The Driver Behavior Telematics Feedback Mechanism

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Presentation outline

- Introduction and Objective
- Literature Review
- Research Questions
- Methodological Approach
- Naturalistic Driving Experiment
- Feedback Impact on Driver Behavior and Safety
- Feedback Features Effects on Driver Behavior
- Post-Feedback Effect on Long-Term Driver Behavior
- Key Research Findings
- Innovative Contributions
- Challenges Ahead

Introduction and Objective

- Introduction
- Objective of the dissertation

Introduction

- **Road safety** is a **critical public health and societal issue**, as road traffic crashes claim millions of lives and cause severe injuries globally every year:
  - 1.19 million fatalities globally in 2021
  - 20,400 in the European Union in 2023
  - 654 in Greece in 2022

- A substantial percentage of road crashes, **up to 95%, can be attributed to human error**, exclusively or not (Singh, 2015)

- Focus on **driving behavior and naturalistic observations**, primarily examining behavior recording and subsequently analyzing and modeling driver profiles

- **Feedback** to drivers has shown to be a **highly effective method** for enhancing road safety, however there is very **little research that quantify the exact effect** on driver behavior and safety

Objective of the dissertation

➢ The primary aim of this dissertation is to **investigate the comprehensive impact of driver feedback** on driving behavior and safety:

- Across its entire lifecycle - encompassing the pre-feedback, feedback, and post-feedback phases

- Through naturalistic driving conditions among different driver types

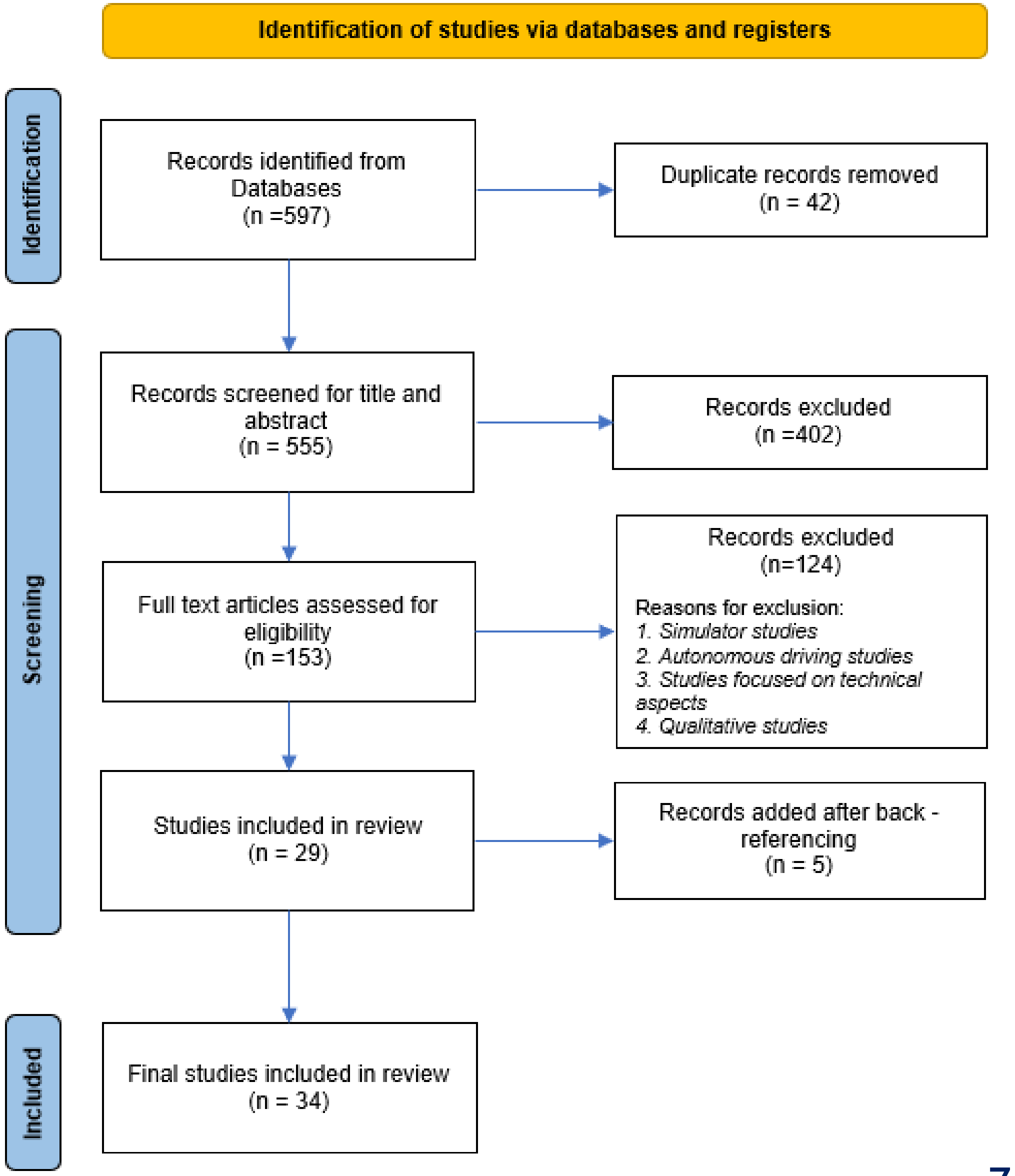
Literature review and Research questions

- Review objective and methodology
- Types of driver feedback systems
- Experimental framework
- Modelling approaches
- Impact on driving behavior and road safety
- Research questions

Review objective and methodology

- The **review aimed** to:
    - Synthesize the **different types and systems of feedback** utilized in naturalistic driving studies
    - Examine the **methodologies used** by researchers to design and evaluate the effectiveness of driver feedback
    - Present **evidence-based findings** on the impact of feedback on driver behavior and safety

- **PRISMA** statement guidelines were used (Moher et al., 2015)
    - Search in **databases**: Scopus, TRID, Web of Science
    - Only **naturalistic driving studies** were included
    - Quantitative studies with a **baseline phase** for comparison
    - Ultimately, **34 international studies** were reviewed



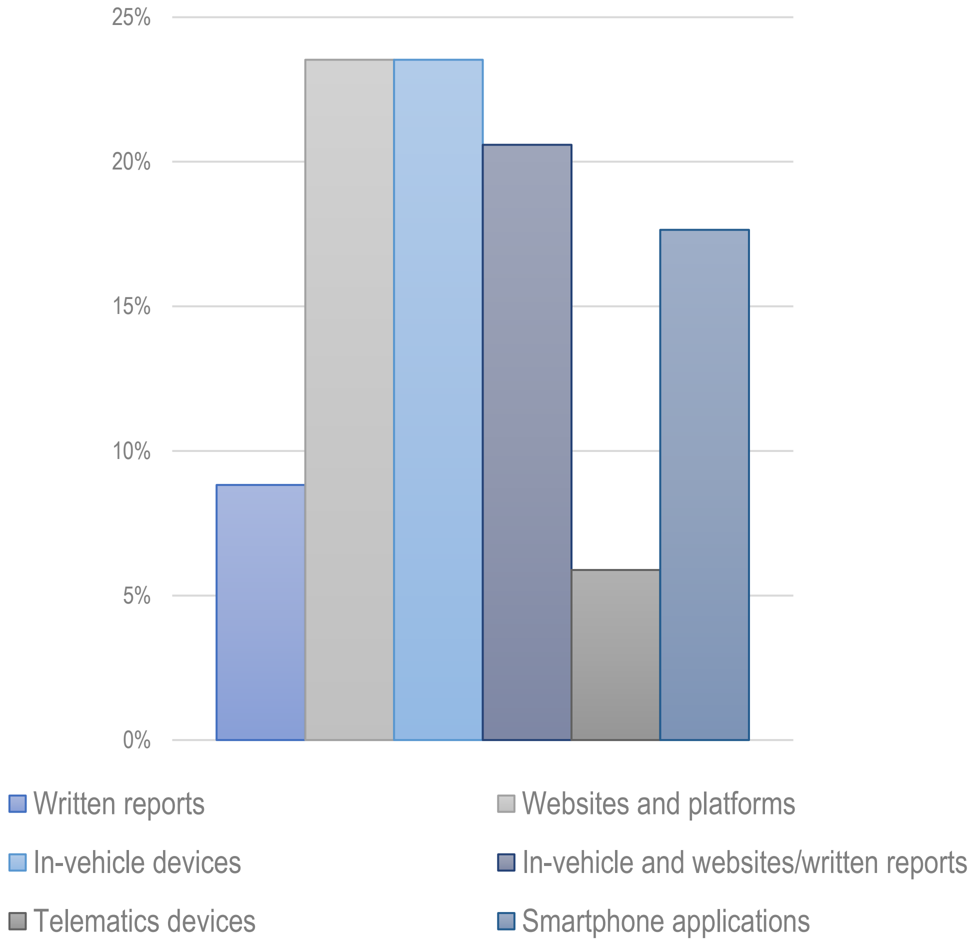
Types of driver feedback systems

- **In-vehicle feedback devices excel in real-time alerts**, providing auditory, visual, or haptic warnings for speeding, harsh braking, or seatbelt use - particularly effective in **improving speed compliance** (Chen & Donmez, 2021)

- **Web-based platforms** provide structured post-trip feedback, often integrating monetary incentives or training programs - **user engagement** can enhance feedback effectiveness (Ellison et al., 2015; Husnjak et al., 2015)

- **Smartphone applications** provide diverse feedback mechanisms, including **color-coded risk levels and customized scoring systems** (Meuleners et al., 2023; Stevenson et al., 2021), allowing for flexible adaptation to different user needs and driving contexts

- **Telematics-based feedback** is widely used in insurance models, but data access limitations hinder large-scale research - studies indicate a positive impact on driver behavior, though **broader applications remain underexplored** (Soleymanian et al., 2019; Ghamari et al., 2022)



Experimental framework

- The experimental framework is essential for **producing valid and interpretable results** in driver feedback studies

- Most studies **combine within-subjects and between-subjects designs**, allowing researchers to control for individual differences and ensure generalizability (Bell et al., 2017; Bolderdijk et al., 2011; Chen & Donmez, 2021; Farmer et al., 2010; Ghamari et al., 2022, etc.)

