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Influence of Vehicle Characteristics on Driving Events Based a Naturalistic Driving Experiment

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Abstract

This paper aims to evaluate the impact of vehicle characteristics on risky driving behavior, focusing on harsh acceleration and deceleration events, within the framework of the H2020 project i-DREAMS. Given the substantial impact of human factors on safe driving behavior, the i-DREAMS project developed a ‘Safety Tolerance Zone (STZ)’ to define the boundary where self-regulated control can be maintained safely. The study utilizes a CatBoost model to analyze data collected from a naturalistic driving experiment with 48 drivers and 4922 trips in total, conducted in three phases: baseline monitoring, post-trip interventions, and a gamification process. The goal is to understand how different vehicle attributes affect aggressive driving behavior under varying conditions. The results indicate that certain vehicle characteristics significantly influence the frequency of harsh events, with the intervention phases showing an impact on driver behavior. Specifically, older vehicles and those with higher engine capacity and horsepower are more likely to engage in acceleration events, where the phase of the experiment and the vehicle's engine capacity have an impact on the existence of the deceleration events. These findings underscore the importance of considering vehicle attributes in designing effective safety interventions and highlight the potential of post-trip feedback to enhance road safety.

Keywords: Vehicle characteristics; Driving behavior; CatBoost model; Safety interventions

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1. Introduction

Road safety is a critical concern worldwide, as road crashes claim the lives of millions and cause countless injuries each year (Singh et al., 2018). Factors such as human behavior, road design, vehicle safety features, environmental conditions, and socioeconomic disparities significantly influence the occurrence and severity of road crashes (European Commission, 2019). A substantial portion of these crashes can be attributed to driver behavior, making it a vital area of focus in traffic safety research (Ivers et al., 2009). In response, the World Health Organization (WHO) and the European Union have set a goal to reduce road crashes by 50% from 2021 to 2030, with a focus on leveraging new technologies to achieve this target (European Commission, 2019; WHO, 2019; Singh et al., 2018).

The integration of automotive telematics and driver monitoring systems provides real-time feedback and safety interventions, which are crucial for improving driver behavior (Petraki et al., 2024). Moreover, advancements in autonomous vehicles and intelligent monitoring systems hold promise for enhancing road safety by minimizing human

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error and creating safer road environments. Thus, the synergy between emerging technologies and behavioral analysis is pivotal in promoting sustainable mobility and achieving significant reductions in road crash fatalities.

Understanding the factors that influence driving behavior is critical for improving road safety and enhancing driver experience. The three main factors contributing to road crashes are the road user, the road environment, and the vehicle, with driver behaviour being the main cause of 95% of road crashes (Singh et al., 2018) and the vehicle being a factor in a smaller proportion of 8.5% of road crashes (Yannis et al., 2018). Among these factors, vehicle characteristics play an important role. Previous research has demonstrated that the design and performance attributes of a vehicle can significantly impact how drivers respond to different driving conditions (Fung et al., 2017). For example, the vehicle's acceleration and deceleration patterns can be used to identify individual drivers and understand their driving behavior. This method has shown promise in distinguishing between drivers based on their naturalistic driving data collected over extended periods (Fung et al., 2017). However, there is limited understanding of how these characteristics interact with external stimuli, such as mobile messages and gamification strategies, to influence driving behavior.

Numerous studies have focused on understanding the impact of various factors on unsafe driving and have sought to develop suitable models for identifying risky driving behavior and establishing intervention frameworks within vehicles. While there have been proposals for various interventions during and post-trip the personalization of these interventions and a direct connection between real-time driving behavior and intervention activation remain areas for improvement. The use of machine learning models, such as Long Short-Term Memory (LSTM) and Gate Recurrent Unit (GRU), for predicting vehicle acceleration based on driving behavior has shown potential in improving the accuracy of these interventions by considering individual driving habits (Zou et al., 2022). Additionally, implementing driver behavior profiling using various smartphone sensors and machine learning techniques can further enhance the understanding of driving patterns and support the development of real-time safety interventions (Fung et al., 2017).

