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HELLENIC INSTITUTE OF
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11th INTERNATIONAL CONGRESS on TRANSPORTATION RESEARCH
Clean and Accessible to All Multimodal Transport
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Identification of safe driving behavior using an ensemble of machine learning algorithms and data from the i-DREAMS experiment

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The i-DREAMS project

➤ 13 Project partners:

- [National Technical University of Athens](#)

[Universiteit Hasselt](#), [Loughborough University](#), [Technische Universität München](#), [Kuratorium für Verkehrssicherheit](#), [Delft University of Technology](#), [University of Maribor](#), [OSeven Telematics](#), [DriveSimSolutions](#), [CardioID Technologies](#), [European Transport Safety Council](#), [POLIS Network](#), [Barraqueiro Transportes S.A.](#)

➤ Duration of the project:

- 48 months (May 2019 – April 2023)

➤ Framework Program:

- [Horizon 2020](#) - The EU Union Framework Programme for Research and Innovation - Mobility for Growth



Roussou Stella, Identification of safe driving behavior using an ensemble of machine learning algorithms and data from the i-Dreams experiment



Introduction

- **Driver behavior** is a contributory factor in over 90% of crashes
- Factors such as **driver's state**, environmental conditions, and traffic circumstances remain significant contributors to traffic collisions
- **Intelligent driving behavior monitoring systems** enable real-time interventions and demonstrate remarkable efficacy in improving road safety
- The combination of autonomous vehicles and intelligent monitoring systems mitigate the impact of **human error** and create a **safer road environment** for all users



Objectives

- Development of a **Neural Network Model** and a **Long-Short Term Memory Model**
- Comparison and contrast of the two machine learning classifiers
- Identification of the **level of risky driving behavior** based the two machine learning techniques
- Association between the key factors of **task complexity** and **coping capacity on risk**



Data Description

➤ The **vehicle data** collected from the naturalistic driving experiment consisted in total of:

- 30 drivers from Germany
- 5,344 trips and
- 84,434 minutes

➤ **Questionnaire data**

- Information collected pre-trial included
- Information collected post-trial included

Phase 1 - Monitoring	Phase 2 - Real time Interventions	Phase 3 - Real time & post-trip interventions	Phase 4 - Real time & post-trip interventions & gamefication
30 German car drivers	30 German car drivers	30 German car drivers	30 German car drivers
1.397 trips	1,322 trips	1,129 trips	1,496 trips
23,617 minutes	19,469 minutes	17,704 minutes	23,644 minutes



Data Description

- Questionnaire data were collected **pre-trial** included:

Entry questionnaire

- Driving style and confidence
- Opinions on driving and safety
- Self-assessment of driver's risk-taking behaviors (speeding, mobile phone use)

Screening questionnaire

- Driver details (age, gender, driving experience, employment status, etc.)
- Vehicle details (model, age etc.)

- Questionnaire data were collected **post-trial** included:

User experience questionnaire

- Opinions on the i-Dreams system (ease of use, works as described)
- Opinions on the i-Dreams smartphone app

Exit questionnaire

- Opinions on the i-Dreams system (improvement of driving, usefulness, trust, clarity of warnings)
- Overall experience rating



Experiment Phases

Phase 1 (Baseline)

- **Intervention:** No
- **Description:** a reference period after the installation of the i-DREAMS system in order to monitor driving behavior without interventions
- **Duration:** 4 weeks

Phase 2

- **Intervention:** Real-time
- **Description:** a monitoring period during which only in vehicle real-time warnings provided using adaptive ADAS
- **Duration:** 4 weeks

Phase 3

- **Intervention:** Real-time + Post-trip
- **Description:** a monitoring period during which in addition to real-time in vehicle warnings, drivers received feedback on their driving performance through the app
- **Duration:** 4 weeks

Phase 4

- **Intervention:** Real-time + Post-trip + Gamification
- **Description:** a monitoring period during which in vehicle real-time interventions were active along with feedback but at the same time gamification elements were also active
- **Duration:** 6 weeks



