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D3.2
Toolbox of recommended data collection tools and monitoring methods and a conceptual definition of the Safety Tolerance Zone

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Responsible Author	Christos Katrakazas, Eva Michelaraki, George Yannis (NTUA)
Contributions from	Christos Katrakazas, Eva Michelaraki, George Yannis (NTUA) Susanne Kaiser, Nina Senitschnig (KFV) Veerle Ross, Muhammad Adnan, Kris Brijs, Tom Brijs (UHasselt) Rachel Talbot, Fran Pilkington-Cheney, Ashleigh Filtness, Graham Hancox (Loughborough University) Eleonora Papadimitriou (TU Delft) André Lourenço, Cátia Gaspar, Carlos Carreiras (CardioID) Christelle Al Haddad, Kui Yang; Constantinos Antoniou (TUM) Chiara Gruden (UM) Petros Fortsakis, Eleni Konstantina Frantzola (OSeven Telematics) Rodrigo Taveira (BARRA)

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Glossary and abbreviations

Abbreviation	Description	Abbreviation	Description	Abbreviation	Description	Abbreviation	Description
AR-HMM	Auto-Regressive Hidden Markov Model	DT	Decision Tree	LDW	Lane Departure Warning	PRC	Percent Road Centre
ATP	Automatic Train Protection	DWT	Discrete Wavelet Transform	LPM	Length Proportion of Merging	RF	Random Forest
AWS	Automatic Warning Systems	ECG	Electrocardiogram	LSTM	Long Short-Term Memory	RNN	Recurrent Neural Network
BGGMM	Bounded Generalized Gaussian Mixture Model	EDA	Electrodermal Activity	LVT	Visual Pursuit Test	SDLP	Standard Deviation of Lane position
BN	Bayesian Network	EEG	Electroencephalogram	MGD	Multivariate Gaussian Distribution	SEM	Structural Equation Model
BRT	Brake Reaction Time	ESRA	European Society of Regional Anaesthesia	ML	Machine Learning	SHRP2	Strategic Highway Research Program 2
BSSS	Brief Sensation Seeking Scale	FCNN	Fully Connected Neural Network	MLE	Maximum Likelihood Estimation	SLI	Speed Limit Indication
CAV	Connected and Autonomous Vehicle	FCW	Forward Collision Warning	MLP	Multi-Layer Perceptron	SSD	Single Shot Multibox Detector
CNN	Convolutional Neural Network	FNN	Fuzzy Neural Network	MMTC	Modified Margin To Collision	SSM	Surrogate Safety Measure
COV	Context Operator Vehicle	GMM	Gaussian Mixture Model	MNL	Multinomial Logit Model	SSS	Sensation Seeking Scale
CRN	Collision Risk Network-level	GSR	Galvanic Skin Response	MTC	Margin To Collision	SSVS	Short Schwartz's Value Survey
CRV	Collision Risk Vehicle-level	TH	Time Headway	MTTC	Modified Time-To-Collision	STZ	Safety Tolerance Zone
CW	CardioWheel	HIOA	Hybrid Input/Output Automaton	MV	Merging Vehicle	SVM	Support Vector Machine
DAS	Driving Anger Scale	HLM	Hierarchical Linear Model	MVPLN	Multivariate Poisson Log-Normal Model	TTA	Time To Accident
DBN	Dynamic Bayesian Network	HMM	Hidden Markov Model	NB	Naive Bayes	TET	Time Exposed-TTC
DBQ	Driver Behavior Questionnaire	HMM-GA	Hidden Markov Model-Genetic Algorithm	NEST	Naturalistic Engagement in Secondary Task	TLC	Time To Line Crossing
DCM	Discrete Choice Model	HR	Heart Rate	NL	Nested Logit	TPB	Theory of Planned Behavior
DDCM	Dynamic Discrete Choice Model	HRV	Heart Rate Variability	O7APP	OSeven application	TPS	Train Protection System
DEA	Data Envelopment Analysis	HSS	Hybrid State System	O7SDK	OSeven Software Development Kit	TPWS	Train Protection and Warning System
DH	Distance Headway	IDM	Intelligent Driver Model	PCW	Pedestrian Collision Warning	t-SNE	t-Distributed Stochastic Neighbor Embedding
DFT	Discrete Fourier Transform	IoT	Internet of Things	PERCLOS	Percentage of eyelid closure	TTC	Time To Collision
DRAC	Deceleration Rate to Avoid Crash	k-NN	k-Nearest Neighbor	PERLOOK	Percentage of time spent not looking ahead	TTZ	Time To Zebra
DSI	Differential Stress Inventory	KSS	Karolinska Sleepiness Scale	PET	Post Encroachment Time	UFCW	Urban Forward Collision Warning
DSM	Driver Status Monitoring	LCS	Latent Choice Set	PPG	Photoplethysmogram	WP	Work Package

Executive summary

This deliverable aims to present the practical conceptualisation of the Safety Tolerance Zone (STZ) in order for the project to transition from a theoretical framework for operational design into the practical implementation of the STZ estimation in the subsequent Work Packages (WPs) of the project. In order for this transition to be outlined, the proposed measurements and technologies for driver monitoring and evaluation need to be contrasted with the sensing capabilities of the technologies available within the project and an appropriate modelling framework must be defined for the STZ.

In order to assure the real-time estimation of the STZ levels and promptly/swiftly trigger adequate interventions, deviations from normal driving must also be identified. Accordingly, a detailed description of driver monitoring measurements which help to determine the STZ levels as well as identify the abnormal driving, is provided within the deliverable. Where applicable, recommendations on measurements along with the corresponding thresholds for detection of events per mode are provided. More specifically, risk factors (e.g. actual speed, harsh acceleration and braking, or aggressiveness) associated with the STZ as well as indicators of abnormal driving (e.g. ECG, hands on the wheel, fatigue, sleepiness) are initially specified. To obtain available thresholds in order to convey the idea of creating a starting point for defining the STZ levels and abnormal driving, a literature review was conducted. The review demonstrated that thresholds are mostly employed detecting high speeds, short time headways and harsh acceleration or braking events in cars. However, limited information on thresholds was found for trucks, buses and rails. Additionally, considerations on how to exploit the available technologies (i.e. CardioID, OSeven, Mobileye) in the experimental setup for all transport models are highlighted.

The final section of the deliverable deals with the mathematical formulation of the STZ in an appropriate modelling framework. Following a thorough literature review of models dealing with driver behavior and collision risk modelling in real-time, the most prominent approaches were found to be Dynamic Bayesian Networks or DBNs (a probabilistic graphical time-series model) and Long Short-Term Memory networks or LSTMs (a deep neural network formulation). In order to allow for more flexibility, and keeping in mind that within the project, post-trip driver evaluations are also to be designed, two approaches, namely Structural Equation Models (SEMs) and Discrete Choice Models (DCMs) were also proposed that provide “static” predictions, in contrast with DBNs and LSTMs which work dynamically (i.e. in real-time). For each of the aforementioned methods or techniques, a brief description of their underpinning procedure is presented, followed by their application for the identification of the STZ levels along with abnormal driving. The most significant practical considerations concerning the modelling of the STZ include the experimentation of the classification algorithm once data become available, the flexibility of the risk indicators with their respective thresholds as well as the problem of data labelling and the specification of driving scenarios, in which STZ levels are most distinctive.

Finally, the project subsequent steps comprise the coding of the models, in an appropriate programming framework, and an extensive experimental testing and tuning of the models using data from driving simulator and on-road trials, in order to guarantee the effective and correct real-time identification of the STZ levels as well as the proper triggering of interventions for road safety enhancement.

1 Introduction

About the *i*-DREAMS project

The overall objective of the *i*-DREAMS project is to setup a framework for the definition, development, implementation, testing and validation of a context-aware safety envelope for driving ('Safety Tolerance Zone'), within a smart Driver, Vehicle & Environment Assessment and Monitoring System (*i*-DREAMS). Taking into account driver background factors and real-time risk indicators associated with the driver state, driving performance and driving task complexity, a continuous real-time assessment will be made to evaluate and determine if a driver is within acceptable boundaries of safe operation. Accordingly, safety-oriented interventions will be developed to avoid and mitigate increasing risk scenarios by promptly informing, advising or warning the driver in real-time and in an effective way as well as on an aggregated level, after driving, through an app- and web-based gamified coaching platform, thus reinforcing the acquisition of safer driving habits/behaviors.

Figure 1 reviews the conceptual framework to be tested in a simulator study during the three stages of the on-road trials in Belgium, Germany, Greece, Portugal and the United Kingdom on a total of 600 participants representing car, bus, truck and rail drivers, respectively. Specifically, the Safety Tolerance Zone (STZ) is subdivided in three phases, i.e. 'Normal driving phase', the 'Danger phase', and the 'Avoidable accident phase'. For the real-time evaluation of the STZ, the monitoring module in the *i*-DREAMS platform will continuously collect and process data for all the variables related to the vehicle and driving environment context. Regarding the operator, however, continuous data registration and processing will be mainly restricted to mental state and behavior. Finally, it is worth mentioning that slow changing, constant, static, or quasi-static variable data pertaining operator competence, personality, socio-demographic background and health status, will be collected via survey questionnaires.

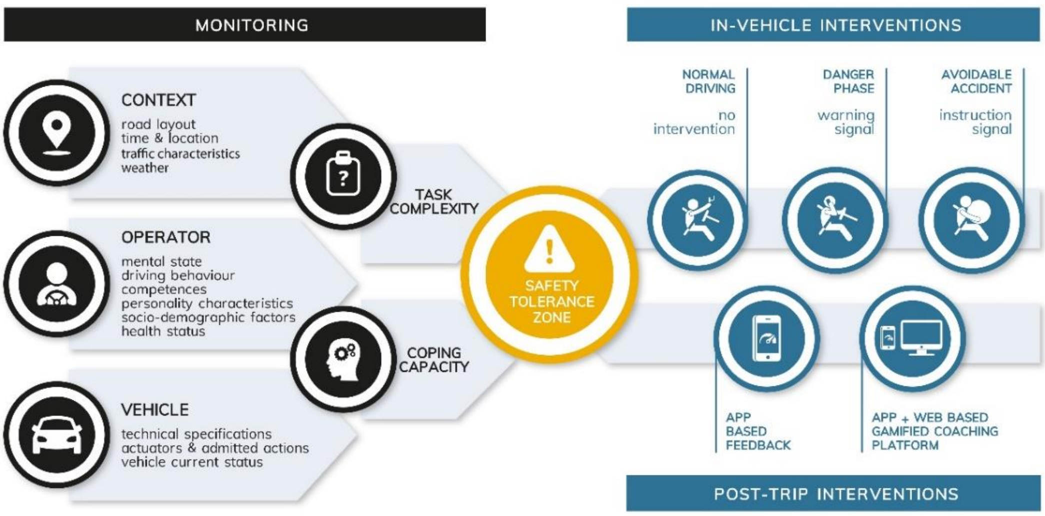

Figure 1: Conceptual framework of the i-DREAMS platform

The key output of the project will be an integrated set of monitoring and communication tools for safety intervention and driver support, including in-vehicle assistance, feedback and notification tools as well as a gamified platform for performance review, both self-determined and fleet manager goal setting associated with rewarding incentive schemes, coaching and tailoring training along with community building tools. Finally, a user-licence Human Factors database with anonymized data from both simulator and on-road experiments will be developed.[1]

About this report

The STZ is the core concept of the *i*-DREAMS project. This report aims to explicitly describe the practical conceptualisation of the STZ to develop the theoretical framework for operational design, presented in Deliverable 3.1, towards a fully functional methodology to be implemented in the forthcoming experimental setups (i.e. in WP4). In order to fulfil this purpose a trilateral correspondence is needed between the list of available technologies, the factors and indicators that need to be monitored (as described in Deliverable 2.1) and the translation of the measurements into meaningful STZ levels and the triggering of interventions (Deliverable 2.2). As a result, the ultimate outcomes of this deliverable will be the provision of a toolbox, a list of viable options of the most useful data collection and monitoring tools as well as the suggestion of a mathematical framework to realize the STZ in real-world driving situations. With regards to the state-of-the-art measuring tools, several physiological and behavioral indicators, such as distraction/inattention, fatigue, emotions or forward collision warning are proposed for real-time, while performance measurements such as speeding, harsh acceleration, braking or risky hours driving are also mentioned for post-trip processing.

Furthermore, as different aspects related to the actual driving context (e.g. driver stress, time schedules, workload, frustration) can explain why drivers deviate from their "normal" way of driving, by accepting higher risks and engaging in increased risky driving behaviors (e.g. speeding, harsh accelerations, dangerous overtaking), the identification and detection of abnormal driving episodes becomes one of the most relevance to STZ estimation.

Chapter 2 covers recommendations on driver and environment monitoring measurements, enabling the STZ estimation. Based on these recommendations, Chapter 3 provides a list of thresholds for measurements to detect STZ levels and abnormal driving. The major part of this deliverable is dedicated to the mathematical modelling of the STZ (Chapter 4), where three different methodological formulations are given in order to turn the available measurements into meaningful information on the level of driving safety. Finally, Chapter 5 draws practical conclusions and gives recommendations on the following steps of the project.

[2] Further general project information can be found on the website: https://idreamsproject.eu

2 Data collection tools

2.1 Consolidation of previous project findings

This chapter aims at revisiting the pre-selection of driving measuring tools discussed in project's Deliverable 2.1 (Kaiser et al., 2020) in order to select the most appropriate to be used for STZ estimation. The preceding, underlying work was conducted by means of comprehensive literature search and technology review in order to capture the state-of-the-art approaches to driver state and environment monitoring and was documented …. , as documented 2.1

The i-DREAMS modes – needs for completing the picture

Regarding state-of-the-art measuring tools for monitoring drivers and the driving environment, most of available evidence concerns car driving. Wherever possible, a separate assessment was made for the other *i*-DREAMS modes - bus, truck, train and tram. In its most basic version this conveys an assumption on the transferability of conclusions for passenger vehicles across other modes. Nevertheless, such assumptions will still have to be confirmed by actual application and, if necessary, adapted or finely tuned in an iterative process.

Driver state monitoring

The term "driver state" is not a universal concept with a standard definition, nor is "mental state". State, however, is largely perceived as the current condition that can change continuously. Within this project, mental state comprises safety relevant cognitive aspects (attention, fatigue, workload) and emotional aspects (including arousal and stress), although complex interactions can be established between those two categories. Emotions, for example, can shift driver's attention and disrupt his focus. Measuring constituent constructs – as opposed to measuring one aggregated overall mental state – is important for this work due to a requirement to effectively provide appropriate and necessary real-time and post-trip interventions. Therefore, the groundwork for measuring the drivers' mental state is focused on attention and distraction, fatigue and sleepiness, emotions and stress as well as impairment.

<u>Distraction and inattention</u>

Most of the literature on real-time measures of distraction and inattention concerns visual distraction such as a diverted view as well as cognitive distraction which is also reflected in vision related variables (e.g. narrowed scanning patterns, PRC: percent road centre). Eye-tracking systems are commonly used for measuring gaze behavior (viewing and scanning patterns). Head tracking facilitates detecting drivers not attending to the roadway with the corresponding indicator PERLOOK (percentage of time spent not looking ahead per time interval). Distraction due to the use of a mobile phone can be tracked via the activity of the device itself. Surrogate safety measures of distraction and attention include lateral and longitudinal control of the vehicle and can be used to identify deviations from normal driving. Those parameters are already essential parts of the *i*-DREAMS system. However, the source of impairment is harder to determine. Therefore, additional equipment for the trials might prove beneficial, especially in view of selecting the most appropriate intervention. An eye tracking system or plain camera would be suitable to measure the discussed parameters. While eye tracking requires calibration of the system and thus support from research staff, cameras facing the drivers require well trained algorithms to reliably detect events of interest. Both limitations pose a substantial challenge, requiring careful consideration.

<u>Fatigue and sleepiness</u>

As seen for distraction, fatigue and drowsiness/sleepiness[2] are most commonly measured by means of eye tracking, with blink rate and PERCLOS (percentage of eyelid closure) proven to be the most robust ocular indicators. Heart rate (HR) and heart rate variability (HRV) can be considered promising physiological indicators for fatigue and drowsiness, although their robustness towards inter-individual differences and confounding factors can be sometimes challenged. Both methods can be considered minimally invasive, since eye tracking is contact free and HR measures can be derived from CardioWheel technology, which is available for the *i*-DREAMS project. Nevertheless, it should be mentioned that CardioWheel may not be utilized for passenger cars or rails, so it could be useful to have some kind of wearable measure for these. The gold standard for monitoring fatigue and sleepiness, however, is considered to be EEG (electroencephalogram). Despite EEG equipment is getting easier to use it still can be considered highly intrusive and thus should be excluded from consideration for *i*-DREAMS'DREAMS'DREAMS' system. As for driving performance measures, lane deviation speed variability, steering wheel movements and following distance can be reliably used as a surrogate measure to infer about sleepiness. However, especially for fatigue and sleepiness, a timely warning or instruction should be given to the driver before driving performance is impacted.

Since all the current behavioral and physiological real-time measurement methods have strengths and drawbacks, leaving room for improvement, the use of multiple measures and indicators could help increase reliability and validity. Again, an eye tracking or camera system to monitor the driver's level of sleepiness/fatigue is recommended to supplement the CardioWheel.

<u>Emotions</u>

Measuring emotions is a challenging endeavour since the term 'emotion' is rather an umbrella term than an agreed upon concept being commonly used to refer driving impacts that affect, mood, stress etc. For valid measurements, exact definitions and disclosing theoretical assumptions are important. Among the studies reviewed for the project, anger/frustration/aggression, stress and fear/anxiety are the best studied emotion categories, indicated by the combination of levels of arousal and valence. Physiological signals are mainly used to determine levels of emotions, most frequently by means of electrodermal activity and cardiac measurement, such as electrocardiogram, HR or HRV. Like attention and fatigue/sleepiness, real-time emotion measuring does not yet have a standard procedure that many can agree upon. Therefore, a complementing measure in addition to CardioWheel or a smart wristband could facilitate ensuring reliability and validity of measurements. This could be a wrist worn Electrodermal Activity (EDA) sensor or a (thermal) camera for facial feature tracking.

<u>Impairment</u>

Continuous monitoring of driver impairment due to substance use (alcohol, drugs, medicines) is still under development or lack sufficient validity. Nonetheless, wearables with touch-, breath- and ocular-based sensors are entering the market. In addition, the impact of drugs and medicines on the driver's state and thus driving behavior is much less clear compared to alcohol. As for alcohol, wrist-worn transdermal sensors have the most potential. It should be noted that this would require yet another device for the *i*-DREAMS participants. What is more, from an ethical viewpoint the instruction to the participant through the *i*-DREAMS platform

[2] While fatigue results from a monotonous task or performing a task for a long period of time, sleepiness or drowsiness is caused by insufficient or poor sleep. The latter can only be mitigated by sleeping whereas fatigue is overcome already by quitting the task.

should be the discontinuation of driving. As a result, it can be assumed that impairment will not be focused on within the *i*-DREAMS project.

Ensuring reliability and validity of driver state monitoring

Reliability and validity of the different measurement methods are a major concern for all the driver states described above. Although respective technological and research progress rapidly, desired levels are not yet achieved by default. This calls for using multiple physiological/behavioral measurement methods and thus, complementing the cardiac measure derived from the CardioWheel to elevate the quality criterions. One further argument is that no physiological/behavioral is the measure of choice for all of the constructs (attention, fatigue/sleepiness, emotions).

Conclusions from the technology review for driver state monitoring

Measuring tools for monitoring the driver's mental state were identified on basis of the reviewed scientific studies. Those tools were subject to review with the aim of assessing their expediency for application in both the simulator and on-road tests. The criteria for the assessment are intrusiveness, validity and reliability (if available), the number of constructs covered (attention, fatigue/sleepiness and emotions) and overall fit for setting up the tests.

Some tools used by researchers in the past were excluded from further scrutiny if the manufacturer or vendor went out of business or the equipment in question was never commercially available (prototype or self-use only). Furthermore, all EEG equipment was excluded as the level of intrusiveness is judged to be high. While an EEG cap is acceptable in a simulator setting, it is inappropriate for the on-road testing in terms of acceptability but also feasibility with on-going support from the project staff would be required for the set-up. This, furthermore, applies to eye-tracking devices as well.

Considering the various criteria, biometric steering wheels (measuring HR) as well as wrist worn wearables (measuring EDA and HR) turned out most promising. Sensors placed at the steering wheel are among the most non-intrusive options, with the exception of trams or trains. Wearables for the wrist are also excessively intrusive and can be easily applied to rail modes. However, concerning on-road tests, the latter must be put on by the participant for each drive, hence potentially compromising the naturalistic driving character that is desirable. What's more, for measuring attention and fatigue, neither EDA nor HR are the most robust indicators.

Whereas a biometric wheel is available through the project partner CardioID, complementary wearables can be considered low-cost. For instance, 'Empatica E4' device was used in several studies (E4 wristband, 2019). Comparable devices should, however, be considered, such as 'EmotiBit' (EmotiBit, 2019), which has the comparative advantage of being independent from the company's cloud and thus easier to integrate with the on-board gateway.

Traits and driver characteristics

Several personal factors that determine the driver's capacity to cope with the task demand change continuously within the timescale of a single journey and therefore, their evaluation in real-time, while driving, is unnecessary. Factors such as personality traits, driving experience or health status, known to affect driving safety, are relatively stable over time. Although those traits and personal characteristics are not measured in real-time, they are important for *i*-DREAMS and will potentially be assessed in a priori. This data will serve different purposes: some are important control variables facilitating the improvement of the *i*-DREAMS platform, some might even be investigated for modelling the Safety Tolerance Zone. Nevertheless, as traits and driver characteristics are mostly "static", in terms of one-off measurements, traits and driver characteristics will be solely considered for triggering the interventions, rather than for modelling the STZ levels. The reason behind this assumption is that for example, risky drivers will basically get warnings under less urgent kinematic conditions, which may result in them finding the warnings to be annoying. All captured traits and characteristics will be compiled within the *i*-DREAMS research data base and should be considered for the customization of interventions. The relevant constructs and variables pertain to the following categories:

- Competences
- Personality traits
- Habitual behavior
- Health condition and factors
- Socio-demographic factors

Some of the factors can simply be queried in a questionnaire (age, year of obtaining driving permit etc.) others require standardised, validated and normed performance testing (e.g. reactivity). Objectivity and validity are obvious arguments in favour of performance and personality tests, while costs and required equipment are often the disadvantages of such tests. In summary, the decision results from the optimal quality of data and efficiency. Table 1 provides an overview of personal factors suggested to be measured, including recommended methods and what purpose this data could serve. Details on the mentioned tests and surveys can be found in *i*-DREAMS' Deliverable 2.1 (Kaiser et al., 2020).

Table 1: Driver characteristic variables recommended to collect from i-DREAMS participants, suggested measurement method and potential purpose of use in the project are also provided

Category	Construct	Recommended measurement method	Potentially include in STZ concept	Validation of inter-individual differences in real-time measure, control variables	Potential for customized intervention
Competences	Emotional regulation	Perth Emotion Regulation Competency Inventory (self-report questionnaire)	no	yes	no
	Stress regulation	Differential stress Inventory (DSI)	no	yes	no
	Attention regulation	Trail making test (Version Trail A)	no	yes	no
	Risk-taking	- Sensation Seeking Scale (SSS-V) - Items from the Manchester Driver Behavior Questionnaire (DBQ)	no	yes	yes
	Hazard perception	Perception of hazards and coping test	yes	no	yes

Category	Construct	Recommended measurement method	Potentially include in STZ concept	Validation of inter-individual differences in real-time measure, control variables	Potential for customized intervention
	Reactivity	Reaction Test (RT)	yes	no	yes
	Visual perception, orientation	Visual Pursuit Test (LVT)	no	no	yes
Personality	Sensation seeking	Brief Sensation Seeking Scale (BSSS)	no	no	yes
	Anger proneness	Deffenbacher Driving Anger Scale (DAS)	no	yes	no
Habitual/past driving behavior	Speeding	DBQ subscale 'ordinary violations' - ESRA2	no	yes	no
	Tailgating	- DBQ item 23 - ESRA2	no	yes	no
	Fatigued driving	ESRA2	no	yes	no
	Distracted driving	ESRA2	no	yes	no
	Aggressive driving	- ADBQ subscale 'conflict behavior' - DDDI, subscale 'aggressive driving'	no	yes	no
Health, diseases	Neurological	Question on any known conditions	no	no	no
	Musculoskeletal	Question on any known conditions	no	no	no
	Cardio-vascular	Question on any known conditions	no	yes	no
	Sleep pattern, quality	- Epworth Sleepiness Scale - Berlin Questionnaire (Sleep apnoea)	no	yes	yes
	Vision impairment	Question on any known conditions	no	yes	yes
	Hearing impairment	Question on any known conditions	no	no	yes
Socio-demographics	Age, gender, nationality, issue date of driver licence	Closed question (provide response options)	no	no	yes
	Level of education, socio-economic status, occupation	Closed question (provide response options)	no	no	yes
	Cultural identity	Short Schwartz's Value Survey (SSVS)	no	no	yes

Task complexity and demand

Beside the current state of the driver and their overall characteristics, the quantity and complexity of the driving task will also determine when a warning or instruction is to be triggered to the driver. Main approaches found in the literature to collect real-time information on the current task demand comprise both physiological measures and driving performance measures. Self-reported task demand, which is also considered in many scientific studies, will not be covered at this point due to its impracticability for continuous measurement. However, self-reported task demand may be useful for repeated post-trip questionnaires to compare measured and reported demand as well as for validation of measures in the simulator study. Furthermore, context (environment) variables which are known to impact task demand include road layout, weather, traffic as well as time of day, especially with regards to accident risk prediction or after event analyses. All of those factors can be measured with equipment available to the consortium (e.g. with a dashboard cam).

With regard to physiological and behavioral measures, the number and duration of eye fixations as well as cardiac measures are the most reliable indicators. While the latter is recorded by the CardioWheel, a supplementary vision-based recording device would improve reliability and validity.

Constant variability in the lateral vehicle position in relation to the lane axis are important indicators of increased task demand. Both are reliably measurable with an in-vehicle OBD device. Compared to physiological and behavioral indicators, driving performance measures are, however, less informative regarding the underlying influencing factors. In this context, the concept of task difficulty homeostasis is noteworthy. It postulates that drivers dynamically maintain the perceived task difficulty within certain boundaries that conform to their corresponding preferences and self-assessed capabilities. Perceived task difficulty results thus the perceived capability combined with task demand and driver's actual skills and expertise. The main mechanism for adjustment when task difficulty is outside of the preferred margins is reducing or increasing speed.

Main conclusions from the preliminary works and the literature at a glance

1. Most of the evidence is based around car driver studies. The transferability of some of the findings to trucks, buses, rails will partly be determined in an iterative process and by trial and error
2. 'Mental state', 'emotions', 'distraction' etc. are theoretical constructs that require deciding on one of the plethora of definitions and theoretical concepts.
3. Using complementary driver state monitoring devices provides for increased validity and reliability as well as a broader portrait of the actual real-time state
4. Selecting the appropriate combination of devices with algorithms and methods is a trade-off between achievable validity and efficiency
5. A complementary wrist-worn (EDA) device would facilitate the valid measurement of emotional constructs, a camera-based system (facial feature or eye tracking) would facilitate measuring fatigue/sleepiness and attention
6. Compromising the naturalistic driving character of the trials by using devices that have to be put on or activated before driving should be considered carefully and borne in mind when analysing the data
7. The potential to consider the drivers' traits and characteristics in the calculation of the STZ should be explored further

2.2 Overview of available technologies

The purpose of this section is to give a detailed description of instantaneous measurements that will be used for real-time in-vehicle evaluation of STZ levels and abnormal driving... In the following sections, recommendation for each mode concerning the actual and practical STZ implementation are discussed.

CardioID

As stated in Section 2.1, several methods are available, yet no standards are recommender for inferring driver's state and driving task demand. Furthermore, the ideal scenario, monitoring all the parameters referred to in the literature regarding driver's state is only possible through the use of vast array of sensors which would lead to a prohibitively expensive solution. In the case of task demand, analogous rational is applicable. On the contrary, many driving/vehicle parameters are often objectively analysed and several tools are already available on the market. The setup to be selected by *i*-DREAMS project must therefore aim for the optimal achievable balance, usability, interference with naturalistic observations, budget and possible/eventual future exploitation plans.

In what concerns driver's state monitoring, the real-time measurement of physiological and behavioral indicators will be leveraged by devices that that have embedded physiological sensing capability for measuring vital signs and allow the extraction of several driver status monitoring (DSM) parameters. In particular, CardioWheel (CW) device allows the driver's electrocardiogram (ECG) acquisition in a seamless way, using only the hands as point of contact. The ECG enables the extraction of driver ID, can produce a driver change alert, and also allows the verification if the driver is using both hands on the Wheel (extracting the %hands on Wheel), and computation of HRV parameters. It also provides a steering angle that is used in commercial solutions (e.g. Mercedes and other OEM) for evaluating driving behavior. The combination of these inputs provides an estimator for sleepiness.

Figure 2: CardioWheel and extracted parameters

In modes of transport where CW is unfeasible (i.e. rails as a result of not featuring a steering wheel), the alternative is to use a wearable capable of measuring the photoplethysmogram (PPG). Similarly to ECG, using PPG is also possible to extract the tachogram of the driver and infer HR and HRV parameters. Some wearables combine the acquisition of ECG with other measurements, such as electrodermal activity (EDA) and peripherical temperature (device on the right of the Figure 3).

