Long-Term Effects of Driver Feedback on Harsh Braking Behavior: Insights from Survival Models

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Introduction

- **Driver feedback systems** are frequently used to encourage safer driving habits by **targeting behaviors** like harsh braking, harsh accelerations, speeding and mobile use while driving

- While research consistently shows that these interventions **lead to short-term improvements** during the feedback period, their long-term effectiveness is **less examined**

- Many drivers revert to their old habits after the feedback ends, highlighting the need to better **understand what drives this relapse**

Objectives

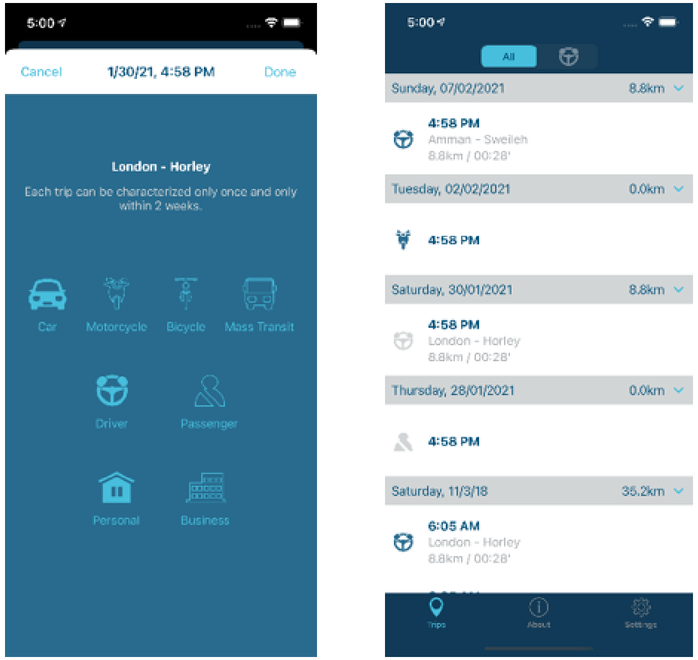
- This study focuses on the relapse patterns of harsh braking behavior once feedback interventions are withdrawn

- Using survival analysis methods, this study evaluates how long drivers sustain improved behavior, identify key relapse predictors, and explore the influence of individual and contextual factors on long-term outcomes

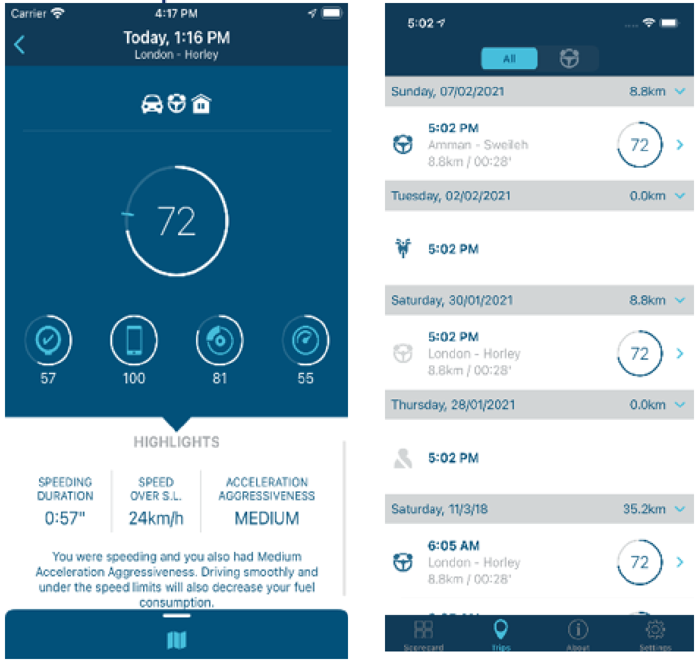
Naturalistic Driving Experiment

- This study examined data from **31 drivers over 21 months**, generating a total of 24,904 trips
- **Driving behavior indicators** were measured **across three phases**:
  1. baseline (before feedback)
  2. feedback
  3. post-feedback
- During the feedback phase, drivers received regular **post-trip feedback**, which was **withdrawn in the post-feedback phase**

