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Are electric vehicles riskier? A comparative study of driving behaviour and insurance claims for internal combustion engine, hybrid and electric vehicles

Kevin McDonnell [a,*], Barry Sheehan [a], Finbarr Murphy [a], Montserrat Guillen [b]

[a] University of Limerick, Limerick KB3-040, Ireland
[b] Universitat de Barcelona, Av. Diagonal, 690, 08034, Barcelona, Spain

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ABSTRACT

Electric vehicles (EVs) differ significantly from their internal combustion engine (ICE) counterparts, with reduced mechanical parts, Lithium-ion batteries and differences in pedal and transmission control. These differences in vehicle operation, coupled with the proliferation of EVs on our roads, warrant an in-depth investigation into the divergent risk profiles and driving behaviour of EVs, Hybrids (HYB) and ICEs. In this unique study, we analyze a novel telematics dataset of 14,642 vehicles in the Netherlands accompanied by accident claims data. We train a Logistic Regression model to predict the occurrence of driver at-fault claims, where an at-fault claim refers to First and Third Party damages where the driver was at fault. Our results reveal that EV drivers are more exposed to incurring at-fault claims than ICE drivers despite their lower average mileage. Additionally, we investigate the financial implications of these increased at-fault claims likelihoods and have found that EVs experience a 6.7% increase in significant first-party damage costs compared to ICE. When analyzing driver behaviour, we found that EVs and HYBs record fewer harsh acceleration, braking, cornering and speeding events than ICE. However, these reduced harsh events do not translate to reducing claims frequency for EVs. This research finds evidence of a higher frequency of accidents caused by Electric Vehicles. This burden should be considered explicitly by regulators, manufacturers, businesses and the general public when evaluating the cost of transitioning to alternative fuel vehicles.

1. Introduction

By 2030, EV sales forecasts predict that 60 % of all new vehicle registrations will be Electric Vehicles (EVs) (International Energy Agency 2022). These figures suggest that there will be 350 million EVs sold, and thus 350 million EVs on our roads. EVs differ internally from their internal combustion engine (ICE) counterparts, as the electric motor feeds directly to the vehicle's wheels, increasing torque output. Further differences include single-pedal driving, automatic transmission and regenerative braking. Despite their substantial vehicle design and operational changes, no extensive analysis in the literature currently exist comparing the risk profiles and driving behaviours of EV, Hybrid (HYB) and ICE Vehicles. Unfamiliar vehicle operation, extended mileage capabilities, flammable battery materials, and a growing prevalence of EV usage on our roads expose the public to new risks. This study provides an in-depth risk analysis of EVs and HYBs, comparing their risk profiles and driver behaviours with their ICE counterparts. Additionally, leveraging a novel telematics and claims dataset of a fleet 14,642 Dutch drivers. This paper finds that EVs and HYBs incur more at-fault claims than ICEs and are costlier when considering first-party damages claims. Therefore, regulators, road safety authorities and current and prospective owners should know about these risks and demand strategies to mitigate these significant burdens.

Governments have introduced numerous policies and incentives to stimulate and grow EV sales in the EU, UK and US. For example, the availability of tax incentives or purchase grants reduces the initial vehicle costs and increases vehicle sales (Wee et al., 2018; Yan, 2018; Santos and Davies, 2020). For example, the EV/HYB share of newly registered vehicles in Europe in 2021 was 18 %, 12.5 % in the UK and 3.2 % in the US (US DOT, 2019; EEA, 2022; SMMT, 2023). However, despite these incentives, the long-term costs of EV ownership can diminish these initial savings as battery replacement costs or higher

* Corresponding author.
E-mail addresses: Kevin.McDonnell@ul.ie (K. McDonnell), Barry.Sheehan@ul.ie (B. Sheehan), Finbarr.Murphy@ul.ie (F. Murphy), mguillen@ub.edu (M. Guillen).

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insurance costs create a cost parity to ICEs (Parker et al., 2021).

EVs operate solely on electricity received from the battery pack. Accommodating the electric motor and battery pack in an EV requires alterations from the existing ICE design. These differences are primarily evident in engine operation, pedal control and fuel type. The EV engine differs significantly from its ICE counterpart by incorporating and maximizing power output from the electric motor. Unlike the ICE, the electric motor feeds directly into the vehicle's wheels independently, providing higher torque output (Emadi et al., 2008; Mutoh et al., 2008). Additionally, higher torque directly fed into each wheel significantly improves EV traction control and acceleration capabilities (Hori, 2004). EVs are automatic, further improving the acceleration profile of the vehicle. Despite the improvements in engine performance, the EV has reduced mileage capabilities compared to the ICE, requiring frequent and prolonged battery recharging. Methods to improve fuel performance, such as regenerative braking, can improve battery efficiency by 26 % (Liu et al., 2020). Regenerative braking recycles the kinetic energy produced during vehicle deceleration to charge the EV battery. Reducing contact with the accelerator starts the regenerative braking, allowing for complete accelerator/deceleration control from a single pedal. Single-pedal driving can accommodate 90 % of driving, with an additional brake for improved traction on a slippery surface or during an emergency (Xu et al., 2016).

Despite the unfamiliarity of single-pedal driving and regenerative braking, numerous studies suggest that driving behaviour improves when switching from ICE to an EV. For example, Rolim et al. (2013) describe drivers altering their behaviour by driving slower to preserve battery charge. Additionally, Labeye et al. (2016) found that regenerative braking assisted in drivers becoming more safety conscious, with 19 % of drivers altering their behaviour by anticipating distances and braking slowly. These findings are consistent with previous studies that describe drivers as feeling safer or better after using an EV (Friis and Gram-Hanssen, 2013; Helmbrecht et al., 2014; Ryghaug and Toftaker, 2014). However, despite improved driver habits, Labeye et al. (2016) identified that 22 % of drivers found the mental workload of operating and switching to an EV stressful compared to ICE. Also, the same study mentioned that gaining familiarity with EV vehicle controls caused a distraction. Additionally, a concern for EV drivers and pedestrians is the reduced noise of vehicle operation. Due to a reduction in engine and machine components, these inherent vehicle design differences between EVs and ICE reduce the noise created by the EV in motion, thus posing a potential risk to pedestrians (Cocron and Krems, 2013). A further study by Edwards et al. (2024) found that EV pedestrian causality rates are 2.76 times higher than those of ICE vehicles, indicating that pedestrian risk is justified.