- **Sample characteristics vary widely**, from small-scale (15 drivers, Aidman et al., 2015) to large-scale studies (40,000+ drivers, Soleymanian et al., 2019)

- Studies highlight the importance of **monitoring risk indicators** (speeding, harsh braking, mobile phone use) and **structuring feedback phases** varying from 2 phases (Meuleners et al., 2023; Strömberg et al., 2013), 4 phases (Bell et al., 2017), even to 6 phases (Kontaxi et al.,2023)

- The **duration of experiments ranges** from a few weeks (Aidman et al., 2015) to 24 months (Wouters & Bos, 2000), with longer studies providing insights into long-term behavioral changes

Modelling approaches

Choice of analysis depends on experimental design

- Within-subjects studies use repeated measures models (e.g., GLMM, GEE, ANOVA) to **account for individual differences** (Birrell & Fowkes, 2014; Kontaxi et al., 2021b).
- Between-subjects studies rely on t-tests, Mann-Whitney U, ANCOVA, and Poisson regression to **compare independent groups** (Farah et al., 2014; Reagan et al., 2013).

Regression-based approaches for behavioral insights

- Linear and logistic regression models assess **relationships between feedback and driving performance** (Chen & Donmez, 2021; Merrikhpour et al., 2014)
- Fixed-effects and Poisson regression help analyze **event-based safety indicators** like harsh braking (Farmer et al., 2010; Soleymanian et al., 2019)

Advanced mixed-effects and repeated measures models

- GLMMs **capture driver-specific variability** in behaviors such as speeding and phone use (Kontaxi et al., 2021b; Stevenson et al., 2021)
- Generalized Estimating Equations (GEE) address **correlated data in repeated driving observations** (Bell et al., 2017; Ghamari et al., 2022)

Machine learning for predictive analytics

- XGBoost and SHAP analysis improve behavior **predictions and feature importance ranking** (Ziakopoulos et al., 2023)

Impact on driving behavior and road safety

➢ Feedback can improve driving behavior and road safety and reduce:
- **Speeding** by 5%–74% (Camden et al., 2019; Mazureck & Van Hattem, 2006)
- **Harsh events** by 10%–52% (Kontaxi et al., 2021b; Soleymanian et al., 2019)
- **Safety incidents** by 8%–52% (Takeda et al., 2011; Toledo & Shiftan, 2016)
- **Road crashes** by up to 20% (Wouters & Bos, 2000)

➢ Real-time and post-trip feedback help, but **timing and delivery matter** (Strömberg & Karlsson, 2013; Stevenson et al., 2021).

➢ Optimal **feedback frequency** is crucial; too frequent reporting may cause desensitization (Molloy et al., 2023).

➢ **Gamification and peer comparison** improve driver safety scores (Ghamari et al., 2022; Peer et al., 2020).

➢ **Financial incentives** further improve speed compliance, especially on highways (Chen & Donmez, 2021; Bolderdijk et al., 2011)

➢ **Post-feedback effects are inconsistent**; some drivers maintain safer behavior, others relapse (Ghamari et al., 2022; Merrikhpour et al., 2014)

Research questions

1. How does **feedback influence** driver behavior in terms of **speeding and mobile phone use** while driving?

2. How does **feedback influence** driver safety in terms of **harsh events**, such as harsh accelerations and harsh brakings?

3. **Do different feedback features have different effects** on driver behavior and safety? Which feature demonstrates the most significant impact?

4. How does the **post-feedback effect influence long-term driver behavior and safety**, and to what extent are the changes sustained after the feedback is removed?

5. **How can advanced statistical techniques be applied to understand the mechanisms of driver feedback** and develop more individualized, data-driven approaches for driving behavior change?

Methodological Framework

- Methodological Framework

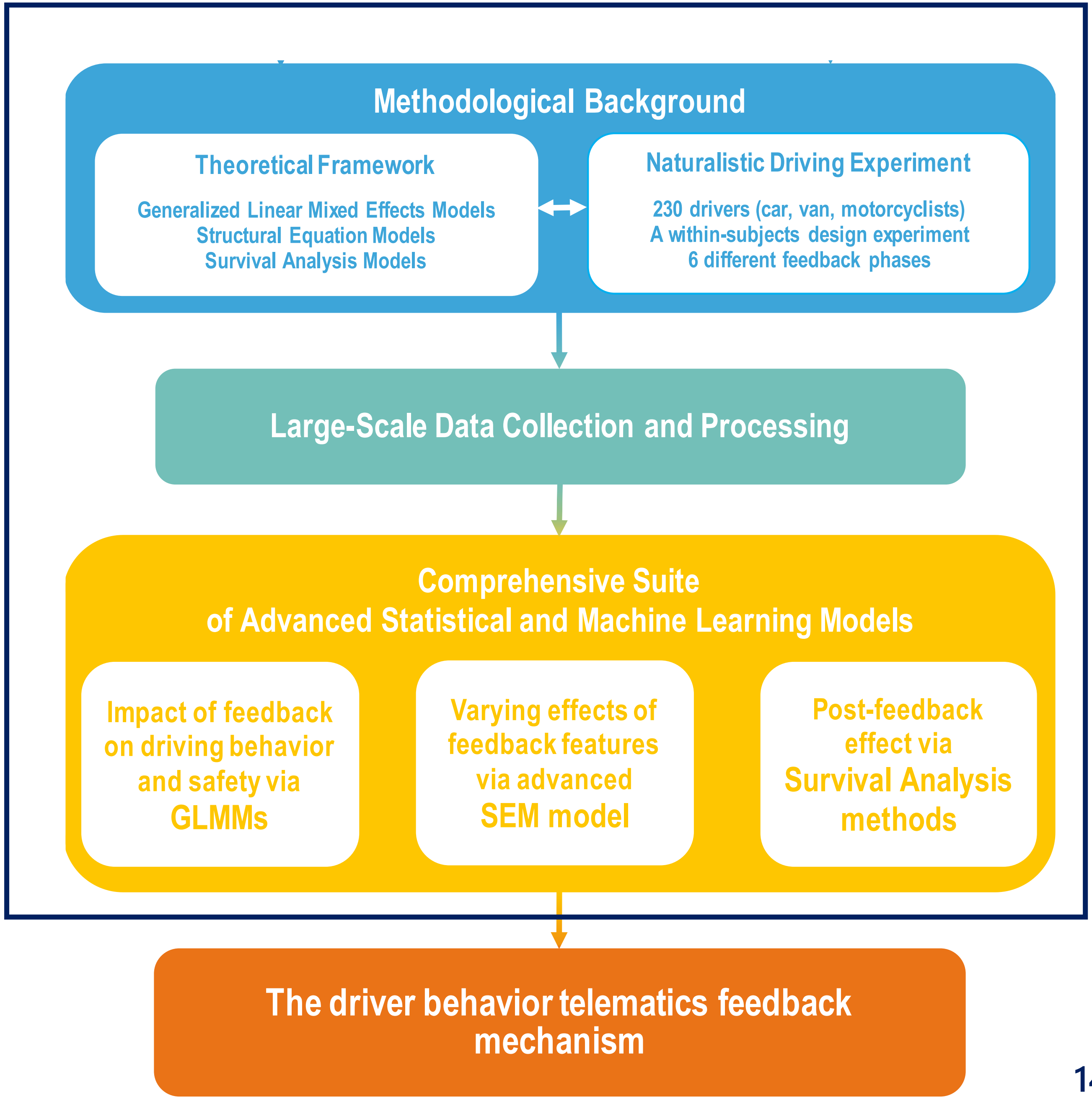
Methodological framework

Study Design
- Naturalistic driving experiment with 230 drivers across six feedback phases

Data Collection
- High-resolution driving data from smartphone sensors

Modeling Approaches
- GLMMs: Impact of feedback on driving safety
- SEM: Influence of specific feedback features
- Survival Analysis: Long-term post-feedback effects

Key research findings
- Driver behavior telematics feedback mechanism



Naturalistic Driving experiment

- Experimental framework
- Smartphone application
- Self-reported questionnaire data
- Big data processing
- Summary statistics

Experimental framework (1/2)

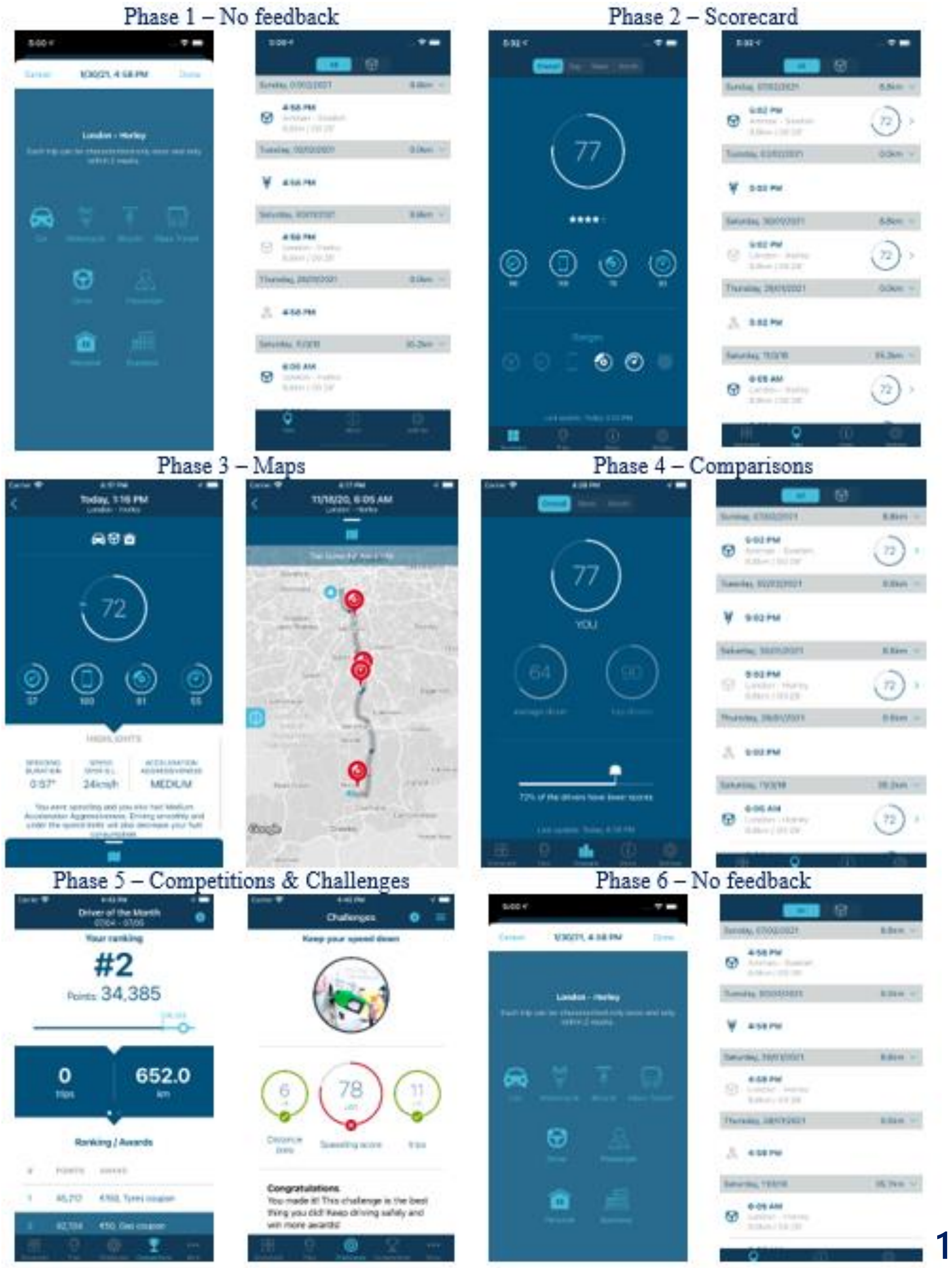
- ND study examines **telematics feedback's impact** on driving behavior and safety
- **Three key pillars**: Impact on different driver groups, feedback feature effects, and post-feedback behavior
- **Within-subjects experimental design** to track individual changes across six feedback phases
- Naturalistic driving experiment with **230 participants** (car drivers, professional drivers, motorcyclists)
- Recruitment via email invitations and partnerships, **ensuring GDPR compliance**

