Conceptualizing a Safety Tolerance Zone: A Machine Learning Framework for Vehicle-Driver-Environment Interaction

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20th International Road Safety on Five Continents Conference
(RS5C 2025)

Leeds, UK, 3-5 September 2025

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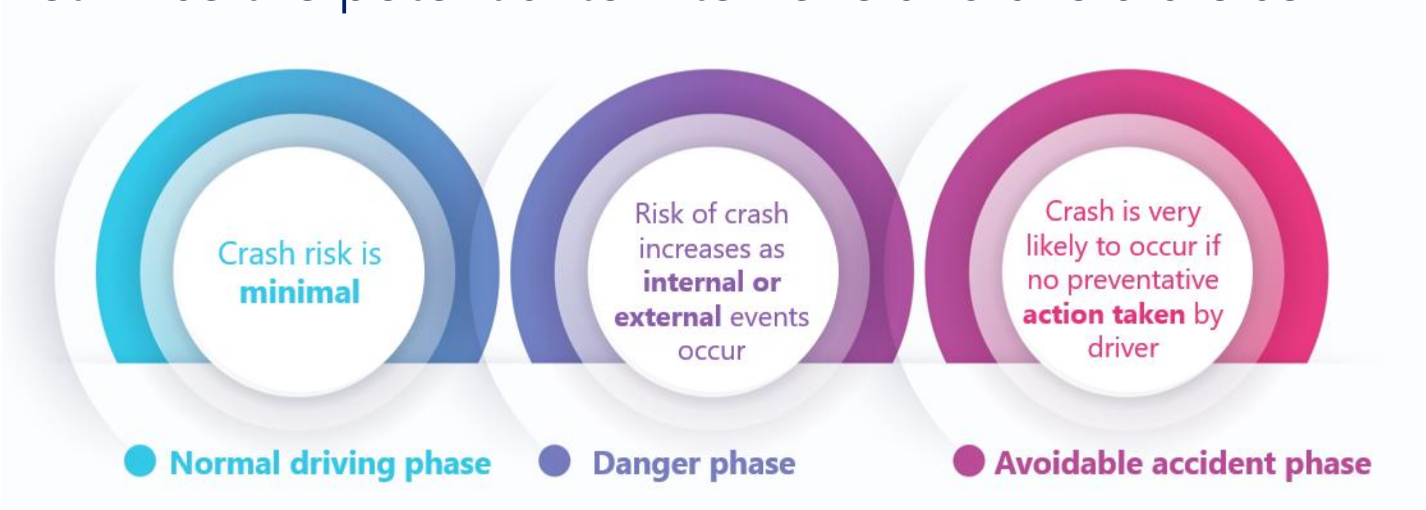
Introduction

- **Driver behaviour**, measured through metrics, such as speeding, headway or mobile phone use, is a critical indicator of road safety and driving performance
- **Multiple factors can contribute to a crash** and are related to any part of the transport system and the interaction among its elements
- **Human operator** does not act in isolation
- They are an **integral part of the transport system** which is made up of a complex interaction of drivers, vehicles, infrastructure, other environmental factors and the rules and regulations that govern them

Safety Tolerance Zone (STZ) Concept

- Safety Tolerance Zone (STZ) is the time/distance available to implement safe response actions in the event of a potential crash
- A 'multi-phased' construct, consisting of three different phases:
  - ✓ **Normal driving phase**: there is no indication that a collision scenario is likely to unfold at that time
  - ✓ **Dangerous phase**: the potential for developing a collision scenario is detected
  - ✓ **Avoidable accident phase**: a collision scenario is actually starting to develop, but the driver still has the potential to intervene and avoid a crash



Objectives

- Assessment of **road, vehicle and behavioural risk indicators** for the definition of the Safety Tolerance Zone (STZ)

- Identification of the **level of risky driving behaviour** through:
  - Development of a Neural Network Model
  - Comparison and contrast of three machine learning classifiers

Experimental Design

Driving simulator experiment:

- 55 drivers
- 165 trips across different road environments
- 2 months

Three location types:

- Six-lane two-way highways
- Rural undivided two-lane roads
- Urban single-lane roads

Three consecutive scenarios:

- Customized interventions in safety-critical situations (i.e. close to the boundary of the STZ) were proposed
- Real-time and in-vehicle warnings

Experiment Phases

Scenario 1 (Baseline)

- **Intervention:** NO
- **Description:** a reference period to monitor driving behaviour without interventions
- **Duration:** 15 minutes