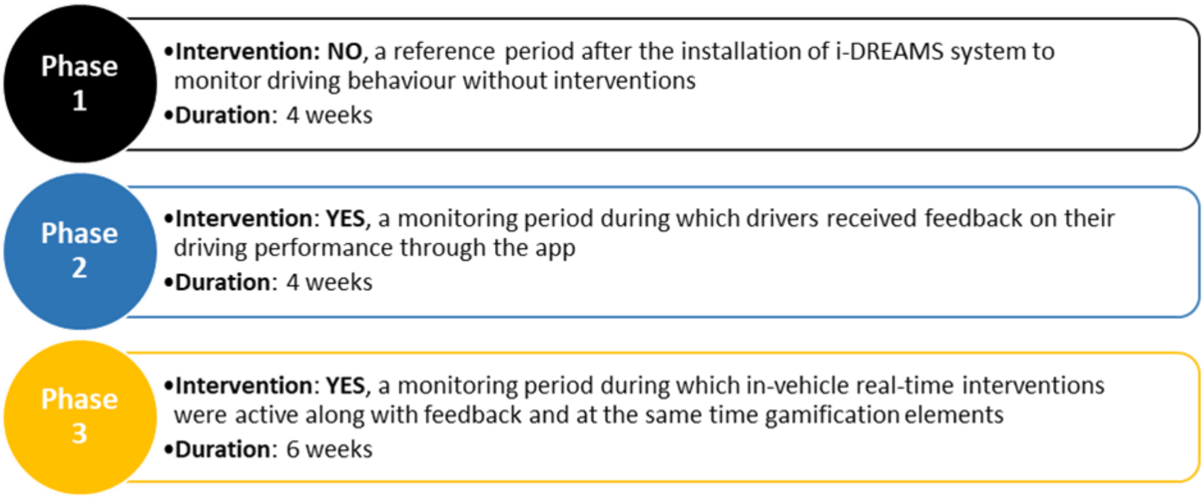
Considering the importance of post-trip interventions, the overall aim of the European Union’s Horizon 2020 i-DREAMS project was to set up a platform and system that provides timely interventions to keep drivers in a safe driving area. Specifically, i-DREAMS aims to setup a framework for the definition, development and validation of a context-aware ‘Safety Tolerance Zone (STZ)’ for driving. The experimental design of the i-DREAMS on-road study conducted in Athens, Greece consists of three Phases, the baseline phase during which the driving behaviour is monitored without receiving any interventions in case of risky driving, and the other two Phases during which post-trip interventions are provided to the drivers.

In line with the primary objective of the i-DREAMS project, this study aims to explore the dynamic interplay between vehicle characteristics and driver behavior, particularly focusing on how different vehicle attributes influence acceleration and deceleration events under various conditions. By leveraging machine learning models, the study seeks to uncover patterns that can inform the design of targeted safety interventions. Through a comprehensive analysis of data from the i-DREAMS project, the study endeavors to contribute valuable insights into the development of personalized and real-time safety measures aimed at reducing road crashes and enhancing overall traffic safety.

The paper is structured in the following manner. At the beginning, a detailed introduction to the project and its general objective is highlighted with a literature review presented concerning the analysis of driving behavior. The research methodology is outlined, including the explanation of collecting the data and the theoretical foundations of the underlying models employed. Finally, the results of the study are presented, followed by significant conclusions regarding the effect of vehicle characteristics and phase on the driving behavior derived from the acceleration and deceleration events.

1.1. The i-DREAMS naturalistic driving experiment in Greece

Phase 1 served as the baseline phase, where driving behavior was monitored without interventions for risky driving events. This phase aimed to establish a comparison between driving behavior with and without safety interventions. The baseline measurements were conducted over a 4-week duration. Phase 2 spanned four weeks and involved post-trip interventions. The i-DREAMS post-trip interventions can be qualified as digital-or internet-based interventions via app and are to be understood as combining e-coaching with virtual coaching. Finally, in Phase 3, which lasted six weeks, gamification features were introduced to the drivers. Unlike the previous phase, drivers were rewarded or received benefits for practicing safe driving behavior. A competitive element was introduced through the leader board function.



Phase 1

- **Intervention: NO**, a reference period after the installation of i-DREAMS system to monitor driving behaviour without interventions
- **Duration**: 4 weeks

Phase 2

- **Intervention**: **YES**, a monitoring period during which drivers received feedback on their driving performance through the app
- **Duration**: 4 weeks

Phase 3

- **Intervention**: **YES**, a monitoring period during which in-vehicle real-time interventions were active along with feedback and at the same time gamification elements
- **Duration**: 6 weeks

Fig. 1. The i-DREAMS on-road experiment interventions

The system employed flexible thresholds to determine the STZ status, which defines three risk levels: low (crash risk is minimal), medium (risk of crash increases as internal /external events occur), and high (crash risk is further increased if no preventative action taken by driver). In the framework of this paper, it must be noted that events are presented in the following two severity levels ‘medium’, and ‘high’, which correspond to the ‘Danger’ and ‘Avoidable crash’ driving Phases of the STZ.