Experimental design	Feedback phases	Duration
one group / within-subjects design	• baseline • scorecard • maps • peer comparison • competitions • no feedback	21 months

Mode of Transportation	Number of Invited Candidates	Number of Drivers	Percentage of Total Drivers
Passenger Vehicles	260	176	76.5%
Professionals (Car/Van)	80	27	11.7%
Motorcycles	55	22	9.6%
Bicycles	10	5	2.2%
Total	405	230	100%

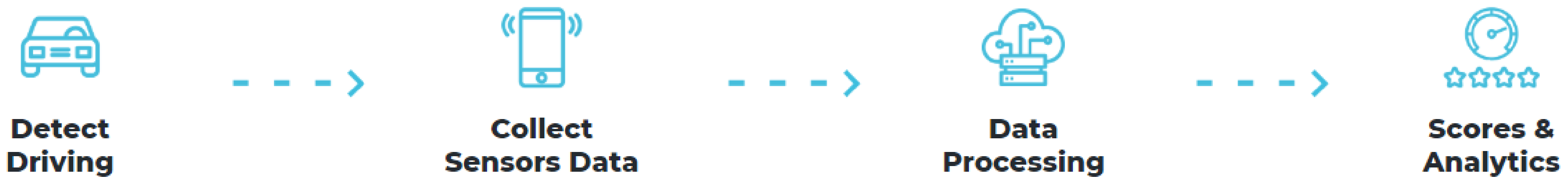
Experimental framework (2/2)

- The experiment consists of **6 different phases** differing in the type of feedback provided to drivers:
  - **Phase 1** - **trip list and characterization** accessible to the application user
  - **Phase 2** - **Scorecard** enabling scoring per trip
  - **Phase 3** - **Maps and Highlights** providing further information per trip
  - **Phase 4** - **Comparisons** between drivers
  - **Phase 5** - **Competitions and challenges** with prizes for safe driving
  - **Phase 6** – back to Phase 1 - all additional **feedback removed from the drivers**



Smartphone application data

- OSeven Telematics **customized BeSmart app** records driver behavior using smartphone sensors and advanced APIs
- Automatic **driving detection** identifies vehicle trips and activates data collection
- **Collected data includes** GPS, accelerometer, gyroscope, phone activity, and driving status



- **Advanced processing & ML algorithms** detect speeding, harsh events, and mobile phone use
- **Driver scoring system** evaluates risk exposure based on trip distance, time, and violations
- **Custom motorcycle mode** adjusts scoring for two-wheelers, excluding phone use metrics

Self-reported questionnaire data

- **Questionnaire designed to assess** driving habits and behavior, based on established research

- **Four sections:**
  - Driving Experience
  - Vehicle Characteristics
  - Driving Behavior
  - Demographics

- Driving Behavior section includes **accident history and self-assessed driving skills**

- Customized questionnaires for **different vehicle types** (cars, motorcycles, professional drivers, bicycles)

BESMART

Driver Behavior Questionnaire

A. Driving Experience – Trips

1. Participant Email:
2. When did you obtain your car driver's license?
3. How many years of driving experience do you have, regardless o
4. How many days per week do you use your car? (1 to 7 options)
5. Approximate kilometers driven per week (<20 to 150+ options)
6. Average daily trips as a driver (1 to 5+ options)
7. Average daily trip length in kilometers (1-2 to 30+ options)
8. Approximate yearly kilometers driven (<5,000 to >20,000 optio

B. Vehicle

9. Ownership status (Personal, family-owned, rented, company veh
10. Engine capacity (<1001cc to >2000cc options)
11. Vehicle age (<5 years to >15 years options)
12. Average fuel consumption (<5lt/100km to >15lt/100km option

C. Driving Behavior

13. Accident history (last 3 years, with or without fault):
    a. Total number of accidents you have been involved in.
    b. Accidents with injuries.
    c. Accidents with only material damages.
14. Traffic violation fines in the last 3 years (0 to >3 options)
15. Statements on driving behavior (Never to Always scale):
    a. Exceeding speed limits

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    b. Harsh braking
    c. Aggressive acceleration
    d. Sudden turns
    e. Mobile phone use while driving
16. Compliance with speed limits (1: Not at all, 5: Very much):
    a. Highway
    b. National roads
    c. Urban roads
17. Driver self-assessment (1 to 5 scale):
    a. How careful you perceive yourself to be?
    b. How aggressive you perceive yourself to be?

D. Demographic Data

18. Gender (Male, Female, Other)
19. Age (ranges: 18-24 to ≥65)
20. Marital status (Single, Married, Divorced, Widowed)
21. Household size
22. Family annual income (<10,000 to >30,000 options or 'Prefer not to say')
23. Education level (Primary to Doctorate and Other)
24. Familiarity with smartphone applications (1: Very low, 5: Very high)

Big data processing

- **Large-scale driving data** was processed and structured for statistical analysis
- **Database variables** included trip details, harsh events, speeding, and mobile phone use
- **Postman API** was used to extract trip data efficiently for specific time periods
- **Data was anonymized and securely stored**, ensuring compliance with privacy regulations
- **Separate datasets** were generated for **cars and motorcycles** to enhance analysis accuracy
- Overall, high-resolution data were collected from **106,776 trips**, covering a **total of 1,317,573 kilometers** and **30,532 hours of driving from 230 drivers**

Summary Statistics

Speeding Reduction Across Phases

- Car drivers showed a substantial reduction in speeding percentage from Phase 1 to Phase 2, with a relatively stable trend in later phases
- Professional drivers maintained lower speeding rates

Mobile Phone Use Decline

- Car drivers exhibited a decline in mobile use from Phase 1 to Phase 6, indicating a positive impact of feedback interventions

Variability in Harsh Events

- Harsh accelerations and braking showed mixed trends across phases
- Car drivers saw an initial decline in harsh accelerations but fluctuations in later phases, while motorcyclists displayed high variability

Motorcyclists' High Risk Behavior

- Motorcyclists exhibited consistently higher rates of harsh events and speeding across all phases

Descriptive statistics of the per driver values of the recorded **driving behavioral indicators** (mean value and the respective standard deviation in parenthesis)

Speeding percentage (%)	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
Car drivers	5.98 (0.05)	3.66 (0.03)	3.63 (0.04)	4.38 (0.04)	3.25 (0.04)	3.88 (0.04)
Professional drivers	-	1.61 (0.02)	0.78 (0.01)	0.96 (0.01)	1.05 (0.01)	2.26 (0.01)
Motorcyclists	10.42 (0.09)	7.91 (0.09)	9.58 (0.12)	9.23 (0.09)	7.86 (0.08)	9.09 (0.07)
Mobile use percentage	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 4**	**Phase 5**	**Phase 6**
Car drivers	4.20 (0.06)	3.58 (0.05)	3.89 (0.06)	3.66 (0.06)	3.03 (0.07)	2.83 (0.04)
Professional drivers	-	0.80 (0.01)	0.76 (0.01)	0.82 (0.01)	1.00 (0.02)	1.44 (0.01)
Motorcyclists	-	-	-	-	-	-
Harsh accelerations per 100km	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 4**	**Phase 5**	**Phase 6**
Car drivers	9.31 (9.76)	9.01 (8.21)	10.62 (9.89)	10.51 (11.33)	8.81 (9.49)	8.33 (5.61)
Professional drivers	-	0.58 (1.07)	0.59 (0.98)	1.04 (1.51)	0.42 (0.65)	2.09 (1.21)
Motorcyclists	48.38 (29.77)	19.76 (19.66)	28.53 (28.83)	19.26 (14.74)	8.27 (10.30)	12.24 (13.83)
Harsh braking per 100km	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 4**	**Phase 5**	**Phase 6**
Car drivers	18.04 (14.14)	17.35 (11.94)	18.31 (10.70)	17.35 (11.90)	12.08 (9.94)	13.71 (8.31)
Professional drivers	-	2.57 (3.39)	2.24 (2.89)	2.90 (3.04)	1.37 (2.13)	4.79 (1.58)
Motorcyclists	31.36 (24.36)	26.38 (22.27)	39.95 (41.94)	33.81 (33.81)	13.68 (9.77)	18.18 (9.80)

Feedback Impact on Driver Behavior and Safety

- Analysis approach
- Mobile use among car drivers
- Speeding behavior among motorcyclists
- Harsh events among professional drivers

GLMM analysis approach

Generalized Linear Models

- Extend traditional regression methods by allowing the **dependent variable to follow distributions from the exponential family**, such as Poisson, binomial, or Gaussian
- For count data, such as the frequency of harsh events (e.g., harsh braking or harsh acceleration) per trip, a **Poisson distribution is typically used**

Generalized Linear Mixed-Effects Models

- Extend GLMs by adding **random effects to account for grouping** or clustering in the data, such as repeated measures for the same drivers

GLMM with Random Intercepts

- A GLMM with random intercepts models **variability in the baseline frequency** of the examined indicator across drivers while keeping the effect of predictors constant

