Introduction

➢ The purpose of this Diploma Thesis research is to correlate stated and revealed driver behavior

➢ Data obtained from smartphone sensors are exploited

➢ The key surrogate road safety metrics of harsh accelerations and harsh brakings are examined

Bibliography

➢ Studies based on driving behavior using data from smartphones

The consensus is that driving behavior tracking systems improve road safety performance. However, monitoring needs to be maintained over time.

➢ Studies correlating stated and revealed driving behavior using data from smartphones

Combining methods of estimation and calculation eliminates the disadvantages of singular methods and increases result accuracy.

Data Collection Process

➤ 19 drivers were recruited

➤ They installed the OSeven application for driver monitoring

➤ They conducted their usual daily trips (naturalistic driving)

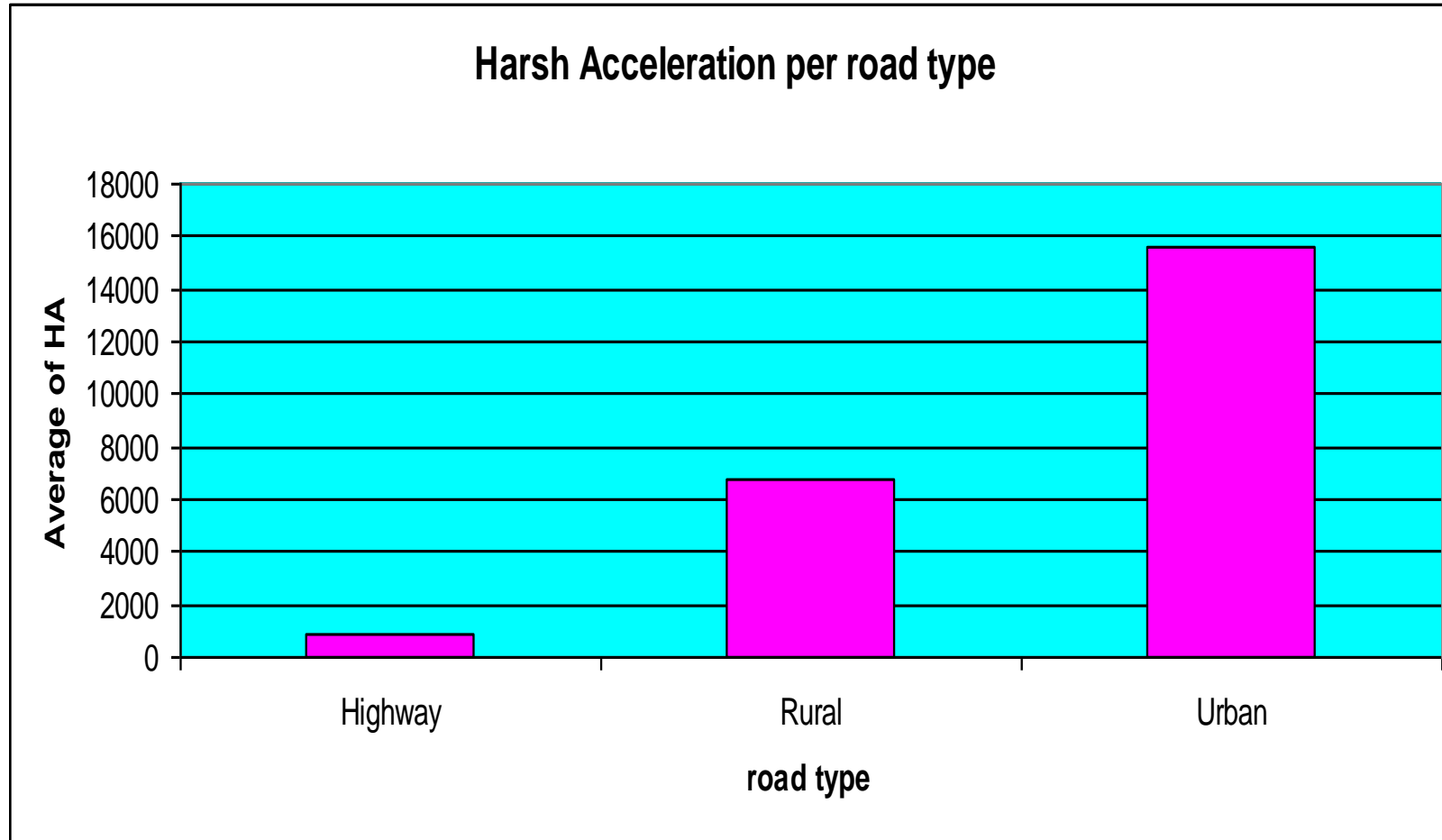**Detect Driving** - - - > **Collect Sensors Data** - - - > **Data Processing** - - - > **Scores & Analytics**

➤ Drivers also responded to targeted questionnaires for stated behavior data collection

RSS 2022

Descriptive Statistics

➤ More harsh acceleration events in urban environments

Harsh Acceleration per road type

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Statistical model analysis

➤ **Poisson models** were developed [IBM SPSS 21.0]:

➤ **Multicollinearity tests** were conducted to ensure no bias is introduced to model coefficients.

