

FERSI Conference

Implementing evidence-based road safety measures
Removing barriers and enhancing public support

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Measuring the impact of driver behavior telematics in road safety

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Background

- The **telematics industry is growing and changing rapidly** due to the continuous advancements in Internet of Things (IoT), connectivity, and sensor hardware
- **Data are recorded** either by vehicle OBDs or smartphones sensors and transmitted to a control center
- The high penetration rate of **smartphones and social networks** provide new opportunities and features to monitor and analyze driver behaviour by adopting **low-cost collection and processing methods**



Objective

- Measuring the **impact of driver behavior telematics** in road safety using data from:
 - Smartphone devices
 - Naturalistic driving experiment



Experimental Design

- The naturalistic driving experiment consists of 2 phases differing in the **type of feedback provided** to drivers:
 - Phase 1 - **no feedback to drivers** - only the trip list and the vehicle characterization were accessible - 12 weeks duration
 - Phase 2 - **personalized feedback** in means of a trip list and a scorecard regarding driver behavior, namely speeding, harsh breaking, harsh acceleration, mobile phone use - 10 weeks duration
- A total of **26,619 trips** from a sample of 65 car drivers and 13 motorcyclist riders



The Telematics Application

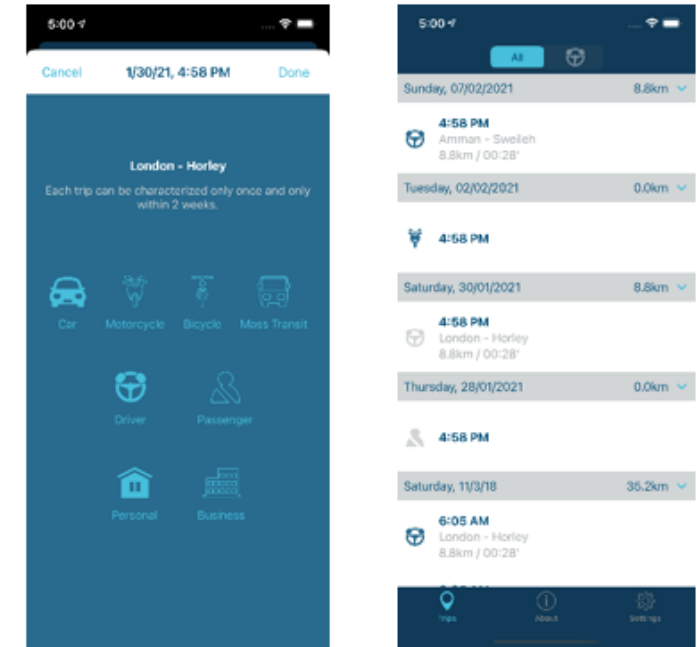
➤ Driving behavior characteristics

- Speeding
- Harsh braking/ acceleration/ cornering
- Mobile phone use

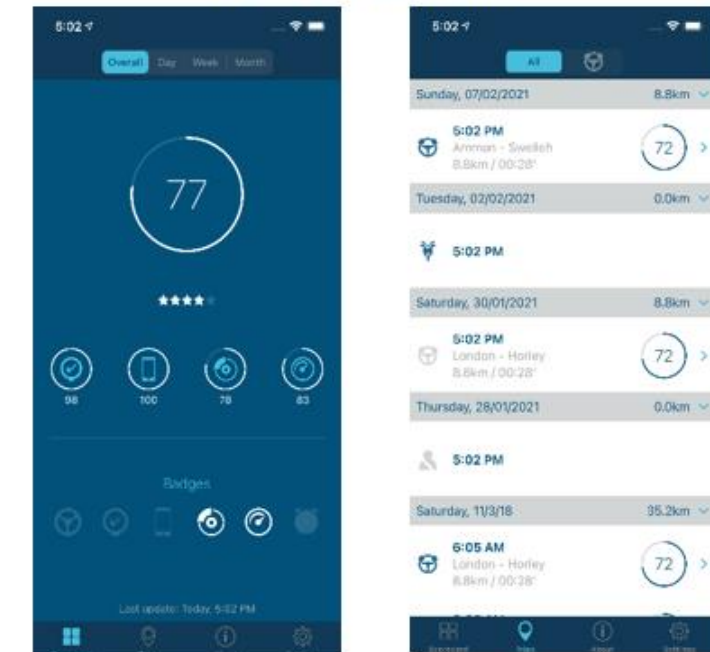
➤ Travel behavior characteristics

- Total distance
- Total duration
- Road network type
- Risky hours driving
- Vehicle type

