National Technical University of Athens
School of Civil Engineering
Department of Transportation Planning and Engineering

Doctoral Dissertation

Improving driver safety tolerance zone through holistic analysis of road, vehicle and behavioural risk factors

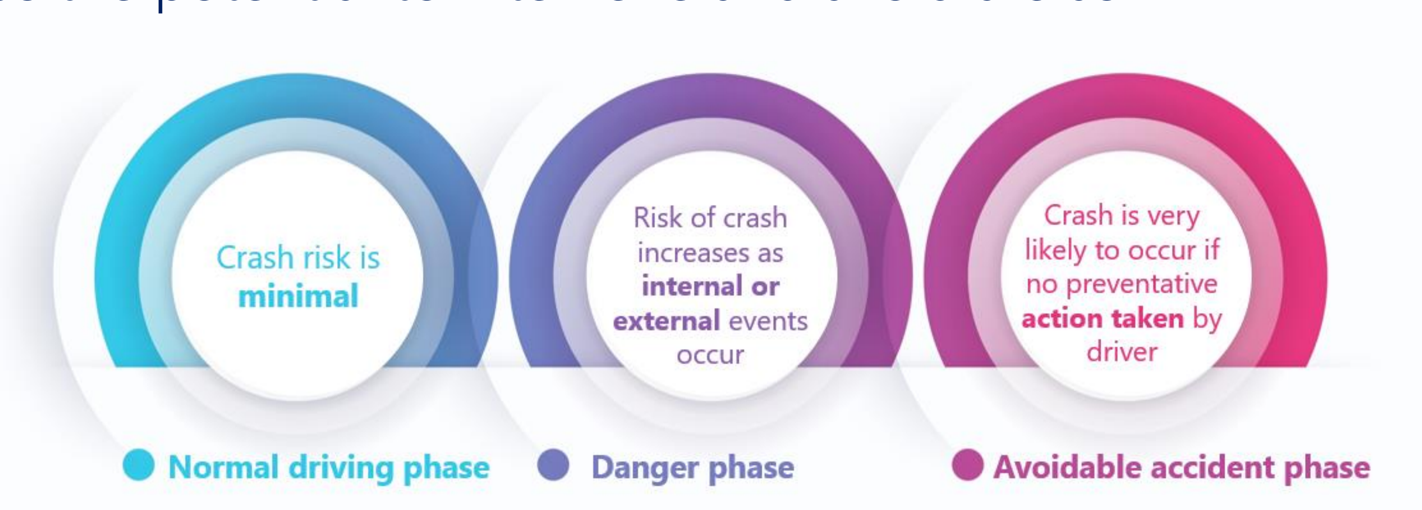
Eva Michelaraki

Supervisor: George Yannis, Professor NTUA

Athens, October 2024

Safety Tolerance Zone (STZ) Concept

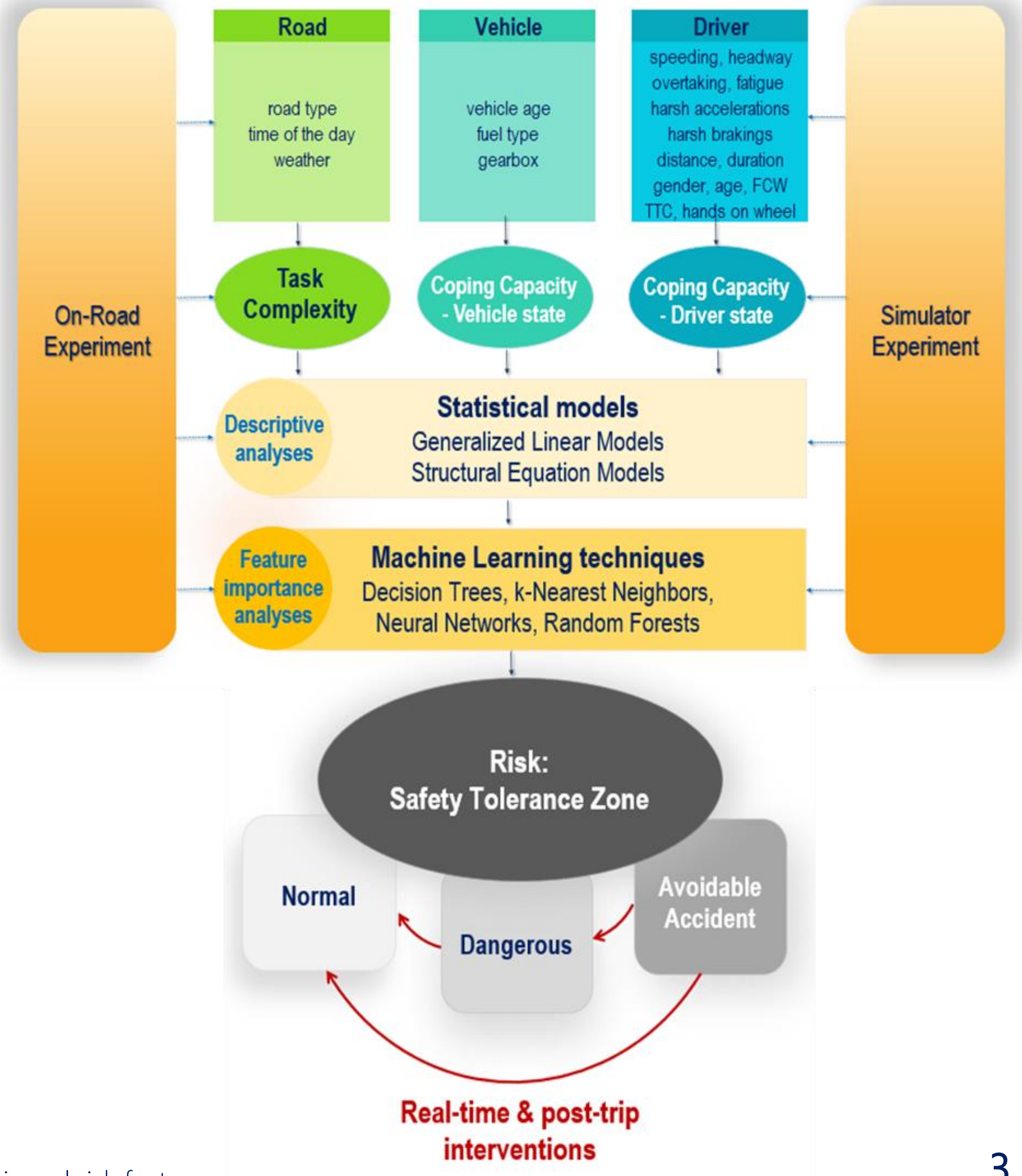
- Safety Tolerance Zone (STZ) is **the time/distance available to implement corrective actions safely** (in the potential course towards a crash)
- A '**multi-phased**' construct, consisting of three different phases:
  - ✓ **Normal driving phase**: there is no indication that a collision scenario is 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



Conceptual Framework

- Task complexity relates to the current status of the real-world context in which a vehicle is being operated:
  - ✓ road layout (i.e. highway, rural, urban)
  - ✓ time of the day
  - ✓ weather conditions

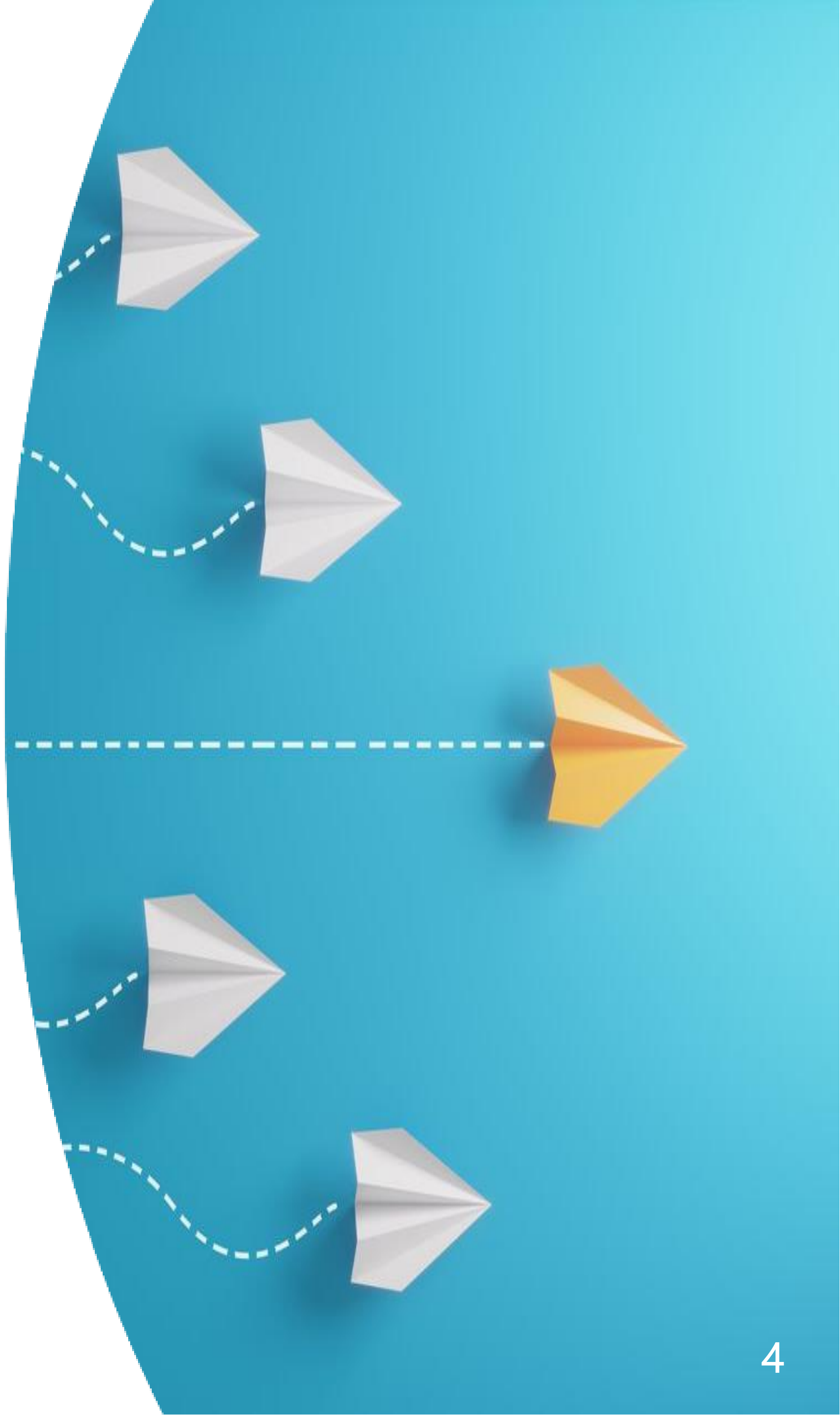
- Coping capacity refers to the ability of drivers and road systems to manage and respond effectively to various challenges and stressful situations encountered while driving. It is dependent upon two underlying factors:
  - ✓ vehicle state (e.g. technical specifications, current status)
  - ✓ driver state (e.g. driving behaviour, sociodemographic profile)



Objectives of the Dissertation

- A holistic approach to improve driver Safety Tolerance Zone through the analysis of road, vehicle and behavioural risk factors

- Identification of the impact of task complexity and coping capacity on crash risk



