6%

Table 1. *Cont.*

Variable	Definition	Proportion
Presence of medians	Yes	22.7%
	No	70.6%
	Unknown *	6.7%
Visibility	Good visibility	73.8%
	Good visibility—rainfall/snowfall	13.8%
	Poor visibility	5.2%
	Unknown *	7.2%
Road surface conditions	Dry	56.7%
	Wet	26.8%
	Snowy/icy	9.7%
	Unknown *	6.8%

Note: units mean all the road users, including vehicles, pedestrians, bicycles, etc.; * means the information is unavailable in the raw crash data.

2.1. Collision Features

Crash severity is the primary concern of traffic safety studies. However, due to privacy concerns, NPRA does not provide crash severity information in the data. Many researchers have demonstrated that accident size, i.e., the number of involved units in an accident, has a strong positive correlation with crash severity [16,17,19]. That is, with the increase in involved traffic units, accidents would tend to be more severe. Therefore, accident size is taken as a surrogate for crash severity here. According to Table 1, most EV crashes involve two or more units, and only 9.6% of them are single-unit ones.

In terms of collision type, the rear-end collision is the most common one and accounts for 34.6% of EV crashes. Rear-end collisions usually occur due to improper car-following operations [24,25]. The high proportion of rear-end collisions in EV crashes has also been found in other studies [26], which might be attributed to the single-pedal regenerative braking systems of EVs. Due to their unfamiliarity with vehicle performance and driving characteristics, drivers might mistakenly step on the pedal or inadvertently step too much, which leads to unexpected accelerations/decelerations [27]. Angle collisions account for 34.2% of EV crashes, indicating that EV crashes are very likely to occur at intersections.

In terms of the accident category, 11.9% and 16.5% of EV accidents involve pedestrians and bicycles, respectively, which indicates the huge threat of EVs to those vulnerable road users. As mentioned in the literature review, many studies have found EVs greatly threaten the safety of pedestrians/cyclists due to their silent engines. A former study of the Norway EV crashes from 2011 to 2018 shows that 31.5% of them involved pedestrians/bicycles [2]. Our study further confirms this issue. In addition, the proportion slightly decreased, which implies that the risks of EVs colliding with those vulnerable road users might decrease.

2.2. Time Features

Figures 1 and 2 show the distributions of EV crashes by day of week and time of day, respectively. As shown in Figure 1, most EV crashes occur on weekdays, and EV crashes on weekends are obviously fewer. The finding is consistent with the former study [2]. On one hand, people travel less on weekends. On the other hand, the limited range of EVs means that they are mainly used for local commuting travel on weekdays rather than long-distance leisure travel on weekends. As a result, there are fewer EVs on the road during weekends, leading to fewer EV crashes.

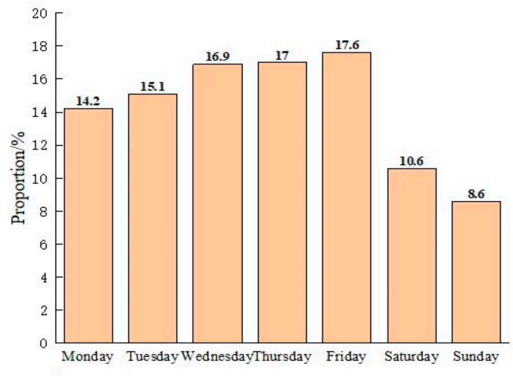

Figure 1. Distribution of EV crashes by day of week.

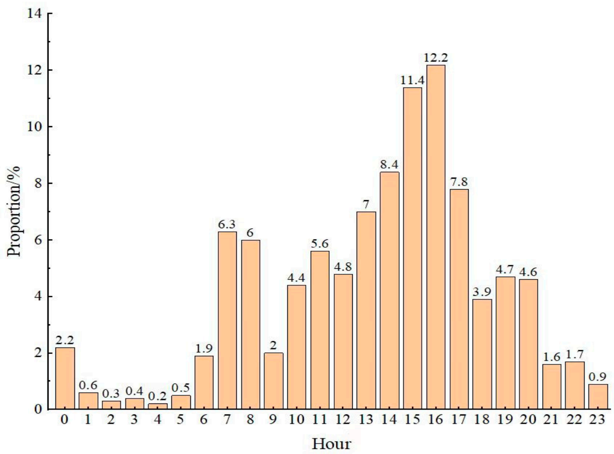

Figure 2. Distribution of EV crashes by time of day.