Methodological Overview

- A **Neural Network (NN)** was carried out involving 30 car drivers from Germany and a large database consisting of 5,344 trips was collected and analyzed
- **Long-Short Term Memory Network (LSTM)** was also developed with the same dataset in order to compare the two machine learning techniques
- The **classification algorithms** are **evaluated** using the:
 - Accuracy
 - Precision
 - Recall
 - f1-score
 - False Alarm Rate



Neural Networks (NNs) Results

- NNs were employed to investigate if real-time **prediction of the STZ is feasible**
- Phase was considered as an **independent variable** and the analysis was performed for the whole dataset
- The algorithms has an **accuracy** of more than **94%** with a **false alarm rate** of only **6%**
- The **NNs classification** algorithms act as preparatory step towards the LSTM classification
- The **confusion matrix** was produced for the two independent variables

Predictors utilized for Neural Networks		
Variables	Headway	Speeding
Phase	×	×
Age	×	×
Average Speed	×	×
Harsh acceleration	×	×
Harsh events low	×	
Headway level total	×	
Speeding level 0		
Speeding level total		

Confusion data matrix for headway and speeding					
Variable	TP	FP	FN	TN	Sum
Headway	33378	0	1400	82	34860
Speeding	2178	1987	63	30632	34860

Assessment of classification model for headway and speeding						
Variables	Accuracy	Precision	Recall	f1-score	G-Means	FA Rate
Headway	95.98%	100.00%	95.97%	97.95%	97.97%	0.00%
Speeding	94.12%	52.29%	97.19%	68.00%	71.29%	6.09%



Long Short-Term Memory (LSTM) Results

- LSTMs were trained to **predict «dangerous» speeding and headway level**. The sequence is implicit in the way that the data was collected or organized, even if it's not immediately apparent from the predictors themselves
- A LSTM could still be used in this case to **model and make predictions** based on the implicit sequence in the data
- The accuracy of less than 60% may not be sufficient, however, the required level of accuracy depends on the specific use case and the risks involved
- The output of prediction models can be used for ongoing analysis and monitoring of road safety performance, in order to **identify trends and patterns that can inform future interventions** and improvements

Predictors utilized for Long Short-Term Memory Networks for speeding					
Variables	v1	v2	v3	v4	v5
Phase	x	x	x	x	x
Age	x	x	x	x	x
Average Speed	x	x		x	x
Harsh acceleration events	x	x	x		x
Harsh acceleration	x	x	x		
Speeding level 0	x	x	x		
Speeding level 1					x
Speeding level total	x	x	x	x	x
Headway level total				x	
Accuracy (%)	57.82	57.82	57.82	57.11	57.82

Predictors utilized for Long Short-Term Memory Networks for headway				
Variables	v1	v2	v3	v4
Phase	x	x	x	x
Age	x	x	x	x
Average Speed		x	x	x
Harsh events high	x		x	
Harsh events lows		x		
Harsh acceleration		x		
Headway level -1			x	
Headway level 0	x			
Headway level total	x	x	x	x
Speeding level total				x
Accuracy (%)	57.39	55.5	57.82	57.39



Discussion

- Training and validation of the ensemble of algorithms and the deployment of **real-time applications**, such as in-vehicle systems or mobile applications provide drivers with immediate feedback and guidance on their driving behavior
- **Predictive real-time analyses** demonstrated that it is possible to predict the level of STZ with an **accuracy of up to 95%**
- **Post-trip explanatory studies** showcased the capacity of state-of-the-art econometric models to shed light on the complex relationship of risk with the interdependence of task complexity and coping capacity
- Machine learning algorithms can recognize specific driving patterns associated with safe driving. These algorithms proved to be the **best approach** to capture **complex relationships** between various driving parameters and predict the likelihood of potential risks or crashes



Conclusions

- Understanding task complexity, coping capacity and crash risk is vital for developing targeted interventions and countermeasures to **create a safer driving environment**, reduce the number of crashes, and ultimately save lives
- Understanding how drivers **perceive and react to interventions** based on safe driving behavior identification, and optimizing their effectiveness while minimizing potential negative impacts, can enhance their acceptance and engagement
- Future research could consider **incorporating contextual information** into the models. Factors such as weather conditions, road infrastructure, and traffic patterns, to enhance the accuracy and applicability of the models in diverse driving environments or personalized driver modeling where individual driver characteristics like age, and driving style could be used





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