Methodological Steps

Selection of risk factors
of task complexity (road) and
coping capacity (vehicle and driver)

Exploitation of data
from a large
on-road and driving
simulator experiment

Development of **statistical**
analysis and **machine**
learning techniques

Conceptual framework
for the identification
of the Safety Tolerance Zone
through real-time and post-trip interventions

PhD Overview

- Literature Review
- Research Questions
- Methodological Approach
- The Experiments
- On-Road & Simulator Analyses
- Key Research Findings
- Innovative Contributions
- Future Challenges

Literature Review

Effects of exogenous factors on task complexity

Effects of external context on task complexity

Effects of vehicle state on coping capacity

Effects of mental state on coping capacity

Effects of driving performance indicators on coping capacity

Literature Review

250 papers included

Effects of socio-demographic characteristics on coping capacity

List of technologies monitoring task complexity and coping capacity

Effectiveness of real-time interventions

Effectiveness of post-trip interventions

Driver behaviour methodologies/techniques to model STZ

Literature Review

- A total of 250 papers were included in the final review
- Systematic search of relevant scientific and grey literature, according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA)
- Literature was searched within scientific databases: Scopus, ScienceDirect, Google Scholar and PubMed
- The inclusion criteria for selecting relevant studies were:
  - ✓ Search term included in title, abstract or key words
  - ✓ Studies published from 1990 and onwards
  - ✓ Language: studies published as English
  - ✓ Source: peer-reviewed journals before peer-reviewed conference papers before scientific papers/articles

Factor	Key words	Screened papers	Included papers
Task complexity – exogenous factors	"task complexity" OR "task demand" AND "driving measures" OR "performance measurements" OR "driver characteristics" OR "driving monitoring" OR "workload" OR "traffic conditions" OR "traffic" OR "weather" OR "road layout" OR "time of day"	829	31
Task complexity - cognitive	"task complexity" OR "task demand" AND "cognitive workload" OR "mental workload" OR "physiological indicators" OR "brain activity" OR "eye tracking measures" OR "heart-related metrics"	439	11
Coping capacity - vehicle	"coping capacity" OR "driver state" AND "vehicle" AND "fuel type" OR "transmission" AND "gearbox" OR "vehicle age" OR "tire pressure"	63	8
Coping capacity - distraction	"coping capacity" OR "driver state" OR "distraction" OR "distracted" OR "inattention" OR "inattentive" AND "driver monitoring" OR "driver measure"	210	32
Coping capacity - fatigue	"coping capacity" OR "driver state" AND "fatigue" OR "sleep" OR "sleepiness" OR "tired" OR "drowsy" OR "drowsiness" OR "alert" OR "monotony" OR "mental fatigue" OR "weariness" OR "bored"	107	17
Coping capacity – driver behaviour	"coping capacity" OR "driver state" OR "speed" OR "speeding" AND "headway" OR "overtaking" OR "illegal overtaking" OR "harsh events" OR "accelerations" OR "harsh brakings" OR "deceleration" AND "driving performance" AND "driving behaviour"	195	20
Coping capacity – socio-demographic	"coping capacity" OR "driver state" OR " socio-demographic " OR "personality" AND "gender" OR "age" OR "driving experience" OR "education level" AND "driving performance" OR "driving behaviour"	213	10
Technologies	"objective measures" OR "in-vehicle device" AND "in-vehicle data" OR "CarChip" OR "global positioning system" OR "GPS" OR "sensors" OR "radars" OR "on-board diagnostic system" OR "OBD" OR "OBD-II" OR "intelligent speed adaptation design" OR "ISA device" OR "camera" OR "electronic device" OR "smartphone" AND "technologies" OR "driving behaviour" OR "driving behaviour" OR "driving exposure" OR "speed" OR "driving distance" OR "on-road behaviour" OR "on-road behaviour"	169	25
Real-time interventions	"real-time interventions" OR "in-vehicle interventions" OR "real-time feedback" OR "real-time technology" OR "feedback" AND "car drivers"	70	23
Post-trip interventions	"post trip intervention technology" OR "post trip feedback" OR "feedback" OR "interventions" OR "feedback technology" AND "car drivers"	175	14
Modelling techniques	"risk level" OR "crash risk" OR "collision risk" AND "real-time" OR "model" AND "modelling" AND "driver behaviour models" OR "driver behaviour" OR "abnormal driving" OR "road safety" AND "risk" OR "structural equation models"	211	59
			250

Safety Interventions

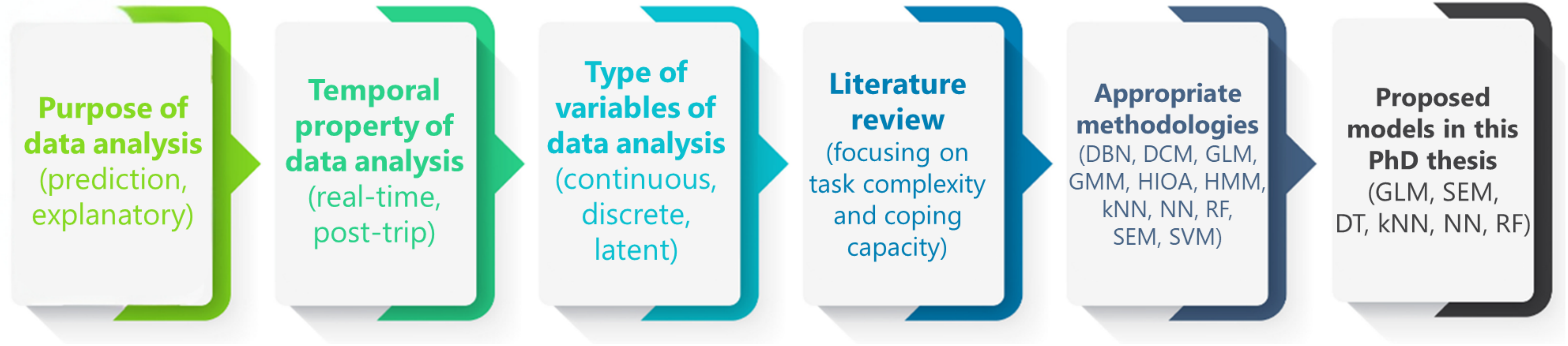
- A safety intervention is a provided set of information, guidance, warnings, feedback or notifications that drivers receive based on a personalized identification of driving episodes (Michelaraki et al., 2023; Kinnear et al., 2013)

- Real-time interventions are in-vehicle interventions which are triggered while travelling when specific conditions arise (Beckjord & Shiffman, 2014):
  - ✓ auditory
  - ✓ visual
  - ✓ haptic

- Post-trip interventions provide feedback after the end of a trip, and on the principle that drivers self-monitor their driving history and identify their behavioural weaknesses (Michelaraki et al., 2021)

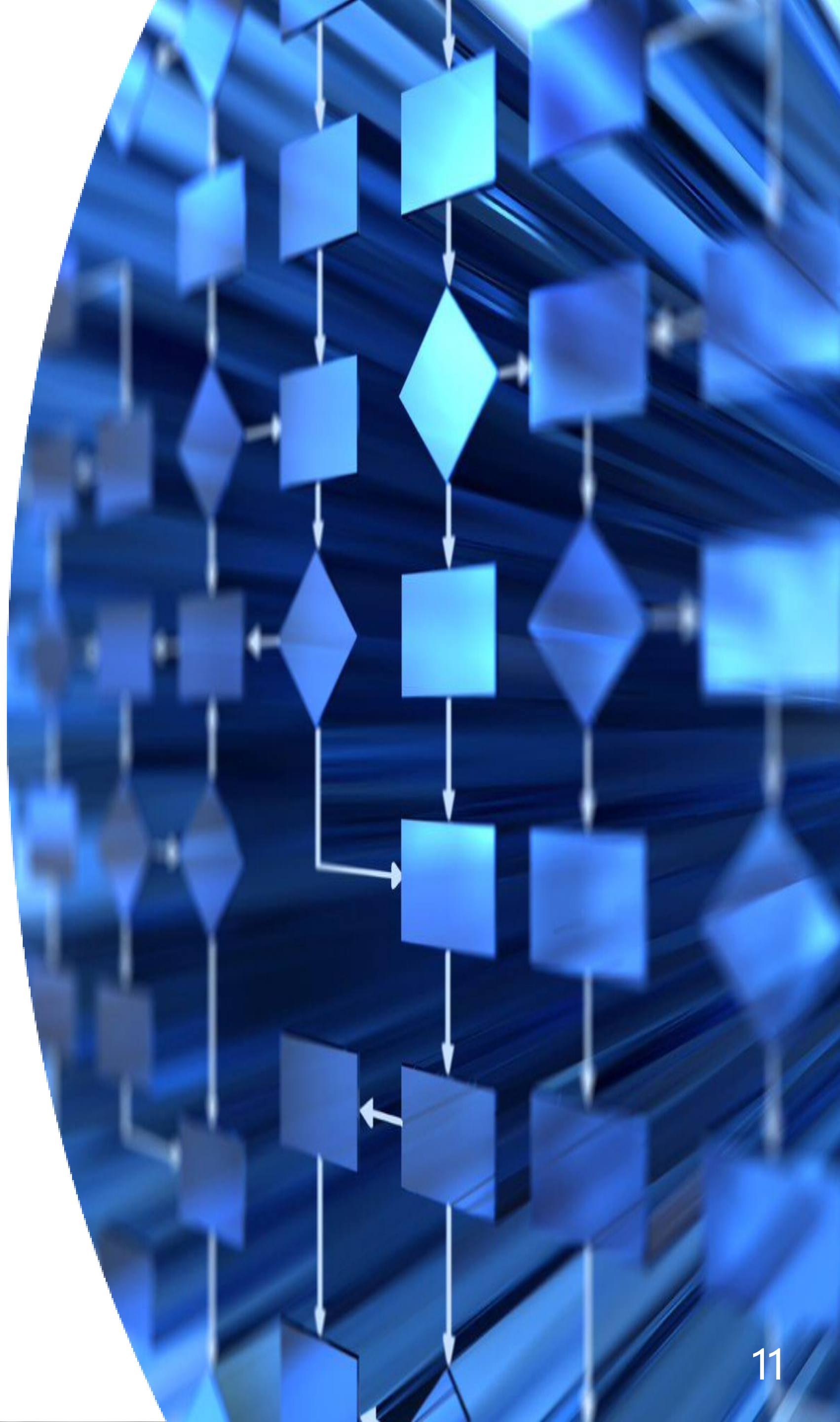
Modelling the STZ

- Predicting driving behaviour by employing mathematical driver models, obtained directly from the observed driving-behaviour data, has gained much attention in literature (McDonald et al., 2020)
- The most appropriate models, able to correlate driving behaviour with the probability and the severity of a crash risk, were proposed (Michelaraki et al., 2021a)
- The selection of an appropriate modelling framework depends highly on the research questions being asked, the available data and the specific context of each study