Li-ion is commonly used in EV batteries, as this battery technology has been shown to improve range, reduce battery weight and increase energy density and capacity (Chen et al., 2012). However, unlike traditional battery technologies, Li-ion is more flammable. Numerous studies identify the risk of battery thermal runaway as a potential cause of increased fire danger in electric vehicles (Feng et al., 2018; Ouyang et al., 2019; Wang et al., 2019). For example, Hannan et al. (2017) identified that extreme temperatures affect battery performance, potentially leading to increased battery operating temperature and subsequent ignition. Additionally, failure of the EV battery may lead to the release of toxic and flammable materials (Sun, Bisschop, et al., 2020). These flammable materials pose an additional safety concern for the vehicle's occupants, as in the event of a traffic accident, physical damage to the battery pack exposes the occupants to significant fire risks (Victor Chombo et al., 2021). In the event of a fire, handling or extinguishing an EV fire is problematic. Wöhrl et al. (2021) identify the need to approach and prepare for EV fires differently compared to ICE.

In addition to potential fire risks, another consideration for prospective users, businesses and government agencies pivots on battery production and replacement costs. In numerous EV battery studies, researchers identified the electric battery cost between 33 % and 50 % of the vehicle (Zhou et al., 2011; Hannan et al., 2018; König et al., 2021). In their paper, Pelletier et al. (2017) determine that batteries require replacement when charging capacity lowers by 20 %. Additionally, Wikner and Thiringer (2018) discuss the implications of over-charging the electric battery, contributing to a 52 % degradation of the battery lifetime. For example, the expected lifetime of a battery is ten years (Pelletier et al., 2017; Wikner and Thiringer, 2018); this level of degradation can reduce this to 5 years, contributing to high battery replacement costs (McDonnell et al., 2021). Insurers are also exposed to these costs, as depending on the nature of a claim, a damaged battery may need replacement at the insurer's expense. However, despite the current risk of battery cost, there is an expectation that these costs will reduce as battery technology improves (Ding et al., 2019).

This study leverages granular driving movements recorded from a telematics device and insurance claims data to provide detailed profiles of driver risk during the operation of different vehicle fuel types. A telematics device records acceleration, deceleration, braking, cornering and GPS data. The telematics device can transmit these data to a central source via a sim card or save it locally for further analysis (McDonnell et al., 2021). The telematics device is a reliable and accurate mechanism to model driving behaviours (Siami et al., 2021). In addition, combining driver behaviour data with insurance policy claims further enhances the risk profiling capabilities of these devices, enabling the prediction of risky behaviours that leads to accidents (Guillen et al., 2019). These devices can also ascertain safe or eco-friendly driver profiles (Tseng et al., 2015; Bian et al., 2018), providing an in-depth view of altered driver behaviour when using EVs.

Within the insurance industry, bespoke insurance products, such as Usage-Based Insurance (UBI), leverage high-fidelity telematics datasets to obtain accurate risk prediction capabilities (Husnjak et al., 2015). For example, three separate studies by Baecke and Bocca (2017); Ayuso et al. (2019); Guillen et al. (2019) demonstrate an improvement in the predictive capabilities of their risk forecasting and pricing models when combining telematics and claims data. In particular, these studies identify, through the telematics device, dynamic changes in driver behaviour leading to accidents otherwise uncaptured without the device.

Following an extensive literature review, we found no extant research investigating EVs' and HYBs' risk profiles compared with ICE. By leveraging a novel telematics and accident claims dataset, this research highlights emergent differences in driver behaviour, at-fault claim likelihoods, and EV ownership's financial ramifications. We investigated whether risky driving behaviour profiles diverged according to vehicle fuel type (EV, HYB and ICE), such as harsh acceleration, braking manoeuvres, harsh cornering, and speeding violations. Additionally, we trained a Logistic Regression Model to deliver unique insights into divergent risk profiles between each vehicle fuel type. Our claims data supplements our analysis by providing claim statistics and finances. Thus, this research delivers greater awareness of the advantages and risks of adopting EVs for regulators, policyholders, businesses, and the general public. Furthermore, understanding the underlying trends of driver style and behaviour associated with EVs allows these stakeholders to make informed decisions about the future expansion of EVs.

2. Data

This study uses a novel telematics with associated insurance claims dataset recorded in the Netherlands from Jan 2022 to Oct 2022. The telematics data contains 125 million commercial fleet vehicle trips recording the vehicle's trip distance, duration of in transit, speed violations, and aggregated driving events such as harsh acceleration, braking, speeding and cornering manoeuvres. The dataset includes 14,642 vehicles, of which 2,174 are alternative fuel vehicles, i.e., EV and HYB. Of the 2,174 alternative fuel vehicles, 830 are EVs, and 1,344 are HYB. The rest of the 12,468 vehicles are ICE. There are a total of 71

features recorded by the telematics box. Of these 71 features, 30 variables are included in the study due to their completeness and relevance to the research objectives. Omitted variables include sensitive driver information, country codes and redundant time variables. Greenval DAC, a non-life insurer specializing in fleet insurance, provides access to this unique dataset. The driver's demographic data, such as age and sex, are unavailable due to the anonymization process.

The data used in this study contains aggregations of driver data at the trip level, where a trip defines the start and end of a journey. We pre-process the data by aggregating it based on a rolling average of variables per vehicle, an aggregated count, or an aggregated sum total. For example, the distance variable records the distance in kilometres travelled by the driver and the rolling average aggregates a driver's trip data over the observation period. Equally, we apply aggregated counts or sum totals to extract vehicle mileages, harsh manoeuvres events and trip counts. As an additional pre-processing step, we remove highly correlated values by calculating a correlation matrix of each variable and removing correlated variables greater than 0.95. Finally, we calculate the interquartile range of the data points, selecting values less than or equal to 75 %, thus removing anomalies and noise.