Table 1. Phases of the STZ.

STZ level	Driving Phase	Description	Interventions
1	Normal driving phase	Crash risk is minimal	no real-time interventions were necessary
2	Danger phase	Risk of crash increases as internal /external events occur	a visual warning like a message is presented
3	Avoidable crash phase	Crash is very likely to occur if no preventative action taken by driver	a more intrusive instruction signal (e.g., visual warnings like flashes and auditory warnings like beeps) is provided

The primary objective of the i-DREAMS platform is to maintain drivers in the normal driving phase as much as possible. When this isn't achievable, the platform aims to prevent the transition from the danger phase to the avoidable crash phase.

1.2. The data selection

A naturalistic driving experiment was carried out involving 48 drivers from Greece and a database of 4922 trips was created. The dataset captures a comprehensive view of driving behavior across the three different Phases of the experiment (Phase 1, Phase 2, and Phase 3). The naturalistic driving experiment driving data collected concerns a variety of data about Safety Promoting Goals (SPG) and Performance Objectives (PO). The SPG refer to behaviours that can be logically linked to the safety outcomes, based on existing empirical evidence. It must be noted that the acceleration and deceleration events results are summarized in a total number which derives from the 'high' and 'medium' events (10).

Table 1. Descriptives of events per 100 km for SPG and PO

Safety Promoting Goals	Performance Objectives	Severity Level	Events per 100 km					
			Baseline Phase		Post-trip Phase		Post-trip & Gamefication Phase	
			Mean	STD	Mean	STD	Mean	STD
Speed Management	Speeding	Medium	7	15	6	14	6	13
		High	25	33	24	32	21	29
Vehicle Control	Acceleration	Medium	3	10	4	13	2	9
		High	1	11	2	9	2	9
	Deceleration	Medium	6	15	6	14	5	13
			3	11	3	11	3	9
Driver Fitness	Distraction	n/a	23	60	23	57	17	48
Distance (km) per trip		n/a	9	15	8	15	10	18
Duration (min) per trip		n/a	17	15	17	14	18	15

The vehicle characteristics were collected through a questionnaire administered to participants. This questionnaire included detailed questions about various aspects of their vehicles, such as brand, model, age, fuel type, engine capacity, horsepower, and gearbox types. Participants were asked to provide specific information on their vehicles, ensuring a diverse set of features for analysis. This data allows for an in-depth examination of how different vehicle attributes and intervention Phases influence driving behavior, particularly focusing on acceleration and deceleration events. The purpose of the i-DREAMS interventions is to effectively increase driver safety by supporting drivers in their driving task.

2. Methods

For the analysis, Categorical Boosting (CatBoost) algorithms were employed. Gradient Boosted Decision Trees (GBDTs) are a powerful tool for classification and regression tasks in Big Data. CatBoost, short for categorical boosting, is a powerful supervised ML algorithm developed by Yandex, specifically designed to handle categorical features effectively. Since its debut in late 2018, researchers have successfully used CatBoost for machine learning studies involving Big Data. Furthermore, as a Decision Tree based algorithm, CatBoost is well-suited to machine learning tasks involving categorical, heterogeneous data. Another important feature of CatBoost is its sensitivity to hyper-parameters and the importance of hyper-parameter tuning (Hancock et al., 2020).

CatBoost is based on gradient boosting of decision trees and uses one-hot encoding to handle categorical data. Like XGBoost, CatBoost also encompasses multiple Classification and Regression Trees (CART). Its adaptability and effectiveness have made it a top performer in numerous ML competitions. CatBoost is designed for increased speed, accuracy, and ease of use (Prokhorenkova et al., 2018). The core boosting technique in CatBoost is based on the superimposition of new tree models in the errors and residuals of previous models. The tree ensemble is then combined to reach the final prediction. The loss function of CatBoost includes two terms: (i) a training loss term and (ii) a regularization term to control model complexity and prevent over-fitting (Dorogush et al., 2018). In essence, CatBoost applies a mapping function between variables, where a regression tree ensemble model uses a number of functions K additively to predict y, so that (Prokhorenkova et al., 2018):

$$\hat{y} = \varphi(x_i) = \sum_{k=1}^{K} f(x_i) \tag{1}$$

Where $\hat{y}$ is the predicted value of the original dependent (or response) variable y and $x_i$are the independent (or explanatory) n variables across i observations. The loss function expresses the distance between training data and predicted values and is defined as $l(\hat{y}_i, y_i)$. A common choice of l is the mean squared error for a set of parameters φ_i (Friedman, 2001):

$$l(\varphi_i) = \sum_{\iota=1}^{I} (\hat{y}_i - y_i)^2 \tag{2}$$

A penalizing term,$\Omega(f)$, is also introduced for model complexity control such that:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \|c\|^2 \tag{3}$$