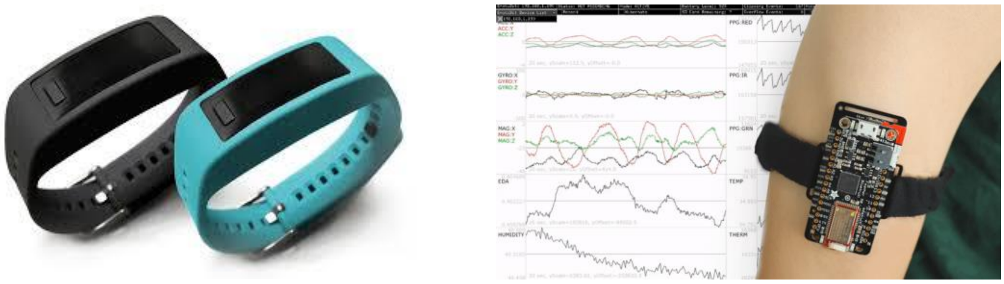

Figure 3: Possible wearables (PulseOn – left; Emotibit – right)

In addition, a wearable technology, called Feel, is the first wristband for emotional tracking (Feel, 2018). Specifically, Feel is a water-resistant leather bracelet that is designed to alert drivers when their body sends off biometric signals indicating that they are under stress or having extreme emotions. It also contains four integrated sensors, which include galvanic skin response, blood volume pulse, EDA, HR and HRV and skin temperature. The device is fairly less clunky and could greatly increase trials' user acceptance. Moreover, this technology communicates with a smartphone app, which implies that could in theory communicate with *i*-DREAMS gateway. Emotion related data could be provided as a closed output, whereas HR and HRV should be available as raw data. The integrated sensors on the wristband measure and track biosignals throughout the day, while the mobile application visualizes the results and provides personalized recommendations to improve emotional health. By leveraging on their knowledge and development, it may a good solution to speed up implementation of emotions/distraction –related indicators with a huge development and cost overheads.

Figure 4: Feel wearable technology

Regarding task demand, as described in Deliverable 2.1, there are several possible perspectives for measurement. The perspective of cognitive workload is, in an indirect way, measured by the use of DSM systems. The measure as an indirect result of exogenous factors can be integrated using the information provided by traffic web-services, road-layout map analysis. Alternatively, in a more direct way, the work load can also the measured by using systems that monitor the road and the distance to the neighbour vehicles, such as Mobileye collision avoidance system.

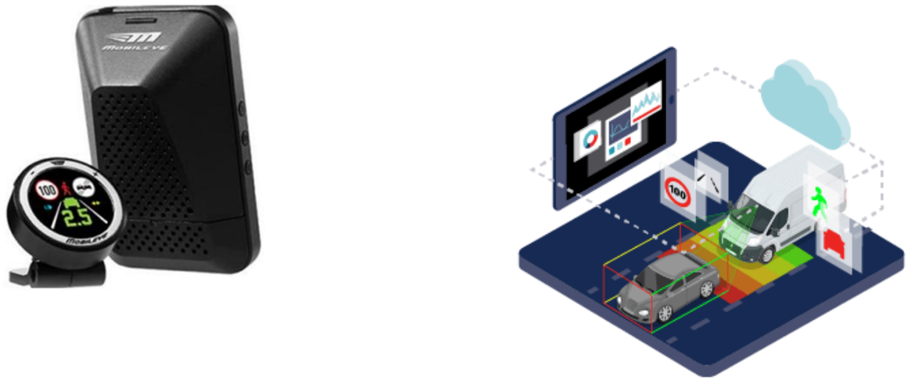

Figure 5: Mobileye collision avoidance system

Mobileye system allows to extract headway monitoring information, detect vehicle ahead, trigger forward collision warning (FCW), and urban forward collision warning (UFCW), trigger involuntary lane departure warning (LDW), detect pedestrian ahead, and trigger pedestrian collision warning (PCW). Moreover, it detects traffic signs in real-time, triggering speeding alerts - speed limit indication (SLI) and forbidden overtaking signs. That together with data acquired from the vehicle allows for the creation of indexes related with the percentage of speeding, including contextual overspeed rather than being limited the maximum speed limit for vehicle type. The system also reads information from the vehicle CAN and produces a low visibility indicator.

Moreover and to allow a better understanding of the actual road, a dashcam can be used to record the driving process. However, because the analysis of the entire driving process is a highly task and requires automatic tagging systems, a real-time perspective may falls outside the scope of this project (e.g. GDPR permission).

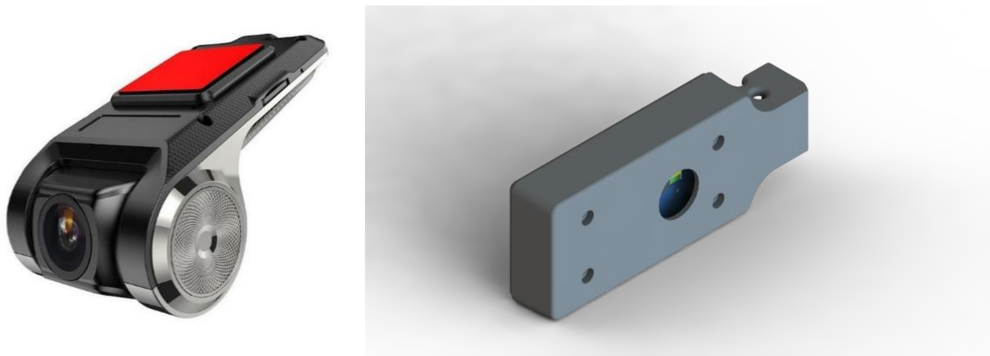

Figure 6: Dashcams – (left - commercial solution; right - CardioID Dashcam & GPS)

Nevertheless, these cameras without special processing are able to provide meaningful and relevant details, including a daylight indicator, roadway scene video evidence triggered by events.

Additionally, vehicle parameters, whose data can be exchanged and acquired through the vehicle CAN, using OBD-II or alterative interfaces (e.g. FMS), are of special interest for ecodriving analysis. There are different possible solutions in the market, with differences regarding the local access to the data, and complexity of the extracted indicators.

Figure 7: OBD-II dongles (Geotab – left; ELM327 – right)

Trip identification (i.e. start/end trip time, total trip time) and average speed can be easily obtained directly from OBD. Moreover, most OBD devices monitor inertial information, allowing the determination of number of harsh accelerations, braking or aggressive driving events. It is worth mentioning that harsh accelerations or braking refer to a driver event when more force than normal is applied to the vehicle's accelerator or brake system and both can be important indicators of aggressive or unsafe driving behavior (Kevin Aries, 2019).

The combination of all these inputs must be performed locally to enable the continuous estimation of the driver performance in a particular STZ phase, accordingly, determine the necessity of the real-time interventions. Several solutions are available on the market for edge Internet of Things (IoT) computing, but the complexity of interfaces that is required to combine all the sensors available needs extensive customization of already existing solutions, or the creation of a tailored made design which would be better for future exploitation plans.

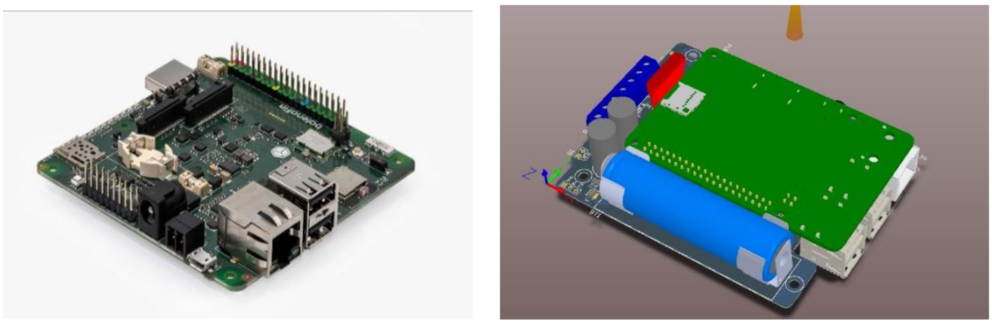

Figure 8: IoT platforms (Balena – left; CardioID GW – right)

These IoT platforms are connected to the vehicle CAN, contextualizing the events and the trip with vehicle events, and may also be connected to the other CAN interfaces. Additionally, these platforms have a GPS chip and provide geostationary satellite localization services (GNSS), conveying the geolocation of all detected events. CardioID GW includes also an inertial unit that can be used for driving behavior analysis (i.e. for evaluating harsh acceleration /deceleration /cornering events, number of harsh accelerations and brakes, average trip speed). The sampling frequency of the parameters available from CardioID is presented in Table 2.

Table 2: Sampling frequency of values of the parameters provided by CardioID (“Event” denotes that a measurement is available, once a corresponding event is detected)

Data Type	Sampling Frequency
CardioWheel – Raw ECG	1000Hz
CardioWheel – Inter-beat Intervals	About 1Hz
CardioWheel – Hands-On-Detection	Event
CardioWheel – Raw Motion	200Hz
CardioWheel – Driver Change Detection	Event
CardioWheel – Fatigue Detection	Event
Mobileye – Raw CAN messages	Event
Mobileye measurements (Headway)	About 10Hz
Mobileye – Warning System	Event
CardioID Gateway – GNSS	1Hz
CardioID Gateway – Raw vehicle CAN messages	Event
CardioID Gateway – Dash Cam (triggered on specific events)	Event
PulseOn Wristband - PPG	25Hz
Emotibit - PPG	100Hz
ELM327 OBD Device	Event

OSeven

OSeven developed a software development tool (O7SDK) for Android and iOS operating systems, incorporated within the OSeven application (O7APP), in order to collect the required data from the smartphone sensors and relay it to the OSeven platform for processing.

The O7APP via the O7SDK detects driving without requiring any user action. During driving the O7APP records data via the O7SDK from the smartphone sensors (“Primary Data”). The recording starts whenever driving is detected and ends at any stop of driving with duration equal or more than five minutes. The Primary Data is provided to the O7SDK during the recording by the smartphone’s operating system manufacturers and developers (indicatively Apple: iOS, Google: Android) and is then collected and stored in the OSeven platform. The recording does not involve the recording of any activity or content of any other application installed in the smartphone or any personal data of the users.

The OSeven platform is the infrastructure (indicatively but not limited to front end, back end, data base, machine learning algorithms, driving behavior models, statistical models, campaigns, gamification schemes, loyalty programs) as a complete information system that has been developed by OSeven. It comprises individual applications and numerous Application Programming Interfaces (APIs). The OSeven platform, whose advanced design enables it to collect, store, process and analyze high volumes of driving behavior data, has been developed by OSeven and it is hosted in recognized and acknowledged cloud service providers in the European Union (indicatively Amazon, Microsoft).

The main Primary Data is the following:

- Date/Time: the recording date/time/timestamp for Primary Data.
- GPS Data: geographic longitude, geographic latitude and altitude of the device position, horizontal and vertical accuracy of the GPS recording, movement speed and vehicle direction and heading.

- Accelerometer data: Acceleration values on the three local axes (x, y, z) of the smartphone, including and excluding the acceleration of gravity.
- Gyroscope data: Angular velocity values on the three local axes of the smartphone.
- Values of the angles formed by the local axes of the smartphone to the North and to the horizontal plane (ground).
- Activity Data (Motion and Fitness / Activity Recognition): Data provided by Apple and Google companies related with the activity of the user as it is recognized by the smartphone operating system (indicatively but not limited to, walking, stopping, driving).
- Smartphone device data. It is provided by Google and Apple and includes indicatively but not limited to, the manufacturer's brand, the device model, the name and version of the operating system and the type of smartphone sensors (e.g. accelerometer, gyroscope, compass, etc.).
- Push Notification Token Data: A unique alphanumeric code produced by Apple and Google companies, which is sent to a smartphone. This code is associated with a single installation of the O7APP. In case of uninstalling and reinstalling of the O7APP by the user, a new code is generated indicating the day and time that it was generated.
- The sign in/out to/from O7APP date and time.

The frequency of the values collected by the sensors varies and in some cases is not in the control of the application, since it is decided by the operating system of the device. The minimum frequency for all data is 1Hz, i.e. OSeven collects one or more values for every sensor per second.

Using the Primary Data OSeven platform calculates a variety of post-trip parameters related with driving behavior and many of these can easily be computed in real time.

A variety of different parameters can be calculated, such as the following:

- Start trip time: The time the trip started (hh:mm:ss).
- End trip time: The time the trip ended (hh:mm:ss).
- Total trip distance: Total distance travelled (m).
- Trip duration: Total trip time (sec).
- Type of the road network: e.g. urban, rural, highway (given by GPS position and integration with map providers e.g. OpenStreetMaps or/and Google Maps).
- Speed: average, max trip speed (km/h),
- Speeding: average speed over speed limit (km/h), duration of speeding (sec), exceedance of speed limit (km/h), percentage of time over the speed limit (%) – calculated based on speed limit data from map providers e.g. Google, OSM, etc.)
- Distraction (With over 98% accuracy): Distraction caused by mobile use (talking, texting, internet navigation).
- Braking: Frequency (number of harsh brakes), intensity and aggressiveness of harsh brakes (low, medium, high).
- Acceleration: Frequency (number of harsh accelerations), intensity and aggressiveness of harsh accelerations (low, medium, high).
- Driving during increased risk time of the day: Distance travelled between 12 am and 5 am (m).

- Driver-passenger / mode recognition (with over 92% accuracy): determine the transportation mode and if the user is the driver or a passenger using a set of ML algorithms.
- Scores (overall and per category: speeding, mobile use, acceleration, braking)

Figure 9: O7APP trip details screen

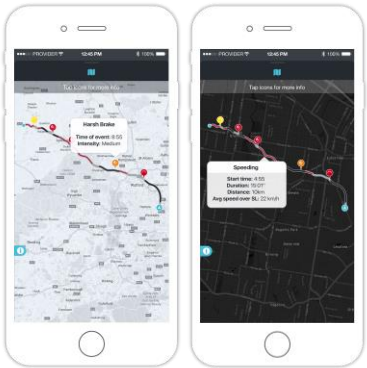

Figure 10: O7APP map visualization

Figure 11: O7 portal visualization of driving behavior metrics

Table 3 provides a list of the available driver monitoring tools provided by tech-partners, while Tables 4, 5, 6 and 7 give an overview of the available measurements for cars, trucks, buses as well as trains and trams. Specifically, the template highlights the risk factors monitored associated with the STZ as well as those parameters that contribute to abnormal driving detection. In addition, the metrics and shortcomings of the devices used to acquire driving data, such as in-vehicle technologies, wearables, smartphone, steering wheel sensors or dash cameras, are also evaluated. Moreover, a description of outcome variables used to detect each factor (i.e. standard deviation of speed or aggregation level), as well as the type of these variables (i.e. numeric, categorical or continuous) is given. It is also investigated if the evaluation of each factor provides real-time or post-trip feedback and focus is given on task demand or coping capacity. Furthermore, it is discussed if the indicators are tested in simulator or onon-road conditions and a segmentation per transport mode to be monitored (i.e. passenger car, bus, truck and rail) is made. Relevant indicator or measurement thresholds, either numeric or categorical values, often used to detect increased risk factors and abnormal behavior. The detection reliability and accuracy levels and respective evaluation estimation procedures, as well as the percentage of valid detections and how validity is measured are also described in Table 3. With regards to the usability, reported evidence of ease of use or driver/operator interaction with monitoring and feedback setup as well as reported evidence on how the device and the measurements or indications become trusted and accepted by the driver/operator are addressed. Finally, practical implications, such as special aspects to be taken into account for the experiments as well as modifications are also considered. Person-related characteristics, such as personality/attitude or other personal characteristics are included in the Table 3.

Table 3: List of available driver monitoring tools provided by tech-partners

Partner	Factors monitored	Device	Outcome variable(s)	Real-time/Post-trip evaluation	Task Demand/ Coping Capacity	Experiment setup	Transpo rt Mode	Thresholds for detection	Accuracy	Validity	Usability	Acceptance	Practical Implications	Modifications	Person-related characteristi cs
OSeven	harsh accelerations	smartphone	number of harsh accelerations per trip (frequency), level of intensity of harsh acceleration (low, medium, high), location on the map of the harsh accelerations	post-trip	task demand	on-road	Car	The detection is based on data driven / data fusion / fusion / ML methods and therefore a specific limit cannot be provided.	>95% (the estimation is based on OBD data and annotated experiments)	95%	Easy usability	High acceptance	No practical implications. Available to all devices and Operation System versions that are compatible with the O7APP.	No	No
OSeven	acceleration aggressiveness	smartphone	acceleration aggressiveness (low, medium, high)	post-trip (real-time under development)	task demand	on-road	Car	The detection is based on data driven / data fusion / fusion / ML methods and therefore a specific limit cannot be provided.	100%	100%	Easy usability	High acceptance	No practical implications. Available to all devices and Operation System versions that are compatible with the O7APP.	No	No
OSeven	harsh brakes	smartphone	number of harsh brakes per trip (frequency), level of intensity of harsh brakes (low, medium, high), location on the map of the harsh brakes	post-trip	task demand	on-road	Car	The detection is based on data driven / data fusion / fusion / ML methods and therefore a specific limit cannot be provided.	>95% (the estimation is based on OBD data and annotated experiments)	95%	Easy usability	High acceptance	No practical implications. Available to all devices and Operation System versions that are compatible with the O7APP.	No	No
OSeven	braking aggressiveness	smartphone	braking aggressiveness (low, medium, high)	post-trip (real-time under development)	task demand	on-road	Car	The detection is based on data driven / data fusion / fusion / ML methods and therefore a specific limit cannot be provided.	100%	100%	Easy usability	High acceptance	No practical implications. Available to all devices and Operation System versions that are compatible with the O7APP.	No	No

Partner	Factors monitored	Device	Outcome variable(s)	Real-time/Post-trip evaluation	Task Demand/ Coping Capacity	Experiment setup	Transport Mode	Thresholds for detection	Accuracy	Validity	Usability	Acceptance	Practical Implications	Modifications	Person-related characteristics
OSeven	speeding	smartphone	start time of speeding (hh:mm), speeding duration (sec), average speed over speed limit (km/h), percentage of driving time above speed limit (%),location of speeding section on the map	post-trip	task demand	on-road	Car	The speed limit as it is provided by a technology provider (e.g. OpenStreetMaps, Google Maps) to OSeven	>98% (the estimation is based on comparison of several map providers and annotated experiments)	98%	Easy usability	High acceptance	No practical implications. Available to all devices and Operation System versions that are compatible with the O7APP. For real time a source for the speed limits is required.	Yes	No
OSeven	mobile use (driver distraction)	smartphone	start time of mobile use (hh:mm), mobile use duration (sec), location of mobile use on the map	post-trip (real-time under development)	coping capacity	on-road	Car	The detection is based on data driven / data fusion / fusion / ML methods and therefore a specific limit cannot be provided.	>98% (the estimation is based on annotated experiments)	98%	Easy usability	High acceptance	No practical implications. Available to all devices and Operation System versions that are compatible with the O7APP.	No	No
OSevenn n	risky hours driving (default value that can be customized: 00:00-05:00 am)	smartphone	distance travelled during risky hours (m)	post-trip	coping capacity	on-road	Car	The limits that are defined for risky hours driving.	100%	100%	Easy usability	High acceptance	No practical implications. Available to all devices and Operation System versions that are compatible with the O7APP.	Yes	No
CardioID	Headway Monitoring	Mobileye	Numeric (seconds)	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on mode/ driving behavior			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style	Regional differences - driving style from country to country	Yes (if the output device enables it)	

Partner	Factors monitored	Device	Outcome variable(s)	Real-time/Post-trip evaluation	Task Demand/ Coping Capacity	Experiment setup	Transpo rt Mode	Thresholds for detection	Accuracy	Validity	Usability	Acceptance	Practical Implications	Modifications	Person-related characteristi cs
CardioID	Headway Level	Mobileye	Numeric (level)	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on mode/ driving behavior			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style	Regional differences - driving style from country to country	Yes (if the output device enables it)	
CardioID	Speed Limit Indication	Mobileye	Numeric (km/h or miles/h)	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on country rules/ driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style	Regional differences - driving style from country to country	Yes (if the output device enables it)	
CardioID	Blinkers On	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Pedestrian Ahead	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Pedestrian CollisionCollision Warning	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Vehicle Ahead	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Forward CollisionCollision Warning	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Urban Forward CollisionCollision Warning	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	

Partner	Factors monitored	Device	Outcome variable(s)	Real-time/Post-trip evaluation	Task Demand/ Coping Capacity	Experiment setup	Transport Mode	Thresholds for detection	Accuracy	Validity	Usability	Acceptance	Practical Implications	Modifications	Person-related characteristics
CardioID	Lane Departing Warning	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Weather Conditions (Wipers On)	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Low Visibility Warning	Mobileye	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Trip Duration (Start-End Time)	Mobileye or GW	Numeric (time)	Post-trip		On-road/ Simulated	Car/ Bus/ Truck				High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style		Yes (if the output device enables it)	
CardioID	Vehicle Speed	Mobileye	Numeric	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on country rules/ driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style	Regional differences - driving style from country to country	Yes (if the output device enables it)	
CardioID	% Overspeed	Mobileye+GW	Numeric (0-100%)	Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on country rules/ driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style	Regional differences - driving style from country to country	Yes (if the output device enables it)	
CardioID	Position (GPS)	GW	Numeric (lat/long/alt)	Real-time/ Post-trip	Task demand/ Coping capacity	On-road	Car/ Bus/ Truck				High Usability				
CardioID	Acceleration Data	GW/O7	Numeric (m/sec2)	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style			

Partner	Factors monitored	Device	Outcome variable(s)	Real-time/Post-trip evaluation	Task Demand/ Coping Capacity	Experiment setup	Transpo rt Mode	Thresholds for detection	Accuracy	Validity	Usability	Acceptance	Practical Implications	Modifications	Person-related characteristi cs
CardioID	RPM + Speed	GW+OBD	Numeric (r/min)	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style			
CardioID	Daylight Indicator	GW+CAM	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck				High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style			
CardioID	Roadway Scene Video Bases on Event	GW+CAM	Video	Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck				High Usability				
CardioID	Driver Change	CardioWheel	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck				Requires User Cooperation				Yes
CardioID	Drowsiness/Sleepin ess	CardioWheel / Wristband	Categorical (KSS)	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD			Requires User Cooperation				
CardioID	Driver Fitness - Interbeat Interval (IBI)	CardioWheel / Wristband	Numeric (ms)	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck				Requires User Cooperation				
CardioID	Lead On (Hands-on-Wheel)	CardioWheel	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck				Requires User Cooperation				
CardioID	GSR/EDA Events	Wristband*	Categorical	Real-time/ Post-trip	Task demand/ Coping capacity	Simulated	Simulator				Requires User Cooperation				
CardioID	Harsh Acceleration	GW / O7	Numeric	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style			

Partner	Factors monitored	Device	Outcome variable(s)	Real-time/Post-trip evaluation	Task Demand/ Coping Capacity	Experiment setup	Transport Mode	Thresholds for detection	Accuracy	Validity	Usability	Acceptance	Practical Implications	Modifications	Person-related characteristics
CardioID	Harsh Braking	GW / O7	Numeric	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style			
CardioID	Harsh Cornering	GW	Numeric	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style			
CardioID	Reverse Direction	GW / O7	Numeric	Real-time/ Post-trip	Task demand/ Coping capacity	On-road/ Simulated	Car/ Bus/ Truck	TBD - depends on driving style			High Usability	User feedback has shown that drivers take into account the notifications and improve their driving style			

Table 4: Overview of available measurements in cars

i-DREAMS use case Car	Unit	CardioID gateway	Wristband	Mobileye	(ELM327)	cloud traffic service	Smartphone app
Available sensor functionality		GPS, dashcam, (accelerometer)	PPG sensor	intelligent camera	OBD-II		accelerometer, GPS, magnetometer, gyroscope
computing power available for *i*-DREAMS calculations		Yes	no	no	no		yes (limited)
data storage		dedicated SD-card	no	no	no		non-dedicated phone memory
data transmission		CAN, WIFI, Ethernet, BLE	BLE	CAN	Bluetooth		WIFI, BLE, 3G/4G
powered by		vehicle	battery	vehicle	vehicle		battery
Environment							
time headway (TH)	sec			X			
headway level	integer			X			
speed limit indication (SLI)	km/h			X			
forbidden overtaking sign	yes/no			X			
wipers active (on CAN)	yes/no			X			
turn indicator activation/deactivation (on CAN)	yes/no			X			
pedestrian ahead detected	yes/no			X			
pedestrian collision warning (PCW)	yes/no			X			
vehicle ahead detected	yes/no			X			
forward collision warning (FCW)	yes/no			X			
urban forward collision warning (UFCW)	yes/no			X			
left lane departure warning	yes/no			X			
right lane departure warning	yes/no			X			
low visibility indicator	yes/no			X			
congestion indicator	yes/no					X	
daylight indicator	yes/no	(X)					

i-DREAMS use case Car	Unit	CardioID gateway	Wristband	Mobileye	(ELM327)	cloud traffic service	Smartphone app
driving during risky hours	yes/no	X			X		X
roadway scene video	mp4	X					
start trip time	hh:mm:ss	X			X		X
end trip time	hh:mm:ss	X			X		X
time since trip start	hh:mm:ss	X			X		X
total trip time	hh:mm:ss	X			X		X
Vehicle							
vehicle speed (CAN)	m/sec			X	X		
ground speed (GPS)	m/sec	X					X
position (GPS)	x,y	X					X
accelerometer data	m/sec2	(X)					X
fuel usage	l/100km				X		
RPM	r/min				X		
diagnostic trouble codes	raw				X		
Driver							
PPG signal	raw		X				
driver identification	driver ID						X
attention level / sleepiness	level (0-100)		X				
mobile phone use	yes/no + percentage of driving time						X
interbeat interval	milliseconds		X				
Accel/Brake aggressiveness indicator	Low/med/high						X
harsh acceleration / brake	yes/no	(X)					X
%overspeed	percentage of driving time	(X)			X		X
number of harsh accelerations	count	(X)					X
number of harsh brakes	count	(X)					X
average speed over speed limit	km/h	(X)			X		X
average trip speed	km/h	(X)			X		X

i-DREAMS use case Car	Unit	CardioID gateway	Wristband	Mobileye	(ELM327)	cloud traffic service	Smartphone app
available in real-time							
available in real-time but in vehicle computation needed							
not available for real-time interventions, available only after post-trip processing							
(X) = can be implemented if needed							

Table 5: Overview of available measurements in trucks and buses

i-DREAMS use case Truck & Bus	Unit	CardioID gateway	CardioWheel	Mobileye	ELM327	cloud traffic service	(Smartphone app)
Available sensor functionality		GPS, dashcam, (accelerometer)	ECG, accelerometer	intelligent camera	OBD-II		accelerometer, GPS, magnetometer, gyroscope
computing power available for *i*-DREAMS calculations		YesYes	no	no	no		yes (limited)
data storage		dedicated SD-card	no	no	no		non-dedicated phone memory
data transmission		CAN, WIFI, Ethernet, BLE	BLE	CAN	Bluetooth		WIFI, BLE, 3G/4G
powered by		vehicle	vehicle/battery	vehicle	vehicle		battery
Environment							
time headway (TH)	sec			X			
headway level	integer			X			
speed limit indication (SLI)	km/h			X			
forbidden overtaking sign	yes/no			X			
wipers active (CAN)	yes/no			X			
turn indicator activation/deactivation (CAN)	yes/no			X			
pedestrian ahead detected	yes/no			X			

i-DREAMS use case Truck & Bus	Unit	CardioID gateway	CardioWheel	Mobileye	ELM327	cloud traffic service	(Smartphone app)
pedestrian collision warning (PCW)	yes/no			X			
vehicle ahead detected	yes/no			X			
forward collision warning (FCW)	yes/no			X			
urban forward collision warning (UFCW)	yes/no			X			
left lane departure warning	yes/no			X			
right lane departure warning	yes/no			X			
low visibility indicator	yes/no			X			
congestion indicator	yes/no					X	
daylight indicator	yes/no	(X)					X
driving during risky hours	yes/no	X			X		X
roadway scene video	mp4	X					
start trip time	hh:mm:ss	X			X		X
end trip time	hh:mm:ss	X			X		X
time since trip start	hh:mm:ss	X			X		
total trip time	hh:mm:ss	X			X		X
Vehicle							
vehicle speed (CAN)	m/sec			X	X		
ground speed (GPS)	m/sec	X					X
position (GPS)	x,y	X					X
Accelerometer data	m/sec2	(X)					X
Fuel usage	l/100km				X		
RPM	r/min				X		
Diagnostic trouble codes	raw				X		
Driver							
ECG signal	16bit unsigned integer		X				
Driver identification	Driver ID		X				X
Driver change	event		X				
Hands on wheel	yes/no		X				

i-DREAMS use case Truck & Bus	Unit	CardioID gateway	CardioWheel	Mobileye	ELM327	cloud traffic service	(Smartphone app)
%hands on wheel	percentage of driving time		X				
Attention level / sleepiness	level (0-100)		X				
Mobile phone use	percentage of driving time						X
Steering wheel accelerometer	degrees		X				
Interbeat interval	milliseconds		X				
aggressivenessgressivenessgressiveness indicator	Low/med/high						X
harsh acceleration / deceleration	yes/no	(X)					X
%overspeed	percentage of driving time	(X)			X		X
number of harsh accelerations	count	(X)					X
number of harsh brakes	count	(X)					X
average speed over speed limit	km/h	(X)			X		X
average trip speed	km/h	(X)			X		X
Available in real-time							
Available in real-time but in vehicle computation needed							
Not available for real-time interventions, available only after post-trip processing							
(X) = can be implemented if needed							

Table 6: Overview of available measurements in trams

i-DREAMS use case Trams	Unit	CardioID gateway	Wristband Emotibit	Wristband PulseOn	Mobileye	(Geotab)	cloud traffic service	(Smartphone app)	On tram recorder	Guardian System
Available sensor functionality		GPS, dashcamera, (accelerometer)	GSR/EDA, Thermistor, PPG, humidity, temperature, accelerometer, gyroscope, magnetometer	PPG sensor	intelligent camera	OBD-II, GPS, Accelerometer		accelerometer, GPS, magnetometer, gyroscope		
computing power available for *i*-DREAMS calculations		yes	no	no	no	no		yes (limited)		
data storage		dedicated SD-card	dedicated SD-card	no	no	no		non-dedicated phone memory		
data transmission		3G/4G, CAN, WIFI, BLE	WIFI, BLE,	BLE	CAN	3G/4G		WIFI, BLE, 3G/4G		
powered by		vehicle	battery	battery	vehicle	vehicle		battery		
Environment										
time headway	sec				X					
headway level	integer				X					
speed limit indication (SLI)	km/h				X					
forbidden overtaking sign	yes/no									
wipers active	yes/no								X	
turn indicator activation/deactivation (on tram recorder)	yes/no									
pedestrian ahead detected	yes/no				X					
pedestrian side of vehicle detection	yes/no				X[1]					
pedestrian collision warning (PCW)	yes/no				X					
vehicle ahead detected	yes/no				X					
forward collision warning (FCW)	yes/no				X					
urban forward collision warning (UFCW)	yes/no				X					
left lane departure warning	yes/no				X					

i-DREAMS use case Trams	Unit	CardioID gateway	Wristband Emotibit	Wristband PulseOn	Mobileye	(Geotab)	cloud traffic service	(Smartphone app)	On tram recorder	Guardian System
right lane departure warning	yes/no				X					
blind spot detection					X[3]					
low visibility indicator	yes/no				X					
congestion indicator	yes/no						X			
daylight indicator	yes/no	(X)								
driving during risky hours	yes/no	X						X	X	
roadway scene video	mp4	X								
start trip time	hh:mm:ss	X						X	X	
end trip time	hh:mm:ss	X						X	X	
time since trip start	hh:mm:ss	X						X	X	
total trip time	hh:mm:ss	X						X	X	
Vehicle										
vehicle speed (on tram recorder)	m/sec				X				X	
ground speed (GPS)	m/sec	X				X		X		
position (GPS)	x,y	X				X		X		
Accelerometer data	m/sec2	(X)				X		X		
Electricity usage	l/100km									
Physical prevention of over-speeding (PPOS) device activation (on tram recorder)									X	
Driver										
ECG signal										
PPG signal			X	X						
GSR/EDA signal			X							
body temperature			X							
Driver identification	driver ID							X		
Driver change	event									
Attention level / sleepiness score	level (0-100)		X	X						
Attention level / sleepiness alarm	yes/ no									X