Extant research suggests that external driving contexts increase driver risk likelihood (Masello et al., 2023). Driving contexts refer to road conditions or type (highways, rural and urban roads), road speed, traffic conditions, daylight (day, dusk, night), and weather conditions. Our dataset contains road type, lighting conditions and speeding values. However, other contextual information, such as weather events and traffic information, is unavailable. Despite these missing factors, our dataset contains the most significant contextual factors for inferring driver risk (Abellán et al., 2013; Guillen et al., 2020; Masello et al., 2022, 2023). Table 1. contains detailed descriptions of the variables used in this study.

In addition to the telematics data, Greenval DAC has also provided claims data for risk analysis of EVs. The claims extract covers a period from Jan 2022 to June 2023. There are 12,424 claims spanning this period, with 4,703 claims linked to a telematics box from Jan 2022 to Oct 2022. Since this study compares the risk profiles of ICE and alternative fuel vehicles, we exclude non-crash-related claims. We define an at-fault claim as all First-party and Third-party damages and liabilities for which the offending vehicle's driver was responsible. Reducing the dataset to at-fault claims yields 3,318 claims associated with a telematics device. Given the 14,642 vehicles in the dataset, 22.66 % have an at-fault claim. These high percentages of at-fault claims for fleet or commercial vehicles are typical within fleet insurance research (Lynn and Lockwood, 1999; Wouters and Bos, 2000; Noll et al., 2020).

Finally, we extend our research to the potential financial burdens of alternative fuel vehicles, especially in the context of at-fault vehicle claims. Thus, we define first-party damages as the invoiced cost of vehicle repairs associated with an at-fault claim that has occurred. These first-party damages, therefore, provide further context to the previously unexplored risks of EVs and HYBs compared to ICE, particularly their financial implications. However, within the European Union, GDPR stipulates that sensitive information such as driver telematics data and policyholder data must undergo anonymization by a third party before being used for analysis Thus, we define first-party damages by the following intervals: [0–200], [200–500], [500–1,000], [1,000–5,000], [5,000–10,000] and [10,000 +]. Table 2 contains a breakdown of first-party damage costs of vehicles with an at-fault claim.

3. Methodology

This research presents a unique perspective on EVs' and HYBs' associated risks compared to ICEs. In particular, we focus on driving behaviour profiling, at-fault claims and first-party damage analysis. Comparing differences in behavioural profiles, claims, and finances provides a holistic view of imminent and extant vehicle risk when considering an alternative fuel vehicle. Thus, our methodology is as follows: Driver Behaviour Profiling, Claim Prediction and First-Party Damage Analysis.

Table 1
Telematics variables used in the study. All values are continuous numerical values unless specified. These are the aggregated trip values for each vehicle throughout the observation period. Values are aggregations of trip values where a trip defines the start and completion of a journey.

Variables	Descriptions	Data Type
Distance_mean	Mean distance travelled	Values recorded in kilometres
Distance(urban/road/highway)_mean	Mean distance travelled per road type	Values recorded in kilometres
Distance(daytime/innight/atdusk)_mean	Mean distance travelled per time of day	Values recorded in kilometres
Mileage_total	Total mileage travelled	Values recorded in kilometres
Mileage(urban/road/highway_total)_total	Total mileage travelled per road	Values recorded in kilometres
Mileage(daytime/innight/atdusk)_total	Total mileage travelled per time of day	Values recorded in kilometres
Harshaccelerationcount_mean	Mean count of harsh acceleration events	Numerical float value e.g. 1.1
Harshaccelerationcount_total	Aggregated total of harsh acceleration events	Numerical float value e.g. 1.1
Harshbrakecount_mean	Mean count of harsh braking events	Numerical float value e.g. 1.1
Harshbrakecount_total	Aggregated total of harsh braking events	Numerical float value e.g. 1.1
Giunstablespeed_mean	Mean risk score of unstable speeding events	Numerical float value e.g. 1.1
Giunstablespeed_total	Aggregated risk score of unstable speeding events	Numerical float value e.g. 1.1
Giexcessivespeedonsafety_mean	Mean risk score of excessive speeding events	Numerical values from 0 to 2
Giexcessivespeedonsafety_total	Aggregated risk score of excessive speeding events	Numerical float value e.g. 1.1
Lanechangecount_mean	Mean count of lane changes made	Numerical float value e.g. 1.1
Lanechangecount_total	Aggregated count of lane changes	Numerical float value e.g. 1.1
Corneringcount_mean	Mean count of harsh cornering events	Numerical float value e.g. 1.1
Corneringcount_total	Aggregated count of harsh cornering events	Numerical float value e.g. 1.1
Trip_count	Aggregated total of trips	Numerical value e.g. 1,2,3
Bodytype	Body type of vehicle	Sedan, Van, Estate, Coupe, Hatchback, Truck
Brand	Vehicle Brand	String column of brand
Fueltype	Type of fuel used by vehicle	Petrol, Diesel, Hybrid & EV

3.1. Driver behaviour profiling

Splitting the set of aggregated driver data into each fuel type category reveals the driver risk profiles for each subgroup. To infer statistically significant differences between the risk profiles of each subgroup, we implement a Student's *t*-test between EV vs ICE, EV vs HYB and ICE vs HYB. The Student's *t*-test compares the sample means of two sample groups and determines their relationship. If the p-value of the returned *t*-test is $p < 0.05$, we reject the null hypothesis that there is no statistical difference between the two groups. Alternatively, values greater than this threshold indicate that we fail to reject that there exists no difference between the two groups. **Equation (1).** contains a formal

Table 2
Detailed first-party damage costs for each fuel type with an associated at-fault claim. Each column contains the percentage distribution of first-party damages per fuel group.. 34% of HYBs and EVs have damages over €1,000. 72% of damages incurred by ICE are less than €1000 compared to 65% of EVs and HYBs.