Phase 1 – No feedback



Phase 2 – Scorecard



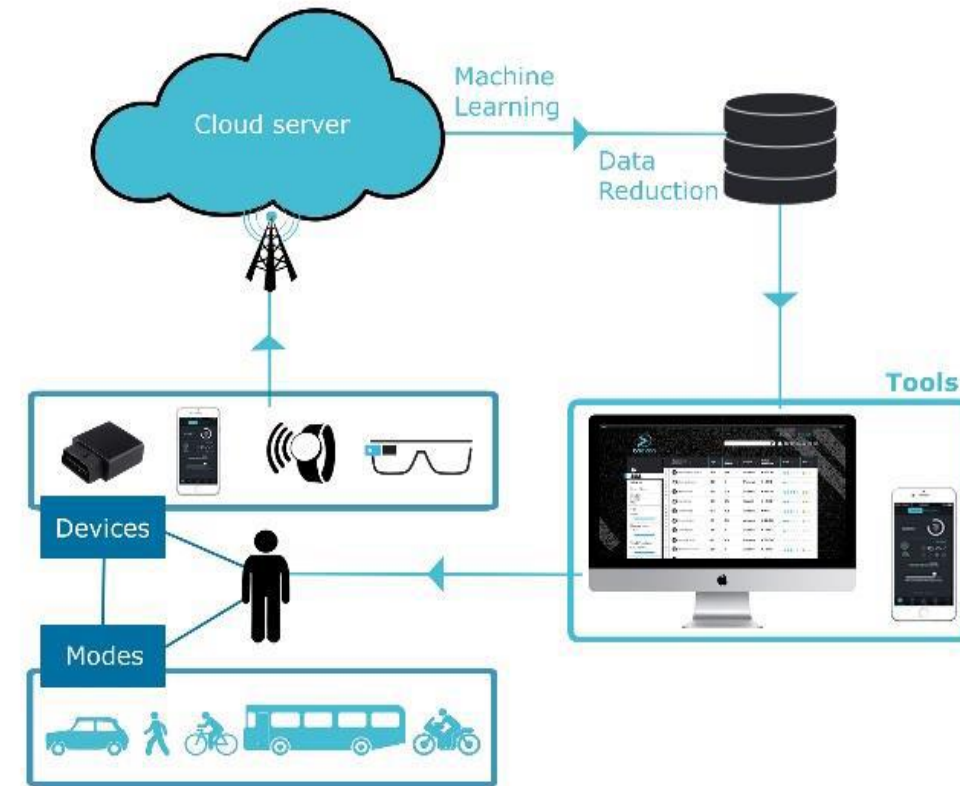
Smartphone data collection (1/2)

- A **user-friendly smartphone app** developed by **OSeven Telematics** to record user's driving behaviour (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**
- **Data are stored** in a sophisticated database where they are managed and processed



