Comparative Analysis of Machine Learning Models for Predicting Risky Driving Behaviors from a Naturalistic Experiment

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Background

- Factors such as driver's state, environmental conditions, and traffic circumstances remain significant contributors to traffic collisions.
- Road crashes mainly result from driver behavior, but vehicle features also play a role.
- Previous research has demonstrated that the design and performance attributes of a vehicle can significantly impact how drivers respond to different driving conditions.
- Intelligent driving behavior monitoring systems enable real-time interventions and demonstrate remarkable efficacy in improving road safety
- Horizon 2020 i-DREAMS project: framework to define a Safety Tolerance Zone (STZ) and test interventions in real driving conditions.
- This study used naturalistic driving data from 48 drivers across 4,922 trips.
- This study focuses on predicting risky driving behaviors (harsh acceleration/deceleration) using machine learning models (CatBoost, Random Forest, XGBoost).

Objectives

- Compare predictive performance of ML models (CatBoost, XGBoost, Random Forest).
- Evaluate the influence of vehicle characteristics on risky driving behavior.
- Identify the most influential vehicle attributes (age, engine capacity, horsepower, fuel type, gearbox, brand).
- Assess the effect of phased interventions (baseline, post-trip feedback, gamification) on risky events.
- Provide evidence for data-driven safety measures and support personalized interventions to improve road safety.

Data Collection

Data sources:

- In-vehicle monitoring systems: **harsh acceleration, harsh deceleration**, speeding, distraction.
- **Driver questionnaires**: vehicle brand, model, age, fuel type, engine capacity, horsepower, gearbox.
- Dataset enriched with: safety-promoting goals (SPG), performance objectives (PO), intervention phase.
- Sample: **48 drivers in Greece; 4,922 trips recorded**.

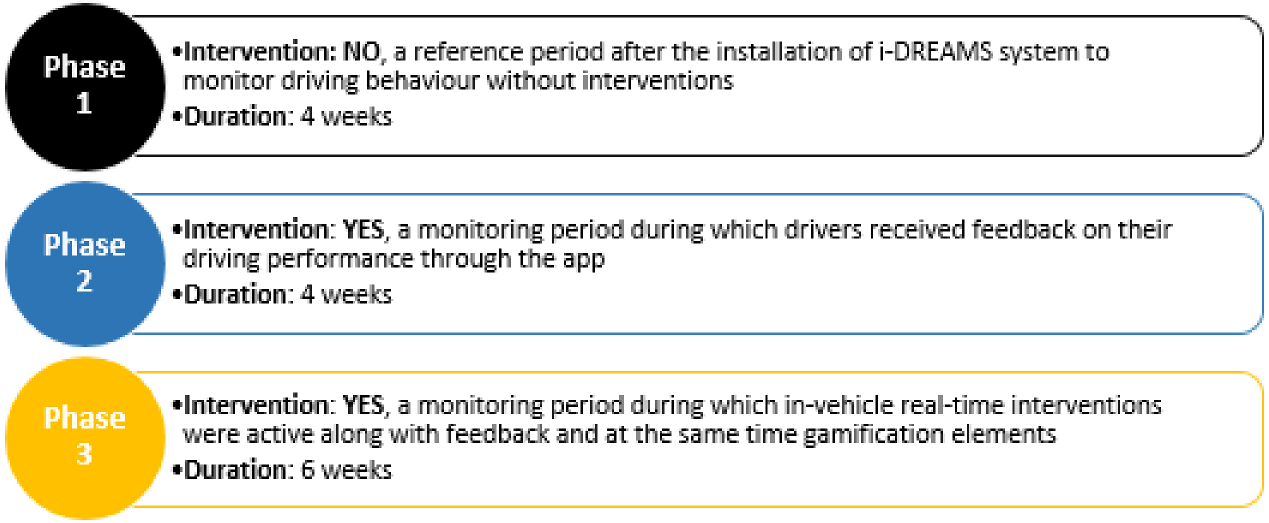


Figure 1: The i-DREAMS on-road experiment interventions

Safety Promoting Goals	Performance Objectives	Severity Level	Events per 100 km					
			Baseline Phase		Post-trip Phase		Post-trip & Gamification 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	2	11	2	9	2	9
	Deceleration	Medium	6	15	6	14	5	13
		High	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

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

Machine Learning Models

CatBoost:

- Gradient Boosted Decision Trees
- Native handling of categorical features
- Robust, less preprocessing required.

