Identification of safe driving behavior using an ensemble of machine learning algorithms and data from the i-DREAMS experiment

Stella Roussou[1*], Thodoris Garefalakis[2], Eva Michelaraki[3], Christos Katrakazas[4], Christelle Al Haddad[5], Md Rakibul Alam[6], Constantinos Antoniou[7], Tom Brijs[8], George Yannis[9]

[1,2,3,4,9]National Technical University of Athens, Department of Transportation Planning and Engineering, 5 Heroon Polytechniou str., 15773, Athens, Greece
[5,6,7]Technical University of Munich, Chair of Transportation Systems Engineering, Arcisstrasse 21, 80333, Munich, Germany
[8]UHasselt, School for Transportation Sciences, Transportation Research Institute (IMOB), Agoralaan, 3590 - Diepenbeek, Belgium

E-mail[1] *corresponding author: s_roussou@mail.ntua.gr
E-mail[2]: tgarefalakis@mail.ntua.gr
E-mail[3]: evamich@mail.ntua.gr
E-mail[4]: ckatrakazas@mail.ntua.gr
E-mail[5]: christelle.haddad@tum.de
E-mail[6] rakibulmd.alam@tum.de
E-mail[7]: c.antoniou@tum.de
E-mail[8]: tom.brijs@uhasselt.be
E-mail[9]: geyannis@central.ntua.gr

Abstract

The i-DREAMS project aims to setup a framework for the definition, development and validation of a context-aware 'Safety Tolerance Zone (STZ)' in order to keep drivers within the boundaries of safe operation. The objective of this study is to compare and contrast two machine learning methods (i.e., Long-Short-Term-Memory Networks and a shallow Neural Network) to identify the safety level of participants driving naturally within the i-DREAMS on-road field trials. To achieve this objective a number of trips from a sample of 30 German drivers were collected and fed to the aforementioned machine learning methods in order to identify factors leading to risky behavior throughout the experiment stages. The results confirm the positive effect of i-DREAMS real-time and post-trip interventions in improving driving behavior significantly, whereas Neural Networks seem to outperform the rest of the algorithms considered.

Keywords: *On-road field trials, driving behavior, Long-Short-Term-Memory Network (LSTM), Neural Network, Machine Learning*

Περίληψη

Το έργο i-DREAMS στοχεύει στη ανάπτυξη ενός πλαισίου ορισμού, ανάπτυξης και επικύρωσης μιας "Ζώνης ανοχής ασφάλειας (STZ)" με γνώμονα το περιβάλλον, προκειμένου οι οδηγοί να παραμένουν εντός των ασφαλών ορίων λειτουργίας. Στόχος της παρούσας μελέτης είναι η σύγκριση και η αντιπαράθεση δύο μεθόδων μηχανικής μάθησης (δηλ. Δίκτυο μακράς βραχυπρόθεσμης μνήμης και ένα Νευρωνικό δίκτυο) για τον προσδιορισμό του επιπέδου ασφάλειας των συμμετεχόντων που οδηγούν στο πλαίσιο των δοκιμών πεδίου του έργου i-DREAMS. Για την επίτευξη αυτού του στόχου συλλέχθηκε ένας αριθμός διαδρομών από ένα δείγμα 30 Γερμανών οδηγών και τροφοδοτήθηκε στις προαναφερθείσες μεθόδους μηχανικής μάθησης, προκειμένου να εντοπιστούν οι παράγοντες που οδηγούν σε επικίνδυνη συμπεριφορά κατά τη διάρκεια των πειραματικών σταδίων. Τα αποτελέσματα επιβεβαιώνουν τη θετική επίδραση των παρεμβάσεων του i-DREAMS σε πραγματικό χρόνο και σημαντική βελτίωση της οδηγικής συμπεριφοράς μετά την διαδρομή, ενώ τα νευρωνικά δίκτυα φαίνεται να υπερτερούν έναντι των υπόλοιπων εξεταζόμενων αλγορίθμων.