GLMM with Random Slopes

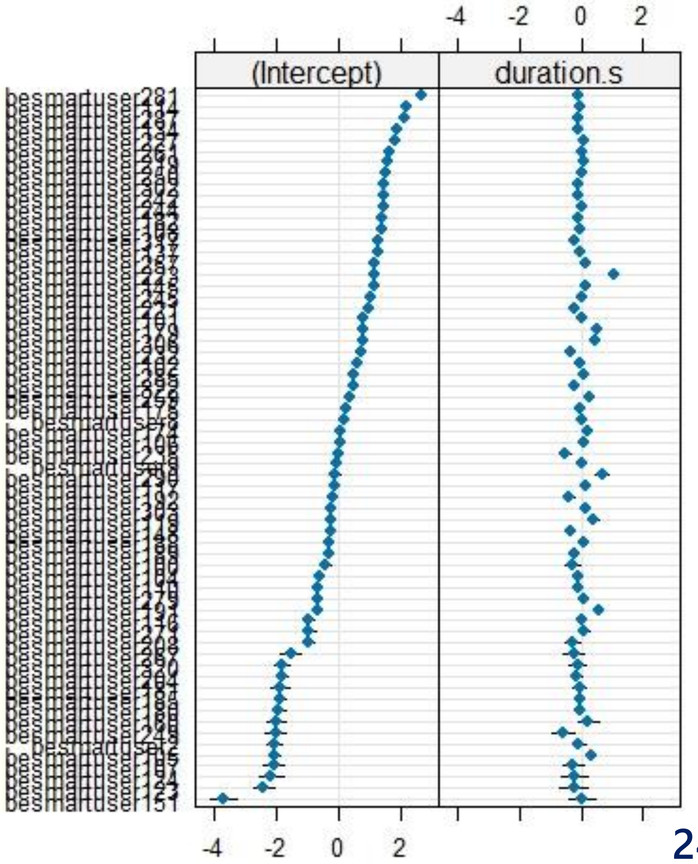
- A GLMM with random slopes further extends the model by allowing **the effect of a predictor**, such as trip duration or distance, to vary across drivers

Mobile use among car drivers (1/2)

- Overall, during the **two first phases of the experiment** a large dataset of **21,167 trips** from a sample of **65 car drivers** were recorded
- To model the percentage of mobile use per trip for the participant drivers, **GLMMs were fitted via maximum likelihood and using z-factor scaling**
- The most informative configuration of random effects included **both random intercepts and random slopes** in the GLMMs to capture unique driver traits

	Age groups			
	<25	25-55	>55	Total%
Male	0	27	3	46%
Female	3	31	1	54%
Total %	5%	89%	6%	100%

Model Family	Model Configuration	D.f.	AIC	BIC	logLik	χ^2
GLM	Fixed effects only [baseline]	7	267329	267385	-133658	–
GLMM	Fixed effects & Random Intercepts	8	193060	193123	-96522	74271.3
GLMM	Fixed effects, Random Intercepts & Random Slopes	10	191573	191652	-95777	1490.9



Mobile use among car drivers (2/2)

	Overall model				Urban Model				Rural Model				Highway			
Random Effects																
Group	Variable	SD	Variance		Variable	SD	Variance		Variable	SD	Variance		Variable	SD	Variance	
Identifier	**Intercept**	1.4024	1.9667		**Intercept**	1.3711	<0.001		**Intercept**	1.6843	<0.001		**Intercept**	3.536	12.506	
	duration	0.2827	0.0799		**duration**	0.0008	<0.001		**duration**	0.0007	<0.001		**duration**	1.931	3.731	
Fixed Effects																
Variable	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**
Intercept	**0.6528**	0.1754	3.7220	**<0.001**	0.4750	0.1721	2.7590	0.006	-0.2269	0.2102	-1.0790	0.281	**-4.1676**	0.4586	-9.0880	**<0.001**
Driver Feedback	**-0.4276**	0.0081	-52.5660	**<0.001**	**-0.3687**	0.0083	-44.2790	**<0.001**	**-0.1180**	0.0095	-12.4290	**<0.001**	**0.5490**	0.0235	23.4120	**<0.001**
Trip duration	**0.1514**	0.0374	4.0440	**<0.001**	**0.0004**	0.0001	3.9160	**<0.001**	**0.0008**	0.0001	8.5510	**<0.001**	**0.6892**	0.2451	2.8120	**0.0049**
Harsh accelerations	**0.0424**	0.0034	12.4380	**<0.001**	**-0.0131**	0.0013	-9.8620	**<0.001**	**0.0511**	0.0044	11.5500	**<0.001**	**0.0883**	0.0055	16.0250	**<0.001**
Risky hours	**-0.0543**	0.0046	-11.6940	**<0.001**	**-0.3298**	0.0124	-26.6670	**<0.001**	**-0.0114**	0.0012	-9.5000	**<0.001**	**-0.0653**	0.0097	-6.7170	**<0.001**
Morning Rush	**-0.3390**	0.0124	-27.4020	**<0.001**	**0.1533**	0.0088	17.3810	**<0.001**	**-0.2634**	0.0136	-19.3220	**<0.001**	**-0.4071**	0.0281	-14.4940	**<0.001**
Afternoon Rush	**0.1586**	0.0089	17.9030	**<0.001**	0.4750	0.1721	2.7590	0.007	**0.1624**	0.0104	15.6600	**<0.001**	**-0.4439**	0.0285	-15.5990	**<0.001**
AIC	191573.2				214914.1				191416.0				59690.4			
BIC	191652.3				214985.3				191495.1				59769.5			
logLik	-95776.6				-107448.0				-95698.0				-29835.2			

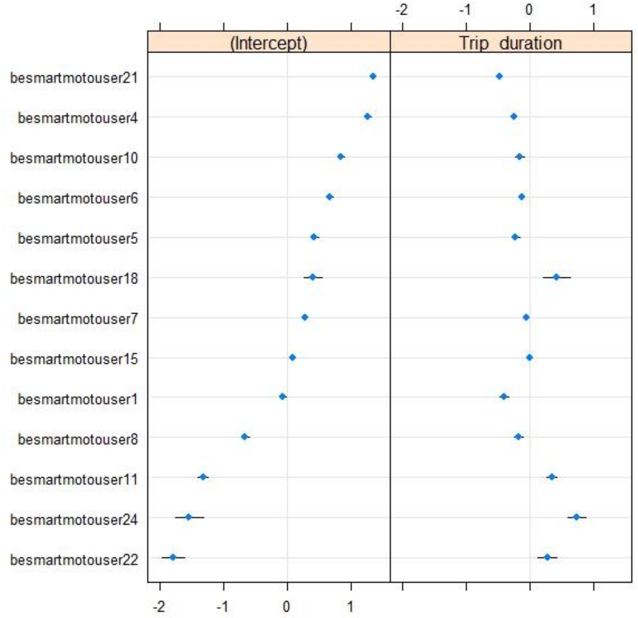
- Feedback demonstrates **consistent effectiveness in reducing mobile use in overall, urban, and rural contexts**, but their impact varies by setting, with reduced effectiveness in rural areas and an **unexpected positive association on highways**
- The substantial variability in **random intercepts** suggests **notable differences in baseline mobile use** while driving levels among drivers
- **Moderate variability in trip duration** highlights differences in how trip length affects mobile use while driving behavior

Speeding behavior among motorcyclists

- To model the percentage of speeding per trip for the participant riders, **GLMMs were fitted via maximum likelihood and using z-factor scaling -> GLMM with random intercepts and random slopes**

- Overall, during the **two first phases of the experiment** a large dataset of **3,537 trips** from a sample of **13 motorcyclists** (4 female, 9 male and aged 25-34 (n=9), 35-45 (n=4)) were recorded

	Overall model				Urban Model				Rural Model			
Random Effects												
Group	Variable	SD	Variance		Variable	SD	Variance		Variable	SD	Variance	
Identifier	**Intercept**	0.9935	0.9870		**Intercept**	3.081	<0.001		**Intercept**	3.081	<0.001	
	duration	0.3397	0.1154		**duration**	0.004	<0.001		**duration**	0.004	<0.001	
Fixed Effects												
Variable	**Estimate**	**S.E**	**z value**	**Pr(>|z|)**	**Estimate**	**S.E**	**z value**	**Pr(>|z|)**	**Estimate**	**S.E**	**z value**	**Pr(>|z|)**
Intercept	**1.898**	0.276	6.874	**<0.001**	**1.810**	0.351	5.152	**<0.001**	-	0.870	-0.689	-
Rider Feedback	**-0.144**	0.013	-10.911	**<0.001**	**-0.031**	0.011	-2.801	**0.005**	**-0.420**	0.019	-22.01	**<0.001**
Trip duration	**0.194**	0.095	2.030	**0.042**	**0.001**	0.000	3.563	**<0.001**	**0.003**	0.001	2.819	**0.004**
Harsh accelerations	**0.246**	0.005	53.127	**<0.001**	**-**	-	-	**-**	**0.056**	0.002	28.986	**<0.001**
Risky hours	**0.018**	0.003	5.161	**<0.001**	**0.006**	0.013	7.279	**0.001**	**0.019**	0.002	8.611	**<0.001**
Morning Rush	**0.066**	0.015	4.356	**<0.001**	**0.093**	0.013	-22.969	**<0.001**	**0.130**	0.020	6.551	**<0.001**
Afternoon Rush	**-0.287**	0.015	-18.826	**<0.001**	**-0.303**	0.351	5.152	**<0.001**	**-0.436**	0.023	-19.27	**<0.001**
AIC	37114.1				54460.9				34576.3			
BIC	37175.9				54516.4				34638.0			
logLik	-18547.1				-27221.4				-17278.2			



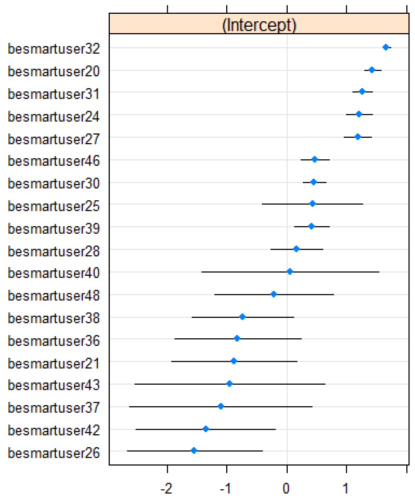
- Rider feedback **decreases** the probability of engaging in **speeding behavior by 14.5% overall**, 3.0% in urban areas, and 34.3% in rural areas

Harsh events among professional drivers

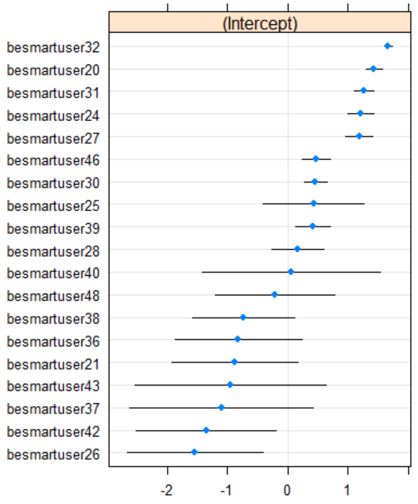
- To model the number of harsh events per trip for the participant professional van drivers, **GLMMs were fitted via maximum likelihood and using z-factor scaling -> GLMM with random intercepts**
- Overall, during the **two examined phases of the experiment** a large dataset of **5,345 trips** from a sample of **19 professional drivers** (all male, aged 25-34 (n=9), 35-45 (n=9), and 45-54 (n=1)) were recorded