[3] Contingent on tram based Mobileye Shield+ system

i-DREAMS use case Trams	Unit	CardioID gateway	Wristband Emotibit	Wristband PulseOn	Mobileye	(Geotab)	cloud traffic service	(Smartphone app)	On tram recorder	Guardian System
Mobile phone use	percentage of driving time									
Interbeat interval	milliseconds		X	X						
safetybelt attached	yes/no									
aggressiveness indicator	?							X		
harsh acceleration / brake	yes/no	(X)						X	X	
%overspeed	percentage of driving time	(X)						X		
number of harsh accelerations	count	(X)						X	X	
number of harsh brakes	count	(X)						X	X	
average speed over speed limit	km/h	(X)						X		
average trip speed	km/h	(X)						X	X	
Available in real-time										
Available in real-time but in vehicle computation needed										
Not available for real-time interventions, available only after post-trip processing										
(X) = can be implemented if needed										

Table 7: Overview of available measurements in trains

***i*-DREAMS use case Trains**	**Unit**	**CardioID gateway**	**Wristband Emotibit**	**Wristband PulseOn**	**Mobileye**	**(Geotab)**	**cloud traffic service**	**(Smartphone app)**	**On train recorder**
Available sensor functionality		GPS, dashcamera, (accelerometer)	GSR/EDA, Thermistor, PPG, humidity, temperature, accelerometer, gyroscope, magnetometer	PPG sensor	intelligent camera	OBD-II, GPS, Accelerometer		accelerometer, GPS, magnetometer, gyroscope	
computing power available for idreams calculations		yes	no	no	no	no		yes (limited)	
data storage		dedicated SD-card	dedicated SD-card	no	no	no		non-dedicated phone memory	
data transmission		On train recorder, WIFI, BLE	WIFI, BLE,	BLE	On train recorder	3G/4G		WIFI, BLE, 3G/4G	
powered by		vehicle	battery	battery	vehicle	vehicle		battery	
Environment									
time headway	sec								
headway level	integer								
speed limit indication (SLI)	km/h				X				
forbidden overtaking sign	yes/no								
wipers active (On train recorder)	yes/no								X
turn indicator activation/deactivation	yes/no								
pedestrian ahead detected	yes/no								
pedestrian collision warning (PCW)	yes/no								
vehicle ahead detected	yes/no								
forward collision warning (FCW)	yes/no								
urban forward collision warning (UFCW)	yes/no								
left lane departure warning	yes/no								

i-DREAMS use case Trains	Unit	CardioID gateway	Wristband Emotibit	Wristband PulseOn	Mobileye	(Geotab)	cloud traffic service	(Smartphone app)	On train recorder
right lane departure warning	yes/no								
low visibility indicator	yes/no				X				
congestion indicator	yes/no								
daylight indicator	yes/no	(X)							
driving during risky hours	yes/no	?						X	X
roadway scene video	mp4	X							X
start trip time	hh:mm:ss	X						X	
end trip time	hh:mm:ss	X						X	X
time since trip start	hh:mm:ss	X						X	X
total trip time	hh:mm:ss	X						X	X
Vehicle									
vehicle speed	m/sec				X				X
ground speed (GPS)	m/sec	X				X		X	
position (GPS)	x,y	X				X		X	
Accelerometer data	m/sec2	(X)				X		X	
Electricity/ Fuel usage	l/100km					X			X
RPM	r/min								X
Automatic warning system (AWS)									X
Automatic train protection (ATP)									X
Train protection and warning system (TPWS)									X
Driver									
ECG signal									
PPG signal			X	X					
GSR/EDA signal			X						
body temperature			X						
Driver identification	driver ID							X	
Driver change	event								
Attention level / sleepiness	level (0-100)		X	X					

i-DREAMS use case Trains	Unit	CardioID gateway	Wristband Emotibit	Wristband PulseOn	Mobileye	(Geotab)	cloud traffic service	(Smartphone app)	On train recorder
Mobile phone use	percentage of driving time								
Interbeat interval	milliseconds		X	X					
safetybelt attached	yes/no								
aggressiveness indicator	?							X	
harsh acceleration / brake	yes/no	(X)						X	
%overspeed	percentage of driving time	(X)						X	
number of harsh accelerations	count	(X)						X	X
number of harsh brakes	count	(X)						X	X
average speed over speed limit	km/h	(X)						X	
average trip speed	km/h	(X)						X	
Available in real-time									
Available in real-time but in vehicle computation needed									
Not available for real-time interventions, available only after post-trip processing									
(X) = can be implemented if needed									

2.3 Recommendations on driver measurements per mode

In this section emphasis is given on driver state measurements and technologies. It is also investigated which of the available measurements should be used for practical implementation for the STZ and which of them can detect abnormal driving. Measurements should be considered for each factor with regards to the model and for experimental output. Also, a distinction per transport mode is made taking into account functionality, availability and cost. Finally, It is noteworthy that considered factors include accuracy, validity, suitability for the respective transport mode, usability as well as users' acceptability, as discussed below.

- The *i*-DREAMS driver and vehicle monitoring equipment should require as less attentional or physical effort as possible in order to avoid drivers to be distracted or to abandon the use of the system. Hence, measurement technology should preferably be powered by the vehicle and switch on and off automatically at the beginning and end of trips (i.e. no manual intervention by the driver needed) and should monitor the driver 'silently in the background' (i.e. not actively interfering with the driver). Also, the exchange of data, either wired or wireless, between different sensors and control units should take place without manual intervention of the driver.
- The *i*-DREAMS driver and vehicle monitoring technology must support the identification and prediction in real-time of risky events (e.g. dangerous headway) and must provide relevant data to trigger real-time in-vehicle safety related interventions (warnings), as well as feed post-trip interventions. Hence, the driver and vehicle monitoring technology must enable interfacing with other data collection and control units in the vehicle for the exchange, integration and processing of other relevant sensor data (i.e. from the road environment).
- The *i*-DREAMS driver and vehicle monitoring equipment should not interfere with normal operations while driving to avoid distraction, physical and visual obstruction which could lead to safety-related or ergonomic adverse outcomes.
- The *i*-DREAMS driver and vehicle monitoring equipment should enable faultless identification of the driver, especially when multiple drivers may operate the same vehicle. Otherwise a potential risk exists of assigning data incorrectly, to a different/wrong driver.
- The *i*-DREAMS driver and vehicle monitoring equipment should achieve high accuracy and low latency levels in terms of the real-time identification of relevant driver behavioral constructs, such as fatigue and inattention/distraction. Otherwise, the detection of such events may not allow for timely in-vehicle interventions.
- Transport companies and public service operators work in a highly competitive market with relatively low profit margins. As a result, having in mind potential future exploitation strategies, *i*-DREAMS technology must take this commercial context into account for its technology design. For example, the large scale adoption of after-market eye tracking technology, although potentially very effective to measure driver distraction and fatigue, is not acceptable in a practical (commercial) setting as long as these technologies require significant investments (in the order of several thousands of euros per vehicle). Expensive investments in driver monitoring technologies are therefore unacceptable. The selection of driver monitoring technologies must therefore find a good balance between effectiveness and cost.

2.3.1 Cars

With regards to the car mode, it is important to examine the available driver state monitoring technologies for the measurement of vehicle and operator capacity in the *i*-DREAMS field trials. Distinctive features from each of the measurement instruments are indicated in boldface.

- Wristband: is a technology alternative to CardioWheel which identifies driver **attention level, fatigue or sleepiness** through PPG and ECG for the cases where vehicles cannot be equipped with CardioWheel technology. Other driver state indicators such as GSR/EDA signals, body temperature and interbeat interval can be measured from wristband through thermistor, humidity, accelerometer, gyroscope or magnetometer.
- OBD-II device: which acquires real-time vehicle telematics data such as **vehicle speed**, frequency and severity of over speeding, **fuel usage and RPM**. Depending on the model and type of vehicle, **additional CAN data** may be available. In case fuel usage and RPM are not of primary concern for safety purposes, the OBD-II device might be omitted from the car use case because all other relevant variables are already captured by the OSeven smartphone app or the CardioID Gateway (such as speed, acceleration/deceleration, etc).
- CardioID GW: uses **ground speed and position**, dashcam and **accelerometer data** for determining the position of the driver within the STZ and trigger appropriate in-vehicle interventions in real-time. Vehicle trajectory and speed (GPS), frequency and severity of over speeding, accelerometer data (e.g. harsh acceleration, deceleration and cornering) and trip start and duration (i.e. task related fatigue) are some parameters estimated in real-time conditions. In parallel, CardioID GW also provides data for post-processing such as percentage of driving time, number of harsh accelerations or brakes, average speed over speed limit as well as average trip speed.
- OSeven smartphone app: uses accelerometer, GPS, magnetometer and gyroscope data in order to identify whether the driver's mobile phone is in use or not, determine vehicle trajectory and thus vehicle or ground speed (GPS speed), frequency and severity of over speeding, **accelerometer data** (harsh acceleration, brake), position, distance per road type (i.e. highway, rural, urban), trip start and duration (i.e. task related fatigue). It is worth mentioning that there are some parameters that are not available in real-time but they are available for post-trip processing, using WiFi or 3G/4G. These parameters include the percentage of driving time, number of harsh accelerations or brakes and average trip speed. Finally, the percentage of speeding and average speed over speed limit will be provided while the speed limit is available either by the traffic signs or the map provider via internet. Consequently, as these parameters are only available for post-trip interventions, OSeven could work on a solution for real-time processing but accuracy and effectiveness of just-in-time procedures may not be ensured at this stage.

To sum up, vehicle telematics data from OBD-II and smartphone (i.e. actual speed, harsh acceleration, deceleration or cornering, RPM) and operator state data (i.e. ECG, fatigue indicator) from wristband are available within the *i*-DREAMS project.

2.3.2 Trucks and buses

In this section, an assessment will be made with respect to the selection of technologies for the measurement of vehicle and operator capacity for heavy vehicles, including trucks and buses, in the *i*-DREAMS field trials. It is worth mentioning that bus and trucks will be treated jointly in this section as they share several common elements for the purpose of the field trials as well as the experimental setup which motivates the same choice of monitoring technologies in both vehicle types:

- Trucks and buses share similar characteristics in terms of size and weight. Both are large and heavy vehicles and therefore also share common challenges toward road safety.
- From the online stakeholder survey (for detailed results, Deliverables 3.1 and D9.1 are referred) and from accident statistics, it became clear that buses and trucks share similar severe collision types, including rear-end collisions and head-on collisions. Close following

another vehicle, sudden braking, stress (time pressure), inattention and fatigue are important contributing risk factors.

- The same vehicle (truck or bus) is often operated by multiple professional drivers (e.g. drivers working in different time shifts), a scenario less commonly observed for private vehicles.
- Trucks and buses are operated by transport companies or public service organizations having both a professional interest in maintaining high road safety standards and minimizing vehicle downtimes.
- The installation environment in terms of available space, CAN interface, etc. bears significant similarities between trucks and buses.
- Trucks and buses are vehicles with a high investment cost, they have on average a much higher yearly and longer useful life-cycles vehicle mileage and higher end-of-life mileage in comparison to most private cars. This allows for a higher cost of adding after-market safety technologies in comparison to private cars because given the investment can be depreciated over a larger time period and higher mileage.

From the list of available monitoring technologies provided in section 2.2, the following are proposed for implementation in the *i*-DREAMS field trials to measure vehicle and operator state (i.e. operator capacity) in the context of trucks and buses. Distinctive features from each of the measurement instruments are indicated in boldface.

- CardioWheel: measures operator state data, such as **ECG** while driving and derives a **drowsiness** and **fatigue** indicator. Current commercial systems are already starting to leverage the analysis of behaviors consequence of fatigue and drowsiness to infer about driver state, however such approach bears the risk of delayed detection and thus may fail to warn drivers opportunely. Hence, although different drowsiness warning systems exist already commercially, the technology proposed within i-Dreams in real-time, being detected even before drowsiness and fatigue start to impair the driver coping capacity. This device also measures the **steering wheel angle**, which is also used as indicator of driver's state. Drowsiness is known as an important contributor to collisions, hence it should be included in the *i*-DREAMS solution. Different levels of drowsiness may potentially be linked to the STZ concept, i.e. not only waiting to warn the driver when he should pull aside and stop driving but informing drivers about potential coping/compensation strategies. However, the main disadvantage of this technology is that is **not suitable to be fitted to a passenger car or rail** for the trials due to the need to remove upholstery or having the device visible. Nevertheless, if the technology is proven sound, in the future it could easily be integrated by OEMs during the manufacturing process.
- Wristband: for **identification of driver fatigue through PPG** as an alternative technology in case the vehicle cannot be equipped with CardioWheel technology.
- OBD-II device: for the real-time measurement of vehicle speed, frequency and severity of over speeding, **fuel usage and RPM**. Depending on the model and type of vehicle, **additional CAN data** may be available.
- OSeven smartphone app: for distraction (i.e. **mobile phone use while driving**), vehicle trajectory, the measurement of vehicle speed (GPS speed), frequency and severity of over speeding, accelerometer data (harsh acceleration and brake), trip start and duration (i.e. task related fatigue) and the calculation of a **driving aggressiveness indicator**. It must be noted that currently the OSeven app has not been built for use in heavy vehicles (truck, bus). **It is therefore currently still under investigation if a smartphone app for real-time measurements will be used or not.**

- CardioID GW: for the **fusion of data** from the different measurement instruments above (based on BLE), as well as for the measurement of vehicle trajectory and speed (GPS), frequency and severity of over speeding, accelerometer data (harsh acceleration, deceleration and cornering), trip start and duration (i.e. task related fatigue). The CardioID GW will also serve as a **central edge computing unit** to calculate in real-time the position of the driver within the STZ, to trigger appropriate in-vehicle interventions in real-time, and to **upload data for post-processing** and post-trip interventions to the *i*-DREAMS cloud platform (using WiFi, 3G/4G).

The estimation of driver fatigue, hands on the wheel, mobile phone use, vehicle speed, aggressiveness indicator and trip duration will feed into the STZ as important indicators of driver coping capacity.

2.3.3 Trains and trams

Trains and trams operate differently from the other modes included in the project (car, bus, truck), and trains even more so compared to trams. Both run on tracks rather than on the road, although trams do share the road with other road users along parts of their routes. Trains have signalling systems in place which help to control the environment in which they operate in, and neither trams nor trains have similar dashboards or vehicle controls compared to cars, trucks or buses. There has also been limited research into driver state monitoring in trains and trams compared to the other modes. Therefore, these factors need to be taken into consideration when applying the findings and recommendations of driver state and environment monitoring to trains and trams.

Certain safety systems are already in place in trains. While these do not monitor the state of the driver, if drivers fail to respond to a warning signal, do not reduce speed, or pass a stop signal, which could be due to inattention, distraction, or fatigue and sleepiness, the system automatically applies breaks. In the UK several transport companies have additionally installed driver monitoring systems into their fleets, including in certain trams, as for example the Guardian[4] system by Seeing Machines. Aimed at detecting distraction and fatigue events, Guardian uses face and gaze tracking to measure the drivers head position and eye closure, triggering alarms if certain safety parameters are exceeded. The system also includes a forward-facing camera to provide footage of track or path conditions. In comparison to the Mobileye system, Guardian provides information and monitoring of driver state and just external footage, whereas Mobileye uses environmental and contextual information to aid in collision avoidance and improve driver behavior. Currently, no such applications have been used in trains.

In terms of applying measures to monitor driver state in trains and trams, it appears that the most applicable and useful measures will be those that comprise of wearable technologies or measures obtained from a driver facing camera. It was concluded that attention monitoring systems would be easily transferable, with distraction/attention typically being measured by head/gaze/eye trackers, dashboard cameras, smartphone applications and wearables. Real-time eye tracking and cameras are one of the most frequently reported devices used for distraction/attention and could be applied to trains and trams. Monitoring distraction and attention would be an important feature for trains and trams as both drivers may be required to drive monotonous stretches of track for extended periods of time and then attend to signals

[4] https://www.seeingmachines.com/guardian/

or navigate through/along complex traffic intersections, although trams may be sharing the road with other road users and thus those drivers need to remain attentive to any changes.

In relation to fatigue and sleepiness, these states are typically measured using EEG, eye tracking, performance measures, subjective responses or cardiac measures. As with all the modes, there are practicality issues of using EEG, and performance measures are not overly useful for trains. Eye tracking (blink rate, PERCLOS) and cardiac measures, however, could be applicable. Eye tracking is used to detect sleepiness both in experimental studies and has been incorporated into commercial products, using cameras to monitor eye position, blinking, and closure. The recent focus within the literature has been to develop ECG measures which have potential to be used for fatigue/sleepiness monitoring. However, as trains and trams do not have a steering wheel the same as cars, buses or trucks, the ECG measures would have to be wearable or integrated into the controls in some way (e.g. the driving control for trains and trams), although this would likely just be one hand. Emotion, anger, stress and fear could potentially be measured using multiple measures such as ECG, EDA and cameras. Again, as trains and trams have no steering wheel to take ECG measures, wearable technologies must be used. In order to be possible to obtain these measures for train and tram drivers.

Overall, it may be possible and feasible to monitor abnormal driving in train and trams by focusing on driver states such as distraction, inattention, fatigue and sleepiness, using ECG and eye tracking via cameras. Due to the differences in the cab of the trains and trams, CardioWheel would not be able to be used, however the technology could be used in the form of a wearable.

2.4 Recommendations on environment monitoring

In this section, emphasis is given on task demand. It is important to examine which technologies work better and for which factors with regards to the model and for experimental output. In addition, as mentioned in the previous section 2.3, a distinction per transport mode is made with regards to functionality, availability and cost, as well as other considered factors will include accuracy, validity, suitability, usability and acceptability. It is investigated which of the available measurements to be used for practical implementation of the STZ and the detection of abnormal driving behavior.

2.4.1 Cars

Changes in the objective state-of-the-world are not only caused by the motion and actions controlled by the vehicle operator, but also other phenomena external to the vehicle operator’s control as well (i.e. physical conditions of the road environment or the vehicle being operated, climatological circumstances, weather or time of the day). The state-of-the-art and technology available to the consortium evidenced that many of such external factor, i.e the (context) environment (al context), can be monitored using the vast array of (existing) technologies at the disposal of the consortium. Distinctive features for each technology are indicated in boldface.

- Mobileye: is an intelligent vision based commercial system that warns the driver when a specifit set of risk scearios are detected, e,g, whenever a driver. Specifically, it measures parameters such as **time headway** (TH) and headway level and monitors **speed limit** indication signals (SLI), begin and end of a **forbidden overtaking zone**, wipers activity (i.e. rainy weather), turn indicator activation/deactivation, detection of pedestrian ahead, potential pedestrian collision warning (PCW). Moreover, it detects **vehicles ahead** with

respect to a lead vehicle (all motorized vehicles) , in order to provide a **forward collision warning** (FCW) or an urban forward collision warning (UFCW), left and right **lane departure** warning and **low visibility** indicator (i.e. bad weather, direct sunlight). In addition, Mobileye implements some sort of similar STZ concept based on fixed independent and oblivious thresholds of potentially relevant driving environment (i.e. adverse weather) or operator context variables both in real-time and driver's relevant background data. Intervention technology and warnings strategies (i.e. visual, auditory) would be the same as used currently by Mobileye (i.e. EyeWatch).
- OSeven smartphone app: measures general environment data such as driving during **hours of increased risk**, **start and end trip time** as well as **total trip time**. It should be mentioned that these parameters are not available for real-time interventions but only for after trip processing, but they can be readily implemented if needed.
- CardioIDCam: captures road environment data by recording video clips pertaining detected dangerous events. CardioIDCam will only **store roadway scene videos** during generated Mobileye warnings or when extreme events are detected (e.g. during harsh acceleration, braking, tailgating, lane departure)**.**
- OBD-II device: which identifies **start and end trip time** and **total trip time**, providing real-time and post-trip interventions and feedback to car drivers and will also capture speed profile evaluation that can also provide cues regarding distraction.
- Digital road map data: uses GPS chip, magnetometer and gyroscope in order to provide annotated trip data with **geolocated risk-related events** and **captured road video data** on the *i*-DREAMS web user dashboard and smartphone app.

All aforementioned variables provide a multi-dimensional measurement of environment parameters in order to identify risky driving behavior and consider departure from both typical and user-specific profiles. Road environment data from a dashcam (capturing video about detected dangerous events) and Mobileye (i.e. TH, speed signs and several warnings related to lane departure, insufficient headway) will be available in real-time for many car drivers and, in itself, this is a wealth of data for analysis.

2.4.2 Trucks and buses

Similar to section 2.3.2, trucks and buses will be treated jointly with respect to the selection of measurement technologies for monitoring the road environment.

From the list of available monitoring technologies in section 2.2, the following are proposed for implementation in the *i*-DREAMS field trials to measure aspects of task demand in the context of trucks and buses. Distinctive features for each technology indicated in boldface.

- Mobileye: enables the measurement of **time headway** and **time-to-collision** with respect to a lead vehicle and monitors for the **presence of vulnerable road users** in front of the vehicle (pedestrian or bicyclist), **current speed limit**, begin and end of **a forbidden overtaking zone**, **rainy weather** (i.e. based on use of wipers), **poor visibility** (e.g. bad weather, direct sunlight), and unintended left and right **lane departure**.
- OSeven smartphone app: for the measurement of **driving during risky hours** and time of day in general. Since the use of the OSeven smartphone app for driver monitoring in trucks and buses is still under investigation, it is possible that this item will be removed from the final technology set.
- CardioIDCam: a dashcam continuously filming the road environment in front of the vehicle and integrated into the CardioGW. CardioIDCam will only **store roadway scene videos** during generated Mobileye warnings or when extreme events are detected (e.g. during harsh acceleration, braking, tailgating, lane departure)**.**

- Digital road map data: to show to the participant at the end of the day an overview of annotated trip data (i.e. with geolocated risk-related events and captured road video data) on the *i*-DREAMS web user dashboard and smartphone app.

The relevance of the above data for the estimation of task load is of crucial importance. In particular, Mobileye data will provide critical indicators of task complexity imposed by the road environment. For example, the system only provides to the driver TH information which could be an important independent variable in the STZ model in order to define the risk level in real-time. When task load imposed by the road environment increases and indicators of reduced operator state are identified, the different threshold levels of the STZ can then be changed dynamically in real-time, thus adding increased value when compared to convention/past ADAS systems (see more info in section 3 and 4).

In the post-trip intervention framework (for details see Deliverable 3.3) drivers will receive feedback and scores (by means of a smartphone app and web-based dashboard) on their driving performance under different situations of increased task demand, reduced operator capacity and the departure from conventional/typical user driving profile. The post-trip intervention framework will also adopt gamification techniques to continuously engage and motivate drivers to improve their driving behavior aimed at developing safer drivers.

2.4.3 Trains and trams

The environment that trains and trams operate in is different to the road environment, which needs to be taken into consideration when considering environment monitoring. While trams share parts of their environment with other road users, often travelling on tracks which are on, or cross, the road, the environment of trains is operationally different and fundamentally to that of cars, buses or trucks. Trains run on independent tracks, occasionally crossing roads at level crossings, and at high speed. Signals control the environment trains operate in, organizing and controlling the distances between other trains, when to pass other trains, and who has priority. Because of these and other factors, several aspects of environment monitoring may not be relevant to trains.

Existing systems already in place for train operations aid in place for train operations which aid in environment monitoring. Trains are installed with various warning systems such as Train Protection Systems (TPS), which use train detection and movement to safeguard train operations and aim to reduce the risk of driver error leading to accidents. Automatic Train Protection (ATP) systems monitor actual speed and enforce speed limits by applying brake applications if speed is exceeded, and Automatic Warning Systems (AWS) provide in cab warnings to the drivers of the next signal, which the drivers must ‘cancel’ otherwise the train brakes automatically. The Train Protection and Warning System (TPWS) was developed for British railways and applies full brakes if the speed limit is exceeded or if a train travels past a stop signalalal. AWS and TPWS are used in all trains by law in the UK.

Systems such as Mobileye, which use forward facing cameras to help with collision avoidance may be less applicable to trains. A system may be useful to detect obstructions on the tracks, however, due to the speed at which trains can travel, by the time an alert has sounded, a driver may not have time to react. In relation to tram operations, Mobileye would be much more applicable, due to the shared environment trams operate in, and trams having a more immediate ability to stop when hazards are detected.

In terms of task demand and cognitive workload, trams may experience a more dynamic environment with further environmental factors to consider. Train drivers may experience stretches of monotonous driving, followed by more active tasks such as stations, busy intersections and crossings. Several environmental factors may also be less applicable to train operations. For the case of trains travelled distances are often substantially larger than for the case of trams with potential implications for shot brake in between trips. Weather may also be less of an important factor for trains and trams apart from extreme weather which could restrict visibility (signals, obstructions) or passage. Time of day is an important consideration in relation to night work and possible fatigue and sleepiness of drivers rather than in relation to environmental factors that may impact driving.

The findings from WP2 indicate that task demand and task complexity can be measured using EEG, vehicle kinematics and skin conductance, as well as eye tracking and ECG, although the most frequent measure of task demand are physiological measures. The majority of these measures would be from wearables or taking measurements directly from the driver, which could be applicable to both trains and trams, however, they need to be realistic in terms of working environment. In relation to information processing and task performance the most representative and most used tools are Galvanic Skin Response (GSR), in-vehicle information or cameras. Vehicle information such as lane deviation, longitudinal/lateral movement, headway or collision warnings would most likely not be applicable to train or tram operations, however speed or braking metrics could potentially be informative, particularly in trams. Collison warnings may work for trams in shared environments if systems detect other vehicles or vulnerable road users.

With regard to alerts, haptic and auditory warnings would be feasible but would have to work in the context of the work environment. Findings from Deliverable 2.2 suggest carefully chosen nomadic devices for visual and auditory warnings, which would work if adapted to suit train and tram operations.

As for post-trip feedback, an app could potentially be adapted to suit train and tram operations, providing information on driver performance in relation to speed, signals, braking, attention, fatigue etc. Outputs may be different for train and trams, and therefore the metrics provided, or the technology used to collect the data.

Overall, certain elements of environmental monitoring could be applicable to trains and trams, however, would most likely need to be adapted to suit the operation. Vehicle metrics could be recorded and would be useful for post-trip feedback and as an indication of abnormal driving, however trains and trams already have systems in place which aid with this. Mobileye could be useful and adapted to trams, due to their shared environment with other road users. It is also important to note that the majority of *i*-DREAMS testing with trains will likely be completed just in a simulated environment, due to the nature of the operation, rather than naturalistic field tests.

2.5 Implications for the *i*-DREAMS platform

The application of the presented technology for the different modes requires several design considerations. Each vehicle is different, and requires some degree of retrofitted technologies, even though ADAS devices are designed to be retrofitted in every situation, there are preferable use-cases.

For example, CardioWheel can be installed using a steering wheel cover, or directly upholstering the steering wheel. The last case is only possible if the steering wheel is removed from the vehicle. Regarding the steering wheel covers, different diameters are available (but private car owners prefer not to install covers, so the preferable use-cases are trucks and buses). The battery life can also be an issue, but taking in consideration the trial duration, the risk is minimum having in mind that typical LiPo batteries and charge-discharge cycles have at least 500 cycles before performance degradation reduces their capacity to around 80/85% of the original value.

The quality of the CardioWheel data is also very dependent on user cooperation, in the sense that both hands on wheel are required. It is possible to trigger alerts trying to get user attention in order to maximize the periods of continuous contact with the steering wheel. Furthermore, Electromagnetic Compatibility interference can contaminate the signal due to power line noise that can be found in laboratorial scenarios, even if in-vehicle environment is typically more preserved. Additional filtering is being developed to ensure sustained high data quality. Another relevant aspect of the installation is the power interface that will preferably be available via slipring, although it may not be possible for all test cases. As an alternative, CW can be powered using a battery, but, in such cases, it becomes necessary to recharge it from time-to-time, , which may require a more frequent interaction between users and field trial staff and thus condition/bias the naturalistic aspect /conception of the trial.

The Mobileye system can be installed in almost all existing vehicles, but the effort for installation differs significantly from vehicle to vehicle, in particular regarding the connection with vehicle CAN signals, which are typically available through OBD-II interface, but in some cases are found in alternative/proprietary (e.g. ISO K-Line standard interface). The restriction of vehicles that can be part of the experiments is being considered, but since it will make the recruitment process harder it is still under discussion.

Regarding the use of OBD-II monitoring devices, the compatibility is guaranteed with almost all light vehicles, but for trucks and buses, there are variations that may lead to the impossibility to read all the available information.

Additionally, regarding the vehicles' warranty and the liability associate with the installation process, special care is being taken to devise a minimally invade installation procedure. The power interface will be performed, whenever possible, as means of fuse-splitters, assuring that there are no soldering connections with the car electrical installation, and the data acquisition will be performed using a CAN sensor that uses inductive principles.

Another crucial step consists in ensuring the validity of acquired data. The proper determination of the driver identity is one of the key steps required both CardioWheel and OSeven device and applications allow the determination of the driver identity. However, this step requires the learning of the ECG profile and driver behavior in a previous moment. There is a potential threat that these biometric and behavior data do not meet the required quality, but prior to their implementation will be performed to guarantee data quality.

