Understanding Behavioral Relapse in Driving: A Trip-Based Survival Analysis of Risk Indicators Post Feedback

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Abstract. Driver feedback systems have demonstrated short-term effectiveness in mitigating risky behaviors such as speeding, harsh events, and mobile phone use. However, the long-term sustainability of these improvements, especially after feedback is withdrawn, remains a critical concern for transport safety research. This study investigates the relapse patterns of risky driving behaviors following the removal of feedback interventions, aiming to quantify behavior persistence and inform the design of long-term safety strategies. Naturalistic driving data from 31 car drivers were collected over a 21-month period encompassing baseline, feedback, and post-feedback phases. A total of 24,904 trips were analyzed. Survival analysis techniques, namely Kaplan-Meier estimates, were applied to four key risk indicators: harsh accelerations, harsh braking, speeding percentage, and mobile phone use percentage. The temporal evolution of each behavior was examined based on trip counts rather than calendar time to reflect driving exposure. Results show that relapse was most rapid for harsh braking and acceleration, while phone use exhibited the slowest decline in behavior persistence. Trip-based survival analysis offers valuable insights into feedback durability and the need for reinforcement mechanisms to maintain safer driving behavior over time.

Keywords: Road Safety, Driver Feedback, Smartphone Data, Post-Feedback Behaviour, Survival Analysis Techniques

1 Introduction

In recent years, monitoring driver behavior has gained increasing recognition within the transportation sector [1]. Yet, researchers continue to face challenges in collecting accurate, real-time driving data through cost-effective means. The widespread use of smartphones presents new opportunities in this respect, as smartphone applications offer affordable and accessible solutions for data collection. They enable both trip analysis and the provision of direct feedback to drivers, which can help reduce crashes and casualties [2]. Moreover, naturalistic driving experiments supported by smartphones allow for the unobtrusive observation of drivers in their everyday environment, providing a more realistic assessment of driver behavior [3].

Feedback-based interventions have therefore been widely explored as a tool to improve driver behavior and enhance road safety [4,5]. However, evidence of their long-term effectiveness remains mixed. Some studies report that improvements in driver behavior persist beyond the feedback period. For example, in a study [6], researchers found that bus drivers maintained safer driving practices after the intervention ended, while in another study [7], they observed that although improvements diminished somewhat, behavior remained better than baseline.

Taken together, these findings reveal a clear research gap: while feedback can influence driving behavior, its long-term effects remain uncertain and appear to vary depending on contextual factors such as driver characteristics, vehicle type, and the nature of the intervention [8]. Addressing this gap, the present study leverages large-scale naturalistic driving data collected via smartphone sensors to evaluate the post-feedback effects on key risk indicators, including speeding, harsh braking, harsh acceleration and mobile phone use. Specifically, survival models are applied to analyze whether, and to what extent, feedback contributes to lasting improvements in driver behavior.

2 Methodology

2.1 Experiment design

As part of a research project, a 21-month naturalistic driving experiment was conducted between July 2019 and March 2021, involving 230 participants across 106,776 trips. The primary objectives were to identify critical risk factors through continuous driver monitoring and to test feedback features aimed at improving skills, reducing errors, and lowering crash risk. The experiment was structured into three phases. Phase 1 served as the baseline, where drivers were monitored through the smartphone application but received no behavioral feedback. Phase 2 progressively introduced different feedback features, while Phase 3 returned to a no-feedback condition to allow for analysis of post-feedback effects.

For this study, a subset of 31 car drivers who participated in all phases, baseline, feedback, and post-feedback, was analyzed. Over the 21-month period, this group completed 24,904 trips, with each driver contributing at least 20 trips during the post-feedback phase, ensuring sufficient data for evaluating the long-term impacts of feedback interventions.