	0—200	200—500	500 – 1000	0–1000 (Combined)%	1000—5000	5000—10000	1000—10000 (Combined %)	10000+
EV	38.56 %	12.94 %	13.77 %	65.27 %	31.95 %	1.65 %	34.7 %	1.1 %
HYB	44.81 %	6.64 %	14.06 %	65.51 %	31.83 %	1.85 %	34.45 %	0.77 %
ICE	43.3 %	14.09 %	14.57 %	71.96 %	26.42 %	1.45 %	28.01	0.14 %

definition of the Student's *t*-test.

$$t = \frac{\overline{x}1 - \overline{x}2}{\sqrt{(s^2\left(\frac{1}{n1} + \frac{1}{n2}\right))}} \tag{1}$$

Where t is the t statistic, x is the sample means of each group, s is the combined standard deviation, and n is the number of observations. Two assumptions relate to the *t*-test: 1) a similar variance between each group, and 2) two sample sizes are equal. The sample sizes for EV, HYB and ICE violate assumption two; additionally, each sample distribution is right-skewed, indicating an unequal variance between each group, violating the first assumption. Therefore, we employ Kruskal-Wallis H test to determine the statistical significance between the parameters of each fuel group. The Kruskal-Wallis H test is a ranked non-parametric version of the *t*-test test designed to compare two or more groups. Additionally, the assumptions and conditions of usage for the Krustal rank and signed sum test aligns with the distributions for EV, HYB and ICE driver profiles. For example, the following assumptions hold for this dataset:

1. Stipulates that the dependent variable is ordinal or continuous, i.e., higher values indicate increased levels of risk.
2. The independent variables are categorical (EV, ICE and HYB).
3. Independence of observations, or drivers do not migrate to another vehicle.
4. The groups do not follow a normal distribution.

Given these assumptions, this test is appropriate for our given dataset. **Equation (2)**. defines the Kruskal-Wallis H test.

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \tag{2}$$

Where N defines the total number of observations across all groups and k is the number of groups.R_i and n_i describe the sum of ranks for the sample in the ith group and the size of the ith group, respectively. The Kruskal-Wallis H test indicates whether there are statistical differences between each test group. However, as an omnibus method, the breakdown of how each group differs is not calculated. Therefore, a posthoc statistical test such as Dunn's Test provides further information about each subgroup (Dinno, 2015). Dunn's test performs pairwise calculations between each subgroup and returns alpha to signify their statistical difference.

3.2. Claim prediction

In addition to driver behaviour profiling, we gain a deeper understanding of a driver's potential and apparent risk through predictive analysis of at-fault claims. In this vein, we use a predictive model to ascertain any significant divergent at-fault claim likelihoods between each vehicle fuel group. A common approach to predicting at-fault claims is to employ a Generalized Linear Model. The GLM is a generalized form of the Linear Regression model, with the added benefit of choosing underlying distribution and link function. Additionally, the GLM is inherently interpretable, allowing for straightforward interpretation of model results (Guelman, 2012). Therefore, the GLM can assist in uncovering potential causes of at-fault claims. However, accident data are frequently heterogeneous and influenced by unobserved factors. Consequently, the application of random parameter logit models may be considered. However, such models are particularly appropriate for aggregated data, as demonstrated in the work of Anastasopoulos and Mannering (2011). Notably, these models are most effective when the response variable is not heavily imbalanced, which contrasts with our current dataset characterized by a substantial number of zero values. Thus, the selection of the Logistic Regression model remains appropriate.

We treat the prediction of at-fault claims as a classification problem, where at-fault claims occurred equals 1. The binomial distribution and logit link function are the most suitable for binary classification. These distribution and link function variants combine to create a Logistic Regression model. **Equation (3)**. provides a formal definition of a Logistic Regression Model.

$$p(x) = \frac{1}{1 + e^{-(\beta_{0+}\beta)_1 x}} \tag{3}$$

Where $p(x)$ defines the probability of the dependent variable equal to 1 given the characteristics x, and β_0, β are the parameters of the linear model and $(\beta_{0+}\beta)_1 x$ is the linear predictor that combines the parameters and the covariates. We define a baseline or reference value for the Logistic Regression model to ascertain whether there are divergent at-fault claim likelihoods between ICE, EV, and HYB. As the at-fault claims risk assessment of ICE is a well-researched area, we select ICE as a natural baseline value for our model. Any statistical deviations away from the risk profiles of ICE indicate either greater or reduced causal likelihoods. Additionally, the Logistic Regression model returns model coefficients and p-values, indicating the significance of a feature on model decisions. We train a separate Logistic Regression model for EV vehicles only to determine potential likely causes of at-fault claims when they occur. We train our models with an 80/20 train/test split, retaining sufficient data for training purposes and the remaining data for validation and generalization. During the training process, we perform cross-validation using F1 score to reduce the effects of class imbalance in this dataset. Additionally, we focus on F1 Score and Area Under the Curve to determine model performance.

3.3. First-party damage analysis

Finally, analyzing first-party damages of associated at-fault vehicle claims provides additional insight into determining the potential financial risks and burdens when switching to EVs or HYBs from ICE. As outlined in **Section 2**. we defined first-party damages and their subsection of at-fault claims within the dataset. We obtain the sample percentages between each interval of first-party damages for each fuel group to determine their allocation to a specific interval. For example, higher sample percentages within the lower intervals for first-party damages indicate a lower impact of financial risk to the policyholder. Conversely, higher percentages allocated to more extreme intervals of first-party damages indicate a significant financial burden to the policyholder.

4. Results

4.1. Driver profiles

Driver behaviour studies comparing ICE to EVs reveal that single-pedal usage and increased acceleration exhibit different or altered driving behaviours in drivers of EVs (Labeye et al., 2016). Therefore, we investigated whether risky driving behaviour profiles diverged according to vehicle fuel type (EV, HYB, ICE), such as harsh acceleration, braking manoeuvres, harsh cornering, and speeding violations. Table 3 contains the median values for each harsh manoeuvre group. Comparing the median values of the distributions of harsh manoeuvres reveals that EVs have fewer harsh events than ICE but record more harsh events than HYBs for cornering, acceleration, and braking. However, the harsh acceleration averages for EV and ICE differ only by 0.03. EV drivers have the lowest median value of each speeding distribution, with a value of 0.14. HYBs and ICE score 0.16 and 0.2, respectively. HYBs have the lowest median values for all other harsh event distributions; conversely, ICEs record the highest median values. Fig. 1 contains the driver profile distributions for each harsh manoeuvre.