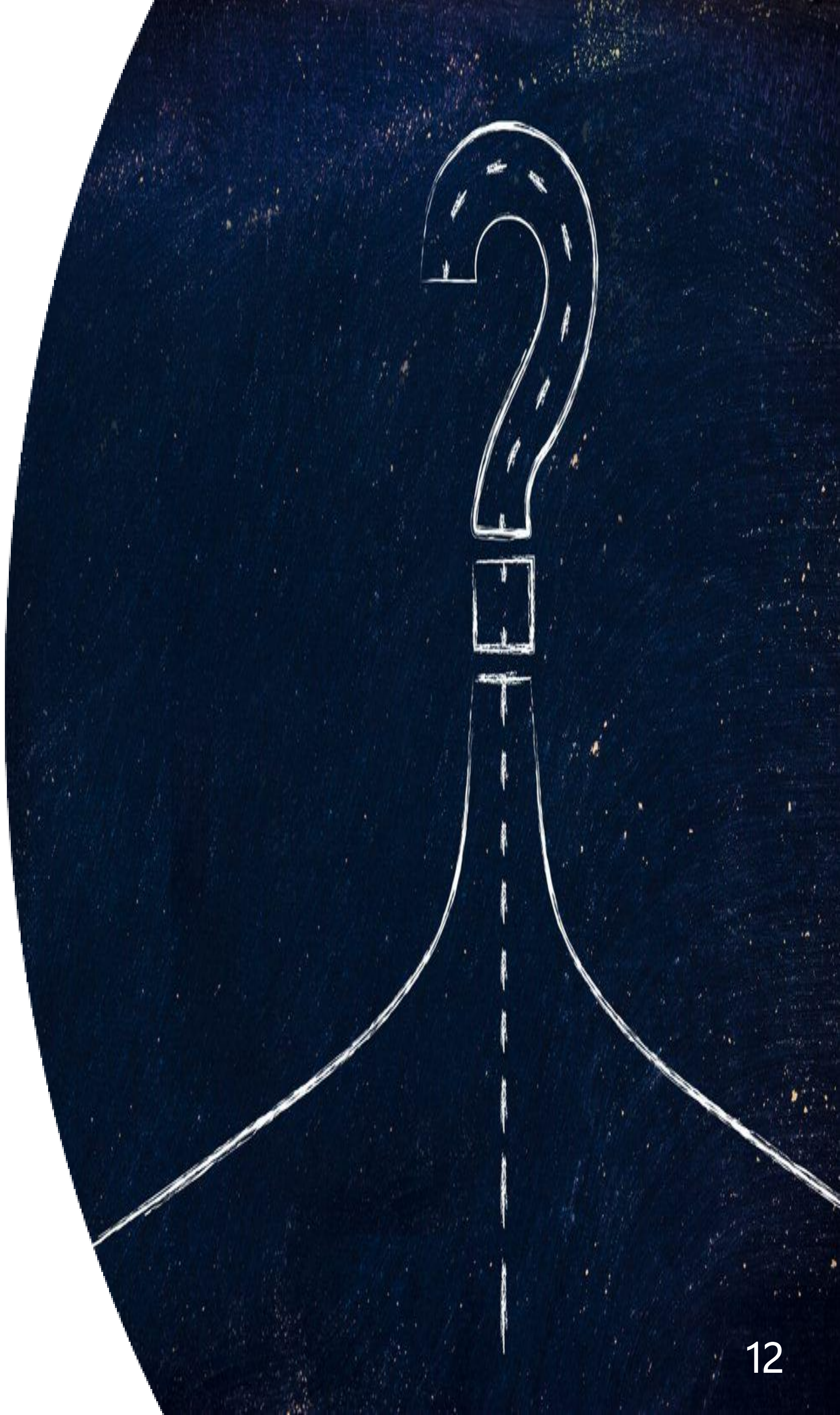
Modelling Approaches

- Discrete Choice Models (DCM): relate crash propensity to unintentional driving volatility and other factors (Wali et al., 2019)
- Dynamic Bayesian Networks (DBN): take into account uncertainties on the relationships among variables (Lefèvre et al., 2012)
- Generalized Linear Models (GLM): understand the relationships between crashes and potential causal factors (Papadimitriou et al., 2019)
- Neural Networks (NN): classify crash severity based on road type, speed before crash and the use of protective devices (Sohn & Shin, 2001)
- Random Forests (RF): preferred choice for identifying risky driving behaviour (Shangguan et al., 2021)
- Structural Equation Models (SEM): powerful tool for analysing the complex interplay between observed variables and latent constructs (Papantoniou et al., 2019)
- Support Vector Machines (SVM): handle high-dimensional datasets (Roy et al., 2015)
- Other methods: Binary Multilevel Logit Models, Clustering Models, eXtreme Gradient Boosting, Hidden Markov Models, Hierarchical Linear Models, Gaussian Mixture Models, etc.

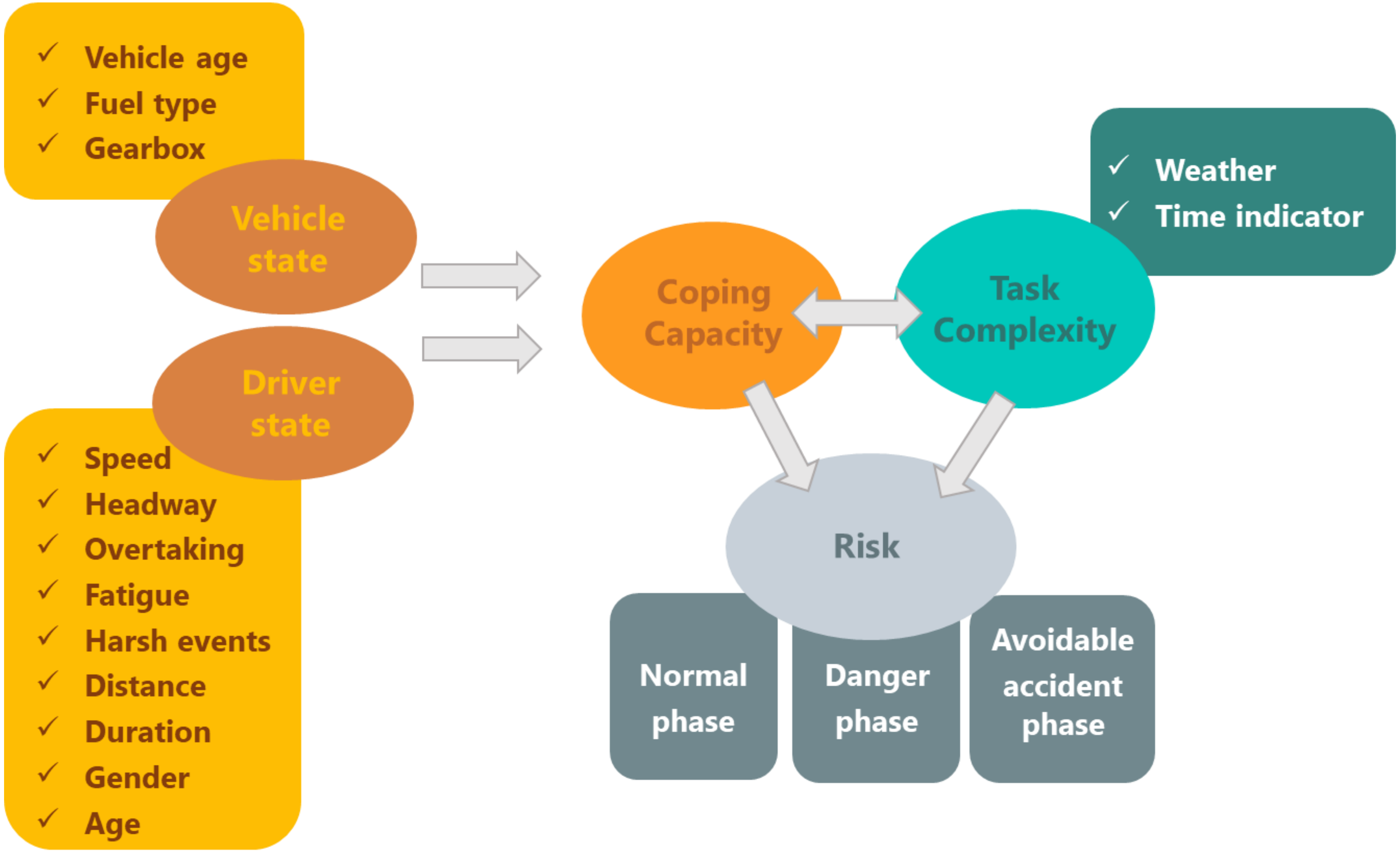


Research Questions

- Which are the most crucial factors for the prediction of the STZ level?
- How can a Safety Tolerance Zone be conceptually defined and operationally implemented based on vehicle-driver-environment factors?
- What is the impact of the inter-relationship between task complexity and coping capacity on risk?
- How can safety interventions be evaluated in terms of keeping the driver within safe boundaries?
- How do the performance and insights from the on-road experiment compare with those from the simulator experiment?



Methodological Approach



Statistical Models

- Generalized Linear Models: for exploratory analysis in order to identify the key correlations between multiple variables and driving performance outcomes (i.e. speeding/headway events)

- Structural Equation Models: for latent analysis in order to quantify the effect between latent and observable variables of task complexity and coping capacity with complex relationships (i.e. crash risk)

SEM constitutes the key component of this PhD thesis, as task complexity, coping capacity and risk are latent/unobserved concepts which are estimated from specific observed parameters

Machine Learning Classification Algorithms

- **Decision Tree (DT)**: used due to their simplicity and ability to handle categorical data, such as vehicle features and road conditions
- **Extreme Gradient Boosting (XGBoost)**: evaluate the significance of various variables in forecasting STZ and select the most appropriate independent variables
- **k-Nearest Neighbors (kNN)**: a non-parametric method that excels in capturing local patterns within the data and can identify non-linear relationships that might be overlooked by tree-based methods
- **Neural Networks (NN)**: “black-boxes” appropriate due to their ability to model non-linear relationships and capture hidden patterns in high-dimensional data
- **Random Forest (RF)**: provide enhanced stability and accuracy by aggregating multiple Decision Trees, which mitigated overfitting and improved generalization to new data