As depicted in Figure 2, EV accidents exhibit clear bimodal peaks in the daytime: one is the morning peak (7:00 a.m.–8:00 a.m.), and another is the afternoon peak (3:00 p.m.–5:00 p.m.). Additionally, very few EV accidents occur at night.

2.3. Roadway Features

Speed could directly impact crash outcomes. Here, 76.1% of EV accidents occurred on medium- and low-speed (<80 km/h) roads, while only 23.9% of them occurred on high-speed (≥80 km/h) roads. The finding is generally consistent with the study analyzing the Norway EV crash data from 2011 to 2018 [2]. In Norway, most high-speed roadways are primarily used for long-distance travel. The small proportion of EV crashes on high-speed roads implies that EVs might be used more for local commuting travel than long-distance travel due to the range concern from another perspective.

Here, road locations were classified into junctions and segments. The former includes intersections, T-junctions, roundabouts, exits, etc., while the latter includes areas outside exits, tunnels, underpasses, etc. The results indicate that 55.4% of EV accidents occurred on segments. Additionally, 70.6% of EV accidents occurred on roads without medians, which could prevent vehicles from running in the opposite direction.

2.4. Environment Features

Visibility and road surface conditions could also greatly affect driving safety. Here, 87.6% of EV accidents happen in good visibility conditions, while only 5.2% occur in poor visibility conditions. In addition, only 9.7% of EV accidents occurred in snowy/icy road surface conditions. Considering Norway has a long, harsh winter [28], the proportion is small. It is known that low temperatures could greatly impair battery performance.

Thus, drivers might use EVs less. In addition, drivers might also be more cautious in harsh weather.

3. Models

In order to quantitatively identify the important factors affecting the EV accident size, a regression analysis is conducted here. Since the accident size is divided into four categories in order, the ordered logit model (OLM) is adopted here. The OLM divides a multi-categorical dependent variable into multiple binary data points in order and calculates the probability of the dependent variable falling into each category with the logit model, respectively. Compared to the common multinomial logit model, the OLM could take care of the order change of dependent variables and has been widely adopted in traffic crash analysis [3,29]. The OLM is built as follows:

$$y_i = \begin{cases} 1, {y_i}^* \le \mu_1 \\ 2, \mu_1 < {y_i}^* \le \mu_2 \\ 3, \mu_2 < {y_i}^* \le \mu_3 \\ 4, \mu_3 \le {y_i}^* \end{cases} \tag{1}$$

$${y_i}^* = X_i\beta + \varepsilon_i \tag{2}$$

$$F(\varepsilon_i) = \frac{1}{1 + \exp(-\varepsilon_i)} \tag{3}$$

where,

i is the accident number;
y_i is the size of the ith accident, i.e., 1, 2, 3, or 4;
${y_i}^*$ is the hidden continuous dependent variable of the ith accident;
μ_1, μ_2, and μ_3, are the constant cut-off points, $\mu_1 \le \mu_2 \le \mu_3$;
X_i is the independent variable vector of the ith accident;
β is the regression coefficient vector;
ε_i is the random error of the ith accident, and follows a Logistic distribution.

Figure 3 shows the probability distribution of the ordered logit model. It can be found that, μ_1 is the cut-off point for determining whether the accident size is larger than 1, μ_2 is the cut-off point for determining whether the accident size is larger than 2, μ_3 is the cut-off point for determining whether the accident size is larger than 3.

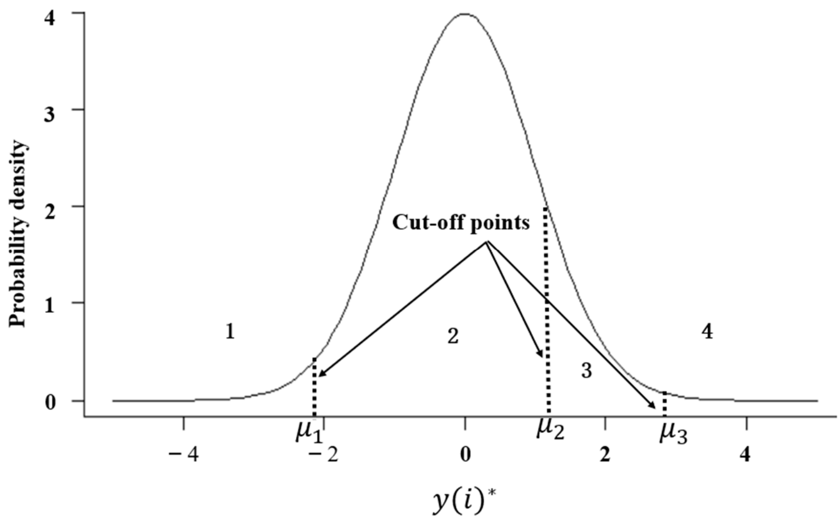

Figure 3. The probability distribution of the ordered logit model.