As defined in **Section 3**. we employ Kruskal-walis and Dunn's test to determine if statistically significant differences exist between each distribution of the mean harsh manoeuvres per trip. The results from the Kruskal-walis tests reject the null hypothesis of no difference between each distribution, indicating differences between these groups' driver profiles. Further, employing a posthoc test such as Dunn's identifies the groups with the most significant differences. Table 4 and Table 5 contain the results of each test for the Kruskal-Walis and Dunn's tests. These tests reveal that each group differs significantly from the other for all harsh manoeuvre distributions, with all p-values less than the threshold for statistical significance. These results further strengthen the assertion of different risk profiles for a given vehicle fuel type. Comparing and analyzing claims data for each vehicle fuel type will reveal how these different driver profiles translate to potential crash risk.

4.2. At-fault claim and first-party damages analysis

In conjunction with the driver behaviour profile analysis, this research has access to a unique claims dataset described in **Section 2**. Our results highlight critical information describing divergent risk profiles from EVs and HYBs compared to ICE. Firstly, when we analyze the at-fault claims made by each vehicle fueltype, we find that HYBs and EVs have made 5.8 % and 3.2 % more at-fault claims than ICE. For additional context, we highlight mileage as a traditional key risk indicator, whereby higher road exposure increases the likelihood of experiencing a claim. (Ayuso et al., 2019). However, both HYB and EV have lower average mileages than ICE but have a higher percentage of at-fault claims, indicating that the lower average mileages do not offset road exposure risk.

Additionally, we consider first-party damages to be an indicator of potential financial risk experienced by a policyholder in the event of an at-fault claim. Our results reveal that EVs and HYBs have the highest first-party damage costs compared to ICE. For example, 34.7 % of EVs and 34.45 % of HYBs incur first-party damage costs greater than €1,000, a 6.7 % and 6.45 % increase in costs compared with ICE vehicles. Additionally, 2.75 % of EVs and 2.26 % of HYBs incur first-party damage costs of over €5,000 compared to 1.59 % of ICEs.

Table 3
Median values for harsh manoeuvres per trip for each fueltype. HYBs have the lowest median acceleration, braking and cornering events. EVs record the lowest median speeding profiles. However, the difference between EV and ICE harsh acceleration distributions is minimal. ICE has the largest median values per harsh event category.

	Acceleration	Braking	Speed	Cornering
EV	1.25	0.32	0.14	1.79
HYB	0.87	0.29	0.16	1.63
ICE	1.28	0.34	0.20	1.94

4.3. Logisitc regression model results

Our Logistic Regression, defined in **Section 3.2**, uses ICE as a reference or baseline value and approximates the at-fault claim likelihoods of EVs and HYBs against this norm. Thus, our model plays a crucial role in identifying the potential increase or decrease in risk when switching to an EV or HYB. Our results show that EVs return a model coefficient of 0.2108 and a p-value of 0.015. Conversely, HYBS return a model coefficient of 0.075 and a p-value of 0.281. These results show that EVs demonstrate divergent at-fault claim probabilities from ICEs with increased expected risk. HYBs do not show statistical significance and share risk profiles similar to ICEs. Additionally, we highlight the model's performance metrics to endorse the authenticity of our results. The model returns an adjusted r2 score, log loss and Akaike Information Criterion of 0.036, −7573.9 and 0.01. Due to the heavy class imbalance within this dataset, AUC and F1-Score are more appropriate for validating model performance. The model scores an AUC of 0.62 and an F1 score of 0.41. The AUC score indicates the model could accurately separate 62 % of the classes of at-fault claims and no claim incurred. The F1-score is a combined measure of recall and precision, and thus, the model has moderate success at identifying true negatives and positives. These combined results indicate that the model could predict positive (at-fault claims) and negative (no claims) with moderate success. For completeness, we tested XGBoost, Random Forest, and SVM Machine Learning models. These models obtained scores similar to those of our Logistic Regression model. For example, Logistic Regression shares the highest AUC-ROC and F1-Score with Random Forest and XGBoost, respectively. Additionally, when considering interpreting model scores and output, the Logistic Regression model is inherently interpretable compared with Machine Learning models (Verbelen et al., 2018; Sun, Bi, et al., 2020; McDonnell et al., 2023). As a result, we chose the LR model to proceed with the analysis. The ML model results are contained in Table A.1. When comparing our results against the AUC scores of Logistic Regression models used in telematics studies, we find that our results are within the range of 0.5 to 0.6 Paefgen et al. (2013), Baecke and Bocca (2017) and Pesantez-Narvaez et al. (2019). Table 6 displays the model's coefficients and p-values and performance metrics.

We trained an additional Logistic Regression model using only EVs to determine the possible causes of increased at-fault claim likelihoods. This EV-only model identifies trip distances as significant to an increase in at-fault claim likelihoods, with a coefficient value of 2.04 and a p-value of 0.027. These results align with other highly cited research identifying mileage or road exposure as a key indicator of increased claim risk (Lemaire et al., 2016; Ayuso et al., 2019). The EV-only model returns an AUC score of 0.55 and an F1 score of 0.36. Table 7 displays the coefficients and p-values from the EV-only model.

5. Discussion

5.1. Driving behaviour profiles

Driver behaviour studies comparing ICE to EVs reveal that single-pedal usage and increased acceleration exhibit different or altered driving behaviours in drivers of EVs (Friis and Gram-Hanssen, 2013; Helmbrecht et al., 2014; Ryghaug and Toftaker, 2014; Labeye et al., 2016). Therefore, there is an expectation that statistical differences exist between the driver behaviours of each fuel group. We use a mix of Kruskal Wallis and Dunn's Test to ascertain if there are significant statistical differences in the means of some telematics trip information for each driver. Our results show that the Kruskal-Wallis test rejects the null hypothesis of equality of the mean per trip distribution between all harsh manoeuvre groups, indicating statistical differences between the