The aggregation of various data sources produced by different devices is a challenge, and the IoT gateway that will be used needs to be programmed to assure real-time interaction between them. Additional measures of safeguard in each device should be implemented, guaranteeing that whenever synchronization cannot be achieved no data loss will happen. This gateway must also have enough computing power to support real-time processing of sensor data, calculate derived variables/indicators, identify the level of abnormal driving, estimate the current position within the STZ and trigger appropriate interventions. Nevertheless, the implementation to be performed will take into consideration the available computing power and optimize it for edge computing. Furthermore, CardioWheel gateway inertial unit can be used for driving behavior analysis, through 4GB of RAM and a CPU with 4 A72 cores running at 1.5GHz. The gateway can be coupled with tensor processing unit - TPU like CORAL from Google - to increase its computing power namely for deep learning inference.

The vehicle selection process that will be conducted in the recruitment phase, must follow some clear and standardised guidelines in order to assure the installation procedure takes place in the seamless possible way. It is foreseeable that the installation will require always the interconnection with the vehicles' CAN.

The O7APP is compatible with Android software version 6.0 and later, iOS 11.4 and later. Regarding iOS mobile phone devices, the Application is compatible with iPhone devices 5s or later (with the exception of iPhone 5c). All data recording is "live" during driving and therefore the data recording procedure can be immediately adjusted to real-time interventions. The OSeven algorithms, though, are formulated up to now as post-trip evaluation algorithms. Several components, e.g. speeding can be easily transformed to real-time (as long as the data is available), whereas the customization of other components, e.g. harsh events, mobile use requires further validation.

3 Thresholds of interest

3.1 General

A key task in defining the *i*-DREAMS platform concerns the identification of adequate thresholds that are necessary to distinguish the different phases constituting the STZ. Contrarily to Deliverable 2.1, where parameter and indicator thresholds have been reviewed, more objective information with regards to threshold values about driver state and behavior can be provided in the current part of the document. This section, aims defining the basis of the already reviewed indicators, which are their typical values and suitable thresholds that enable the identification of the three different stages of the STZ. Accordingly, the chapter is organized as follows: firstly, the considered indicators are presented and a brief definition of each one is given; then, considerations regarding the specific modes addressed within *i*-DREAMS are proposed; furthermore, the three stages of the STZ are revisited and the connection between each of them and the selected thresholds are also explained. Finally, popular values and thresholds are reported for each indicator, highlighting the mode and the STZ phase they relate to.

3.1.1 Definition of the indicators

This chapter recalls the indicators of driver performance in relation to longitudinal and lateral movement. It should be noted that the parameters relate mainly to road traffic, as train/tramway's behavior is constrained by the railway itself. This implies that, as reported in Deliverable 3.1, for those specific modes any indicator would be irrelevant for lateral movement, whereas for longitudinal movement, headway measures could be relevant for trams, as they operate in the urban environment, but less so for trains, whose longitudinal movement is strictly regulated by a complex automated signals network and well establish priority rules. Nevertheless, some observations about the train/tram mode will be provided.

As far as road transport is concerned, the summarized indicators are spread both for cars and heavy duty vehicles mode. The following indicators, are listed below:

- Acceleration is found in previous studies referring to hard/extreme acceleration (Rolim et al., 2014), which have been widely correlated with situations of increasing danger.
- Deceleration-Rate-to-Avoid-Crash (DRAC) is defined as the differential speed between the following and the lead vehicle divided by their closing time (Shi et al., 2018).
- Time headway (TH) is the elapsed time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point (Mahmud et al., 2017).
- Distance Headway (DH) is the distance between corresponding points of the lead and host vehicles at any given time (Salim et al., 2010).
- Time-To-Collision (TTC) is the time that remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained (Laureshyn et al., 2010).
- Brake-Reaction-Time (BRT) is a parameter used to assess the stopping sight distance and to determine if the driver involved in an accident, reacted in "acceptable" time (Summala, 2000).
- Time-Exposed-TTC (TET) refers to the total time a vehicle is exposed in risk situations, i.e. the time a TTC-event remains below a defined TTC-threshold (Mahmud et al., 2017).

- Time-To-Zebra (TTZ) is the distance to the zebra crossing divided by the speed and it is calculated as the time left for the car to reach the zebra crossing when the pedestrian is approaching the curb (Niezgoda et al., 2012).
- Time-to-Accident (TTA) is the time remaining to an accident from the moment that one of the road users starts an evasive action, if they had continued with unchanged speed and directions (Mahmud et al., 2017).
- Post-Encroachment-Time (PET) refers to the time interval between the moment when two road users cross the point where their respective paths intersect (Laureshyn et al., 2010).
- Margin-To-Collision (MTC) refers to the ratio between the summation of the inter-vehicular distance and the stopping distance of the lead vehicle and the stopping distance of the following vehicle (Mahmud et al., 2017).
- Standard Deviation of Lane Position (SDLP) reflects the degree of vehicular control a driver exerts in any particular driving situation (Mahmud et al., 2017).
- Time-To-Line-Crossing (TLC) indicates the time it takes to reach the lane marking, assuming uniform motion, i.e. constant speed and heading, as per the 1st Newton law (Niezgoda et al., 2012).

As it is recalled in (Bella and Russo, 2011), existing longitudinal collision avoidance systems typically rely on 2 criteria for the activation of collision avoidance:

- Worst-case scenario: in this approach the system seeks to keep the minimum distance necessary for the vehicle to stop in case of a sudden brake of the leading car;
- TTC: the system calculates the time remaining until a collision between two vehicles would have occurred if the collision course and speed difference are maintained.

Based on these two criteria, alternative triggering strategies emerge: the kinetic one, which determines the minimum distance to stop safely by calculating the deceleration and reaction time at the current moment; and the perceptual approach, based on TTC calculation.

Examples of the former are Mazda's, PATH's and Stop Distance algorithms, whereas the latter can be found in Honda's, Honda's CMBS and Hirst and Graham's algorithms. It is worth mentioning that Mobileye also employs TTC for FCW. Table 8: summarizes the thresholds used by these existing systems.

Table 8: Acceleration, minimum distance and TTC thresholds used in various existing systems

Algorithm's name	Acceleration [m/s2]	Min Distance [m]	TTC [s]
Mazda	6	5	-
Stop Distance	5	-	-
PATH	6	5	-
Honda	-	-	2,2
Honda's CMBS	-	-	3 (attention phase) <2 (prevention phase) <1 (action phase)
Hirst and Graham	-	-	3

3.1.2 Considerations about buses and trucks

When dealing with trucks and buses, differences and similarities have to be considered when comparing to cars. Since these are also to road mode, their safety behavior can be evaluated using same indicators applied for light passenger vehicles. Nevertheless, both vehicular features and driver characteristics significantly differ: indeed, physical and operational features of heavy vehicles influence time headway, acceleration and deceleration (Weng et al., 2014), thus affecting the time needed for the bus and trucks to stop, being higher or longer than for cars. On the other hand, the professionalism and experience of drivers allow them to have shorter brake reaction times (Markkula et al., 2013).

Relevant thresholds were suggested by Lehmer et al. (2005) for assessing safety benefits provided by warning systems performing a FOT on Volvo trucks. It specifically addresses TTC, lateral acceleration and reaction time. Two kinds of thresholds were considered: the first defines (in relation to kinds and not thresholds) the conditions for an event to be triggered, whereas the second one identifies conflict levels, namely conservative, medium and aggressive.

For an event to be triggered, Lehmer et al. (2005) proposed the following conditions:

- Longitudinal deceleration: >0.25g with brakes applied
- Lateral acceleration: >0.20g
- TTC: <4s
- Following interval:<0.5s

The thresholds combination to be observed in order to establish conflict severity is shown in Table 9:

Table 9: Thresholds for reaction time and deceleration distinguished for different severity levels (Lehmer et al., 2005)

Thresholds	Reaction time [s]	Required Deceleration [m/s^2]
Conservative	1.5	2,44
Medium	1.0	3,05
Aggressive	0.5	3,66

Also, Bao et al. (2012) time headway and brake reaction time as truck safety indicators. It was found that in normal, day-light conditions the mean headway is 3.10s, while minimum time headway values 1.26s, 0.92s and 0.89s respectively for dense, moderate and sparse traffic conditions. Finally, driver brake reaction time was found to be 1.88s in baseline conditions, with a shorter BRT with daylight conditions (1.69s) than during night-time. Additionally, authors suggest a minimum of 2.5s headway time for truck drivers.

3.1.3 Considerations on trains and tramways

Due to the particular configuration of the railway mode (trains and tramways), the indicators applied to road transport cannot be applied for safety assessment. As a matter of fact, in railway system, safety is mainly reliant on infrastructure sensors (Katz and Schulz, 2013). Unfortunately, while many historical crash data studies about railway systems have been developed in literature, conveying a wide overview of the factors inducing accidents (Restel and Wolniewicz, 2017, Kyriakidis, Hirsch and Majumdar, 2012, Naznin, Currie and Logan, 2018), few studies concerning safety indicators and related thresholds have been found.

Mode specificities pertaining trains limit the establishment of parallels and comparisons with road modes. Some examples of these are the fixed configuration of the infrastructure, the highly constrained operator behavior and the signal-respect-based movement of trains, which lead to deterministic movement patterns, the proximity of tracks, which requires a very precise position detection, high punctual densities and the topology of the lines, which can impair signal reception (Lehner et al., 2008).

As mentioned also in Deliverable 3.1, trains are not free to move laterally, so indicators about this behavior cannot be applied. Longitudinal behavior, on its turn, is governed by the strict respect for the signalization and by adjusting/monitoring speed. Keeping in mind these observations, the most used safety element is the concept of Signal Passed At Danger (SPAD), which indicates the event of a train failing to a signal showing red danger stop (Kyriakidis et al., 2012). As it can be easily understood, this measure denounces a situation of already existing danger and thus cannot be used as preventive parameter to define the different STZ phases.

Literature about railway safety, specifically focusing on Protection and Warning Systems as well as on SPADs, Connor and Schmid (2019) and Nikandros and Tombs (2007) also highlight monitoring vehicle's speed as the core element for reducing the risk of SPADs. When compared to trains, tramways add some possible considerations: operating mainly in urban areas implies they often interact with road traffic, thus allowing the assumption that some of the recalled road safety indicators (e.g. acceleration, DRAC, TTC, TTA, PET) could be also applied, with suitable adaptations, to the interaction among trams with other road participants. Li (2018) emphasizes that, similarly to what happens with cars, trams are required attention for preventing lateral collisions with other vehicles and vulnerable road users, such as pedestrians and cyclists. Nevertheless, the obvious differences in sizes and weight does not a allow tams to be totally comparable to cars. Also, Li (2018) suggests the possibility of referring to driverless car studies to obtain useful information suitable for trams, though taking into account the recalled restrictions.

3.1.4 Theoretical connection among the thresholds and the three STZ stages

Since the STZ concept proposed in the current project is new, there is no straightforward connection between the values and thresholds of the indicators reported in literature and the different STZ stages. As a result, some assumptions must be made in order to link the measurable parameters and their values to define the recalled STZ phases. For the sake of completeness, here the stages of STZ and their definitions are reported and the theoretical link with the parameters thresholds is identified.

Specifically, as reported in Deliverable 3.1, where the Safety Tolerance Zone is conceptualized, the STZ comprises three phases, namely: "Normal driving", "Dangerous driving" and "Avoidable accident", which are defined as follows:

- Normal Driving is the subzone of the STZ where, based on current conditions in the objective state-of-the world, there is no indication that a collision scenario is likely to unfold at that point of time.

- Dangerous Driving refers to the phase of the STZ where, based on current conditions in the objective state-of-the-world, the potential for developing a collision scenario is detected.
- Avoidable accident is that particular stage of the STZ where, based on current conditions in the objective state-of-the-world, a collision scenario is actually starting to develop, but the vehicle operator still has the potential to intervene and avoid a crash.

In literature, risk indicators are usually measured referring to normal driving behaviors, e.g. when creating and analysing driving cycles and for detecting possible dangerous situations, reporting discrete values, which define the boundary between the two conditions. In some particular cases, the defined safety levels (e.g. Honda CMBS inTable 8: Table 8:), may bare some connection with the STZ phases. To adapt them to the needs of the concept, ranges which relate to the three stages need to be identified, instead of discrete limits. Leveraging the available, reviewed information, the following connections have been established since Normal driving represents the majority of the driving conditions and considers only situations where no collision is going to happen, frequent values of the recalled parameters are used to define the range for this STZ phase, where the term frequent values describes measures obtained during driving cycles in which no increased risk scenarios are developed. On the other hand, Danger phase becomes by the range of measures in between the previously identified stages. Finally, the Avoidable Accident phase is defined by the range of values, exceeding the discrete thresholds found for dangerous situations.

3.1.5 Ranges and thresholds

In literature Collision Warning Systems can be found for light vehicles, including variables of interest and respective thresholds. Fewer studies are however available referring to trucks/buses and indications concerning rail modes are seldom provided. Moreover, while for some indicators, the values reported by different studies tend to agree, for other parameters there are significant divergences. Although many indicators have been defined for surrogate safety studies, not all of them are often utilized. Particularly, the most addressed safety parameters are acceleration/deceleration, TH, TTC and BRT. As for other indicators, even though thresholds may be found for cars these are not available and thus cannot be proposed for remaining transport modes

Therefore, once these thresholds and ranges become and are implement, extensive testing will be carried out to verify their reliability by triggering correct, useful and timely alerts. Table 10: summarizes the indicators and respective thresholds, which can be used in the definition of the STZ levels.

Table 10: Proposed thresholds for i-DREAMS modes

Indicator	CARS			TRUCKS / BUSES		
	Normal	Dangerous	Avoidable	Normal	Dangerous	Avoidable
Acceleration	<0.31g	0.31g – 0.45g	> 0.45g	<0.25g (deceleration)	0.25-0.3	>0.3
DRAC	<3.3m/s^2	3.35-3.4m/s^2	>3.4 m/s^2			
TH	1.8s – 2.8s	0.6s - 1.4/1.8 s	<0.6s	>2.5s	2.5s – 1.26s	<1.26s
TTC	>3/3.5s	1.5s – 3s	<1/1.5s	>4s		

Indicator	CARS			TRUCKS / BUSES		
	Normal	Dangerous	Avoidable	Normal	Dangerous	Avoidable
BRT	3.5s-4.0s			1.69/1.88s	1.69s-1.5s	<1.0s
TTZ	3s-5s	<3s				
TTA			<1/1.5s			
PET			<1/1.5s			
MTC			<1			
TLC		<1s				

As previously recalled, unfortunately, for rail modes only distance of 8m appears to be incredibly small in case of normal and dangerous conditions, being the values over 8m for normal driving and under 5m for dangerous driving situations, respectively.

3.2 Recommendations on triggering interventions

3.2.1 Driving style recognition and their incorporation in *i*-DREAMS real-time intervention approach

Background

Extensive literature has been devoted to predict/recognize driving style given a particular objective, e.g. safety, fuel economy and behavioral analysis. The majority of the studies include only vehicle-associated parameters obtained from sources such as vehicle sensors, sensor installed in smartphone devices or other custom-built devices. These studies are based on/build on the assumption that changes in these parameters (speed, fuel consumption, acceleration, throttle, braking power and frequency, throttle, jerk, sharp turn, and deceleration) may also be influenced by the environment and driver state (Khan and Lee, 2019). Based on the review of existing literature, a general procedure can be employed. Driving style is proposed below:

- Firstly, based on the specific objective (i.e. safety), classification levels are set out for a driving style. Often discrete levels are considered such as normal driving, aggressive driving and dangerous driving. Most studies consider 2 to 5 level to characterize the degree to which driver departures from the normal driving behavior (Khan and Lee, 2019). The classification can be attributed to the drivers using relevant risk indicator variables by following one of two alternative approaches:

  1) Using some rules, experts opinions/driving behavior or a following a questionnaire-based approach and thresholds values of certain important risk indicator variables (Jachimczyk et al., 2018; Teimouri and Ghatee, 2018).
  2) Using unsupervised clustering technique (k-mean, fuzzy clustering method etc.) to label driving behavior based on threshold values of key risk indicator variables. This method is claimed to have better reliability as it rules out subjective judgements and uses the same dataset employed to model driving style recognition (Shi et al., 2019; Xue et al., 2019).

  The more common variables (risk indicators) are listed below:
  - TTC or a modified, e.g. inverse TTC (Chen and Qin, 2019; Shi et al., 2019; Xie et al., 2019; Xue et al., 2019).

- MMTC (Xie et al., 2019).
- Time gap/Time headway (Chen and Qin, 2019; Xie et al., 2019; Zhu et al., 2019).
- Crash potential index (Shi et al., 2019).
- Longitudinal acceleration beyond ±0.3g (Fazeen et al., 2012; Chen et al., 2019; Zhu et al., 2019).
- Lateral acceleration beyond ±0.3g (Chen et al., 2019; Fazeen et al., 2012).
- Lane changing behavior (Chen et al., 2017).

- The next step concern the extraction of driving features from the dataset, which are then related to driving styles labelled in the initial step. Most studies used trajectory-based dataset in this context, either from vehicle or smartphone sensors. For example, Shi et al. (2019) extracted 64 features from trajectory data set that are composed of velocity, acceleration, position, time gap etc. These features are basically derived statistics from distribution of variables (such as mean, kurtosis, median, range, standard deviations, various percentiles values, etc.). The selection of variables found on these studies is mostly dependent on the available dataset as there is no general agreement found in the literature on the recommended set of signals and sensors. This is also true for variables used for classifying driving style (Khan and Lee, 2019; Taubman-Ben-Ari et al., 2004).
- The features extracted from vehicle trajectory dataset of labelled driving styles are then associated together. This is done mostly by using machine learning algorithms such as Support Vector Machine (Wu et al., 2018; Xue et al., 2019), Random Forest (Wu et al., 2018; Xue et al., 2019), XGBOOST (Shi et al., 2019), Generalized mixture model (Zhu et al., 2019), Neural network-based model (Wijnands et al., 2018), Hidden Markov Model (Xie et al., 2019) and Markov Chain model (Xiong et al., 2018). A recent study (Zhang et al., 2018) also employed deep machine learning technique for this purpose. Results provided contradictory evaluation when comparing the quality/success of the different methods regarding the prediction of driving behavior and showed that these techniques can predict driving styles with over 70% accuracy.

Driving style recognition and STZ concept

The STZ is a theoretical concept and is central to the *i*-DREAMS platform. It is described as the zone where the task demand may need special actions from the driver to cope with them. Within *i*-DREAMS, the STZ is considered to have three phases (as reported in Deliverable 3.1), namely, Normal driving phase, Danger phase and Avoidable accident phase. The latter two dictate the need for real-time interventions. Based on the consideration of the type of accident risk the *i*-DREAMS platform may handle, the driving style recognition can be considered as a critical input in the modelling framework that controls the intervention triggering mechanism for different risk situations. For example, in the case of rear-end collision risk situation, within *i*-DREAMS, it is planned to control the TTC thresholds (a value of TTC before the real-time intervention) in such a manner that these can be dynamically adjusted (e.g. in adverse weather conditions TTC threshold value can be increased). Similarly, during the episode where a driver is departing from its normal behavior, TTC thresholds can be assigned a larger value, and therefore, the driver would be warned much earlier when compared to an episode when his/her behavior is recognized as normal. This can be applied to other risk-situations that will be covered within *i*-DREAMS.

A user's driving style can thus be characterized as Normal driving or Abnormal driving based on certain classification/clustering algorithms as usually done during the initial step of the procedure. In principle, there can be multiple intermediary states between Normal and Abnormal driving. Ideally, the clustering algorithm applied to the dataset will be able to provide an exact number of states represented from the datasets and the following considerations are required:

1. Driver's vehicle trajectory dataset that contains the information about events and other variables, which are required to be measured over time. Often, as the literature demonstrates, Normal and Abnormal driving styles cannot be determined as a certain time event, but needs to be determined as an episode within a certain trip (i.e. driving context). The time window of the episode is strictly dependent on the frequency within which variable values are available from the given technology. Studies can be found using distinct tie windows, ranging from 3 seconds up to 5 minutes. Sliding time window (let's say of a 5 sec period) is a time window, where a next second is added and the first second of a time window is dropped to develop a partially overlapping time window in case the data frequency is per second.

   For each driver, based on the sliding time window technique, as employed in other studies, such as Chen et al. (2019), variables/risk indicators values (if available at 1 second interval) are averaged for the length of sliding window. Higher weight can also be considered for the values of variable corresponding to the new second that is just added to the time window while averaging. This step produces the dataset which follows a time interval equal to the length of time window. However, because of the use of sliding window technique, there is almost no loss of data granularity and at the same time it provides an advantage that time window has a larger length. For example in Figure 12, the first row indicate data availability for each second time interval for let say 11 seconds, the first time window is composed of taking an average of values of data for the first 5 seconds. The next time window is composed of dropping the data values of the 1st second and at the same time adding the data values of the 6th second and then take the averages. The process is then further repeated.

2. There exists a possibility that certain criteria/threshold values relating to important risk indicators can be set as a priori, to distinguish the Normal and Abnormal states from driving according to the risk as given in Table 11. Cluster algorithm can also be used to classify/label a time window as an episode of normal driving or abnormal driving and those prior threshold values can be uses as a guidelines for labelling or validating the cluster. This is shown arbitrarily in Figure 12, where e.g. 4th time window and 7th time window are indicating episode of abnormal driving. More detail on this are provided in the next sub-section.

3. The next step, in the context of *i*-DREAMS, could be different here compared to the general approach followed in the literature where the aim is to associate/correlate trajectory features with identified clusters of driving style. In relation to *i*-DREAMS the technologies will be installed in the vehicles, and along with the trajectory data all other risk indicators variables values will be available, so it is not required to develop a model that associates trajectory features with driving style; however, a distance function/classification algorithm (e.g. K-NN algorithm or Jaccard index) can be applied on the test data (obtained based on the values of variables of a sliding window) to predict the class of driving style to which it belongs.

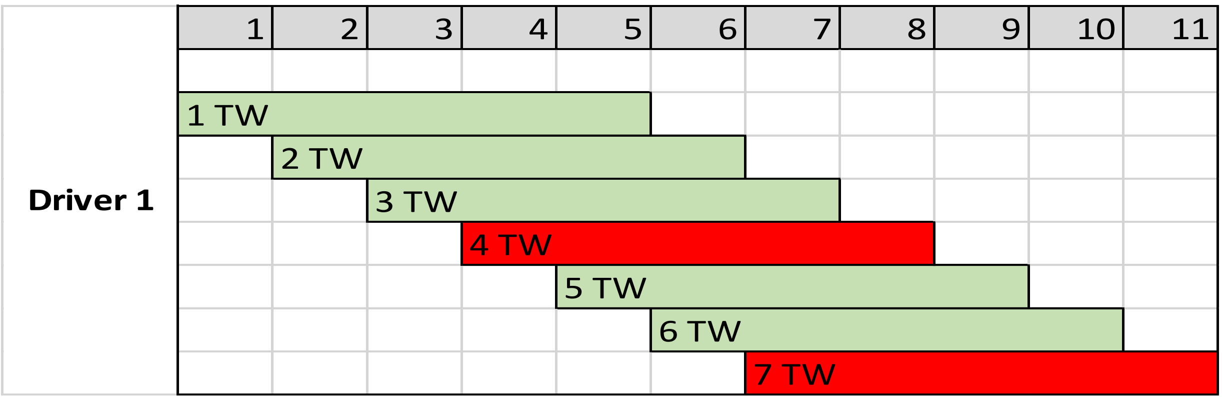

Figure 12: Sliding time windows (TW) of Normal and Abnormal driving style episodes for a particular driver (green colour present an episode of normal, red colour represent an episode of Abnormal driving)

3.2.2 *i*-DREAMS technology and risk indicators for driving styles with recommendation of threshold values

Determining driving style within a driving simulator experiment would mostly be impracticable, since it would require numerous hours of driving for each individual to clearly identify his respective driving style. Therefore, it is foreseeable that the required data may only be available as input for on-road trials within *i*-DREAMS. Given the *i*-DREAMS technology, limited risk situations (accident types) can be covered such as rear-end collision, or collision with pedestrians ahead. Lane departure warning is also available to cover head-on collision in situations, where driving is carried out on two-lane roads. It is, therefore, recommended that a driving style or behavior recognition and their indicator are generalised and applicable for all risk situation that one is able to capture with the available technology. Table 11 provides an overview of available variables (risk indicator) that could be used to identify normal and abnormal driving behavior in cars, buses and trucks. The threshold values provided in the table could be used as a guidelines to label the clusters which are taken from the existing literature. As the clustering mechanism itself able to identify what would be the threshold values of risk indicators for each driver, however, it is always useful to validate the labelling process of the clusters and the values mentioned in Table 11 can be useful in this aspect. More exploratory work is required when the data is available to see which variables/risk indicators are more appropriate. It is also possible that certain variables in Table 11 can be given high weight to appropriately distinguish between normal and abnormal driving styles. This can also help distinguish what causes abnormal driving behavior.

Table 11: Risk indicators/variables and their threshold values to recognize abnormal driving behavior

Variables/Risk Indicator	Car			Bus/ Truck		
	i-Dreams technology	Units	Threshold value to classify for abnormal driving	*i*-Dreams Technology type	Units	Threshold value to classify for abnormal driving
Time headway	Mobileye	Sec	2.0 sec[4]	Mobileye	Sec	2.5 sec[4]
Speed Exceedance[2]	Mobileye	Km/hr	10%[5]	Mobileye	Km/hr	5%
Speed at turns indication[3]	Mobileye	Km/hr	5%	Mobileye	Km/hr	5%

Variables/Risk Indicator	Car			Bus/ Truck		
Pedestrian Collision Warning	Mobileye	Indicator	Yes	Mobileye	Indicator	Yes
Forward Collision Warning	Mobileye	Indicator	Yes	Mobileye	Indicator	Yes
Urban Forward Collision Warning	Mobileye	Indicator	Yes	Mobileye	Indicator	Yes
Left lane departure warning	Mobileye	Indicator	Yes	Mobileye	Indicator	Yes
Right lane departure warning	Mobileye	Indicator	Yes	Mobileye	Indicator	Yes
Long driving hours	CardioID Gateway	Hh:mm:ss	4-6 hours	CardioID Gateway	Hh:mm:ss	8 hours[6]
Longitudinal Acceleration /deceleration	CardioID Gateway	m/sec^2	Beyond ±0.3g[7]	CardioID Gateway	m/sec^2	Beyond ±0.3g
Driver Attention Level (Sleepiness level)	Wristband	Level (0-100)	50[8]	N/A	N/A	N/A
Stress level using Interbeat Interval	Wristband	milliseconds		CardioWheel	milliseconds	
Stress level using PPG and GSR/EDA signal	Wristband	--		CardioWheel (ECG signal)	---	
Harsh acceleration	CardioID Gateway	Indicator	Yes	CardioID Gateway	Indicator	Yes
Hands on Wheel	N/A	N/A	N/A	CardioWheel	Indicator	Yes
Steering Wheel Accelerometer	N/A	N/A	N/A	CardioWheel	degrees	

[1]Threshold value recommended and subject to change when algorithms are implemented to distinguish between normal and abnormal driving style, these are based on finding of existing literature
[2]Processed variable based on speed limit indication and vehicle speed
[3]Processed variable based on turn indication activation and vehicle speed exceedance
[4]Xue et al (2019)
[5]Based on 10% +2mph rule
[6]Recommended 8 hours before breaking for professional truck and bus drivers, for cars it is considered around 4-6 hours
[7]Fazeen et al (2012) and Chen et al (2019)
[8]Based on Honda system where 4 bars are used to represent driver attention level, when 2 bars are detected, low attention is indicated; therefore a value below is considered here as an indication of driver decreased attention

4 The mathematical model of the STZ

4.1 Brief description of the STZ

Within a transport system, a driver can be regarded as a human operator (technology assisted) self-regulating control over transportation vehicles in the context of crash avoidance. The concept of the STZ within the *i*-DREAMS platform attempts to describe short of the range at which self-regulated control is considered safe. It is based on Fuller's Task Capability Interface Model (Ray Fuller, 2011, 2005, 2000) which states that loss of control occurs when the demand of a driving task outweighs the operator's capability. The STZ comrises three phases: Normal driving phase, Danger phase and Avoidable accident phase. Within a transport system, a driver can be viewed as a human operator (technology assisted) self-regulating control over transportation vehicles in the context of crash avoidance. The concept of the STZ within the *i*-DREAMS platform attempts to describe the point at which self-regulated control is considered safe. It is based on Fuller's Task Capability Interface Model (Ray Fuller, 2011, 2005, 2000), which states that loss of control occurs when the demand of the driving task outweighs the operator's capability). The STZ contains three phases: normal driving phase, danger phase and avoidable accident phase.

The Normal driving refers to the phase where conditions at that point in time suggest that a crash is unlikely to occur and therefore the crash risk is low and the operator is successfully adjusting their behavior to meet task demands. Fundamental goal of the *i*-DREAMS platform is to keep drivers within this normal phase. The danger phase is characterised by changes to the Normal driving that suggest a cash may occur and therefore, there is an increased crash risk. At this stage a crash is not inevitable but becomes more likely. The STZ switches to the Danger phase whenever instantaneous measurements detect changes that imply an increased crash risk. Lastly, the switch to Avoidable Accident phase occurs when a collision scenario is developing but there is still time for the operator to intervene in order to avoid the crash. In this phase, the need for action is more urgent as if there are no changes or corrections in the road or rail traffic system or an evasive manoeuvre is performed by the operator a crash is very likely to occur.

The *i*-DREAMS platform is composed of two modules. The first is the monitoring module that takes measurements relating to the "Context" (environment including infrastructure), "Operator" (driver state and demographic characteristics) and "Vehicle" (technical specifications and current state). These measurements are used to infer the demands of the driving task and the driver's capability to cope with these demands. These measurements and inferences on its turn used to estimate in which phase within the STZ the driver is operating within at each moment in time. The second module is the in-vehicle intervention module, that is responsible for keeping the driver within the Normal phase of the STZ all the times, either by providing a warning or instruction during driving (real-time intervention) or providing information with detailed feedback on the trip as well as improving their performance once the driving task has ended (post-trip intervention). The STZ phase, within which the driver is operating, dictates the type of real-time intervention that is delivered. In the Normal driving phase, no intervention is needed. If it is detected that a driver has entered the Danger phase, a warning or advice should be given. Entering the Avoidable accident phase also requires an intervention, but this may need to be more specific and provide an instruction signal, which impels the operator to take a decisive action.