Driver monitoring and feedback were facilitated through a smartphone application developed by OSeven (www.oseven.io), designed to assess and enhance driving behavior. The app utilizes the smartphone's sensors and APIs to capture detailed trip data, which is stored locally and then uploaded to a secure cloud database for processing. Using advanced signal processing, machine learning algorithms, data fusion, and big data techniques, all compliant with Greek and European GDPR regulations, the raw data is transformed into meaningful safety indicators. **Fig. 1** depicts and summarizes the OSeven data flow system

Fig. 1. The OSeven data flow system

These indicators cover both exposure variables (e.g., trip distance, driving duration, road type, rush hour conditions) and behavioral variables (e.g., speeding episodes, severity of harsh braking or acceleration, and mobile phone distraction). **Fig. 2** illustrates examples of the app's feedback features across the different experimental phases. For further details on data processing and metadata derivation, the reader is referred to earlier studies from the same research project [9,10]

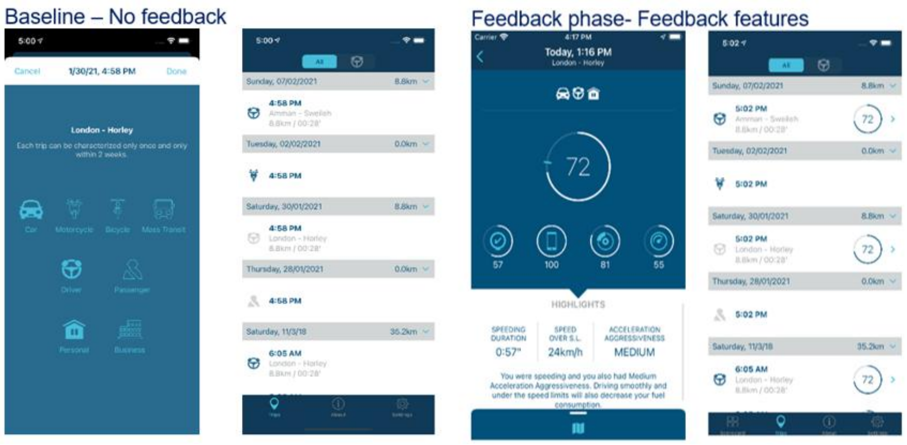

Fig. 2. Example screenshots from the application features in Phase A – Baseline (left) and Phase B – Feedback phase (right)

2.2 Theoretical background

Survival analysis has become a widely used method for studying driving behavior, as it models the time until critical events such as harsh braking, near-crashes, or collisions occur [11,12]. A key advantage of this approach is its ability to handle censored data, trips with no adverse events, while incorporating covariates such as driver characteristics and trip conditions.

In this study, the event is defined as a relapse in driving behavior, measured when a driver's risk indicator exceeds a predefined threshold. This threshold corresponds to the mean indicator's rate during the feedback phase, when active interventions were in place. Surpassing this rate in the post-feedback phase signals behavioral relapse.

The duration variable represents the number of trips until a relapse occurs. Formally, the duration T is a continuous random variable with distribution F(t) and density f(t), reflecting the probability of relapse at trip t.

The survival rate S(t) gives the probability that a driver will maintain driving behavior below the speeding threshold for a given number of trips, denoted by t. This can be interpreted as the probability of no relapse occurring within that period. Mathematically:

$$F(t) = P(T < t) = \int_0^t f(t)dt \qquad (1)$$

where F(t) is the cumulative probability of a relapse occurring by trip t.

The Kaplan-Meier estimator, also known as the product-limit estimator, is a non-parametric statistical method used to estimate the survival function from time-to-event data (*27*). It is commonly applied in fields such as medicine, engineering, and social sciences to understand the likelihood of an event (e.g., failure, relapse) occurring over time, especially when data include censored observations (i.e., when the event has not occurred for some subjects by the end of the observation period).

The Kaplan-Meier survival function S(t) is defined as the probability that the event of interest has not occurred by a certain time t:

$$S(t) = P(T \geqslant t) \qquad (2)$$

where T represents the time to event. The Kaplan-Meier estimator calculates the survival probability at each time point where an event occurs, updating the cumulative survival probability accordingly. The survival probability at each event time tj is calculated by:

$$\hat{S}(t) = \prod_{t_j \leq t} \left(1 - \frac{d_j}{n_j}\right) \qquad (3)$$

Where:

- d_j is the number of events (e.g., relapses, failures) occurring at time t_j
- n_j is the number of subjects at risk just prior to time t_j

All survival analyses were performed in R Studio. The survfit function was used to generate Kaplan-Meier curves for survival probability visualization.