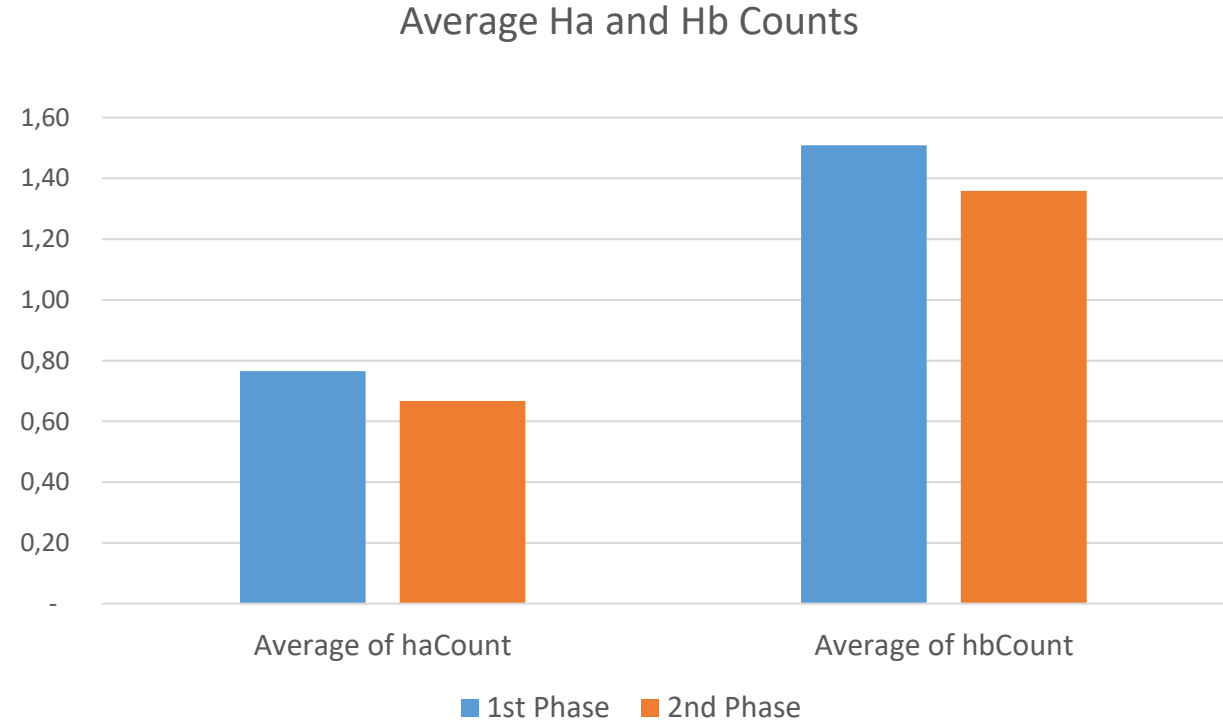
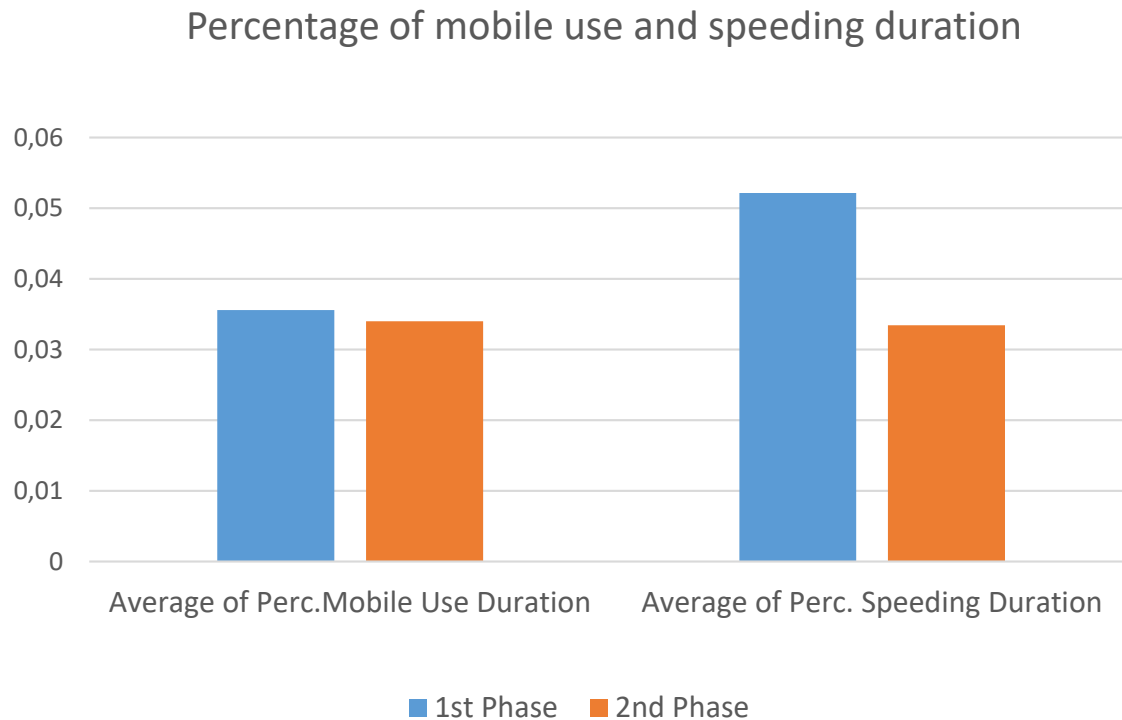
Smartphone data collection (2/2)

- **Indicators are designed using:**
 - machine learning algorithms
 - big data mining techniques
- **The database analyzed** was in .csv format
 - Drivers' trips are stored per row, the characteristics of which are stored in each column's variables
- **State-of-the-art technologies** and procedures in compliance with standing Greek and European personal data protection laws (**GDPR**)