Model Evaluation Metrics

Goodness-of-fit measures

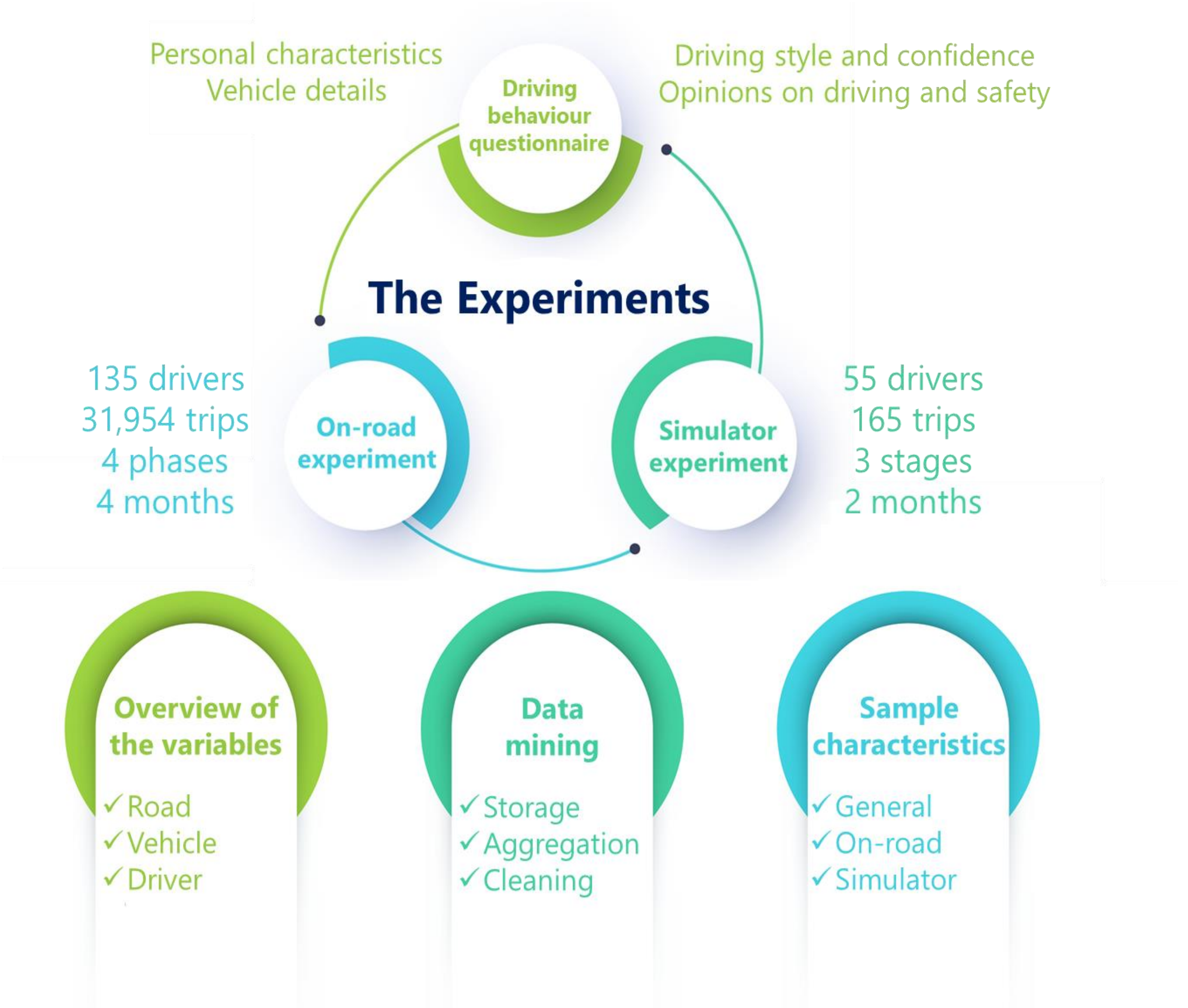
- Comparative Fit Index → CFI > 0.90
- Tucker Lewis Index → TLI > 0.90
- Goodness of Fit Index → GFI > 0.90
- Root Mean Square Error Approximation → RMSEA <0.05

Classification performance metrics

- Accuracy (fraction of predictions that are correctly classified)
  → (TP + TN)/P + N
- Precision (fraction of correct predictions for a certain class)
  → TP/(TP + FP)
- Recall (fraction of instances of a class that were correctly predicted) → TP/(TP + FN)
- F1-Score (harmonic mean of Precision and Recall)
  → 2 * (Precision * Recall)/(Precision + Recall)

The Experiments

Experiments were carried out in naturalistic and simulator as part of **the i-DREAMS research project:**



On-Road Experiment

Exploitation of a large database consisting of:

- 135 drivers
- 31,954 trips
- 4 months

The naturalistic experimental design has been subdivided into four consecutive phases:

- Phase 1: monitoring (baseline measurement)
- Phase 2: real-time intervention
- Phase 3: real-time intervention and post-trip feedback
- Phase 4: real-time intervention and post-trip feedback and gamification

Simulator Experiment

Exploitation of a large database consisting of:

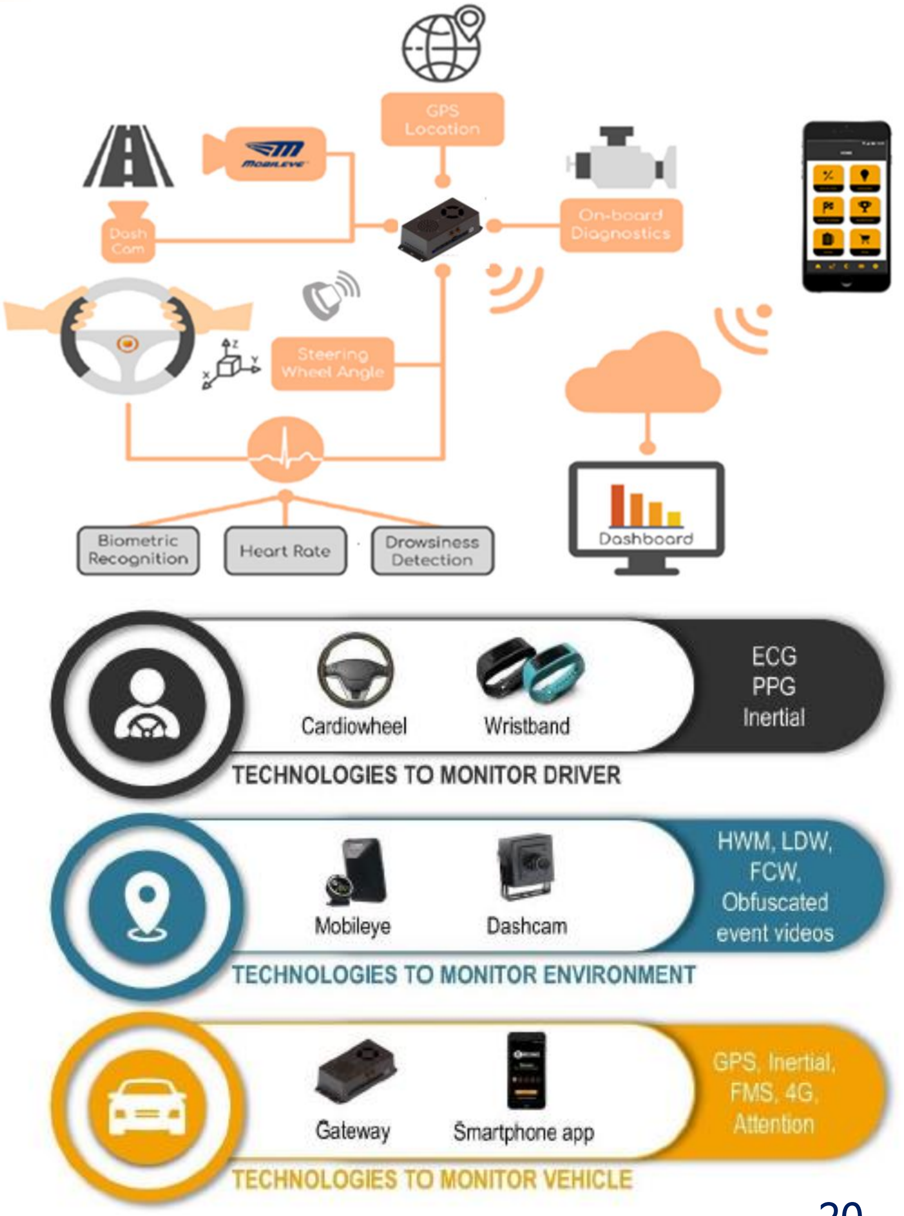
- 55 drivers
- 165 trips
- 2 months

The simulator experimental design has been subdivided into three consecutive phases:

- Scenario 1: monitoring: a scenario in order to monitor driving behaviour to provide baseline measurement (i.e. without the use of interventions)
- Scenario 2: interventions: a scenario in order to influence driving behaviour with fixed timing thresholds (and/or message and/or display)
- Scenario 3: interventions with modifying condition (i.e. distraction): a scenario in order to influence driving behaviour with variable timing thresholds (and/or message and/or display)

Data Collection Technologies

- **CardioWheel/Wristband**
  Measurements: (variability of) heart rate
- **Mobileye in conjunction with DashCam**
  Measurements: forward collision warning, pedestrian collision warning, lane departure warning, wipers, risky times (day/night/dusk), left/right turn indicator
- **Real-time interventions implemented on CardioID Gateway**
  Measurements: speeding, headway, illegal overtaking and fatigue warnings
- **Smartphone application**
  Measurements: speeding, harsh accelerations, harsh brakings, distraction (mobile phone use)



Driving Behaviour Questionnaire

Qualitative data from a questionnaire were collected in order to obtain **driver socio-demographic information and drivers' driving attitudes and feedback**:

- Personal details
- Vehicle details
- Current use of and opinions on different ADAS
- Driving style and confidence
- Opinions on driving and safety
- Self-assessment of driver's risk-taking behaviours
- History of crashes and traffic violations
- Fatigue and sleepiness during driving
- Health and medical conditions

Advanced Driving Assistance Systems (ADAS)

1) **Which Advanced Driving Assistance Systems are present in your car? (multiple answers possible)**
   - ☐ Adaptive cruise control
   - ☐ Forward collision warning
   - ☐ Night vision and pedestrian detection
   - ☐ Traffic sign recognition
   - ☐ Lane keeping assistance
   - ☐ Blind spot warning
   - ☐ Drowsiness alert
   - ☐ Parking assist
   - ☐ High speed alert
   - ☐ Automatic emergency braking
   - ☐ Other: ....

2) **How often do you use the following Advanced Driving assistance Systems that are present in your car?**

	Almost never	Sometimes	Often	Almost always	Not applicable
Adaptive cruise control					
Forward collision warning					
Night vision and pedestrian detection					
Traffic sign recognition					
Lane keeping assistance					
Blind spot warning					
Drowsiness alert					
Parking assist					
High speed alert					
Automatic emergency braking					
Other:					

Driver attitude

9) **Please indicate to which extent you agree with the following statements.**

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
People stopped by the police for close-following are unlucky because lots of people do it.	1	2	3	4	5
It is quite acceptable to take a slight risk when overtaking.	1	2	3	4	5
I know exactly how fast I can drive and still drive safely.	1	2	3	4	5
Some people can drive safely even though they only leave a small gap behind the vehicle in front.	1	2	3	4	5
Even driving slightly faster than the speed limit makes you less safe as a driver.	1	2	3	4	5
I think it is okay to overtake in risky circumstances as long as you drive within your own capabilities.	1	2	3	4	5
It's okay to drive faster than the speed limit as long as you drive carefully.	1	2	3	4	5
I know exactly what risks I can take when I overtake.	1	2	3	4	5
It is quite acceptable to drive closer to the vehicle in front than is recommended.	1	2	3	4	5
Sometimes you have to drive in excess of the speed limit in order to keep up with the traffic flow.	1	2	3	4	5

Safety motive

10) **Please rate your own driving skills in regard to the following situations or manoeuvres.**

	Very weak	Weak	Not weak, nor strong	Strong	Very strong
Paying attention to other road-users	1	2	3	4	5
Keeping sufficient following distance	1	2	3	4	5
Adjusting the speed to the conditions	1	2	3	4	5
Conforming to the speed limits	1	2	3	4	5

Thresholds

- The purpose of real-time interventions was to keep drivers within the normal phase of the STZ or avoid the transition from the danger to the avoidable accident phase

- Real-time interventions were triggered based on crucial inputs from the implementation of the STZ

STZ level	Speeding thresholds	Headway thresholds
Normal	< 10% over the speed limit	> 2 sec
Danger	< 10% over the speed limit and > 15% over the speed limit	1.4 sec and < 2 sec
Avoidable accident	> 15% over the speed limit	< 1.4 sec