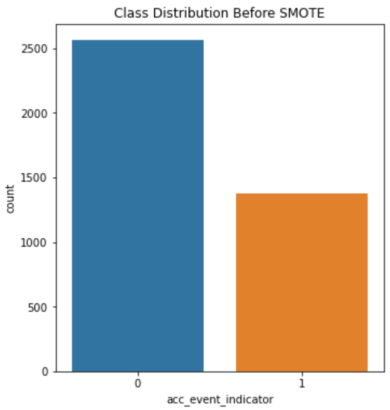
XGBoost:

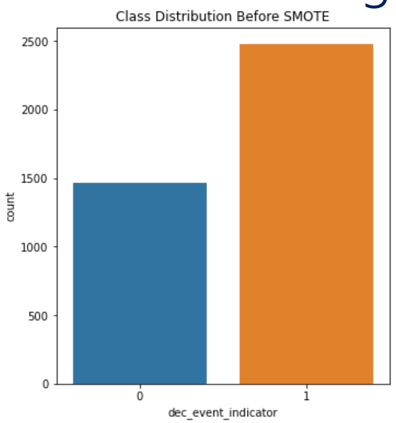
- Optimized Gradient Boosting
- Strong recall & speed
- Regularization reduces overfitting.

Random Forest:

- Ensemble of decision trees (bagging)
- Stable, easy to interpret
- Biased toward majority class in imbalance.

- Dataset was split by 80% training and 20% testing, preserving class distribution.
- Class imbalance addressed with SMOTE during model training.





Model Results

	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

Random Forest:

- Lower AUC (68% accel, 58% decel).
- Easy to interpret, but poor with rare risky events.
- Biased towards majority (non-risky) class.

XGBoost:

- Recall 72% (accel), 63% (decel).
- Sensitive to outliers but superior minority-class detection.
- Best at detecting risky behaviors.

CatBoost:

- Precision 76% (accel), 65% (decel).
- Stable across conditions (confirmed by cross-validation)
- Balanced performance, strong with categorical data.

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

Feature Importance

- Top predictors: vehicle age, vehicle brand, engine capacity, intervention phase.
- Most influential predictors for acceleration events:
  - Vehicle Age (older vehicles linked with risky accel. events).
  - Engine Capacity & Horsepower (higher values → more aggressive driving).
- Most influential predictors for deceleration events:
  - Intervention Phase (baseline vs. feedback vs. gamification), followed by
  - Vehicle Brand and Engine CC.
- Other relevant factors: gearbox type, fuel type.

