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

Armira Kontaxi*[1], George Yannis[2]

[1] Research Associate, Department of Transportation Planning and Engineering, National Technical University of Athens, Greece
[2] Professor, Department of Transportation Planning and Engineering, National Technical University of Athens, Greece

Abstract

Introduction
Feedback systems are frequently used to encourage safer driving habits by targeting behaviors like harsh braking, harsh accelerations, and speeding. 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. This study focuses on the relapse patterns of harsh braking behavior once feedback interventions are withdrawn. Using survival analysis methods, this paper evaluates how long drivers sustain improved behavior, identify key relapse predictors, and explore the influence of individual and contextual factors on long-term outcomes.

Methods
This study examined data from 31 drivers who participated in a naturalistic driving experiment over 21 months, generating a total of 24,904 trips. Harsh braking events, calculated per 100 kilometers, were measured across three phases: baseline (before feedback), feedback, and post-feedback. During the feedback phase, drivers received regular feedback, which was withdrawn in the post-feedback phase.

Survival analysis techniques were used to assess relapse in harsh braking behavior during the post-feedback phase. Relapse was defined as a return to harsh braking rates higher than the average during the feedback phase.

Kaplan-Meier survival curves provided an overview of relapse trends, showing how long improved behavior persisted after feedback ended. To investigate individual and contextual factors affecting relapse, Cox Proportional Hazards (Cox-PH) model with frailty

was implemented to account for differences between drivers. Additionally, the Weibull Accelerated Failure Time (AFT) model with clustered heterogeneity was used to estimate survival times directly, identifying predictors that either delayed or accelerated relapse. Finally, the Random Survival Forest (RSF) model was employed to detect complex, non-linear relationships between predictors for a more robust analysis.

Key variables analyzed included driver demographics (age and gender), vehicle characteristics (engine capacity), trip duration, and contextual factors like the time of day (peak vs. off-peak hours). Model performance was evaluated using various metrics such as concordance indices (C-index), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

Results

The Kaplan-Meier survival curves revealed that relapse rates increased steadily over time. Initially, 81.5% of drivers maintained improved harsh braking behavior during the first 50 trips of the post-feedback phase. However, this dropped to 61.4% by 100 trips and further declined to 40.3% by 150 trips, meaning nearly 60% of drivers reverted to their pre-feedback harsh braking levels by the end of the study. This pattern underscores the temporary nature of behavior improvements once feedback is withdrawn.

The Cox-PH model with frailty highlighted significant relapse predictors. Drivers aged 35–54 were less likely to relapse compared to those aged 18–34 ($\exp(\beta) = 0.190$, $p = 0.002$). Drivers with vehicles larger than 1400cc had a higher likelihood of relapse ($\exp(\beta) = 2.898$, $p = 0.039$). Morning peak hours were associated with a lower risk of relapse compared to off-peak hours ($\exp(\beta) = 0.732$, $p = 0.002$). Longer trips slightly increased relapse risk ($\exp(\beta) = 1.005$, $p = 0.024$), possibly due to fatigue or prolonged driving. Gender and self-reported aggressiveness were not statistically significant predictors, although self-reported aggressiveness approached significance ($\exp(\beta) = 2.617$, $p = 0.063$). The Cox model achieved a moderate predictive accuracy, with a concordance index of 0.653.

The Weibull AFT model with clustered heterogeneity reinforced these findings. Drivers aged 35–54 and 55+ exhibited longer survival times before relapse compared to younger drivers ($\beta = 0.360$, $p = 0.010$ and $\beta = 0.624$, $p = 0.005$, respectively). Vehicles with engine capacities above 1400cc were linked to shorter survival times ($\beta = -0.508$, $p = 0.012$). Longer trips also reduced survival times ($\beta = -0.008$, $p = 0.027$). This model performed better than the Cox-PH model, with a concordance index of 0.724 and good model fit metrics (AIC = 9501.4, BIC = 9558.4).

The RSF model provided the highest predictive accuracy by identifying non-linear interactions among variables. Variable importance analysis ranked vehicle engine capacity, age group, and trip duration as the most influential predictors of relapse, followed by gender and self-reported aggressiveness. The RSF model outperformed others in terms of prediction error, achieving the lowest RMSE (91.92) and MAE (70.67). However, its interpretability was limited compared to the Cox-PH and Weibull AFT models, as it does not produce direct estimates of hazard ratios or survival times.

Discussion and Conclusions

The study highlights the critical role of sustained feedback in maintaining long-term improvements in driver behavior. Although feedback interventions significantly reduced harsh braking rates during the feedback phase, relapse was common once feedback was withdrawn. Key factors such as age and vehicle engine capacity influenced the likelihood of relapse, suggesting that tailored feedback systems could enhance the effectiveness of these interventions.

Kaplan-Meier survival curves provided a clear visualization of relapse trends, while the Cox-PH and Weibull AFT models offered valuable insights into the effects of individual and contextual factors. The Weibull AFT models showed the best balance between interpretability and predictive performance, while the RSF model excelled at prediction but lacked transparency.

These findings have important implications for the design of feedback systems. Incorporating sustained or intermittent feedback, coupled with targeted reinforcement strategies, could help minimize relapse. Future research should consider additional contextual factors like traffic conditions and driver workload to deepen our understanding of relapse dynamics.

Selected references

Ghamari, A., Rezaei, N., Malekpour, M. R., Azadnajafabad, S., Jafari, A., Ahmadi, N., Bhalla, K., Shahraz, S., Bose, D., & Farzadfar, F. (2022). The effect of non-punitive peer comparison and performance feedback on drivers' behavior using the telematics: The first randomized trial in Iran. Journal of Safety Research, 82, 430–437. https://doi.org/10.1016/j.jsr.2022.07.010

Merrikhpour, M., Donmez, B., & Battista, V. (2014). A field operational trial evaluating a feedback-reward system on speeding and tailgating behaviors. Transportation Research

Part F: Traffic Psychology and Behavior, 27(PA), 56–68. https://doi.org/10.1016/j.trf.2014.09.002