The conceptual state of the STZ changes dynamically depending upon changes in the driving conditions/system of which the operator is an integral part. The drivers' self-regulated control has many influences, one of which is the driver's own perception of the driving conditions. Drivers seek to maintain a level of risk that they are comfortable with and continuously adapt their behavior to achieve the subject to a complex network of underlying motivations, not all of which relate to safety. This implies that drivers may choose to intentionally behave in a way that objectively would be considered unsafe (i.e. travelling close to a vehicle ahead). A driver's subjective appraisal of risk does not necessarily therefore correspond to that calculated with objective measures, nevertheless the driver would still be classed as operating within the Danger or Avoidable accident phases of the STZ (Ray Fuller, 2011). Drivers may choose to behave in a way that objectively would be considered unsafe (i.e. travelling close to a vehicle ahead). A driver's subjective appraisal of risk does not necessarily therefore correspond to that calculated with objective measures, nevertheless the driver would still be classed as operating within the Danger phase or Avoidable accident phase of the STZ.

4.2 Problem formulation

In order to model the STZ, the available data as well as the potential outcome of the model need to be considered. For suggesting a positive outcome, the data to be used as input for the model will be available in real-time, as the measurements of task demand and coping capacity are going to be sequential. Furthermore, as the STZ is the "trigger" for real-time and post-trip interventions, the algorithm outputs are required also to be provided online as in real-time and hence both dynamic and static modelling approaches need to be considered. As previously mentioned, the STZ has three levels: Normal driving, Danger and Avoidable accident phases. Distinguishing between these three levels in real-time, turns STZ modelling into a ternary classification problem, where raw measurements need to be classified as belonging to one of the three existing levels. This classification problem however implies that the feed to the training part of these algorithms needs to be conveniently labelled. The following section reviews both static and dynamic approaches that could be employed to convert driving behavior data into meaningful STZ information.

4.3 Literature Review on relevant models

Predicting driving behavior by employing mathematical driver models, obtained directly from the observed driving-behavior data, has gained much attention in literature (Girma et al., 2019; Kanaan et al., 2019; McDonald et al., 2019; Xue et al., 2019; Zou et al., 2018). Several models have been used to address road safety and the estimation of driving behavior, many of which in the context of experimental studies, including driving simulator studies and field operational trials and/or naturalistic driving studies. A review of safety models can be found in (Hughes, Newstead, Anund, Shu, & Falkmer, 2015), where the authors noted inconsistency in the language of safety models and emphasized that additional factors should be investigated, such as the effect of organizational culture, emergency responses, the health system and economic influences on-road safety. In their opinion, there are models with potential to improve road safety, but yet to be applied. Accordingly, the aim of this section is to examine different models as well as methodologies that include the relationship and interaction between task demand and coping capacity. Several state-of-the-art methodological approaches that enable the modelling of crash risk in real-time are evaluated. In addition, a focus will be made on the modelling and methodologies that detect normal and abnormal driving. As a result, the most suitable model, able to estimate driving behavior and crash risk as well as identify abnormal driving, will be employed for the scope of the *i*-DREAMS project. Literature was searched within popular scientific databases such as Scopus, ScienceDirect and Google Scholar. All studies were screened on the basis of their title and abstract in order to select the studies presented in the following review. An example of key words used per factor analysed, as well as the number of screened and included papers is given on Table 12.

Table 12: Key words, screened and included papers per factor analysed

Key words	Screened papers	Included papers
"risk level" OR "crash risk" OR "collision risk" OR "accident risk" AND "real-time" OR "model" AND "modelling" AND "driver behavior models"	74	21
"driver behavior" OR "abnormal driving" AND "real-time" OR "model" AND "modelling" AND "driver behavior models"	73	14
"road safety" AND "risk" AND "structural equation"	49	14

4.3.1 Machine Learning vs Other Conventional Statistical Models

The nature of multiple real world driving behavior data is intricate and poses complex chalanges. To this end, specialized machine learning and statistical algorithms have been developed in order to overcome these problems.

Machine Learning (ML) algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task (Koza et al., 1996; Burr, 2008). Alternatively, ML models have been used in a wide variety of applications, for which it is/especially in cases where it is difficult or infeasible to develop a conventional algorithm for effectively performing the task.

On the contrary, statistical algorithms contain variables that can be used to explain relationships between other variables. These models are used either to infer something about the relationships within the data or to create a model that can predict future values. Statistical models use sampling, probability spaces, assumptions and diagnostics in order to make inferences.

Consequently, the major difference between machine learning and statistical models is indeed their purpose. Machine learning models are designed to make the most accurate and repeatable predictions possible, while statistical models are designed for inference about the relationships between variables, as well as the significance of those relationships.

4.3.2 Approaches concerned with safe/dangerous driving

In the present section, several models and methodologies that correlate driving behavior with the probability and the severity of an accident risk are examined.

Definition of safe/dangerous driving

First of all, it is important to establish a definition of safe and dangerous driving. As a starting point, safe driving can be regarded as the practice of using driving strategies that minimize the probability of risk or the severity of a crash and thus help avoiding accidents by predicting hazardous situations on the road (Justen, 2008). Conversely, dangerous driving is found when an individual's driving falls below the expected level of a careful and competent driver (Dula and Geller, 2003). It can also be classed as dangerous driving scenarios where the vehicle being driven is in a dangerous condition and not suitable to be on public roads. Several models have been formulated that quantify the relationship between crashes, near crashes and crash-relevant conflicts (Wu et al., 2014). These variables can be thought of as outcomes with an ordered level of severity.

Bayesian Networks

In recent years, BNs have been quite popular in modelling massive amounts of data with the need for data aggregation and model flexibility (Li et al., 2014; Tandon et al., 2016). Lefèvre et al. (2012) proposed a DBN which focused on intersection accidents caused by driver errors. Their approach was formulated as an inference problem where intention and expectation were estimated jointly for the vehicles converging to the same intersection and the proposed solution was validated by field experiments using passenger vehicles. The results demonstrated the ability of the algorithm to issue a warning in dangerous situations, and the benefits of taking into account interactions between the vehicles when reasoning about situations and risk at road intersections. The use of the Bayesian formalism allowed to take into account uncertainties on the relationships between the variables. The intuitive formulation of risk provided the required flexibility for safety applications relevant to both ADAS and autonomous driving. However, information about drivers' actions, such as steering angle and pedal pressure were not taken into account. In addition, Zhu et al. (2017) utilized a hierarchical BN model to investigate the relationship between observed vehicle motion and a driver's historical crash involvements through the hidden layers of driving behavior and crash risk. The results suggested that the contextual model performs significantly better than the non-contextual model. The method was also effective in handling massive trajectory data and flexible in the data aggregation process. However, the contextual indicators have been more comprehensive by including more variables beyond current roadway type, traffic and relative speeds.

Katrakazas et al. (2019) developed a new risk assessment methodology that integrates a collision risk network-level (CRN) with collision risk vehicle-level (CRV) estimates in real-time under the joint framework of interaction-aware motion models and DBN. Results indicated an enhancement of the interaction-aware model by up to 10%, when traffic conditions were deemed as collision-prone. The network-level collision information could assist not only the identification of "dangerous" road users but also act as a safety net for all the motion planning levels and is suitable for Connected and Autonomous Vehicles (CAVs). It is however noteworthy that the extracted probabilities for all the scenarios were not sufficiently high and the scenarios were built on some assumptions and without highly detailed vehicle-level data. The work by Shankar et al. (2008) pointed out that hierarchical DBN can be used to reflect how driver decisions are made: driver-level predictors, such as years of driving, can be used to parameterize the effects of event attributes and context. There were found some advantages related to parameter uncertainty, sample specificity and extensibility to large data sets, which can capture driver differences over time and space, but non automated storage of data through the DAS with a flag for potential risk was identified.

A review of computational Bayesian econometrics and statistics applied to transportation modelling problems in road safety analysis and travel behavior (Daziano et al., 2013) presented Bayes estimators as a potential alternative to outperform frequentist estimators, especially in small samples and weakly identified models. Bayesian models, particularly the Multivariate Poisson log-normal model (MVPLN), were used to estimate the probability of an individual being a high-risk driver (Wu et al., 2014), using SHRP2 data: (data from a 100-Car Naturalistic Driving Study dataset containing driver-related information such as stress, coffee intake, sleeping hours, etc.), providing results in accordance to the ones from the previous studies and national surveys.

Support Vector Machines

Yokoyama and Toyoda (2015) used Support Vector Machines (SVMs) with Gaussian kernel and an analysis method of driving behaviors based on large-scale and long-term vehicle recorder data to support fleet driver management by classifying drivers by their skill, safety, physical or mental fatigue and aggressiveness. The entropy-like model and Kullback Leibler divergence model that aim to emphasize the behavioral departure from average drivers were proposed for the classification. The results have shown that these methods can successfully find some informative driving operation behaviors that might cause accidents and examined a large scale log of vehicle data recorder. However, the frequencies at rare bins were small with short term operation. In the proposed method operator's geo-location and weather were not taken into consideration, while a daily review of vehicle recorder data might not have the ability to distinguish an abnormal and unsafe behavior. SVM and k-means algorithms have also been applied to recognize normal, aggressive or risk driving style based on the trajectory risk levels (Xue et al., 2019). Specifically, Discrete Fourier Transform (DFT), Discrete Wavelet Transform (DWT) and statistical methods were adopted to extract the effective features from trajectory data to enable the driving style recognition. The results indicated that the proposed SVM method was a more appropriate method, which can be effectively used to label the driving style, by comparison with RF, kNN and Multi-Layer Perceptron (MLP) algorithms, displaying an accuracy of 91.7%, a precision of 92.8% and a recall of 81.8%. The model with machine learning algorithm helped to evaluate the collision risk on the road network with high accuracy and also provided real-time decision support to drivers, but road conditions and traffic flow level which influence driving style were not taken into consideration.

Fuzzy Logic Models

Machine learning techniques have been used in primarily traffic flow modelling and second in road safety analysis. Imkamon et al. (2008) proposed a new Fuzzy Logic inference system which can record driving events, detect unsafe or risk driving behavior and classify levels of hazardous driving by employing data from sensors that measure three different perspectives (an ECU reader, an accelerometer, and a camera). The test results showed that the system can perform well compared with human opinions. However, the current system had a limitation of day-time operation due to constraints. In addition, Chong et al. (2013) trained a fuzzy rule-based neural network to model the acceleration of a car-following vehicle. Fuzzy logic was used to discretize traffic state and action variables and reinforcement learning was used for the neural network to learn driving behavior from naturalistic data. On the one hand this paper showcased the application of fuzzy rules on continuous variables with high R-squared values, but on the other hand the choice of model parameters and the number of car-following events were limited (ten in total). Fuzzy deep learning was also applied for traffic incident detection (El Hatri and Boumhidi, 2018), where the authors performed a comparison of machine learning models based on MSE with detection rate and mean time to detection as criteria. Their implementations showcased a high detection rate, low false alarm rate and a back-propagation feature to adjust the parameters in the deep network, although model validation was done on highly artificial street network and incident occurrences. The standard deviation of detection time was not given, indicating questionable potential for applying this algorithm.

Gaussian Mixture Models

Gaussian Mixture Models (GMMs) were used to improve the probability density function (PDF) by introducing the driver’s unresponsive samples. Zhou et al. (2019) utilized Multivariate Gaussian Distributions (MGDs) in order to model driving behavior in critical risk situations as well as driver’s evasive manoeuvres before the collision. The maximum likelihood estimation

(MLE) method was chosen to estimate the parameters of MGD. The results of the models were in accordance with the results in previous studies and a strong influence of risk indicators was identified, especially from velocity and TTC. However, the typical sampling rates in EDR might cause different sampling accuracy among data samples and the influence of vehicle width and small lateral deviation of collision position were not considered.

Random Forests

Four machine learning algorithms: RF, Deep Neural Network, Multilayer Feedforward Neural Network, and t-Distributed Stochastic Neighbor Embedding (t-SNE), were applied to work zone events within NDS data (Chang and Edara, 2018). The RF algorithm had the best performance in classifying NDS data into crashes, near-crashes, and baseline using pre-event variables. The prediction accuracy for work zone events was 97.7% for three classes: crash, near-crash, and baseline and 88.7% for two classes: crash and near-crash. These accuracies were significantly higher than a Naïve predictor's accuracies of 62.6% and 74.2%, respectively. The high accuracies of RF models indicated that these models can be used to predict the occurrence of a safety critical event by only using pre-event variables. However, it should be mentioned that RFs tend to produce anomalous response or prediction surfaces. That might be a bad feature for the *i*-DREAMS project, where the algorithm could end up changing states often at a boundary because of the categorization of continuous inputs.

Task-Capability Interface Models

A key use the STZ concept on the Task-Capability Interface model by Ray Fuller (2000) regarding driving as a task. The model assumes the driver has limited capabilities (task capability) and compares them to the actual effort required for driving (task demand). This qualitative model considered attitude, motivation, personality as well as numerous factors related to the driver in determining crash risk, by introducing a Task-Capability Interface where every positive development has rewarding consequences and every negative event has punishing consequences. A quantitative attempt was made by Saifuzzaman et al. (2015), who applied a Task-difficulty modification on Gipps' and Intelligent Driver (IDM) car-following models, based on driver's satisfaction with current speed. Although they only used trajectory data from driving simulator trials, their models could reproduce human factor induced collisions, unlike the original Gipps and IDM, and have been found to consistently and notably outperform traditional models in both normal and distracted car-following scenarios. An advancement of the Task-Capability model regarding data collection was made in Machiani and Abbas (2016), who used real-time field measurement of vehicle trajectory data in order to assess the level of safety at signalized intersections based on task demand on dilemma zones. However, the level of safety at signalized intersections may have been misinterpreted due to the lax definition of dilemma zone and the insufficient capture of vehicle trajectories from video.

Clustering Models

Clustering techniques have been used by researchers to categorize drivers who are compliant and non-compliant. Xue et al. (2019) developed a driving style recognition method (safe, low-risk, high-risk, dangerous) based on vehicle trajectories from video recordings and k-means clustering, failing however to take into account road conditions and traffic flow levels. An individually-tailored, real-time feedback-reward system for in-vehicle interventions was installed in driver's own vehicles and its effect was researched in a field trial with 37 participants by Merrikhpour et al. (2014). Drivers were clustered by compliance rate, pre and post interventions, in more speed and headway compliant and less speed and headway compliant and the results showed that speed limit and headway compliance increased with post-intervention in the non-compliant group. However, it is not clear if the observed benefits were due to either feedback, or reward, or the unique combination of both. The study by Wang and Xu (2019) using SHRP2 data followed a two-level approach; first, a K-means algorithm was adopted to classify drivers into groups of high, moderate or low risk level and second, logistic regression models for each risk group indicated the probability of each driver getting involved in an incident. Drivers themselves participated in this study by validating any traffic event using an in-vehicle event button and by self-assessing their behavior due to inattention and inexperience errors.

Hybrid Input Output Automaton

According to Bouhoute et al. (2014), a Hybrid Input Output Automaton (HIOA) is a formal model that used to describe discrete and continuous behavior of a system. A driver-centric approach to model risky driving behavior in vehicular ad hoc networks was proposed. Their advantage consisted of providing a better analysis of hybrid systems. The constructed automaton corresponded to the supposed behavior of the driver in one trip, exploration of other states possible in next trips. The goal of the proposed example was to illustrate the idea of the modelling approach and how it can be applied. Consequently, despite the constructed model may be useful to predict the driver behavior in the future, prevent unsafe situations and provide more comfort to the driver, the implementation of the model and the learning process have been not implement yet.

Hierarchical Linear Models

According to Papazikou et al. (2019), Hierarchical Linear Models (HLMs) or multilevel mixed effects linear regression models were used to investigate the feasibility of crash risk indicators and examine the factors affecting TTC. In particular, naturalistic driving studies (NDS) data from the Strategic Highway Research Program 2 (SHRP2) were analyzed in order to look into the whole crash sequence, from a normal driving situation until a crash or a near-crash event. The model results revealed that longitudinal and lateral acceleration as well as yaw rate can be reliable indicators for detecting deviations from normal driving. Moreover, TTC values were affected by vehicle type, speed of the ego vehicle, longitudinal acceleration and time within the crash sequence. Nevertheless, different crash types and event severity, road geometry and traffic conditions were not considered.

Binary Multilevel Logit Models

Jovanis et al. (2011) used standard binary Multilevel Logit models. Driver attributes included permanent characteristics, such as age and years of driving experience and driving style, which was intended to convey the level of risk the driver was willing to accept while undertaking the driving task. Event attributes included descriptors of the situation as it unfolded during the event. Driver attributes, such as impairment and distraction, captured in the few seconds around the crash were included as event attributes. Multilevel models revealed that heterogeneity was a problem in estimating event-based models because some drivers had been involved in multiple events, which needed to be recognized in the model formulation. The particular advantage of the multilevel approach was that it used a structure that reflected how driver decisions were made: drivers with particular characteristics found themselves in certain contexts in which they executed specific driving manoeuvres, which led to certain outcomes.

Structural Equation Models

Structural Equation Models (SEMs) has been widely used for modelling road user behavior and safety. The self-reported behavior of car drivers (Dong et al., 2019), motorcyclists (Topolšek and Dragan, 2018) or pedestrians (Dinh et al., 2020) are typically modelled in relation to other human factors (attitudes, behavior, motivations) or external factors. SEM has been used to model other behavioral aspects in the form of latent variables e.g. driving anger (Du et al., 2018), speeding behavior (Javid and Al-Hashimi, 2019; Leandro, 2012), or perceived risk. Several related studies focus on distraction related factors. For instance, Li et al. (2014) considered the perceived risk of distracted driving as a latent variable, and associated it with other latent constructs, namely distractibility, self-reported distracted driving behavior and personal acceptability of distracted driving, through a questionnaire survey. In Chen and Donmez (2016), a latent variable 'technology related distraction engagement' was estimated on the basis of other latent variables (attitudes, norms or personality) The above mentioned studies are focused mainly on analyzing inter-relationships between ethical and psychological factors related to safety, and use SEM to mathematically represent existing conceptual frameworks such as the theory of planned behavior (TPB) or the Driver Behavior Questionnaire (DBQ – and its four constructs namely errors, violations, aggressive violations and lapses); but in most cases, they are not targeted to actual traffic risk estimation.

One family of studies uses SEM for macroscopic traffic safety analysis at regional or national level. Shah et al. (2018) used a Data Envelopment Analysis (DEA) technique to estimate a composite indicator of risk, and then developed a SEM to model (composite) risk in relation to a number of additional composite variables/latent constructs namely institutional framework, legislation, user and vehicle factors, infrastructure factors, management factors and financial impact. Dimitriou et al. (2019) made a cluster analysis to group countries and developed a set of SEMs to model global mortality statistics (in terms of mortality rates per population, per vehicle fleet etc.) in relation to various socioeconomic constructs such as economy, demographics, road network and traffic enforcement characteristics.

At a more microscopic level but within the same purpose, in Elyasi et al. (2018), a macroscopic analysis of the relationships between the main crash components i.e. the traffic, the human and the road, was carried out through SEM, in which road safety was defined as a latent construct measured through daily and hourly crash rates. Najaf et al. (2018) developed a composite indicator of traffic safety on the basis of several indicators (mostly different crash rates) and associated it with a number of constructs reflecting characteristics of urban areas i.e. walkability, connectivity, economic indicators, congestion, infrastructure etc. Another broad family of studies focus on the association of driving behavior with crash risk – that being conceptualized through various types of latent constructs. In an earlier study (Ma et al., 2010) a questionnaire was used to estimate latent variables of the safety attitudes, perceptions and behaviors of professional drivers (taxi and bus drivers). A SEM was built to explore associations between crash risk and attitudes, perceptions, violations (aggressive or ordinary), and safety concerns of drivers; where the likelihood of crash was thereby modelled as a latent variable on the basis of self-reported recent and historical crash involvement.

Papantoniou et al. (2019) considered 'driver error' as a latent variable which can be observable by a set of driving indicators measured in a simulator drive; relevant indicators were for instance the hitting of side bars, lane departures and high engine revolutions per minute. Subsequently, they developed a SEM to associate driver error with exogenous factors such as driver age and gender, road type and experience. The same simulator dataset also used by

Papantoniou (2018) in order to develop a SEM on driver performance as a latent variable – in this case as well, it was associated with observable driver and road characteristics, as well as with different types of distraction (mobile phone use, conversation with passenger). Zhao et al. (2019) used a similar approach to model driving performance as a latent variable measured by means of driving simulator metrics and developed a SEM associating it with factors of driver characteristics, illegal actions and attitudes – these “independent” variables came from a combination of simulator and questionnaire metrics. Useche et al. (2019) developed SEM to describe relationships between risky behaviors, risk perception, knowledge of traffic norms and cycling intensity (all latent constructs on the basis of a structured questionnaire) and the self-reported cycling crash frequency in the last 5 years. An earlier study of the same authors (Useche et al., 2018) focused on the differences of risky cycling behavior as a latent variable between male and female cyclists. Constantinou et al. (2011) used a SEM to associate various personality factors (sensitivity to reward, disinhibition, impulsiveness, experience, violations) with the number of self-reported number of offenses and accident outcomes.

Only one study was found which uses real driving data to model collision risk while driving. More specifically, Ding et al. (2019) used a set of on-road experiments to calculate crash risk as a latent variable on the basis of two surrogate safety measures (SSM), namely TTC and DRAC in car-following situations. Observed driving metrics as well as driver visual perception elements were used to build a set of perceptual and environment related constructs and develop a SEM of latent crash risk.

4.3.3 Discussion and Recommendations for *i*-DREAMS

With regards to safety and risk level, several models and methodologies have been examined. Firstly, DBNs were found to be the most effective and extensible in handling massive trajectory data, as well as flexible for safety applications in the data aggregation process (Lefèvre et al., 2012; Shankar et al., 2008; Zhu et al., 2017). The use of the Bayesian formalism allowed to take into account uncertainties on the relationships between the variables (Lefèvre et al., 2012). However, variable selection, assumptions and non highly detailed vehicle-level data were found to be some of the shortcomings of this approach (Katrakazas et al., 2019). SVMs successfully found some informative driving operation behaviors with high accuracy and extracted the effective features from trajectory data enable the driving style recognition (Xue et al., 2019; Yokoyama and Toyoda, 2015). It is also important to mention that in the proposed method operator's geo-location, weather, road conditions or traffic flow level which influence driving style were not taken into consideration. High accuracies of RFs showed that these models can be used to predict the occurrence of a safety critical event by only using pre-event variables (Chang and Edara, 2018).

In addition, SEM approaches have been widely used for modelling road user behavior and safety and allowed for different hypotheses on the structural model/path diagrams for the relationships between variables to be systematically tested. This may lead to a robust conceptual framework for the analysis. Although SEM was built to explore associations between crash risk and attitudes, perceptions, violations and safety concerns of drivers, it found to be less pertinent for the purposes of real-time prediction of the STZ events. SEM were unlikely to be able to clearly capture the crash development phase over a short time and the lack of representing dynamics made SEM of limited potential for real-time estimation. Moreover, in MGDs and GMMs, a strong influence of risk indicators was identified, especially the velocity and TTC (Zhou et al., 2019). However, the influence of vehicle width and the small lateral deviation of collision position were not considered. Test results of Fuzzy logic models had shown that the system can perform well compared with human opinions but there was a limitation of day-time operation due to constraints of the image processing algorithm (Imkamon et al., 2008). Finally, standard binary Multilevel Logit models and HLMs found less effective (Jovanis et al., 2011; Papazikou et al., 2019), while HIOA formal models and their learning process considered as an early stage of an introduction work, so the implementation of the model is considered as a further work (Bouhoute et al., 2014).

Overall, RFs and other non-parametric and black-box models that chop up continuous measures at arbitrary cut points can be very good at prediction, but in a real-time application, they may jump back and forth among the three states in a way that is unexpected and not user-friendly. The DBNs will have smoother transitions because the state at time t is directly informed by the state at time t-1.

4.3.4 Approaches concerned with abnormal driving

In this section, models and methodologies often used to detect abnormal driving behaviors from normal ones in identifying different abnormal types of driving are described. Different aspects related to the actual driving situation, driver stress, time schedules, workload or frustration can explain why drivers accept higher risks and engage in more risky driving behaviors such as speeding, harsh acceleration or deceleration, perform an illegal or dangerous overtaking (i.e. abnormal driving). There is an increasing body of recent literature aiming at identifying and predict abnormal driving. Techniques such as deep learning, kNN, Convolutional Neural Networks (CNNs), Long Short-Term Memory Models and other have previously been used to identify episodes of abnormal driving behavior, mostly based on real-time telematics data.

Definition of abnormal driving

Prior to diving into the review and discussion of potentially suitable mathematical models, one must define clearly the concept of abnormal driving. Although abnormal driving behaviors vary with respect to drivers, driver’s appearances under abnormal driving conditions will be different from the normal one (Chiou et al., 2016). Additionally, most traffic accidents can be positively linked with abnormal driving behavior, which can, in principle, be detected by analysing driving data, e.g. time series of vehicle speed, brake pressure, fully depressed or rapidly changing and steering angle (Shi et al., 2015). For instance, large vehicle speed and throttle position might imply that the driver is in a hurry or careless. A comparison with the models under real driving conditions can be made in order to identify that a driver is in a normal or abnormal driving situation.

Long Short-Term Memory Models

Girma et al. (2019) proposed deep learning-based models, called LSTM models, to predict and identify drivers based on their individual’s unique driving patterns based on vehicle telematics data. Results showed that the proposed model prediction accuracy remained satisfactory and outperformed other approaches despite the extent of anomalies induced in the data. Even under increasing noise and outliers effect, the proposed approach maintained its accuracy above the acceptable value, 88%, while other models’ accuracy fell below 40%. Neural network-based models such as LSTM performed better than Fully Connected Neural Network (FCNN), Decision Tree (DT) or RF, by avoiding over-fitting on the noise. Bao et al. (2019) trained a spatiotemporal convolutional LSTM network to determine a crash risk scale and to calibrate a crash risk alarm threshold. Their data comprised large-scale taxi GPS data, population data, weather and land use features, and they was used to compare econometric and machine learning models. Econometric models performed better than machine-learning models in weekly crash risk prediction tasks, while they exhibit worse results than machine-learning models in daily crash risk prediction tasks. However, because taxi trips were not representative of the general mobility patterns in a city, this study entails a significant sample bias problem.

Hidden Markov Models

It is worth mentioning that in several studies, Hidden Markov Models (HMMs) were proposed to monitor and effectively detect normal and abnormal driving behavior and have demonstrated success at predicting time-sequential data and found to generate high accuracies in driver state prediction (Lee et al., 2018). Furthermore, Kanaan et al. (2019) used HMMs built on a naturalistic driving data, in particular, the Naturalistic Engagement in Secondary Task (NEST) dataset, in order to identify abnormal driver behavior and detect distraction. GPS speed and steering wheel position were analyzed to classify the existence of off-path glances and secondary task engagement, while lateral and longitudinal acceleration were used to estimate motor control difficulty associated with the driving environment. The results evidenced a high accuracy of 77% in detecting secondary task engagement and long off-path glances and an accuracy of 60% for the evaluation of motor control difficulty. HMM and a deep learning model such as Single Shot Multibox Detector (SSD) were used in order to select information that cause driver distraction and a high detection accuracy of braking operation was confirmed (Hashimoto et al., 2019).

Additionally, Zhang et al. (2014) used HMMs to model individual characteristics of driving behavior based on accelerator and steering wheel angle data and managed to reach a maximum prediction accuracy of 85%. Studies suggest that the model works very well in practice for several important applications and is well suited to model the variation in the driving signals across drivers. The work by Zhang et al. (2014) proved that individual difference are a factor which cannot be ignored in driving behavior model and that HMM can be effective in modelling it. Furthermore, HMMs for driver behavior near intersections was trained using Genetic Algorithm combined with Baum-Welch Algorithm based on the hybrid-state system (HSS) framework (Amsalu and Homaifar, 2016). The models were tested using naturalistic driving data and the proposed framework improved the HMM accuracy in estimating the driver's intention when approaching an intersection by over 10% higher accuracy. The accuracy of the HMM-GA model was better that the HMM model trained with Baum-Welch and as a result, HMM-GA model gave the best recognition performance over the HMM model. Abe et al. (2007) found that driver’s “hasty state” had effect on Auto-Regressive Hidden Markov Model (AR-HMM) model parameters such as gas pedal stroke and brake pedal stroke, and also on autonomic nervous and abnormal activity.

Random Forests

McDonald et al. (2019) analyzed a set of driver behavioral and physiological features in order to detect abnormal driving using seven different advanced machine learning approaches, on model prediction performance. Results showed that RF algorithms, trained using only driving behavior measures and excluding driver physiological data, displayed the highest accuracy in classifying driver distraction. In addition, a combination of RF and SVM with a linear kernel function algorithm has also revealed high accuracy levels.

Gaussian Mixture Models

The work by Angkititrakul et al. (2011) is noteworthy for developing a stochastic driver-behavior model based on Gaussian Mixture Models (GMMs). The proposed model can characterize individual driver better than universal models in both short-term and long-term predictions by using the observed driving data. Nevertheless, there were identified some disadvantages with the proposed model, while mass data should be collected and processed in-time in order to establish individual driver models more accurately. A comparison between the GMM and PWARX-based driver models, the GMM-based modelling revealed a good performance using the actually observed parameters, however, it was more sensitive to the approximation errors of the input parameters as in the recursive prediction. As for PWARX-based modelling, although not showing advantage at the short-term prediction, it performed better than the universal GMM-based model at the long-term prediction. Wang et al. (2018) developed a personalized driver model, including a Bounded Generalized Gaussian Mixture Model (BGGMM) to capture the driving characteristics of non-Gaussian and bounded support while an HMM was employed to describe the dynamic processes of driving tasks. Experimental results of modelling car-following behaviors demonstrated that the proposed BGGMM-HMM achieved the best performance in accuracy and robustness to handle data with non-Gaussian distribution bounded support, compared to traditional GMM-based models, but at the expense of severe computation overheads given its structural complexity.