Keywords: *Δοκιμές στο πεδίο, οδηγική συμπεριφορά, Δίκτυο μακράς βραχυπρόθεσμης μνήμης (LSTM), Νευρωνικό Δίκτυο, Μηχανική μάθηση*

1. Introduction

Road safety constitutes a major public health issue nowadays, with approximately 1.3 million human lives lost each year from crashes. Additionally, 20 to 50 million people experience non-fatal injuries that may lead to short-term or long-term diseases or disabilities (World Health Organization, 2018). Prior research suggests that driver behavior is a contributory factor in over 90% of crashes (Petridou & Moustaki, 2000). Consequently, there is a significant benefit in driving behavior analysis as an important part of traffic safety research (Ellison et al., 2015). As a result, the European Union and the World Health Organization have established a goal of decreasing fatal traffic crashes by 50% between 2021 and 2030, with a special emphasis on the contribution of emerging technology in the field of road safety.

Road safety is influenced by a multitude of risk factors, including the driver's state, environmental conditions, and traffic circumstances (Aljanahi et al., 1999; Wegman, 2017). Despite advancements in technology and infrastructure, human error remains a significant contributor to traffic collisions (Staubach, 2009). However, the ongoing progress in the domain of autonomous vehicles seeks to enhance road safety by minimizing the reliance on human drivers (Mahajan et al., 2020). Furthermore, the implementation of intelligent driving behavior monitoring systems, which enable real-time interventions, has demonstrated remarkable efficacy in improving road safety (Michelaraki et al., 2021). By combining the benefits of autonomous vehicles and intelligent monitoring systems, there is a strong potential for mitigating the impact of human error and creating a safer road environment for all users.

In recent times, the research community has played a vital role in the progression of Intelligent Transportation Systems (ITS) and specifically in the development of Connected and Automated Vehicles (CAVs). Numerous published studies have focused on comprehending the impact of various factors on unsafe driving, aiming to create suitable models for identifying risky driving behavior and establishing a framework for interventions within the vehicle. While there have been proposals for various interventions both during and post trip (Michelaraki et al., 2021; Roy et al., 2022), there is a lack of personalization in these interventions and a direct connection between real-time driving behavior and the activation of interventions.

The primary goal of the i-DREAMS project, funded by the European Commission Horizon2020 initiative (https://idreamsproject.eu/), is to establish, develop, test, and validate a 'Safety Tolerance Zone' (STZ) to ensure safe driving behavior`. By continuously monitoring risk factors associated with task complexity (e.g., traffic conditions and weather) and coping capacity (e.g., driver's mental state, driving behavior, and vehicle status), i-DREAMS aims to determine the appropriate level within the STZ and create interventions that maintain the driver's operation within acceptable safety limits. The STZ comprises three levels: 'Normal', 'Dangerous', and 'Avoidable Accident'. The 'Normal' level implies that the likelihood of a crash is low, while the 'Dangerous' level indicates an increased possibility of a crash, though it is not inevitable. The 'Avoidable Accident' level suggests a high probability of a crash occurring, but there is still time for drivers to take action and prevent it. The key distinction between the 'Dangerous' and 'Avoidable Accident' levels lies in the more urgent need for intervention in the 'Avoidable Accident' level.

Based on the i-DREAMS principles and objectives, this paper aims to develop, compare, and contrast machine learning techniques to identify the level of risky driving behavior. To achieve this goal several trips from a sample of 30 German drivers were collected and two machine learning classifiers were developed (i.e., LSTM and a Neural Network).

The paper is structured in the following manner. Firstly, it begins with a thorough introduction to the project, highlighting its main objective. Next, a comprehensive review of existing literature on driving behavior analysis using machine learning techniques is presented. The process of collecting data is then explained in detail. The research methodology is outlined, including the theoretical principles underlying the models employed. Finally, the results of the study are presented, followed by significant conclusions regarding the association between key factors like task complexity and coping capacity on risk.

2. Background

Simulator studies and naturalistic driving studies (NDS) approaches have been widely utilized in recent years to examine unsafe driving behavior (Osman et al., 2019). According to (Wang et al., 2020), there are certain traffic, driver, vehicle, and environmental factors that affect the risk of driving. Furthermore, recent studies focus on identifying driving behaviors and categorizing them as risky or safe in order to improve road safety (Yang et al., 2021). Researchers utilized models to evaluate unsafe driving behavior based on the driver's state (Ghandour et al., 2021) and based on specific features of the driver, such as demographics (Song et al., 2021), in a more anthropocentric approach. Other studies (Shangguan et al., 2021; Shi et al., 2019; Yang et al., 2021) have proposed models for identifying unsafe driving based on characteristics related to driving behavior, such as speed, time to collision, and time to headway.