	Harsh accelerations				Harsh brakings			
Random Effects								
Group	Variable	SD	Variance		Variable	SD	Variance	
Identifier	**Intercept**	1.07	1.145		**Intercept**	1.125	1.266	
Fixed Effects								
Variable	**Estimate**	**S.E**	**z value**	**Pr(>|z|)**	**Estimate**	**S.E**	**z value**	**Pr(>|z|)**
Intercept	-3.530	0.341	-10.342	**<0.001**	-2.384	0.292	-8.161	**<0.001**
Competition	-1.053	0.218	-4.821	**<0.001**	-0.906	0.117	-7.738	**<0.001**
Trip duration	0.443	0.025	17.363	**<0.001**	0.447	0.009	45.106	**<0.001**
Weekend	-0.414	0.174	-2.369	**0.017**	-0.290	0.084	-3.432	**<0.001**
AIC	2323.6				6196.7			
BIC	2356.5				6229.7			
logLik	-1156.8				-3093.4			

Harsh accelerations



Harsh brakings



- The present research quantifies the **positive impact of the 30-day competition** on both examined human risk factors
- Rewarding safe driving behavior and providing drivers with **motivations and incentives within a social gamification scheme** has successful results

Feedback Features Effects on Driver Behavior

- SEM analysis approach
- SEM results on driver behavior

SEM analysis approach

- **Structural Equations Models (SEM) are a multivariate method** that supports both multiple-input and multiple-output modeling

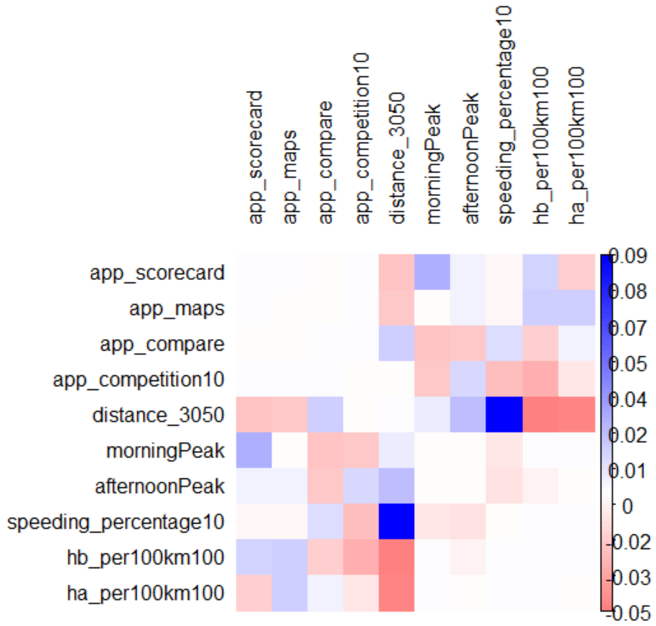
- SEM are used to **formulate several unobserved constructs as latent variables** from different types of variables collected through the naturalistic driving experiment

- **Path analysis**, a subset of SEM, focuses on modeling the **structural relationships** between variables

- The proposed SEM structure retained **two latent unobserved variables**:
  - **Feedback**, expressing the influence of the different features of the smartphone app
  - **Exposure**, expressing the influence of the exposure metrics

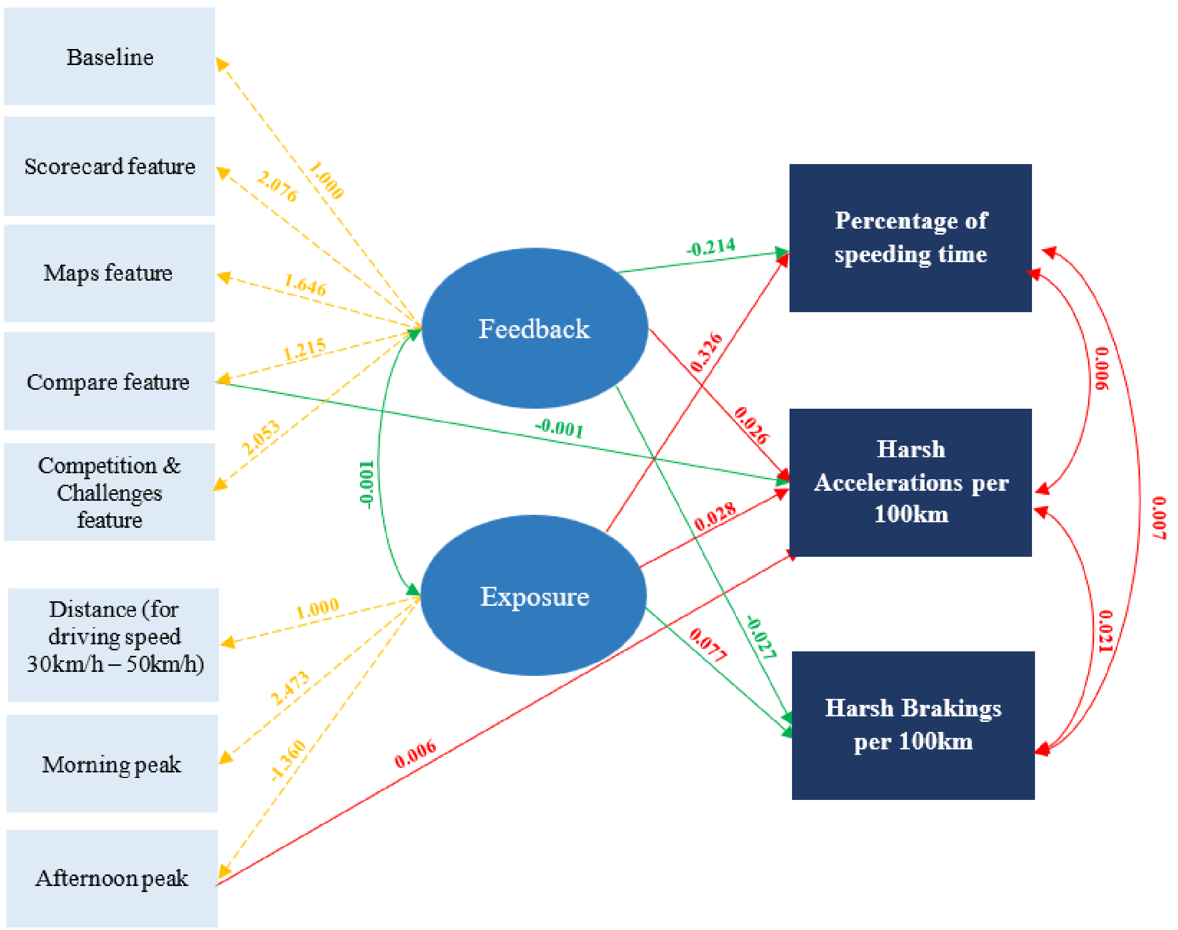
SEM Results (1/2)

- SEM model of **Percentage of speeding time**, **Harsh Brakings per 100km** & **Harsh Accelerations per 100km**
- **All four examined goodness-of-fit measures** and the signs of the estimated coefficients indicate an excellent model fit
- The **relatively low range of residual values** (maximum absolute value = 0.09) supports the robustness of the model



SEM Components		Parameters	Estimate	S.E.	z-value	P(>|z|)
Latent Variables	Feedback	Baseline	1.000	–	–	–
		Scorecard feature	2.076	0.014	148.640	**0.000**
		Maps feature	1.646	0.010	157.864	**0.000**
		Compare feature	1.215	0.029	41.754	**0.000**
		Competition & Challenges feature	2.053	0.038	54.447	**0.000**
	Exposure	Distance (for driving speed 30km/h – 50km/h)	1.000	–	–	–
		Morning peak	2.473	0.350	7.072	**0.000**
		Afternoon peak	-1.360	0.129	-10.579	**0.000**
Regressions	Percentage of speeding time	Intercept	**0.409**	0.003	138.941	**0.000**
		Exposure	**0.326**	0.043	7.627	**0.000**
		Feedback	**-0.214**	0.014	-15.655	**0.000**
	Harsh Accelerations per 100km	Intercept	**0.099**	0.001	95.037	**0.000**
		Exposure	0.028	0.010	2.769	0.006
		Feedback	**0.026**	0.004	6.493	**0.000**
		Competition & Challenges feature	**-0.001**	0.000	-2.748	**0.000**
		Afternoon peak	**0.006**	0.002	3.095	**0.002**
	Harsh Brakings per 100km	Intercept	**0.184**	0.001	158.258	**0.000**
		Exposure	**0.077**	0.014	5.542	**0.000**
		Feedback	**-0.027**	0.005	-4.976	**0.000**
Covariances	Percentage of speeding time	Harsh Brakings per 100km	0.007	0.001	7.686	**0.000**
	Harsh Accelerations per 100km	Percentage of speeding time	0.006	0.001	9.526	**0.000**
	Harsh Brakings per 100km	Harsh Accelerations per 100km	0.021	0.000	75.739	**0.000**
	Feedback	Exposure	-0.001	0.000	-5.558	**0.000**
Goodness-of-fit measures		CFI	0.940			
		TLI	0.944			
		RMSEA	0.049			0.845
		SRMR	0.025			

SEM Results (2/2)



Feedback

- The **scorecard feature has the highest positive estimate** at 2.076 ($p < 0.001$), indicating its crucial role in modifying driving habits
- These **feedback mechanisms are effective** in reducing the percentage of speeding time and harsh braking incidents, although there is a slight increase in harsh accelerations

Exposure

- Exposure factors, particularly the **times of day**, play a significant role in driving behaviors
- **Morning peak exposure** is associated with increased driving aggressiveness

Regressions

- Feedback mechanisms **significantly reduce speeding and harsh braking events**, underscoring their critical role in promoting safer driving practices
- While feedback **slightly reduces harsh accelerations during competitions**, it also shows a slight positive association with them

Covariances

- Covariance analysis highlights **strong positive correlations among all driving indicators**, illustrating how aggressive driving patterns often involve multiple risky behaviors
- A **negative correlation between feedback and exposure** indicates that increased feedback reduces exposure to risky driving conditions

Post-Feedback Effect on Long-Term Driver Behavior

- Survival analysis approach
- Survival curves
- Cox-PH model with frailty
- Weibull AFT model with clustered heterogeneity
- Random Survival Forest
- Method comparison

Survival analysis approach

- **Analyzes time-to-event data**, modelling the time until a specific event occurs
  - **Event:** Here, an "event" is defined as a **"relapse" in driving behavior**, when the driver's behavioral indicator exceed a predefined threshold => the mean behavioral indicator rate observed during the feedback phase
  - **Duration Variable** (Time to Event): The duration variable in this analysis is represented by **the successive number of trips taken until a relapse event occurs** (i.e., harsh acceleration rate exceeds the feedback phase threshold)