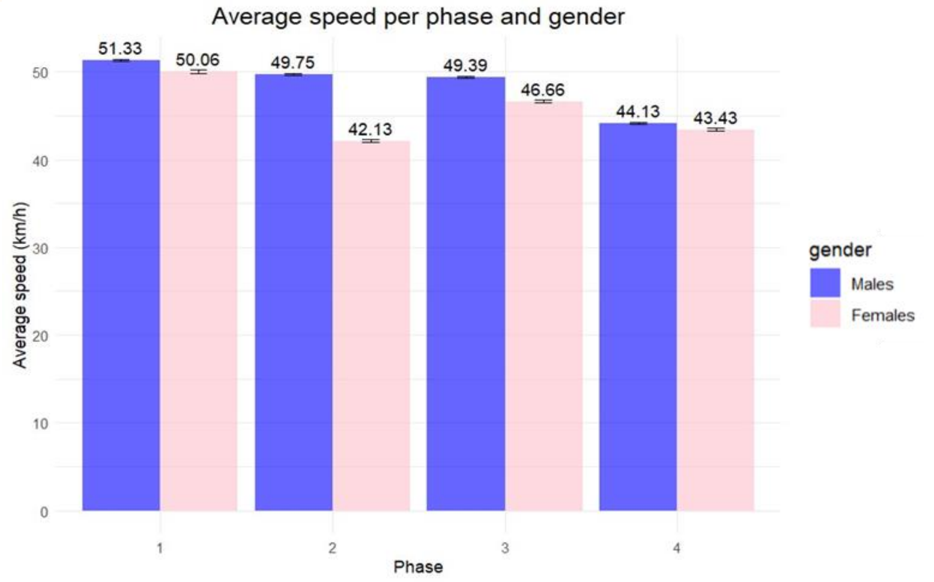
Driver Characteristics

- **Distribution of participants**: 40% per gender in order to avoid an overly skewed gender factor
- In phase 2, where real-time interventions were added, **average speed reduced by 7.7%** compared to phase 1, which likely provided immediate feedback and encouraged safer driving
- In phase 4, a **significant 13.8% decrease in average speed** was observed compared to phase 1, indicating that the combination of interventions, feedback, and gamification effectively worked, as drivers managed to improve their driving behaviour

Age group	Male		Female		Total	
On-road experiment						
20-34	33	38%	23	47%	56	**41%**
35-55	28	33%	17	35%	45	**33%**
55+	25	29%	9	18%	34	**25%**
Total	**86**	**100%**	**49**	**100%**	**135**	**100%**
Simulator experiment						
20-34	18	60%	12	48%	30	**55%**
35-55	7	23%	10	40%	17	**31%**
55+	5	17%	3	12%	8	**15%**
Total	**30**	**100%**	**25**	**100%**	**55**	**100%**
	116		**74**		**190**	

Sample Characteristics

- Male drivers had higher average speeds and were more aggressive compared to female drivers
- When real-time interventions were introduced, female drivers reduced their average speed by approximately 15.9% compared to the baseline conditions
- Younger drivers (aged 20-34) appeared to have the highest average speeds and exhibited more aggressive driving behaviours compared to older age groups, due to a combination of greater risk tolerance
- The highest reduction was found in phase 4 for the experienced drivers (aged 35-55), indicating that interventions, feedback and gamification were particularly effective for this group



On-Road & Simulator Experiment Analyses

On-road VS **Simulator**

The Experiments

On-road

Statistical
- Generalized Linear Models
- Structural Equation Models

Machine Learning
- Decision Trees
- k-Nearest Neighbors
- Neural Networks
- Random Forests

Simulator

Statistical
- Generalized Linear Models
- Structural Equation Models

Machine Learning
- Decision Trees
- k-Nearest Neighbors
- Neural Networks
- Random Forests

Regression Analysis (GLM) - Speeding

- **Time indicator was positively correlated** with speeding, which means that higher speeding events occur at night compared to during the day
- **Wipers was negatively correlated** with speeding, indicating that there are more speeding events during good weather conditions
- **Vehicle age was found to be positively correlated** with speeding, meaning that as vehicles get older, the likelihood of speeding incidents increases
- It was demonstrated that **several indicators of coping capacity – driver state**, such as duration or harsh accelerations had a positive relationship with speeding, indicating that as the values of the aforementioned independent variables increase, speeding also increases

On-road

Variables	Estimate	Std. Error	z-value	Pr(|z|)	VIF
(Intercept)	-0.692	0.005	-13.233	< .001	-
Time indicator	4.146	2.892	17.795	< .001	1.108
Weather	-0.058	0.008	-7.609	< .001	1.007
Fuel type - Diesel	-2.170	1.858	-5.015	< .001	4.522
Vehicle age	1.515	1.974	-18.259	< .001	3.279
Gearbox - Automatic	-3.345	3.754	-3.610	< .001	5.119
Duration	7.146	2.892	39.522	< .001	1.108
Distance	8.641	3.718	44.903	< .001	1.129
Harsh accelerations	5.963	2.235	23.485	< .001	2.934
Harsh brakings	6.088	2.073	28.947	< .001	2.925
Gender - Female	-17.320	1.811	-0.625	0.053	1.542
Age	-1.130	2.243	-10.387	< .001	5.773
Summary statistics					
AIC	609639.61				
BIC	430352.66				
Degrees of freedom	829132				

Simulator

Variables	Estimate	Std. Error	z-value	Pr(|z|)	VIF
(Intercept)	0.334	0.036	9.241	< .001	-
Time indicator	0.363	0.026	13.866	< .001	1.022
Weather	-0.395	0.072	-5.485	< .001	1.023
Distance	-7.299	1.101	-6.631	< .001	1.191
Harsh accelerations	0.374	0.047	8.050	< .001	1.022
Harsh brakings	-1.180	0.100	-11.835	< .001	1.021
FCW	2.685	0.586	4.580	< .001	1.001
Headway	0.317	0.030	10.610	< .001	1.150
Summary statistics					
AIC	62281.66				
BIC	55695.05				
Degrees of freedom	49232				

Regression Analysis (GLM) - Headway

- Interestingly, time indicator was negatively correlated with headway, which means that drivers tend to keep safer distances from the vehicle in front of them during the night
- Fatigue and hands-on wheel were positively correlated with headway. For instance, fatigue can impair a driver's ability to maintain consistent headway, resulting in more frequent adjustments and closing gaps
- Female drivers performed fewer headway events and tended to be more cautious in maintaining following distances compared to male drivers
- On the other hand, age was positively correlated with headway, indicating that older drivers tend to have more headway events, which could be due to various factors, such as slower reaction times, leading to a greater need to maintain safe following distances

On-road

Variables	Estimate	Std. Error	z-value	Pr(|z|)	VIF
(Intercept)	-0.339	0.003	-14.275	< .001	-
Time indicator	-4.713	1.527	-3.086	0.002	1.001
Weather	0.059	0.007	7.852	< .001	1.003
Fuel type - Diesel	-3.432	1.906	-8.094	< .001	3.888
Vehicle age	3.194	1.601	9.942	< .001	4.765
Gearbox - Automatic	-5.122	1.213	-4.032	0.003	2.851
Duration	8.283	3.969	19.871	< .001	1.279
Harsh brakings	5.707	2.456	32.562	< .001	3.396
Harsh accelerations	4.590	2.201	25.239	< .001	3.404
Average speed	7.686	5.019	36.273	< .001	1.103
Gender - Female	-2.097	1.349	-2.775	< .001	1.495
Age	3.764	1.879	3.203	< .001	6.119
Summary statistics					
AIC	568996.716				
BIC	339955.846				
Degrees of freedom	822164				

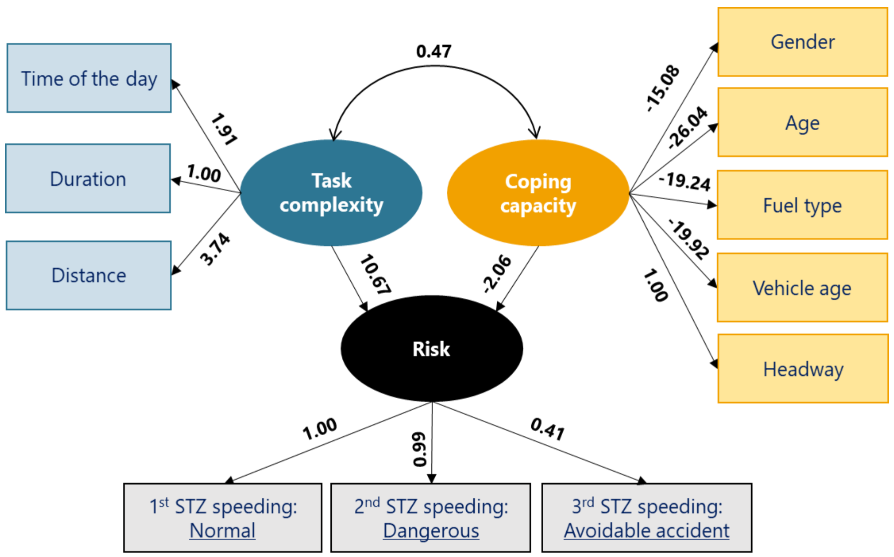
Simulator

Variables	Estimate	Std. Error	z-value	Pr(|z|)	VIF
(Intercept)	0.859	0.221	3.896	< .001	-
Time indicator	-0.690	0.318	-7.443	< .001	1.209
Average speed	0.742	0.080	9.231	< .001	1.020
Time to collision	0.004	3.116	14.300	< .001	1.018
Duration	-5.658	1.395	-4.057	< .001	1.040
Fatigue	5.088	1.587	3.206	0.001	1.114
Hands on wheel	5.369	2.311	2.323	0.020	1.076
Summary statistics					
AIC	4546.08				
BIC	4141.62				
Degrees of freedom	33820				

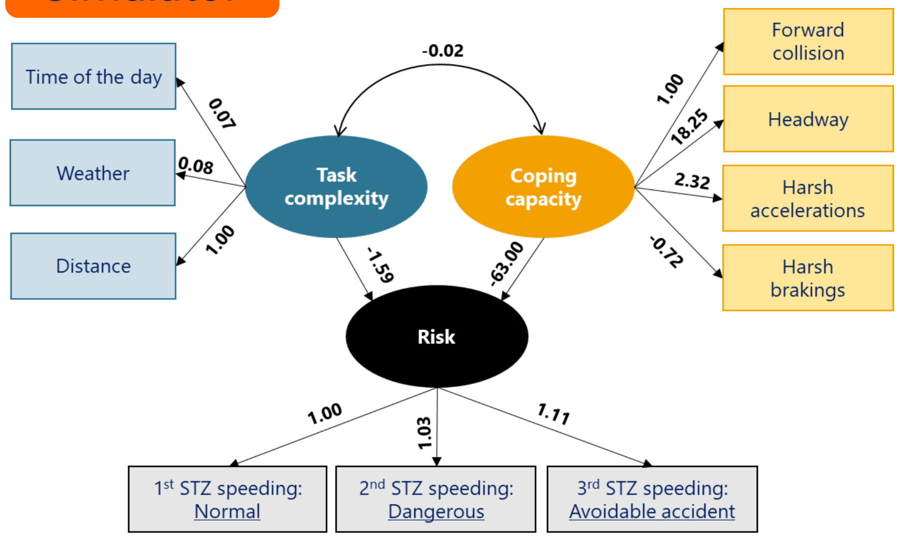
Latent Analysis (SEM) - Speeding

- In on-road experiment results, higher task complexity was associated with higher coping capacity, implying that drivers coping capacity increases as the complexity of driving task increases
- Task complexity was positively correlated with risk, as crucial indicators, such as the time of day and weather conditions can significantly affect crash risk
- On the other hand, in simulator experiment results, task complexity and coping capacity were inter-related with a negative correlation, implying that when tasks become more complex and demanding, participants generally find it harder to manage and cope with the associated stress and challenges
- Task complexity and risk revealed a negative relationship, probably due to the fact that complex tasks often require more detailed planning and greater attention to detail, which can mitigate potential risks
- In both cases, coping capacity and risk showed a negative coefficient, indicating that drivers with higher coping capacity are generally better at managing and mitigating risks