Furthermore, the continuous development of Intelligent Transportation Systems (ITS) as well as the increasing availability of real-time data streams from in-vehicle sensors, GPS systems, and mobile devices has opened new opportunities for the application of machine learning models in real-time risk prediction and Advanced Driver Assistance Systems (ADAS). By continuously analyzing sensor data and contextual information, these models can provide timely alerts and warnings to drivers, assist in making safer driving decisions, and contribute to the prevention of crash.

In recent years classification models have been widely used to identify risky driving behavior. Several studies have explored the application of ML and DL techniques for classifying risky driving behaviors. One of the primary advantages of employing machine learning models for studying risky driving behavior is their ability to handle complex, nonlinear relationships within datasets. For example, (Shangguan et al., 2021) used four classifiers (i.e., RF, XGBoost, SVM and MLP) to predict risky driving behavior based on four safety levels. (Yang et al., 2021) employed two classification algorithms to identify and assess different levels of unsafe driving behavior utilizing a driving simulator dataset. Moreover, (Saleh et al., 2017) developed an LSTM-based model to identify driving behavior using sensor data, based on three levels of driving behavior (i.e., normal, drowsy, or aggressive) defined by the authors.

While ML and DL techniques offer promising results for classifying risky driving behaviors, there are several challenges to consider. These include data collection and preprocessing, feature selection, model generalizability, and interpretability of the learned representations. Overcoming these challenges is essential to ensure the reliability and applicability of ML and DL models in real-world driving scenarios.

In conclusion, ML and DL models have emerged as valuable tools for understanding, predicting, and addressing risky driving behavior. By leveraging the power of advanced algorithms and vast amounts of data, these models hold the potential to revolutionize road safety efforts, reduce crashes, and save lives. Continued research, development, and collaboration in this field are crucial for fully realizing the benefits of advanced algorithms on safer driving behaviors and road safety improvements.

3. Data Description

Within the i-DREAMS project, a naturalistic driving experiment was carried out involving 30 drivers from Germany and a large database of 5,344 trips and 84,434 minutes was created. The on-road trial experiment was carried out in four phases:

- Phase 1: monitoring - 30 German car drivers, 1,397 trips (23,617 minutes)
- Phase 2: real-time interventions - 30 German car drivers, 1,322 trips (19,469 minutes)
- Phase 3: real-time & post-trip interventions - 30 German car drivers, 1,129 trips (17,704 minutes)
- Phase 4: real-time. post-trip interventions & gamification - 30 German car drivers, 1,496 trips (23,644 minutes)

Figure 1 provides an overview of the different phases of the experimental design of the i-DREAMS on-road study.