Scenario 2

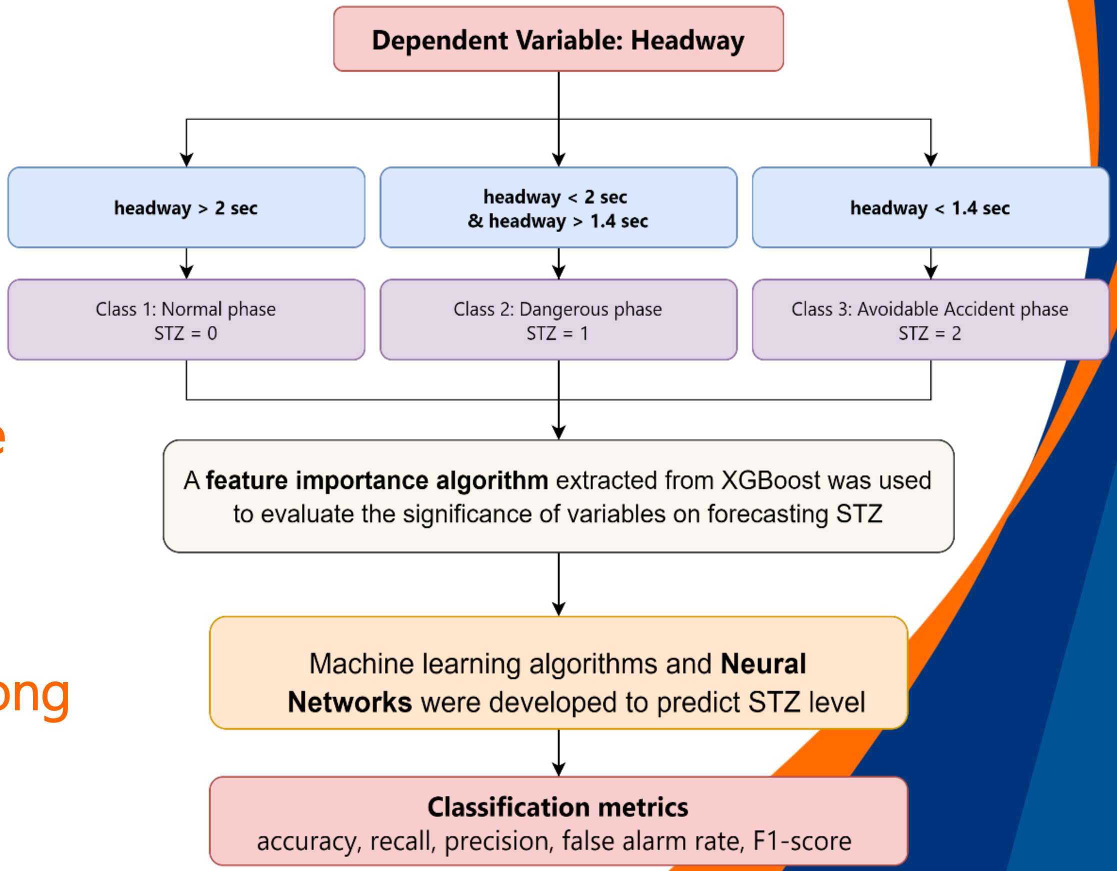
- **Intervention:** Real-time
- **Description:** an intervention scenario influencing driving behaviour with fixed timing thresholds (and/or message and/or display)
- **Duration:** 15 minutes

Scenario 3

- **Intervention:** Real-time
- **Description:** an intervention scenario with modifying condition influencing driving behaviour with variable timing thresholds (and/or message and/or display)
- **Duration:** 15 minutes