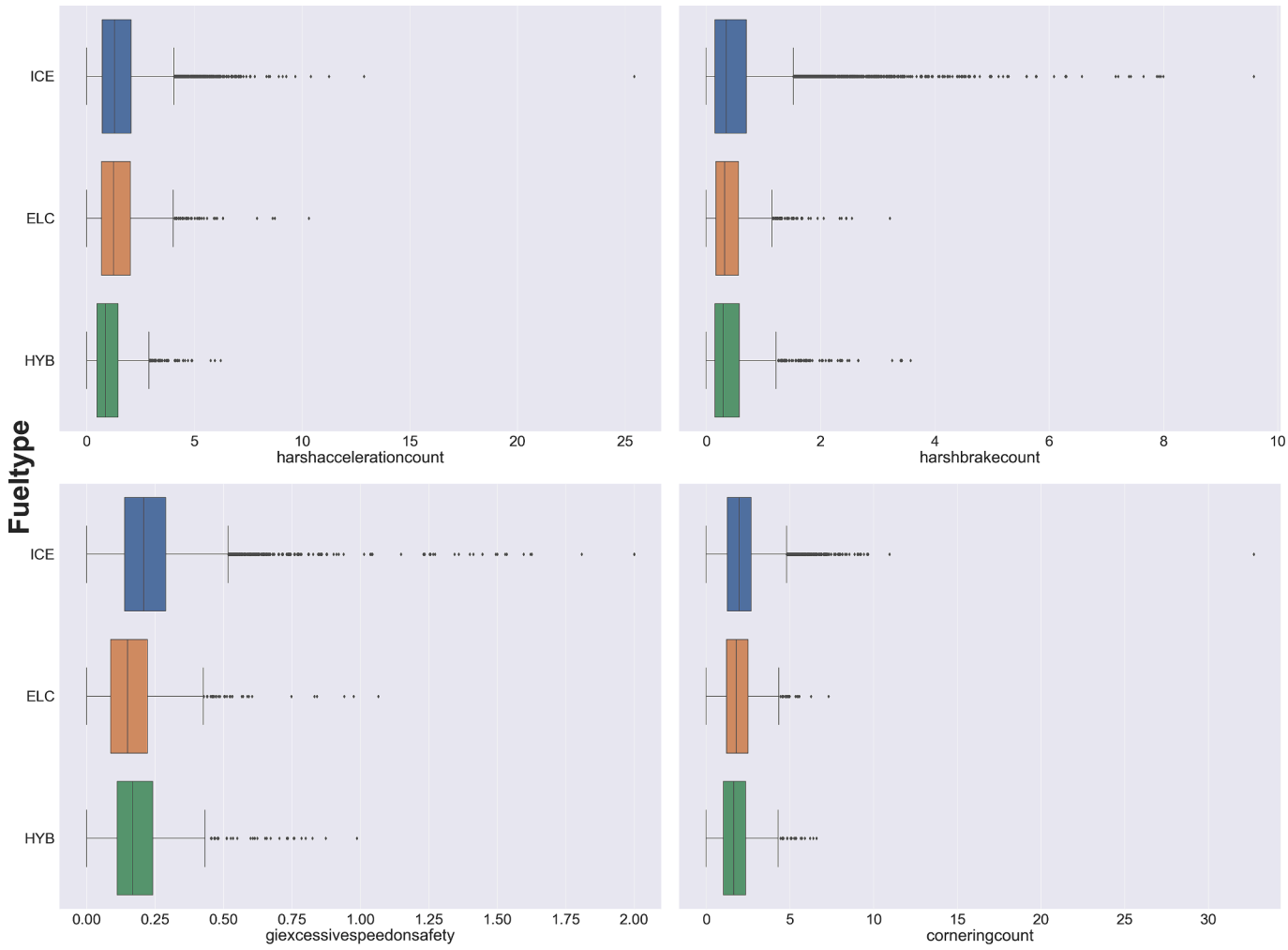

Fig. 1. Boxplots of harsh manoeuvres for each fuel group. ICE consistently has the largest median of each group. EVs have similar trends to ICE, but record the lowest median values for speeding. HYB records the lowest median values for harsh acceleration, braking and cornering events. The blue distribution represents ICE, orange EV and Green HYB.

Table 4
Results of the Kruskal-Wallis H test containing p-values for each fuel group tested. Where values are less than 0.05, reject the null hypothesis of no statistical difference between groups. Values displayed are p-values for each harsh manoeuvre. All values are less than the threshold of 0.05, indicating a strong statistical difference between each group. A posthoc test such as Dunn's Test will reveal the statistical difference between each group.

	Acceleration	Braking	Speed	Cornering
EV vs HYB vs ICE	<0.01	<0.01	<0.01	<0.01

Table 5
Results for Dunn's Test for each group. Where values are less than 0.05, reject the null hypothesis of no statistical difference between groups. Each group is orthogonal, signifying only a difference between each distribution. Only EVs and HYB show no statistical difference for harsh braking profiles. All other p-values are less than the 0.05 threshold and thus signify a statistical difference between each group.

	Acceleration	Braking	Speed	Cornering
EV vs ICE	<0.01	<0.01	<0.01	<0.01
EV vs HYB	<0.01	**0.52**	<0.01	<0.01
ICE vs HYB	<0.01	<0.01	<0.01	<0.01

Bolded values indicate values where p-value is greater than 0.05.

distributions for each fuel group. Using Dunn's test, we gain deeper insights into the specific differences for each group rather than the omnibus Kruskal-Wallis method. Dunn's test reveals that the distribution of the means per trip of harsh manoeuvres between each fuel group show statistical differences except for the harsh braking profiles of EVs vs. HYBs. In this case, Dunn's test fails to reject the null hypothesis of no change, indicating that these distributions are similar. Our results indicate that a driver's inherent driving behaviour changes when switching vehicle fuel type, whereby EVs and HYBs show substantial statistical differences from ICEs.

5.2. Claims and driver profile analysis

Mileage has traditionally assisted transportation researchers in inferring the likelihood of a driver's at-fault claim (Paefgen et al., 2013; Ayuso et al., 2019). Our analysis of each fuel type shows that EVs and HYBs have lower average mileages than ICE. In isolation, the lower recorded mileages in EVs and HYBs and their driver profiles suggest that ICEs should have a higher probability of incurring an at-fault claim than alternate energy fuel-type vehicles. However, the claims data contrasts this assumption by providing evidence of increased at-fault claim occurrences in EVs through predictive modelling and risk analysis. Despite HYBs recording a 6 % increase in at-fault claims compared to ICE, our Logistic Regression model showed no divergence in risk profile to ICE. The contrast between apparent safer driver behaviours and actual

Table 6
Returned model coefficients and p-values form the Logistic Regression model. We hold ICE as a baseline or reference value and include an intercept. EVs show statistical significance and an increase in at-fault claim likelihood compared to ICE. HYBs do not show statistical significance, and we accept the null hypothesis of no change. The model scores 0.601 AUC and 0.41 F1 Score.