Baseline – No feedback



Feedback phase- Feedback features



The Smartphone Application

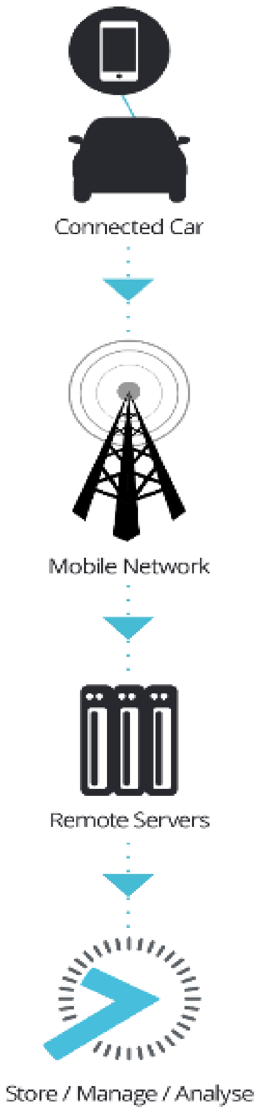
- A mobile application to record user's driving behavior (automatic start / stop)

- A variety of APIs is used to read mobile phone sensor data

- Data is transmitted from the mobile App to the central database

- Driving behavior indicators are designed using:
  - machine learning algorithms
  - big data mining techniques

- State-of-the-art technologies and procedures in compliance with standing Greek and European personal data protection laws (GDPR)



Modelling Approach

Survival analysis models the time until a specific event occurs

- **Event: "relapse" in driving behavior**, when the driver’s behavioral indicator exceed a predefined threshold
- **Duration Variable** (Time to Event): Represented by **the successive number of trips taken until a relapse event occurs**

The Kaplan-Meier curves

- Calculation of the survival probability at each time point where an event occurs

Cox proportional hazards (Cox-PH) Model with Frailty

- Semi-parametric regression method estimating the effect of covariates on the **hazard function,** accounting for heterogeneity in grouped data

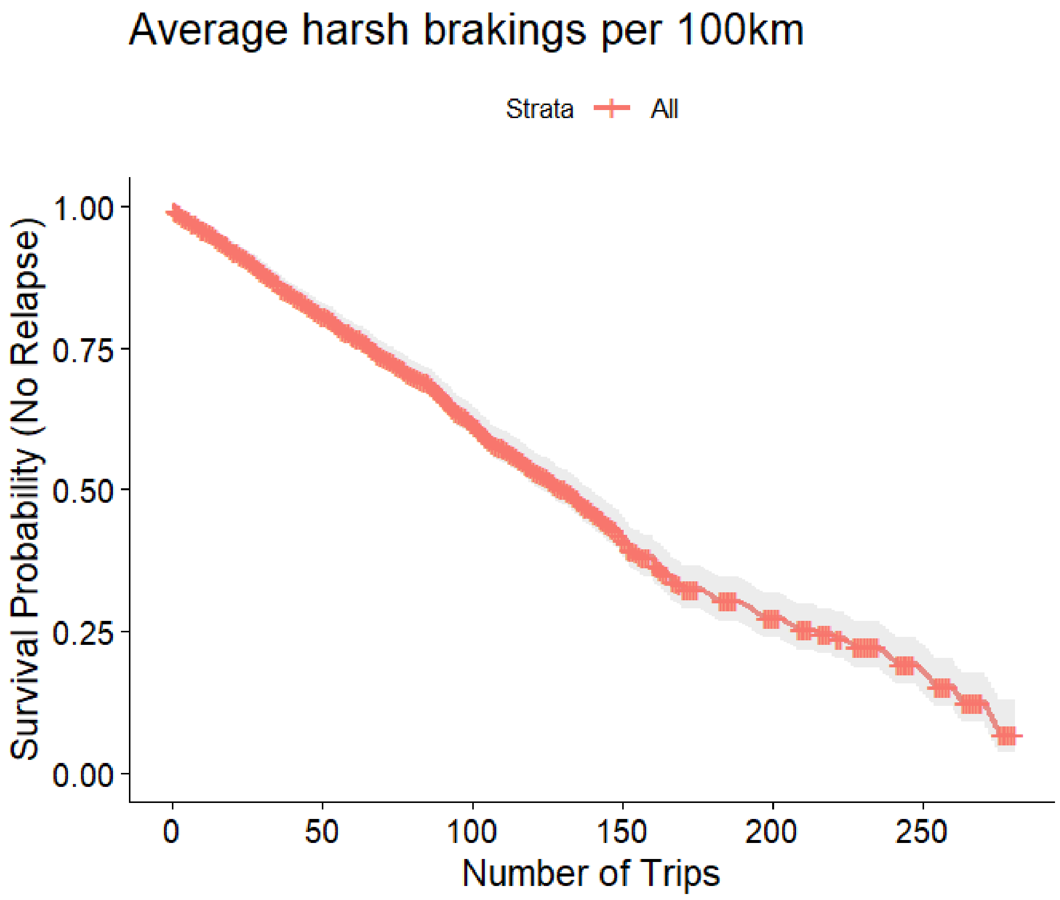
Weibull AFT Model with Clustered Heterogeneity