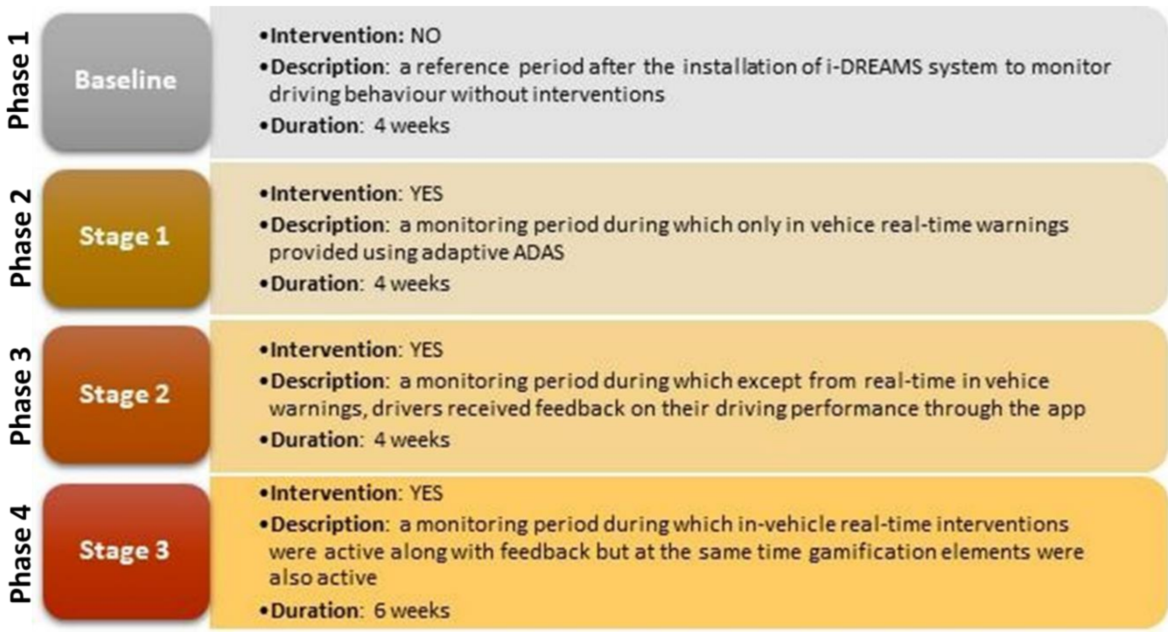

***Figure 1:** Overview of the different phases of the experimental design of the i-DREAMS on-road study*

In addition to the vehicle data, questionnaire data were also collected both before and after the trial.

Information collected pre-trial included:

- Screening questionnaire: driver details (age, gender, driving experience, employment status, etc.), vehicle details (model, age, etc.).
- Entry questionnaire: current use of and opinions on different ADAS, driving style and confidence, opinions on driving and safety, self-assessment of driver's risk-taking behaviors (e.g., speeding, mobile phone use), crash and offence history, sleepiness and driving, medical conditions.

Information collected post-trial included:

- User experience questionnaire: opinions on the i-DREAMS system - except for Greece, in which an alternative driving experiment without the use of i-DREAMS in-vehicle system was used - (ease of use, works as described), opinions on the i-DREAMS smartphone app (ease of use, usefulness).
- Exit questionnaire: opinions on the i-DREAMS system (improvement of driving, usefulness, trust, clarity of warnings, etc.), experience of driving situations, driver behavior (driving and non-driving related behaviors), overall experience rating.

4. Methodological Overview

4.1 Neural Networks (NNs)

An Artificial Neural Network (ANN) is a highly complex, non-linear, parallel processor with a natural propensity for storing experimental knowledge and making it available afterward. A multi-layer perceptron ANN is typically made up of three kinds of layers: an input layer, an output layer, and one or more hidden layers. The input layer receives the values of the explanatory variables, i.e., the input data. The hidden layer, made up of m neurons, adds up the weights of the input values of the various explanatory variables, and calculates the complex association patterns. With regards to the hidden layer, activation function applies a non-linear map to the linear transformation of input values, introducing nonlinearity into the model. A single hidden layer is usually enough for crash analysis applications, but the definition of the number of neurons in it is generally the object of experimentation. For the output layer, the values of the various hidden neurons are summed, and the network's output values are presented (Garefalakis et al., 2022; Silva et al., 2020).

4.2 Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory Models (LSTMs) are a special kind of RNN, capable of learning long-term dependencies (Girma et al., 2019). They work tremendously well on a large variety of problems and are now widely used. LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior and not something they struggle to learn. All recurrent LSTMs have the form of a chain of repeating modules of neural network.

LSTMs use ”memory block” in the hidden unit to capture the long-term dependencies that may exist in the data (Girma et al., 2019). This memorizing capability of LSTM has shown the best performance across many time-series tasks, such as activity recognition, video captioning, language translation. The cell state (memory block) of LSTM has one or more memory cells that are regulated by structures called gates, which control the addition of new sequential information and the removal of useless ones to and from memory, respectively. Gates are a combination of sigmoid activation functions and an element-wise multiplication or Hadamard product and they are used to control information that passes through the network. An LSTM is often composed by three gates, namely forget, input, and output gates, which are described below:

- Forget gate: Forget gate decides what information to keep or remove from the cell state. The first step in LSTM is to decide what information are going to throw away from the cell state. This decision is made by a sigmoid layer called the “forget gate layer.”
- Input gate: Input gate decides what new information to add and how to update the old cell state, C_{t-1}, to the new cell state C_t for the next memory block. This has two parts. First, a sigmoid layer called the “input gate layer” decides which values we’ll update. Next, a tanh layer creates a vector of new candidate values, $C_{t'}$, that could be added to the state. Then the old cell state C_{t-1} updates into the new cell state C_t and the old state is multiplied by f_t.
- Output gate: Output gate filters out and decides which information to produce as an output from a memory block at a given time step t. This output will be based on cell state but will be a filtered version. First, a sigmoid layer, which decides what parts of the cell state are going to output, is run. Then, the cell state, used as tanh (to push the values to be between −1 and 1) and multiply it by the output of the sigmoid gate, in order to take and output the parts needed.

4.3 Model goodness-of-fit measures

For the classification models the confusion matrix and the corresponding metrics will be utilized. In order to compare the classification performance of the several configurations (hyperparameters and mix of considered inputs), well-established machine learning error metrics were calculated. The following metrics were utilized, based on the **confusion matrix**, which provides True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) metrics. The classification algorithms are evaluated using the **accuracy, precision, recall, f1-score, and false alarm rate** as defined below.

Accuracy, which represents the proportion of correctly classified observations, is defined as:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

Precision, which quantifies the number of positive class predictions that actually belong to the positive class, is defined as follows:

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Recall, also known as True Positive Rate, is defined as follows:

$$Recall = \frac{TP}{TP+FN} \quad \textbf{(3)}$$

F1score, which combines precision and recall into a single measure, is defined as follows:

$$f1 - score = \frac{2x\,(Precision)x\,(Recall)}{(Precision)+(Recall)} \quad \textbf{(4)}$$

False alarm rate is defined as follows:

$$False\ Alarm\ Rate = \frac{FP}{FP+TN} \quad \textbf{(5)}$$

5. Results

5.1 Neural Networks (NNs)

In order to investigate if real-time prediction of the STZ is also feasible, two feed-forward multi-layer perceptrons were also applied on a subset from the total dataset of the German car drivers (Ndrivers=30, trips=5340). In order to identify the effect of phase on the prediction, the analysis considered phase as an independent variable and the analysis was performed for the whole dataset, rather than per phase as the analyses in Chapter 4. The algorithms had an accuracy of more than 94% with a false alarm rate of up to only 6%. The Neural Networks (NNs) classification algorithms acted as preparatory step towards the LSTM classification that is shown in the next subsection. The predictors utilized for the models are shown in Table 1.

Table 1: *Predictors utilized for Neural Networks*

Variables	Headway	Speeding
Phase	x	x
Age	x	x
Average speed	x	x
Harsh acceleration	x	x
Harsh events low	x	
Headway level total	x	
Speeding level 0		
Speeding level total		

After the application of the models, the identified confusion matrix was produced for the two independent variables (i.e. headway and speeding), as shown in Table 2.

Table 2: *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

From the confusion matrix, the following metrics were estimated and are depicted in Table 3.

***Table 3:** Assessment of classification model for headway and speeding*

Variable	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%

Figure 2 illustrates the performance of Neural Network classification on headway and speeding STZ level.