Therefore, the probability of each accident size can be calculated as shown in Equation (4). It can be found that when β is positive, with the increase of independent variables, the probability of accident size being 1 would decrease, and the probability of accident size being 4 would increase. That is, the accident size tends to be small; when β is negative, with the increase of independent variables, the probability of accident size being 1 would increase, and the probability of accident size being 4 would decrease. That is, the accident size tends to be large; when β is zero, it means dependent variables are insignificant.

$$\begin{cases} P(y_i = 1|X_i) = P(y_i{}^* \leq \mu_1|X_i) = F(\mu_1 - X_i\beta) \\ P(y_i = 2|X_i) = P(\mu_1 < y_i{}^* \leq \mu_2|X_i) = F(\mu_2 - X_i\beta) - F(\mu_1 - X_i\beta) \\ P(y_i = 3|X_i) = P(\mu_2 < y_i{}^* \leq \mu_3|X_i) = F(\mu_3 - X_i\beta) - F(\mu_2 - X_i\beta) \\ P(y_i = 4|X_i) = P(y_i{}^* > \mu_3|X_i) = 1 - F(\mu_3 - X_i\beta) \end{cases} \tag{4}$$

To ensure accuracy and reliability of the estimation results, the EV crashes are preprocessed first before making the regression analysis. First, crashes with unknown information are removed. Ultimately, 739 EV accidents are kept in regression analysis, and they account for 79.5% of the original data. Then, many variables have been reorganized to reflect their features more precisely. For instance, the day of week is reclassified into weekday and weekend; the time of day is divided into four categories, i.e., a.m. peak (7:00 a.m.–8:00 a.m.), daytime (9:00 a.m.to 2:00 p.m.), p.m. peak (3:00 p.m.–5:00 p.m.), and nighttime (6:00 p.m. to 6:00 a.m.), to better capture the different traffic operations at different times. Finally, collision type and accident category are not adopted, as they have very strong collinearity and might confound the estimation results. Table 2 provides a summary of the variables used in the regression analysis.

Table 2. A Summary of Variables Used for Regression Analysis to Accident Size.

Variable	Definition	Proportion
Dependent		
Accident size	Number of involved units—1	9.2%
	Number of involved units—2	73.2%
	Number of involved units—3	13.1%
	Number of involved units—≥4	4.5%
Independent		
Weekend	0 if it occurred on weekdays	80.4%
	1 if it occurred on weekends	19.6%
Time of day	AM peak (7:00 a.m.–8:00 a.m.)	11.8%
	Daytime (9:00 a.m.–2:00 p.m.) (Baseline)	32.3%
	PM peak (3:00 p.m.–5:00 p.m.)	32.1%
	Nighttime (6:00 p.m.–6:00 a.m.)	23.8%
Speed limit	Low (<50 km/h)	24.9%
	Medium (50~80 km/h) (Baseline)	50.3%
	High (≥80 km/h)	24.8%
Road location	Junction	43.7%
	Segment (Baseline)	56.3%
Presence of medians	Yes	24.0%
	No (Baseline)	76.0%
Visibility	Good visibility (Baseline)	78.9%
	Good visibility-rainfall/snowfall	15.0%
	Poor visibility	6.1%
Road surface conditions	Dry (Baseline)	61.0%
	Wet	28.3%
	Snowy/icy	10.7%

4. Results

The OLM is built in R with the "MASS" package [29,30], and the estimation results of the OLM are presented in Table 3. The findings indicate that most explanatory variables do not show statistically significant effects on the accident size, except time of day, speed limit, and presence of medians. The interpretation of the results is provided below.

Table 3. Estimated Results of the OLM for the EV Accident Size.

Variable	Value	Std. Error	*t* Value	95% Confidence Interval	Odds Ratio
Weekend	−0.367	0.218	−1.686	(−0.797, 0.057)	0.693
a.m. peak	−0.268	0.293	−0.914	(−0.845, 0.304)	0.765
p.m. peak	0.380	0.206	1.841	(−0.024, 0.786)	1.462
Nighttime	−0.489	0.237	−2.066	(−0.955, −0.027) *	0.614
Speed limit—Low	0.116	0.205	0.565	(−0.286, 0.517)	1.123
Speed limit—High	0.485	0.220	2.201	(0.053, 0.918) *	1.624
Junction	−0.128	0.180	−0.714	(−0.482, 0.224)	0.879
Presence of medians	0.809	0.207	3.901	(0.403, 1.216) *	2.246
Good visibility-Rainfall/Snowfall	0.188	0.299	0.630	(−0.397, 0.774)	1.207
Poor visibility	0.116	0.399	0.291	(−0.668, 0.893)	1.123
Road surface condition—Wet	−0.099	0.253	−0.391	(−0.596, 0.394)	0.906
Road surface condition—Snowy/Icy	−0.423	0.316	−1.340	(−1.041, 0.194)	0.655

Note: *, significant at 95% confidence interval.