Figure 1: Feature Importance Plot for Acceleration Events

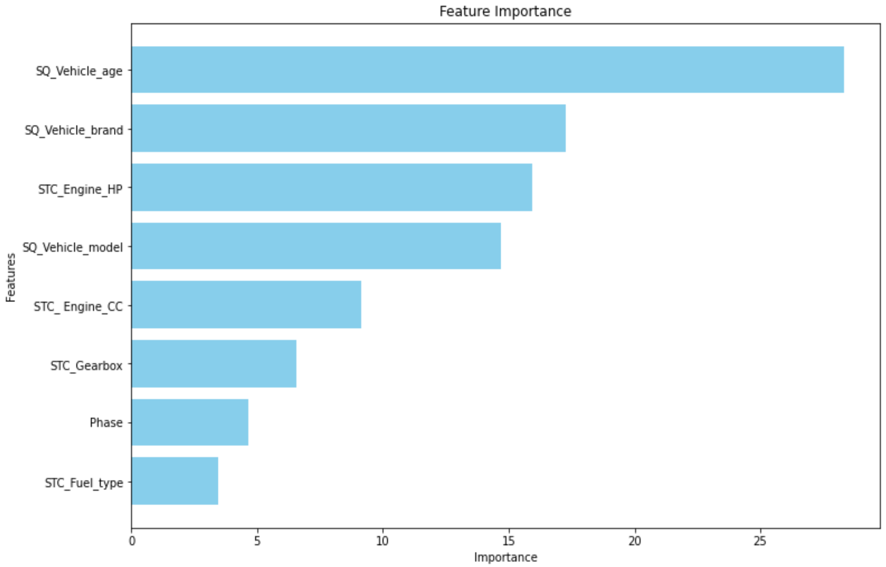
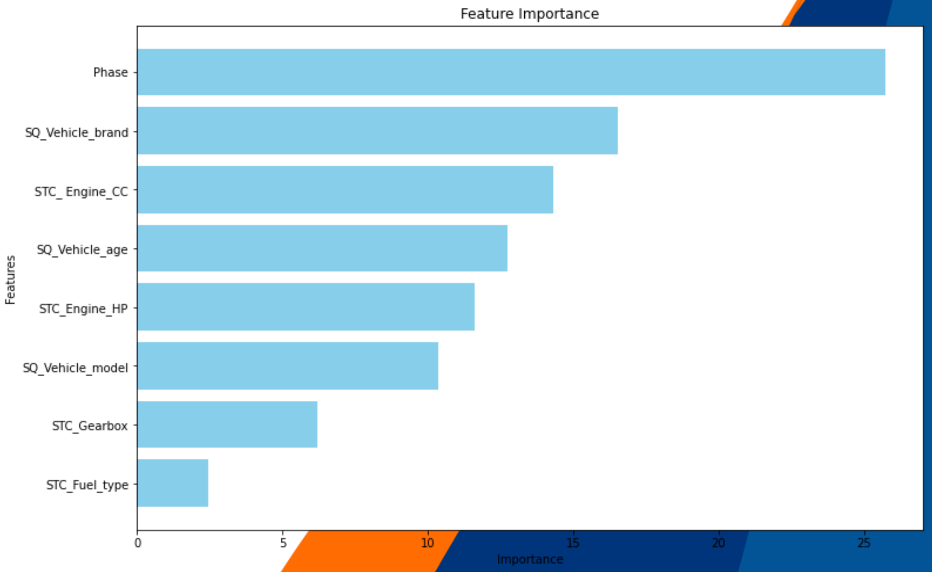


Figure 2: Feature Importance Plot for Deceleration Events



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

Table 1: Feature Importance Plot for Acceleration Events

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

Table 2: Feature Importance Plot for Deceleration Events

Discussion

- CatBoost: best balance of precision and accuracy.
- XGBoost: most effective at identifying risky behavior.
- Random Forest method is easy to interpret, but weaker on imbalanced data.
- Post-trip feedback and gamification reduced risky events.
- Vehicle characteristics significantly influence risky driving behaviors.
- ML models provide richer insights than traditional methods for road safety.
- Results confirm that combining vehicle data with interventions can guide effective safety policies

Conclusion & Future Work

- Machine Learning enables targeted vehicle safety interventions.
- XGBoost and CatBoost show promise in real-world risk prediction.
- **Vehicle age and performance attributes** (engine, horsepower) strongly linked to risky events.
- Phased interventions (especially gamification) improve safe driving.
- For Future Work, **expansion of the dataset** (more drivers, diverse vehicle types, varied road conditions) is needed.
- Integrate real-time traffic, **weather**, and driver state factors.
- Explore **deep learning** (LSTMs, transformers) for sequential driving behavior.
- Embed predictive models into ADAS & insurance risk profiling tools.

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