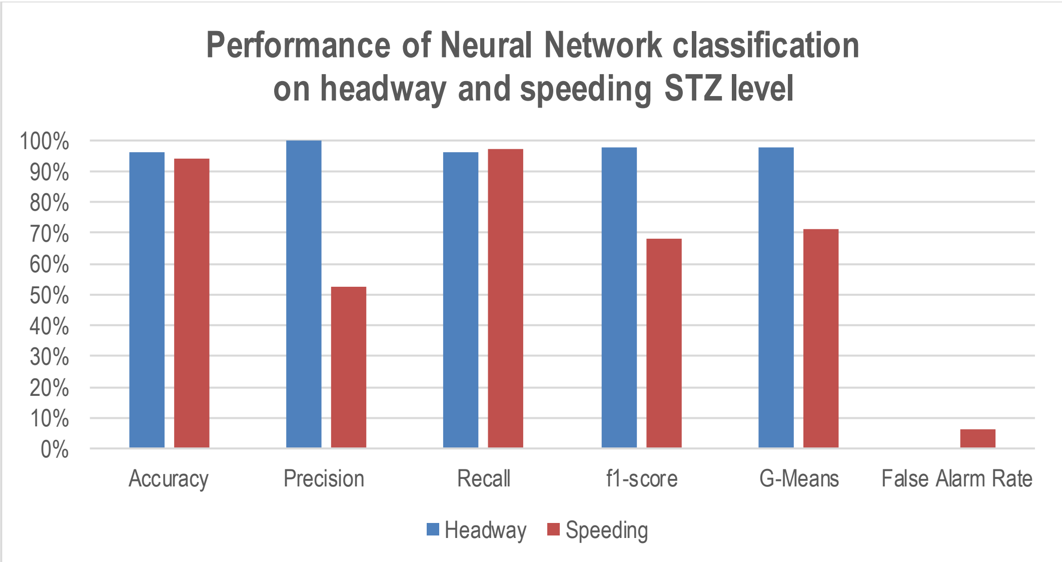

***Figure 2:** Performance of Neural Network classification for headway and speeding*

The results shown in Figure 2*: Performance of Neural Network classification for headway and speeding*

are in line with relevant literature on real-time safety evaluations (Silva et al., 2020), as well as previous project analyses utilized on simulator data (Garefalakis et al., 2022). Precision, f1-score and G-means metrics are probably lower due to the greater amount of 'normal' STZ level instances as compared with 'dangerous' conditions.

5.2 Long Short-Term Memory (LSTM)

5.2.1 Speeding

Following the development of simple NN classifiers, Long Short-Term Memory Networks (LSTMs) were trained in order to predict 'dangerous' speeding level. As shown in Table 4, the speeding LSTM did not achieve significant results, only reaching 57.82% accuracy after the developed trials. Although LSTM is often used for sequence modeling, it is worth mentioning that the sequence may not always be explicitly visible in the predictors themselves. In some cases, the sequence may be implicit in the way that the data is organized or structured. For example, in time series data, the sequence is often defined by the order in which the data was collected over time. In this case, the LSTM is used to model and make predictions based on the temporal dependencies and patterns in the data. In other cases, the sequence may be less obviously related to time, but still exist in the way that the data is organized. For example, in natural language processing, the sequence may be defined by the order of words in a sentence or text document. Thus, 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. An LSTM could still be used in this case to model and make predictions based on the implicit sequence in the data. The predictors utilized for the models applied for speeding are shown in Table 4.

***Table 4:** 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

5.2.2 Headway

Similarly with speeding, LSTMs could not find the dangerous level of headway as well. Perhaps this is because of a lack of data or speed-related indicators to identify the different levels. The predictors utilized for the models applied for headway are shown in Table 5.

***Table 5:** 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 low		x		
Harsh acceleration		x		
Headway level -1			x	
Headway level 0	x			
Headway level total	x	x	x	x

Variables	v1	v2	v3	v4
Speeding level total				x
Accuracy (%)	57.39	55.5	57.82	57.82

It should be noted that an accuracy of less than 60% may not be sufficient for a high-performance intervention system, as it could result in a relatively high number of false alarms or missed detections. However, the required level of accuracy depends on the specific use case and the risks involved. For instance, in a system designed to detect potential crashes or safety hazards, a higher level of accuracy may be necessary in order to ensure the safety of drivers and other road users. As for the use of prediction models by an intervention system, the output of the models can be used in a variety of ways. In particular, the prediction models can generate real-time alerts or warnings to drivers or other stakeholders, such as traffic control centers or emergency responders. The models can also be used to trigger automated interventions, such as adjusting the speed of a vehicle or activating safety features like automatic braking systems. In addition, 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.

6. Conclusions

This paper aims to develop, compare and contrast machine learning techniques in order to identify the level of risky driving behavior. To achieve this goal, several trips from a sample of 30 German drivers were collected and two machine learning classifiers were developed (i.e., LSTM and a Neural Network).