3 Results

3.1 Descriptive statistics

Before modelling the survival probabilities of the indicators, descriptive statistics are first presented to provide an overview of the experiment across its different phases. The sample of the remaining 31 drivers is 55% female and 45% male, with the largest age group being 18–34 years (45%). **Table 1** shows the summary statistics for the monitored driving indicators during the different phases for the study sample. The results show improvements during the feedback period, particularly in reducing mobile phone use and speeding, though partial relapse is observed in the post-feedback phase, while harsh events (accelerations and brakings) fluctuate with smaller changes.

Table 1. Summary statistics for critical driving indicators during the different phases

Indicators	Baseline	Feedback	Post-Feedback
Mean of the percentage of mobile phone use while driving (sd)	3.34% (0.11)	2.17% (0.09)	2.33% (0.09)
Mean of the percentage of speeding while driving (sd)	5.42% (0.09)	2.81% (0.06)	3.74% (0.07)
Mean of harsh accelerations per 100 km (sd)	6.68 (17.27)	6.88 (18.72)	7.96 (19.67)
Mean of harsh braking per 100km (sd)	16.86 (27.15)	14.47 (26.50)	16.734 (29.55)

3.2 Survival Analysis

The Kaplan-Meier curve is a stepwise function that visually represents the survival probability over time. Its primary advantage lies in its ability to handle censored data, which is particularly useful in studies where subjects may not experience the event by the end of the observation period. The Kaplan-Meier survival curve shows the proportion of drivers who continue to maintain improved driving behavior without relapse across successive trips. The survival probability is recalculated at each relapse event, giving a stepwise depiction of the declining survival rate as drivers accumulate trips post-feedback. Indicatively, results from the Kaplan-Meir method are shown for harsh brakings in **Table 2**, while the Kaplan-Meier survival curve for the four indicators is shown in **Fig. 3**.

Table 2. Kaplan-Meier results for harsh braking survival probability

Time (number of trips)	Survival	std.err	lower_CI	upper_CI
1	0.995928	0.001355	0.993276	0.998586
2	0.991361	0.001973	0.987501	0.995236
3	0.987676	0.002357	0.983067	0.992307
4	0.984885	0.002612	0.979779	0.990016
5	0.981592	0.002884	0.975956	0.987261
6	0.975888	0.003304	0.969433	0.982386
7	0.972054	0.003558	0.965104	0.979053
8	0.968668	0.003769	0.961309	0.976084
9	0.966227	0.003914	0.958585	0.97393
10	0.96376	0.004057	0.955841	0.971744
50	0.845138	0.009333	0.83705	0.853637
100	0.704418	0.013772	0.69801	0.712012
150	0.493307	0.017859	0.48978	0.509873
200	0.425595	0.019916	0.419199	0.43753