Parameters	Coefficients	P>|z|
Intercept	−1.2991	0.000
EVs	0.2108	**<0.05**
HYBs	0.0754	0.281
Distance_mean	0.4345	0.139
Distanceurban_mean	−0.0509	0.591
Distanceroad_mean	−0.1407	<0.05
Distancehighway_mean	0.2107	0.298
Distancedaytime_mean	−0.2682	0.129
Distanceatdusk_mean	0.0328	0.800
Mileage_total	0.1795	0.656
Mileageurban_total	0.2180	0.142
Mileagehighway_total	−0.2371	0.154
Mileageday_total	0.0131	0.964
Mileagedusk_total	−0.0602	0.311
Mileagenight_total	−0.2663	0.096
Harshbrakecount_mean	0.2098	0.051
Lanechangecount_mean	−0.1602	0.061
Corneringcount_mean	−0.1353	0.213
Harshbrakecount_total	0.0839	0.516
Lanechangecount_total	0.0908	0.351
Coneringcount_total	0.1935	0.229
Giunstablespeed_mean	−0.1885	**<0.05**
Giexcessivespeedonsafety_mean	−0.1822	0.063
Giunstablespeed_total	0.0884	0.565
Giexcessivespeedonsafety_total	0.2597	0.106
Trip_count	−0.1293	0.381
Model results with 10-fold CV		
AUC	0.62	
F1-Score	0.41	

Bolded values indicate p-values less than threshold of 0.05.

Table 7
The model coefficients and p-values form the EV-only Logistic Regression model. The mode highlights distance_mean as statistically significant for an increase in EV-related at-fault claims. The model scores 0.55 AUC and 0.36 F1 Score.

Parameters	Coefficients	P>|z|
Intercept	−1.1695	0.000
Distance_mean	2.0424	**<0.05**
Distanceurban_mean	−0.2220	0.486
Distanceroad_mean	−0.2614	0.123
Distancehighway_mean	−0.5299	0.427
Distancedaytime_mean	−1.0970	**<0.05**
Distanceatdusk_mean	−0.4284	0.310
Mileage_total	−0.6692	0.760
Mileageurban_total	0.0765	0.885
Mileagehighway_total	0.5127	0.553
Mileageday_total	0.7880	0.628
Mileagedusk_total	−0.2289	0.447
Mileagenight_total	−0.0929	0.890
Harshbrakecount_mean	0.2427	0.568
Lanechangecount_mean	0.0558	0.861
Corneringcount_mean	−0.3794	0.344
Harshbrakecount_total	−0.2673	0.634
Lanechangecount_total	−0.1676	0.632
Coneringcount_total	0.8624	0.177
Giunstablespeed_mean	−0.0731	0.806
Giexcessivespeedonsafety_mean	−0.4472	0.275
Giunstablespeed_total	−0.4130	0.550
Giexcessivespeedonsafety_total	0.6974	0.278
Trip_count	−0.4931	0.274
Model results with 10-fold CV		
AUC	0.55	
F1-Score	0.36	

Bolded values indicate p-values less than threshold of 0.05.

recorded claims data suggests that although EVs exhibit fewer harsh manoeuvres than ICE, these behaviours do not translate into reducing the driver's risk of claiming an at-fault incident. Instead, EV drivers have a higher chance of incurring an at-fault claim than ICE.

We further illustrate EVs' increased at-fault claim potential compared to ICE when considering urban mileage. Vehicles with high exposure to urban environments record higher at-fault claim potentials than vehicles with limited exposure (Guillen et al., 2019). Therefore, urban mileage exposure may inadvertently account for the increased EV at-fault claims liklihoods. However, our model accounts for this by including urban mileage covariates. The results in Table 6 show no discernable differences between the urban road exposures of ICE and EVs, indicating that an increase or decrease in urban road exposure did not affect our results. Our findings contrast a study by Edwards et al. (2024), which found a rise in EV pedestrian casualties, particularly in urban settings. Regardless of urban road exposure, EVs demonstrate an increased at-fault claim and pedestrian risk likelihood than ICEs.

Research on driver contexts finds that weather events, road types, traffic conditions, and daylight contribute to risk and may influence at-fault claims within our study. However, when analyzing the EV-only model, our results show a negative correlation between daytime driving and increased likelihood of at-fault claims. Equally, the global model returns a statistically significant negative correlation between distance travelled on rural roads and at-fault claims. When comparing these models, EVs show reduced risk when driving during daytime hours but do not share the global reduction in risk when travelling on rural roads. In both models, no other driver contextual variable was statistically significant. Missing factors such as weather or traffic information may improve our models. However, driver context studies find that dry conditions show the highest risk outcomes (Mihăiţă et al., 2019; Masello et al., 2022, 2023), a conclusion mirrored in a European report in the Netherlands, where our dataset originates. External factors influence driver risk, and despite the unavailability of some of these contextual factors, our model includes the most prevalent features.

Our results from the Logistic Regression model reveal that EV drivers are more susceptible to risk and have higher chances of experiencing an at-fault claim than ICE. Therefore, it is prudent to investigate the likely cause of at-fault claims to explain the increased risk. Our EV-only model identifies trip distances as statistically significant to increasing at-fault claim likelihoods. In essence, the more road exposure experienced by EV drivers greatly increases their risk compared to an ICE driver. When considering that EVs have shorter achievable driver distances due to battery limitations and lower average mileage than ICE, EV drivers will likely experience more at-fault claims with less mileage than ICE. However, a study by Elvik (2023) finds that the accident rate declines as a function of miles driven; thus, more EV mileage may reduce EV at-fault claims. Given the marginal difference in the mileages of EVs vs ICE (12,555 km/year for EVs vs 14,371 km/year for ICE), the at-fault claims for EVs may experience a slight reduction in the at-fault claim rate with increased mileage but still have an overall higher rate than ICE. Additionally, our findings contradict previous EV driving behaviour studies, where EV drivers felt safer after becoming familiar with EV controls and having more experience with the vehicle (Helmbrecht et al., 2014; Labeye et al., 2016).