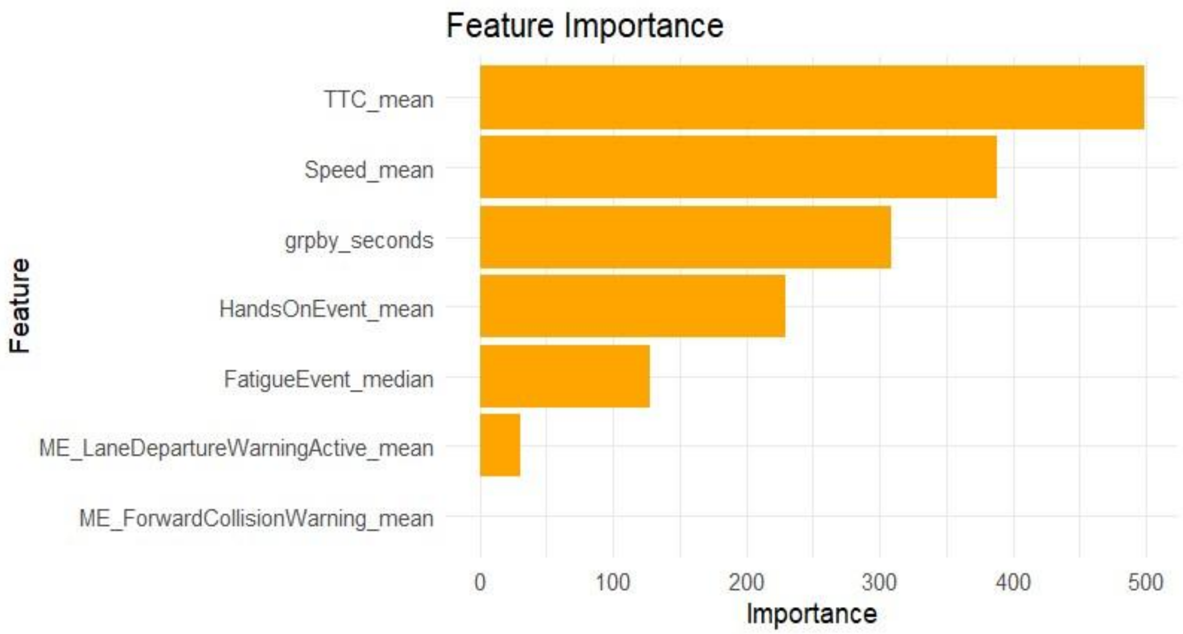
Methodological Approach

- A feature importance algorithm was used to evaluate the significance of variables on forecasting STZ
- A Neural Network model was implemented for real-time data prediction
- A comprehensive assessment of the performance of three machine learning classifiers (i.e. Decision Trees, Random Forests and k-Nearest Neighbors) was implemented.
- These classification models were selected due to their strong performance and widespread use for identifying unsafe driving patterns and real-time risk prediction
- Evaluation based on several metrics, such as accuracy, precision, recall, false alarm rate and F1-score



Feature Importance Analysis

- According to the feature importance analysis, time-to-collision, average speed, driving duration, hands-on event and fatigue found to be the **most influential factors among all examined indicators**
- Conversely, parameters such as lane departure warning or forward collision warning had a **negligible impact on STZ headway**



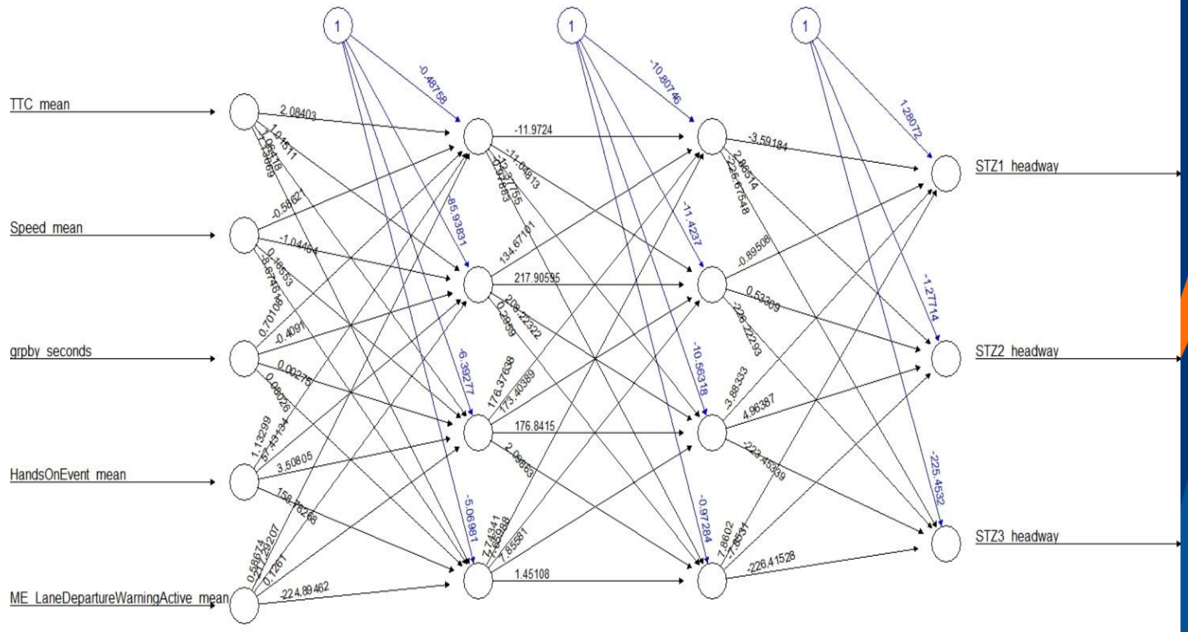
Neural Networks Results

- The multi-layer NN model applied consisted of **five neurons in the input layer** (i.e. TTC, average speed, duration, hands-on event and LDW) and **three neurons in the output layer** (i.e. STZ1, STZ2, STZ3)