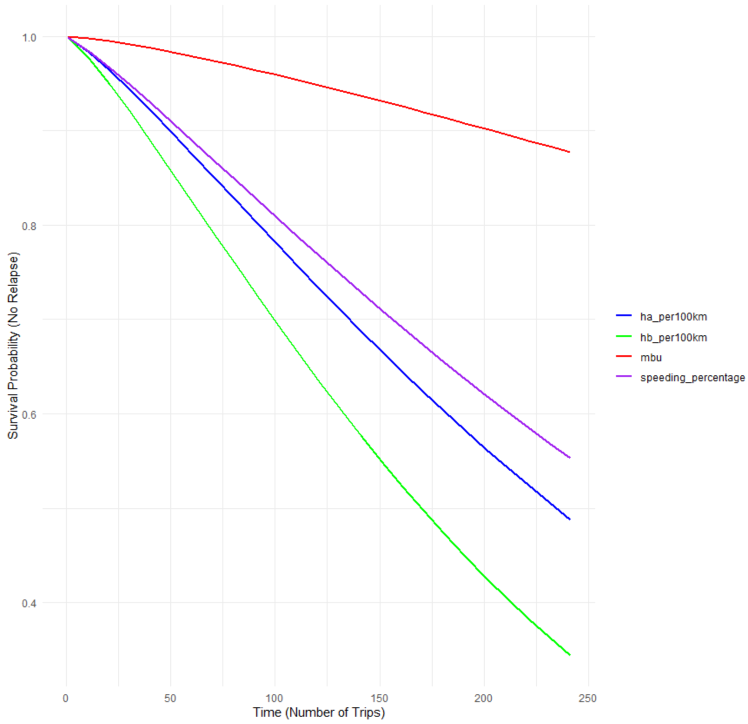

Fig. 3. Kaplan-Meier survival curves for the four behavioural indicators

The diagram presents the Kaplan-Meier survival curves for four driving behavior indicators: harsh acceleration (blue), harsh braking (green), mobile phone use (red), and speeding percentage (purple). The y-axis represents the survival probability (no relapse), while the x-axis indicates time in number of trips. At the beginning of the observation period, all indicators start at a survival probability of 1.0, meaning no relapse has occurred. As the number of trips increases, the survival probability declines at different rates across indicators. Harsh braking shows the steepest decline, followed by harsh acceleration and speeding percentage, while mobile phone use decreases more gradually, maintaining the highest survival probability throughout the trip horizon.

More precisely, by around 50 trips, survival is ~0.98 for mobile phone use, ~0.91 for speeding, ~0.90 for harsh acceleration, and ~0.85 for harsh braking. At 100 trips, probabilities drop to ~0.96 (mobile phone use), ~0.81 (speeding), ~0.78 (harsh acceleration), and ~0.70 (harsh braking). At 150 trips, survival is ~0.94 (mobile phone use), ~0.71 (speeding), ~0.67 (harsh acceleration), and ~0.49 (harsh braking). Finally, by 200 trips, the probabilities fall further to ~0.90 for mobile phone use, ~0.62 for speeding, ~0.57 for harsh acceleration, and ~0.43 for harsh braking. Overall, harsh braking shows the fastest decline, while mobile phone use remains the most sustained improvement.

4 Discussion and Conclusions

Survival analysis techniques were applied to a dataset of 24,904 trips from 31 car drivers, each contributing at least 20 trips in the post-feedback phase, to investigate the long-term effects of driver telematics feedback on driving behavior. The analysis focused on relapse patterns in mobile phone use, speeding, harsh braking, and harsh accelerations, utilizing Kaplan-Meier survival curves. The findings demonstrate the effectiveness of feedback interventions in achieving significant short-term behavioral improvements during the feedback phase. However, the post-feedback phase reveals varied relapse tendencies, emphasizing the need for sustained interventions to maintain these improvements over time.

The Kaplan–Meier survival analysis highlighted clear relapse trends, with survival probabilities steadily declining as the number of trips increased in the post-feedback phase. For harsh acceleration, survival dropped from ~90% at 50 trips to ~67% at 150 trips. Harsh braking showed the steepest decline, falling from ~85% at 50 trips to ~49% at 150 trips. Speeding followed a similar downward trajectory, decreasing from ~91% at 50 trips to ~71% at 150 trips. By contrast, mobile phone use exhibited greater resilience, maintaining ~98% at 50 trips and still ~94% at 150 trips, although a gradual relapse was also apparent. These patterns underscore the transient nature of feedback effects and emphasize the need for sustained or adaptive reinforcement mechanisms to preserve safer driving behavior over time.

While this study provides valuable insights into the dynamics of driver feedback and behavioral relapse, several limitations should be acknowledged. First, the relatively small sample size constrains the generalizability of the findings, as broader patterns across different driver populations and contexts may not be fully captured. Second, the analysis did not explicitly account for external traffic and environmental conditions—such as congestion levels, weather, or road infrastructure—which may interact with driver behavior and feedback effectiveness. Third, the focus remained largely macroscopic, emphasizing aggregated indicators rather than the micro-level decision-making processes that occur during individual driving events.

Future research could address these limitations by integrating more granular datasets that capture traffic flow, contextual dynamics, and moment-to-moment driver decisions, thereby providing a richer behavioral perspective [13]. Expanding the study to include larger and more diverse samples, as well as testing across different geographic and cultural contexts, would further improve the robustness and applicability of findings. Ultimately, such advances would allow for a more nuanced understanding of how driver feedback operates over time and under varying conditions, strengthening the evidence base for sustainable road safety interventions.

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