Predictive real-time analyses demonstrated that it is possible to predict the level of STZ with an accuracy of up to 95%, while 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, such as Neural Networks, can be trained using the i-DREAMS data to 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. Once the ensemble of algorithms was trained and validated, real-time applications have been deployed, such as in-vehicle systems or mobile applications in order to provide drivers with immediate feedback and guidance on their driving behavior. This feedback could help drivers make informed decisions, improve their driving habits, and reduce crash risk.

The identification of safe driving behavior through the ensemble of machine learning algorithms and i-DREAMS data has the potential to revolutionize road safety interventions. By leveraging the power of data-driven insights and advanced analytics, this approach can contribute to creating a safer driving environment, reducing the number of crashes, and ultimately saving lives.

Future research could consider incorporating contextual information into the models. This could include factors such as weather conditions, road infrastructure, and traffic patterns, to enhance the accuracy and applicability of the models in diverse driving environments. In addition, personalized driver modeling could also be another area of interest, where individual driver characteristics like experience, age, and driving style are taken into account. This can help tailor interventions and feedback to each driver's specific needs, leading to more effective behavior change.

It is worth noting that analyzing the long-term impact of interventions based on safe driving behavior identification is also crucial. Evaluating the effectiveness of these interventions in reducing crash rates, injuries, and overall road safety can provide insights into their sustained effects over time. Furthermore, investigating the implementation and evaluation of real-time intervention systems based on safe driving behavior identification is essential. Assessing the effectiveness of these systems in providing timely feedback, alerts, or interventions to drivers can help prevent potential crashes or hazardous situations.

Lastly, the consideration of human factors and driver engagement is important as well. 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. The generalizability and scalability of the developed models and interventions should also be assessed. Exploring their applicability across diverse populations, geographic locations, and vehicle types, as well as addressing potential challenges and adaptations, will ensure their broader impact in improving road safety. By addressing these research areas, it is easier to understand safe driving behavior identification, refine intervention systems, and ultimately contribute to improving road safety, reducing the number of crashes, and preventing injuries on our roads.

Acknowledgements

The research was funded by the EU H2020 i-DREAMS project (Project Number: 814761) funded by European Commission under the MG-2-1-2018 Research and Innovation Action (RIA) and co-financed by the European Union – European Regional Development Fund (ERDF) and Greek national funds through the Operational Program "Competitiveness, Entrepreneurship and Innovation" (EPAnEK) of the National Strategic Reference Framework (NSRF) – Research Funding Program: SmartMaps – Smart city mapping for safer and eco driver behaviour through smartphone sensor big data.

References

Aljanahi, A. A. M., Rhodes, A. H., & Metcalfe, A. V. (1999). Speed, speed limits and road traffic accidents under free flow conditions. *Accident Analysis & Prevention*, *31*(1–2), 161–168. https://doi.org/10.1016/S0001-4575(98)00058-X

Ellison, A. B., Greaves, S. P., & Bliemer, M. C. J. (2015). Driver behaviour profiles for road safety analysis. *Accident Analysis & Prevention*, *76*, 118–132. https://doi.org/10.1016/j.aap.2015.01.009

Garefalakis, T., Katrakazas, C., & Yannis, G. (2022). Data-Driven Estimation of a Driving Safety Tolerance Zone Using Imbalanced Machine Learning. *Sensors*, *22*(14). https://doi.org/10.3390/s22145309

Ghandour, R., Potams, A. J., Boulkaibet, I., Neji, B., & Al Barakeh, Z. (2021). Driver Behavior Classification System Analysis Using Machine Learning Methods. *Applied Sciences*, *11*(22). https://doi.org/10.3390/app112210562

Girma, A., Yan, X., & Homaifar, A. (2019). Driver Identification Based on Vehicle Telematics Data using LSTM-Recurrent Neural Network. *2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI)*, 894–902. https://doi.org/10.1109/ICTAI.2019.00127

Mahajan, V., Katrakazas, C., & Antoniou, C. (2020). Prediction of Lane-Changing Maneuvers with Automatic Labeling and Deep Learning. *Transportation Research Record*, *2674*(7), 336–347. https://doi.org/10.1177/0361198120922210