On-road



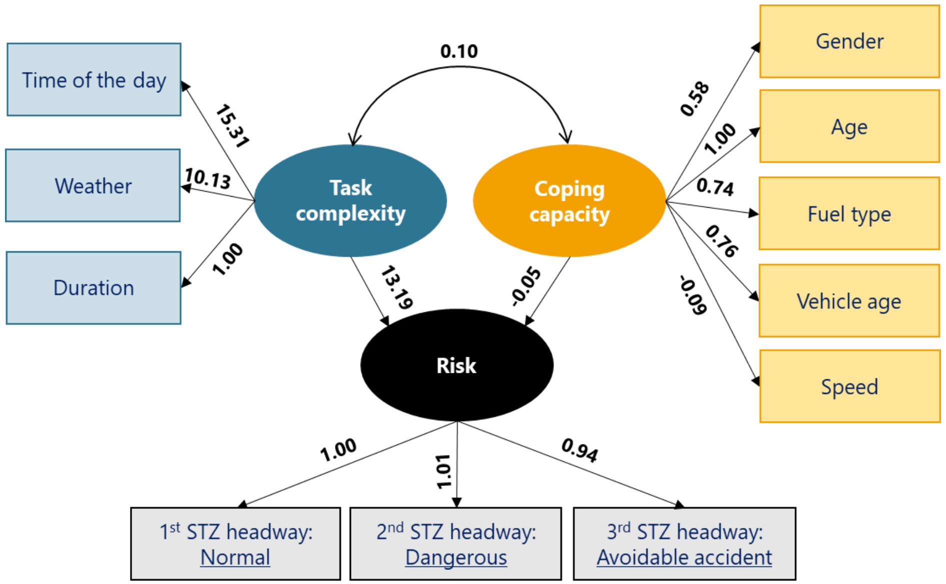
Simulator



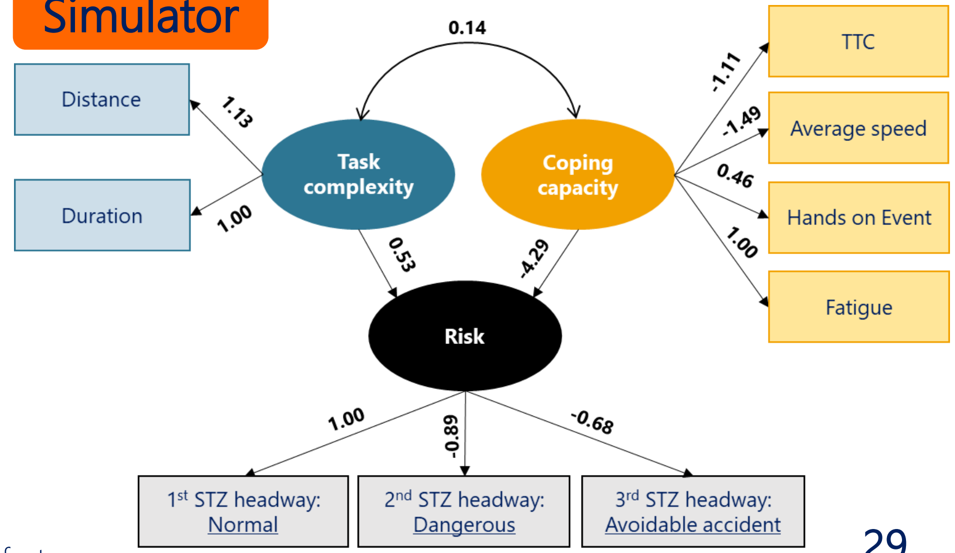
Latent Analysis (SEM) - Headway

- **Consistent results** across both experiments revealed in the models applied for STZ headway
- **In both on-road and simulator experiment results**, higher task complexity was associated with higher coping capacity, implying that drivers coping capacity increases as the complexity of driving task increases
- Task **complexity was associated with higher risk**, due to factors like, time of day and weather conditions, which exacerbate the challenges of complex tasks, leading to reduced attention and delayed responses
- **Coping capacity showed a negative correlation with risk**; drivers with higher coping abilities managed complex situations better, reducing crash likelihood

On-road

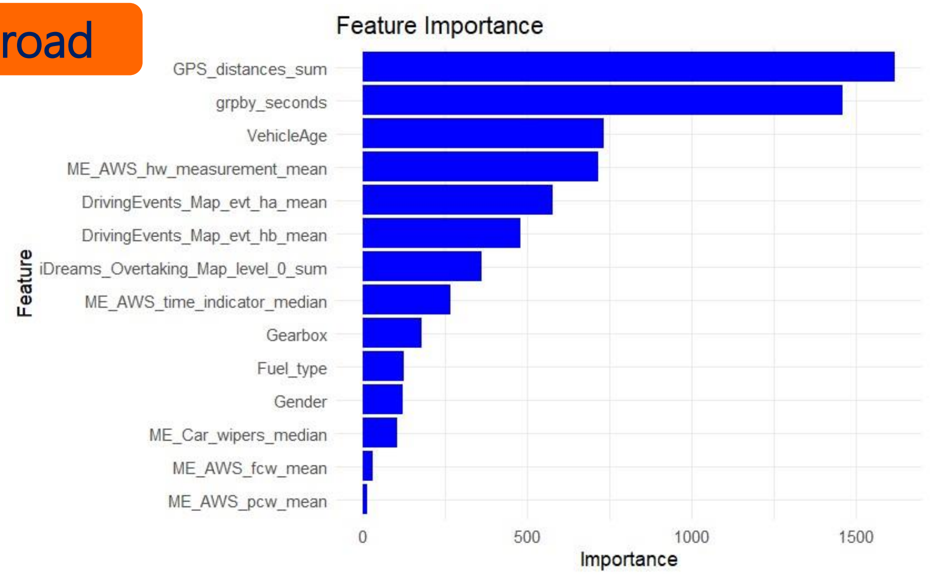


Simulator



Feature Importance Analysis (XGBoost) - Speeding

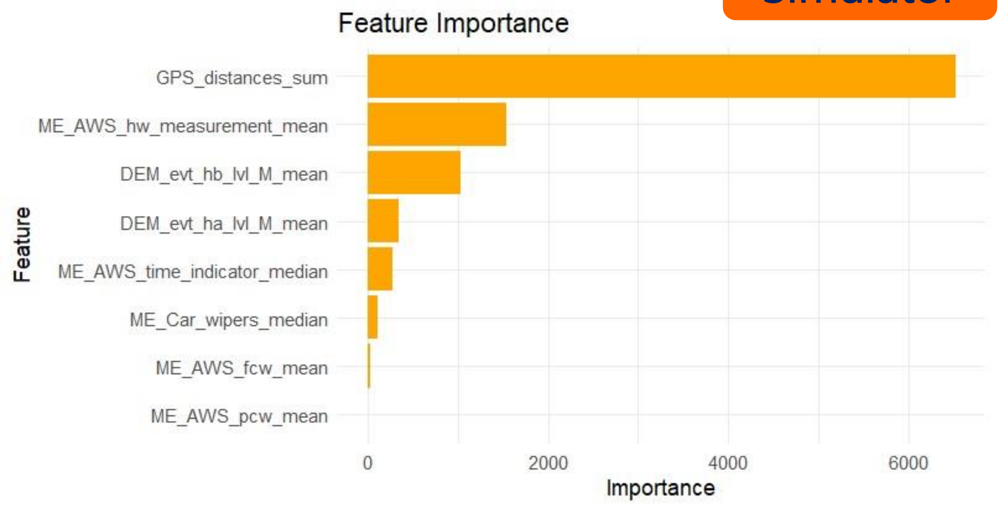
On-road



- According to the feature importance analysis for speeding, distance travelled, duration, vehicle age, headway, harsh accelerations, harsh brakings, overtaking and time indicator emerged as the most important factors among all examined indicators

- Conversely, parameters related to task complexity (i.e. car wipers), coping capacity – vehicle state (i.e. fuel type and gearbox) and coping capacity – driver state (i.e. forward collision warning, pedestrian collision warning, gender) were less significant

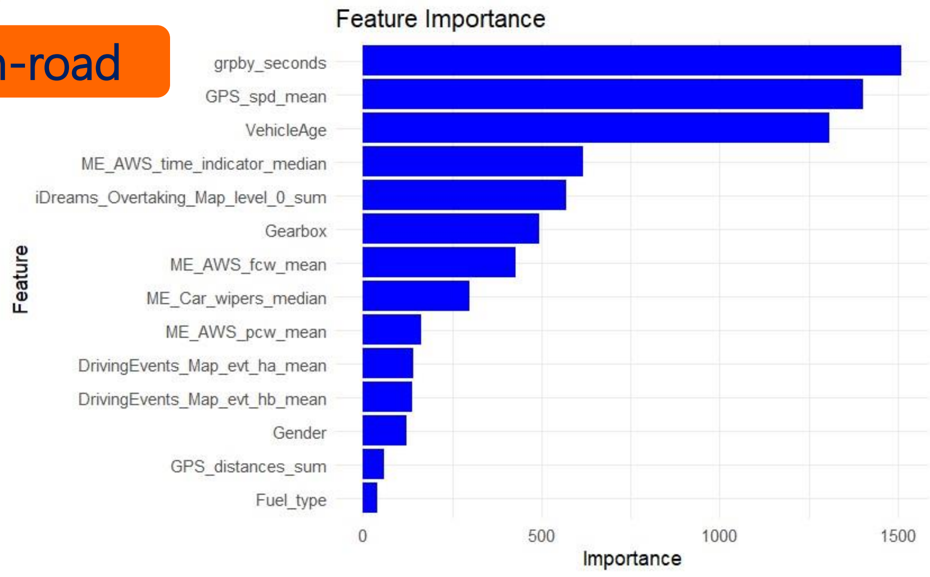
Simulator



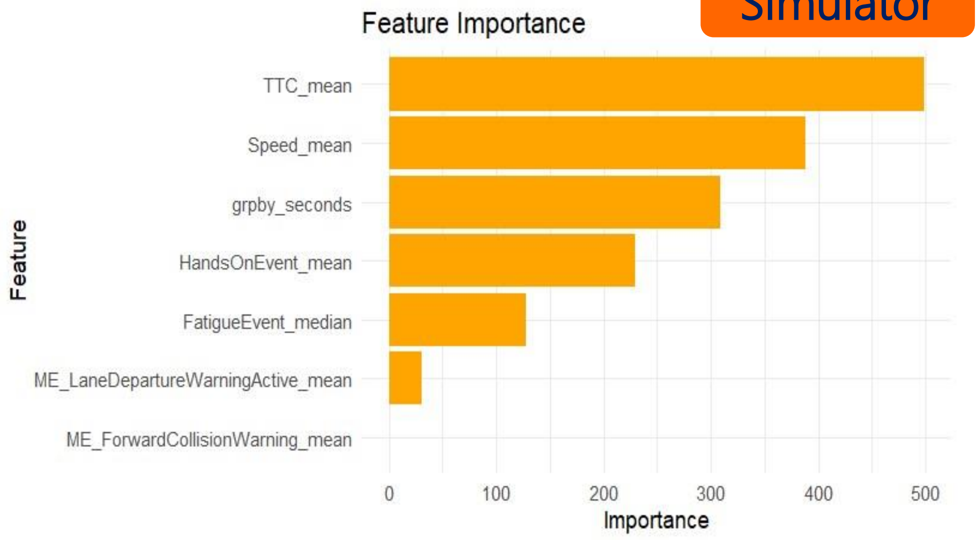
Feature Importance Analysis (XGBoost) - Headway