Descriptive statistics – car drivers

- Both types of **harsh events** (accelerations and brakings) are **reduced** in the 2nd phase of the experiment

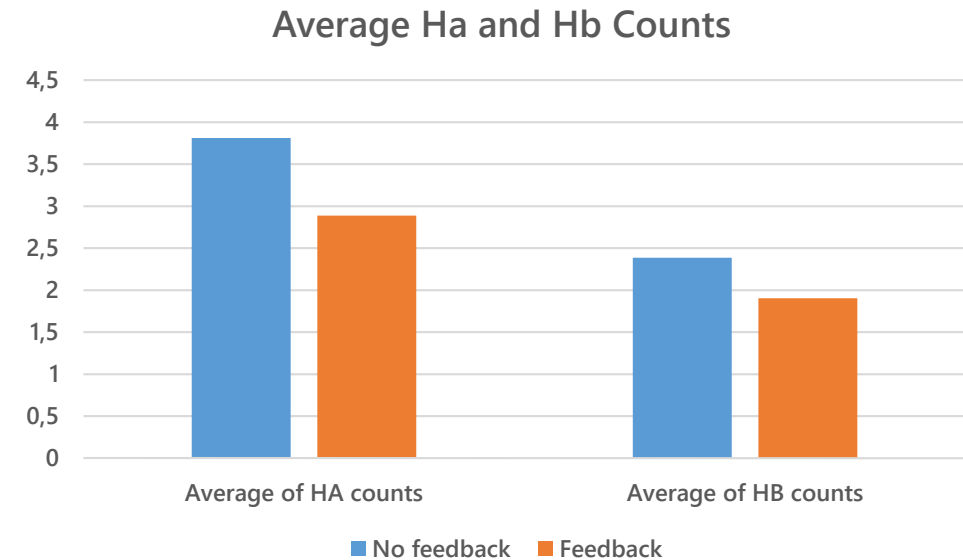
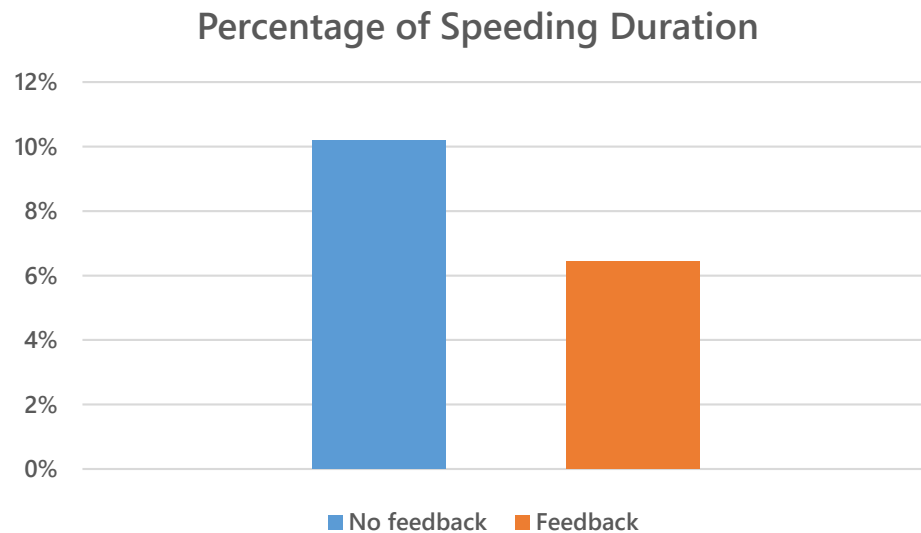


- The percentage of **driving above the speed limits and driving while distracted** by the mobile phone is **reduced in the 2nd phase** of the experiment



Descriptive statistics – motorcyclist riders

- Both types of **harsh events** (accelerations and brakings) are **reduced** when feedback is provided to riders



- The percentage of **driving above the speed limits** is **reduced** in the **2nd phase** of the experiment



Methodology

➤ Analysis scope

- Among the recorded risk factors, the **frequency of harsh events** per trip for the car drivers and the **percentage of speeding** per trip for motorcyclist riders are chosen to be investigated in the present study

➤ Selection of **statistical method**:

- Need for event prediction - data counting (data modeling)
- **Generalized Linear Mixed-Effects Models** (GLMMs) to capture different driving behaviors, given by the following formula:

$$\log(\lambda_i) = \beta_{0i} + \beta_{ji}x_{ji} + \beta_{n-1}x_{n-1} + \varepsilon$$