Bivariate extreme value models

Bivariate extreme value models have been used to integrate surrogate safety measures (SSM) in predicting the number of crashes in urban context. In their first attempt to train a bivariate threshold excess model for crash identification on freeway entrance merging areas, Zheng et al. (2018) used road geometries, video recordings, and crash records to estimate the severity of events based on post encroachment time (PET) and length proportion of merging (LPM). Their uncertainty on the chosen combination of safety surrogate measures resulted in a second research attempt on the same issue, which calibrated the aforementioned bivariate extreme value model this time near signalized intersections, encompassing different traffic conflict indicators i.e. TTC, Modified Time-to-Collision (MTTC), PET, and DRAC. This new research cleared the uncertainty on the combination of SSM, but relied again on very limited crash data, reasonably enough, as actual crashes are rare events.

Discrete Choice Models

Chu et al. (2017) used Discrete Choice Models (DCMs) to model manoeuvres and gap-acceptance at urban expressway in merging traffic streams considering safety, road geometry, and traffic conditions, based on video trajectory observations. Gap acceptance of MVs on expressways was evaluated offline and driving behavior was evaluated based on the risk level (relative distance, time to collision) to identify the TTC thresholds for MVs to accept or reject a gap. The study concluded that latent choice models outperforms the multinomial and nested logit models, with geometry and traffic conditions as significant. Models used included a multinomial logit model (MNL), a nested logit model (NL), and a latent choice set model (LCS) to indicate the TTC thresholds for a merging vehicle (MV) to reject or accept a gap. The LCS model allowed exploration of the latent choice made by MVs; a limitation could be the assumption of decision point for merging behavior, which might have influenced when the interaction between merging vehicles began and, as a consequence, the TTC indicator. A review of Dynamic Discrete Choice Models (DDCM) can be found in Cirillo and Xu (2011) who described applications of DDCMs on market research and then compared the dynamic models based on short- to medium-term vehicle-holding decisions. According to the authors DDCMs can represent dynamically many decisions in travel behavior and incorporate temporal effects in transportation models, although their disadvantages are massive data requirements and the relative computational complexity in their application.

Wali et al. (2019) used DCMs to relate crash propensity to unintentional driving volatility and other factors. In their study, driving volatility was characterized (intentional vs. unintentional) in relation to driving decisions in both longitudinal and lateral directions and its fluctuations/variation across drivers involved in normal driving, crash, and/or near-crash events; volatility indices, as leading indicators of near-crash and crash events, were linked with safety critical events, crash propensity, and other event specific explanatory variables. In addition, Koutsopoulos and Farah (2012) used latent class models for car-following data on a highway including as input variables vehicle position, lane, speed, acceleration and deceleration. The latent class models included a mixture of acceleration, deceleration, do-nothing: estimate desired speed to preceding vehicle (offline), using Maximum Likelihood Estimation, leading to better than superior to those of traditional car-following models. Cirillo and Xu (2011) reviewed the application of DDCMs on short-to medium term vehicle-holding decisions and presented applications of such models on market research. DDCM were found to represent many dynamic decisions (changing over time) in travel behavior. Moreover, Aguirregabiria and Mira (2010) proposed methods for the estimation of dynamic discrete choice structural models; considering single-agent models, competitive equilibrium models and dynamic games. Authors also provided programming codes for estimation models.

Wang and Xu (2019) used DCM for prediction and factor identification for crash severity, and compare MNLs with RF which predicts better but the observed differences are not dramatic; yet RF can automatically capture the non-linear effects of continuous variables and reduce the influence of collinearity relationships existing among explanatory variables. It should be mentioned that the models presented above are all static, whereas in *i*-DREAMS the safety monitoring environment is highly dynamic and changing in real-time. There is therefore a need for a dynamic problem formulation: DDCMs are thereby considered.

Car-following models

Traditional car-following models have been the interest of many researchers, who aimed at improving the classical algorithm to increase its accuracy. Sangster et al. (2013) proposed an optimization algorithm using filtered, smoothed and discretized time-based vehicle trajectories, to calibrate a new car-following model; proving more accurate than the classical IDM. In their study, however, a significant difference was found between the original and the filtered data. Koutsopoulos and Farah (2012) developed a latent class-like DCM using a compensatory frequency database (10 Hz),,, to create a desired mixture of acceleration, deceleration or do-nothing. The resulting model outperformed traditional car-following models. An important drawback of the study concerned the lack of consideration of traffic status (free flowing, congested etc.), although their framework recognized the potential existence of different traffic states.

Discussion and Recommendations for *i*-DREAMS

With regards to abnormal driving behavior, several models and methodologies have been investigated. LSTMs revealed the highest accuracy, compared with other models examined. Specifically, the proposed model maintained its accuracy above the acceptable value 88%, while other models' accuracy fell below 40%. LSTM had an inherent ability to remember temporal information in data and conserve it for many time steps, unlike other conventional machine learning approaches (Girma et al., 2019). HMMs were found to generate high detection accuracies in driver state prediction and performed very well in practice for several important applications (Amsalu and Homaifar, 2016; Hashimoto et al., 2019; Kanaan et al., 2019; Zhang et al., 2019). The performance could be further improved by including additional vehicle-based measures as predictors, using different techniques for creating balanced classes in the training datasets (Kanaan et al., 2019). Moreover, the HMMs were limited to contextual information representation, based on the hypothesis that the output observations were strictly independent and the current state was only related to the previous state. It is worth to emphasize that most of the state-of-the-art analysis on driving behavior has been evaluated in driving simulator context so it could be useful to test in on-road environment conditions (Abe et al., 2007).

An alternative approach to the mathematical modelling of STZ is proposed using DCMs, which are commonly used for specifying models for mode choice, travel demand modelling, behavioral analysis such as user satisfaction, but have been applied to safety models to a less extent. However, DDCM applications found to have econometric problems pertaining to household decisions for car ownership, or other problems, where states changed every year or months. Furthermore, DDCM might be computationally very expensive and this dynamic problem estimation may be challenging and even unfeasible in real-time. Imbalanced data as well as the thresholds between different safety levels were some of the examined limitations of this approach. Moreover, RFs and SVMs with a linear kernel using driver behavior input were some of the highest performing algorithms for accurately classifying driver behavior and distraction, multiclass classifier with cognitive and visual secondary tasks (McDonald et al., 2019). It should be noted that data wasn't in realistic but in a simulator-based scenario, hence generalizing these findings beyond the task or environment should be assessed cautiously. Additionally, kNNs were affected by unbalanced training data, which resulted in higher time complexity when calculating the distance from the unknown sample to all known samples. Lastly, BGGMMs with HMMs achieved the best performance in accuracy and robustness to handle data with non-Gaussian and bounded support, compared to the traditional GMM-based models but at the expense of a substantially increased due to its structural complexity (Wang et al., 2018).

Table 13 summarizes the models used by each of the proposed approaches to measure driving behavior and crash risk and detect abnormal driving, with the positive and the negative aspects of each methodology. Also, a summary of previous work on driver behavior detection with the research goal and modelling techniques can be found in Table 17, as shown in Annex A.

Table 13: Summary of driving behavior models with positive and negative aspects

Models	Positive	Negative
Dynamic Bayesian Networks (DBNs) (Shankar et al., 2008, Lefèvre et al., 2012; Zu et al., 2017; Katrakazas et al., 2019)	effective in handling massive trajectory data, flexible in the data aggregation process, identification of dangerous road users, act as a safety net for all the motion planning levels, take into account uncertainties on the relationships between the variables, parameter uncertainty, sample specificity, and extensibility to large data sets, capture driver differences over time and space, investigation of individual (driver-level) parameters themselves as random effects	the contextual indicators can be more comprehensive and include more variables beyond current roadway type, relative speed and traffic speed, extracted probabilities for all the scenarios are not high enough, the scenarios were built on some assumptions and without highly detailed vehicle-level data, information about drivers' actions such as steering angle and pedal pressure are not taken into account, non-automated storage of data through the DAS with a flag for potential risk
Hidden Markov Models (HMMs) (Zheng et al., 2014; Amsalu and Homaifar, 2016; Lee et al., 2018; Kanaan et al., 2019; Hashimoto et al., 2019)	high accuracy in driver state prediction, accurate results with a performance comparable to human observer, HMM work very well in practice for several important applications, the variations in the driving signals across the drivers can be modelled	limited to contextual information representation, based on the hypothesis that the output observations were strictly independent and the current state was only related to the previous state, the performance of the models can be improved by including additional vehicle- based measures as predictors, using different techniques for creating balanced classes in the training datasets, different driving scenarios of interest can include lane change, lack of sensitivity on parameter variation that arise due to noise in the training observations, the simulator had not a perfect biofidelity, the brake imitated real operation poorly
Auto-Regressive Hidden Markov Models (AR-HMMs (Abe et al., 2007)	driver's hasty state has effect on AR-HMM model parameters such as gas pedal stroke and brake pedal stroke, and also on autonomic nervous activity	an experiment could be closer to real hasty situation, individualization difficulty, problems with setting thresh for hastiness, states on driving behavior were found in driving simulator so it must be tested if the same phenomena can be seen in real driving for practical use
K-means (Van Ly et al., 2013; Xue et al., 2019)	extract the effective features from trajectory data to facilitate the driving style recognition	road conditions and traffic flow level are not taken into consideration
K-Nearest Neighbor (kNN) (Van Ly et al., 2013; McDonald et al., 2019)	simple, easy to understand, versatile and one of the top most machine learning algorithms that find its applications in a variety of fields	unbalanced training data, which resulted in higher time complexity when calculating the distance from the unknown sample to all known samples

Models	Positive	Negative
Structural Equation Models (SEMs) (Ma et al., 2010, Constantinou et al., 2011, Shah et al., 2018, Papantoniou, 2018, Elyasi et al., 2018, Useche et al., 2018, Najaf et al., 2018, Dimitriou et al., 2019, Zhao et al., 2019, Papantoniou et al., 2019, Usechea et al., 2019, Ding et al., 2019)	different hypotheses on the structural model / path diagrams can be tested, allows for different hypotheses for the relationships between variables to be systematically tested, exploratory factor analysis may shed light on the number and type of latent variables that can be extracted by the available indicators	less pertinent for the purposes of real-time prediction, developed on aggregated data, unlikely to be able to clearly capture the crash development phase over a short time, lack of representing dynamics makes SEM of limited potential for real-time estimation
Discrete Choice Models (DCMs) (Aguirregabiria et al., 2010, Cirillo and Xu, 2011, Koustopoulos et al., 2012, Chu et al., 2017, Wali et al., 2019, Wang et al., 2019)	cluster the driving events, classify a new driving event, predict the next safety state, calculate the safety level utility, predict the probability of being in a certain level	imbalanced data, econometric problems pertaining to household decisions for car ownership, very expensive, not feasible real-time
Support Vector Machines (SVMs) (Yokoyama and Toyoda, 2015; Xue et al., 2019)	high accuracy, extract the effective features from trajectory data to facilitate the driving style recognition, the highest performing algorithms for accurately classifying driver behavior and distraction, multiclass classifier with cognitive and visual secondary tasks, examination of a large scale log of vehicle data recorder, this method successfully finds some informative driving operation behaviors	road conditions and traffic flow level which influence driving style are not taken into consideration, the frequencies at rare bins are small and the operation will not occur in short term, daily review of vehicle recorder data may not have the ability to distinguish an abnormal and unsafe behavior, geo-location of the operation or weather were not taken into account
Gaussian Mixture Models (GMMs) (Angkititrakul et al., 2011; Wang et al., 2018; Zhou et al., 2019)	strong influence of risk indicators, especially the velocity and TTC, best performance in accuracy and robustness to handle data with non-Gaussian and bounded support, model adaptation in both short-term and long- term predictions over the universal (unadapted) models	different sampling accuracy among data samples, the influence of vehicle width and small lateral deviation of collision position are not considered, substantial computational cost due to its structural complexity, mass data must be collected and processed in-time in order to establish individual driver models more accurately
Naive Bayes (NBs) (McDonald et al., 2019)	high performance and efficient implementation	sample attributes were independent from each other, lower classification performance when the number of sample attributes or the correlation between attributes became larger
Long Short-Term Memory Models (LSTMs) (Girma et al., 2019, Bao et al., 2019)	high accuracy above the acceptable value 88%, LSTM has an inherent ability to remember temporal information in data and keep it saved for many time steps than the other conventional machine learning approaches, the proposed model efficiently learns individual unique driving patterns from the data to identify the driver	extent of anomalies and noise- induced in the data

Models	Positive	Negative
Random Forests (RFs) (Chang and Edara, 2018; McDonald et al., 2019)	high performance for accurately classifying driver behavior and distraction, multiclass classifier with cognitive and visual secondary tasks, high accuracies of Random Forest models show that these models can be used to predict the occurrence of a safety critical event by only using pre-event variables	distraction mitigation systems should focus on driver behavior–based algorithms that use complex feature generation techniques, cautious about generalizing these findings beyond the task or environment explored, quality of data received from the sensors, many variables are textual or categorical and not numerical, using pre-event data that provide clues into the factors leading to their occurrence are not utilized
Hierarchical Linear Models (Papazikou et al., 2019)	useful in enhancing existing ADAS, more effectively and timely detect and stop an early deviation before it culminates in a crash	different crash types, event severity, road geometry and traffic conditions are not considered
Binary Multilevel Logit Models (Jovanis et al., 2011)	driver-level predictors parameterize the effects of event attributes and contexts, binary logit model estimates with context-only predictors, including the coefficient mean, standard error, and odds ratio	each observation of outcome was treated as independent, non-event (baseline) events are not contained but they are costly to obtain
Fuzzy Logic Models (Imkamon et al., 2008, Chong et al., 2013, El Hatri and Boumhidi, 2018)	the test results show that the system can perform well compared with human opinions	limitation of day-time operation due to constraints of the image processing algorithm
Hybrid Input/Output Automaton Models (HIOAs) (Bouhoute et al., 2014)	better analysis of hybrid system, theory of stochastic learning automata was used to define transitions and construct the automaton	the implementation of the model and the learning process are not completely implemented yet
Single Shot Multibox Detector Models (SSDs) (Hashimoto et al., 2019)	high detection accuracy and contributing confidence and can be narrowed based on this value	actual driving behavior and the usefulness are not examined

4.3.5 Discussion and Recommendations for *i*-DREAMS

A first challenge, within this framework, is the conceptualisation and estimation of the risk component. In *i*-DREAMS risk is defined on the basis of a three-stage STZ, namely Normal driving phase, Danger phase and Avoidable accident phase. The time dimension is prominent in this concept. With regards to the models and methodologies investigated, it is very important to identify the most suitable approach that can model driving behavior, recognize safe or dangerous driving and detect abnormal behavior.

It was revealed that DBNs were the most effective and extensible in handling massive trajectory data, as well as flexible for safety applications in the data aggregation process (Lefèvre et al., 2012; Shankar et al., 2008; Zhu et al., 2017), while variable selection, assumptions and non highly detailed vehicle-level data were found to be some of the shortcomings of this approach (Katrakazas et al., 2019).

LSTM models had the highest accuracy, with a significant accuracy above the acceptable value 88%, compared with other models' accuracy which was below 40%. LSTM had an inherent ability to remember temporal information in data and keep it saved for many time steps compared with other conventional machine learning approaches (Girma et al., 2019, Bao et al., 2019).

With regards to an initial SEM concept, it was expected that risk can be considered, at an aggregate level, as measurable through the Danger Phase events and the Avoidable Accident events. At the same time, changes in values of risk factors (coping capacity related or task complexity related) can be associated with increases in risk. An advantage of the SEM approach was that it may allow for different hypotheses for the relationships between variables to be systematically tested. Exploratory factor analysis may shed light on the number and type of latent variables that can be extracted by the available indicators. Subsequently, different hypotheses on the structural model/path diagrams can be tested. This may lead to a robust conceptual framework for the analysis. At the same time, there is added value for explanatory purposes: one of the objectives of *i*-Dreams is to identify and quantify the significant impacts of different human factors on risk and the complex mechanism underlying them. On the other hand, SEM found to be less pertinent for the purposes of real-time prediction of the STZ events. SEM was developed on aggregated data which, even if available at a fine level of aggregation, were unlikely to be able to clearly capture the crash development phase over a short time. The lack of representing dynamics made SEM of limited potential for real-time estimation. Data-driven approaches and dynamic models are more pertinent on that purpose.

Finally, an alternative approach to the mathematical modelling of the STZ was proposed. DCMs were found to be a different approach, following the same logic as SEMs. However, this method seemed to be less effective as it might be computationally very expensive and even not feasible in real-time.

Overall, while SEM and DCM in its standard form may not be suitable for STZ estimation, the insights obtained by SEM and DCM in the framework of post-processing analysis may be useful for the improvement of the real-time prediction models, and for the general understanding of risk mechanisms. A hybrid model incorporating latent variables into real-time prediction models might be an optimal approach to modelling risk in *i*-DREAMS. Lastly, it is important to investigate these different approaches in the next sections where both real-time and post-trip processing will be examined.

4.4 Mathematical modelling

The literature review in the previous section revealed that four of the modelling approaches could be more suitable for modelling the STZ within the *i*-DREAMS project. In particular, DBNs, LSTMs, DDCs and SEMs were the deemed the most appropriate. This section will provide the mathematical formulation of the STZ model according to these popular methodologies, in order to provide flexibility in the practical implementation of the STZ estimation algorithm. To this end, a brief description of each algorithm is presented, followed by an explicit description of the proposed models.

4.4.1 Brief description of algorithms

Structural Equation Models (SEMs)

Structural Equation Models (SEMs) represent a natural extension of a measurement model and establish a mature statistical modelling framework. These models are designed to deal with several difficult modelling challenges, including cases in which some variables of interest to a researcher are unobservable or latent and are measured using one or more exogenous variables, endogeneity among variables, and complex underlying social phenomena. SEMs are widely used for modelling complex and multi-layered relationships between observed and unobserved variables. Observed variables are objectively measurable, whereas unobserved variables are latent constructs – analogous to components in a factor/principal component analysis. SEMs have two components: a measurement model and a structural model. The measurement model is used to determine how well various observable exogenous variables can measure (i.e. load on) the latent variables, as well as the related measurement errors. The structural model is used to explore how the model variables are inter-related, allowing for both direct and indirect relationships to be modelled. In this sense, SEMs differ from ordinary regression techniques in which relationships between variables are strictly.

The general formulation of SEM is as follows (Washington et al., 2011):

$$\eta = \beta * \eta + \gamma * \xi + \varepsilon \qquad (1)$$

where:

- η is a vector of endogenous variables
- ξ is a vector of exogenous variables
- β and γ are matrices of coefficients to be estimated
- ε is a vector of regression errors

The measurement models are then as follows (Chen, 2007):

$$\mathrm{x} = \Lambda_{\chi x} * \xi + \delta \qquad \text{(2) for the exogenous variables}$$

$$\mathrm{y} = \Lambda\,\Lambda_{\gamma\gamma} * \eta + \zeta \qquad \text{(3) for the endogenous variables}$$

where:

- x and δ are vectors related to the observed exogenous variables and their errors
- y and ζ are vectors related to the observed endogenous variables and their errors
- Λ_x, Λ_y are structural coefficient matrices for the effects of the latent exogenous and endogenous variables on the observed variables

The structural model is often represented by a path analysis, showing how a set of 'explanatory' variables can influence a 'dependent' variable. The paths can be drawn in order to reflect whether the explanatory variables are correlated causes, mediated causes, or independent causes to the dependent variable.

The structural model concerns on how the model variables are related to one another. SEMs allow for direct, indirect, and associative relationships to be explicitly modelled, unlike ordinary regression techniques which implicitly model associations. It is the structural component of SEMs that enables substantive conclusions to be made about the relationship between latent variables, and the mechanisms underlying a process or phenomenon. Because of the ability of SEMs to specify complex underlying relationships, SEMs lend themselves to graphical representations and these graphical representations have become the standard means for presenting and communicating information about SEMs. Similar to factor and principal components analyses, SEMs rely on information contained in the variance–covariance matrix. Alike other statistical models, SEMs require the specification of relationships between observed and unobserved variables. Unobserved variables also include error terms that reflect the portion of the latent variable not explained by their observed counterparts. In a SEM, there is a risk that the number of model parameters sought exceeds the number of model equations needed to solve them. Thus, there is a need to distinguish, with fixed and free parameters being set by the analyst and free parameters being estimated from the data. The collection of fixed and free parameters specified in the model implies a particular variance-covariance structure in the data, which is compared to the observed variance-covariance matrix to assess model fit.

Figure 13 shows a graphical representation of two different linear regression models with two independent variables, as is often depicted in the SEM nomenclature. The independent variables X_1 and X_2, shown in rectangles, are measured exogenous variables, with direct effects on variable Y_1, are correlated with each other. The model depicted in the bottom of the Figure reflects a fundamentally different relationship among variables. Variables X_3 and X_4 directly influence Y_2, but variable X_4 is also directly influenced by variable X_3. The two models imply different var-cov matrices. Both models also reveal that although the independent variables have direct effects on the dependent variable, they do not fully explain the variability in Y, as reflected by the error terms, depicted as ellipses in the Figure 13. The additional error term, e_3, describes and comprises the portion of variable X_4, which cannot by fully explained by the effect of variable X_3. Latent variables, if added to these models, would also be depicted as ellipses in the graphical representation of the SEM.

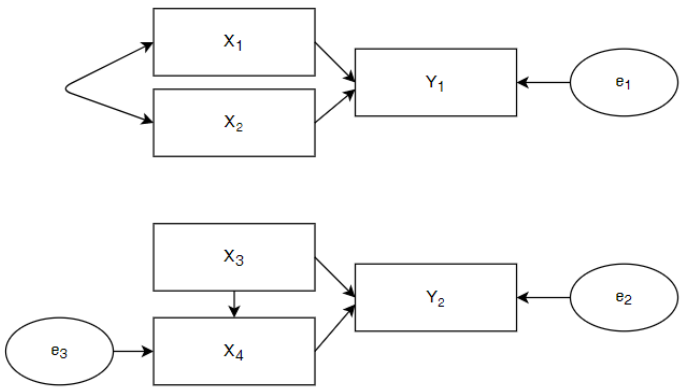

Figure 13: SEMs depicting standard linear regression model with two variables

(Dynamic) Discrete Choice Models

DDCMs are generalized discrete choice models that model an individual's choices among a set of discrete alternatives that have future implications. These models assume that observed choices result from an individual's maximization of the present value of utility and are known as discrete choice models of dynamic programming. Related literature and applications of DDCMs have been found in econometrics. One of the first applications of this model was proposed by John Rust (1987), for an engine replacement model. Another, more recent, example is formulated in Semenova (2018) as an Entry Game with a Long-Lived and a Short-Lived Player: an example of Apple's decision to release a new phone.

Many more examples can be found in econometrics. Cirillo and Xu (2011) give an overview of these models for transportation, including short- to medium-term vehicle-holding decisions.

Dynamic single-agent models, can be formulated as follows and as adapted from Aguirregabiria (2017).

At each time period t in a given time horizon *T*, an agent chooses $a_t \in A = \{0, 1, \dots, J\}$ to maximize.

$$E_t\left(\sum_{j=0}^{T} \beta^{S}\, U\left(a_{t+j}, s_{t+j}\right)\right) \qquad (4)$$

where:

- $s_t s_t s_t$ follows a controlled Markovian process with transition $f(s_{t+1}|a_t, s_t)$ and is a function of observable variables x_t and unobservable variables ε_t; $s_t = (x_t, \varepsilon_t)$
- β is the discount factor $\in (0,1)$ (which can be assumed as constant for a given state)
- *U* is the utility function and depends on both observable and unobservable variables
- $U(a_t, s_t) = U(a_t, x_t, \varepsilon_t) = \pi(a_t, x_t) + \varepsilon_t(a_t)$
- E_t is the present utility value

The problem can be written as a Bellman equation, solved by the value function $V(s_t)$

DBNs

A Bayesian Network (BN) is a directed acyclic graphical model that can express a joint probability distribution of a large set of variables (Sun and Sun, 2015). Usually, BNs are utilized for learning causal relationships and hence are ideal for investigating the effect of interventions by combining new and prior knowledge data. The core of BNs is the attempt to infer a "hidden" state based on a group of available observations. A simple BN structure is exemplified Figure 14:

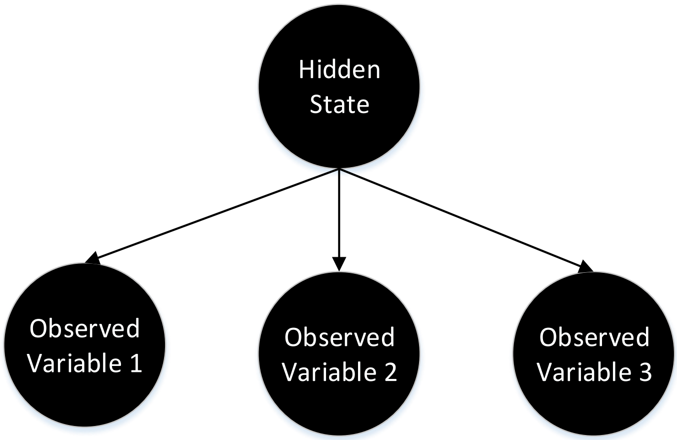

Figure 14: A BN example

In Figure 14, the arrows depict the causal dependency between the variables, and the nodes depict probabilistic layers associated with a probability distribution.

A DBN is an expansion of a BN to model sequential time series data. In a DBN, the hidden state in time slice *t* is represented by a set of N_H random variables as $H_t^{(i)}$, $i \in \{1, \dots N_H\}$, each of which could be discrete or continuous. Likewise, the observed variables can be represented by a group of N_O random variables as $O_t^{(j)}$, $j \in \{1, \dots N_O\}$. In state-space DBNs, along with the set of hidden and observed layers, a transition model $P(H_t|H_{t-1})$, an observation model $P(O_t|H_t)$ and the distribution of the initial state $P(H_0)$ need to be defined. With the distributions defined, the joint distribution of a DBN can be expressed as:

$$P\left(H_{0:T}\ ,O_{0:T}\ \right) = P(H_0)\prod_{t=1}^{T} P(H_t|H_{t-1})\,P(O_t|H_t) \qquad (5)$$

An illustration of temporal dependencies on a simple BBN is depicted in Figure 15.

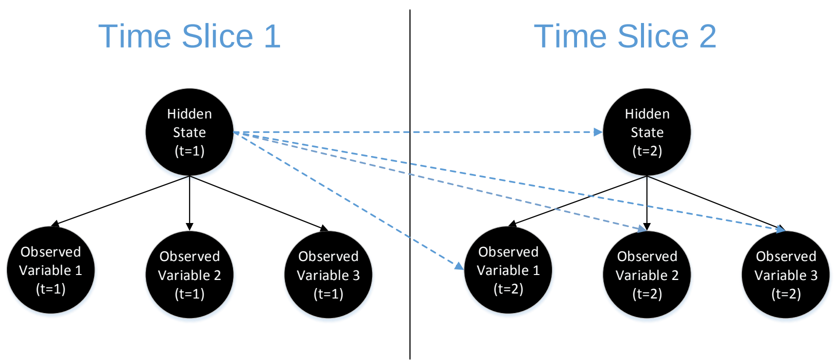

Figure 15: An example of a DBN (Bold arrows depict causalities in the same time slice while dashed lines depict temporal dependencies)

Long Short-Term Memory networks (LSTMs)

Long Short-Term Memory Models (LSTMs) are a special kind of RNN, capable of learning long-term dependencies (Gers et al., 2015). 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 a dot (scalar) multiplication operation, 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 schematised in Figure 16.

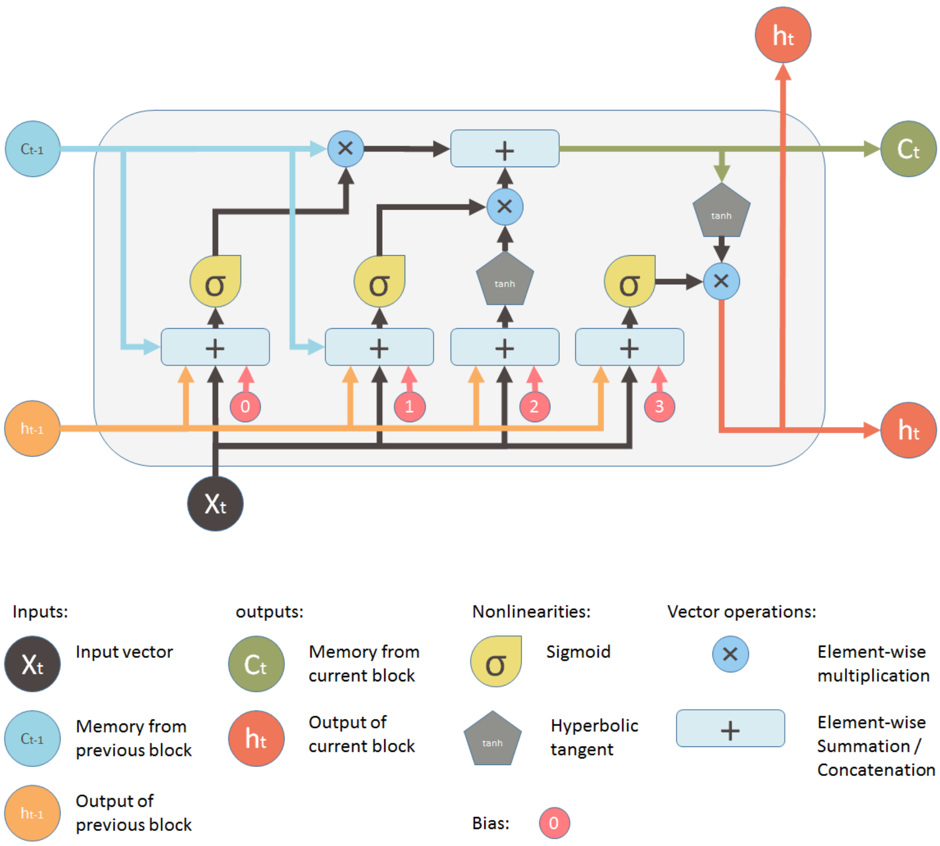

Figure 16: Long-Short Term Memory block graphical representation (Yan, 2016)

An LSTM has three of these gates, to protect and control the cell state:

- **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.” It looks at h_{t-1} and x_t, and outputs a number between 0 and 1 for each number in the cell state C_{t-1}.