4.1. Time Factors

The findings displayed in Table 3 suggest that the weekend is insignificant. That is, EV accidents occurring on weekdays and weekends do not show significant differences regarding the accident size. In terms of the time-of-day indicators, the a.m. peak and p.m. peak have insignificant effects either. Compared to the non-peak daytime period, a.m. and p.m. peaks feature by congested traffic with low speeds, and drivers are also expected to be more focused, making it unlikely to lead to large-scale severe traffic accidents. However, nighttime shows a significant negative effect, with the regression coefficient being −0.489. That is, compared to the non-peak daytime period, the EV accident size at night tends to be smaller. It is thought that while fatigue and other factors might increase the likelihood of accidents at night, traffic volumes are also expected to be much smaller, which means that nighttime accidents might only involve very limited units.

4.2. Roadway Factors

Regarding the speed limit, a high speed limit has a significant positive impact on the EV accident size, with the estimated parameter being 0.485 and the odds being 1.624. That is, EV accidents on high-speed roads are 62.4% more likely to involve one more unit than those on medium-speed roads. It is thought that high-speed roadways often have larger traffic volumes, along with faster travel speeds and more heavy vehicles, such as trucks, etc. As a result, accidents on high-speed roads might affect more vehicles, resulting in more severe consequences. Meanwhile, a low speed limit shows insignificant effects, which is also thought to be reasonable, as drivers are expected to be able to respond faster in low-speed scenarios to avoid severe traffic accidents.

In terms of roadway location, junctions do not show significant effects on the EV accident size. While junctions are often characterized by complex traffic environments with many conflict points, they are also subject to stricter traffic control measures, such as signal lights and cameras, which might somehow restrict the occurrence of severe crashes. In contrast, the presence of medians has significantly positive effects on accident size. Compared to EV accidents occurring on roadways without medians, those occurring on roadways with medians are 124.6% more likely to involve one more unit. It is thought that for crashes involving medians, vehicles need to run through all the lanes laterally, which increases the odds of colliding with vehicles on other lanes. Meanwhile, roadways with medians typically experience higher traffic volumes, which also easily leads to more units involved in accidents.

4.3. Environment Factors

Neither of the visibility indicators has significant effects on the EV accident size. Road surface condition indicators do not have significant effects either. This suggests that even in low-visibility or bad weather conditions, it might not necessarily result in a larger accident. This might be because drivers take extra precautions in such scenarios, carefully assess traffic conditions, and adjust accordingly to avoid mass accidents. Additionally, in these cases, many people may choose to adopt public transportation, which would reduce traffic flow and the occurrence of large-scale accidents.

5. Conclusions and Discussion

In the pursuit of sustainable development, many countries are working towards reducing energy consumption and emissions in transportation. As a result, vehicle electrification has gained momentum, leading to a great increase in the number of EVs on the road. However, the unique technical features of EVs, such as low noise, a single pedal, and quick acceleration, have also brought many new safety challenges. Aiming at EV safety, some studies have been conducted, but only a few of them focus on identifying the EV safety features with real accident data. Using the EV crash data from Norway from 2020 to 2021, this study aims to comprehensively figure out the features of EV traffic safety.