Where γ, λ are penalizing coefficients, T is the number of leaves in the regression tree. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf, creating a flowchart, and c is the weight assigned to each leaf. Splits refer to the decision points in the decision tree where the data is divided based on feature values. Each split creates branches that lead to further subdivisions, ultimately resulting in a tree structure where the leaves represent the final predicted values. Having obtained the loss function, $l(\hat{y}_i, y_i)$, and the penalizing term, $\Omega(f)$, the objective function can be formulated as:

$$L(\varphi_i) = \sum_{i=1}^{I} l(\hat{y}_i, y_i) + \sum_{k=1}^{K} \Omega(f) \tag{4}$$

As with most ML methodologies, CatBoost features a number of tunable model hyperparameters that can be optimized before or during cross-validation of results, such as (CatBoost, 2022):

- Learning rate: Governs the magnitude of iterations for minimizing the cost function.
- Depth: Governs the maximum depth of the tree.
- L2_leaf_reg: L2 regularization term on weights.
- Bagging temperature: Controls the amount of randomness in bagging.
- Border count: Number of splits for numerical features.
- Random strength: Controls the intensity of randomness when scoring splits.

Following good ML practices, the hyperparameters of CatBoost algorithms should be tuned initially before their final executions, and their predictions should subsequently be evaluated with model evaluation metrics. The highly non-linear, tree ensemble structure of CatBoost makes it resilient against bias from multicollinearity effects (Hancock, 2020). For classification algorithms, model performance is evaluated by the predictive performance of each configuration in terms of correct classifications. In binary classification, this is mainly supported by the confusion matrix of the test subset and the related ROC-AUC scores. It should be noted that CatBoost is robust to multicollinearity compared to linear models, like many other tree-based algorithms, and is not bound on the assumption of independence between features.

3. Results

The i-DREAMS project dataset was analyzed using CatBoost algorithms to predict harsh acceleration and deceleration events, with the results presented in this section. The analyses were conducted using Python, following the guidelines provided by the CatBoost development team (CatBoost, 2022) and Prokhorenkova et al. (Prokhorenkova et al., 2018). The dataset was split into training and test subsets with an 80%-20% ratio, maintaining similar class distributions for the dependent variables. This resulted in a substantial number of observations for both training and test subsets, ensuring robust model evaluation.

Given the class imbalance in the dataset as demonstrated in Figure 2, Synthetic Minority Over-Sampling Technique (SMOTE) was applied. The imbalanced class could potentially affect the model’s performance. SMOTE was used to generate synthetic samples for the minority class, thus balancing the class distribution and improving the model’s ability to generalize across both classes.

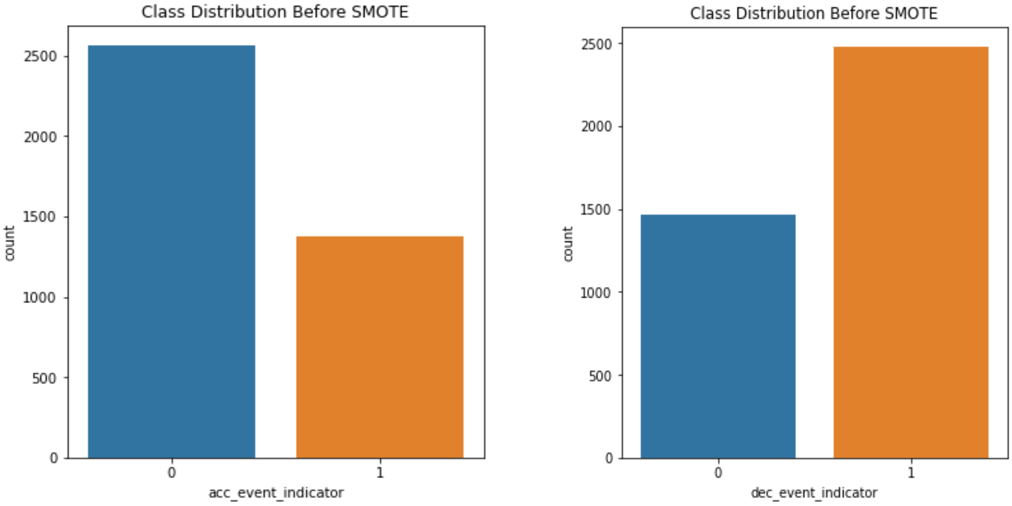


Fig. 2. (a) Class Imbalance for the acceleration event; (b) Class Imbalance for and deceleration event