➤ Model for **harsh acceleration** event counts

   Driving experience, Inj. Crash involvement, Driver/Vehicle age, Profession, Cautious driver self-characterization

➤ Model for **harsh braking** event counts

   Driving experience, Inj. Crash involvement, Driver Age, Fines sustained (3y), Vehicle ownership, Skillful driver self-characterization
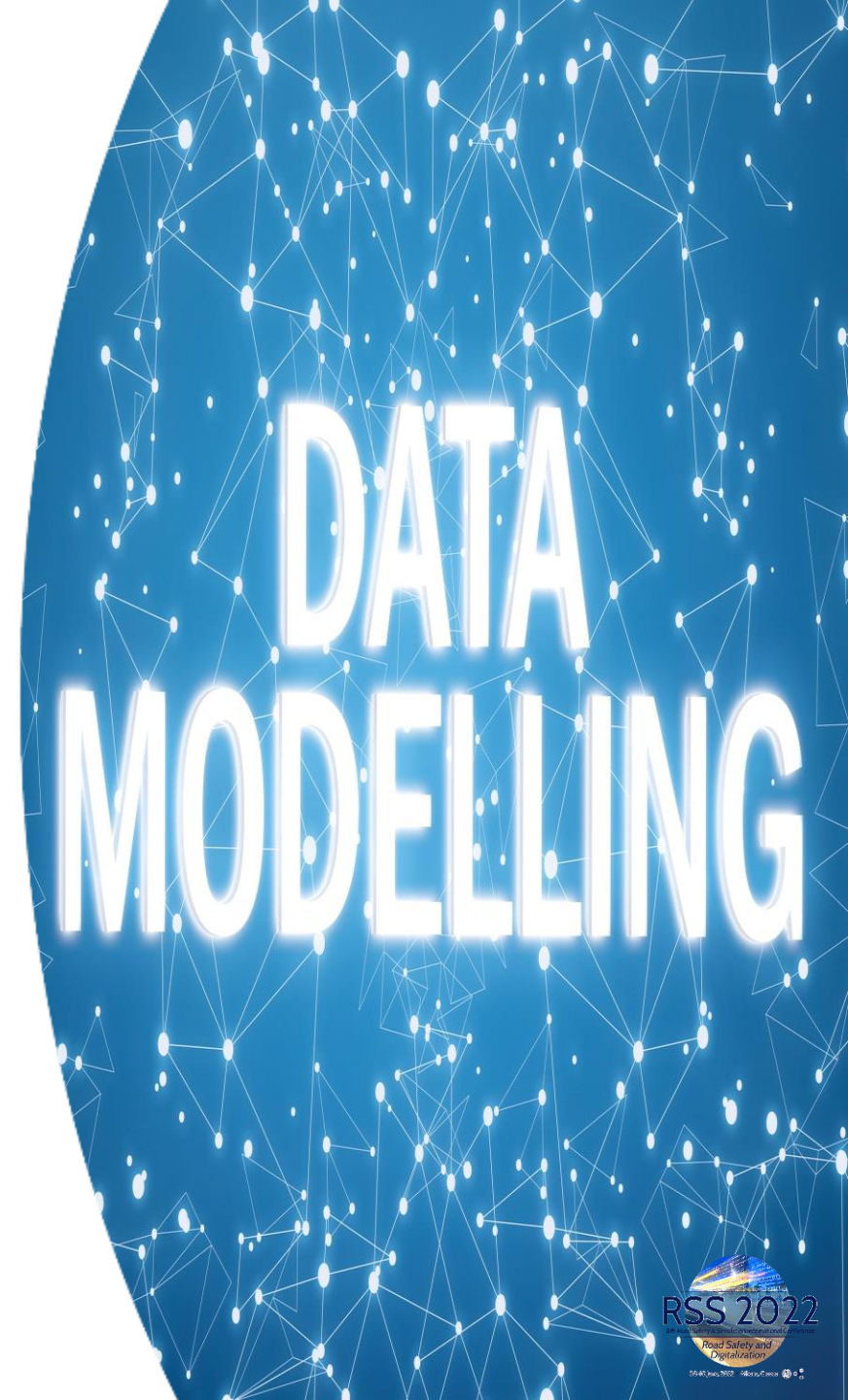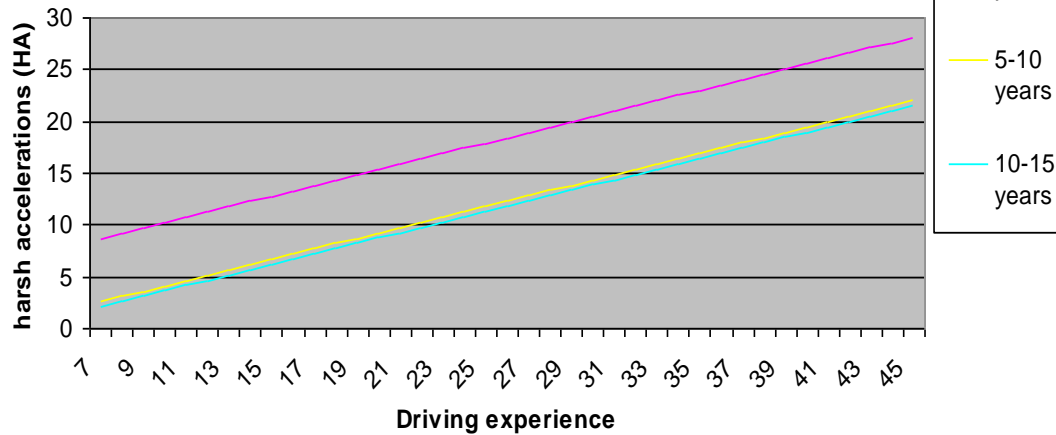
Statistical model results