5.3. Financial implications of EV ownership

In addition to our claim analysis, we conducted a first-party damage analysis to investigate the potential and unexplored financial risks of EV and HYB ownership. Our first-party damage analysis reveals that a third of all EVs and HYBs at-fault claims resulted in costs of over €1,000 compared to 28 % for ICE. When considering the replacement costs and operating lifetime of EV batteries, current owners and prospective buyers face significant costs as high as one-third of the cost of the vehicle (König et al., 2021). Given the increased likelihood of incurring an at-fault claim with less mileage and significant first-party damages and

battery costs, alternative energy vehicles are riskier with a higher financial burden than ICE.

Our research demonstrates that first-party damages for EVs are significantly higher than those of ICE. Combining these findings with emerging fire safety concerns in previous EV-related studies paints a pessimistic view of alternative energy vehicles, exposing current and prospective buyers to increased financial and individual risks (Hannan et al., 2017; Sun, Bisschop, et al., 2020). Some progress towards reducing the costs associated with EV batteries, such as Solid-State batteries, may reduce the financial burden of replacing or repairing EVs (Sun, 2020).

5.4. Societal considerations

Our results present an emergent risk for consumers, businesses, and policymakers when considering EVs due to their increased at-fault claim probabilities and financial hurdles. In contrast to these risks, EV adaptation can reduce greenhouse gas (GHG) emissions compared with ICE, as demonstrated in environmental research (Canals Casals et al., 2016; Un-Noor et al., 2017; Wu et al., 2018). Our findings place a significant responsibility on manufacturers, insurers, regulators, and academics to mitigate the expected adverse effects of EV adoption and ownership in terms of increased at-fault claims and financial costs. For example, updating non-life insurance models for EVs would protect policyholders against undue financial burdens while protecting non-life insurance lines of business with more appropriate premium pricing. Additionally, current EU, UK and US legislation focuses on battery charging facilities and financial incentives for EVs with no outlook on EV risk (Capuder et al., 2020; Singh et al., 2020). Legislative authorities should consider the risks presented in this research when developing legislation and driver risk mitigation strategies. Recognizing these risks would help introduce a safer driving experience and promote EV adoption. For example, nascent EU regulation on mandatory ADAS systems could alleviate the burden of EV driver risk (European Union, 2024); equally, the potential introduction of reduced replacement battery costs and improved battery performance may reduce EV's financial burdens.

6. Conclusion

This research investigates alternative energy vehicles' previously unexplored risks by comparing driver profiles, analyzing vehicle at-fault claims data, and first-party damage costs compared to traditional ICE vehicles. EVs have inherently different engine, transmission, and pedal control designs than ICEs, leading to inherently different driving profiles and harsh manoeuvres. However, despite recording fewer harsh driving events, these do not translate into reducing EV at-fault claims. In contrast, EV drivers have a higher chance of experiencing an at-fault claim than ICE drivers. Equally, our research finds that despite their lower average mileage than ICE, lower road exposure for EV drivers does not reduce their risk of experiencing an at-fault claim. When analyzing at-fault claims, we find a 4 % increase in crashes from EVs and a 6 % increase for HYBs compared to ICE. However, when tested with a Logistic Regression model, HYBs do not display any further concerns of increased at-fault claim risk. These results indicate that EVs have a higher risk profile than traditional ICE vehicles.

Our research shows drivers' driving behaviour changes significantly when switching to HYBs or EVs. Using Kruskal Wallis, we reject the null hypothesis of no statistical differences between groups for the distribution of mean harsh events per trip. When testing the distributions of each fuel type using Dunn's test, we find that all returned p-values are less than the 0.05 threshold, and thus, we reject the null hypothesis of no change. These results indicate that the driving profiles of each group differ significantly, with HYBs consistently showing the most significant change. EVs share similar characteristics (particularly in harsh acceleration) to ICE but demonstrate fewer harsh events overall, with HYBs having the fewest harsh driving events per trip.

Our research extends the usage of two Logistic Regression models to uncover potential divergent risk profiles between ICE, EV and HYB. Our model identifies EVs as having a statistically significant different risk profile against a reference value of ICE. These results mean EVs are more likely to experience an at-fault claim than ICE. Additionally, we train a further EV-only Logistic Regression model to uncover the causes of these increased EV at-fault claims and find that trip distances are a significant causal factor. Our models obtain an AUC score of 0.62 and 0.55 for global and EV-only models with an F1 Score of 0.41 and 0.36, respectively.

Further investigation into first-party damage costs reveals that over one-third of EVs and HYBs incur damages of over €1,000 when being involved in an accident. When considering the battery and potential replacement costs, these values indicate a significant financial burden to current and prospective buyers of EVs. Combining these financial burdens with our risk analysis and emerging fire risks of lithium-ion batteries indicates that EVs and HYBs contribute significant risk to their owners, policymakers and businesses. Without intervention from the aforementioned stakeholders and manufacturers, EV and HYB drivers will experience a higher likelihood of at-fault claims and substantial first-party damages compared with traditional ICE vehicles. This increase in driver risk will create a barrier to alternate fuel vehicle adoption, rendering previous efforts ineffective.

A limitation of this study is the absence of traffic, weather, driver demographic, and policyholder information. However, we assume that fleet insurance's homogeneous nature reduces this potential bias. Further research should contrast EVs' safety benefits and risks with the potential climate benefits of EV adoption.

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Kevin McDonnell: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Barry Sheehan:** Writing – review & editing, Supervision. **Finbarr Murphy:** Writing – review & editing, Supervision, Funding acquisition. **Montserrat Guillen:** Writing – review & editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

Appendix

Table A.1
The returned scores for all Machine Learning models tested against the EV dataset. Results also include GLM for comparison. GLM and Random Forest obtain highest AUC-ROC score, with Random Forest socring higher in recall. Equally, the GLM shares the highest F1-Score value with XGBoost.

	Precision	Recall	F1-Score	AUC-ROC	Accuracy
Decision Tree	**0.30**	0.51	0.38	0.58	0.61
Random Forest	0.27	**0.77**	0.40	**0.62**	0.46
XGBoost	0.28	0.76	**0.41**	0.50	0.63
SVM	0.22	0.50	0.37	0.55	0.22
GLM	**0.30**	0.59	**0.41**	**0.62**	0.58

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