Hyperparameter tuning with 5-fold cross-validation was carried out to mitigate overfitting and enhance the model´s performance for harsh acceleration and deceleration events. The objective was to determine the internal model configuration that provided the highest classification accuracy. The process of selecting, running, and comparing these combinations was automated using available Python libraries (scikit-learn, pandas, NumPy). The optimized hyperparameters of the final CatBoost model for harsh and medium acceleration and deceleration events are presented in Table 3.

The manual fine-tuning and optimization were conducted to ensure the best possible performance of the CatBoost model in predicting harsh acceleration and deceleration events, providing a robust and reliable tool for analyzing and improving road safety measures in the context of the i-DREAMS project. The detailed results and performance metrics of the optimized CatBoost model are discussed in the following sections. Once the optimal model was determined, feature importance metrics were extracted for the contributing variables. Given the observed modest class imbalance in the dataset, class weights were adjusted to investigate potential predictive performance improvements.

Table 3. Hyperparameter Tuning Results for CatBoost Model of Harsh Acceleration and Deceleration events

Hyperparameter	Examined range	Optimized Value for Harch Acceleration events	Optimized Value for Harch Deceleration events
Learning rate	0.01 - 0.29	0.1	0.1
Iterations	150 - 450	150	450
Depth	3 - 11	3	11
L2 Leaf Reg.	1-10	10	1
Subsample	0.4-0.99	0.4	0.4
Border Count	32-128	32	128
Class Weights	{0: 0.5, 1: 10}	{0: 1.0, 1: 0.785}	{0: 1.0, 1: 0.5}
Random State	Fixed at 42	42	42

The feature importance analysis provides insights into which variables have the most significant impact on predicting harsh acceleration and deceleration events. The gain metric, shown in Table 4, measures the importance of each feature in the dataset based on the total gain of the splits in which the feature is used. A higher gain value indicates a more substantial impact on the model's predictions.

3.1. CatBoost Results for Acceleration Events

Table 4. CatBoost optimized model feature importance based the Acceleration Indicator

Hyperparameter	Examined range	Optimized Value
1	Vehicle Age	28.323
2	Vehicle Brand	17.258
3	Horsepower	15.928
4	Vehicle Model	14.700
5	Engine CC	9.158
6	Gearbox Type	6.543
7	Phase	4.646
8	Fuel type	3.440

It is evident that the most significant feature influencing the model's predictions is "Vehicle Age," with a substantial importance score compared to other features. This indicates that older vehicles are more likely to experience harsh acceleration events. Following this parameter, "Vehicle Brand" and "Engine Capacity" are also crucial predictors, suggesting that the design and performance attributes of a vehicle significantly affect driving behavior. "Horsepower" has a substantial gain importance score, highlighting its impact on driving aggressiveness. "Gearbox Type" and "Fuel Type" also play significant roles, indicating the influence of these characteristics on driving patterns. The "Phase" of the experiment (baseline, post-trip, gamification) also emerged as a significant factor, with different Phases affecting driver behavior differently.