The Kaplan-Meier curves

- Calculation of the survival probability at each time point where an event occurs, updating the cumulative survival probability accordingly

Cox proportional hazards (Cox-PH) Model with Frailty

- Semi-parametric regression method estimating the effect of covariates on the **hazard function**,
- To account for heterogeneity in grouped data, the Cox-PH model can incorporate **frailty terms**,

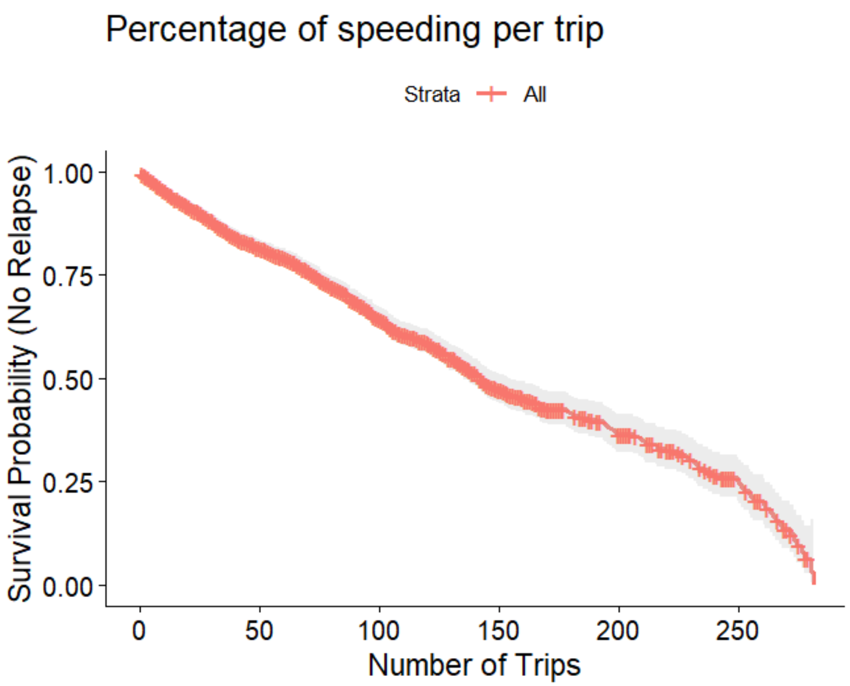
Weibull AFT Model with Clustered Heterogeneity

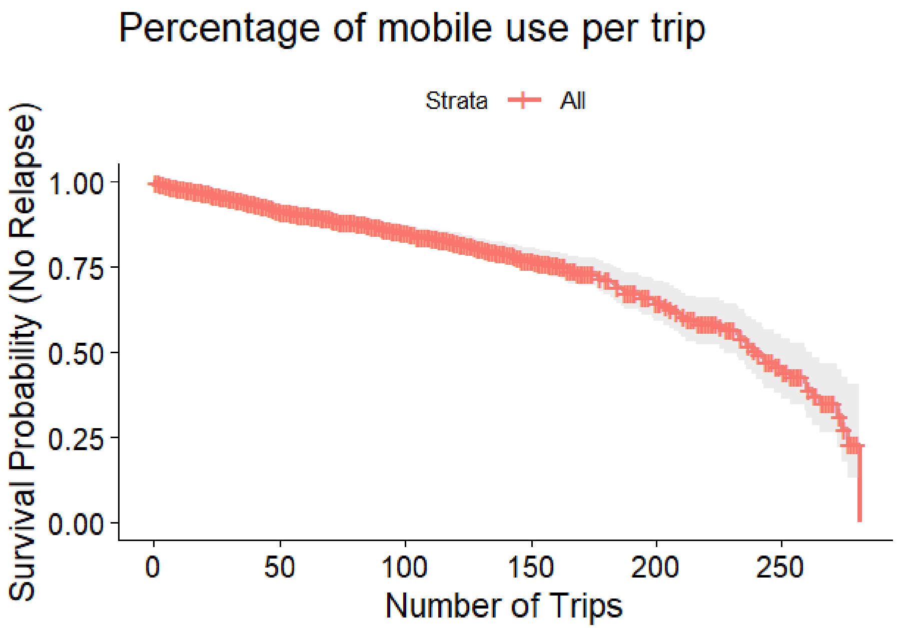
- Directly **models survival time as a function** of covariates and random error, making it a flexible parametric approach for survival analysis
- To account for clustering and unobserved heterogeneity, the model includes **random effects,**

Random Survival Forest (RSF)

- Extends random forests to time-to-event data
- The cumulative hazard function is estimated using an ensemble of decision trees

Survival curves of relapse in speeding and mobile use





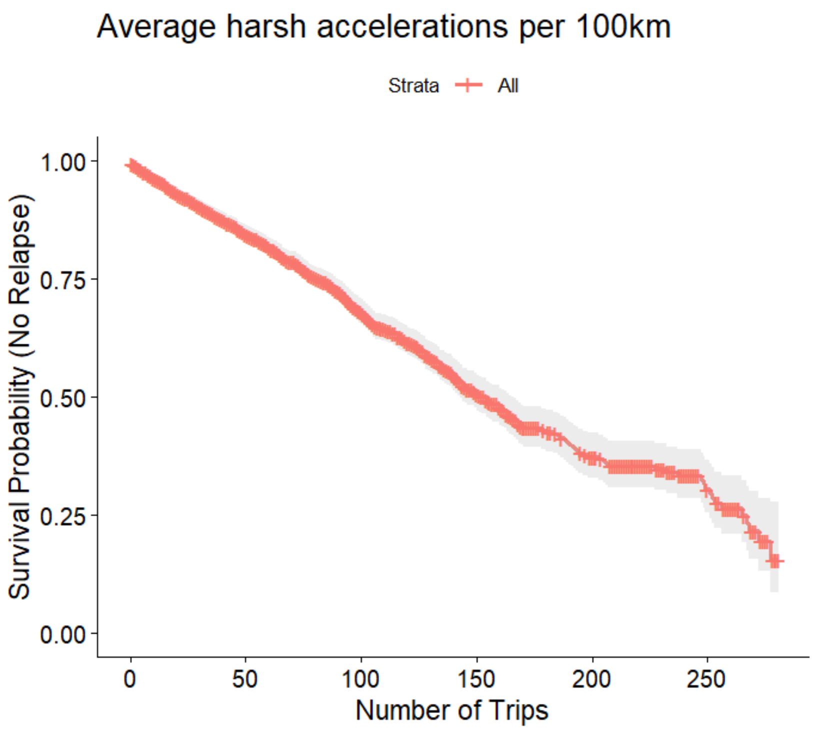
The **survival probability decreases** as the number of trips increases:

- **50 trips**: Approximately 82.3% of drivers maintain lower speeding levels
- **100 trips**: The survival probability reduces to 65.2%
- **150 trips**: Around 46.8% of drivers maintain improved behavior, showing a significant relapse among the remaining drivers

In the early stages, the survival probability remains high, indicating that drivers initially maintain reduced phone use during driving:

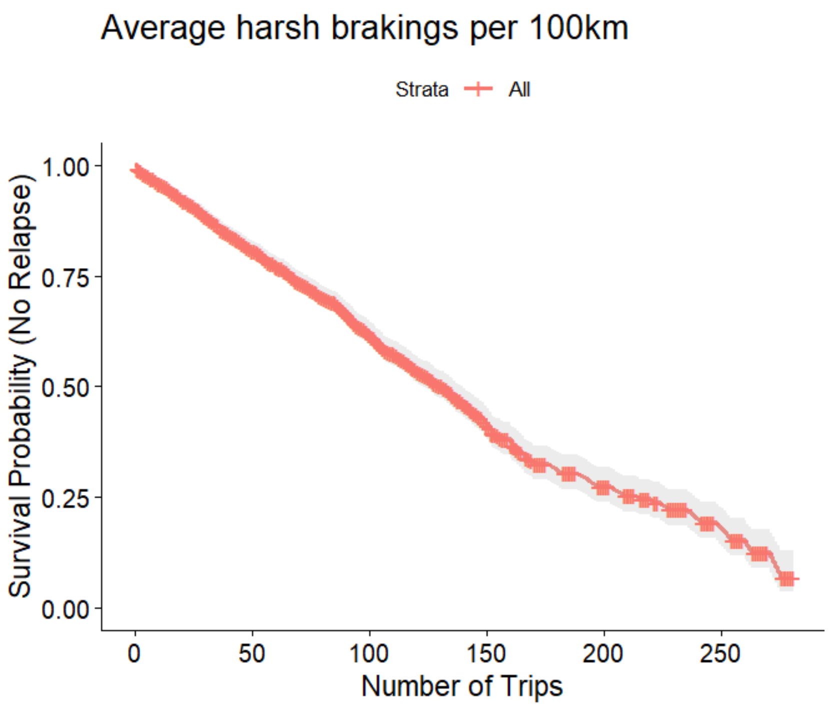
- **50 trips:** About 91.7% of drivers still show restraint in phone use, indicating a slower relapse pattern compared to other indicators
- **100 trips:** The survival probability decreases to approximately 84.8%, showing a steady increase in mobile use

Survival curves of relapse in harsh events



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

- **50 trips:** Approximately 84.8% of drivers still maintain improved behavior (no relapse)
- **100 trips**: about 68.7% of drivers
- **150 trips**: **49.2%**, suggesting that nearly half of the drivers have relapsed to pre-feedback levels of harsh acceleration



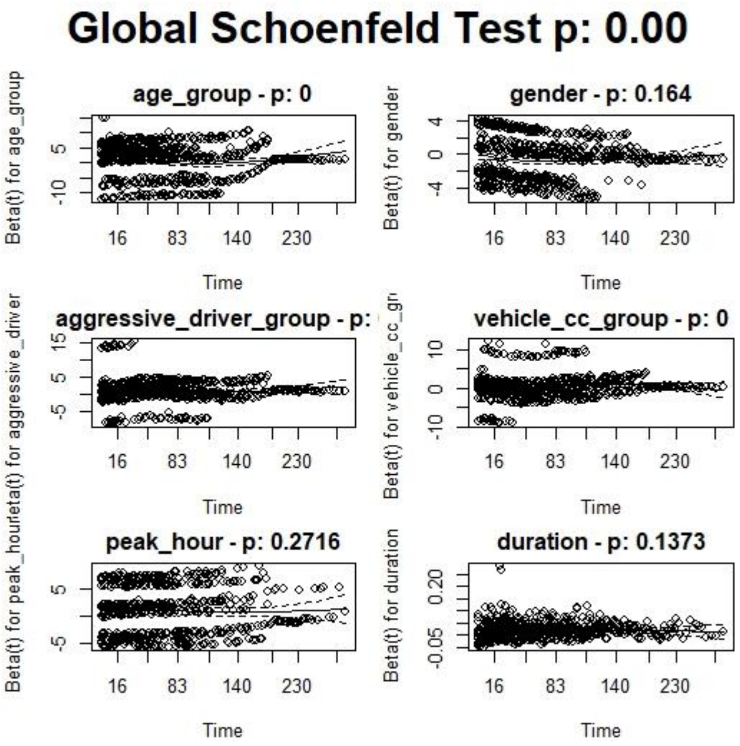
As the number of trips increases, the survival probability declines:

- **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

Relapse in harsh accelerations - Cox-PH model with frailty

Random Effects					
Group	Variable	SD	Variance		
Identifier	Intercept	1.189	1.415		
Metrics	chisq	df	p	AIC	BIC
Integrated loglik	489	9.00	0.00	471	431.4
Penalized Loglik	584	26.66	0.00	530.7	413.2
Fixed Effects					
Variable	**Coef**	**Exp(Coef)**	**SE(Coef)**	**z**	**p**
Participant's age					
Age [18-34]	Ref.				
Age [35-54]	**-1.851**	0.156	0.652	-2.84	**0.004**
Age [55+]	-0.930	0.394	1.020	-0.91	0.362
Participant's gender					
Female	Ref.				
Male	-0.653	0.520	0.520	-1.25	0.209
Self-reported aggressiveness					
Low	Ref.				
High	1.176	3.243	0.651	1.81	0.070
Participant's vehicle cc					
<1400cc	Ref.				
>1400cc	0.500	1.649	0.677	0.74	0.459
Peak hour					
Off peak	Ref.				
Morning peak	**-0.244**	0.783	0.110	-2.21	**0.026**
Afternoon peak	**-0.368**	0.691	0.108	-3.39	**<0.001**
Trip duration	**0.011**	1.011	0.002	4.75	**<0.001**
Concordance Index (C-index):	0.675				
AIC	7588.86				
BIC	7740.94				

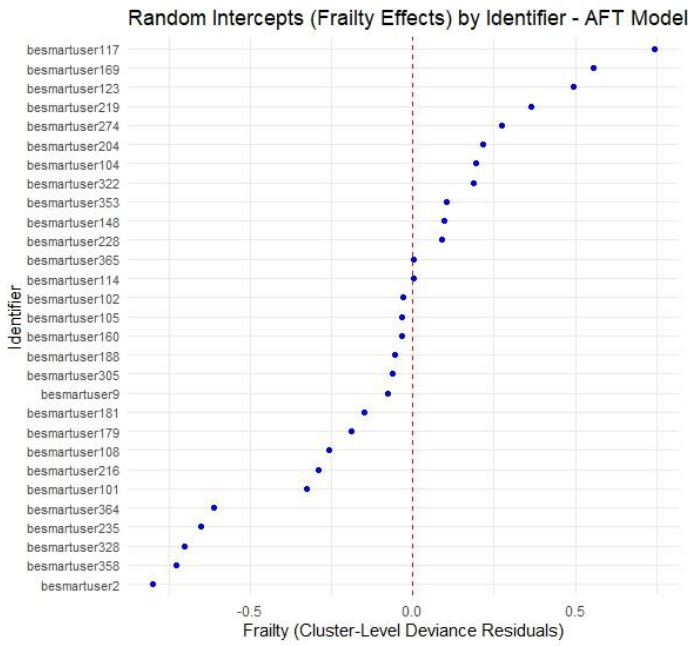
- Significant unobserved **heterogeneity exists across drivers**, as indicated by a random intercept sd = 1.189 and variance of 1.415, reinforcing the need for random effects in the model
- **Key predictors of relapse** include age group [35-54], peak hour and trip duration

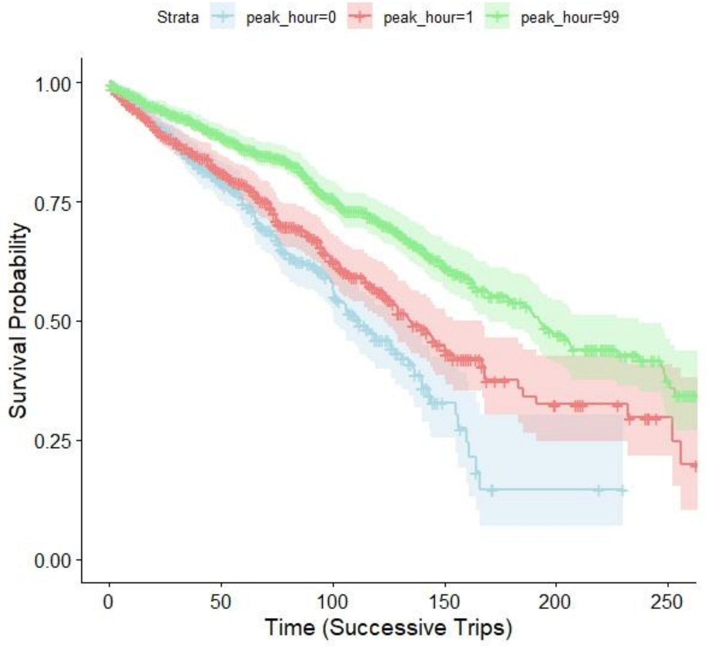


The Schoenfeld test results indicate that the **proportionality assumption is violated**, as $p<0.05$

Relapse in harsh accelerations - Weibull AFT model with clustered heterogeneity

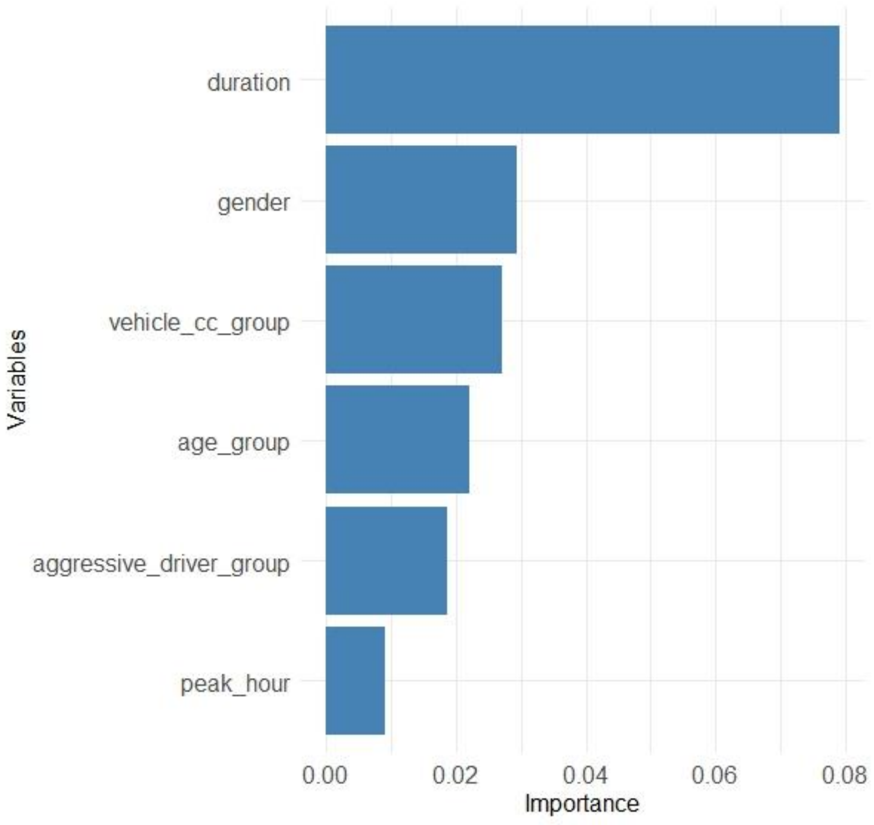
Variable	Value	Std. Err	(Naive SE)	z	p
(Intercept)	5.011	0.362	0.091	13.82	**<0.001**
Participant's age					
Age [18-34]	Ref.				
Age [35-54]	**0.245**	0.21892	0.078	1.12	**0.042**
Age [55+]	0.387	0.2108	0.169	1.84	0.085
Participant's gender					
Female	Ref.				
Male	0.382	0.27019	0.073	1.41	0.157
Self-reported aggressiveness					
Low	Ref.				
High	**-0.643**	0.25925	0.115	-2.48	**0.013**
Participant's vehicle cc					
<1400cc	Ref.				
>1400cc	**-0.008**	0.28301	0.110	-0.03	**0.046**
Peak hour					
Off peak	Ref.				
Morning peak	0.189	0.10928	0.084	1.73	0.083
Afternoon peak	**0.411**	0.13258	0.080	3.11	**0.001**
Trip duration	**-0.015**	0.00332	0.001	-4.58	**<0.001**
Log(scale)	-0.253	0.083	0.032	-3.05	0.002
Scale	0.776				
Loglik(model)	-3842.7				
Loglik(intercept only)	-3944.9				
Chisq	204.41				<0.001
Number of Newton-Raphson Iterations	8				
Concordance Index	0.677				
AIC	7705.44				
BIC	7762.49				





- **Self-declared aggressive drivers relapse faster,** while afternoon peak hours delay relapse
- **Frailty effects confirm driver variability**; survival plots show higher survival in afternoon peak hours
- **Model's concordance index** shows moderate accuracy, highlighting individual and situational relapse influences

Relapse in harsh accelerations- Random Survival Forest



Type	Survival
Number of trees	30
Sample size	2220
Number of independent variables	6
Mtry	2
Target node size	5
Variable importance mode	permutation
Splitrule	logrank
Number of unique death times	196
OOB prediction error (1-C)	0.32969

- **Trip duration is the strongest predictor** of relapse in harsh accelerations, surpassing all other factors
- RSF model shows **moderate accuracy** (RMSE: 91.36, MAE: 69.63) with **reasonable discrimination** (1-C index: 0.33)
- RSF captures **complex interactions, complementing survival models** in understanding relapse behavior dynamics

Relapse in harsh accelerations – Method comparison

Aspect	Weibull AFT Model	Cox Model with Frailty	Random Survival Forest (RSF)
Purpose	Models survival time directly	Models hazard rate	Captures non-linear effects
C-index	0.677	0.675	0.670
AIC	7705.44	7588.86	N/A
BIC	7762.49	7740.94	N/A
Key Predictors	Age, aggressive driver group, duration	Age, Aggressive driver group, vehicle_cc_group, duration	Duration, gender, vehicle_cc_group
Frailty Effects	Accounted (Clustered Heterogeneity)	Accounted (Shared Frailty)	Implicitly handled (Non-parametric)
Prediction Error (RMSE/MAE)	RMSE: 92.81, MAE: 71.30	RMSE: 173.08, MAE: 152.21	RMSE: 91.36, MAE: 69.63
Strengths	Interpretable, adjusts for clustering	Handles heterogeneity flexibly	Captures complex interactions
Weaknesses	Assumes Weibull distribution	Assumes proportional hazards	Less interpretable