A description analysis is conducted first. In terms of collision type, rear-end collision is found to be the primary collision type of EV accidents, which is thought to be highly correlated to the one-pedal regenerative braking system of EVs. This study is one of the pioneering ones confirming the frequent occurrences of rear-end collisions for EVs with solid crash data. In terms of the accident category, up to 28.4% of EV accidents involve pedestrians/cyclists, which confirms that EVs pose a huge threat to those vulnerable road users [2,3]. It should be highly related to their silent engines. In addition, EV accidents are found to mainly occur during weekday peak hours, on medium- and low-speed roadways, in good visibility conditions, and on dry road surfaces. Then, this study establishes an ordered logit model to identify the key factors affecting the accident size, the surrogate of crash severity here. It is found that time of day, speed limit, and presence of medians have statistically significant impacts on the EV accident size. Compared to daytime, the EV accident size at nighttime is significantly smaller. As is known, there are far fewer vehicles on the road at nighttime. Researchers have demonstrated that traffic volume has a positive impact on accident size [16,18], as larger traffic volumes mean vehicles have larger chances to hit or run into other vehicles, leading to larger accident sizes. Therefore, EV crashes at nighttime are expected to involve fewer vehicles, leading to smaller accident sizes. Compared to medium- and low-speed roads, the EV accident size is significantly larger on high-speed roads. High-speed roads usually have larger traffic volumes and more heavy vehicles. In addition to the role of traffic volumes, heavy vehicles usually have larger sizes, larger masses, and longer stopping distances than passenger cars, which makes them easy to lose control in hard-braking scenarios. Therefore, when crashes occur, heavy vehicles are very likely to run off their lanes to collide with vehicles on other lanes. In addition, their cargos might also fall and pose serious threats to the following vehicles. Additionally, after crashes occur, it might also be hard for the following vehicles to bypass them safely due to their larger sizes. All these factors would contribute to the occurrence of multi-vehicle crashes. Actually, many studies have demonstrated that the involvement of heavy vehicles would greatly aggravate crash severity and increase accident size [17,18,22,31,32], and Reuben et al. even pointed out that trucks had the largest impact on increasing accident size [16]. At the same time, compared to roads without medians, the EV accident size on roads with medians was also found to be significantly larger, which is consistent with the finding of Reuben et al. [16]. It might be attributed to several facts. Firstly, like high-speed roads, roads installed with medians are also usually the high-class ones with larger traffic volumes and more heavy vehicles. Secondly, median-related crashes are found to be mainly caused by negligent/risky driving [33,34], as drivers may feel more relaxed and comfortable on median-divided roadways. In those situations, drivers might tend to change lanes frequently, speed, etc., all of which greatly increase the odds of colliding with other vehicles. Actually, another study has shown that crashes caused by drivers' faults are more likely to lead to multi-vehicle crashes, especially 3- or 4-vehicle crashes [17]. Thirdly, after vehicles collide with medians, it would also be hard for the following vehicles to bypass them smoothly in high-speed conditions due to the limited spaces around medians, easily leading to secondary crashes.

Based on the research results, some countermeasures can be formulated to address the EV safety issue. Firstly, considering the huge threat of EVs to pedestrians/cyclists, more distinguishable warning sound systems should be developed for EVs to alert pedestrians/cyclists in advance when EVs approach them. Secondly, aiming at the prevailing rear-end collisions, further studies are suggested to explore the role of the single-pedal regenerative braking systems of EVs. Meanwhile, installing a precise forward collision warning system to remind drivers to maintain a safe distance might also be beneficial. Thirdly, considering EVs are very likely to be ignited or explode in high-speed explosions, special attention should be paid to their safety on high-speed roadways.

Although this study conducts a comprehensive analysis of the Norwegian EV crashes and provides many new insights regarding EV safety, there are still some limitations. Firstly, inappropriate driver behaviors are often the direct causes of traffic accidents, but they may not be identified by the crash data. Naturalistic driving data has been widely proven to be valuable in analyzing driver behaviors under various scenarios [35,36], but most existing studies target ICEVs. Therefore, future studies may consider collecting the naturalistic driving data of EVs to figure out their risky driver behaviors. Compared to ICEVs, EVs are equipped with many more advanced sensors, which makes it easy to collect many types of driving data, such as coordinates, speed, acceleration, etc. Secondly, driver demographic features often play significant roles in traffic accidents, but due to privacy concerns, such information is unavailable here. Future studies should take them into account when they are available to identify the role of drivers. Thirdly, this data includes both PHEVs and BEVs, which may have different safety features. For example, PHEVs are still equipped with engines. However, they are not separated in this study. Future studies may make separate analyses of them to obtain more precise results when such information is available. Fourthly, to analyze the ordered categorical crash data like this study, the more advanced methodologies, such as the random parameters OLM [37], the heteroscedastic OLM [38], and the mediator OLM [39], have been proven to be more powerful than the ordinary OLM, but they also need more data to obtain credible estimation results. With the accumulation of EV crashes over time, future studies might adopt these methods to obtain more accurate results. Finally, it is important to compare EV crashes with ICEV crashes to comprehensively understand the model results. However, due to the policy issue, ICEV crash data are unavailable for this study. In the future, when ICEV crashes are available, it strongly suggests that a comparison of EV crashes and ICEV crashes should be made to precisely identify their differences.

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