Results – car drivers (1/2)

➤ GLMMs for harsh acceleration counts

Parameter	GLMM for Phase 1					GLMM for Phase 2				
	Estimate	s.e.	p-value	Sig.	Relative Risk Ratio	Estimate	s.e.	p-value	Sig.	Relative Risk Ratio
Intercept	-0.927	0.091	0.000	***	0.395	-1.127	0.085	0.000	***	0.324
Maximum Speed	0.321	0.022	0.000	***	1.378	0.412	0.021	0.000	***	1.509
Percentage of Speeding Duration	0.074	0.013	0.000	***	1.076	0.035	0.012	0.003	**	1.035
Percentage of Mobile Use Duration	0.042	0.011	0.000	***	1.042	-	-	-	-	-
Log(Total Trip Duration)	0.848	0.051	0.000	***	2.334	0.729	0.050	0.000	***	2.073
Log(Total Trip Distance)	-0.231	0.050	0.000	***	0.793	-0.087	0.046	0.047	*	0.916



Results – car drivers (2/2)

➤ GLMMs for harsh braking counts

Parameter	GLMM for Phase 1					GLMM for Phase 2				
	Estimate	s.e.	p-value	Sig.	Relative Risk Ratio	Estimate	s.e.	p-value	Sig.	Relative Risk Ratio
Intercept	-0.182	0.067	0.006	**	0.833	-0.313	0.075	0.000	***	0.731
Maximum Speed	0.327	0.016	0.000	***	1.387	0.331	0.015	0.000	***	1.395
Percentage of Speeding Duration	0.097	0.010	0.000	***	1.102	0.081	0.009	0.000	***	1.084
Log(Total Trip Duration)	0.885	0.045	0.000	***	2.423	0.723	0.038	0.000	***	2.061
Log(Total Trip Distance)	-0.298	0.036	0.000	*	0.742	-0.082	0.033	0.015	*	0.921



Results – motorcyclist riders

➤ GLMMs for the percentage of travelled time above the speed limits

Trip Parameter	Overall model		Urban roads		Rural roads	
	B	p-value	B	p-value	B	p-value
Intercept	1.898	<0.001	1.810	<0.001	-	-
Rider Feedback	-0.145	<0.001	-0.031	0.005	-0.420	<0.001
Trip duration	0.194	0.042	0.001	<0.001	0.003	0.004
Harsh accelerations	0.248	<0.001	-	-	0.056	<0.001
Risky hours	0.018	<0.001	0.006	0.001	0.019	<0.001
Morning Rush	0.067	<0.001	0.093	<0.001	0.130	<0.001
Afternoon Rush	-0.286	<0.001	-0.303	<0.001	-0.436	<0.001
AIC	37114.1		54460.9		34576.3	



Findings– car drivers (1/2)

➤ Impact of detailed trip parameters

- Maximum **speed**, the percentage of **speeding** duration and **total trip duration** positively correlated with both harsh event frequencies
- On the other hand, the exposure metric of **total trip distance** negatively correlated with both harsh event types
- The percentage of **mobile use duration**, significant only for harsh accelerations with a small positive correlation



Findings – car drivers (2/2)

➤ Impact of driver feedback

- Initial findings highlight **speeding and mobile phone use reduction** when personal feedback is provided to drivers
- Both types of **harsh events** (accelerations and brakings) are also **reduced** by providing drivers with feedback
- The present achievements open **new venues for measuring the impact of driver behavior telematics** on critical human risk factors



Findings – motorcyclist riders

- The present research contributes a preliminary example of the **quantitative documentation of the impact of personalized rider feedback** on speeding
- **Trip length** and riding during the **morning rush** and **night-time risky hours** are exposure metrics significantly associated with the odds of speeding while riding
- **Harsh accelerations** are also associated with the odds of someone exceeding the speed limits, outlining a pattern of an overall **unsafe riding behavior**



Conclusions

- Telematics have a **great potential for the improvement of driving behaviour** by:
 - **identifying unsafe behaviours** resulting from speeding, harsh events, distraction and thus creating the driver's safety "footprint"
 - **developing measures** by means of **novel technology applications**, allowing to inform, notify, motivate and train the drivers to reduce their errors and their accident risk
- Telematics benefits can be seen as a guide for the design of **more efficient and longer-lasting** driver safety behaviour measures
- Need for newer and more flexible **data management models** in terms of data sharing and protection



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