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \qquad (6)$$

- **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.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (7)$$

$$C_{t'} = tanh(W_c[h_{t-1}, x_t] + b_c) \quad (8)$$

$$C_t = f_t * C_{t-1} + i_t * C_{t'} \quad (9)$$

- **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.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (10)$$

$$h_t = o_t + \tanh(C_t) \quad (11)$$

where:

- Xt and h_t: input and output of the memory cell
- h_{t-1}: input from previous state
- f_t, i_t, o_t: activation function of forget, input and output gates
- W_f , W_i, W_C, W_o: weights of forget, input, candidate and output gates
- b_f , b_i, b_c, b_o: biases of forget, input, candidate and output gates
- C_t and $C_{t'}$ candidate cell and updated cell state value

4.4.2 Application to STZ modelling

Structural Equation Models

According to the *i*-DREAMS concept of the STZ, ‘risk’ results from the interaction of ‘task complexity’ and ‘coping capacity’. However, all three core aspects are unobserved/ latent variables, which although not directly measurable may be estimated observed measures, as shown in Figure 17. For example:

- Task Complexity as a latent variable can be measured by metrics and indicators related to the road layout (i.e. speed limits, number of lanes, road type), time of day, traffic density & composition and weather (i.e. precipitation, visibility).
- Coping Capacity is also a latent variable, including two distinct aspects, both latent variables themselves. Operator State as a latent variable can be estimated based on numerous relevant indicators. In fact, there are even operator state aspects that are latent variables themselves. For instance: mental state can be inferred on the basis of metrics on alertness, attention, emotions, etc., although one may assume "indirect" measurement and by so conserve the term measured. Behavior can also be estimated using metrics such as speeding, harsh acceleration / braking / cornering, seat belt use, etc. However other more comprehensive constructs may be eventually estimated.
- Risk as a latent variable can be measured by indicators such as Danger phase events and Avoidable accident phase events, as detected by the STZ implementation.

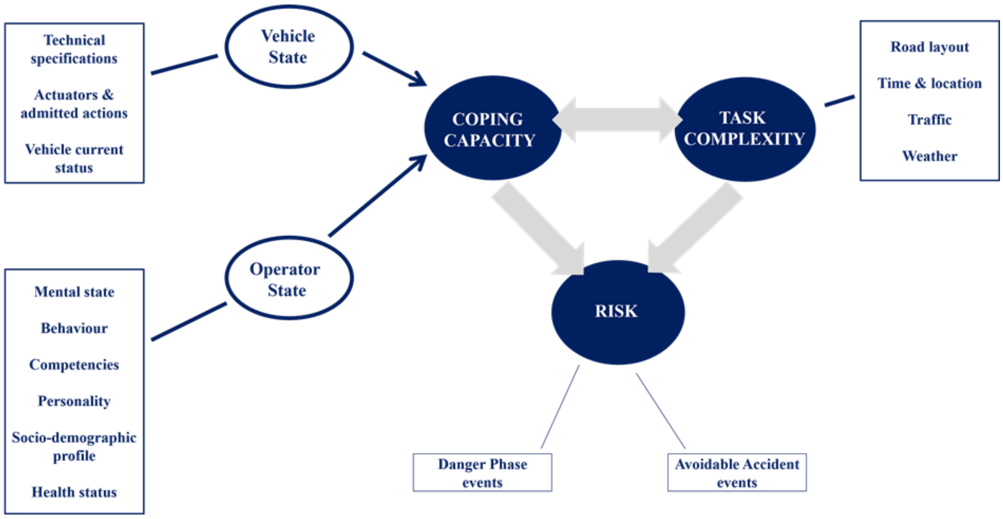

Figure 17: Path diagram of a SEM approach to i-DREAMS

In Figure 17, the measurement model uses the processed sensor data (indicators – these are shown in boxes) to estimate the various latent variables (these are shown in ellipses). The structural model estimates the correlations between factors based on the assumed paths. It should be mentioned here, that, as mentioned in Chapter 2, personality traits and driver characteristics are going to be solely used for triggering post-trip intervention and not for modelling the STZ. These variables are included for that purpose in Figure 17.

In order to estimate this model, two steps may be considered:

- An exploratory factor/Principal Component Analysis, in which the measurement model will be consolidated by means of testing different structures. This will allow on the one hand to identify the components of coping capacity and task complexity, for example, is mental state a separate component as initially assumed? Are there specific risk factors, e.g. distraction, fatigue etc., that warrant to be considered as separate components. On the other hand, the indicators with strongest loading for each component can be identified.
- A confirmatory analysis in the form of SEM, in which the structural model may reveal the relationships and interactions between coping capacity (as a whole or through its separate components) and task complexity, and their eventual impact on risk.

Dynamic Discrete Choice Models (DDCMs)

Before developing such models, preliminary steps may include clustering driving observations, and then training a transition process (Markov process) to enable the prediction subsequent events based on a current driving event (safety level), the next one. To summarize, this approach could follow the steps presented in Figure 18, as done in Antoniou et al. (2013) for dynamic data-driven local traffic state estimation and prediction. Steps a to c, described below, convey the offline training of the model, while steps d to f serve to predict the probability of a new observation (driving event) being in a safety zone. The steps are detailed as follows.

Model training:

a. Clustering driving events (observations) into three clusters as postulated in the STZ, into: Normal driving, Danger and Avoidable Accident phase. Many algorithms can be compared including Model-Based Clustering as used by Antoniou et al. (2013), neural networks, and Random Forests as in Wang and Xu (2019). An interesting approach would also be to test the ideal number of clusters and compare with what is postulated in the STZ.

b. Estimate the transition process: train a Markov process to predict the next state based on the last few states
c. Estimate the STZ model with one utility per cluster for an ordered model with one utility (one utility for an ordered model, with the estimation of cut-off values or thresholds between different levels)

Model prediction:

d. Classify a new driving event
e. Predict the next safety state
f. Calculate the safety level utility
g. Predict the probability of being in a certain level

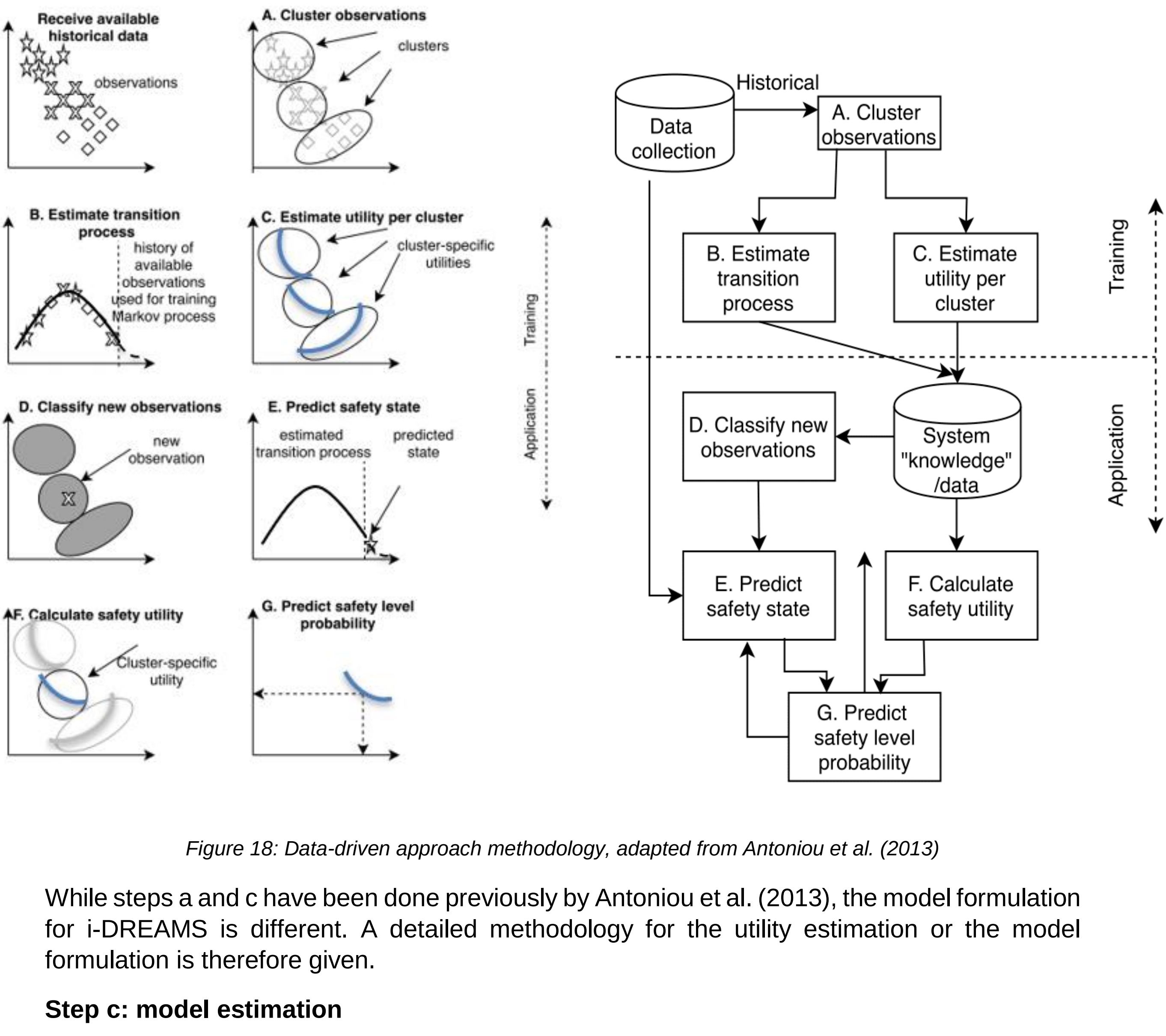

Figure 18: Data-driven approach methodology, adapted from Antoniou et al. (2013)

While steps a and c have been done previously by Antoniou et al. (2013), the model formulation for i-DREAMS is different. A detailed methodology for the utility estimation or the model formulation is therefore given.

Step c: model estimation

- The essence of the proposed DDCM approach has different fundamental aspects, in addition to discrete choice model properties.
- Discrete responses
- Latent variable model: aiming at identifying different driver types/driving styles or aggressiveness indices: which can be ordered
- Dynamic: continuous driving data

- The safety levels are potentially an ordered logistic model: from normal, to dangerous (avoidable), dangerous (unavoidable)

The ordered model could also be nested with two nests: Normal and Abnormal driving nest (avoidable accident, unavoidable accident).

The dependent variable or output in this model are the different driving behaviors/safety zones as Normal, Dangerous and Avoidable accident, which are potentially ordered (or not: multinomial logit) and are a function of the dynamically changing states of the vehicle (vehicle parameters), the road conditions (environment parameters), the driver/physiological (driver parameters), and the static variables (not changing over time or very slowly changing, such as driver demographics and/or attitudes obtained from the questionnaire; which are not really static but slowly changing, especially when compared to the time frame/duration of a single journey).

The overall safety level is defined as “normal” in the sense that the “objective” risk factors/safety-critical events, and the driver’s own perception lead to a situation in which there is no meaningful risk of the driver engaging in an incident in the following time step.

The methodology for this model (Step c) can be further divided in two sub-steps: a first one concerning the estimation of a static model for the safety tolerance zone, and a second one going to a dynamic model.

<u>Estimation of a **static model**, for a given period</u>
As previously mentioned, the procedure starts by estimating a multinomial model and then explores an ordered model. A later step could consider an integrated choice and latent variable model, as in Ben-Akiva et al. (2002). In the below formulation, a generalized utility equation is given, which can be substituted by different utilities for each alternative or one for the ordered model considering a formulation of the threshold calculations.

Assuming one latent variable for one agent (driver) n and for alternative *i*, the structural equations are as follow:

$$U_{ni}U_n = X_{ni}\boldsymbol{\beta_1}X_n\beta_2 + Z^*_{ni}\boldsymbol{\beta_l}Z^*_n\beta_l + \varepsilon_{ni}\varepsilon_n \text{ ; } \varepsilon_{ni}\varepsilon_n \text{ } standard \text{ } logistic \quad (12)$$
$$Z^*_{ni} = YX_{ni}\boldsymbol{\lambda_l}Z^*_n = X_n\lambda_l + \omega_{ni}\omega_l \text{ ; } \omega_{ni}\omega_l \sim N(0,\textstyle\sum\Omega) \quad (13)$$

where:

- $U_{ni}U_n$ is the utility for agent *n* for alternative *i*, X_{ni} and Y_{ni} are subsets of the explanatory variable X_n, β_2 is the coefficient of the explanatory variables, $\boldsymbol{\beta_{12}}$ is the coefficient vector (to estimate) of the explanatory variables of the utility, $Z^*_{ni}Z^*_n$ is the vector of latent variable(s), $\boldsymbol{\beta_l}$ is the coefficient vector (to estimate) of the latent variables and $\varepsilon_{ni}\varepsilon_n$ the error term of the utility, assumed to follow a standard logistic regression
- $\boldsymbol{\lambda_l}$ is the explanatory variable, λ_l is the coefficient vector (to estimate) of the explanatory variable in the modelling of the latent part, and $\omega_{nil}\omega_{ni}\omega_l$ are the error terms, assumed to be normally distributed

In addition, the latent variable may be able to explain some indicators I_{ni} given from questionnaires on attitudes and perceptions. The resulting measurement model equation is:

$$I_{ni}I_n = Z^*_{ni}\boldsymbol{\alpha}Z^*_n\alpha + \delta_{ni}\delta_n \quad (14)$$

where:

- $\boldsymbol{\alpha}$ is the coefficient vector (to estimate) for the measurement equations and δ_{ni} is the error component, which is assumed to follow a normal distribution

For Within the context of *i*-DREAMS, a hypothesis is made that the utility of the Safety Tolerance Zone includes a latent variable indicating the driving style or the aggressiveness index,, which can be ordered. The above equations become:

$$U_{safety} = X_{ni}\boldsymbol{\beta_{12}}X_n\beta_2 + Z^*_{ni}\boldsymbol{\beta_l}Z^*_n\beta_l + \varepsilon_{ni}\varepsilon_n \qquad (15)$$

$$Z^*_{ni} = Driving\ aggressiveness^*_{ni} = X_{ni}\boldsymbol{\lambda_l} + \omega_{ni} \qquad (16)$$

$$Z^*_n = Driving\ aggressiveness^*_n = X_n\lambda_l + \omega_{nl} \qquad (16)$$

Notes:

a- Alternative candidate for the latent variable could include driving risk or risk perception. This could also be “abnormal driving”. However, a question arises: can a particular subject “normal driving” style be by default a rather risky or dangerous behavior; therefore the “abnormal” driving would actually be similar to another person’s “normal” driving?

b- Additionally, the latent variable for driver aggressiveness, could be generalized to driving behavior.

The full path diagram for the latent variable model is given in Figure 19:

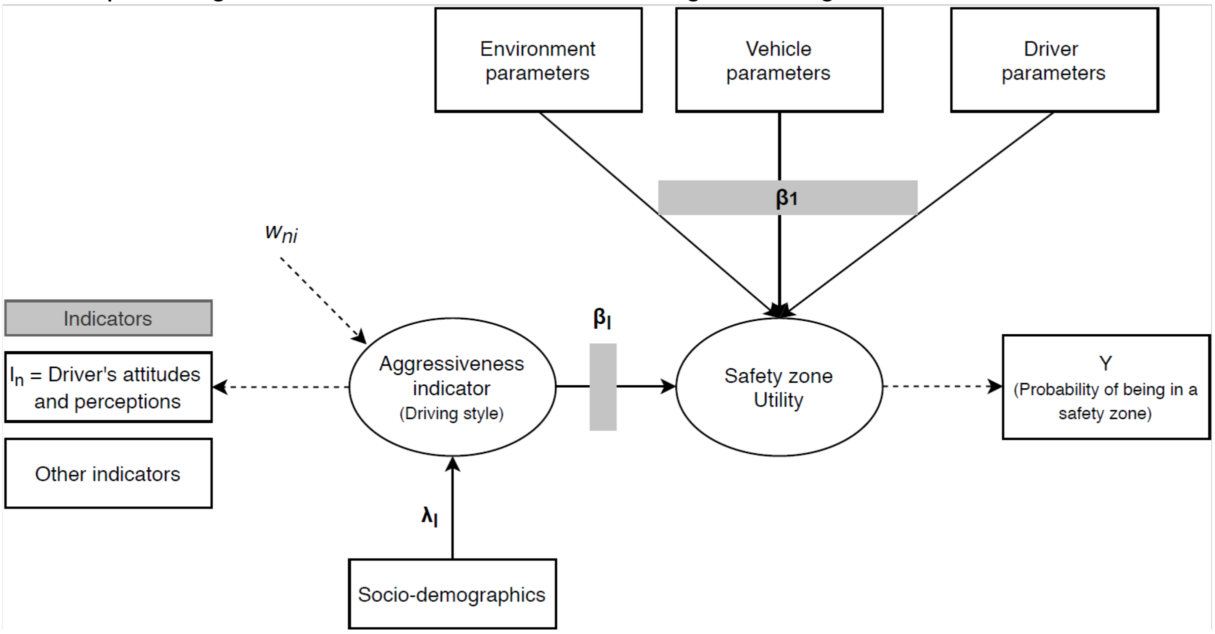

Figure 19: Full path diagram of hybrid choice and latent variable model of Safety Tolerance Zone

<u>Estimation of a **dynamic model**, for a given period</u>

Building from the static discrete choice model, an interest in modelling DCM dynamically arises, as many of the variables depicted in Figure 19: are indeed dynamic.

Question of interest: can the aggressiveness indicator or other driving style latent variable be considered static i.e. having enough driving data; it would be easy to estimate it, and it doesn’t subsequently change over time? Factors influencing the latent variable are likely to remain static; however this needs to be tested, and they are not restricted to socio-demographics, as could be suggested by the Full Path Diagram.

It is useful to break Equation 15 into the following structure, as the explanatory variables assumed to be a function of dynamic (γ_{nt}) and static parameters (μ) :

$$X_n = f(t) = \gamma_{nt}\gamma_{nt}\gamma_{nt} + \mu \qquad (17)$$

The following hypothesis can then be tested. As the coefficient related to the static variable needs to be estimated only once, the model formulation becomes simplified:

$$U_{safety,\ t} = (\gamma_{nt} + \mu)\beta + Z_n^* \beta_l + \varepsilon_n = \gamma_{nt}\,\beta_\gamma + \mu\beta_\mu + Z_n^*\beta_l + \varepsilon_n \quad (18)$$

Based on the same assumption that the latent variable is only explained by static variables: Firstly, a static model is estimated in order to solve for the latent variable (by taking enough observations over time), as are the static explanatory variables coefficients. The equation above can then be reformulated into a dynamic discrete choice model with the following utility for each safety level at each time t:

$$U_{safety,\ t} = \gamma_{nt}\,\beta_\gamma + \mu\beta_\mu + Z_n^*\beta_l + \varepsilon_n \quad (19)$$
$$Z_n^* = Driving\ aggressiveness_n^* = X_n\lambda_l\lambda_l + \omega_n \quad (20)$$

where:

- β_γ is the coefficient to estimate for dynamic parameters at every time step. Hence, for this particular case, the new dynamic choice model would consist of only solving β_γ at every time step.

Note, however, that the above consists of only looking at agent/driver n. By considering all agents/drivers: the problem is reformulated to a maximization problem integrating over all agents.

The optimization problem can be written as a Bellman equation and follows a Markov decision process. This is to be further explored in the later stages, as it is uncertain whether the *i*-Dreams can be solved using DDCMs. Moreover, it depends on the choice: estimate the problem or solve it, in addition to the choice of the time-period and time steps. The choice of time-steps is a relevant challenge for any method.

For estimation, commonly employed methods to estimate structural parameters are Maximum Likelihood Estimation and method of simulated moments.

On its turn, examples of full-solutions methods include nested fixed point (NFXP) algorithm by John Rust (1987) and the mathematical programming with equilibrium constraints (MPEC) by Kenneth et al. (2012).

Non-solution methods estimate structural parameters without fully solving the backwards recursion problem for each parameter. This, in turn, requires additional assumptions although being often realistic. However, the dynamic problem estimation may be challenging or even unfeasible real-time. The proposal by Hotz and Miller (1993) is therefore an exploration of this method, based on conditional choice probabilities. It should be noted that most DDCM applications have been econometric problems pertaining to household decisions for car ownership, or other problems, where states changed every year or months. In the case of the STZ, time steps vary from seconds to potentially milliseconds.

DBNs

In order to "sketch" the outline of the DBN model, all the necessary variable layers need to be a priori. In the *i*-DREAMS proposal, risk was defined as the outcome of the interaction between task demand and coping capacity, whereas both of the variables would be identified through measurements on the environment, the vehicle and the operator. As a result, four variables layers, where each layer includes one or more random variables, should be included in the DBN: task demand, coping capacity, indicators of context/operator/vehicle characteristics and sensor measurements. Following the principles of Bayesian Programming (Bessiere et al., 2013), the DBN can be formulated following four steps:

1. Definition of variables
2. Proposed joint distribution
3. Parametric forms, and finally
4. Risk estimation

Variable/Layer definition

Before diving into DBN details it is critical to establish the key variable definitions in the context of the STZ.

Task Demand: is the state of the world that imposes challenges upon the task of driving, i.e. the state in which the driver needs to handle the vehicle sufficiently. What is captured by the layer is the probability that the environment imposes significant challenges to the task of driving such that an accident might occur, as the variable cannot be directly measured. On the environment, task demand is therefore/thereby classified as a hidden variable.

The variable consists of three states:

- Low (normal) task demand
- Increased (dangerous) task demand
- High (avoidable accident) task demand

Coping Capacity: is the ability of the driver to address the imposed task demand. It is not only driven by cognitive and affective appraisal but also includes other factors such as:

- Expertise (may be included within cognitive)
- Physiological (reaction time)
- Diagnosed or undiagnosed Medical conditions
- Drug/alcohol ingestion

In other words, coping capacity can be defined as the probability that the vehicle operator is in a sufficient state to focus on driving. This is also a hidden variable, i.e. its states will be inferred based on the available observations.

The variable consists of three states:

- High (normal) coping capacity
- Decreased (dangerous) coping capacity
- Low (avoidable accident) coping capacity

Filtered ontext Operator Vehicle (COV) measurements: The variables monitored by the *i*-DREAMS platform concerning task demand, driver and vehicle state. These will be used to evaluate the “status” of the context-operator-vehicle system, based on which (or part of it) the current task demand and coping capacity will be inferred. This is also a hidden variable as it will be inferred based on the actually available raw observations. For example, if inattention is to be defined as a variable, it cannot be directly measured, but it is going to be inferred from suitable physiological indicators. This layer represents the probability of the true “state” of the indicators underlying the raw measurements captured by sensors.

The layer consists of the variables included in the COV list, as shown in Figure 20:. Some of them (e.g. Personality characteristics, socio-demographics) are static/uniform, whereas others are dynamic (they change continuously over time), e.g. traffic characteristics, alertness and attention. The layer depicts the set of the variables in the COV list, describing the context, operator and vehicle "system" at each time instant.

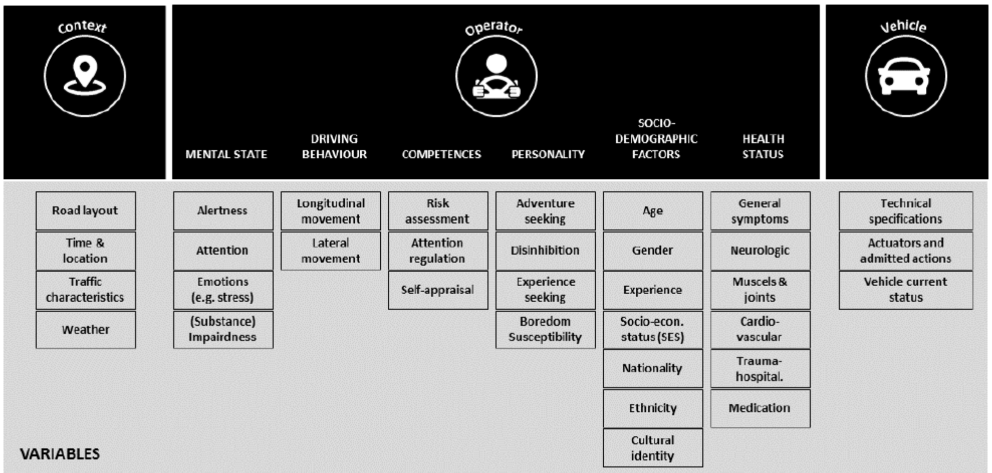

Figure 20: The COV Variables

Sensor observations are the raw measurements from the available technologies with regards to the COV indicators, and thus are observed variables.

<u>The relationship between the layers</u>

In order to define the structure of the DBN, the relationship between the variables needs to be defined. Initially, the raw sensor measurements will be observed. By filtering these raw measurements, the COV indicators will become available. Hence, the COV indicators rely on the raw sensor measurements. Furthermore, the COV indicators will be used in order to determine the coping capacity of the operator and the task demand at each time moment. Hence, the two layers of coping capacity and task demand depend on the COV indicators. Finally, as the operator's capacity indicates the ability of the driver to operate safely with regards to the task imposed, the operator's capacity depends on the demand of the task. As a result, the relationship between the different probabilistic layers is the one depicted in Figure 21.

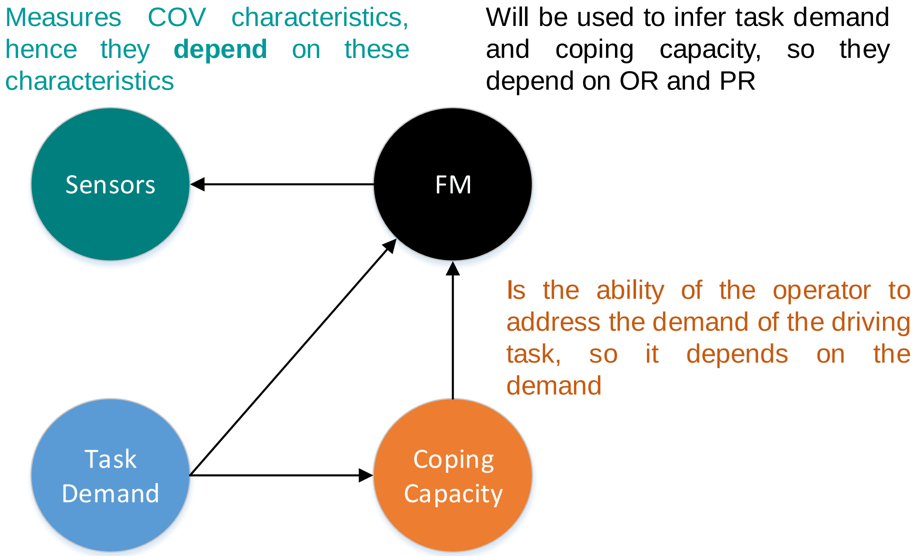

Figure 21: The relationship between the variables in one time moment

With regards to the time dependencies, it is assumed that the status of each hidden layer (i.e. Task Demand, Coping Capacity and Filtered COV measurements) depends on its status in the previous time moment. Furthermore, as coping capacity and task demand will be predicted by the available COV indicators, it is assumed that the filtered measurements will influence the status of task demand and coping capacity in future time steps. As a result, the time dependencies are assumed to be similar to Figure 22.

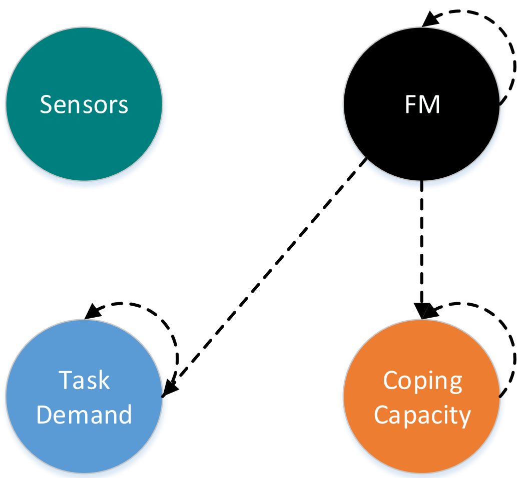

Figure 22: The time dependencies between the layers

<u>The proposed DBN structure</u>

Combining the layer dependencies as these were described in Figures 20 and 21, the proposed DBN structure along with the proposed characteristics to estimate task demand and coping capacity is the one depicted in Figure 23.

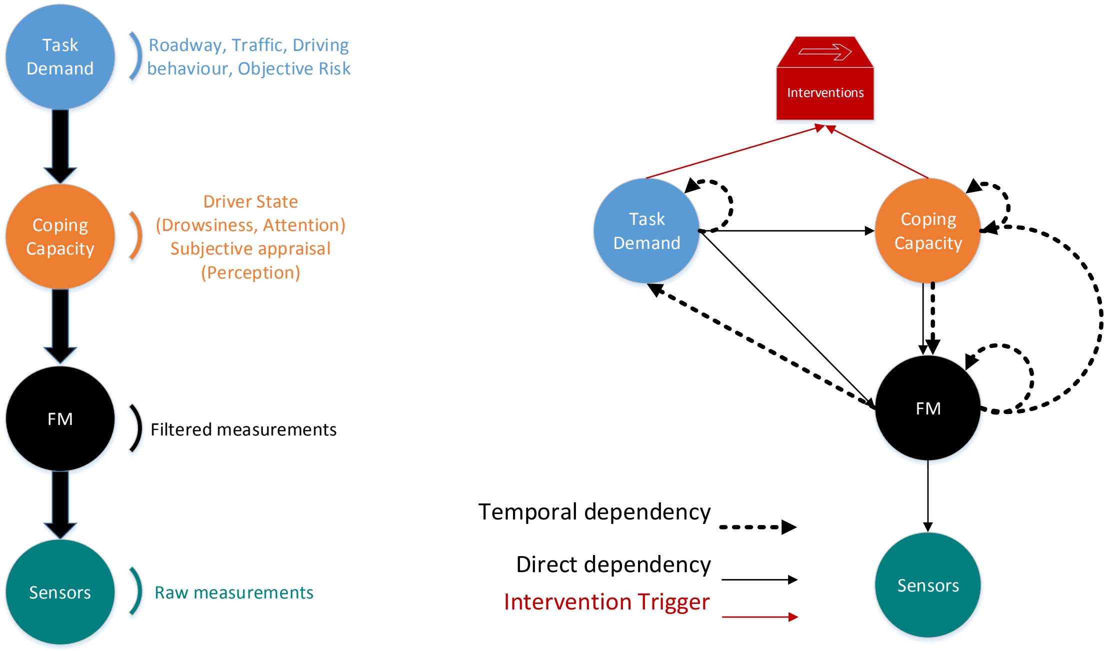

Figure 23: The proposed DBN for STZ modelling

The proposed DBN can be described by the joint distribution:

$$P(TD^{0:T}, CC^{0:T}, FM^{0:T}, Z^{0:T})$$
$$= P(TD_0, CC_0, FM_0, Z_0) \prod_{t=1}^{T} P(TD_t|TD_{t-1}FM_{t-1})\ P(CC_t|TD_tCC_{t-1}FM_{t-1})\ P(FM_t|FM_{t-1}TD_tCC_tCC_{t-1})P(Z_t|FM_t)$$

, $t \in \mathbb{N}\ and\ t \leq T$ (21)

where:

- TD: Task Demand
- CC: Coping Capacity
- FM: Filtered COV Measurements
- Z: Raw measurements
- t: current time step
- T: Total time of measurements

Parametric forms

Task Demand: The expected task demand $P(TD_t|TD_{t-1}FM_{t-1})$ is derived from the previous task demand and the available indicators on environment variables. There exists no formula to estimate task demand based on the measured variables, but a function that correlates task demand with the thresholds (Chapter 4) of available environmental variables (Chapter 2) can be used for providing current task demand information modified by a constant to depict the relationship between the current and the previous task demand.

$$P(TD_t|TD_{t-1}FM_{t-1}) = f(Environment, Vehicle\ variables, TD_{t-1}) \quad (22)$$

Coping Capacity: The current coping capacity $P(CC_t|TD_tCC_{t-1}FM_{t-1})$ can be estimated through functions that correlate the effect of task demand on coping capacity (Faure et al., 2016) modified by a factor to take the previous coping capacity into account.

$$P(CC_t|TD_tCC_{t-1}FM_{t-1}) = f(Driver,\ TD_t, CC_{t-1}) \quad (23)$$

Filtered Measurements: $P(FM_t|FM_{t-1}TD_tCC_tCC_{t-1})$ is the probability of the indicator values based on the current task demand and coping capacity as well as their previous values and the previous coping capacity can be mapped based on the specific scenarios that will be tested in the simulators. In that way, specific ranges of values or task demand- and coping capacity-specific measurements along with their corresponding probabilities of appearance can be identified.