- **Key predictors vary by model**: AFT and Cox models emphasize aggressive driving and trip duration, while RSF identifies gender and vehicle engine capacity as additional influential factors
- **Weibull AFT model** balances **interpretability and accuracy** (C-index: 0.677), effectively handling frailty effects
- **RSF model achieves best predictive performance** (RMSE: 91.36, MAE: 69.63) but lacks deeper interpretability
- **Cox model** struggles with **proportional hazards assumption**, leading to higher prediction errors (RMSE: 173.08)
- **Model method choice** depends on **priorities**: Weibull AFT for interpretability and RSF for accuracy

Relapse in harsh braking – Method comparison

Aspect	Weibull AFT Model	Cox Model with Frailty	Random Survival Forest (RSF)
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

Relapse in speeding – Method comparison

Aspect	Weibull AFT Model	Cox Model with Frailty	Random Survival Forest (RSF)
Purpose	Models survival time directly	Models hazard rate	Captures non-linear effects
C-index	0.70	0.696	0.704 (OOB)
AIC	8632.26	8549.06	N/A
BIC	8689.31	8708.31	N/A
Key Predictors	Trip duration, aggressiveness, age group	Trip duration, aggressiveness, age group	Trip duration, age group, aggressive driving
Frailty Effects	Accounted (Clustered Heterogeneity)	Accounted (Shared Frailty)	Implicitly handled (Non-parametric)
Prediction Error (RMSE/MAE)	RMSE: 92.47, MAE: 70.91	RMSE: 146.59, MAE: 130.41	RMSE: 91.87, MAE: 70.17
Strengths	Interpretable, adjusts for clustering; Accounts for driver-specific effects	Handles heterogeneity flexibly; Provides interpretable hazard ratios	Captures complex interactions; Robust to outliers, identifies non-linear effects
Weaknesses	Assumes Weibull distribution; Sensitive to outliers	Assumes proportional hazards; Lower predictive accuracy	Less interpretable; Requires larger datasets

- **Weibull AFT model** balances interpretability and accuracy (C-index: 0.70, RMSE: 92.47, MAE: 70.91)
- **Cox model** shows comparable discrimination (C-index: 0.696) but (RMSE: 146.59) **higher prediction errors**
- **RSF model achieves best predictive performance** (C-index: 0.704) but lacks interpretability
- **Model choice depends on priorities**: Weibull AFT for interpretability, RSF for prediction

Relapse in mobile use – Method comparison

Aspect	Weibull AFT Model	Cox Model with Frailty	Random Survival Forest (RSF)
Purpose	Models survival time directly	Models hazard rate	Captures non-linear effects
C-index	0.773	0.737	0.755
AIC	3976.995	3371.426	N/A
BIC	4034.048	3513.939	N/A
Key Predictors	Age group, aggressive driver group, vehicle CC, duration	Age group, aggressive driver group, duration	Age group, duration, vehicle CC group, aggressive driving
Frailty Effects	Accounted (Clustered Heterogeneity)	Accounted (Shared Frailty)	Implicitly handled (Non-parametric)
Prediction Error (RMSE/MAE)	RMSE: 92.47, MAE: 70.91	RMSE: 105.87, MAE: 85.41	RMSE: 85.87, MAE: 65.41
Strengths	Interpretable, adjusts for clustering; Highlights significant predictors	Adjusts for heterogeneity across clusters; Provides interpretable hazard ratios	Captures complex relationships; Robust to outliers
Weaknesses	Assumes Weibull distribution; Sensitive to deviations and outliers	Lower discrimination ability; Assumes proportional hazards	Less interpretable; Weaker numerical precision compared to parametric models

- **Weibull AFT model performs best** (C-index: 0.773), balancing interpretability and predictive accuracy
- **Cox model** has best model fit (AIC: 3371.426) but lower discrimination (C-index: 0.737)
- **RSF achieves lowest prediction errors** (RMSE: 85.87, MAE: 65.41) but lacks interpretability
- **Model choice depends on goals**: Weibull AFT for interpretation and RSF for accuracy

Conclusions, Contributions and Limitations

- Key research findings
- Innovative scientific contributions
- Limitations of the dissertation
- Challenges ahead

Key research findings (1/3)

Feedback significantly reduced risky behaviors

- Speeding among motorcyclists decreased by a factor of 13.5% overall and 34.3% in rural areas
- Mobile phone use among car drivers dropped significantly in urban areas and rural areas but increased on highways

Harsh events were notably reduced through feedback

- Harsh accelerations decreased by 12% and harsh braking by 10% in car drivers
- Feedback in urban and rural environments had the strongest impact in reducing these events

Scorecards were the most effective feedback tool

- Scorecards had the highest influence on safe driving by providing clear and actionable insights
- Maps and peer comparisons also contributed significantly to behavior improvements

Key research findings (2/3)

Gamification and incentives effectively improved driving behavior

- Professional drivers in a gamified system reduce harsh accelerations by a factor of 65.2% and harsh brakings by 59.6%
- Competitions and challenges significantly motivated safer driving behavior among the pool of car drivers

Speeding and harsh braking were highly interrelated

- Covariance analysis showed speeding often leads to harsh braking, indicating aggressive driving tendencies
- Reinforces the need for multi-faceted interventions addressing multiple risky behaviors simultaneously

Key research findings (3/3)

Post-feedback relapse occurred, emphasizing the need for continuous interventions

- Survival probabilities for improved driving declined over time, with speeding relapse reaching 46.8% by 150 trips, harsh accelerations 49.2%, and harsh braking 40.3%
- Mobile use showed slightly greater resilience, maintaining 75.6% survival at 150 trips

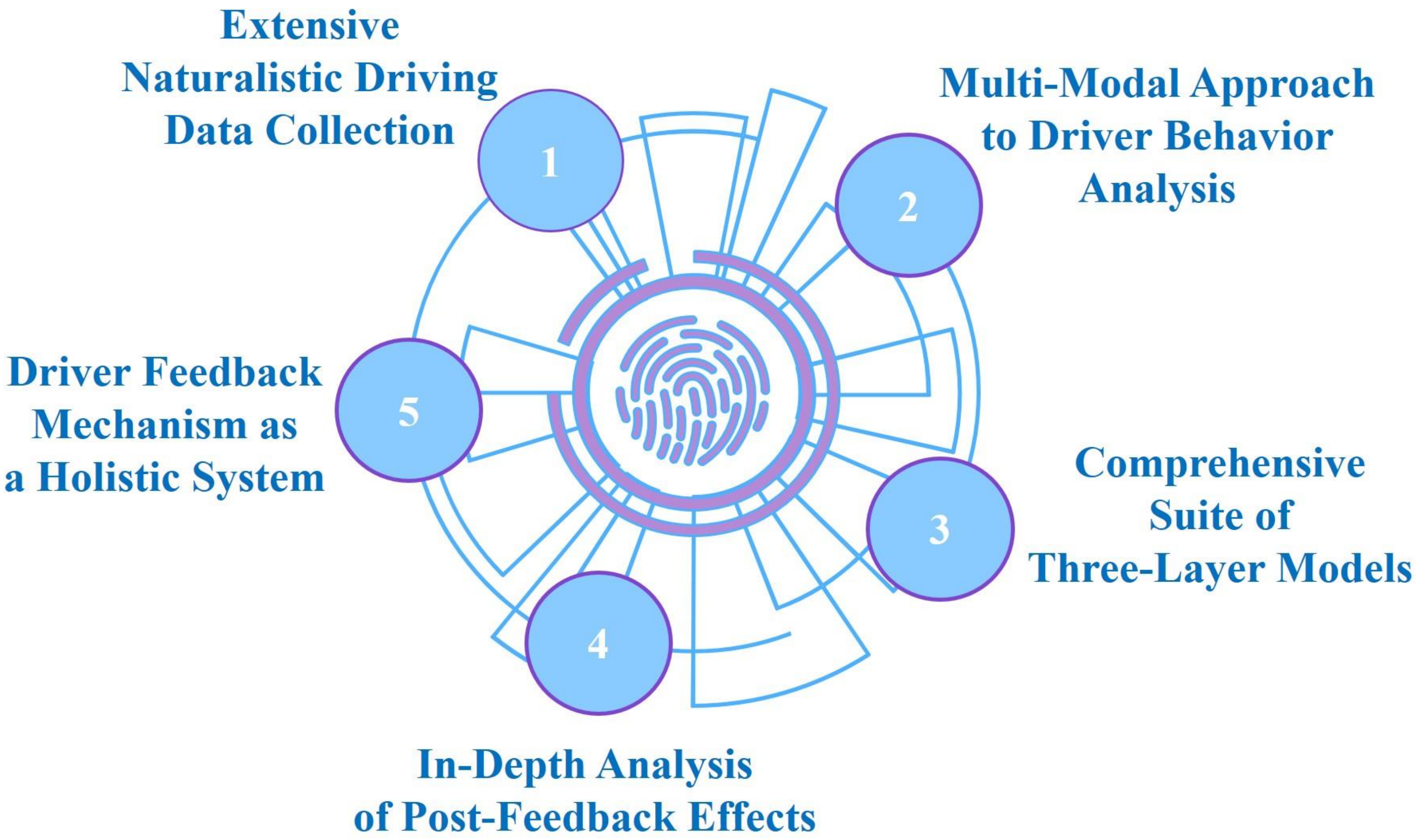
Trip duration emerged as a dominant predictor of relapse

- Longer trips increased the likelihood of relapse across all indicators
- Morning peak hours increased the relapse while afternoon peaks favored the survival of improved behavior

Weibull AFT model provided the best balance of interpretability and accuracy

- C-index ranged between 0.677 and 0.773, making it the most reliable for relapse prediction
- Captured significant variability across drivers, reinforcing the role of frailty effects

Innovative scientific contributions



Challenges ahead

Integration of real-time traffic, weather, and environmental data

- Incorporating external data sources can improve the contextual accuracy of driving behavior analysis

Scaling studies to diverse geographic locations

- Conducting research across different regions and driving cultures will enhance the generalizability of findings

Long-term evaluation of feedback sustainability

- Understanding behavior change over years, rather than months, is critical for designing lasting interventions

Adapting feedback mechanisms to evolving vehicle technologies

- The rise of connected and autonomous vehicles requires adaptive, real-time feedback integration for future road safety improvements

The Driver Behavior Telematics Feedback Mechanism

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