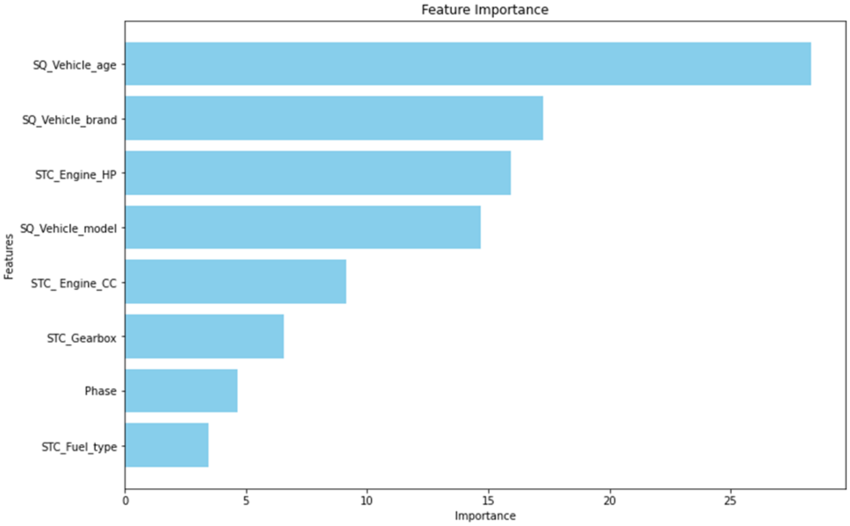


Fig. 3. CatBoost Feature Importance Plot for Acceleration Events

3.2. Model Performance Evaluation for Acceleration Events

The model's performance on the test set was evaluated using precision, recall, and F1-score metrics for each class, along with overall accuracy. These metrics provide a comprehensive understanding of how well the model distinguishes between risky and non-risky driving events.

For the class representing non acceleration events, the model achieved a precision of 0.76, indicating that 76% of the instances predicted as non acceleration events were correctly identified. The recall for this class was 0.83, meaning the model correctly identified 83% of all actual non acceleration events. The F1-score, which balances precision and recall, was 0.79 for non acceleration events, demonstrating a high level of accuracy in predicting these events.

For the class representing acceleration events, the precision was 0.61 indicating that 61% of the instances predicted as acceleration events were correctly identified. The recall for risky events was 0.50, meaning the model correctly identified 50% of all actual risky instances. The F1-score for acceleration events was 0.55, reflecting moderate performance in predicting these events.

The overall accuracy of the model was 0.70, suggesting that the model correctly predicts the occurrence of harsh and medium acceleration events 70% of the time. The macro average for precision was 0.68, providing an unweighted average of the model's performance across both classes. The weighted average, which accounts for the class imbalance, indicated that the model maintains a precision of 0.71, recall of 0.71, and F1-score of 0.71 across the dataset.

Table 5. Classification Report (Acceleration Events)

	0 (No acc. events)	1 (acc. events)	
precision	0.76	0.61	0.73
recall	0.83	0.50	0.72
f1- score	0.79	0.55	0.72
Accuracy			0.70
Macro avg	0.68	0.68	0.68
Weighted avg	0.71	0.71	0.71

The confusion matrix provides an overview of the model's performance in predicting harsh and medium acceleration events. The model accurately identified a significant number of non-acceleration events (true negatives) and risky events (true positives), demonstrating its ability to classify driving behaviors effectively. However, there were instances of misclassification, with some non-risky events predicted as risky (false positives) and vice versa (false negatives). Despite these misclassifications, the model shows a balanced ability to distinguish between risky and non-risky driving events, which is crucial for developing effective safety interventions.

Table 6. Confusion Matrix (Acceleration Events)

	Predicted No acc. events	Predicted acc. events
Actual Non Acc. Events	538	109
Actual Acc. Events	170	168

3.3. CatBoost Results for Deceleration Events

Table 7. CatBoost optimized model feature importance based the Deceleration Indicator

Hyperparameter	Examined range	Optimized Value
1	Phase	25.730
2	Vehicle Brand	16.547
3	Engine CC	14.330
4	Horsepower	12.727
5	Vehicle Age	11.615

6	Vehicle Model	10.374
7	Gearbox Type	6.221
8	Fuel type	2.452

The most significant feature influencing the model's predictions, as demonstrated in Table 7 and Figure 4, is "Phase," with a substantial importance score compared to other features. This indicates that the different Phases of the experiment (baseline, post-trip, gamification) significantly affect driver behavior and the driver´s deceleration events. Following this parameter, "Vehicle Brand" and "Engine CC" are also crucial predictors, suggesting that the design and performance attributes of a vehicle significantly affect driving behavior. "Horsepower" has a substantial gain importance score, highlighting its impact on driving aggressiveness. "Vehicle Age," "Vehicle Model," "Gearbox Type," and "Fuel Type" also play significant roles, indicating the influence of these characteristics on driving patterns.