Raw measurements: For the probability of the raw measurements $P(Z_t|FM_t)$ a sensor model based on Agamennoni et al. (2011), and the Student t-distribution can be followed.

STZ and abnormal driving identification

In order to assess the STZ levels and abnormal driving situations, a comparison between the layers of task demand and coping capacity needs to be defined. In order to identify avoidable accident or dangerous STZ levels, the following probability is proposed to be inferred

$$P(TD \neq normal \cup CC \neq normal\ |Sensors) \quad (24)$$

The aforementioned probability refers to situations that task demand and coping capacity are beyond normal operations (i.e. increased or high task demand with decreased or low coping capacity) given the available sensor observations. Examples of the different STZ levels according to task demand and coping capacity are highlighted in Table 14: If abnormal driving is detected, then the influence of abnormal driving could be added into coping capacity so that it is included in STZ calculation.

Table 14: Different STZ levels according to task demand and coping capacity

Task Demand	Coping Capacity	STZ Level
High	Low	Avoidable Accident
High	Decreased	Dangerous
High	High	Normal
Increased	Low	Avoidable Accident
Increased	Decreased	Dangerous
Increased	High	Normal
Low	Low	Dangerous
Low	Decreased	Normal
Low	High	Normal

Inference

As in such mathematical models exact inference is intractable in real-time, a sequential importance sampling filter (Lefèvre et al., 2013) can be used.

LSTMs

With regards to LSTMs, the problem of defining the STZ levels becomes more straightforward, since LSTMs as a sub-category of Deep Neural Networks act like “black-boxes” (Xu et al., 2013) and thus the only input that needs to be provided to the model are labelled time series data. An illustration of the proposed approach using LSTMs is given in Figure 24.

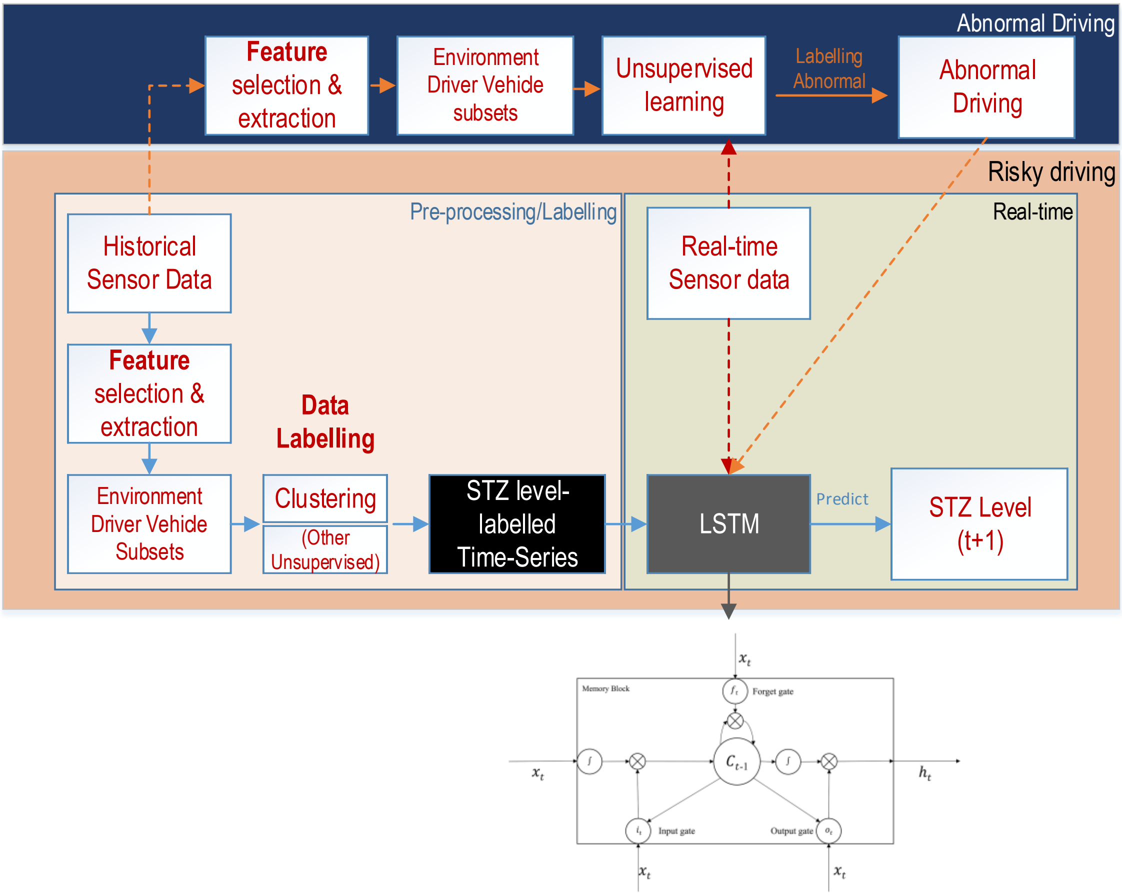

Figure 24: STZ modelling using LSTMs

In the proposed solution with LSTMs, historical sensor data will be used to extract and select features of the measurements to obtain the most important for STZ level detection. Afterwards, the most important measurements for monitoring the environment the vehicle and the driver become the input to an unsupervised learning algorithm that will group together measurements according to task demand and coping capacity, which, in turn, will act as input for training the LSTM model. After training the LSTM model with the labelled time-series data, the available real-time sensor data will be used as input for the model to predict the STZ level in the subsequent time. With regards to abnormal driving detection, collected historical measurements from the *i*-DREAMS technologies may also be used as input for an unsupervised learning approach grouping together measurements correlated with normal operation of a vehicle and those departing from normal driving behavior. The detection of abnormal driving may thereby become a valuable input to the STZ LSTM model.

4.5 Practical considerations

Practical considerations for implementing driving style recognition and incorporating into *i*-DREAMS platforms

There are a few practical considerations that need to be considered while implementing driving style recognition notion into the modelling framework, as an input variable.

Use of driving simulator and data collection period

As already indicated, recognising profiles of drivers requires extensive data of the pertaining to each driver, so that an algorithm could can be trained to identify a particular driving style. The collection of such an extensive dataset is often not possible from in a driving simulator, as it is difficult to recruit individuals who can spend hours in a virtual environment. It is, therefore, decided suggested that driving style recognition will only be incorporated included in on-field experiments. Additionally, in order to have sufficient dataset for each driver, it is recommended that at least 4-weeks of driving data are collected, for proper for driving style recognition. It is assumed that within this duration, drivers have made a sufficient amount of trips and have experienced a significant of situations, covering most driving scenarios each particular driver may find, which may give place to episodes of abnormal driving.

Experimentation of classification algorithm

A vast array of clustering algorithms can be found in the literature to be used for studying driving style profiles from vehicle and telematics datasets. The literature has reported mixed and conflicting results. And, as a result, it is not entirely clear which algorithm works best. Therefore, at this point definitive decision cannot be made about the use of a particular algorithm. However, some prominent algorithms (such as k-means, KL- divergence, SVM, MLP, etc.) will be tested once the dataset becomes available. Key performance indicators may be then determined for each algorithm to compare their efficiency in the form of confusion matrix along with considerations on its implementation within on-board devices to be used to recognize episodes of specific driving style in real-time and by so facilitate real-time intervention. A potential compromise between inaccuracies of predicting a sliding time window into a wrong driving style class and the feature practical implementation may be required to be considered. However, efforts will be made to reduce the extent of this compromise. Finally, smoothness of predictions according to measurements should be considered, especially in real-time situations. Black-box models (e.g. NNs) usually chop up continuous measures at arbitrary cut points and may jump back and forth among the three states of the STZ in a way that is unexpected and not user-friendly. DBNs usually have smoother transitions because the state at time t is directly informed by the state at time t-1, but this should be further examined during the simulator and on-road trials.

Experimentation and change of risk indicators and their thresholds

The thresholds values provided in Table 10 convey the understanding from existing literature and provide the necessary starting point to develop criteria for distinguishing classes of driving styles. However, extensive experiments will be carried out by varying these values (excluding indicator variables). It is also important to investigate if the clustering algorithm divides data into more than two classes. Additionally, some important risk indicator variables may be given an increased weightage within the process to promote the effectiveness of an algorithm. Furthermore, because several variables are introduced, it may be necessary to normalise these variables before being used in the analysis.

Usefulness of driving style recognition into post-trip interventions

During the post-trip intervention phase of the project, the information on driving style episodes is of great importance. Along with the feedback on special events, this information can also be fed to the drivers and intervention interventions can be set up that aiming at decreasing the abnormal driving episodes from driving data. The implementation of driving style recognition in the on-board devices will make sure that for each trip this data would also be available for post-trip intervention. Post-trip intervention on driving style is a more meaningful intervention compared to an intervention that focuses uniquely around a specific aspect of safety as driving style recognition covers a wide range of indicators.

Data Labelling and specification of specific scenarios for STZ modelling

As mentioned in Section 4.2, the problem of identifying the STZ levels is a classification one. Since classification is a supervised learning problem, in order to train the algorithms data must be labelled (i.e. there needs to be a distinction of measurements corresponding to the three levels of the STZ). In order to accelerate the procedure of training the model(s), specific risk scenarios need to be considered for STZ calibration. These scenarios along with the corresponding measurements that are needed, are depicted in Table 15.

Table 15: List of specific risk scenarios

Accident type	Contributing risk factors / behavior	Support system	Required metrics	Availability on-road	Availability in simulator
Head-on collision	Lane departure Risky overtaking	Lane departure warning Overtaking assistant	Position within lane (in Mobileye Research version, not in standard version) Vehicle in blind spot + Opposite vehicle speed and location + Acceleration potential + Posted speed limit	YES NO	YES YES
Rear-end collision	Following lead vehicle too closely	Headway collision warning	Time headway + TTC towards lead vehicle + Vehicle speed	YES	YES
Collision with vulnerable road user	Dangerous overtaking bicycle or moped on shared lane Dangerous approach of zebra crossing	Bicycle overtaking assistant Pedestrian detection warning	Time headway TTC towards bicycle Vehicle speed Vehicle speed Pedestrian detection & distance	NO NO	YES YES
Run off road accident	Driving while drowsy Driving while distracted	Lane departure warning Lane departure warning	Position within lane (Mobileye Research, not in standard version) Drowsiness indicator (CardioWheel)CardioWheel Position within lane (Mobileye Research) + Distraction detected (OSeven app)	YES YES	YES YES

5 Conclusions and next steps

This deliverable aimed at providing a toolbox of available measurements, thresholds and indicators as well as reviewing potential conceptualisations in order to identify and evaluate the three different STZ levels. The challenge in providing a list of thresholds for the four modes (i.e. car, bus, truck and rail) with regards to the STZ often concerns available measurements availability. Although technologies might hinder the evaluation of all the required parameters for a holistic driver and environmental monitoring, Chapters 2 and 3, provided a variety of measurements and corresponding thresholds to identify dangerous on-road situations.

Summarizing the contents of Chapters 2 and 3, Table 16 presents a list of proposed driver monitoring indicators with their available threshold values.

Table 16: List of proposed driver monitoring indicators along with the available threshold values (✓: A threshold can be defined but no standard value is indicated by the literature or technology company)

	Available threshold values		
Proposed measurements	**Cars**	**Trucks/Buses**	**Rails**
ECG signal	✓	✓	
drowsiness	✓	✓	X?
Fatigue	✓	✓	✓
steering wheel angle		✓	
PPG signal	✓	✓	X?
GSR/EDA signal	✓		X?
Sleepiness	50[5]		✓
distraction (via mobile phone use)	✓	✓	
interbeat interval	✓		
aggressiveness indicator	✓	✓	
harsh acceleration / deceleration	0.31g	0.25g	
speed exceedance (based on speed limit indicator and vehicle speed)	10%[6]	5%[5]	
speed at turns indication (based on turn indication activation)	5%[5]	5%[5]	
RPM	✓	✓	
time headway (TH)	2.0 sec[4]	2.5 sec[4]	
headway level	✓		
pedestrian collision warning (PCW)	2sec	✓	
vehicle ahead detected	✓		
forward collision warning (FCW)	2.7sec	✓	
urban forward collision warning (UFCW)	✓	✓	
left lane departure warning	✓	✓	
right lane departure warning	✓	✓	
low visibility indicator	✓	✓	

[5] 0-100 level
[6] Per cent over the speed limit plus 2 miles per hour (mph)

	Available threshold values		
Proposed measurements	Cars	Trucks/Buses	Rails
long driving hours	4-6hours	8hours[7]	
driving during risky hours	✓	✓	
roadway scene video	✓	✓	

With regards to the mathematical conceptualisation of the STZ both dynamic (i.e. DBNs and LSTMs) and static (i.e. SEMs and DCMs) approaches are proposed. DBNs and LSTMs were chosen due to their efficiency and flexibility in real-time predictions, whereas SEMs and DCMs were chosen as they can enable explanatory analysis on precursors of the STZ levels. Although a dynamic DCM can be formulated, real-time efficiency might arise as a problem and in that case, DCMs are going to be implemented statically. The reasonre are twos behind the suggestion of both dynamic (online) and static (offline) prediction techniques: i) to enable for flexibility with regards to the technical implementation of the model and ii) to exploit the online/offline characteristics for the activation of real-time/post-trip interventions. For all the proposed approaches, a labelled dataset is needed for training and this should be taken into consideration for the data collection.

The outcome of the present deliverable also dictates that the project following work steps include:

- The “translation” of the mathematical models into code, so that they are ready for technical implementation.
- The testing, calibration and enhancement of the mathematical models during the simulation and on-road experiments to assure a sufficient and efficient data collection as well as timely initiation of the interventions.

[7] Recommended 8 hours before breaking for professional truck and bus drivers, for cars it is considered around 4-6 hours

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Annex A: Detailed literature review of models and techniques

Table 17: Summary of models and techniques of related driver behavior systems

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
2019	Katrakazas et al.	speed, lateral and longitudinal position, acceleration, heading	safe or dangerous behavior during automated driving (safe, collision or conflict-prone traffic conditions)	real-time	risk level (probability)	highway, rural, urban	Dynamic Bayesian Network (DBN)	interaction-aware motion models, collision risk network-level (CRN), collision risk vehicle-level (CRV)	statistical
2019	Papazikou et al.	driver factors (age, gender, miles driven previous year), vehicle kinematics (vehicle type, speed, yaw rate, lateral and longitudinal acceleration, deceleration) and factors related to the time within the event sequence (system timestamp, system timestamp squared)	TTC	real-time	risk level (probability)	highway, rural, urban	Hierarchical Linear Model (or multilevel mixed effects linear regression model)	Strategic Highway Research Program 2 (SHRP2 NDS) method	statistical
2019	Xue et al.	acceleration, relative speed, relative distance, Inversed Time to Collision (ITTC), Time-Headway (THW), Modified Margin to Collision (MMTC)	safe, high risk, low risk, dangerous	real-time	risk level (probability)	highway, rural, urban	K-means algorithm, Supporting Vector Machine (SVM)	Discrete Fourier Transform (DFT), Discrete Wavelet Transform (DWT) methods (inference)	machine learning
2019	Zhou et al.	longitudinal velocity, longitudinal deceleration, lateral acceleration, yaw rate, steering wheel angle and service of brake	TTC	real-time	risk level (low, medium, high)	highway, rural, urban	Multivariate Gaussian Distribution (MGD) model, Gaussian Mixture Model (GMM)	maximum likelihood estimation (MLE) method, Expectation–maximization (EM) algorithm	statistical
2019	Girma et al.	speed, time	original, anomalous and noisy data	real-time	abnormal driving (probability)	city way, parking space, motorway	Long Short-Term Memory (LSTM) model	Time series algorithm method: Recurrent Neural Networks (RNNs)	machine learning

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
2019	Kanaan et al.	GPS speed, steering wheel position, lateral and longitudinal acceleration	long off-path glance, secondary task engagement and motor control difficulty	real-time	abnormal driving (low, medium, high)	highway, rural, urban	Hidden Markov Model (HMM)	Baum-Welch algorithm uses Maximum Likelihood Estimation (MLE), Naturalistic Engagement in Secondary Task (NEST) dataset (inference)	machine learning
2019	McDonald et al.	physiological (breathing rate, heart rate, and perinasal perspiration) and driving behavioral (brake force, lane offset, speed, and steering angle) data	normal or abnormal driving	simulator	abnormal driving (low, medium, high)	highway	Random Forest (RF)	Time Series Feature Extraction based on Scalable Hypothesis tests	machine learning
2019	Hashimoto et al.	driver’s vehicle position data, appearing objects, and brake pedal data	positive or negative data	simulator	abnormal driving (probability)	highway, rural, urban	Hidden Markov Model (HMM), Single Shot Multibox Detector (SSD) model	Likelihood threshold method (inference), time series clustering and probabilistic modelling based on HMM	machine learning
2019	Bao et al.	crash data, large-scale taxi GPS data, road network attributes, land use features, population data and weather data	crash risk scale, spatiotemporal analysis of crash risk	real-time	risk level (aggregated spatiotemporal steps)	urban	Spatiotemporal convolutional long short-term memory network. Four commonly-used econometric models, and four state-of-the-art machine-learning models are selected	Comparison of econometric models with machine learning models based on the usual goodness of fit measures (MSE, MAE, MAPE)	machine learning

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
							as benchmark methods		
2019	Wang et al.	naturalistic car driving data from cameras, GPS, speedometer, accelerometer and radar. Total of 19133 trips and 162000 km.	risk groups, estimation of the probability of each individual being a high-risk driver	offline	risk level (classification; calculation of probability)	urban	K-means clustering, Logistic regression models	Strategic Highway Research Program 2 (SHRP2 NDS) method; clustering and then regression analysis based on principal components	statistical
2019	Zheng et al.	near signalized intersections, vehicle trajectories and lengths, crash records including information such as location, date, time, crash type, crash severity, crash occurrence, more details on the direction of travel of incident vehicles, the lane incident vehicle occupied, and the total number of involved vehicles	number of crashes	offline	risk level (probability)	urban	Bivariate extreme value model	Bivariate extreme value model to integrate different traffic conflict indicators for road safety estimation, validation with actual crash data by four traffic conflict indicators, TTC, MTTC, PET, and DRAC	statistical
2019	Dimitriou et al.	economy, demographics, road network and enforcement characteristics	global mortality rates 2010, 2013		Rates		SEM	Cluster	Statistics
2019	Useche et al.	risky behaviors, risk perception, knowledge of traffic norms and cycling intensity	cyclists crash frequency		Number		SEM		Self-report
2019	Papantoniou et al.		driver error in simulated driving	simulator	Driver error		SEM		
2019	Zhao et al.	driver characteristics, illegal actions and attitudes	driver behavior	simulator	Driver performance		SEM		

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
2019	Ding et al.	visual perceptual, vehicular, and roadway factors	car following on curves		Crash risk		SEM		SSM
2018	Wang et al.	vehicle speed, acceleration, throttle opening, braking force, engine speed, steering angle	driving maneuvers, driving preference/styles, decisions	real-time	abnormal driving (probability)	highway, rural, urban	Bounded Generalized Gaussian Mixture Model (BGGMM), Hidden Markov Model (HMM)	Expectation Maximizationmethod consisting of E-Step and M-Step, log-likelihood function (inference)	machine learning
2018	El Hatri et al.	artificial data on a grid network, containing traffic information including the mean speed of vehicles traveling on a lane, the lane occupancy rate, the current traffic flow and the flow rate at previous time intervals, also artificially created incidents	traffic incident detection	real-time	no monitoring of driving behavior, rather prediction of traffic incidents based on the macroscopic characteristics of traffic flow	urban	Fuzzy deep learning based traffic incident detection, initialized through a Stacked Auto-Encoder (SAE) model	Comparison of machine learning models based on MSE. Detection rate and mean time to detection as criteria.	machine learning
2018	Zheng et al.	road geometrics, video recordings, and crash records	number of crashes	offline	risk level (probability)	urban motorway	Bivariate threshold excess models with different parametric distribution functions	Severity of events based on post encroachment time (PET) and length proportion of merging (LPM), crashes relating to merging events on freeway entrance merging areas	statistical
2018	Shah et al.	institutional framework, infrastructure, legislation, EMS, user	modelling risk in Asian countries		Composite		DEA/SEM		DEA
2018	Najaf et al.	walkability, connectivity, economic indicators, congestion, infrastructure	safety of urban areas		Composite		SEM		Statistics

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
2018	Elyasi et al.	human, road, traffic	relationships between crash risk factors		Crash risk		SEM		Statistics
2018	Useche et al.	Knowledge of rules, cycling intensity, risk perception, distress	Risky cycling behavior per gender		Risky behavior		SEM		Self-report
2018	Papantoniou		Driver performance in simulated distracted driving	simulator	Driver performance		SEM		
2017	Chang and Edara	inattention, speeding and driving under influence, driver characteristics, pre-incident variables	crash, near-crash and baseline pre-event risk	real-time	risk level (probability)	highway, rural	Random Forest (RF)	classification	machine learning
2017	Zhu et al.	driver's emotions, behavior, individual driving risk and crash frequency, vehicle speed, acceleration, braking events, vehicle motion, total exposure as mileage of travel	crash or near-crash risk	real-time	risk level (probability)	freeway, ramp, arterial, highway, minor road	Bayesian Network Network (DNN)	Monte Carlo Marconian Chain (MCMC) method (inference), Poisson regression process	statistical
2017	Chu et al.	interpolated vehicle trajectory observation sets extracted from video data, vehicle density from detectors	gap acceptance by merging vehicles (MVs) on urban expressways	offline	risk level (relative distance, time to collision)	urban motorway	Discrete choice models, including a multinomial logit model (MNL), a nested logit model (NL), and a Latent Choice Set model (LCS)	Analyses to indicate the TTC thresholds for an MV to reject or accept a gap.	statistical
2016	Amsalu and Homaifar	lateral acceleration, speed, yaw rate, steering wheel angle, odometer, turn signals	predicted maneuvers	real-time	abnormal driving (probability)	highway	Hidden Markov Model based on Genetic Algorithm (HMM-GA)	Baum-Welch Algorithm, Hybrid-State System (HSS) framework	machine learning

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
2016	Machiani et al.	real-time field measurement of vehicle trajectory data	level of safety at signalized intersections	real-time	risk level (safety surrogate histograms)	urban, intersections, dilemma zone	Vehicle speed data and their corresponding TTC values were extracted from the time-space diagram for each vehicle pair	Level of safety at signalized intersections (inference)	visual
2015	Yokoyama and Toyoda	physical/mental fatigue, aggressiveness, acceleration, jerk (the derivative of acceleration with respect to time), yaw velocity	safe or unsafe behavior	real-time	risk level (probability)	highway, rural, urban	Support Vector Machine (SVM) model	Gaussian kernel function (classification), entropy-like and KL divergence methods (purpose)	machine learning
2015	Saifuzzaman et al.	trajectory data from driving simulator experiment, human factors	following vehicle acceleration and spacing	real-time	risk level (based on driver capability)	urban, simulator	Task Difficulty Car-Following (TDCF) model applied on Gipps' and Intelligent Driver (IDM) car-following models, based on driver's satisfaction with current speed	Interaction between driving task demand and driver capability	optimisation
2014	Zhang et al.	accelerator, deceleration, turning uniform motion, steering wheel, changing lane, overtaking processes	accelerator and steering wheel data	simulator	abnormal driving (probability)	highway, rural, urban	Hidden Markov Model (HMM)	Baum-Welch algorithm, Forward-Backward algorithm	machine learning
2014	Bouhoute et al.	external environment signals (traffic signs, collision warnings), vehicle characteristics and driving actions performed (velocity, acceleration, deceleration, lane used by the vehicle, following distance, steering angle)	convenient (safe state), tolerable (temporarily safe state) or risky (unsafe state) driving behavior	real-time	risk level (probability)	highway	Hybrid Input/Output Automaton (HIOA) formal model, Vehicular Ad-hoc Network (VANET)	rectangular hybrid automata (classification)	online passive learning automata process

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
2014	Merrikhpour et al.	speed limit compliance rate, headway time compliance rate, age, gender, speed limit zones,	clusters, compliance rates pre and post-intervention	real-time interventions, offline evaluation	risk level	rural, urban and suburban		Pair-wise comparisons of concurrent noncompliance rate, before and after interventions	statistical
2014	Wu et al.	Virginia Tech Transportation Institute 100-Car Naturalistic Driving Study dataset and driver-related information such as stress, coffee intake, sleeping hours etc.	the number of traffic safety events and crashes while controlling for driver characteristics and severity level	offline	risk level (probability)	rural, urban and suburban	Multivariate Poisson log-normal model (MVPLN)	association between the number of traffic safety events and crashes while controlling for driver characteristics; count regression models are suitable	statistical
2013	Sangster et al.	car-following events recorded across eight drivers, latitude, longitude, horizontal speed, distance to preceding vehicle	speed of car-following vehicle	offline	continuous collection of car-following data	highway	Car-following models with parameter calibration (optimisation) based on RMSE	Optimisation based on RMSE, filtering and smoothing vehicle trajectories, discretisation of trajectories based on time, analytical car-following models	statistical
2013	Chong et al.	naturalistic car driving data	acceleration of vehicle	offline	car-following data	highway	Fuzzy rule-based neural network	Fuzzy logic is used to discretise traffic state and action variables and reinforcement learning method is used for neural network to learn driving behavior from naturalistic data	machine learning
2013	Daziano et al.	simulation data from three-legged intersections in California	construction of intervals	review	review	rural, urban and suburban	Hierarchical Bayes methods, Bayesian Markov chain Monte Carlo methods	Review of computational Bayesian econometrics and statistics applied to transportation modelling problems in road safety analysis and travel behavior	statistical

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
2012	Lefèvre et al.	geometry, topology, pose, speed, distance traveled, intention to stop, expectation, physical, behavioral variables	traffic situation and risk at road intersection, maneuver intention	real-time	risk level (probability)	highway, rural, urban	Dynamic Bayesian Network (DBN)	Vehicle-to-Vehicle (V2V) wireless communication links	statistical
2012	Koutsopoulos et al.	vehicle position, lane, speed, acceleration and deceleration at 0.1s	acceleration of vehicle	offline	collection of car-following data	urban motorway	Discrete choice model. Latent class-like model. Creates a desired mixture of acceleration, deceleration or do-nothing in order to estimate the desired speed to the preceding vehicle	Joint distribution of sequence observations, maximisation of the likelihood function	statistical
2011	Angkititrakul et al.	acceleration,deceleration, vehicle velocity, following distance, gas-pedal pattern	car-following behavior	real-time	abnormal driving (probability)	highway, rural, urban	Gaussian mixture model (GMM)	maximum a posterior (MAP)	statistical
2011	Jovanis et al.	driver attributes, demographic (gender, years driving, age) and physiological (visual or other impairments), event attributes (precipitating event), driving contexts (road, environment, and traffic conditions at time of event)	crash, near crash, critical incident, non-crash risk	real-time	risk level (probability)	highway, rural, urban	standard binary Multilevel Logit model	quasi-likelihood method, Taylor series expansion, linearization method (purpose)	statistical
2011	Constantinou et al.	sensitivity to reqard, disinhibition, impulsiveness, experience, violations	Young drivers offenses and accidents		Number		SEM		Self-report
2010	Ma et al.	attitudes, perceptions, violations (aggressive or ordinary), concern	Behavior and safety of public transport drivers		Likelihood of crash		SEM		Self-report
2008	Imkamon et al.	acceleration, velocity, engine rpm, free driving space, change in left/right view according to driver's vision	3 levels of hazardous driving	real-time	risk level (high, medium, low)	highway, rural, urban	Fuzzy logic model	KLT algorithm	statistical

Year	Author	Input variables	Output variables	Evaluation	Monitoring driving behavior	Road environment	Utilized model	Method	Technique
2008	Shankar et al.	contextual (roadway, environmental, traffic), surrogate (precipitating factors, incident triggers) and driver (attitudinal, profile) variables	crash or non-crash risk	real-time	risk level (probability)	freeway, non-freeway	hierarchical Dynamic Bayesian model (DBM)	Case Control method, Cohort based design method (purpose)	statistical
2007	Abe et al.	driver's state (driver is in hurry or not, stress, heart rate, heart rate variability), acceleration, stop, coasting, braking	vehicle speed, gas pedal stroke, brake/ no-brake pedal stroke	simulator	abnormal driving (high, medium, low)	highway, rural, urban	Auto-Regressive Hidden Markov Model (AR-HMM)	Probability calculation	machine learning