- Similar patterns were also observed for the feature importance analysis for headway
- It was revealed that duration, average speed, vehicle age, time indicator, time to collision, overtaking, gearbox and car wipers found to be the most influential factors among all examined indicators
- Conversely, parameters such as pedestrian collision warning, harsh events (i.e. harsh accelerations and harsh brakings) and gender were less significant
- Lastly, variables related to distance travelled and fuel type had a negligible impact on STZ headway

On-road



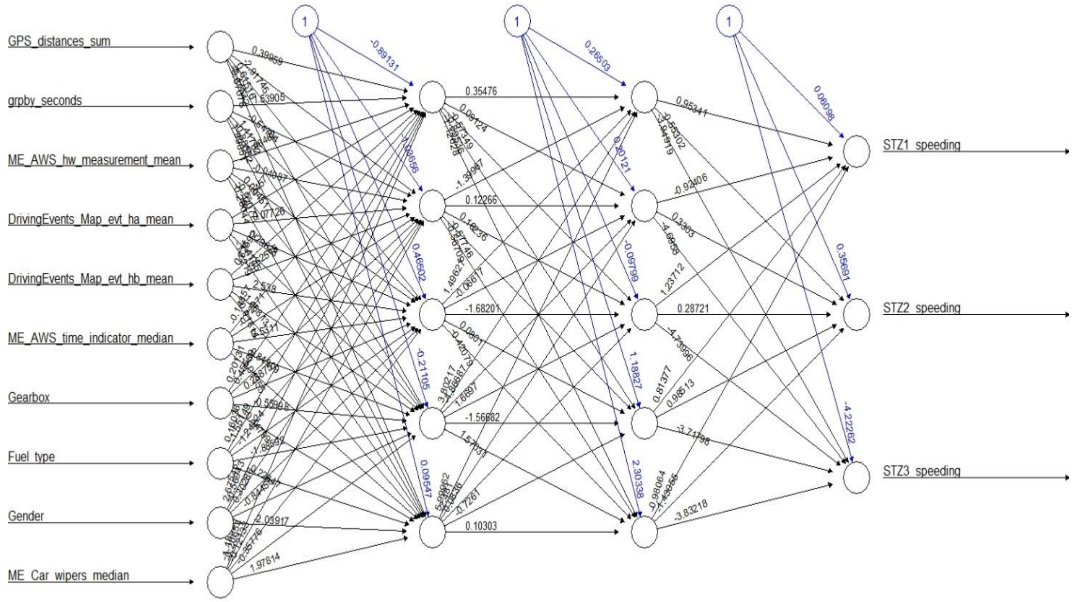
Simulator



Neural Networks - Speeding

On-road

- **Ten neurons in the input layer**: distance travelled, duration, headway, harsh accelerations, harsh brakings, time indicator, gearbox, fuel type, gender and wipers
- **Three neurons in the output layer**: STZ1, STZ2, STZ3
- **Two hidden layers** (represented by circles), each hidden layer node receives inputs from the previous layer, processes them and passes the output to the next layer
- The **training subset (80%)** was used to train the models, while the **test subset (20%)** was used to evaluate their performance
- **Overall accuracy**: 80% (the model is 80% accurate in making a correct prediction)
- **Precision**: 82% (the model is 82% accurate regarding a positive sample)
- **Recall**: 79.9% (the model is 79.9% accurate on predicting safety-critical classes (i.e. “dangerous” and “avoidable accident”), which means that can be trusted in its ability to detect positive samples in a satisfactory degree)

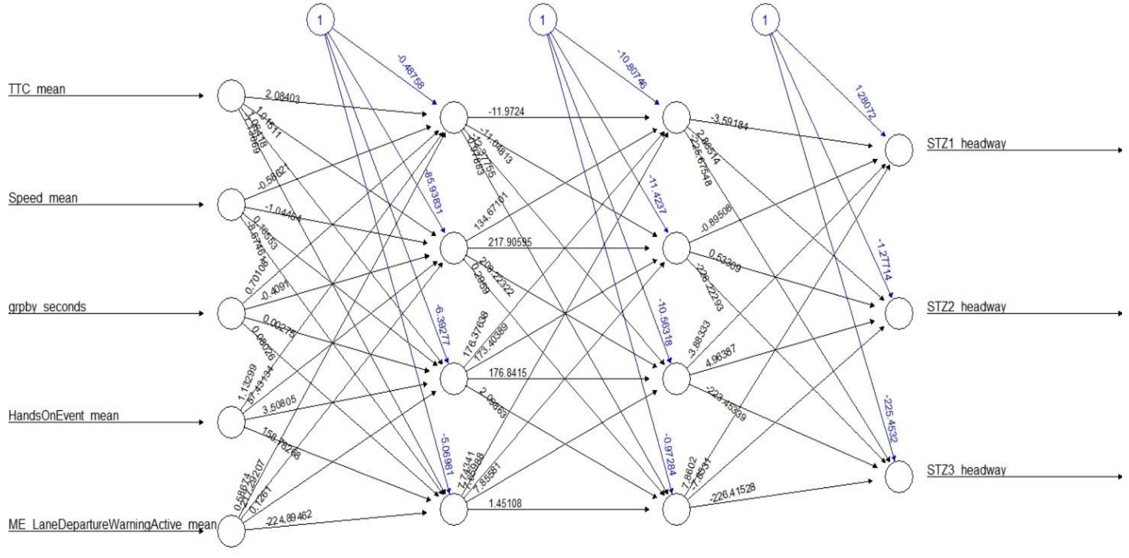


Model Fit measures	0	1	2	Total
Accuracy	0.893	0.854	0.854	0.801
Precision	0.868	0.811	0.750	0.823
Recall	0.892	0.788	0.713	0.799
F1 Score	0.826	0.815	0.759	0.800
False alarm rate	0.167	0.256	0.279	0.201

Neural Networks - Headway

Simulator

- **Five neurons in the input layer**: Time to collision, average speed, duration, hands-on event and lane departure warning
- **Three neurons in the output layer**: STZ1, STZ2, STZ3
- **Two hidden layers** (represented by circles), each hidden layer node receives inputs from the previous layer, processes them and passes the output to the next layer
- **Overall accuracy**: 89.8% (the model is 89.8% accurate in making a correct prediction)
- **Precision**: 91.2% (the model is 91.2% highly accurate regarding a positive sample)
- **Recall**: 90.6% (the model is 90.6% accurate on predicting safety-critical classes (i.e. “dangerous” and “avoidable accident”), which means that can be trusted in its ability to detect positive samples in a satisfactory degree)
- The model can **adequately predict the STZ for headway**



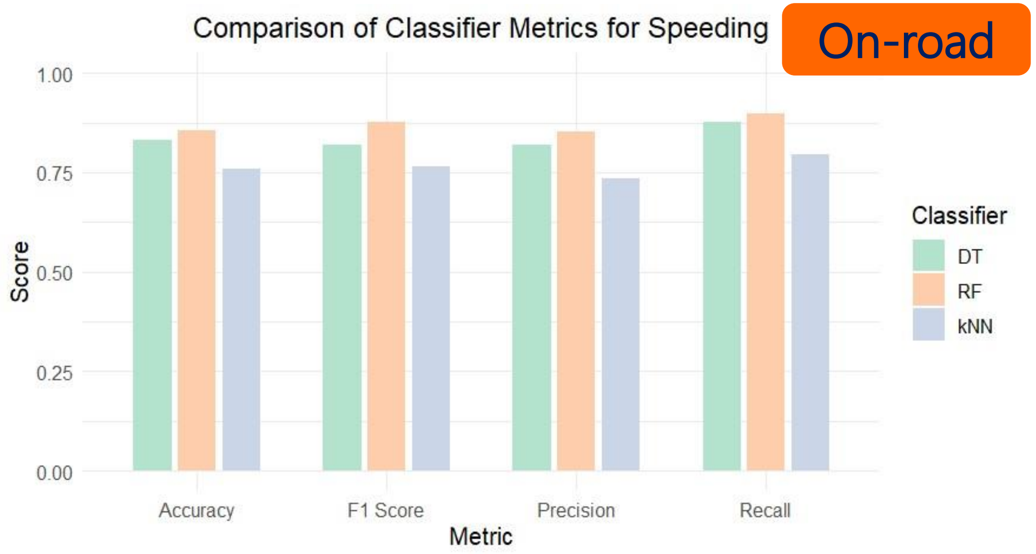
Model Fit measures	0	1	2	Total
Accuracy	0.907	0.973	0.915	0.898
Precision	0.876	0.968	0.853	0.912
Recall	0.899	0.946	0.842	0.906
F1 Score	0.887	0.957	0.847	0.899
False alarm rate	0.287	0.114	0.257	0.153

Machine Learning Techniques (DT, RF, kNN) - Speeding

- **Response variable**: STZ speeding
- The **training subset (80%)** was used to train the models, while the **test subset (20%)** was used to evaluate their performance
- **Overall accuracy**: DT: 83.2%, RF: 85.7%, kNN: 75.8%
- The RF model found to have the **best performance across all metrics**, followed by the DT, and finally the kNN model
- The RF model demonstrates high accuracy, precision, recall and F1 scores, making it the **most reliable for predicting speeding** in different phases

Model Fit measures	0	1	2	Total
Accuracy				
DT	0.824	0.802	0.871	0.832
RF	0.857	0.831	0.882	0.857
kNN	0.799	0.772	0.703	0.758
Precision				
DT	0.835	0.757	0.879	0.821
RF	0.811	0.735	0.917	0.852
kNN	0.747	0.728	0.692	0.736
Recall				
DT	0.934	0.846	0.851	0.877
RF	0.946	0.869	0.875	0.898
kNN	0.803	0.707	0.763	0.794
F1 Score				
DT	0.840	0.784	0.833	0.819
RF	0.868	0.703	0.692	0.876
kNN	0.794	0.748	0.719	0.764