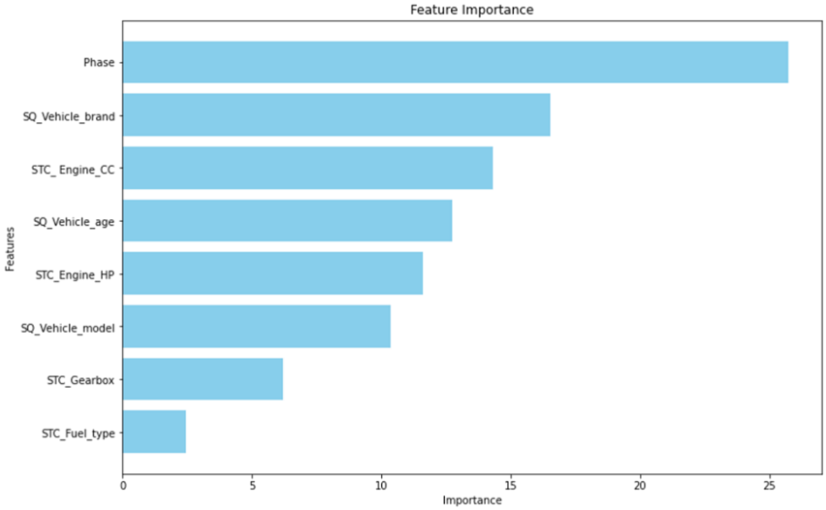


Fig. 4. CatBoost Feature Importance Plot for Deceleration Events

3.4. Model Performance Evaluation for Deceleration Events

For the class representing non deceleration events, the model achieved a precision of 0.50, indicating that 50% of the instances predicted as non deceleration events were correctly identified. The recall for this class was 0.46, meaning the model correctly identified 46% of all actual non deceleration events. The F1-score, which balances precision and recall, was 0.48 for non deceleration events, reflecting moderate performance in predicting these events.

For the class representing deceleration events, the precision was 0.66 indicating that 66% of the instances predicted as deceleration events were correctly identified. The recall for risky events was 0.69, meaning the model correctly identified 69% of all actual risky instances. The F1-score for deceleration events was 0.67, reflecting a higher performance comparing to non deceleration events.

Table 8. Classification Report (Deceleration Events)

	0 (No dec. events)	1 (dec. events)	
precision	0.50	0.66	0.59
recall	0.46	0.69	0.60
f1- score	0.48	0.67	0.60
Accuracy			0.60
Macro avg.	0.58	0.58	0.58

Weighted avg.	0.59	0.60	0.60

The confusion matrix in Table 9, as presented below, provides a detailed summary of the model´s performance in predicting harsh and medium deceleration events. The model successfully identified a significant number of non deceleration events (true negatives) and risky events (true positives), indicating its ability in classifying driving behaviors accurately.

Table 9. Confusion Matrix (Deceleration Events)

	Predicted No acc. events	Predicted acc. events
Actual Non Acc. Events	183	211
Actual Acc. Events	185	406

4. Discussion

This study evaluated the impact of vehicle characteristics on driving behavior derived from the acceleration and deceleration events from the naturalistic experiment of i-DREAMS, conducted in Athens, Greece, with the dataset of a number of 4922 trips from 48 drivers. The catboost algorithm proved effective in analyzing the complex interactions between various vehicle attributes and driving events.

The analysis revealed that vehicle age, brand, engine capacity, horsepower, gearbox type, and fuel type are important predictors of harsh acceleration events. Older vehicles were more likely to experience aggressive driving behaviors, a finding consistent with previous research proving that vehicle age can influence driver behavior due to its potential deterioration of vehicle performance over time (Fung et al., 2017). Similarly, the impact of engine capacity and horsepower on driving aggressiveness aligns with studies highlighting the role of vehicle performance attributes in risky driving behaviors (Zou et al., 2022).

For harsh acceleration events, the phase of the experiment emerged as the most significant predictor, indicating that different intervention Phases (baseline, post-trip, gamification) significantly have an impact on the driving behaviour. This finding supports the effectiveness of interventions included in different Phases and modifying driving behaviors, as observed in a number of studies (Zaira et al., 2017). The impact of vehicle brand, engine capacity, and horsepower on deceleration events further underscores the role of vehicle performance in driving behaviors.

Comparing the results of this study with other studies, the CatBoost model's performance in predicting harsh and medium acceleration and deceleration events had an overall accuracy of 72% and 60% accordingly. The use of SMOTE and class weight adjustments helped address class imbalance, a common challenge in modelling driving behaviours (4). Although, the model's moderate performance suggests the need for additional factors such as real-time driving conditions and driver's state, which might have an important role and could be included in the future research.