- STZ1 headway refers to **normal phase**,
  STZ2 headway refers to **danger phase**, while
  STZ3 headway refers to **avoidable accident phase**

- It was revealed that the level of STZ can be predicted with an **accuracy of up to 89.8%**

- Results demonstrated exceptional performance, with strong precision and recall, indicating the model's effectiveness in identifying **positive samples and safety-critical classes**

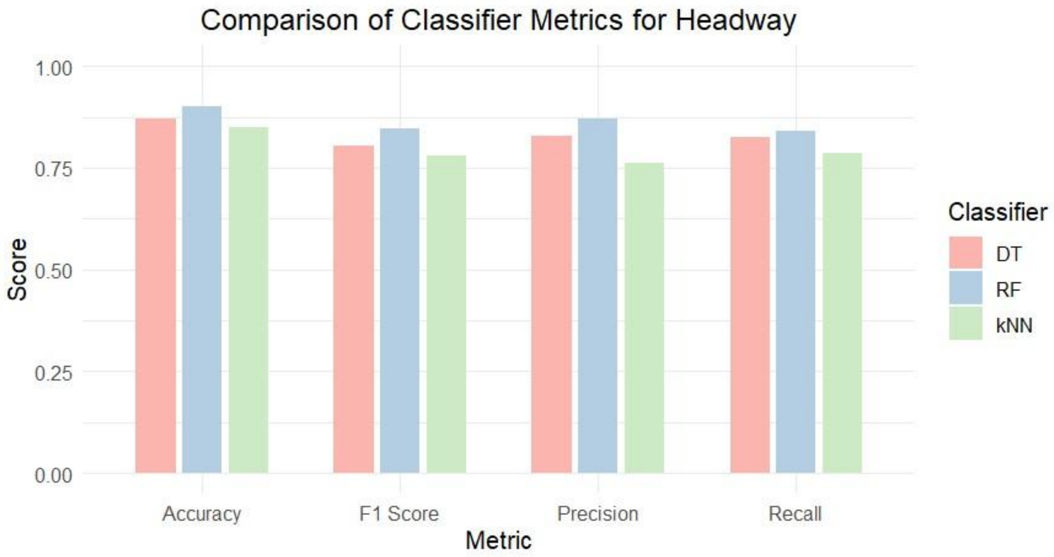


Model Fit measures	0	1	2	Total
Accuracy	0.907	0.973	0.915	0.898
Precision	0.876	0.968	0.853	0.912
Recall	0.899	0.946	0.842	0.906
F1 Score	0.887	0.957	0.847	0.899
False alarm rate	0.287	0.114	0.257	0.153

**0 refers to normal phase, 1 refers to dangerous phase, 2 refers to avoidable accident phase*

Machine Learning Techniques Results

- All models applied (i.e. DT, RF and kNN) exhibited a high level of accuracy, indicating the overall correctness of its predictions
- It was found that RF model outperformed the other classifiers, achieving the highest overall accuracy at 90.1%
- Furthermore, DT showed moderate performance with an accuracy of 87.1%, while kNN demonstrated the lowest performance, with an accuracy of 85.0%
- Among the different methods applied, RF stranded out with the highest accuracy, indicating its ability to accurately classify driving behaviour in a controlled environment



Model Fit measures	0	1	2	Total
Accuracy				
DT	0.959	0.846	0.807	0.871
RF	0.961	0.884	0.858	0.901
kNN	0.922	0.833	0.795	0.850
Precision				
DT	0.865	0.832	0.826	0.830
RF	0.902	0.887	0.834	0.872
kNN	0.790	0.781	0.707	0.763
Recall				
DT	0.835	0.771	0.766	0.826
RF	0.865	0.735	0.704	0.841
kNN	0.795	0.725	0.679	0.786
F1 Score				
DT	0.810	0.793	0.780	0.804
RF	0.830	0.849	0.811	0.847
kNN	0.793	0.771	0.752	0.779

Discussion

- The effectiveness of the NN models in predicting headway levels was encouraging; the level of STZ can be predicted with an exceptional accuracy

- The models performed best in normal driving phases, likely because these conditions were more consistent and made up the majority of the training data

- These results not only showcased their potential for real-world applications but also emphasised their significance in the field of road safety and traffic management

- Machine learning algorithms and data-driven insights can facilitate the identification of safe driving behaviour, enable prompt feedback to drivers and foster a safer driving environment

Conclusions

- Greater understanding of driving behaviour dynamics and improved prediction of risky driving scenarios can enhance the capabilities of the STZ

- The results can be used in practice to provide real-time feedback to drivers, support adaptive driver assistance systems and inform road safety interventions

- Further research avenues should concentrate on evaluating the long-term effects of interventions, assessing real-time systems and considering other human factors and driver engagement

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