Michelaraki, E., Katrakazas, C., Yannis, G., Filtness, A., Talbot, R., Hancox, G., Pilkington-Cheney, F., Brijs, K., Ross, V., Dirix, H., Neven, A., Paul, R., Brijs, T., Fortsakis, P., Frantzola, E. K., &

Taveira, R. (2021). Post-trip safety interventions: State-of-the-art, challenges, and practical implications. *Journal of Safety Research*, *77*, 67–85. https://doi.org/10.1016/j.jsr.2021.02.005

Michelaraki, E., Katrakazas, C., Yannis, G., Konstantina Frantzola, E., Kalokathi, F., Kaiser, S., Brijs, K., & Brijs, T. (2021, October). A Review of Real-Time Safety Intervention Technologies. *7th Humanist Conference*.

Osman, O. A., Hajij, M., Karbalaieali, S., & Ishak, S. (2019). A hierarchical machine learning classification approach for secondary task identification from observed driving behavior data. *Accident Analysis & Prevention*, *123*, 274–281. https://doi.org/10.1016/j.aap.2018.12.005

Petridou, E., & Moustaki, M. (2000). Human factors in the causation of road traffic crashes. *European Journal of Epidemiology*, *16*(9), 819–826. https://doi.org/10.1023/A:1007649804201

Roy, A., Hossain, M., & Muromachi, Y. (2022). A deep reinforcement learning-based intelligent intervention framework for real-time proactive road safety management. *Accident Analysis & Prevention*, *165*, 106512. https://doi.org/https://doi.org/10.1016/j.aap.2021.106512

Saleh, K., Hossny, M., & Nahavandi, S. (2017). Driving behavior classification based on sensor data fusion using LSTM recurrent neural networks. *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, 1–6. https://doi.org/10.1109/ITSC.2017.8317835

Shangguan, Q., Fu, T., Wang, J., Luo, T., & Fang, S. (2021). An integrated methodology for real-time driving risk status prediction using naturalistic driving data. *Accident Analysis & Prevention*, *156*, 106122. https://doi.org/10.1016/j.aap.2021.106122

Shi, X., Wong, Y. D., Li, M. Z.-F., Palanisamy, C., & Chai, C. (2019). A feature learning approach based on XGBoost for driving assessment and risk prediction. *Accident Analysis & Prevention*, *129*, 170–179. https://doi.org/10.1016/j.aap.2019.05.005

Silva, P. B., Andrade, M., & Ferreira, S. (2020). Machine learning applied to road safety modeling: A systematic literature review. *Journal of Traffic and Transportation Engineering (English Edition)*, *7*(6), 775–790. https://doi.org/10.1016/j.jtte.2020.07.004

Song, X., Yin, Y., Cao, H., Zhao, S., Li, M., & Yi, B. (2021). The mediating effect of driver characteristics on risky driving behaviors moderated by gender, and the classification model of driver's driving risk. *Accident Analysis & Prevention*, *153*, 106038. https://doi.org/10.1016/j.aap.2021.106038

Staubach, M. (2009). Factors correlated with traffic accidents as a basis for evaluating Advanced Driver Assistance Systems. *Accident Analysis & Prevention*, *41*(5), 1025–1033. https://doi.org/10.1016/j.aap.2009.06.014

Wang, J., Huang, H., Li, Y., Zhou, H., Liu, J., & Xu, Q. (2020). Driving risk assessment based on naturalistic driving study and driver attitude questionnaire analysis. *Accident Analysis & Prevention*, *145*, 105680. https://doi.org/10.1016/j.aap.2020.105680

Wegman, F. (2017). The future of road safety: A worldwide perspective. *IATSS Research*, *40*(2), 66–71. https://doi.org/10.1016/j.iatssr.2016.05.003

World Health Organization. (2018). *Global Status Report On Road Safety 2018*. World Health Organization. https://www.who.int/publications/i/item/9789241565684

Yang, K., Haddad, C. Al, Yannis, G., & Antoniou, C. (2021). Driving Behavior Safety Levels: Classification and Evaluation. *2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, 1–6. https://doi.org/10.1109/MT-ITS49943.2021.9529309