The confusion matrix analysis highlighted the model´s balanced ability to distinguish between the existence or not of acceleration and deceleration events, despite some misclassifications. This balance is critical for developing effective safety interventions, as accurately predicting the events can give an important input in the timely and targeted interventions to prevent crashes. Findings from studies using machine learning models to predict driving behaviors, where a balance between precision and recall is essential for practical applications (Prokhorenkova et al., 2018).

4. Conclusions

This study evaluated the impact of vehicle characteristics on driving behavior derived from the acceleration and deceleration events from the naturalistic experiment of i-DREAMS, conducted in Athens, Greece, with the dataset of a number of 4922 trips from 48 drivers. The CatBoost algorithm was utilized to analyze the data from the experiment.

The findings of this research highlight the significant impact of vehicle age, brand, engine capacity, horsepower, gearbox type, and fuel type on the acceleration events indicator. As for the case of the deceleration events, the Phase of the experiment was the most critical factor, emphasizing the importance of phased interventions.

The moderate performance of CatBoost model in predictions of risky driving events underscores the complexity of driving behaviors and the need for integrating additional factors, such as real-time conditions and drivers' state, into the models. Thus, a limitation of this research is the lack of the psychological traits of drivers and the real-time external conditions, such as weather, traffic density, or road conditions, which can have an impact on the driving behavior. Moreover, another limitation is the limited dataset consisting of 48 drivers from the city of Athens, a specific geographic location that might affect the generalizability of the results. Future studies should include a larger and more diverse sample to enhance the findings.

Future research should focus on addressing these limitations. Incorporating a broader range of variables to enhance model accuracy, such as the real-time driving conditions and driver´s state is very important and can provide very interesting results. Additionally, exploring the use of other advanced machine learning algorithms could provide further insights into the complex dynamics of driving behaviors. The insights gained from this study can inform the development of targeted and personalized safety interventions, ultimately contributing to the reduction of road crashes and the enhancement of traffic safety.

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References

CatBoost, 2022. Retrieved from CatBoost: https://catboost.ai/en/docs/concepts/parameter-tuning

Dorogush, A. V., Ershov, V., & Gulin, A. (2018). CatBoost: gradient boosting with categorical features support. arXiv preprint arXiv:1810.11363.

European Commission. EU Road Safety Policy Framework 2021–2030 - Next Steps towards "Vision Zero", 2019.

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. Annals of statistics, 1189-1232.

Fung, Nathanael C., et al. "Driver identification using vehicle acceleration and deceleration events from naturalistic driving of older drivers." 2017 IEEE International Symposium on Medical Measurements and Applications (MeMeA). IEEE, 2017.

Hancock, J. T., & Khoshgoftaar, T. M. (2020). CatBoost for big data: an interdisciplinary review. Journal of big data, 7(1), 94.

Ivers, R., T., Senserrick, S., Boufous, M., Stevenson, H. Y., Chen, M., Woodward, and R., Norton. Novice drivers' risky driving behavior, risk perception, and crash risk: findings from the DRIVE study. American Journal of Public Health, 2009, 99(9), 1638-1644.

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). CatBoost: unbiased boosting with categorical features. Advances in neural information processing systems, 31.

Singh, S. (2018). Critical reasons for crashes investigated in the National Motor Vehicle Crash Causation Survey. (Traffic Safety Facts Crash Stats. Report No. DOT HS 812 506). Washington, DC: National Highway Traffic Safety Administration.

Unveiling driving behaviour patterns during a naturalistic driving experiment, Virginia Petraki, Stella Roussou, Christos Katrakazas, Muhammad Adnan, Kris Brijs, Tom Brijs, George Yannis, 2024, 10th Transport Research Area Conference, Dublin, Ireland, April 15-18, 2024.

World Health Organization. Global action plan on physical activity 2018-2030: More Active People for a healthier world. World Health Organization, 2019.

Yannis G., (2018, November). "Road Crashes, Road Behaviour and Safety", Institute of Public Health.IBI S.A. & NAMA S.A., 2009. General Transport Plan of Athens, Final Project Report Prepared for the Athens Urban Transport Organization, Athens

Zaira, M. M., & Hadikusumo, B. H. (2017). Structural equation model of integrated safety intervention practices affecting the safety behaviour of workers in the construction industry. Safety science, 98, 124-135.

Zou, Yajie, et al. "Vehicle acceleration prediction based on machine learning models and driving behavior analysis." applied sciences 12.10 (2022): 5259.