Independent Variables	Model 1 – Harsh accelerations			Model 2 – Harsh brakings		
	bi	ei	ei*	bi	ei	ei*
Driving Experience	0.511	0.006	1.000	0.283	0.009	1.000
Age_vehicle	-6.599	-0.452	38.818			
≥1 Inj. Crash involved	6.226	0.426	36.624	-1.002	-0.168	1.648
Cautious driver	2.855	0.195	16.794			
Age_driver	-0.522	-0.013	2.060	-0.182	-0.011	1.297
Profession: Private Employee	9.816	0.672	57.741			
Vehicle_own_family				-2.613	-0.437	4.298
≥ 1 Fines_last 3y				7.596	1.270	12.493
Skillful_driver				-1.882	-0.315	3.095

Variables are **significant** with p-values ≤ 0.05

Sensitivity Analyses

Driving behaviour depending on the age of the vehicle

Legend: < 5 years, 5-10 years, 10-15 years

X-axis: Driving experience
Y-axis: harsh accelerations (HA)

Driving experience increases harsh acceleration occurrence, **vehicle age** decreases it

Vehicle ownership within family decreases harsh braking occurrence

Driving behaviour depending who owns the vehicle

Legend: Belongs to you, Is a corporate vehicle, Is leased by you, Belongs to another member of your family

X-axis: Driving experience
Y-axis: harsh brakes (HB)
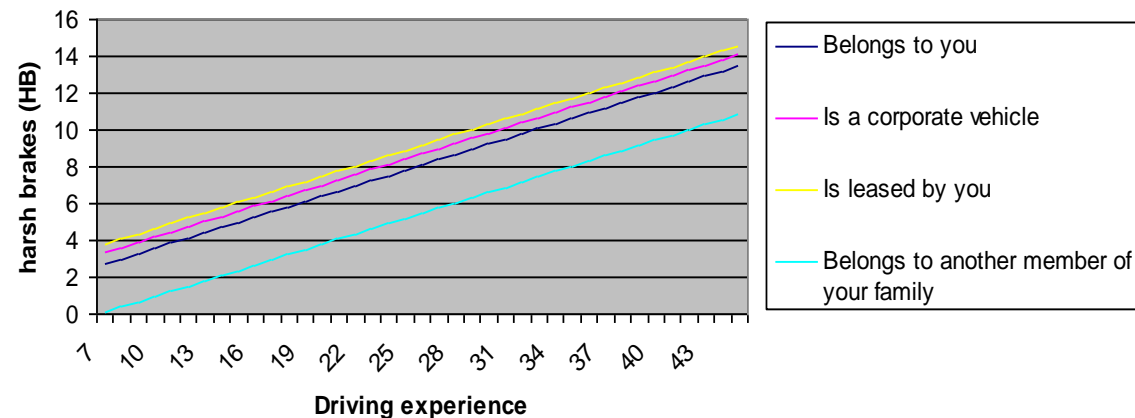
Harsh Acceleration Results

➢ Driving experience,
Involvement in more than one injury crashes,
Self-characterization as Cautious driver &
Profession as a private sector employer
...all increase harsh acceleration counts
generated by drivers

➢ Vehicle age &
Driver age
...decrease harsh acceleration counts generated
by drivers

Harsh Braking Results

➢ Driving experience &
Involvement in more than one fine in the last 3 years
...**increase harsh braking counts** generated by drivers

➢ Driver age,
Involvement in more than one injury crashes,
Vehicle ownership by family members &
Self-characterization as Cautious driver
...**decrease harsh acceleration counts** generated by drivers

Concluding remarks

➢ Data was collected from driver smartphones independent of vehicle

➢ Results can be used as incentives by insurers to conduct further analysis and to reward more cautious drivers

➢ Application-based feedback is already provided; education programs can be further developed

➢ Several GLM functions can be used to model harsh event counts in the future including traffic conditions, multiple cross-sectional samples and comparison of different environments