- Directly **models survival time as a function** of covariates and random error, accounting for clustering and unobserved heterogeneity through **random effects**

Random Survival Forest (RSF)

- Extends random forests to time-to-event data, using an ensemble of decision trees

Results – Survival Kaplan-Meier curves of relapse



As the number of trips increases, the survival probability declines:

- 50 trips: Approximately 81.5% of drivers maintain their improved behavior, with a notable 18.5% relapsing
- 100 trips: The survival probability drops to 61.4%
- 150 trips: The survival probability falls further to 40.3%, indicating that the majority of drivers have relapsed by this stage

Results – Model comparison

Aspect	Weibull AFT Model	Cox Model with Frailty	Random Survival Forest
Purpose	Models survival time directly	Models hazard rate	Captures non-linear effects
C-index	0.724	0.653	0.636
AIC	9501.4	9796.8	N/A
BIC	9558.4	9945.9	N/A
Key Predictors	Age group, vehicle CC group, trip duration	Vehicle CC group, peak hour, trip duration	Vehicle CC group, age group, gender, trip duration
Frailty Effects	Accounted (Clustered Heterogeneity)	Accounted (Shared Frailty)	Implicitly handled (Non-parametric)
Prediction Error (RMSE/MAE)	RMSE: 91.73, MAE: 70.25	RMSE: 121.11, MAE: 102.42	RMSE: 91.92, MAE: 70.67
Strengths	Interpretable, adjusts for clustering	Handles heterogeneity flexibly	Captures complex interactions
Weaknesses	Accounts for driver-specific effects	Provides interpretable hazard ratios	Robust to outliers, identifies non-linear effects

- **Weibull AFT model performs best** (C-index: 0.724), balancing interpretability and predictive accuracy
- **Cox model struggles with proportional hazards**, showing lower C-index (0.653) and higher prediction errors
- **RSF model captures complex interactions**, but low interpretability (C-index: 0.636) limits explanatory power
- **Model choice depends on goals**: Weibull AFT for interpretability, RSF for prediction

Conclusions (1/2)

- **Feedback interventions reduce harsh braking** in the short term
- Once feedback is withdrawn, relapse is common, **nearly 60% of drivers reverted to pre-feedback levels** within 150 trips
- **Age matters**: drivers aged 35+ sustain improvements longer than younger drivers
- **Vehicle characteristics** (engine capacity >1400cc) are linked to faster relapse

Conclusions (2/2)

- **Trip duration influences relapse risk**: longer trips increase the likelihood of relapse
- **Time of day matters**: morning peak hours were associated with fewer relapses
- **Advanced survival models** (Weibull AFT, RSF) improved predictive accuracy compared to Cox-PH
- Study **confirms the need for sustained** or intermittent feedback to preserve safe driving behaviors

Future Challenges

- Preventing behavioral relapse once drivers stop receiving feedback
- Expanding analysis to include traffic conditions, workload, and contextual factors
- Enhancing the interpretability of advanced predictive models like RSF
- Scaling feedback systems sustainably in large fleets and across diverse driver populations

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