On-road

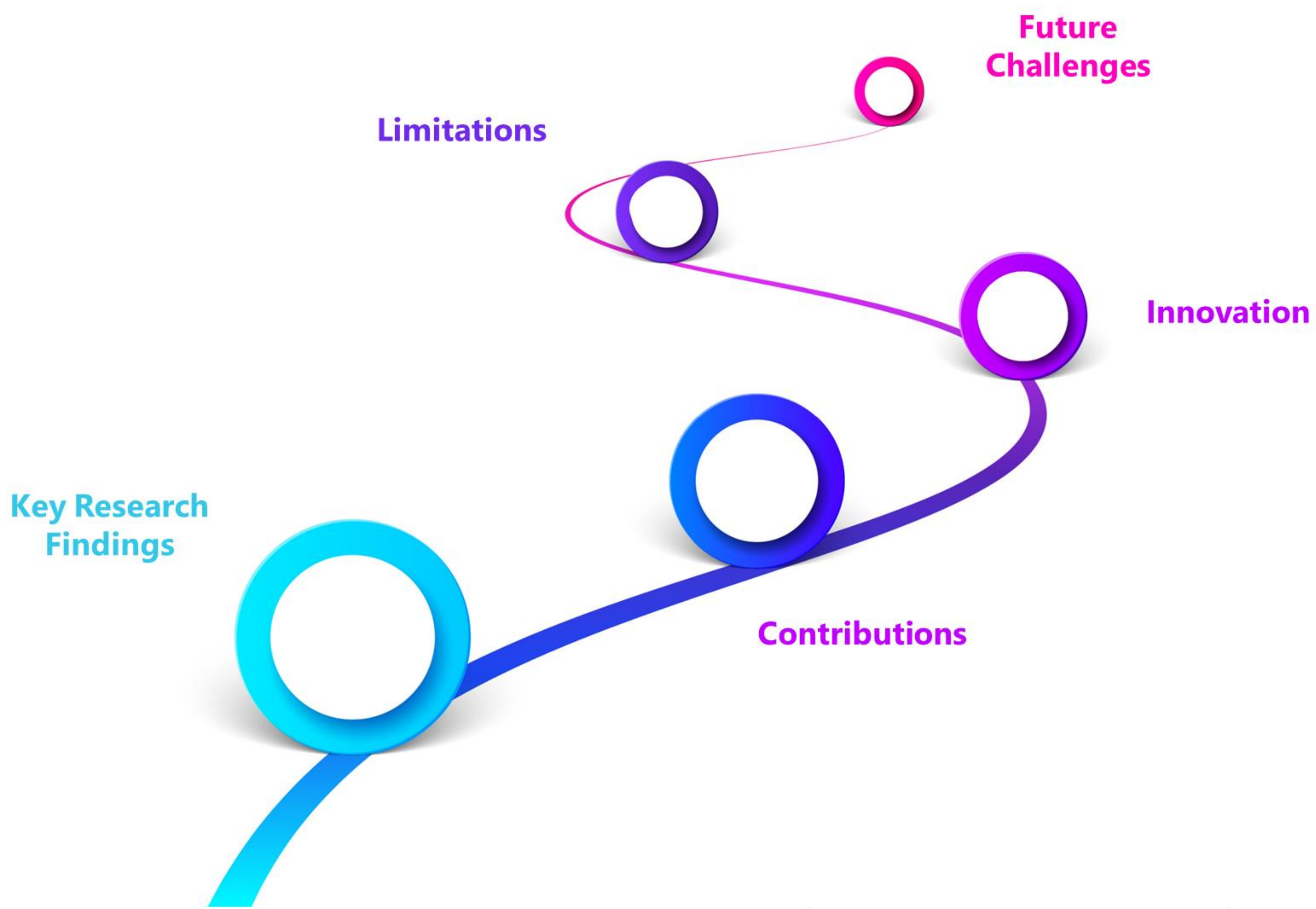


Machine Learning Techniques (DT, RF, kNN) - Headway

- **Response variable**: STZ headway
- The **training subset (80%)** was used to train the models, while the **test subset (20%)** was used to evaluate their performance
- RF consistently outperforms the other classifiers, achieving the highest overall accuracy at 90.1%, precision at 87.2%, and F1-score at 84.7%, with a solid recall of 84.1%.
- These results suggest that **RF is the most effective classifier among the three**, followed by DT, with kNN lagging behind

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

Conclusions



Key Research Findings (1/3)

- Both **real-time and post-trip interventions positively influenced risk** compensation, increased drivers' coping capacity and reduced dangerous driving behaviour

- When safety interventions were introduced during different phases of the experiments, **drivers improved their performance**, became more aware, which led to a noticeable reduction in average speed, greater headways and fewer harsh events

- Additionally, **drivers experienced fewer avoidable accident events** and spent less time in dangerous phases

- **GLMs applied revealed consistent results** across both experiments, suggesting that despite the differing conditions, the fundamental relationships among the variables remained stable

- Latent analysis (through SEM) from the on-road and simulator experiments revealed **complicated effects** of task complexity and coping capacity on risk

Key Research Findings (2/3)

- The results of predictive analyses demonstrated that the level of STZ can be predicted with an exceptional accuracy of up to 90%. Additionally, the models exhibited a low false alarm rate, maxing out at 4%, showcasing their ability to minimise incorrect predictions and unnecessary alerts

- In the on-road experiments, NN exhibited an overall accuracy of 80%. The precision and recall rate indicated a robust ability to identify positive samples and detect safety-critical classes (i.e. "dangerous" and "avoidable accident") effectively

- The RF exhibited higher performance leading in satisfactory accuracy in both on-road and simulator experiments

- The DT model showed moderate performance, while the kNN model consistently had the lowest scores, indicating that it is the least effective for this task

Key Research Findings (3/3)

- Simulator experiments proved to be the **most suitable for predicting STZ levels**
- This is probably due to the **fact that the controlled environment** of the simulator allows for the manipulation of specific variables, which is difficult to achieve in naturalistic on-road settings
- Without the **validation and flexibility** offered by simulators, relying solely on naturalistic data may lead to incomplete or less accurate conclusions, as real-world conditions are often unpredictable and harder to control for critical factors like task complexity and coping capacity

Innovative Contributions of the Dissertation

Comprehensive analysis of all risk factors, including **road environment, vehicle state and driver behaviour**

Dual exploitation of data from both **on-road and simulator** experiments which allows for a detailed and controlled analysis of driver behaviour under different conditions

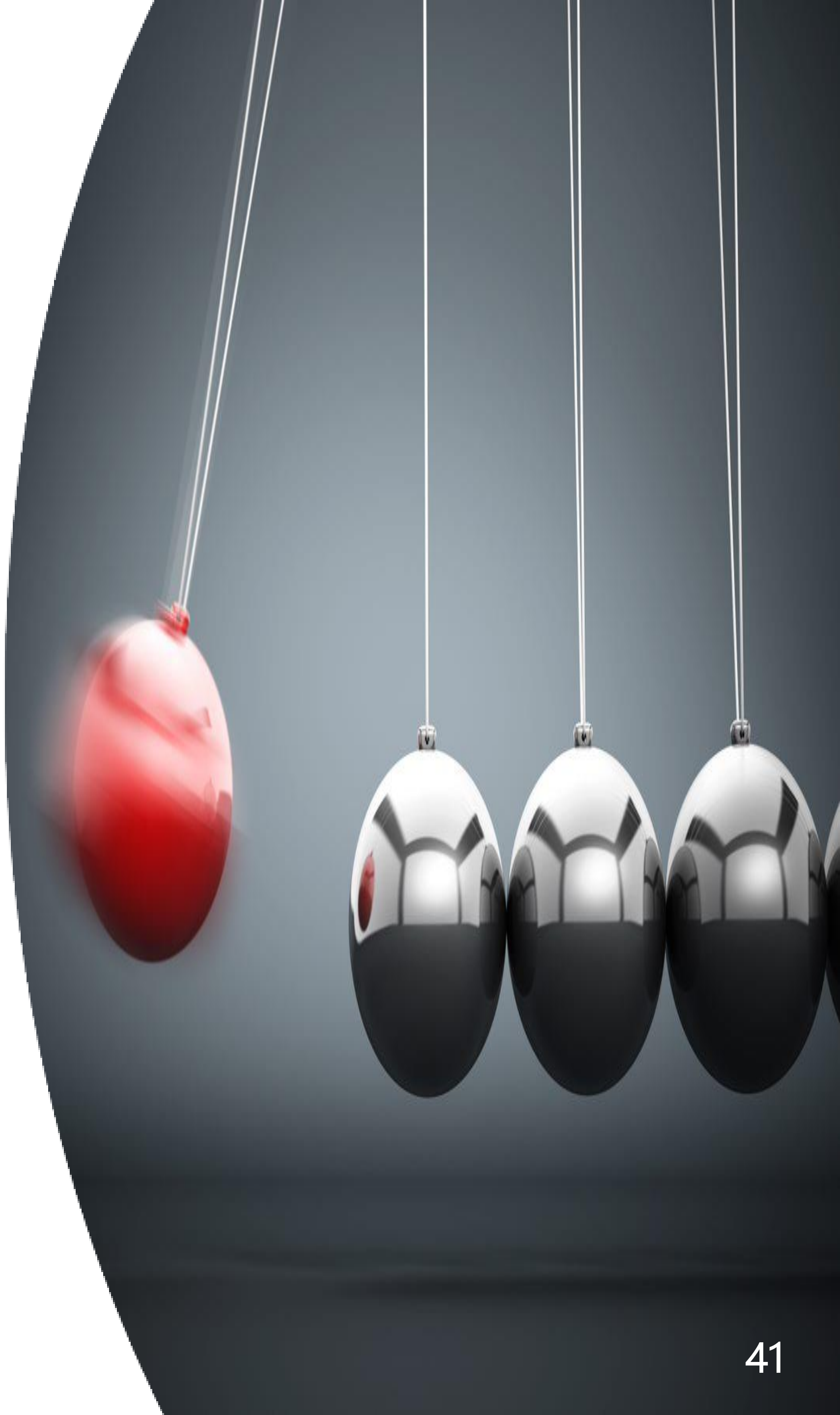
Development of a integrated methodology that combines **statistical models and machine learning techniques**

Implementation of **real-time and post-trip** interventions that prevent drivers from approaching the boundaries of unsafe operation and guide them back into the STZ

Introduction of the Safety Tolerance Zone (STZ) to keep drivers within safe operational boundaries through **normal, danger and avoidable accident phases**

Limitations of the Dissertation

- Potential diversity or differences in driving behaviours across different countries, populations or transport modes were not provided
- Lack of task complexity road data (traffic volumes, flow conditions)
- The impact of participants’ health and medical status was not taken into consideration
- The simulator experimental sample size of drivers was relative small compared to the on-road experiment which may impact the generalizability of the findings



Future Challenges

- **Investigation of other risk indicators**, such as the presence of a passenger, the drug abuse, the alcohol consumption or the seat belt use
- **Comparisons among different countries** or transport modes could be also considered
- Creation of more latent (unobserved) variables, depending on the experimental database and the specific research questions. The effect of several other **driving, medical and neuropsychological parameters** on risk could be also estimated
- **Exploration of additional models** and deep learning techniques (e.g. Long Short-Term Memory) could be considered

National Technical University of Athens
School of Civil Engineering
Department of Transportation Planning and Engineering

Doctoral Dissertation

Improving driver safety tolerance zone through holistic analysis of road, vehicle and behavioural risk factors

Eva Michelaraki

Supervisor: George Yannis, Professor NTUA

Athens, October 2024